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Classifying Climate Change Perceptions of Bean Breeders in Santander-Colombia

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Abstract

Voluntary uptake of climate-adapted beans is driven by farmers' climate change perceptions. Identifying these perceptions and understanding their determinants help public agencies and seed suppliers design tailored engagement strategies to maximize uptake. We perform the first classification of climate change perceptions among farming communities in Colombia. A latent class analysis (LCA) is applied to a survey designed to capture the climate change perceptions of 566 bean farmers in the Colombian department of Santander. A Multinomial Logistic Model is estimated to determine the drivers behind the climate change perceptions identified. Farmers located at lower elevations and who are further away from their urban centres tend to be more concerned about the future economic consequences of climate change. These farmers also tend to seek climatic information for making productive activities. Accordingly, strategies aimed at maximizing the uptake of new drought-resistant bean varieties should focus on these farmers as they seem to be more receptive to uptake them. Moreover, engagement strategies containing information on management alternatives to appraise uncertainties and mitigate some of the severe effects of extreme weather events will generate increased uptake.

JEL Classification: Q15, Q54, C25, C38

Keywords: Agriculture and Environment, Global Warming, Discrete Regressions, Factor Models

1. Introduction

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Colombian agriculture is highly vulnerable to the impacts of climate change (IPCC, 2014; IMF, 2017; Palomino *et al.*, 2015; Buhr et al., 2018). The Intergovernmental Panel on Climate Change (IPCC) forecasts that future climate change will reduce annual precipitation and increase annual average temperatures as well as the prevalence of plant pests and diseases in Colombia. These future patterns are expected to negatively impact 60% of the current Colombian agricultural production areas, generating a reduction in crops' yields (Feola and Binder, 2010; Ramirez-Villegas *et al.*, 2012; Eitzinger *et al.*, 2014).

Common beans (*Phaseolus Vulgaris*) are expected to be particularly affected by climate change. Currently marketed varieties are highly susceptible to climate change (Schoonhoven & Voysest, 1991; CIAT, 2008; Troyo-Diéguez, 2010). Accordingly, a worsened climate will make the cultivation of some of them unprofitable. In addition, some production areas may become unsuitable for common bean production in the future since farms located at low elevations are expected to be mostly affected by droughts and a lack of rainfall (Ramirez-Villegas *et al.*, 2012; Eitzinger *et al.*, 2014; Güiza-Villa *et al.*, 2020). Furthermore, Colombian common bean production is mainly conducted by low-income, small-scale producers (i.e., < 20 ha) located on the Andean Mountains (i.e., between 900 and 2800 masl[1] approximately) (Perfetti *et al.*, 2013). This hilly topography severely restricts the use of heavy machinery or bulky technology because steep hills make the use of heavy technology perilous and prone to accidents and crops' destruction. Consequently, Farmers on the Andean mountains are forced to employ labour-intensive and traditional methods, which constraintheir capacity to utilise bulky technology or heavy machine to adapt to climate change (Ramirez-Villegas *et al.*, 2012; Feola *et al.*, 2014; Acevedo *et al.*, 2016).

Colombian common bean producers can pursue several adaptation strategies at the farm-level (Smit and Skinner, 2002; Clements *et al.*, 2011; Asfad *et al.*, 2013; Niles *et al.*, 2015). For example, Colombian farmers can change the location of their landraces or the plantation calendar; implement technological advances, such as irrigation or vertical farming systems; or, diversify the type and varieties grown. However, some of these adaptations can be too expensive for most Colombian bean producers. For instance, the establishment of indoor or vertical farming systems requires a large upfront investment that very few Colombian bean producers can afford (CIAT, 2016; Zaid *et al.*, 2018). A similar situation occurs with the costs of irrigation systems (Galvis *et al.*, 2018). In addition, as all Colombian bean production areas have a bimodal rainfall pattern that allows at least two cropping seasons in a calendar year, the common bean's optimal planting dates in Colombia are in April/May and September/October (Ramirez-Cabral *et al.*, 2016), which reduces farmers' capacity to modify planting times without affecting yield or profits. Finally, land acquisition is restricted by a low land supply (Ibañez *et al.*, 2011; Feola *et al.*, 2014). Hence, low-income, small-scale bean producers have limited availability of land to change the location of their landraces easily.

