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Work in progress:

Climate Adaptation Through Crop Variety Selection: Farmers' Preferences for Climate-Resilient Rice and Maize Traits in Colombia

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Abstract

Understanding farmers' preferences for climate-resilient crop varietal traits is essential to guide breeding programs toward developing varieties that enhance agricultural adaptation to climate change, ultimately strengthening food security under increasing environmental pressures. This study analyzes Colombian farmers' preferences for climate adaptation and environmental stress tolerance traits in improved rice and maize varieties using Best-Worst Scaling (BWS) methodology combined with random parameters logit (RPL) models.

Data was collected through face-to-face surveys with 565 rice farmers and 800 maize farmers across main producing departments covering diverse agroecological zones and climate risk areas as part of the "Sustainable Agrifood Colombia" project. We evaluated the relative importance of ten key breeding objectives for each crop, with particular emphasis on tolerance to biotic and abiotic climate stressors.

Results reveal significant farmer demand for climate adaptation traits. While grain yield emerges as the most valued attribute for both crops nationwide (27% preference share), climate resilience traits show substantial importance with drought tolerance capturing 13% of maize farmers' preferences. Regional climate variability drives distinct adaptation preferences: rice farmers in the Central region prioritize disease resistance (Burkholderia glumae tolerance, 19%) reflecting bacterial pressure under climate stress, while maize farmers in the Andean region emphasize drought tolerance (17%) and temperature tolerance (16%) significantly above national averages. Farm-level climate exposure influences trait prioritization: large farms (>50 ha) demonstrate stronger preferences for climate resilience traits; rainfed rice farmers emphasize disease resistance over irrigated farmers; and manual maize systems value climate resilience traits significantly more than mechanized systems.

These findings provide actionable insights for climate-smart breeding program resource allocation, with differentiated preferences across climate zones validating the need for targeted climate adaptation approaches. This research contributes to environmental economics and agriculture economics literature by applying choice-based preference methods to understand climate adaptation decisions in developing agricultural systems, providing empirical evidence for designing climate-smart agricultural policies that align with farmers' actual climate adaptation priorities while enhancing agricultural resilience to environmental stressors.

JEL Classification: Q54, Q15, Q12, Q16

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1 Introduction

Rice and maize represent cornerstones of Colombian food security and economic stability. Rice serves as an essential dietary component providing fundamental calories and proteins for both rural and urban populations (Phillips et al., 2023), while contributing to significant yield increases of 1.15-3.36% annually in regions like the Colombian Caribbean (Tatis et al., 2011). Similarly, maize contributes approximately 9% of daily energy intake in the Colombian diet (Govaerts et al., 2019) and supports 391,000 families economically (Tapia Coronado et al., 2022). From an economic perspective, rice contributes 4% of agricultural GDP and 5% of agricultural employment (Díaz Valencia, 2012), while maize accounts for 5% of agricultural GDP (Tapia Coronado et al., 2022). However, both crops face significant production challenges. Despite a 76% increase in national maize production between 1961 and 2016, Colombia's dependence on imports reached 74% by 2016 (Govaerts et al., 2019), while rice sector competitiveness faces ongoing challenges with varying regional profitability (Chica et al., 2016; Dorado Urbano, 2023). Maize yields remain modest at 3.8-3.9 tons per hectare (Tapia Coronado et al., 2022), and trade liberalization through Free Trade Agreements has generated mixed outcomes for both crops (Quispe, 2009; Díaz Valencia, 2012). This situation highlights a critical challenge: understanding what varietal characteristics Colombian farmers prioritize when selecting improved varieties. The success of breeding programs and food security initiatives like the National Maize Plan and "Soya-Maíz proyecto País" (Tapia Coronado et al., 2022) may ultimately depend on aligning variety development with farmers' true preferences regarding factors affecting production, rather than assuming what traits matter most.

International research has highlighted the central role of farmer preferences in the success of breeding programs. Nalley et al. (2016) demonstrated that hybrid rice adoption in the U.S. plateaued when breeders failed to address trade-offs between yield and input costs. Similarly, Shew et al. (2015) found that neglecting farmers' non-agronomic concerns in India, despite gains in disease resistance, hindered the adoption of genetically modified. crops. These studies highlight how misalignment between breeding priorities and farmer preferences can limit the impact of technically superior varieties in agricultural systems.

This research addresses a fundamental question in agricultural development: What varietal traits do Colombian rice and maize farmers prioritize, and how do these preferences vary across different farming systems and regions? Understanding farmer preferences for specific breeding objectives—such as yield potential, disease resistance, climate tolerance, and grain quality—is essential for developing varieties that will be valued and utilized by producers. By capturing trait preferences across Colombia's major rice- and maize-producing departments, six for rice (Casanare, Córdoba, Huila, Meta, Norte de Santander and Sucre) and ten for maize (Antioquia, Arauca, Bolívar, Cesar, Córdoba, Huila, La Guajira, Meta, Tolima, and Valle del Cauca), this study provides a nationally representative view of the heterogeneity in farmer decision-making.

Previous literature in Latin America has laid foundational insights into varietal adoption, but has often focused on institutional or infrastructural barriers, such as access to markets or extension services, rather than the traits of the varieties themselves. Studies by Martinez et al. (2023) and Navarro-Niño et al. (2023) offer useful perspectives on these factors but rarely integrate systematic preference elicitation techniques. When varietal preferences are addressed, the use of conventional rating scales introduces potential for scale-use bias and weak discrimination across options (Finn and Louviere, 1992: Caputo & Lusk, 2020).

Moving beyond adoption studies, some research has attempted to more directly examine crop varietal trait preferences in Colombia. For rice, Arango-Londoño et al. (2020) identified that varietal selection is critical for maximizing yields, with specific preferences for rainfed and irrigated systems, highlighting factors such as yield and seed availability. For common beans, Floro et al. (2018) demonstrated through revealed preference models that farm elevation, household composition, and shorter vegetative cycles are key determinants in Santander. Although specific studies on maize trait preferences in Colombia are lacking, research in similar contexts such as Tanzania (Mutanyagwa, 2017) which indicates that farmers prioritize high yield, drought tolerance, and disease resistance. Pacini et al. (2021) reinforce the importance of integrating farmers' preferences into sustainable intensification programs. This literature suggests opportunities for future research in Colombia using advanced preference elicitation methods that consider local agroecological and socioeconomic contexts while focusing specifically on varietal trait preferences.

This undergraduate thesis contributes to literature in three ways. First, it applies Best-Worst Scaling (BWS) to elicit farmers' preferences for varietal traits more accurately than conventional rating techniques. By forcing respondents to make trade-offs between competing attributes, BWS reveals clearer importance hierarchies while reducing common response biases (Flynn et al., 2007). This is especially valuable in agricultural settings where farmers operate under resource constraints and must make explicit prioritization decisions.

Second, it combines BWS with multinomial and random parameters logit models to quantify preference shares for ten key breeding objectives identified through expert consultation. This modeling framework allows estimation not only of the rank order of traits but also the relative magnitude of preference differences, providing a statistically rigorous foundation for trait prioritization. Incorporating this level of granularity offers breeding programs actionable insights for allocating resources more efficiently and designing varieties that reflect farmers' actual decision-making processes (Areal & Pérez, 2025).

Third, the analysis captures significant heterogeneity in trait preferences across regions, farm sizes, and production systems. Recent studies show that agroecological and socioeconomic factors, such as climate variability or access to technology, significantly shape farmer valuations of varietal traits (Zander et al., 2024; Stetter et al., 2025). By disaggregating results across these dimensions, the study generates empirical evidence to support targeted and locally adapted breeding strategies, avoiding the inefficiencies of one-size-fits-all varietal development. Together, these contributions fill a critical gap in the literature on farmer-centered breeding and offer robust, context-sensitive insights for improving the design and dissemination of improved rice and maize varieties in Colombia.

The main findings reveal that grain yield emerges as the most valued attribute for both crops nationwide, capturing 27% preference share for both rice and maize farmers. However, significant heterogeneity exists across contexts: rice farmers prioritize milling quality (13%) and panicle sterility resistance (11%) as secondary traits, while maize farmers value grain hardness (15%) and drought tolerance (13%). Regional analysis demonstrates substantial variation, with rice farmers in the Central region uniquely prioritizing Burkholderia glumae tolerance (19%) over yield, and maize farmers in Orinoquia showing exceptionally strong yield preferences (36%). Farm size significantly influences trait prioritization, with large farms demonstrating distinctive preferences for climate resilience traits in rice and disease resistance in maize, while production systems reveal that rainfed rice farmers emphasize disease resistance more than irrigated farmers, and manual maize systems prioritize climate resilience traits more than mechanized systems.

The thesis is organized as follows: Section 2 reviews the theoretical frameworks underlying farmer decision-making and previous applications of BWS methodology in agricultural economics, establishing the conceptual foundation for trait preference analysis. Section 3 details our methodological approach, including the experimental design for BWS implementation, data collection procedures across Colombia's diverse agricultural regions, and the econometric models used to analyze preference patterns. Section 4 presents our empirical results on trait preferences for both rice and maize, examining variations across regions (Andean, Caribe, Llanos, and others), farm sizes (small, medium, large), and production systems (irrigated vs. rainfed for rice; mechanized vs. manual for maize), while discussing the implications of these findings for breeding program strategies. Section 5 concludes with key insights on trait prioritization patterns.

2 Literature review

2.1 Prioritizing Breeding Traits

Trait prioritization in breeding programs is critical for aligning genetic improvement efforts with end-user needs and market demands. Recent studies demonstrate that systematic trait selection enhances breeding efficiency by focusing resources on characteristics with the highest stakeholder value (Occelli et al., 2024). For perennial crops like apples, understanding producer preferences for traits such as fruit flavor and crispness directly informs cultivar development strategies (Yue et al., 2013), while gender-responsive approaches reveal distinct preference patterns between male and female farmers that impact adoption rates (McDougall et al., 2022).

Modern breeding programs increasingly integrate multi-omics data and machine learning through strategies like Target-Oriented Prioritization (TOP) to optimize selection for complex trait combinations (Yang et al., 2022). Institutional context matters as well: comparative research between public and private breeding programs has demonstrated that trait emphasis—such as tolerance to abiotic stress or biomass productivity—varies based on sectoral goals and resource constraints(Yue et al., 2017). Taken together, these studies emphasize that effective trait prioritization requires integrating biological feasibility with socioeconomic relevance, often through interdisciplinary and data-driven approach.

Best-Worst Scaling (BWS), also known as maximum-difference scaling, is a method developed in the late 1980s by Jordan Louviere. Since then, it has evolved into a widely accepted method for measuring preferences. The core principle of BWS is that it enables respondents to make comparative judgments about multiple attributes, thereby providing richer data than traditional methods such as ratings or rankings. BWS has gained popularity as a method for assessing preferences in various fields, including health and environmental economics (Davis & Burton, 2022; Mühlbacher et al., 2016). BWS involves respondents selecting the best and worst options from a given set, thereby providing more information per choice task compared to traditional methods (Mühlbacher et al., 2016). This approach helps avoid the weaknesses associated with rating and ranking scales while potentially generating additional insights (Mühlbacher et al., 2016).

While BWS offers methodological advantages, it also presents challenges. One assumption, consistency in respondent utility across “best” and “worst” choices, is often untested, which may limit the validity of certain studies (Davis & Burton, 2022). However, the literature has responded with evolving best practices, including stronger experimental designs and greater attention to response quality (Hollin et al., 2022).

In the field of agricultural economics, BWS has been effectively utilized to understand consumer preferences, risk management strategies, and policy evaluations. For instance, a study published in the International Food and Agribusiness Management Review employed BWS to identify and prioritize risks faced by grain and oilseed farmers in Saskatchewan (Atta & Micheels, 2020). By using a count-based approach alongside latent class cluster analysis, the research highlighted the heterogeneity in farmer responses to production and marketing risks, such as price fluctuations and rainfall variability (Atta & Micheels, 2020). Another application of BWS in agricultural economics involved assessing U.S. consumers' preferences for various agricultural and food policies. The study identified thirteen different policies, providing insights into public opinion on food safety, environmental sustainability, and agricultural support measures (Caputo & Lusk, 2020). These findings can inform policymakers about consumer priorities and help shape future policy decisions.

In summary, BWS has gained prominence overcoming the limitations inherent to rating scales and simple rankings by generating clearer and more differentiated insights (Mühlbacher et al., 2016). Although initially applied to evaluate consumer perceptions of sustainable farming practices in the USA (Sackett et al., 2013), its use has expanded to analyze farmers' preferences, as demonstrated by Ahoudou et al. (2023) in their study of potato producers in Benin. Unlike previous approaches that used traditional producer surveys (Yue et al., 2013), gender-disaggregated analysis (McDougall et al., 2022), or predictive modeling (Yang et al., 2022), BWS offers distinctive advantages for this study due to three fundamental characteristics: (i) the complexity of varietal trait sets, including biotic and abiotic stress resistance, grain quality, and agronomic performance; (ii) the heterogeneity of production environments across the 16 Colombian departments studied; and (iii) the alignment with policy targets defined in national breeding programs. This methodology, when combined with econometric models such as multinomial logit, allows for better understanding of the relative importance of different varietal traits and how these preferences vary according to socioeconomic and productive characteristics, thus addressing the gap identified by Mazzanti (2003) regarding the need to capture preferences in contexts with multiple constraints.

The present undergraduate thesis aims to address these gaps by analyzing the preferences of Colombian farmers for traits of improved rice and maize varieties using Best-Worst Scaling and a multinomial logit model. By focusing on both rice and maize and covering major production areas in Colombia, this study provides a more comprehensive understanding of farmers' preferences across the country. The use of BWS and multinomials logits models allows for a deeper analysis of the relative importance of key breeding traits, including tolerance to biotic and abiotic factors, agronomic characteristics, and grain quality.

2.2 Factors Affecting Rice and Maize Production in Colombia

Rice and maize production in Colombia faces significant limitations that justify the need for genetic improvement programs. Rice, with a national production of 3.5 million tons in 2024 (Fedearroz, n.d.), shows average yields of 5.5 t/ha, considerably lower than the 10.2 t/ha potential achieved in leading countries (Observatorio de Tierras, 2025; Andrade et al.,2025). The main biotic limiting factors include Pyricularia oryzae, which historically causes reductions of up to 50% in yield if not properly managed (Fedearroz, n.d.), and Burkholderia glumae, resp1onsible for severe epidemics between 2011-2014 that reduced national production to approximately 2 million tons (Méndez Molina, 2019). Among abiotic factors, heat stress has become increasingly relevant, especially in low-altitude areas (~1,000 masl) such as the Caribbean and inter-Andean valleys, where high night temperatures favor Burkholderia development and reduce grain filling (Méndez Molina, 2019). These conditions have been further intensified by recurrent El Niño events, increasing climate-related risks in rice cultivation (Li et al.,2024).

Meanwhile, maize presents an even more critical production gap, with imports reaching 6.8 million tons in 2024, representing 81.4% of national consumption (Columna VIP, 2025). This situation is partially explained by the low technification of cultivation, where 50.5% of the area (271,991 Ha) is managed under traditional systems with yields of just 1.57 t/ha, in contrast to 5.25 t/ha for technified maize (DANE, 2004). The most limiting biotic factors for maize include the corn stunt complex, which can reduce yields by up to 90% (Vargas, 2023), and the stem borer (Diatraea saccharalis), responsible for losses between 10-50% depending on planting season (CropLife, 2020). Additionally, tar spot (Phyllachora maydis) represents a growing threat (Hernández Ramos & Sandoval Islas, 2015), while ear rot (Fusarium spp.) has shown significant incidence variations in different production systems, especially under high humidity conditions favored by climate change (Hernández Juárez et al., 2016).

Given this scenarios, the breeding programs of FEDEARROZ, FENALCE, CIAT and CIMMYT have prioritized the development of varieties with disease resistance, including resistance to rice white leaf virus (Morales, 2011), tolerance to abiotic factors, and quality characteristics that respond to market preferences (Morales, 2011; Columna VIP, 2025) in both crops.

3 Methods and Data

A key contribution of this undergraduate thesis is the ability to leverage the national sample to create meaningful subsamples for detailed analysis at the regional, farm size, and production system levels. This analytical approach enables us to examine preference heterogeneity across different farming typologies and geographical contexts, providing insights that would not be possible with smaller, localized studies. The representative nature of the sample allows us to identify whether trait priorities remain consistent across Colombia's diverse agricultural landscapes or whether breeding programs should adopt differentiated strategies based on regional characteristics, farm scale, and production systems. This level of disaggregated analysis represents a significant methodological advancement for understanding farmer preferences in developing country contexts, where agricultural diversity and resource constraints vary substantially across production environments.

3.1 Methods

To assess farmer preferences for rice and maize varietal traits in Colombia, this research implements an integrated methodological approach combining Best-Worst Scaling (BWS) experimental design with Random Parameters Logit (RPL) econometric analysis. The methodology employs structured choice experiments where farmers evaluate trait priorities through object-case BWS tasks, with resulting preference data analyzed using Random Utility Models to capture heterogeneity across different farming contexts. This approach effectively combines the behavioral insights from BWS methodology with the analytical power of discrete choice modeling to reveal genuine preference structures in resource-constrained agricultural decision-making environments.

BWS is a stated-preference method developed by Louviere and Woodworth (1990), designed to elicit ranked preferences through comparative judgment. It avoids scale-use and social desirability bias by forcing explicit trade-offs between alternatives (Finn & Louviere, 1992; Marley & Louviere, 2005). Case 1 (object-case BWS) focuses on assessing the relative importance of a fixed set of items, in this case, varietal traits without the complexity of levels. This method is especially appropriate for trait prioritization in agriculture where farmers operate under resource limitations and must weigh competing goals.