Another adaptation strategy commonly proposed is the use of seeds that are resistant to the changing climatic conditions. This adaptation normally requires the involvement of government agencies and corporations that support the development of new common bean varieties. As a result, the International Center for Tropical Agriculture (CIAT[2]) has been developing bio-fortified and heat- and drought-resistant common beans' varieties[3] for the Colombian market (Schoonhoven & Voysest, 1991; Blair, 2003; Muñoz *et al.*, 2008; CIAT, 2008; Hershey *et al.*, 2013). This work has been advanced mainly considering the agroecological changes expected to occur in current common bean production areas, partially disregarding the role of human agency in decision-making at farm level.

Some studies have shown that one of the determinants of adaptation to climate change is farmers' perceptions and beliefs towards the climatic event (Arbuckle *et al.*, 2015; Zamasiya *et al.*, 2017; Shinbrot *et al.*, 2019). According to the Theory of Planned Behaviour (Ajzen, 1991), perceptions provide the basis for attitude formation, which along with social norms and perceived behavioural control, influences behavioural intentions. When applied to agriculture, farmers' perceptions of and attitudes towards climate change may influence what adaptation practices are adopted. In turn, Construal Level Theory (Liberman and Trope, 2008) indicates that perceptions are formed by the proximity of farmers to the negative effects of climate change, which influences farmers' risk management strategies at farm level (Spence *et al.*, 2012; Niles *et al.*, 2015). Consequently, Colombian farmers' voluntary uptake of the new common bean varieties is expected to partially depend on their awareness of, experience with, and concern about the negative effects of climate change (Barnes *et al.*, 2013; Wang *et al.*, 2018; Eitzinger *et al.*, 2018; Shinbrot *et al.*, 2019). These perceptions also help shape farmers' response to short and long-term public policies and extension and commercial programs that incentivise the uptake of the new bean varieties. As a result, the identification of these perceptions allows public agencies, extension service providers and seed suppliers to design their communication and engagement strategies to maximize the uptake of the new bean varieties (Barnes *et al.*, 2013; Eitzinger *et al.*, 2018). This is especially important in a developing country context where reduced public budgets constrain public capacity to financially support the development and commercialization of new bean varieties, which therefore creates a need for more cost-effective interventions to communities of interest (Blackstock *et al.*, 2010; Barnes *et al.*, 2009; Barnes *et al.*, 2012).

Most of the empirical work carried out on farmers' climate change perceptions in developing countries has been conducted on Asian and African countries (e.g. Maddison, 2007; Gwimbi, 2009; Gbetibouo, 2009), with some studies focusing on Latin America (Pinilla *et al.*, 2012; Zuluaga *et al.*, 2015; Barrucand *et al.*, 2017; Eitzinger *et al.*, 2018; Shinbrot *et al.*, 2019; Soubry *et al.*, 2020). Some of these studies analyse Colombian farmers' awareness of climate change or experience with climatic changes, but do not identify the drivers behind those perceptions. These studies also fail to apply formal statistical procedures to identify the multiplicity of opinions about climate change that have been identified in farming communities in other parts of the world (Brodt *et al.*, 2006; Davies *et al.*, 2007; Barnes *et al.*, 2013; Capstick *et al.*, 2015). Classifying farmers into types or groups and identifying the factors that determine membership to subsequent classifications allow policy makers, extension service providers and seed suppliers to better understand the similitudes and differences that exist among or within the groups identified. Moreover, it allows the design of engagement strategies that consider those differences or similarities (Barnes *et al.*, 2011; Barnes *et al.*, 2012). This is particularly relevant in Colombia where common bean producers' climate change perceptions are expected to be influenced by the elevation of their farms, which implies that the design of engagement and extension service programs should consider farm elevation to maximize impact.

Accordingly, the purpose of this paper is to add to the literature on climate change perceptions in farming communities in tropical systems. By analysing the responses to perceptual questions regarding awareness of, experience with, and concern about climate change of 566 bean producers in the department of Santander —a region in the Northeast of Colombia with a relatively developed market for the common bean— this study provides the first classification of climate change perceptions of bean producers in Colombia using a latent class analysis approach. The determinants of these perceptions are also identified using a Multinomial Logistic Model.

The Santander department is chosen for this study because, according to the 2014 Colombian Agricultural Census, it is the fifth largest producer region of common beans in Colombia (DANE, 2014), and it is expected to be the most affected by climate change among the 6 largest common bean producer regions (Ramirez-Villegas *et al.*, 2012; Eitzinger *et al.*, 2014; Eitzinger *et al.*, 2018). In addition, it has the typical mountainous landscape of the Colombian Andean mountain range, which makes any inference based on this community potentially applicable to any other Colombian region with a similar landscape and elevation-driven weather variation (Perez *et al.*, 2019).

2. Conceptual Framework

2.1. Climate Change Perceptions

The concept of perception is essential in social sciences to understand farmers' adoption of climate change adaptation strategies (IPCC, 2018; Soubry *et al.*, 2020). According to the IPCC, farmers' perceptions of climate change can be considered as subjective evaluations, based on farmers' knowledge of the severity of risks imposed by climate change, that help determine which adaptation strategies farmers adopt (Chen, 2011; IPCC, 2014; Niles *et al.*, 2015; IPCC, 2018). Thus, the success of public adaptation programs depends on how decision-makers at farm level perceive and react to the risks imposed by climate change on agricultural production (Bryan *et al.*, 2013; Mitter *et al.*, 2019; Soubry *et al.*, 2020). In this literature, knowledge and perception are two interactive dimensions of climate change adaptation (Collins, 2004; O'Connor, 2007; IPCC, 2014). We concentrate on measuring climate change perceptions because this perspective provides a narrower focus of inquiry (Bryan *et al.*, 2013; Roco *et al.*, 2014; Mugi-Ngenga *et al.*, 2016; Soubry *et al.*, 2020).

2.2. *Drivers of Climate Change Perceptions*

There is no previous identification of the drivers behind climate change perceptions within farming communities in Colombia. Filling this vacuum is important for at least two reasons. On the one hand, adaptation programs have not considered Colombian farmers' opinions for their design (Soubry *et al.*, 2020), which means that adaptation programs may fail due to a misalignment of farmers' preferences and acknowledged needs with programs' objectives and strategies. On the other hand, international evidence on farmers' climate change perceptions does not entirely serve to inform about Colombian farmers' perceptions because Colombian topography and elevation-driven temperature variation —known as thermal floors— are unlike any other in African or Asian tropical regions. In most bean producing areas in Colombia, elevationvaries substantially from farm to farm, generating a different temperature and rainfall regime. This may greatly influence farmers' climate change perceptions and require a different adaptation strategy contingent on farms' thermal floor (Feola *et al.*, 2014; Eitzinger *et al.*, 2014; Eitzinger *et al.*, 2018).

Existing studies on climate change perceptions in Colombia are qualitative, with some of them focusing on the Colombian general public (Ulloa *et al.*, 2008; Altschuler *et al.*, 2015). They show that Colombians tend to be aware of climate change, but there is neither a systematic analysis of concern about climate change nor an identification of the drivers behind climate change awareness.

The literature identifies several drivers behind climate change perceptions among farming communities around the world (Scoones, 1998; Bryan *et al.*, 2013; Roco *et al.*, 2014; Soubry *et al.*, 2020). One candidate for the Colombian case is elevation. Colombian climate change variations are expected to be elevation-driven, affecting common bean production areas unevenly (Feola *et al.*, 2014). Ramirez-Villegas *et al.* (2012) forecast that farms above 1600 masl will confront more unpredictable seasons and extreme temperatures by 2050 and farms below 1600 masl will face shortages in rainfall and droughts. Hence, elevationmay be a determinant of experience with climatic events or concern about future changes in the weather.

Another potential driver of climate change perceptions is the distance of farms to the urban centre of the municipality where they are located/registered (Ibañez *et al.*, 2011; Shinbrot *et al.*, 2019). All municipalities along the Colombian Andean mountain range are spatially centred on an urban centre, where all shops and commercial centres are established. These urban areas are usually erected in the most accessible geographical areas of each municipality. This is particularly true for common bean producing areas (Ramirez-Villegas *et al.*, 2012; Ramirez-Villegas *et al.*, 2013; Eitzinger *et al.*, 2014; Feola *et al.*, 2014). Then, farms' distance to the largest urban centres within each municipality captures farms' accessibility, which may be affected by changes in the weather. Then, farms located further away from their main urban centres are expected to have more accessibility problems, which may increase farmers' awareness of and concern about climate change. Distance can also be associated to access to information about common problems affecting the farming community of a region. For instance, Shinbrot *et al.*, (2019) find that Mexican farmers located further away from urban centres have less access to information regarding climate change, which makes them less aware of the occurrence of the climatic event.