BWS is particularly appropriate for this research as it forces explicit trade-offs between attributes, revealing true preference hierarchies that reflect real-world decision-making where farmers must prioritize competing varietal traits under resource constraints. Using the object case approach (Case 1), this method captures both preference rankings and their intensity across different farmer typologies, while the econometric framework leverages full information from both "best" and "worst" choices, providing more robust estimates than simple descriptive rankings.

The BWS experiment was structured into five randomized choice sets, each containing five of ten breeding objectives identified by experts from rice or maize breeding programs. This design follows an approximate Balanced Incomplete Block Design (BIBD), ensuring three critical features: (i) balanced frequency and co-occurrence of traits across choice tasks, strengthening statistical validity; (ii) cognitive feasibility by limiting choices to five traits per task, preventing decision fatigue; and (iii) sufficient variation to capture preference heterogeneity across production contexts, farm sizes, and regional conditions. This methodological approach enables identification of priority traits for different farmer segments, providing targeted insights for breeding programs seeking to align varietal development with diverse producer needs.

Following the methodological framework established by Okpiaifo et al. (2020) for BWS applications in agricultural economics, the collected preference data were analyzed using advanced econometric models. Specifically, we employed Random Parameters Logit (RPL) models to account for unobserved heterogeneity in individual farmer preferences.

The econometric framework is grounded in McFadden's (1974) Random Utility Theory, which provides the theoretical basis for modeling individual choice behavior. According to this framework, the utility that farmer n obtains by choosing attribute j in choice set t is defined as equation (1), where X_{njt} are the observable attributes represents the parameters to be estimated, and ε_{njt} is the random error term. As Hoyos (2010) explains, random utility models assume that the utility an individual obtains from an alternative has a deterministic (observable) component and a random (unobservable) component, allowing for a probabilistic analysis of decisions.

$$U_{(njt)} = \beta X_{(njt)} + \varepsilon_{(njt)} \quad (1)$$

An MNL was estimated to obtain average preferences, assuming independence of irrelevant alternatives (IIA) between breeding objective traits. The probability of selecting the best-worst pair (b, w) in set t is shown in equation (2).

$$P(bw|t) = \frac{exp(\beta_b - \beta_w)}{\sum_{(i,j)} exp(\beta_i - \beta_j)} \quad (2)$$

The theoretical foundation for this analysis draws from Train's (2003) "Discrete Choice Methods with Simulation," which provides the comprehensive framework for discrete choice modeling. Train's work is particularly crucial as it demonstrates how Random Parameters Logit (RPL) models address fundamental limitations of standard multinomial logit models, specifically the restrictive assumptions of independence of irrelevant alternatives (IIA) and homogeneous preferences across individuals. Following Train's recommendations, we estimated an RPL model with normally distributed parameters (equation 3) to capture unobserved heterogeneity in farmer preferences. This approach allows for flexible substitution patterns and random coefficient variation across decision-makers, essential when analyzing inherently heterogeneous farmer preferences driven by varying farm characteristics and production constraints.

$$\beta n \ = \ \bar{\beta} + \ \sigma v n, v n \sim N(0,1) \ \ (3)$$

The calculation of preference shares represents a critical component of our analytical framework (4), as these shares provide a quantifiable measure of the relative importance that farmers assign to each varietal breeding trait. In the context of Best-Worst Scaling, preference shares refer to the proportion or weight that each attribute receives within the total set of expressed preferences, derived from the frequency with which a trait is selected as either the best or worst option across all choice tasks. This approach is particularly valuable for our research because it allows us to move beyond simple rankings to obtain precise quantitative measures of trait priorities that reflect the strength of farmers' preferences rather than merely their ordinal position.

$$Sj \ = \frac{exp\left(\hat{\beta} j\right)}{\sum_{(k=1\ )} exp\left(\hat{\beta} k\right)} \ \ (4)$$

The importance of preference shares in our study lies in their capacity to provide an unambiguous prioritization of varietal traits while minimizing common response biases associated with traditional rating scales. By basing the analysis on explicit best-worst choices, preference shares reduce acquiescence bias, social desirability bias, and extreme response tendencies that often compromise the validity of agricultural preference studies. Furthermore, preference shares facilitate direct statistical analysis and modeling, enabling us to construct predictive models of farmer behavior and preferences that are essential for informing breeding program priorities and variety development strategies.

I used conditional logit models to analyze farmers' choices, incorporating heterogeneity through segmentation by productive characteristics. We interpret the estimated coefficients as indicators of relative trait importance, subsequently calculating preference shares using equation (4) as the exponential of each coefficient divided by the sum of exponentials, ensuring shares sum to unity and represent relative probability weights. This approach, combined with Train's framework, allows us to capture how preferences vary according to farm size, production system, and region, providing breeding programs with clear, quantitative guidance on trait priorities for Colombian farmers.

Breeding objectives were defined through expert consultation. Key contributors included María Fernanda Álvarez (CIAT) and Eduardo Graterol (FLAR) for rice, and senior staff Janeth Bolaños Vargas, and Nestor Romero Perilla at CIMMYT for maize. Ten core objectives per crop were identified and are detailed in Table 1.

To enhance clarity in the graphs presented in the following sections, a color palette is used to classify the traits: **blue** refers to production traits, **green** refers to abiotic traits, and **purple** refers to biotic traits. The traits analyzed in this study are defined as follows:

Table 1 Traits rice and maize

Attribute - Type	**Definition**	**Rice**	**Maize**
Production-related characteristics		**Production-related characteristics**	**Production-related characteristics**
Grain yield	Is the quantity or weight of paddy/grains grains harvested per unit area, excluding empty grains, plant debris, or other elements of plant origin or not, that result in grain collection. It can be expressed as weight of green, wet, or clean and dry grains per unit of harvested area	Weight of harvested grain per unit area	Weight of harvested grain per unit area
Milling quality	Refers to the physical characteristics that determine rice grain performance after the milling process. It is expressed as the amount or proportion of whole milled (white) rice that results after the industrial milling process of rice	Performance of rice grain after industrial milling process	—
Grain hardness	Is defined as the force necessary to break the grain and contributes to providing mechanical resistance; normally the market requires hard or semi-hard grains.	—	Physical characteristic determining grain resistance to processing

Attribute - Type	Definition	Rice	Maize
Physical and physiological characteristics		**Physical and physiological characteristics**	**Physical and physiological characteristics**
Panicle sterility resistance	Refers to the lower number or proportion of sterile spikelets or grains, caused by physiological or environmental characteristics that affect plants, when compared to sterility in susceptible varieties	Resistance to sterile spikelets due to environmental factors	—
Shattering resistance	Refers to the lower number or proportion of mature grains that detach from panicles due to wind or slight mechanical movements, when compared to shattering in susceptible varieties	Retention of mature grains in panicles	—
Lodging resistance	Refers to the lower number or proportion of plants fallen or inclined to less than 45% of ground level, when reaching the grain filling and maturation stage, when compared to lodging in susceptible varieties	Plant's ability to remain upright during grain filling	Plant's ability to remain upright until harvest
High temperature tolerance	Refers to the ability of plants to resist and survive under extreme heat conditions without suffering severe damage that affects their growth or yield	Ability to withstand extreme heat conditions	Ability to maintain yield under extreme heat conditions
Drought stress tolerance	Refers to the ability of plants to resist and survive under conditions of prolonged drought periods without suffering severe damage that affects their growth or yield.	—	Plant's ability to withstand water scarcity conditions
Waterlogging tolerance	Refers to the ability of plants to resist and survive under conditions of prolonged periods of excess moisture or waterlogging, without suffering severe damage that affects their growth or yield.	—	Resistance to excess water conditions in soil
Disease and pathogen resistance		**Disease and pathogen resistance**	**Disease and pathogen resistance**

Attribute - Type	Definition	Rice	Maize
Rice blast resistance	Refers to the ability of some varieties to show a low degree of damage caused by the fungus Pyricularia oryzae, when compared to the damage caused by the fungus in susceptible varieties	Resistance to Pyricularia oryzae fungus	—
Burkholderia glumae tolerance	Refers to the ability of some varieties to show a lower degree of damage (mainly grain sterility) caused by this bacteria, when compared to the susceptibility to the bacteria in susceptible varieties	Resistance to bacterial panicle blight	—
Grain discoloration tolerance	Refers to the ability of some varieties to show a lower degree of damage from the pathogen complex that causes grain discoloration, when compared to grain discoloration in susceptible varieties	Resistance to pathogens causing grain discoloration	—
Rice Hoja Blanca Virus resistance	Refers to the ability of some varieties to show a lower degree of damage caused by the virus that causes rice hoja blanca, when compared to the damage caused by the virus in susceptible varieties	Resistance to Rice Hoja Blanca Virus	—
Ear rot resistance	Refers to the ability of some varieties or hybrids to show a lower percentage of ear rot due to the presence of pathogens.	—	Resistance to pathogens causing rot in corn ears
Cercospora resistance	Refers to the ability of plants to tolerate biotic stress produced by the pathogen (Cercospora zeae-maydis) without suffering damage that affects their growth or yield.	—	Resistance to foliar disease caused by Cercospora fungi
Tar spot complex resistance	Refers to the ability of plants to tolerate biotic stress produced by the fungal complex (Phyllachora maydis, Monographella maydis, and Coniothyrium phyllachorae) without suffering damage that affects their growth or yield.	—	Resistance to foliar disease caused by a complex of pathogens
Corn stunt complex resistance	Refers to the ability of plants to tolerate biotic stress from the corn stunt complex transmitted by Dalbulus maidis without suffering severe damage that affects their growth or yield.	—	Resistance to viral complex causing stunting in corn plants

Note: the line "-" in the maize and rice columns means that the objective trait does not apply for that crop.

3.1.2. Preference Variation Across Subpopulations

This analytical approach enables us to examine preference heterogeneity across different farming typologies and geographical contexts, providing insights that would not be possible with smaller, localized studies.

The variables employed in the preference analysis can be categorized as follows:

System Classification:

Rice production systems can be categorized into irrigated and rainfed systems, each with distinct characteristics and performance outcomes. Irrigated rice systems utilize controlled water management with maintained water depths of 5-10 cm throughout the growing season, enabling farmers to achieve consistently high yields averaging 5.4 t/ha globally, with potential yields reaching 8-10 t/ha in temperate regions, and allowing for multiple cropping seasons (1-3 times per year) that contribute to 75% of global rice production (Seck et al., 2012). In contrast, rainfed rice systems depend entirely on natural precipitation patterns and are cultivated in both upland and lowland environments, resulting in significantly lower and more variable yields of 1-2.5 t/ha in lowland areas and approximately 1 t/ha in upland conditions, making them highly vulnerable to climatic variations including droughts, floods, and erratic rainfall patterns that can cause substantial yield losses and production instability (Seck et al., 2012).

For maize, production can be mechanized or manual, representing two distinct approaches to agricultural operations. Mechanized production involves the use of powered machinery and equipment to perform farming activities such as land preparation, planting, cultivation, and harvesting, which significantly improves efficiency and reduces labor requirements (Baudron et al., 2015). In contrast, manual production relies primarily on human labor and basic hand tools, which is common in rural areas of Eastern and Southern Africa where farmers lack access to modern agricultural technology and machinery.

Regional Classification:

To define the categorical variables for producing regions, we used the regional definition from the rice census (DANE & Fedearroz, 2024) for rice, and for maize, we used the regions defined by Ospina Rojas (2003).

For rice, we classified departments into three main regions based on their distinct agro-ecological characteristics: the Andean Region (Antioquia, Huila, Tolima, Valle del Cauca), located in inter-Andean valleys and mountain slopes with moderate temperatures (18-24°C), and predominantly irrigated rice systems using controlled water management from rivers and reservoirs; the Caribbean Region (Bolívar, Cesar, Córdoba, La Guajira), situated in northern coastal plains with tropical climate (26-32°C), low altitude, distinct wet-dry seasons, and mixed irrigated-rainfed production systems; and the Orinoquia Region (Arauca, Meta), characterized by eastern plains (Llanos Orientales) with tropical savanna climate, flat topography, and predominantly rainfed rice production with seasonal flooding patterns (IGAC,2024).

For maize, we classified departments into four agro-ecological zones: Bajo Cauca (Córdoba, Sucre), located in the lower Cauca River valley with tropical climate, flat topography, and predominantly mechanized production; Centro (Huila), situated in the upper Magdalena valley with inter-Andean conditions, moderate temperatures, and mixed production systems; Llanos (Casanare, Meta), characterized by eastern plains with extensive flat areas, tropical savanna climate, and large-scale mechanized agriculture; and Santanderes (Norte de Santander), located in the northeastern Andean region with mountainous topography, varied altitudes, and predominantly smallholder farming systems (IGAC,2024).

Farm Size Categories:

To define farm size categories, we used the size ranges established in the rice census (DANE & Fedearroz, 2024). For maize production units, we adopted equivalent size classifications and defined the following ranges:

- Small Farms less than 10 hectares
- Medium Farms between 10 and 50 hectares
- Large Farms with more than 50 hectares

3.2. Sample design and Data

3.2.1. Stratified Sampling

The study will utilize climate risk zones identified through previous research, focusing on Colombian municipalities exposed to high climate risks as part of the CAS Project. A stratified sample was calculated to be statistically representative of all municipalities experiencing these climate risks, considering criteria such as area planted, number of producers, and geographic distribution. Tolima rice-surveys was excluded from the sampling because it was involved in another project, and due to financial constraints, it was not possible to implement the survey there.

This sampling approach ensures that the preferences captured through the BWS methodology reflect the diversity of production contexts and farmer characteristics across Colombia's rice and maize sectors. The implementation of this stratified sampling strategy resulted in comprehensive geographic coverage across multiple departments, as illustrated in Figures 1 and 2. The final sample achieved broad territorial representation, with rice farms (565 observations) distributed across six departments—ranging from traditional production areas like Sucre (45.31%) and Norte de Santander (20.35%) to emerging regions like Casanare and Meta. Similarly, maize farms (800 observations) were sampled across ten departments, with significant representation in Córdoba (51.88%), Meta (13.75%), and Huila (8.88%), among others.

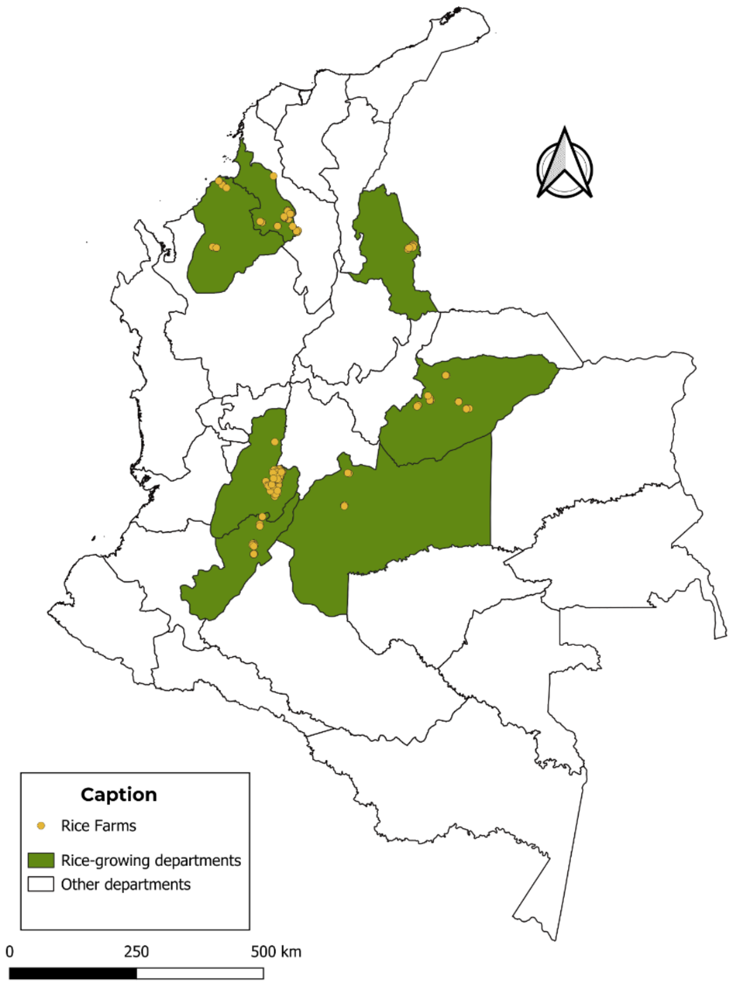

Figure 1 Rice farms locations

Notes: Spatial distribution of the total 565 farms from which data were collected from farmers., the spatial data layers used in this study were obtained from DIVA-GIS (Hijmans et al., 2025), a free-access repository of geographic data.