Colombian farmers' climate change perceptions may also be explained by farm size, crops' yield or the number of crops grown (Mertz *et al.*, 2009; Bryan *et al.*, 2013; Mugi-Ngenga *et al.*, 2016; Nisbet *et al.*, 2015; Thornton *et al.*, 2016; Elum *et al.*, 2017; Eitzinger *et al.* 2018). Farmers with larger farms, larger yields, or more sources of income tend to be wealthier, which makes them less sensitive to the marginal effects of climate change on agricultural economic profits. In addition, intra-seasonal weather variation is also found to be a predictor of perception since it affects farmers' planting decisions throughout the year (Thomas et al., 2007; Rao *et al.*, 2011). Some standard socio-economic factors are also identified as drivers of perception. For instance, farming experience, educational levels, or gender are found to be important determinants of climate change perceptions in farming communities around the world (Maddisson, 2007; Rao *et al.*, 2011; Barnes *et al.*, 2012; Soubry *et al.*, 2020).

Access to climatic information is expected to increase farmers' climate change perceptions (Ramirez-Villegas *et al.*, 2012; Shinbrot *et al.*, 2019). Farmers who are more informed about climatic variations are expected to be more aware of and concerned about climate change. Belonging to a farmers' association is an important determinant of climate change perceptions since these associations are in charge of disseminating information about common problems affecting all members (Barnes *et al.*, 2012). Hence, membership to a farmers' association is expected to increase farmers' awareness of and concern about climate change. In turn, climate change is also expected to increase the prevalence of plant pests and diseases in Colombia (Ramirez-Villegas *et al.*, 2012). Hence, bean breeders who have to apply more pesticides and fungicides are expected to be more aware of and concern about climate change. Ramirez-Villegas *et al.* (2012) and Eitzinger *et al.* (2014) suggest that access to a stable water source may also affect farmers' climate change perceptions. Farms that are closer to urban areas have access to the municipal aqueduct. This service can be considered as a stable water source that is useful for the establishment of irrigation systems, reducing farms' dependence on rainfall. Hence, farmers with access to this water source are expected to be less aware of or concerned about climate change. The variables selected for the study are explained in detail in Table 2 in the appendix.

3. Data and Descriptive Analysis

3.1. The Study Site

Santander's municipalities are located on top of the eastern mountain range of the Colombian Andes. This implies that most farms are on a hilly landscape and agricultural production commonly takes place on the slope of a mountain. Temperature and rainfall depend on the thermal floor in which farms are located. Farms with larger temperatures and less monthly rainfall tend to be at lower elevations where there is also a different agroecological system than at high elevations (IDEAM, 2013). Farmers from Barichara (6.6358° N, 73.2234° W), Curití (6.6063° N, 73.0687° W), San Gil (6.5548° N, 73.1341° W), and Villanueva (6.6709° N, 73.1748° W) (four Santander municipalities) are selected for this study based on three criteria. First, these municipalities are the largest common bean producers in Santander according to the 2014 Colombian Agricultural National Census and all farmers included in the study have experience in bean production. Second, these municipalities have different temperatures and rainfall levels (IDEAM, 2013), which is correlated with their elevation. Villanueva (with an average elevation of 1288 masl) and Barichara (1266 masl) tend to have water deficits, receiving less rainfall and being warmer than Curití (1568 masl) and San Gil (1452 masl). Consequently, Villanueva and Barichara's farmers are expected to have different climatic perceptions than San Gil and Curití's farmers, which in turn is expected to partially depend on farms' elevations. Finally, these four municipalities are on the same climate system and are equally subject to the same regional climatic variations. As a result, the perceptions held by the farmers from a municipality are only affected by the idiosyncratic climatic events affecting their locality and not by climatic variations occurring due to a different regional climate system. Fig. 1 in Appendix A.1 shows a map of the study site.

The survey implemented for the present study is described in full elsewhere (Perez *et al.*, 2019). This information was collected as part of "AgroClimas" project, which is a joint effort of CGIAR and CIAT to characterize common bean production in areas threatened by climate change (Rios *et al.*, 2017). This paper focusses on the section related to climate change perceptions and relies on collected socioeconomic information to explore potential drivers behind climate change perceptions among common bean producers in the region. The household sample consists of 572 farmers, who were interviewed during August/September in 2017. Information is collected through face-to-face interviews as a means of maximizing response from the selected farmers. From the total sample of households, 566 interview responses are usable for analysis. The survey collects information on a variety of factors, such as household composition, household economic, financial, and human capital (Scoones, 1998), and climate change perceptions.