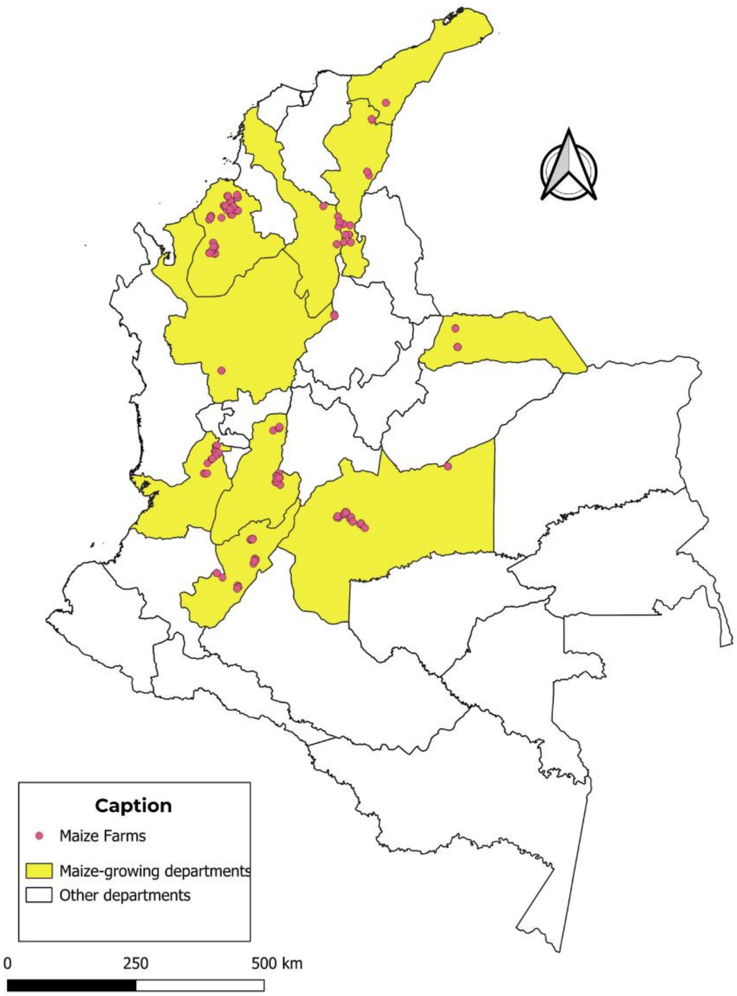

Figure 2 Maize farms locations

Notes: Spatial distribution of the total 800 farms from which data were collected from farmers, the spatial data layers used in this study were obtained from DIVA-GIS (Hijmans et al., 2025), a free-access repository of geographic data.

The target population consisted of farmers from each analyzed crop located in areas identified as having high climate risk. The sampling framework for the BWS modules followed the broader sampling strategy of the CAS project baseline assessment, which was designed to be representative of rice and maize producers across Colombia's agricultural regions.

3.2.2 Data

Data for this study was collected as part of the baseline assessment for the "Sustainable Agrifood Colombia" (CAS, by its acronym in Spanish) project at October - November of 2024. This large-scale initiative aims to reduce the vulnerability of agricultural production to climate threats while minimizing impacts on the competitiveness of Colombia's agricultural sector (Colombia Agroalimentaria Sostenible, 2025).

Data collection was conducted using CsPro (Census and Survey Processing System), an open-source software developed by the U.S. Census Bureau and Harvard University's Data Center for census and survey data collection and analysis. CsPro offers an intuitive interface for questionnaire design and data entry, multilingual support (allowing Spanish implementation), and robust validation features to ensure data quality and consistency during collection. The software enables data export in various formats; we will use CSV format for download and subsequent analysis. CsPro is widely used by statistical institutions and research organizations worldwide, ensuring reliability in our data collection process.

As part of the comprehensive baseline assessment for the Sustainable Agrifood Colombia project, an extensive survey instrument was developed to capture multiple dimensions of agricultural production systems and farmer decision-making processes. The Complete Agricultural Survey (CAS) encompasses 18 distinct modules covering household characteristics, production systems, crop management practices, climatic resilience strategies, economic conditions, and innovation propensity (Table 2).

Table 2 Sustainable agrifood Colombia survey modules - CAS survey modules

Sections	
CAS	**Contents**
A	Identification and location
B	Household’s characteristics
C	Decision making unit
D	Production unit
K	Other crops produced and incomes
Y	Crop production
I, S, R, M, P	Crop management
H	Information and extension services
E	Adverse climatic events
H	Climatic resilience
U	Others source of income
L	Access to credit
W, N	Living conditions
N	Inputs and endowments
Q	Production costs
BWS	Best Worst Scaling

T	Propensity to innovation
O	CAS Pre Register

This comprehensive questionnaire provides detailed information on farmer demographics, decision-making structures, production units, crop diversification patterns, management practices across different crops, access to information and extension services, experiences with adverse climatic events, alternative income sources, credit accessibility, living conditions, input utilization, and production costs. Within this broader survey framework, specific Best-Worst Scaling (BWS) modules were strategically incorporated for both rice and maize production systems to understand farmer preferences regarding breeding traits (see an example of the question in the Appendix A). The BWS modules represent a critical component of the survey design, enabling the quantitative assessment of trait priorities that inform breeding program decisions and agricultural extension strategies.

4 Results and Discussion

4.1 Descriptive Statistics

The rice and maize farmers studied present heterogeneous characteristics according to region. Maize producers, with a sample of 800 surveys, have farms averaging 16.08 hectares, dedicating 6.7 hectares to cultivation, with average yields of 2.79 tons/ha. Maize-growing households consist of 3.9 people, with predominantly male heads of household (82.5%), averaging 52.5 years of age and 6.9 years of schooling. Meanwhile, rice farmers, with 731 surveys, possess larger farms (52.74 hectares on average), dedicating 29.83 hectares to rice, with yields of 4.69 tons/ha. Their households comprise 3.7 people, with family heads mostly men (85.3%), averaging 53.2 years of age and 7.7 years of education. Both groups show significant gaps in access to services: only 15.2% of maize farmers and 27.5% of rice farmers receive technical assistance, while the use of agroclimatic forecasts reaches just 13.2% in maize and 23.8% in rice, highlighting differentiated support needs according to crop and region. (See Appendix B)

The sample composition reveals important characteristics of rice production systems in Colombia. Table 4 shows that rainfed production systems dominate the sample, representing 63.01% of observations (356 farms), while irrigated systems account for 36.99% (209 farms).

This distribution reflects the prevalence of rainfed rice cultivation in Colombia's agricultural landscape, particularly in regions with adequate rainfall patterns.

Table 3 Sample distribution by system rice

System	Freq	Percent
Irrigated	209.00	36.99
Rainfed	356.00	63.01
Total	**565.00**	**100.00**

The geographic distribution of rice farms (Table 5) demonstrates significant concentration in Sucre department (45.31%), followed by Norte de Santander (20.35%) and Huila (13.27%). This distribution aligns with Colombia's traditional rice-producing regions, where Sucre represents the Caribbean coast production area, while Norte de Santander and Huila represent important inland production zones.

Table 4 Sample distribution by department

Department	Freq	Percent
Casanare	49.00	8.67
Cordoba	31.00	5.49
Huila	75.00	13.27
Meta	39.00	6.90
Norte de santander	115.00	20.35
Sucre	256.00	45.31
Total	**565.00**	**100.00**

The maize sample composition (Table 6) shows a predominance of manual production systems, accounting for 53.50% of observations (428 farms), followed by mechanized systems at 32.00% (256 farms), and mixed systems (both manual and mechanized) representing 14.50% (116 farms). This distribution reflects the heterogeneous nature of maize production in Colombia, where smallholder farmers often rely on manual labor while larger operations employ mechanized approaches.

Table 5 Sample distribution by system maize

System	Freq	Percent
Mechanic	256.00	32.00
Manual	428.00	53.50
Both	116.00	14.50
Total	**800.00**	**100.00**

The geographic distribution of maize farms (Table 7) shows strong concentration in Córdoba department (51.88%), followed by Meta (13.75%) and Huila (8.88%). The remaining observations are distributed across seven additional departments, including Antioquia, Arauca, Bolívar, César, Tolima, Valle del Cauca, and La Guajira. This distribution captures both traditional maize-producing regions in the Caribbean coast (Córdoba) and emerging production areas in the Eastern Plains (Meta) and Andean regions (Huila).

Table 6 Sample distribution by department

Department	Freq	Percent
Antioquia	21.00	2.62
Arauca	22.00	2.75
Bolivar	35.00	4.38
Cesar	34.00	4.25

Department	Freq	Percent
Cordoba	415.00	51.88
Huila	71.00	8.88
La guajira	5.00	0.62
Meta	110.00	13.75
Tolima	51.00	6.38
Valle del cauca	36.00	4.50
Total	**800.00**	**100.00**

These sample distributions provide adequate representation across different production systems and geographic regions for both crops, enabling robust analysis of preference heterogeneity. The diversity in production systems (irrigated vs. rainfed for rice; manual vs. mechanized for maize) and geographic coverage ensures that the BWS results can capture the varied priorities and constraints faced by farmers across Colombia's diverse agricultural contexts.

4.2 Results Rice and Maize

The analysis reveals distinct patterns in Colombian farmers' preferences for different attributes across both rice and maize crops, with notable variations by region, farm size, and production system. Grain yield consistently emerges as the most valued attribute nationwide for both crops, commanding a 27% preference share in both rice and maize, with significant coefficients in the RPL models. However, secondary trait preferences diverge notably: rice farmers prioritize milling quality (13%) and panicle sterility resistance (11%), while maize producers value grain hardness (15%) and drought tolerance (13%), in both cases one for quality and the other for abiotic stresses. Regional analysis reveals significant heterogeneity in preferences, particularly evident in rice production where the Central region uniquely prioritizes disease resistance (Burkholderia glumae tolerance, 19%) over yield, contrasting with the Llanos region's strong yield preference (33%). Farm size also influences trait prioritization, with large-scale producers showing distinct preferences for climate resilience in rice (temperature tolerance) and disease resistance in maize (corn stunting resistance). These patterns of preference heterogeneity suggest the need for targeted breeding strategies rather than a one-size-fits-all approach to variety development in Colombia.

4.2.1 Rice

The analysis of trait preferences across different production contexts reveals important patterns of heterogeneity that are crucial for breeding program targeting. We examine these patterns across three key dimensions: production systems (irrigated vs. rainfed), farm size categories, and geographical regions. This multi-dimensional analysis provides valuable insights for developing varieties that meet specific production context needs.

Table 7 Rice estimators

General Preference Model Estimates – Rice

VARIABLES	(1) RPL
Burkholderia glumae tolerance	0.341***
	(0.0688)
Milling quality	0.739***
	(0.0830)
Shattering resistance	0.264***
	(0.0689)
Grain discoloration tolerance	0.273***
	(0.0758)
Rice blast resistance	0.356***
	(0.0822)
Grain yield	1.445***
	(0.0865)
Panicle sterility resistance	0.603***
	(0.0762)
Rice Hoja Blanca Virus resistance	0.131*
	(0.0672)
Lodging resistance	0.191***
	(0.0698)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The analysis of rice variety preferences reveals a clear hierarchy of trait importance among Colombian farmers. Grain yield dominates farmer preferences, accounting for 27% of the total preference share and showing the highest coefficient (1.445) in the preference estimation models. This is followed by milling quality (13%) and panicle sterility resistance (11%), indicating that farmers value both productivity and grain quality characteristics.

Table 8 Preference shares rice

Attribute	**Proportion (%)**	**Rank**
Grain yield	27	1
Milling quality	13	2
Panicle sterility resistance	11	3
Rice blast resistance	9	4
Burkholderia glumae tolerance	9	5
Grain discoloration tolerance	8	6
Shattering resistance	8	7
Lodging resistance	8	8
Rice Hoja Blanca Virus resistance	7	9
High night temperature tolerance[1]	-	10
Total	**100**	

Disease resistance traits occupy intermediate positions, with resistance to Pyricularia and tolerance to Burkholderia glumae each receiving 9% of preference shares. Physical stress tolerance traits such as shattering resistance, lodging resistance, and tolerance to high night

1 High night temperature tolerance serves as the reference point for comparison in the analysis and therefore does not have a preference share value.

temperatures received relatively lower priority, suggesting that while important, these characteristics are secondary to yield, quality, and disease resistance in farmers' varietal choices.

4.2.1.1 Analysis by Production Systems

The Random Parameter Logit analysis reveals distinct preference patterns between irrigated and rainfed rice production systems in Colombia (Figure 3). These differences reflect the contrasting challenges and opportunities in each system.

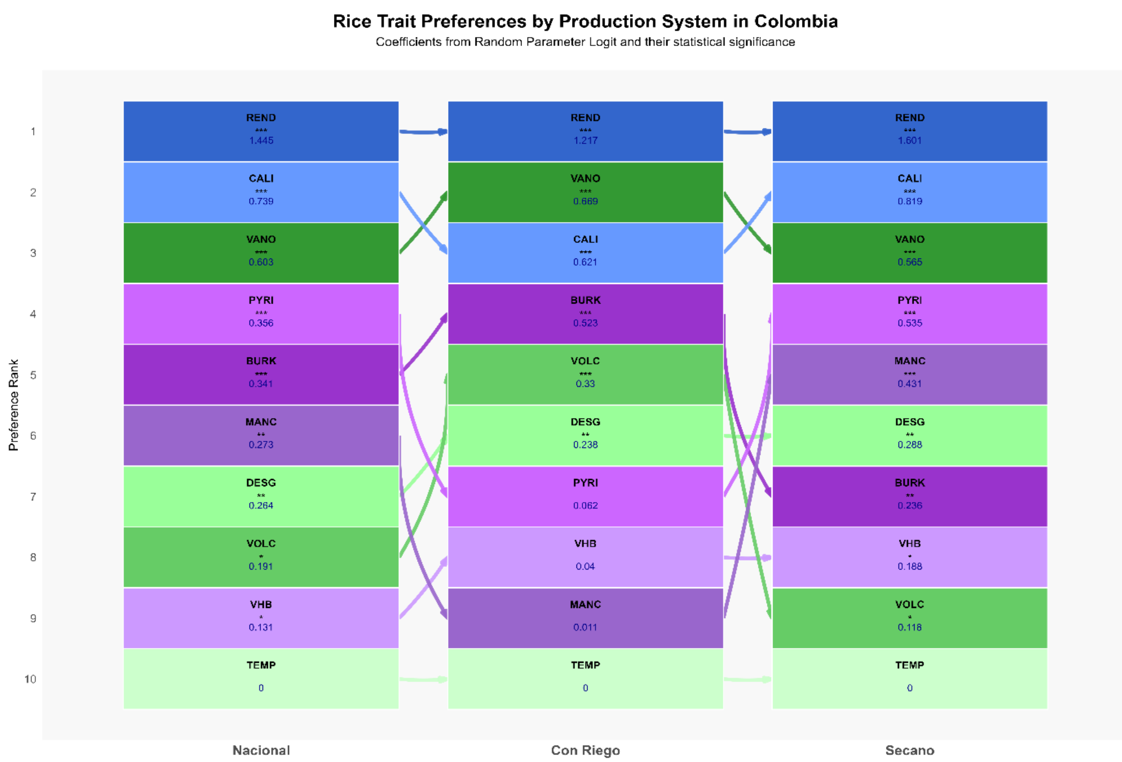

Figure 3 Rice trait preferences ranking by production system in Colombia

Notes: The traits preferences are presented through a comprehensive visualization that combines both preference shares and regression coefficients (Figure 3). The graph displays trait rankings (1-10) for each region, with coefficient values from Random Parameter Logit models shown beneath each trait. Color coding helps identify trait categories: blue represents production-related traits (e.g., - yield), green indicates physical characteristics (- grain sterility), and purple denotes disease resistance traits (- blast resistance). Connecting lines between regions track shifts in trait rankings, allowing for easy identification of preference pattern changes across geographical areas. The statistical significance of coefficients is indicated by asterisks (*** p<0.01, ** p<0.05, * p<0.1). Detailed preference share tables and complete regression results are available in Appendix B .

Rainfed systems in figure 3 show the strongest preference for grain yield (coefficient 1.601-Figure 3), notably higher than the national average (1.445-Table 8). This strong yield preference likely reflects the higher production risks and lower average yields in rainfed conditions. Milling quality (0.819) and panicle sterility resistance (0.665) follow as primary concerns, indicating that rainfed farmers prioritize both market value and stress tolerance.

Irrigated systems showed in figure 3 , grain yield remains important (1.217), its coefficient is lower than in rainfed systems. These farmers show strong preference for panicle sterility resistance (0.660) and milling quality (0.621). The higher ranking of disease resistance traits (BURK, 0.523) suggests that controlled water conditions may create favorable environments for certain pathogens.

Notably, both systems consistently rank temperature tolerance as the lowest priority, while virus resistance maintains low importance across systems. However, the relative importance of disease resistance traits and grain quality characteristics shows significant variation between systems.

This systematic variation in preferences between production systems provides strong justification for targeted breeding strategies. The distinct preference patterns suggest that variety development should consider the specific challenges and opportunities of each production system, rather than pursuing a one-size-fits-all approach.

4.2.1.2 Analysis by Regions

Analysis reveals distinct regional patterns in rice trait preferences across Colombia's main production zones, while also highlighting certain consistent elements (Figure 1). The statistical significance of coefficients (indicated by asterisks in the graph) validates the robustness of these regional variations. At the national level, grain yield (REND) maintains the highest coefficient (1.445), followed by milling quality (CALI, 0.739) and panicle sterility resistance (VANO, 0.603). This hierarchy provides a baseline for comparing regional variations.