3.2. The Survey: Some descriptive statistics of the study site

There are several types of questions used in the literature to measure climate change perceptions (Dunlap, 1998; Capstick *et al.*, 2015). From the myriad of existing questions, three types are important for bean production since they help determine necessity for adaptation (CIAT, 2008). These questions aim at: a) determining farmers' awareness of climate change; b) identifying farmers' past experiences with climatic changes; and, c) determining farmers' degree of concern about future climate change and its future economic consequences.

A sample of questions belonging to each type was selected to design a survey to capture climate change perceptions in the study site. There are two questions associated with awareness of climate change. One of them asks farmers to indicate if they have perceived changes in the weather during their lifetime, giving them the option to answer yes/no. The other one asks farmers to provide a gradient of perception of weather change in the last seven years (from 2010 onwards). In turn, all ten questions associated with experience ask farmers to state if they have experienced a particular climatic event, allowing them to answer yes or not. Finally, there are two questions that capture concern about climate change. One of them asks farmers to provide a degree of certainty in the occurrence of future climate change and the other asks for a gradient of expected economic affectation if the climatic phenomenon indeed occurs.

Table 1 in the appendix presents the exact wording of each question used and the distribution of the answers[4]. This table also shows that 95% of the sample has noticed a change in the weather and nearly 88% has seen that the weather has changed a lot in recent years. Moreover, 91% of the farmers in the sample have been affected by droughts in recent years and 44% by extreme temperatures. Additionally, 89% has been affected by droughts since teenagers, 50% by unpredictable seasons, and 49% by heatwaves. Nearly 76% of the sample considers that future weather is very likely to change and 82% forecasts a medium to high economic impact if climate change actually occurs. Consequently, this survey shows that a large proportion of Santander bean producers are highly aware of climate change, have mainly experienced droughts, extreme temperatures and unpredictable seasons, and consider that future weather is very likely to change, which is expected to cause an important negative economic impact on them.

Table 2 in Appendix A.3 presents the explanatory variables of climate change perceptions selected for this study. The rationale for their selection is laid out in the section 2.2. Table 3 in Appendix A.3 presents their descriptive statistics. One important factor considered for sample selection is farms' elevation. Consequently, 50% of the sample is below 1600 masl and the other 50% is above 1600. The minimum elevationsurveyed is 1264 masl and the maximum 2014 masl. In addition, the distribution of elevation is symmetric around its median value of 1573 masl. Almost all bean producers located near to the urban centres of each selected municipality are included in the sample. As farms are on a mountainous terrain, most bean producers are equidistant to the town's centre, where the retail market for beans is located. In our sample, the nearest farm is located at 2.03 km from its municipality's urban centre and the most distant one is located at 8.16 km. In addition, as transportation costs become a constraining factor for bean production in locations too far away from a municipality's urban centre, the distribution of distance is also symmetric around its median/mean (5.14 km/5.13 km). This implies that the majority of farms are located at 5.14 km from the town's centre. This is evident on Fig 1 (right-hand side, bottom panel), where each black star represents each municipality's urban centre.

Farm size in the selected sample is representative of the farm size of bean producers on the Colombian Andean Mountains (Perfetti *et al.*, 2013). Nearly 70% of the farms in the sample has 2 ha or less and only 2% has more than 10 ha. Consequently, this farming community is mainly composed of small landowners with limited land area to diversify production. In turn, bean yield is more normally distributed, with the majority obtaining around 800 kg/ha. Some of these farmers are more productive, obtaining 1600 kg/ha, whereas there are others that only obtain 100 kg/ha. The latter may be the result of intercropping, which reduce the quantity of beans produced per ha.

Our sample is mainly composed of farmers with only a few years of formal education. Almost 82% of the sample barely finished primary school, only 2% did an undergraduate degree, and none of them has a master's degree or above. In this community, farmers' age is also normally distributed, with the majority of them being 48 years old. The youngest farmer surveyed was 16 years old and the oldest one was 82. We include in the analysis the answers associated to the 16-year farmer because he has lived in this community his whole life working as a common bean producer. Therefore, he satisfies the criteria for sample selection.

Nearly 62% of the farms practice monoculture, with bean production being the only crop grown in the farm, and around 74% has access to the municipal aqueduct. In addition, all farmers in the sample use at least one of type of fungicide or pesticide, with 20% using more than one type of fungicide and 71% using more than one pesticide. Moreover, almost 76% of the farmers surveyed are males, 50% has received climatic information, and only 20% belongs to a farmer's association.