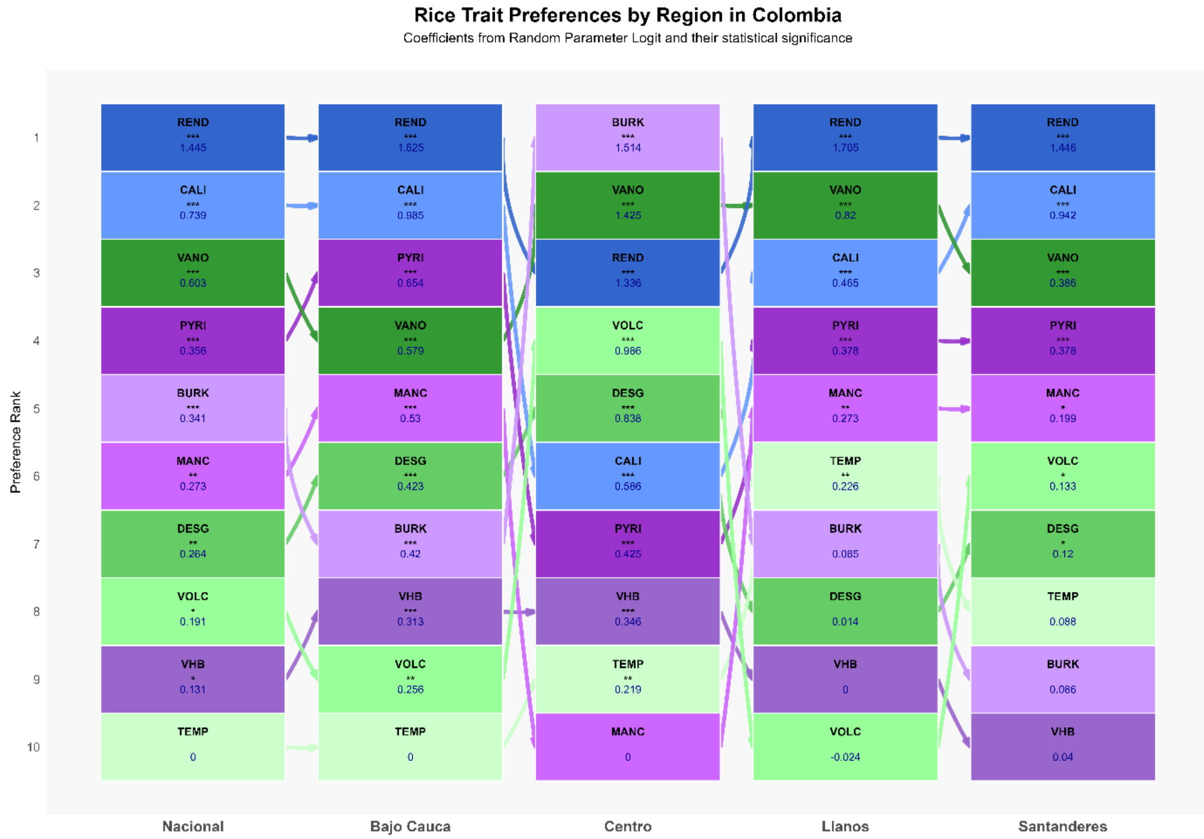

Figure 4 Rice trait preferences ranking by region in Colombia

Notes: The traits preferences are presented through a comprehensive visualization that combines both preference shares and regression coefficients (Figure 4). The graph displays trait rankings (1-10) for each region, with coefficient values from Random Parameter Logit models shown beneath each trait. Color coding helps identify trait categories: blue represents production-related traits (e.g., REND - yield), green indicates physical characteristics (VANO - grain sterility), and purple denotes disease resistance traits (PYRI - blast resistance). Connecting lines between regions track shifts in trait rankings, allowing for easy identification of preference pattern changes across geographical areas. The statistical significance of coefficients is indicated by asterisks (*** p<0.01, ** p<0.05, * p<0.1). Detailed preference share tables and complete regression results are available in Appendix B.

Regional analysis (Figure 4) reveals notable divergences from this national pattern. The Llanos region shows the strongest preference for yield, with the highest coefficient (1.705) among all regions, followed by panicle sterility resistance (0.820). This marked emphasis on yield likely reflects the region's large-scale commercial production systems. In contrast, the Centro region presents a distinctly different preference structure, where Burkholderia glumae tolerance (BURK, 1.514) ranks first, followed by panicle sterility resistance (1.425), with yield ranking third (1.336).

This unique prioritization suggests specific disease pressure challenges in this region. The Bajo Cauca region closely follows the national pattern but with stronger coefficients, showing high preferences for yield (1.625) and milling quality (0.985). Notably, this region places higher importance on Pyricularia resistance (0.654) compared to other regions, indicating particular disease management challenges. The Santanderes region maintains a similar preference structure to the national pattern, with yield (1.446) and milling quality (0.942) as primary concerns. Certain traits show remarkable consistency across regions in their relative importance. Yield consistently maintains high positive coefficients across all regions (ranging from 1.336 to 1.705).

However, disease resistance traits and grain quality characteristics show considerable regional variation in their relative importance, reflecting local production challenges and market requirements. Figure 4 effectively captures these regional variations and consistencies, demonstrating that while some traits maintain their importance across regions, others require specific regional targeting in breeding programs. The detailed statistical data supporting these regional patterns can be found in Appendix B.

4.2.1.3 Analysis by Farm Size Categories

Analysis of trait preferences by farm size reveals interesting patterns of both consistency and variation across different scales of rice production in Colombia (Figure 5). The Random Parameter Logit coefficients demonstrate how farm scale influences trait prioritization while maintaining certain fundamental preferences.

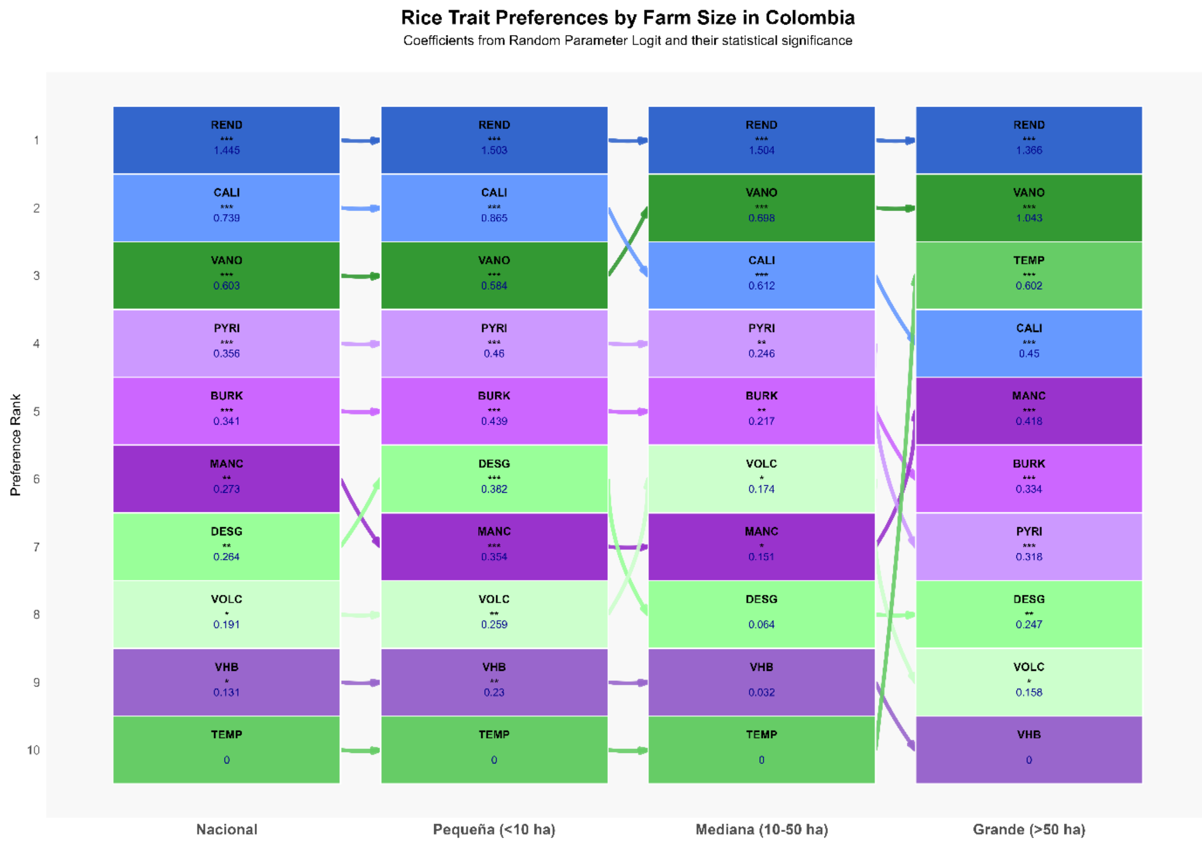

Figure 5 Rice trait preferences ranking by farm size in Colombia

Small-scale farms (<10 ha) in Figure 5show preference patterns closely aligned with the national average, suggesting they represent a significant portion of the farming population. These farmers strongly prioritize grain yield (coefficient 1.503) and milling quality (0.865), followed by panicle sterility resistance (0.584). The similarity to national patterns indicates that small-scale farmers' needs significantly influence overall varietal preferences in Colombia's rice sector.

Medium-scale operations (10-50 ha) maintain high preference for yield (coefficient 1.504) but show an important shift in secondary traits. Panicle sterility resistance emerges as their second priority (1.043), notably higher than in small farms, while milling quality drops to third position (0.612). This shift suggests that as farm size increases, management of physiological stresses becomes more critical, possibly due to larger field sizes and more intensive production systems.

Large-scale farms (>50 ha) present the most distinctive preference profile. While yield remains important (1.366), its coefficient is lower than in other farm categories. These farmers show strong preference for panicle sterility resistance (1.043) and uniquely prioritize temperature tolerance (0.602) among their top three traits. This emphasis on stress tolerance traits suggests that large-scale operations may be more sensitive to environmental risks that can affect large areas simultaneously.

Certain patterns remain consistent across farm sizes. Yield maintains statistical significance and high positive coefficients across all categories, while virus resistance and temperature tolerance consistently rank among the lower priorities. However, the relative importance of disease resistance traits and grain quality characteristics shows notable variation with farm scale.

The visualization effectively demonstrates how breeding programs need to consider farm scale in variety development, particularly when targeting specific production contexts. Detailed statistical data supporting these patterns are available in Appendix B.

4.2.2 Maize

The analysis of trait preferences across different production contexts reveals important patterns of heterogeneity that are crucial for breeding program targeting. We examine these patterns across three key dimensions: production systems (mechanic vs. manual), farm size categories, and geographical regions. This multi-dimensional analysis provides valuable insights for developing varieties that meet specific production context needs.

Table 9 Maize estimators

General Preference Model Estimates – Maize

	(1)
VARIABLES	RPL
Grain yield	1.506***
	(0.0688)
Drought stress tolerance	0.734***
	(0.0654)
Waterlogging tolerance	0.0877
	(0.0612)
High temperature tolerance	0.668***
	(0.0615)
Ear rot resistance	0.356***
	(0.0640)

Grain hardness	0.912***
	(0.0668)
Lodging resistance	-0.0684
	(0.0598)
Tar spot complex resistance	0.0217
	(0.0542)
Cercospora resistance	0.0606
	(0.0510)

Note: Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The analysis of maize variety preferences in Colombia reveals distinct prioritization patterns among farmers. Grain yield emerges as the dominant concern, representing 27% of total preference share with the highest coefficient (1.506-Table 9) in the preference estimation models. Grain hardness follows as the second most important trait (15%), reflecting the critical role of grain quality in market acceptance and storage. Abiotic stress tolerance traits collectively account for a substantial portion of preferences, with drought tolerance and high temperature tolerance representing 13% and 12% respectively. Disease resistance traits occupy intermediate to lower positions in the preference hierarchy, with ear rot resistance at 9% and both Cercospora and tar spot complex resistance at 6% each. This preference structure suggests that Colombian maize farmers prioritize productivity and grain quality, followed by environmental stress adaptation, while considering disease resistance as important but secondary concerns. The relatively low ranking of lodging resistance (5%) indicates that this trait, while relevant, is not a primary constraint in current production systems.

Table 10 Preference shares maize

Attribute	**Proportion**	**Rank**
Grain yield per hectare	27	1
Grain hardness	15	2
Drought stress tolerance	13	3
High temperature tolerance	12	4

Attribute	Proportion	Rank
Ear rot resistance	9	5
Waterlogging tolerance	7	6
Resistance to Cercospora	6	7
Resistance to tar spot complex	6	8
Lodging resistance	5	9
Resistance to corn stunt complex[2]	-	10
Total	**100**	

Table 10 presents the relative importance of different traits for maize production in Colombia, based on the Random Parameter Logit analysis of farmers stated preferences.

4.2.2.1 Analysis by Regions

The analysis of maize trait preferences across Colombia's major production regions reveals distinct patterns that reflect local production challenges and market requirements (Figure 6). The Random Parameter Logit coefficients demonstrate significant regional heterogeneity while maintaining certain fundamental preferences across regions.

[2] Resistance to corn stunt complex serves as the reference point for comparison in the analysis and therefore does not have a preference share value.

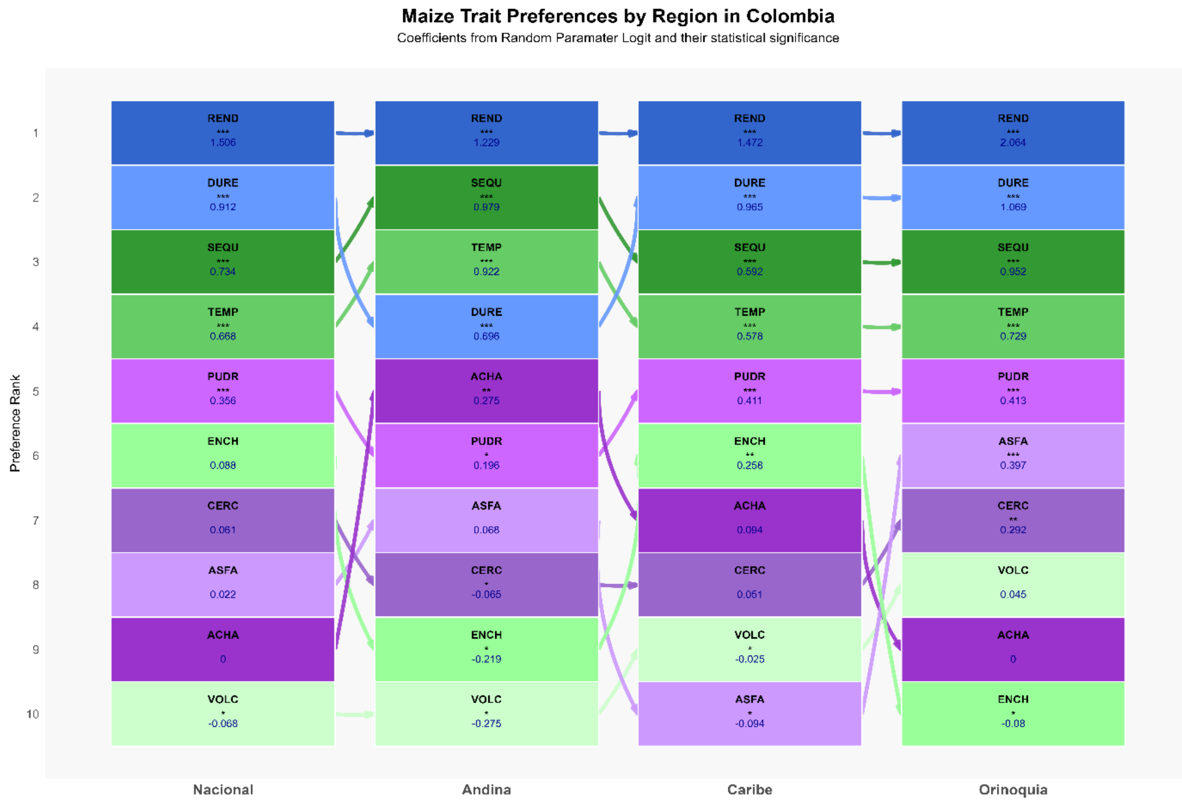

Figure 6 Maize trait preferences ranking by region in Colombia

Notes: The traits preferences are presented through a comprehensive visualization that combines both preference shares and regression coefficients (Figure 6). The graph displays trait rankings (1-10) for each region, with coefficient values from Random Parameter Logit models shown beneath each trait. Color coding helps identify trait categories: blue represents production-related traits (e.g., REND - yield), green indicates physical characteristics (VANO - grain sterility), and purple denotes disease resistance traits (PYRI - blast resistance). Connecting lines between regions track shifts in trait rankings, allowing for easy identification of preference pattern changes across geographical areas. The statistical significance of coefficients is indicated by asterisks (*** p<0.01, ** p<0.05, * p<0.1). Detailed preference share tables and complete regression results are available in Appendix B.

The Orinoquía region shows the strongest preference for grain yield (coefficient 2.064), substantially higher than the national average (1.506). This pronounced yield preference likely reflects the region's role as a major commercial maize production area, where scale economies and mechanization enable higher yield potential. Grain hardness (1.069) and drought tolerance (0.952) follow as primary concerns, indicating the importance of both market quality requirements and adaptation to the region's seasonal dry periods.

In the Caribbean region, while yield remains the top priority (1.472), the preference structure shows more balance among traits. Grain hardness (0.965) and drought tolerance (0.592) are highly valued, reflecting the region's challenging climate conditions and market requirements.

The relatively high coefficient for ear rot resistance (0.411) suggests that disease pressure is a significant concern in this humid coastal environment.

The Andean region presents a distinctive preference profile, with yield (1.229) showing lower relative importance compared to other regions. Notably, drought tolerance emerges as the second most important trait (0.979), followed by temperature tolerance (0.922). This emphasis on abiotic stress tolerance reflects the varied topography and microclimates characteristic of Andean production systems, where environmental stresses can significantly impact productivity.

Certain patterns remain consistent across regions. Yield maintains statistical significance and high positive coefficients throughout, while lodging resistance consistently ranks among the lower priorities, even showing negative coefficients in some regions. However, the relative importance of disease resistance traits and grain quality characteristics shows notable regional variation.

These regional differences in trait preferences have important implications for maize breeding programs in Colombia. The variation suggests the need for region-specific breeding objectives that address local production constraints while maintaining core traits valued across regions. This regional targeting could improve variety adoption rates and ultimately contribute to more resilient and productive maize systems across the country.

4.2.2.2 Analysis by Farm Size Categories

Figure 7 Maize trait preferences ranking by farm size in Colombia

Notes: The traits preferences are presented through a comprehensive visualization that combines both preference shares and regression coefficients (Figure 6). The graph displays trait rankings (1-10) for each region, with coefficient values from Random Parameter Logit models shown beneath each trait. Color coding helps identify trait categories: blue represents production-related traits (e.g., REND - yield), green indicates physical characteristics (VANO - grain sterility), and purple denotes disease resistance traits (PYRI - blast resistance). Connecting lines between regions track shifts in trait rankings, allowing for easy identification of preference pattern changes across geographical areas. The statistical significance of coefficients is indicated by asterisks (*** p<0.01, ** p<0.05, * p<0.1). Detailed preference share tables and complete regression results are available in Appendix B.

The analysis across farm sizes observed in the figure 7 reveals systematic differences in trait prioritization reflecting distinct management capacities and risk profiles. Large-scale operations (>50 ha) uniquely prioritize pest resistance (coefficient 1.384) over yield (1.452), suggesting a shift in focus toward pest management once yield potential is secured through intensive management.

Medium-sized farms (10-50 ha) show the strongest yield preference (1.551) combined with high valuation of grain hardness (1.034) and drought tolerance (0.984), indicating a balanced approach to productivity and risk management. Small-scale producers (<10 ha) demonstrate more evenly distributed preferences across yield (1.523), grain hardness (0.926), and environmental stress tolerance traits (temperature 0.729, drought 0.725), reflecting their need to balance multiple production constraints with limited resources. These scale-dependent variations in trait preferences highlight the importance of considering farm size in variety development and deployment strategies.

4.2.2.3 Analysis by Production Systems

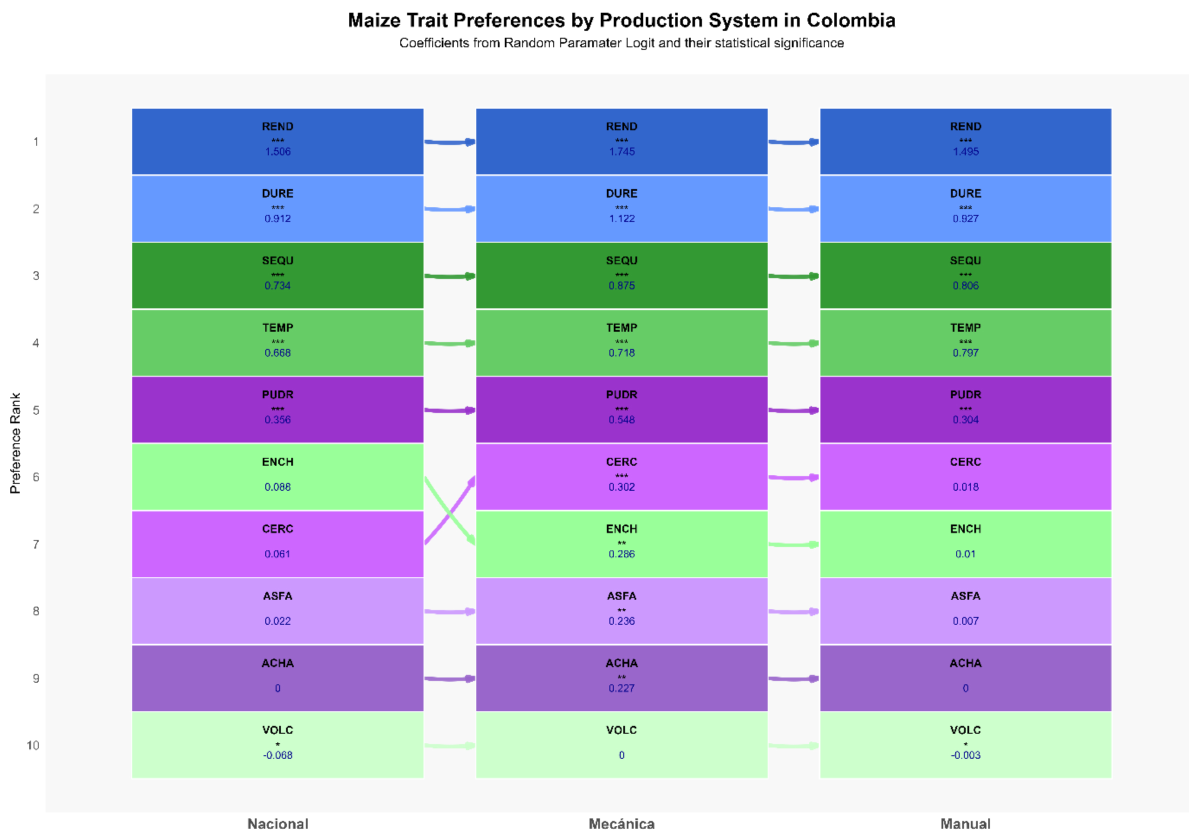

Figure 8 Maize trait preferences ranking by production system in Colombia

Notes: The traits preferences are presented through a comprehensive visualization that combines both preference shares and regression coefficients (Figure 6). The graph displays trait rankings (1-10) for each region, with coefficient values from Random Parameter Logit models shown beneath each trait. Color coding helps identify trait categories: blue represents production-related traits (e.g., REND - yield), green indicates physical characteristics (VANO - grain sterility), and purple denotes disease resistance traits (PYRI - blast resistance). Connecting lines between regions track shifts in trait rankings, allowing for easy identification of preference pattern changes across geographical areas. The statistical significance of coefficients is indicated by asterisks (*** p<0.01, ** p<0.05, * p<0.1). Detailed preference share tables and complete regression results are available in Appendix B.

The analysis of trait preferences across mechanized and manual production systems (Figure 8)reveals important distinctions in prioritization patterns that reflect their different technological and management contexts. Mechanized systems show the highest yield coefficient (1.745) among all production contexts, followed by strong preferences for grain hardness (1.122) and drought tolerance (0.875).

This preference structure reflects the capacity of mechanized operations to maximize yield potential while maintaining grain quality standards. Manual production systems, while also prioritizing yield (1.495), show relatively higher coefficients for temperature tolerance (0.797) compared to mechanized systems (0.718), suggesting greater concern for environmental stress factors in less technified conditions. Disease resistance traits generally receive moderate attention in both systems, though mechanized operations show slightly higher concern for ear rot resistance (0.548) compared to manual systems (0.304), possibly reflecting differences in disease pressure under more intensive production. The consistent low ranking of lodging resistance across both systems suggests this trait has been adequately addressed through current varieties or management practices.

4.3 Rice and Maize Breeding Implications

The analysis of trait preferences in Colombian rice and maize systems reveals important patterns that have direct implications for breeding program strategies. For both crops, grain yield emerges as the dominant trait nationally, accounting for 27% of preference share, which aligns with findings from similar studies in Nigeria (Peterson-Wilhelm et al., 2022). However, this general pattern shows important contextual variations, supporting Hoyos's (2010) emphasis on understanding heterogeneous preferences for effective program design.

Regional heterogeneity in preferences reflects diverse production constraints and market requirements. In rice, the Central region uniquely prioritizes Burkholderia tolerance (19% preference) over yield, paralleling patterns observed in Arkansas where 60% of farmers prioritized Burkholderia tolerance under high disease pressure (Lyman & Nalley, 2013). For maize, the Orinoquia region demonstrates exceptionally strong yield preferences, while the Andean region shows higher prioritization of drought tolerance (13%), reflecting its particular climate vulnerability (Nalley & Lee, 2010).

Production system differences significantly influence trait preferences. In rice systems, disease resistance traits show high significance in rainfed conditions but lose importance in irrigated systems, where lodging resistance gains prominence. Similarly, maize systems show distinct patterns between mechanized and manual production, with mechanized systems showing stronger yield preferences (coefficient 1.745) while manual systems demonstrate higher concern for environmental stress tolerance. These findings align with broader research advocating for climate-smart agriculture practices in Latin America (Banerjee et al., 2021).

Farm size emerges as a crucial factor shaping trait preferences across both crops. Large-scale operations show distinctive preference patterns, particularly regarding climate resilience in rice and disease resistance in maize. These scale-dependent variations reflect differences in management capacity and risk tolerance, supporting findings from participatory breeding studies emphasizing the importance of farm-specific contexts (Zystro et al., 2012). The implementation of decentralized testing and selection processes allows varieties to be evaluated under local conditions, as recommended by participatory plant breeding (PPB) approaches.

The strong emphasis on grain quality traits - ranking second in importance for both crops - highlights the critical role of post-harvest characteristics in varietal adoption. This finding aligns with broader research in Latin America demonstrating how socioeconomic factors interact with agroecological conditions to shape varietal choices (Guimarães, 2005). Studies across Latin America consistently show that crop breeding must account for diverse agroecological zones and socioeconomic contexts to maximize adoption (Guimarães, 2005; OIEA, 2018).

The significant variation in preferences across regions, farm sizes, and production systems suggests that breeding programs should develop differentiated varietal profiles addressing specific contextual needs while maintaining core traits valued across contexts. This approach aligns with current efforts in Latin America to develop resilient crops through various breeding techniques (Alliance for Science, 2020; IAEA, 2018).

5 Conclusions

This study provides valuable insights into Colombian farmers' trait preferences for rice and maize across diverse production contexts. Through the application of Best-Worst Scaling methodology and multinomial logit modeling, we uncovered several key patterns in trait prioritization.

The analysis reveals consistent prioritization of grain yield, accounting for 27% of preference share in both rice and maize systems across Colombia. This finding span different regions, farm sizes, and production systems, confirming yield as the fundamental driver of farmers' trait preferences. Quality traits emerge as the second most important consideration, with farmers prioritizing milling quality (13%) in rice and grain hardness (15%) in maize, reflecting the commercial importance of post-harvest characteristics in market acceptance.

Regional heterogeneity in preferences demonstrates the importance of local context in breeding program design. In rice production, farmers in the Central region uniquely prioritize Burkholderia glumae tolerance (19%) over yield, while Llanos farmers show stronger yield preferences (33%). Similarly, maize producers in the Orinoquia region demonstrate exceptionally strong yield preferences (36%), while Andean region farmers place higher importance on drought tolerance (17%) and temperature tolerance (16%).

Production system differences significantly influence trait priorities. Rainfed rice systems show stronger preferences for disease resistance traits (Pyricularia and grain discoloration), while irrigated systems prioritize lodging resistance. In maize, mechanized systems demonstrate higher yield coefficients (1.745) compared to manual systems (1.495), which show greater concern for environmental stress tolerance.

Farm scale emerges as a crucial factor shaping trait preferences. Large-scale producers show heightened demand for climate-resilient and disease-resistant traits—such as temperature tolerance in rice and corn stunt resistance in maize—suggesting that management capacity and scale economies influence trait valuation (Matuschke & Qaim, 2008). Small and medium-scale farms, by contrast, display more balanced preferences across productivity, quality, and stress tolerance dimensions.

This research contributes to agricultural economics literature by applying choice-based preference methods to improve understanding of trait preferences in developing agricultural systems. The comprehensive coverage of major production areas in Colombia—six departments for rice and ten departments for maize—provides valuable insights for breeding programs and variety dissemination policies in the context of increasing climate vulnerability.

Despite the robust findings, this study has several limitations that suggest avenues for future research. The cross-sectional nature of our data captures preferences at a single point in time, without tracking how these preferences might evolve with changing climate conditions or market demands. While we identify trait preferences, we do not directly measure how these translate into actual adoption decisions, suggesting potential for future research linking stated preferences with revealed adoption behaviors. Additionally, deeper investigation of how socioeconomic characteristics influence trait preferences could further enhance breeding program targeting.

Future studies could also incorporate economic valuation methods to quantify farmers' willingness to accept trade-offs between different traits, particularly between yield potential and climate resilience characteristics. Finally, combining our quantitative findings with participatory approaches could strengthen the connection between statistical preference models and farmers' practical decision-making contexts.

These research directions would build upon the foundation established in this study, further enhancing our understanding of how breeding programs can effectively respond to farmers' needs in Colombia's diverse agricultural landscapes while addressing the growing challenges of climate change and market competitiveness.

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Appendix

Appendix A

Example of Survey Question

The following questions consist of a list of five (5) objectives randomly selected from the list of ten objectives presented in Table 12. In each question, we ask you to carefully read the listed breeding objectives and select among those five which objective you consider most important and least important considering the production conditions on your farm. Please consult the interviewer if you have questions about the meaning of the topics or questions about the procedure.

Below, we present an example question to better understand the procedure.

Example

Consider which of these characteristics is the most important and least important for your production. Mark which of the five characteristics listed below is most important and least important for you.

Table 11 Example of BWS question

Best		**Worst**
☒	**Milling quality**	☐
☐	**Resistance of Pyricularia**	☐
☐	**Panicle sterility resistance**	☐
☐	**Resistance to Rice Hoja Blanca Virus**	☒
☐	**Grain yield**	☐

If you consider "Milling quality" as the most important, then mark that option as the most important. Similarly, if you consider "Resistance to Rice Hoja Blanca Virus" as the least important, mark that option as the least important.

Appendix B

Characterization of Maize Farmers

A total of 800 surveys were conducted for the Maize crop,the initial target number of surveys, covering the country's main Maize-growing regions.the country. The distribution of the sample reflects the importance of each department in Maize production. Córdoba (52%) has the largest number of surveys, highlighting its importance in national production. It is followed by Meta (14%), Huila (9%), Tolima (6%) and Valle del Cauca (5%), while Cesar, Bolivar, Antioquia, Arauca and La Guajira have lower percentages, but reflect the territorial diversity of the crop (Table 12).

Table 12 Distribution of baseline surveys by department - maize crop

Department	Number of Surveys	Percentage (%)
Antioquia	21	3
Arauca	22	3
Bolívar	35	4
Cesar	34	4
Córdoba	415	52
Huila	71	9

La Guajira	5	1
Meta	110	14
Tolima	51	6
Valle del Cauca	36	5
All Departments	**800**	**100**

On average, the farms interviewed have an area of 16.1 hectares, of which 6.7 hectares are dedicated to Maize cultivation, with an average distribution of 1.42 lots per farmer (Table 13). However, there are significant differences between regions. Antioquia has the largest land extensions per farm (49.9 hectares on average), with 17.95 hectares devoted to maize, reflecting the fact that the average number of hectares of land per farmer is 17.95. 17.95 hectares devoted to Maize, reflecting a production model with greater access to land. In Meta, the average farm area is 21.15 hectares, with 14.6 hectares dedicated to Maize, suggesting an intermediate production approach with a higher concentration of cultivated areas.

Table 13 Distribution of average production and yield of farms by department - maize crop

Departments	Farm Area (Ha)	Farm Area in Maize (Ha)	Number of Lots in Maize (#)
Antioquia	49.90	17.95	1.95
Arauca	5.55	5.50	1.00
Bolívar	17.45	4.50	1.28
Cesar	39.14	6.10	1.64
Córdoba	5.00	2.91	1.27
Huila	7.28	3.65	1.50
La Guajira	10.20	4.60	2.20
Meta	21.15	14.60	1.68
Tolima	7.17	6.00	1.23
Valle del Cauca	11.08	9.38	1.20
All Departments	**16.08**	**6.70**	**1.42**

In contrast, departments such as Córdoba, Huila and Arauca have smaller scale farms. In Córdoba, the average farm size is 5.0 hectares, with 2.91 hectares in maize, suggesting a more fragmented production model. Huila and Bolivar have farms of 7.3 and 17.5 hectares on average, respectively, with Maize planted areas of 3.65 and 4.5 hectares. These values reflect less access to land and possibly less technification compared to large producers.

The level of land fragmentation also varies between regions. Antioquia and La Guajira have the highest levels of subdivision, with 1.95 and 2.2 average lots per farmer, respectively, which could indicate agricultural diversification strategies within the farm. Meta and Cesar show an intermediate level of fragmentation, with 1.68 and 1.64 lots on average, while Arauca, Córdoba and Valle del Cauca have lower values (between 1.0 and 1.27 lots on average), suggesting a more consolidated land use.

Production and Yield

The baseline data for the maize crop show high heterogeneity in terms of production and yield, determined by factors such as the production system (traditional or technified), agroecological conditions, the availability of agricultural infrastructure, and the level of technology adoption.

The baseline results show an average production of 15 tons per farm, with an average yield of 2.79 tons per hectare (t/ha) among the maize producers surveyed (see Table 14). These values reflect a great diversity among regions, with differences that can be attributed to the scale of production, the level of technification, the availability of agricultural infrastructure and agroecological conditions. While departments such as Tolima (4.03 t/ha) and Valle del Cauca (3.93 t/ha) reach yields, the yields of other departments, such as La Guajira (1.00 t/ha), Bolivar (1.21 t/ha) and Arauca (1.33 t/ha) show considerably lower yields.