Intra-seasonal weather variation is captured through the standard deviation of total precipitation and the standard deviation of the maximum number of consecutive dry days occurred in the study site. These variables are measured for the two phenological phases of common beans; namely, emergence and vegetative growth (phase 1) and flowering and pod maturation (phase 2) (Schoonhoven *et al.*, 1991; Rao *et al.*, 2011). According to Table 3, larger weather instability occurs during the vegetative phase since both the standard deviation of total precipitation and the standard deviation of the number of consecutive dry days are larger during this phase.

4. Methodology

4.1. Latent Class Analysis

Several approaches have been used to derive typologies of climate change perceptions within farming communities around the world (Barnes *et al.*, 2011; Brodt *et al.*, 2006; Davies *et al.*, 2007; Gorton *et al.*, 2008; Galdiesa *et al.*, 2016). A cross-tabulation or clustering approach is sometimes used to determine the typology, relying on a range of rules of thumb to identify the number of groups in the sample (Hair *et al.*, 2006). To utilize a more formal criterion to identify class membership, a latent class analysis (LCA) approach is employed in this study (Barnes *et al.*, 2013; Botero *et al.*, 2019). Hagenaars *et al.* (2009) describes this methodology in detail.

A LCA employs the answers to the proposed perceptual questions to put all farmers with similar answers in the same class or group. The classification is performed under the assumption that the number of classes is known *a priori*. To identify the optimal number of classes in the sample, classes are iteratively added to the model and a typology is performed per iteration. The optimal number of classes in the sample is the one that minimizes the Bayesian Information Criterion (BIC) (Forster, 2000).

The estimation procedure is explained by Linzer *et al.* (2011). Formally, let us assume that X is a *NxQ* matrix containing the answers to *Q* questions by *N* individuals in the sample. Then, a LCA is a projection from X to Y, where Y is a *Nx1* vector containing in each row the class to which each individual belongs. Each column of X defines a discrete variable with countable domain because the number of possible answers for each question is a strictly positive integer a_q. If there is only one question (i.e., Q = 1), the number of groups in Y coincides with the number of possible answers, a_1, for the unique proposed question. With Q>1 questions, Y may contain as many groups as there are combined answers, $a_1 x a_2 x a_3 \dots\dots x a_Q$. The latter case occurs when all individuals provide differing questions and there are more individuals than possible combined answers. Otherwise, there would be as many groups as there are individuals in the sample because each one defines a separate group.

We perform a separate LCA for the questions associated to awareness of, experience with, and concern about climate change of Table A.1. Consequently, three Y's are obtained. The Y associated to awareness potentially has 8 (=2*4) groups[5], the one associated to experience[6] 1024 groups, and the one associated to concern 20 groups. These vectors can be used as dependent variables to investigate the drivers behind each typology.

4.2. *Multinomial Logistic Regression Model*

Each Y defines a discrete variable with countable domain. Then, a multinomial logistic regression model can be used to identify the drivers behind class membership in each Y [7]. A multinomial logistic regression model estimates the following probabilities using a maximum likelihood estimation method:

$$P(Y_s = i) = \frac{e^{X\beta^{(i)}}}{\sum_{j=1}^{a_s} e^{X\beta^{(j)}}} \quad (1)$$

Where $a_s \in \{a_{awareness}, a_{experience}, a_{concern}\}$ is the total number of categories in each vector $Y_s \in \{Y_{awareness}, Y_{experience}, Y_{concern}\}$, and $\beta^{(i)}$is a *17x1* vector of coefficients associated to the 17 regressors introduced in Table 3. It is worth noticing that equation (1) represents a set of a_s equations for the $\{\beta^{(1)}, \beta^{(2)}, \dots, \beta^{(a_s)}\}$ variables. Greene (2003, 720-763) explains in detail this model and its estimation method. As the units of the estimated coefficients do not have a straightforward interpretation, it is customary to report the relative-risk ratios (RRR) instead. These ratios are computed taking one class of each Y_s as the base and expressing the estimated coefficients of the other classes in terms of that base. Hence, the RRR of the regressor x_r indicates if a marginal change in x_r increases or decreases more the average probability of belonging to the comparison class than to the base one.