Table 14 Distribution of average area of farms and plots of land under maize cultivation by department

Departments	Farmers	Farm production (Ton)	Yield production (Ton/Ha)
Antioquia	21	3.04	1.56
Arauca	22	8.37	1.33
Bolívar	35	3.50	1.21
Cesar	34	8.98	2.00
Córdoba	415	7.22	2.70
Huila	71	12.21	2.17
La Guajira	5	1.50	1.00
Meta	110	39.67	3.53
Tolima	51	23.85	4.03

Valle Del Cauca	36	35.95	3.93
All Departments	**800**	**15.00**	**2.79**

This heterogeneity is consistent with national figures reported by the Ministry of Agriculture and Rural Development (MADR), which estimate an average yield of 5.52 t/ha for technified Maize and 1.83 t/ha for traditional Maize (MADR, 2021b). These data reflect the significant gap between intensive and subsistence or low-scale production models. The mean observed in the baseline is between the two values, below the average for technified Maize, but above the average for traditional Maize, suggesting the coexistence of both production systems in the sample.

The highest yields were recorded in Tolima (4.03 t/ha), Valle del Cauca (3.93 t/ha) and Meta (3.53 t/ha), suggesting greater technification, availability of improved inputs and access to extension services. These departments also reported the highest production volumes per farm, with an average of more than 20 tons, indicating medium or high production scales. In contrast, the lowest yields were observed in La Guajira (1.00 t/ha), Bolivar (1.21 t/ha) and Arauca (1.33 t/ha).

The analysis of extreme values by department confirms the high variability in Maize production. Total crop losses were recorded in 42 cases, with yields of 0.00 tons in departments such as Arauca, Cesar, Córdoba and La Guajira, which were assigned a yield of 0 t/ha to reflect this situation. At the other extreme, exceptionally high values were reported, such as 1,750 tons in Meta, 765 tons in Valle del Cauca and 550 tons in Córdoba, all of which were verified directly with producers. The maximum yield observed was 13.6 t/ha, also in Meta. These results reflect structural gaps in the production systems and highlight the need for differentiated interventions, according to the profile of the producer and the territorial context.

Technical Assistance and Access to Services

Access to technical assistance is a key component for improving productivity, sustainability and adaptation to climate change in maize cultivation in Colombia. However, the baseline results show that only 15.2% of the producers surveyed have received some type of technical assistance in the last year, which shows a low and heterogeneous coverage among regions (see Table 15).

Table 15 Producers that received technical assistance by department - maize crop

Departments	Percentage who received technical assistance services (%)
Antioquia	6 (28.6%)
Arauca	6 (27.3%)
Bolívar	0 (0%)
Cesar	5 (14.7%)

Córdoba	55 (13.3%)
Huila	9 (12.7%)
La Guajira	1 (20%)
Meta	25 (22.7%)
Tolima	8 (15.7%)
Valle Del Cauca	7 (19.4%)
All Departments	**122 (15.2%)**

The departments of Antioquia (28.6%) and Arauca (27.3%) have the highest levels of coverage, although they correspond to a small sample. In contrast, departments with larger numbers of producers, such as Córdoba (13.3%) and Tolima (15.7%), show lower coverage, while Bolívar shows a total absence of technical assistance services (0%). This situation suggests institutional weaknesses or low presence of rural extension programs, especially in traditional maize and small-scale areas.

Table 16 Distribution by department of the thematic content of technical assistance received by producers (%) - general agronomic components - maize crop

Departments	Agroclimatic forecast (%)	Crops production (%)	Managament of plagues and deseases (%)	Soil management and fertility (%)	Manage and control of weed (%)
Antioquia	66.67	83.33	50.00	33.33	0.00
Arauca	0.00	33.33	83.33	0.00	0.00
Bolívar	N.A	N.A	N.A	N.A	N.A
Cesar	20.00	40.00	40.00	60.00	0.00
Córdoba	25.45	61.82	67.27	27.27	9.09
Huila	0.00	44.44	77.78	33.33	0.00
La Guajira	0.00	0.00	0.00	0.00	0.00
Meta	8.00	32.00	76.00	32.00	4.00
Tolima	12.50	25.00	87.50	25.00	0.00
Valle Del Cauca	14.29	42.86	85.71	71.43	28.57
All	**18.85**	**49.18**	**70.49**	**31.15**	**6.56**

Departments

Table 17 Distribution by department of the thematic content of technical assistance received by producers (%) - strategic and business components - maize crop

Departments	Access to comerce (%)	Financial practices (%)	Smart practices in agriculture (%)	Moderns inputs (%)	Manage and use of variaties (%)	Others (%)
Antioquia	33.33	0.00	0.00	0.00	0.00	0.00
Arauca	0.00	0.00	0.00	0.00	0.00	0.00
Bolívar	N.A	N.A	N.A	N.A	N.A	N.A
Cesar	0.00	0.00	0.00	0.00	20.00	0.00
Córdoba	3.64	1.82	9.09	14.55	5.45	1.82
Huila	0.00	0.00	0.00	11.11	11.11	0.00
La Guajira	0.00	0.00	0.00	0.00	100.00	0.00
Meta	4.00	4.00	4.00	4.00	4.00	0.00
Tolima	0.00	0.00	12.50	0.00	0.00	0.00
Valle Del Cauca	0.00	14.29	14.29	14.29	14.29	14.29
All Departments	**4.10**	**2.46**	**6.56**	**9.02**	**6.56**	**1.64**

In addition to the low coverage, there is a strong heterogeneity in the contents and approaches of the technical assistance provided. At the national level, the topics most frequently addressed were pest and disease management (70.5%), crop production (49.2%) and soil and fertility (31.2%), reflecting a focus on basic agronomic components. In contrast, strategic issues were poorly addressed: only 4.1% received assistance in market access, 2.5% in financial management, and 6.6% in smart agricultural practices (CSA). This suggests limited incorporation of sustainability-oriented elements, marketing and adaptation to climate change.

Agroclimatic forecasting

The use of climate information, particularly agroclimatic forecasts, represents a key tool for improving agronomic decision making and reducing the risks associated with climate variability in Maize production. However, the baseline results show a low generalized adoption of this type of service. Only 13.2% of the farmers surveyed reported having used agroclimatic forecasts in their last cropping season (see Table 18), and on average, users applied this information in 2.5 agricultural activities.

Table 18 Use of agroclimatic forecasts by department - maize crop

Departments	Farmers	Porcentage of use (%)	Average of activities
Antioquia	21	19.0	5.2
Arauca	22	4.5	1.0
Bolívar	35	8.6	3.7
Cesar	34	14.7	2.4
Córdoba	415	8.7	2.5
Huila	71	14.1	2.2
La Guajira	5	20.0	1.0
Meta	110	20.9	1.9
Tolima	51	27.5	2.1
Valle Del Cauca	36	25.0	4.2
All Departments	**800**	**13.2**	**2.5**

Departments such as Tolima (27.5%), Valle del Cauca (25%) and Meta (20.9%) show the highest levels of use, although none of them exceed 30% adoption. On the other hand, departments such as Arauca (4.5%) and Bolivar (8.6%) report considerably low levels of use. This may be associated with a combination of factors: low availability of services, lack of capacity to interpret forecasts, or limited perception of climate risk by producers.

In terms of specific uses, producers who do use agroclimatic forecasts report their application mainly in decisions related to soil preparation (67.9%), sowing date (59.4%), choice of varieties (34%) and application of fertilizers (35.8%). This shows that, when it is used, climatic information is valued for decision making in the initial stages of the production cycle.

Table 19 Use of agroclimatic forecasts by type of decision (%) - maize crop

Departments	Prep. Of soils	Planting Date	Elections of varieties	Fertilizers aplication	Nutritional adjustment	Weed control	Pest control	Irrigation requirements	Others
Antioquia	75.0%	75.0%	100.0%	100.0%	75.0%	75.0%	25.0%	0.0%	0.0%
Arauca	100.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Bolívar	100.0%	66.7%	33.3%	66.7%	0.0%	66.7%	33.3%	0.0%	0.0%

Cesar	80.0%	40.0%	20.0%	20.0%	20.0%	20.0%	20.0%	20.0%	0.0%
Córdoba	72.2%	52.8%	30.6%	33.3%	16.7%	16.7%	16.7%	11.1%	0.0%
Huila	80.0%	50.0%	30.0%	20.0%	10.0%	10.0%	20.0%	10.0%	10.0%
La Guajira	100.0 %	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Meta	47.8%	65.2%	34.8%	34.8%	4.3%	17.4%	8.7%	0.0%	0.0%
Tolima	57.1%	71.4%	28.6%	14.3%	7.1%	21.4%	14.3%	0.0%	0.0%
Valle Del Cauca	77.8%	77.8%	44.4%	77.8%	44.4%	55.6%	44.4%	33.3%	11.1%
All Departments	**67.9 %**	**59.4 %**	**34.0%**	**35.8%**	**16.0%**	**23.6 %**	**17.9 %**	**8.5%**	**1.9 %**

The departments with the greatest diversity of uses include Antioquia and Valle del Cauca, where producers apply forecasts in up to five different activities. In contrast, in departments such as Arauca and La Guajira, use is ad hoc and restricted to a single activity. These results reinforce the idea that, beyond coverage, there is an important gap in terms of depth and quality of climate information use.

Access to credit

Access to credit is a determining factor in improving producers' investment capacity, facilitating the adoption of technologies, improving agronomic management and reducing vulnerability to production and climate risks. However, the baseline results show that only 33% of the Maize producers surveyed reported having accessed some type of agricultural credit in the last year, which reflects a moderate level of financial inclusion in this segment (see Table 20).

Table 20 Producers who accessed credit by department - maize crop

Departments	Total Farmers	Farmers that have access to credit (%)
Antioquia	21	7 (33.3%)
Arauca	22	13 (59.1%)
Bolívar	35	2 (5.7%)
Cesar	34	9 (26.5%)
Córdoba	415	99 (23.9%)

Huila	71	32 (45.1%)
La Guajira	5	0 (0%)
Meta	110	65 (59.1%)
Tolima	51	25 (49%)
Valle Del Cauca	36	12 (33.3%)
All Departments	**800**	**264 (33%)**

The highest levels of access were recorded in Arauca and Meta, where approximately 6 out of 10 producers reported having access to credit. This greater financial inclusion could be linked to the presence of more technified productive schemes, greater associativity or links with local financial entities or institutional support projects. Also Tolima (49%) and Huila (45.1%) also stand out, exceeding the national average.

In contrast, departments such as Bolívar (5.7%), Cesar (26.5%) and Córdoba (23.9%) show low levels of access, despite having a significant producer base. In the case of La Guajira, no producer surveyed reported having access to credit, which evidences barriers that may include lack of collateral, informality in land tenure, or scarce presence of rural financial intermediaries.

Socio-demographic characteristics

The sociodemographic characterization of maize-producing households makes it possible to contextualize production results and better target differentiated intervention strategies. At average, the surveyed households are made up of 3.9 people, with a relatively equal distribution between men (1.7) and women (1.6) (see Table 22). However, differences are observed between departments: Córdoba, Huila, Bolívar and La Guajira present averages of more than 4 persons per household, while Arauca (2.5) and Valle del Cauca (3.2) report smaller family structures.

Table 21 Average household size by department - maize crops

Departments	Total Farmers	Average of people in the households		
		Total	Men	Women
Antioquia	16	3.6	2.1	1.3
Arauca	22	2.5	1.4	1.1
Bolívar	35	4.1	1.6	1.6
Cesar	31	3.8	1.5	1.4
Córdoba	398	4.1	1.8	1.7
Huila	68	4.0	1.9	1.3
La Guajira	5	4.1	1.3	2.3

Meta	107	3.5	1.5	1.5
Tolima	50	3.7	1.5	1.6
Valle Del Cauca	30	3.2	1.4	1.5
All Departments	**762**	**3.9**	**1.7**	**1.6**

The population pyramid (see Figure 9) confirms that the age structure of the households is predominantly adult, with a relatively narrow base, which could have future implications for generational succession in the crop.

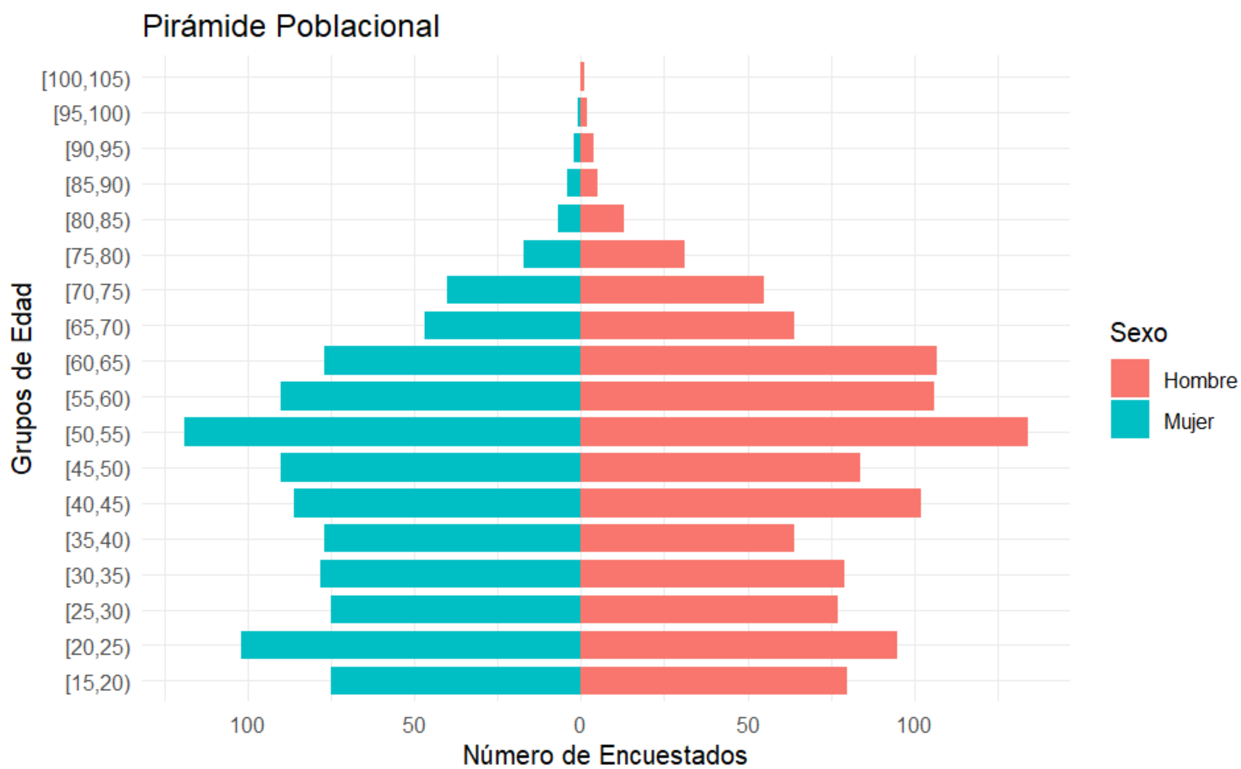

Figure 9 Household population pyramid - maize crop

With respect to the characteristics of the heads of household, the average age is 52.5 years old, with low educational levels: on average, producers have 6.9 years of schooling (see Table 23). Departments such as Valle del Cauca (59.1 years) and Córdoba (54.6 years) have an older population of heads of household, while Meta (45.2 years) has a relatively younger population. At the educational level, La Guajira (10.6 years), Valle del Cauca (8.1 years) and Huila (8.0 years) present the highest averages, while the lowest levels are observed in Bolivar (6.1 years) and Cordoba (6.2 years).

In terms of gender composition, 8 out of 10 heads of household are men (82.5%), confirming a significant gender gap in productive ownership. However, Departments such as Valle del Cauca

(66.7%) and Huila (73.5%) have higher proportions of women at the head of productive units, which may open opportunities for policy approaches with a territorialized gender focus.

Table 22 Characteristics of the head of household by department - maize crops

Departments	**Total Farmers**	**Average characteristics head of household**		
		Age (years)	**Education (years)**	**Men (%)**
Antioquia	16	51.9	7.2	75.0
Arauca	22	50.2	7.5	90.9
Bolívar	35	52.1	6.1	88.6
Cesar	31	52.1	6.8	90.3
Córdoba	397	54.6	6.2	83.1
Huila	68	50.9	8.0	73.5
La Guajira	5	50.2	10.6	80.0
Meta	107	45.2	7.5	84.1
Tolima	50	51.4	7.7	86.0
Valle Del Cauca	30	59.1	8.1	66.7
All Departments	**761**	**52.5**	**6.9**	**82.5**

Characterization of Rice Farmers

The rice crop survey has concluded, with a total of 731 surveys. The distribution of the sample reflects the importance of the country's main rice-growing regions and the municipalities exposed to various climatic risks. Sucre (35%) and Tolima (23%) concentrated the largest number of surveys, followed by Norte de Santander (16%), Huila (10%), Casanare (7%), Meta (5%) and Córdoba (4%) (Table 23).

Table 23 . Distribution of baseline surveys by department - rice cultivation

Departments	**Number of Surveys**	**Percentage (%)**
Sucre	256	35
Norte de Santander	115	16
Meta	39	5
Huila	75	10

Córdoba	31	4
Casanare	49	7
Tolima	166	23
Total	**731**	**100**

On average, the farms interviewed have an area of 52.74 hectares, of which 29.83 hectares are under rice cultivation, with an average distribution of 1.85 lots per farmer (Table 3). However, there are significant variations between regions. Casanare has the largest land extensions per farm (199.9 hectares on average), with 122.7 hectares under rice, reflecting a highly mechanized and large-scale production model, with 122.7 hectares devoted to rice. In Meta, the average farm area is 116.9 hectares, with 51 hectares dedicated to rice, indicating a more intensive production system than in other regions.

Table 24 Distribution of the average area of farms and lots destined for rice cultivation by department

Departments	Farm Area (Ha)	Farm area in rice (Ha)	Number of Lots in rice(#)
Casanare	199.90	122.65	4.00
Córdoba	6.73	5.83	1.27
Huila	11.70	7.60	1.23
Meta	116.90	51.00	2.90
Norte de Santander	8.75	8.45	1.25
Sucre	6.36	3.54	1.10
Tolima	12.7	5.46	1.2
All Departments	**52.74**	**29.83**	**1.85**

In contrast, Sucre, Córdoba, Huila and Norte de Santander have smaller scale farms. In Córdoba, the average farm size is 6.7 hectares, with 5.8 hectares in rice, suggesting specialized production in small units. In Sucre, farms are even smaller, with an average of 6.4 hectares, of which 3.5 hectares are dedicated to rice, reflecting less technification and greater dependence on traditional practices. Huila and Norte de Santander have intermediate production models, with average areas of 11.7 and 8.8 hectares per farm, respectively, with 7.6 hectares in Huila and 8.5 hectares in Norte de Santander devoted to rice.

The level of land fragmentation also varies between regions. Casanare has the highest number of lots per farmer, with an average of 4 lots in rice, which suggests a subdivision of large tracts into operational plots. Meta shows a similar pattern with 2.9 plots per farm, which reflects a structure that may favor greater productive diversification within the same agricultural unit. In the other regions, the average number of rice plots is lower, with 1.27 in Córdoba, 1.23 in Huila and 1.10 in Sucre. This indicates farms with less fragmentation and possibly less crop diversification.

These results show the diversity of rice production models in Colombia. While in Casanare and Meta, highly mechanized and large-scale systems predominate, in departments such as Sucre, Córdoba and Huila, the crop is grown in smaller production units, with less access to technology and greater dependence on traditional practices. The findings are consistent with the reported trends when compared with secondary data. According to the Fifth National Rice Census 2023, the departments of Casanare, Tolima and Meta registered the largest planted and harvested areas of mechanized rice in the country (DANE, 2023). Specifically, Casanare reported a planted area of 206,689 hectares, while Tolima and Meta registered 100,589 and 86,449 hectares, respectively. These data support the baseline survey distribution, where Casanare and Tolima represented a significant proportion of the sample.

Yield production

The baseline data reveal marked differences in rice productivity levels between regions (Table 4). The average yield among the surveyed producers was 4.69 tons per hectare (t/ha), a value slightly lower than the national average of 5.2 t/ha reported for mechanized rice by the Fifth National Rice Census (DANE, 2023).

Table 25 Distribution of average farm production and yield by department - rice crop

Departments	Farmers	Farm production (Ton)	Yield production (Ton/Ha)
Casanare	49	262.56	5.21
Córdoba	31	22.72	4.08
Huila	75	47.17	7.34
Meta	39	128.01	5.94
Norte De Santander	115	33.09	4.42
Sucre	256	8.30	2.94
Tolima	166	41.12	5.95
All Departments	**731**	**47.83**	**4.69**

Huila stood out with the highest yield (7.34 t/ha), followed by Tolima (5.95 t/ha) and Meta (5.94 t/ha), suggesting greater agronomic efficiency possibly associated with soil quality, access to technical services and use of certified seeds. In contrast, Sucre (2.94 t/ha) and Córdoba (4.08 t/ha) recorded the lowest yields.

In terms of volume, Casanare reported the highest average production per farm (262.6 tons), reflecting its extensive production business model. In fact, according to DANE, Casanare recorded 206,689 hectares planted in 2023, consolidating its position as the country's leading rice producer (DANE, 2023).

High intra-regional variability was also observed: for example, in Tolima, yields ranged from 0 to 13 t/ha, and in Sucre, seven producers reported null yields due to total crop loss. These gaps reflect exposure to adverse climatic events, differences in technical capacity and inequalities in access to key inputs (such as fertilizers, certified seeds and irrigation).

Technical Assistance and Access to Services

Access to technical assistance is an essential component for improving productivity, sustainability and adaptation to climate change in rice cultivation in Colombia. However, the baseline data show that only 27.5% of the surveyed producers have received some type of technical assistance, which reflects a limited and unequal coverage among regions (Table 26).

Table 26 Producers who received technical assistance by department - rice crop

Departments	Total Farmers	Percentage who received technical assistance services (%)
Casanare	49	24 (49%)
Córdoba	31	12 (38.7%)
Huila	75	22 (29.3%)
Meta	39	25 (64.1%)
Norte De Santander	115	38 (33%)
Sucre	256	9 (3.5%)
Tolima	166	71 (42.8%)
All Departments	**731**	**201 (27.5%)**

The departments of Meta (64.1%) and Casanare (49%) have the highest levels of coverage, which can be attributed in part to the active presence of Fedearroz, which for more than a decade has been implementing the Massive Technology Adoption Program (AMTEC), designed to improve production efficiency through specialized technical assistance, business management and sustainable practices (Fedearroz, 2023; Finagro, 2022). On the other hand, departments such as Sucre show worrying figures, with barely 3.5% coverage, despite being one of the main ones in terms of number of producers. This low coverage is the main reason for this is the weak implementation of instruments such as the Departmental Agricultural Extension Plans (PDEA), which in many departments are not yet fully operational or lack sufficient resources (ADR, 2024).

Table 27 Distribution by department of the thematic content of technical assistance received by producers (%) - general agronomic components - rice cultivation

Departments	Agroclimatic forecast (%)	Crops production (%)	Managament of plagues and deseases (%)	Soil management and fertility (%)	Manage and control of weed (%)
Casanare	75.00	45.83	70.83	62.50	41.67
Córdoba	41.67	25.00	58.33	25.00	8.33
Huila	22.73	50.00	50.00	31.82	13.64
Meta	56.00	32.00	60.00	44.00	32.00
Norte De Santander	2.63	18.42	89.47	47.37	10.53
Sucre	22.22	22.22	66.67	11.11	0.00
Tolima	21.13	0.00	0.00	16.90	0.00
All Departments	**29.85**	**20.90**	**44.78**	**33.33**	**12.94**

Table 28 Distribution by department of the thematic content of technical assistance received by producers (%) - strategic and business components - rice cultivation

Departments	Access to comerce (%)	Financial practices (%)	Smart practices in agriculture (%)	Moderns inputs (%)	Manage and use of variaties (%)	Others (%)
Casanare	8.33	16.67	37.50	41.67	37.50	0.00
Córdoba	0.00	8.33	16.67	58.33	16.67	0.00
Huila	4.55	0.00	22.73	36.36	9.09	0.00
Meta	4.00	0.00	8.00	28.00	24.00	0.00
Norte De Santander	2.63	2.63	7.89	28.95	5.26	0.00
Sucre	0.00	0.00	22.22	33.33	0.00	0.00

Tolima	14.08	0.00	0.00	0.00	0.00	84.51
All Departments	**7.46**	**2.99**	**11.44**	**22.89**	**10.45**	**29.85**

In addition to coverage, there is a marked heterogeneity in the content and focus of the technical assistance provided. Among the producers who reported having received assistance in the last year, the most frequently addressed topics were pest and disease management (44.8%), soil and fertility management (33.3%), and the use of agroclimatic forecasts (29.9%), reflecting a majority orientation towards conventional agronomic components (see Table 28). In contrast, contents related to strategic aspects of the production system were little addressed: only 7.5% received support in market access, 3% in financial management, and 11.4% in climate-smart agricultural practices (CSA) (see Table 28).

Agroclimatic Forecasting

The use of climate information is an important component for reducing risks, optimizing agronomic decisions and improving the resilience of production systems. However, baseline data show a still limited adoption of agroclimatic forecasts among rice producers: only 23.8% of respondents reported having used this type of information during the last year (see Table 29). This figure is low considering the increasing climate variability affecting the sector and the international recommendations to strengthen decision making based on climate information (FAO, 2023).

Table 29 Use of agroclimatic forecasts by department - rice crop

Departments	Farmers	Porcentage of use (%)	Average of activities
Casanare	49	69.4	4.8
Córdoba	31	41.9	2.6
Huila	75	33.3	3.5
Meta	39	71.8	4.9
Norte De Santander	115	11.3	3.1
Sucre	256	9.4	2.8
Tolima	166	22.3	3.0
All Departments	**731**	**23.8**	**3.7**

In Meta (71.8%) and Casanare (69.4%), the use of forecasts is widely spread among producers, probably thanks to more technified production models. In addition, forecast users report intensive use of this information, applying it in an average of almost five agricultural decisions. At the other extreme, Sucre (9.4%) and Norte de Santander (11.3%) show alarmingly low levels of use, which is aligned with the low levels of technical assistance observed in these regions.

Beyond access, it is also important to analyze how producers use forecasts in practice. At the national level, use is concentrated in key activities of the production cycle, especially in defining the sowing date (79.9%), soil preparation (72.4%), and pest control (44.3%) (see Table 30). These decisions are climate-sensitive and reflect a basic but effective appropriation of agroclimatic information.

Table 30 Use of agroclimatic forecasts by type of decision (%) - rice crop

Departments	Prep. Of soils	Planting Date	Elections of varieties	Fertilizers aplication	Nutritional adjustment	Weed control	Pest control	Irrigation requirements	Others
Casanare	88.2%	88.2%	70.6%	67.6%	32.4%	61.8%	50.0%	23.5%	0.0%
Córdoba	61.5%	92.3%	15.4%	15.4%	15.4%	15.4%	23.1%	15.4%	7.7%
Huila	52.0%	64.0%	44.0%	52.0%	16.0%	36.0%	72.0%	28.0%	0.0%
Meta	89.3%	92.9%	57.1%	85.7%	32.1%	60.7%	60.7%	10.7%	0.0%
Norte De Santander	84.6%	76.9%	53.8%	46.2%	15.4%	23.1%	23.1%	38.5%	0.0%
Sucre	58.3%	87.5%	29.2%	37.5%	12.5%	25.0%	25.0%	8.3%	0.0%
Tolima	67.6%	64.9%	35.1%	35.1%	16.2%	32.4%	35.1%	13.5%	0.0%
All Departments	**72.4%**	**79.9%**	**46.0%**	**51.7%**	**21.3%**	**40.2%**	**44.3%**	**18.4%**	**0.6%**

However, other more strategic decisions, such as nutritional adjustment (21.3%), irrigation management (18.4%) and variety selection (46%), show lower levels of use. This suggests that, although climate information is beginning to be integrated into agronomic decision making, its use is still partial and concentrated in basic practices. The lack of use in more complex decisions could be related to a low technical capacity to interpret forecasts, or to the lack of local tools to translate this information into concrete recommendations.

Access to credit

Access to formal financial services, such as agricultural credit, is a determining factor in improving productivity, facilitating the adoption of technologies and reducing vulnerability to production and climate risks. However, the baseline results reveal partial and unequal coverage in access to credit among the surveyed producers.

At the national level, 47.9% of producers reported having access to credit in the last year (see Table 31). While this proportion represents a relatively high level compared to the historical average of rural access in Colombia-estimated at around 30% according to Finagro and the Mission for the Transformation of the Countryside (DNP, 2015), the differences between departments are marked and reflect structural gaps in financial inclusion.

Table 31 Farmers who accessed credit by department - rice crop

Departments	Total Farmers	Farmers that have access to credit (%)
Casanare	49	41 (83.7%)
Córdoba	31	14 (45.2%)
Huila	75	54 (72%)
Meta	39	31 (79.5%)
Norte De Santander	115	65 (56.5%)
Sucre	256	50 (19.5%)
Tolima	166	95 (57.2%)
All Departments	**731**	**350 (47.9%)**

The highest levels of access were recorded in Casanare (83.7%), Meta (79.5%) and Huila (72%), suggesting better articulation between producers, financial institutions and productive development programs. These regions also coincide with higher levels of technical assistance and use of tools such as agro-climatic forecasts, indicating a more favorable ecosystem for investment and technological adoption. In contrast, Sucre shows a critical situation, with only 19.5% of producers accessing credit. This is consistent with the low levels observed in other institutional indicators such as technical assistance (3.5%) and use of climate forecasts (9.4%).

Tolima and Norte de Santander show intermediate levels, with around 57% coverage. Although above the national average, these departments could benefit from more active strategies to expand access to credit with a territorial approach, especially in subregions with less economic dynamism.

Socio-demographic characteristics

The sociodemographic analysis of rice-producing households provides an understanding of living conditions, family structure and the profile of decision-makers within the production units. This information is key to the design of strategies for technical assistance, financial inclusion and organizational strengthening with a territorial approach.

In general terms, the rice farming households surveyed are composed of an average of 3.7 people, with a relatively balanced distribution between men (1.6) and women (1.4) (see Table

32). Although the differences between departments are not marked, Córdoba and Norte de Santander have the largest households (4.2 and 4.0 persons, respectively), while Tolima has the lowest average (3.1). This variation may reflect differences in family structure, migratory patterns and the level of population aging in the territories.

Table 32 Average household size by department - rice cultivation

Departments	Total Farmers	Average of persons in the households		
		Total	Men	Women
Casanare	49	3.4	1.4	1.4
Córdoba	31	4.2	1.6	1.8
Huila	72	3.6	1.6	1.4
Meta	39	3.9	1.7	1.5
Norte De Santander	115	4.0	1.8	1.5
Sucre	256	3.9	1.6	1.4
Tolima	155	3.1	1.4	1.3
All Departments	**717**	**3.7**	**1.6**	**1.4**

The surveyed population shows a moderately aged structure, with age average of 53.2 years for heads of household (see Table 32 and Figure 10). This pattern is accentuated in departments such as Tolima (57.6 years), Córdoba (54.1 years) and Norte de Santander (53.7 years), which could have implications for the sustainability of generational replacement in rice cultivation. In contrast, Casanare has the lowest average age (44.6 years), which coincides with a more entrepreneurial production model and possibly a greater presence of young producers or farm managers.

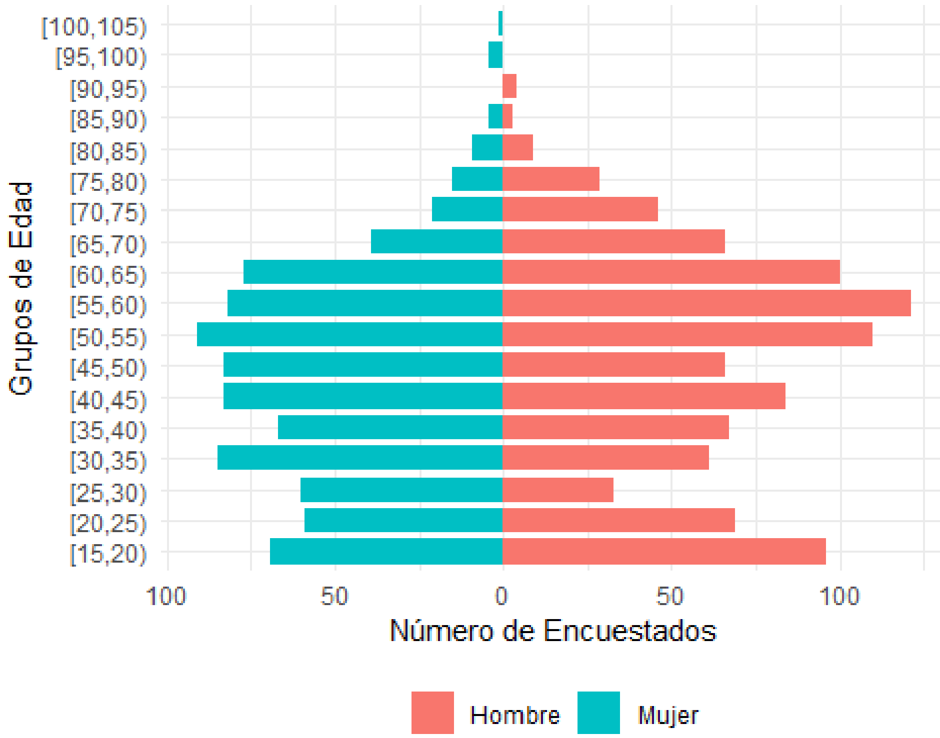

Figure 10 Population pyramid of households - rice production

In terms of educational level, the national average schooling level of heads of household is 7.7 years, with higher values in Meta (11.4 years) and Casanare (11.2 years), and lower values in Sucre (6.5 years) and Norte de Santander (6.7 years). These differences could be associated with both the level of rurality and local education supply, as well as the formalization of productive systems in each region.

Table 33 Characteristics of the head of household by department - rice cultivation

Departments	**Total Farmers**	**Average characteristics head of household**		
		Age (years)	**Education (years)**	**Men (%)**
Casanare	49	44.6	11.2	67.3
Córdoba	31	54.1	8.5	83.9
Huila	72	52.5	9.0	87.5
Meta	39	50.5	11.4	79.5
Norte De Santander	115	53.7	6.7	84.3
Sucre	256	52.5	6.5	85.5

Tolima	154	57.6	7.5	92.2
All Departments	**716**	**53.2**	**7.7**	**85.3**

In terms of gender, 85.3% of the surveyed heads of household are men, which shows a strong masculinization of the decision-making role in the productive unit (See Table 33). This proportion is especially high in Tolima (92.2%), Sucre (85.5%) and Huila (87.5%), which reinforces the need to integrate gender approaches into technical assistance and capacity building strategies.