5. Results

5.1. *Typology*

Table 4 presents the sequence of BIC for the LCA and Table 5 the number of classes found for each sub-set of perceptual questions. Table 5 also shows the distribution of answers per class, expressed as a percentage of the total farmers in each class. Two classes arise from the questions associated to awareness, four classes from the questions associated to experience, and four classes from the questions associated to concern about climate change. The two classes associated to awareness represents 92.9% and 7.1% of the sample respectively; the four classes associated to experience represents 12.4%, 7.1%, 39.2% and 41.3% of the sample respectively; and, finally, the four classes associated to concern represents 7.6%, 13.4%, 60.6% and 18.4% of the sample respectively. Their characteristics are outlined below.

Awareness

Class 1 (92.9%): Farmers in this group consider that the weather has changed a lot in the last 7 years. Hence, climate change for this group is a new reality that is becoming more evident in recent years.

Class 2 (7.1%): This group contains three types of farmers. One type has never noticed a change in the weather in their lifetime. Another type considers that the weather has always been changing during their lifetime, without an evident worsening in the recent past. A final type considers that the weather has always been changing during their lifetime, with an evident worsening in the recent past. Their common characteristic is that they all have noticed the same weather throughout their lifetime, be it one that has never changed or one that is always changing.

Experience

Class 1 (12.4%): This group is composed of farmers who have been mainly affected by droughts, hailstorms, and heatwaves during their lifetime. They have also been affected by storms, but not frosts. Some have also been affected by cold waves. This class contains almost all farmers who were affected by floods and heavy rains.

Class 2 (7.1%): The main characteristic of this group is that these farmers were only affected by extreme temperatures and droughts in the last 7 years.

Class 3 (39.2%): These farmers have been affected by droughts, heatwaves and unpredictable seasons during their lifetime, and by extreme temperatures in the last 7 years.

Class 4 (41.3%): This group contains farmers that have been affected only by droughts during their lifetime.

Concern

Class 1 (7.6%): This group is mainly composed of farmers who do not know if future weather will change or if they will be economically affected if it does. A small proportion of these farmers consider that future weather will not change, but if it does, they will be highly impacted economically.

Class 2 (13.4%): This group contains all farmers who consider that it is very likely that future weather will change and, when it happens, they will have an intermediate economic impact.

Class 3 (60.6%): In this group, all farmers consider that it is very likely that future weather will change and, when it happens, they will be highly impacted.

Class 4 (18.4%): Farmers in this group consider that it is slightly likely that future weather will change, and if it does, they will have a low to an intermediate economic impact.

5.2. Drivers of Class Membership

The regression results are presented in Tables 6. RRRs above 1 indicate that a marginal increase in the associated regressors lead to a larger increase in the probability of belonging to the comparison class than to the base class. R^2 values and LR tests indicate that the selected regressors explain more than 17.66% of the variance of the typologies computed, which implies that these regressors are jointly statistically significant to explain the variability of these typologies. Elevation is an important driver behind experience with and concern about climate change, but it is irrelevant for explaining awareness. In addition, farms located at higher elevations are more likely to experience unpredictable seasons and extreme temperatures than only experiencing droughts. Consequently, farmers located at higher elevations tend to be less concerned about the occurrence of future climate change and its potential economic impacts.

Distance is another important determinant of experience with and concern about climate change but does not help explain awareness. Farms located further away from their urban centres tend to be affected only by droughts, which makes them be concerned about climate change and its future economic impacts. Receiving climatic information does not affect awareness of climate change. However, farmers who receive climatic information tend to be affected only by droughts and be more concerned about the future occurrence of climate change.

Belonging to a farmers' association does not drive farmers' awareness of climate change. Farmers who belong to an association tend to be more affected by extreme temperatures, unpredictable seasons, storms, hailstorms, and cold waves. They also tend to be less certain about the future occurrence of climate change and are not the most concerned about its future economic consequences. Having access to water from the municipal aqueduct does not affect awareness of or concern about climate change. In addition, farmers who have access to this water source tend to be affected by several climatic events, and not only by droughts. This result may be explained by the fact that farms that have access to the municipal aqueduct tend to be closer to their urban centres, which are not only affected by droughts.

Awareness of climate change is mainly explained by farmers' education level and the standard deviation of the number of consecutive dry days during the beans' flowering phase. In other words, farmers that are more educated tend to have perceived a severe change in the weather in recent periods. In addition, farmers who have perceived a severe change in the weather in recent periods have also had a larger variability in the number of consecutive dry days in their farms.