Appendix C

Rice

Analysis by Regions

Table 34 Preference shares by region - rice

Variable	*Bajo Cauca*	*Centro*	*Llanos*	*Santanderes*
Grain yield	27 (1°)	16 (3°)	33 (1°)	28 (1°)
Milling quality	14 (2°)	8 (6°)	10 (3°)	17 (2°)
Rice blast resistance	10 (3°)	7 (7°)	9 (4°)	-
Panicle sterility resistance	9 (4°)	18 (2°)	14 (2°)	10 (3°)
Grain discoloration tolerance	9 (5°)	-	8 (5°)	8 (4°)
Shattering resistance	8 (6°)	10 (5°)	6 (8°)	8 (6°)
Burkholderia glumae tolerance	8 (7°)	19 (1°)	7 (7°)	7 (8°)
Rice Hoja Blanca Virus resistance	7 (8°)	6 (8°)	-	7 (9°)
Lodging resistance	7 (9°)	11 (4°)	6 (9°)	8 (5°)
Rice blast resistance	-	5 (9°)	8 (6°)	7 (7°)

Table 35 Estimation by region -rice

Model Preference Estimates per rice-producing region

VARIABLES	(1) Bajo Cauca - MNL	(2) Bajo Cauca - RPL	(3) Centro - MNL	(4) Centro - RPL	(5) Llanos - MNL	(6) Llanos - RPL	(7) Santanderes - MNL	(8) Santanderes - RPL
Burkholderia glumae	0.420***	0.420***	1.514***	1.514***	0.0850	0.0850	0.0861	0.0861
	(0.0948)	(0.0948)	(0.276)	(0.276)	(0.156)	(0.156)	(0.153)	(0.153)
Milling quality	0.985***	0.985***	0.586***	0.586***	0.465**	0.465**	0.942***	0.942***
	(0.115)	(0.115)	(0.184)	(0.184)	(0.214)	(0.214)	(0.163)	(0.163)
Shattering resistance	0.423***	0.423***	0.838***	0.838***	0.0140	0.0140	0.120	0.120
	(0.0942)	(0.0942)	(0.197)	(0.197)	(0.183)	(0.183)	(0.162)	(0.162)
Grain discoloration tolerance	0.530***	0.530***			0.273	0.273	0.199	0.199
	(0.106)	(0.106)			(0.198)	(0.198)	(0.148)	(0.148)
Rice blast resistance	0.654***	0.654***	0.425*	0.425*	0.378*	0.378*		
	(0.118)	(0.118)	(0.229)	(0.229)	(0.213)	(0.213)		
Grain yield	1.625***	1.625***	1.336***	1.336***	1.705***	1.705***	1.446***	1.446***
	(0.125)	(0.125)	(0.210)	(0.210)	(0.208)	(0.208)	(0.184)	(0.184)
Panicle sterility resistance	0.579***	0.579***	1.425***	1.425***	0.820***	0.820***	0.386**	0.386**
	(0.104)	(0.104)	(0.221)	(0.221)	(0.244)	(0.244)	(0.162)	(0.162)
Rice Hoja Blanca Virus	0.313***	0.313***	0.346	0.346			0.0399	0.0399
	(0.0946)	(0.0946)	(0.227)	(0.227)			(0.159)	(0.159)

Lodging resistance	0.256***	0.256***	0.986***	0.986***	-0.0235	-0.0235	0.133	0.133
	(0.0954)	(0.0954)	(0.238)	(0.238)	(0.204)	(0.204)	(0.174)	(0.174)
H.temperature tolerance			0.219	0.219	0.226	0.226	0.0885	0.0885
			(0.237)	(0.237)	(0.211)	(0.211)	(0.164)	(0.164)
Region	Bajo Cauca	Bajo Cauca	Centro	Centro	Llanos	Llanos	Santanderes	Santanderes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Analysis by Farm Size Categories

Table 36 Preferences shares by size - rice

Variable	*Small (<10 ha)*	*Medium (10-50 ha)*	*Large (>50 ha)*
Grain yield	26 (1°)	29 (1°)	23 (1°)
Milling quality	14 (2°)	12 (3°)	9 (4°)
Panicle sterility resistance	10 (3°)	13 (2°)	17 (2°)
Rice blast resistance	9 (4°)	8 (4°)	8 (7°)
Burkholderia glumae tolerance	9 (5°)	8 (5°)	8 (6°)
Shattering resistance	8 (6°)	7 (8°)	8 (8°)
Grain discoloration tolerance	8 (7°)	8 (7°)	9 (5°)
Lodging resistance	8 (8°)	8 (6°)	7 (9°)
Rice Hoja Blanca Virus resistance	7 (9°)	7 (9°)	-
High temperature tolerance	-	-	11 (3°)

Table 37 Estimations by size - rice

Model Preference Estimates per crop area

VARIABLES	(1) Pequenas - MNL	(2) Pequenas - RPL	(3) Medianas - MNL	(4) Medianas - RPL	(5) Grandes - MNL	(6) Grandes - RPL
Burkholderia glumae tolerance	0.439***	0.439***	0.217*	0.217*	0.334	0.334
	(0.0816)	(0.0816)	(0.129)	(0.129)	(0.236)	(0.236)
Milling quality	0.865***	0.865***	0.612***	0.612***	0.450*	0.450*
	(0.0966)	(0.0966)	(0.167)	(0.167)	(0.272)	(0.272)
Shattering resistance	0.382***	0.382***	0.0637	0.0637	0.247	0.247
	(0.0777)	(0.0777)	(0.160)	(0.160)	(0.229)	(0.229)
Grain discoloration tolerance	0.354***	0.354***	0.151	0.151	0.418	0.418
	(0.0873)	(0.0873)	(0.158)	(0.158)	(0.269)	(0.269)
Rice blast resistance	0.460***	0.460***	0.246	0.246	0.318	0.318
	(0.0924)	(0.0924)	(0.182)	(0.182)	(0.323)	(0.323)
Grain yield	1.503***	1.503***	1.504***	1.504***	1.366***	1.366***
	(0.104)	(0.104)	(0.177)	(0.177)	(0.276)	(0.276)
Panicle sterility resistance	0.584***	0.584***	0.698***	0.698***	1.043***	1.043***
	(0.0835)	(0.0835)	(0.172)	(0.172)	(0.351)	(0.351)
Rice Hoja Blanca Virus resistance	0.230***	0.230***	0.0320	0.0320		
	(0.0766)	(0.0766)	(0.138)	(0.138)		
Lodging resistance	0.259***	0.259***	0.174	0.174	0.158	0.158
	(0.0781)	(0.0781)	(0.147)	(0.147)	(0.297)	(0.297)
High temperature tolerance					0.602*	0.602*
					(0.364)	(0.364)

Tipo de Finca	Pequena (<10 ha	Pequena (<10 ha	Mediana (10-50 ha	Mediana (10-50 ha	Grande (>50 ha	Grande (>50 ha
)						

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Analisys by Production Systems

Table 38 Preference shares by system - rice

Variable	*Rainfed*	*Irrigation*
Grain yield	29 (1°)	23 (1°)
Milling quality	13 (2°)	13 (3°)
Panicle sterility resistance	10 (3°)	13 (2°)
Rice blast resistance	10 (4°)	7 (7°)
Grain discoloration tolerance	9 (5°)	7 (9°)
Shattering resistance	8 (6°)	9 (6°)
Burkholderia glumae tolerance	7 (7°)	11 (4°)
Rice Hoja Blanca Virus resistance	7 (8°)	7 (8°)
Lodging resistance	7 (9°)	10 (5°)
High temperature tolerance	-	-

Table 39 Estimations by system - rice

Estimaciones de Preferencias por Sistema de Riego

VARIABLES	(1) Con Riego - MNL	(2) Con Riego - RPL	(3) Secano - MNL	(4) Secano - RPL
Burkholderia glumae tolerance	0.523***	0.523***	0.236***	0.236***
	(0.124)	(0.124)	(0.0817)	(0.0817)
Milling quality	0.621***	0.621***	0.819***	0.819***
	(0.139)	(0.139)	(0.104)	(0.104)
Shattering resistance	0.238**	0.238**	0.288***	0.288***
	(0.115)	(0.115)	(0.0876)	(0.0876)
Grain discoloration tolerance	0.0106	0.0106	0.431***	0.431***
	(0.118)	(0.118)	(0.0989)	(0.0989)
Rice blast resistance	0.0615	0.0615	0.535***	0.535***
	(0.127)	(0.127)	(0.107)	(0.107)
Grain yield	1.217***	1.217***	1.601***	1.601***
	(0.140)	(0.140)	(0.110)	(0.110)
Panicle sterility resistance	0.669***	0.669***	0.565***	0.565***
	(0.117)	(0.117)	(0.101)	(0.101)

Rice Hoja Blanca Virus	0.0403	0.0403	0.188**	0.188**
	(0.103)	(0.103)	(0.0890)	(0.0890)
Lodging resistance	0.330***	0.330***	0.118	0.118
	(0.105)	(0.105)	(0.0924)	(0.0924)
Sistema	Con Riego	Con Riego	Secano	Secano

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Maize

Analysis by Region

Table 40 Preference share by region - maize

Variable	*Andina*	*Caribe*	*Orinoquia*
Grain yield	22 (1°)	27 (1°)	36 (1°)
Drought stress tolerance	17 (2°)	11 (3°)	12 (3°)
High temperature tolerance	16 (3°)	11 (4°)	10 (4°)
Grain hardness	13 (4°)	16 (2°)	13 (2°)
Ear rot resistance	8 (5°)	9 (5°)	7 (5°)
Tar spot complex resistance	7 (6°)	-	7 (6°)
Corn stunt complex resistance	6 (7°)	6 (8°)	-
Cercospora resistance	6 (8°)	6 (7°)	6 (7°)
Waterlogging tolerance	5 (9°)	8 (6°)	4 (9°)
Lodging resistance	-	6 (9°)	5 (8°)

Table 41 Estimations by region - maize

Estimaciones de Preferencias por Region

VARIABLES	(1) Andina - MNL	(2) Andina - RPL	(3) Caribe - MNL	(4) Caribe - RPL	(5) Orinoquia - MNL	(6) Orinoquia - RPL
Rendimiento de grano/ha	1.504***	1.504***	1.567***	1.567***	2.064***	2.064***
	(0.149)	(0.149)	(0.0854)	(0.0854)	(0.194)	(0.194)
Tolerancia a estres por sequia	1.254***	1.254***	0.687***	0.687***	0.952***	0.952***
	(0.157)	(0.157)	(0.0838)	(0.0838)	(0.169)	(0.169)
Tolerancia a estres por encharcamiento	0.0558	0.0558	0.352***	0.352***	-0.0802	-0.0802
	(0.145)	(0.145)	(0.0743)	(0.0743)	(0.172)	(0.172)
Tolerancia a altas temperaturas	1.197***	1.197***	0.672***	0.672***	0.729***	0.729***
	(0.144)	(0.144)	(0.0807)	(0.0807)	(0.156)	(0.156)
Resistencia a pudricion de mazorca	0.471***	0.471***	0.506***	0.506***	0.413***	0.413***
	(0.147)	(0.147)	(0.0842)	(0.0842)	(0.160)	(0.160)
Dureza del grano	0.971***	0.971***	1.059***	1.059***	1.069***	1.069***
	(0.149)	(0.149)	(0.0811)	(0.0811)	(0.189)	(0.189)
Resistencia al complejo del achaparramiento	0.275*	0.275*	0.0945	0.0945		
	(0.140)	(0.140)	(0.0654)	(0.0654)		
Resistencia a complejo de mancha de asfalto	0.343**	0.343**			0.397**	0.397**
	(0.142)	(0.142)			(0.169)	(0.169)
Resistencia a Cercospora	0.210	0.210	0.145**	0.145**	0.292**	0.292**
	(0.130)	(0.130)	(0.0610)	(0.0610)	(0.133)	(0.133)
Tolerancia a volcamiento			0.0697	0.0697	0.0449	0.0449
			(0.0690)	(0.0690)	(0.172)	(0.172)
Observations	17,760	17,760	47,760	47,760	13,200	13,200
Region	Andina	Andina	Caribe	Caribe	Orinoquia	Orinoquia

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Analysis by Farm Size Categories

Table 42 Preference share sizes – maize

Variable	*Pequeña (<10 ha)*	*Mediana (10-50 ha)*	*Grande (>50 ha)*
Grain yield	27 (1°)	29 (1°)	23 (1°)
Grain hardness	15 (2°)	17 (2°)	10 (3°)
High temperature tolerance	12 (3°)	8 (4°)	7 (7°)
Drought stress tolerance	12 (4°)	16 (3°)	10 (4°)
Ear rot resistance	9 (5°)	7 (5°)	8 (5°)
Waterlogging tolerance	7 (6°)	6 (8°)	-
Cercospora resistance	6 (7°)	5 (9°)	8 (6°)
Tar spot complex resistance	6 (8°)	6 (7°)	6 (9°)
Lodging resistance	6 (9°)	6 (6°)	6 (8°)
Corn stunt complex resistance	-	-	22 (2°)

Table 43 Estimations by area - maize

Estimaciones de Preferencias por Tamano de Finca

VARIABLES	(1) Pequenas - MNL	(2) Pequenas - RPL	(3) Medianas - MNL	(4) Medianas - RPL	(5) Grandes - MNL	(6) Grandes - RPL
Rendimiento de grano/ha	1.523***	1.523***	1.551***	1.551***	1.452**	1.452**
	(0.0726)	(0.0726)	(0.225)	(0.225)	(0.673)	(0.673)
Tolerancia a estres por sequia	0.725***	0.725***	0.984***	0.984***	0.550	0.550
	(0.0678)	(0.0678)	(0.216)	(0.216)	(0.975)	(0.975)
Tolerancia a estres por encharcamiento	0.122*	0.122*	-0.0705	-0.0705		
	(0.0637)	(0.0637)	(0.219)	(0.219)		
Tolerancia a altas temperaturas	0.729***	0.729***	0.306	0.306	0.258	0.258
	(0.0648)	(0.0648)	(0.189)	(0.189)	(0.938)	(0.938)
Resistencia a pudricion de mazorca	0.405***	0.405***	0.0744	0.0744	0.370	0.370
	(0.0669)	(0.0669)	(0.223)	(0.223)	(0.386)	(0.386)
Dureza del grano	0.926***	0.926***	1.034***	1.034***	0.600	0.600
	(0.0700)	(0.0700)	(0.214)	(0.214)	(0.689)	(0.689)
Tolerancia a volcamiento	-0.0597	-0.0597	-0.00321	-0.00321	0.139	0.139
	(0.0627)	(0.0627)	(0.208)	(0.208)	(0.617)	(0.617)
Resistencia a complejo de mancha de asfalto	0.0407	0.0407	-0.0142	-0.0142	0.0741	0.0741
	(0.0565)	(0.0565)	(0.194)	(0.194)	(0.708)	(0.708)
Resistencia a Cercospora	0.0906*	0.0906*	-0.123	-0.123	0.344	0.344
	(0.0531)	(0.0531)	(0.185)	(0.185)	(0.445)	(0.445)
Resistencia al complejo del achaparramiento					1.384**	1.384**
					(0.635)	(0.635)
Tipo de Finca	Pequena (<10 ha	Pequena (<10 ha	Mediana (10-50 ha	Mediana (10-50 ha	Grande (>50 ha	Grande (>50 ha

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Analysis by Production Systems

Table 44 Preference share by system - maize

Variable	Mecánico	Manual
Grain yield	28 (1°)	26 (1°)
Grain hardness	15 (2°)	15 (2°)
Drought stress tolerance	12 (3°)	13 (3°)
High temperature tolerance	10 (4°)	13 (4°)
Ear rot resistance	9 (5°)	8 (5°)
Cercospora resistance	7 (6°)	6 (6°)
Waterlogging tolerance	7 (7°)	6 (7°)
Tar spot complex resistance	6 (8°)	6 (8°)
Corn stunt complex resistance	6 (9°)	-
Lodging resistance	-	6 (9°)

Table 45 Estimations by system - maize

Estimaciones de Preferencias por Sistema de Recoleccion

VARIABLES	(1) Mecanica - MNL	(2) Mecanica - RPL	(3) Manual - MNL	(4) Manual - RPL
Grain yield	1.745***	1.745***	1.495***	1.495***
	(0.141)	(0.141)	(0.0888)	(0.0888)
Drought stress tolerance	0.875***	0.875***	0.806***	0.806***
	(0.127)	(0.127)	(0.0928)	(0.0928)
Waterlogging tolerance	0.286**	0.286**	0.00952	0.00952
	(0.124)	(0.124)	(0.0798)	(0.0798)
High temperature tolerance	0.718***	0.718***	0.797***	0.797***
	(0.128)	(0.128)	(0.0852)	(0.0852)
Ear rot resistance	0.548***	0.548***	0.304***	0.304***
	(0.129)	(0.129)	(0.0877)	(0.0877)
Grain hardness	1.122***	1.122***	0.927***	0.927***
	(0.130)	(0.130)	(0.0922)	(0.0922)
Corn stunt complex resistance	0.227*	0.227*		
	(0.117)	(0.117)		
Tar spot complex resistance	0.236**	0.236**	0.00660	0.00660
	(0.115)	(0.115)	(0.0691)	(0.0691)
Cercospora resistance	0.302***	0.302***	0.0176	0.0176
	(0.109)	(0.109)	(0.0681)	(0.0681)
Lodging resistance			-0.00268	-0.00268
			(0.0771)	(0.0771)
Sistema	Recoleccion Mecanica	Recoleccion Mecanica	Recoleccion Manual	Recoleccion Manual

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1