5.3. Discussion

The analysis shows that most Colombian common bean producers located in regions expected to be highly impacted by climate change are generally aware of the climatic event and concerned about its future economic consequences. This contrasts with the findings of studies carried out in temperate regions, where farmers tend to be less aware of the occurrence of climate change (Barnes *et al.*, 2012; Barnes *et al.*, 2013; Arbuckle *et al.*, 2013), but echoes the findings of studies carried out in tropical regions of Africa and Asia, where a larger proportion of farmers are aware of climate change (Gbetibouo, 2009; Tesfahunegn *et al.*, 2016; Soubry *et al.*, 2020).

Evidence from other parts of Latin America shows that distance is negatively correlated with climate change perceptions (Shinbrot *et al.*, 2019). In contrast, the results of this paper show that climate change perceptions among Santander common bean producers are positively correlated with the distance of farms to their urban centres. Farms located farther away from these urban centres tend to be more affected by droughts or heavy rains since they are usually located either at lower or higher elevations than their urban centres. This implies that these farmers tend to be more concerned about future climate change and its economic consequences. As a result, farm distance can be used as a factor to define marketing strategies for the newly developed varieties.

This paper shows that elevation is an important determinant of climate change perceptions among Santander common bean breeders. In our sample, farms located at lower elevations tend to be mainly affected by droughts, whereas farms located at higher elevations by extreme temperatures and unpredictable seasons. Consequently, farmers living at lower elevations tend to be more concerned about climate change than farmers living at higher elevations. This implies that local public agencies, extension service providers and seed suppliers may focus their engagement strategies on farmers living at lower elevations since they seem to be more receptive to uptake drought-resistant bean varieties.

Access to climatic information has been identified as an important driver of perception among farming communities around the world (Safi *et al.*, 2012; Haden *et al.*, 2012; Arbuckle *et al.*, 2013, Barnes *et al.*, 2013; Niles *et al.*, 2015; Mugi-Ngenga *et al.*, 2016; Zamasiya *et al.*, 2017). Santander farmers affected by droughts tend to search for climatic information to make planting decisions. Therefore, Santander farmers who receive climatic information are expected to be more receptive to use drought-resistant beans. Local public agencies, extension service providers and seed suppliers may initially reach out to communities that seek climatic information to introduce its new varieties of beans in the market.

Finally, international evidence shows that farmers who belong to farmers' associations tend to be more aware of climate change (Barnes *et al.*, 2012; Barnes *et al.*, 2013; Arbuckle *et al.*, 2017). In contrast, Santander farmers who belong to farmers' associations tend to be less affected by droughts, making them less aware of and concerned about the effects of climate change on bean production. Therefore, focusing on farmers who belong to farmers' associations will not secure a maximum uptake of drought-resistant varieties since they do not seem to be particularly affected by this phenomenon, which may reduce their interest in switching from traditional seeds to the new ones.

6. Conclusions

Colombian bean production is expected to be affected by climate change if adaptation measures are not undertaken. Farmers' uptake of technologies for climate change adaptation depends on their climate change perceptions. Our results show that there is a general awareness of climate change among Santander common bean breeders. The vast of majority of these farmers have been affected by droughts and a smaller proportion by unpredictable seasons and extreme temperatures. In addition, a large proportion is certain that future climate change will occur, expecting a moderate to high impact on their economic livelihood. There exists a smaller proportion who consider that future climate change is unlikely to occur and are unconcerned by its occurrence, if it does.

Several drivers of climate change perceptions are identified through a multinomial logistic regression model. This study shows that elevation is an important driver behind climate change perceptions in Santander —an archetypal farming community on the Andean mountains in Colombia— since it determines the type of climatic events experienced by these farmers: Low elevations experience more droughts while high elevations unpredictable seasons and extreme temperatures. Then, farmers located at low elevations are also more concerned about future climate change, expecting to be highly impacted economically when it happens. Distance is another important driver of climate change perceptions within this farming community. Farmers located farther away from their urban centres are more concerned about climate change because they tend to be more affected by droughts and extreme temperatures and variable seasons. Finally, climatic information dissemination is another important determinant of climate change perceptions. Farmers who look for climatic information to make planting decisions tend to be more affected by droughts and be more concerned about the occurrence of future climate change.

Policy interventions can exploit these drivers to increase uptake of climate change adaptation technologies. Strategies can be designed based on the type of climatic event experienced by farmers. They can also use individualized communication strategies, where resources can be focused on those farmers who tend not to look for information to make production decisions, and have farms located at high elevations and close to their urban centres since these farmers tend to have a low climate change perception within this farming community. In that way, public interventions can become more cost-effective in accomplishing its proposed outcomes.

7. References

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A. Appendix

A.1. *Map of the Study Site*

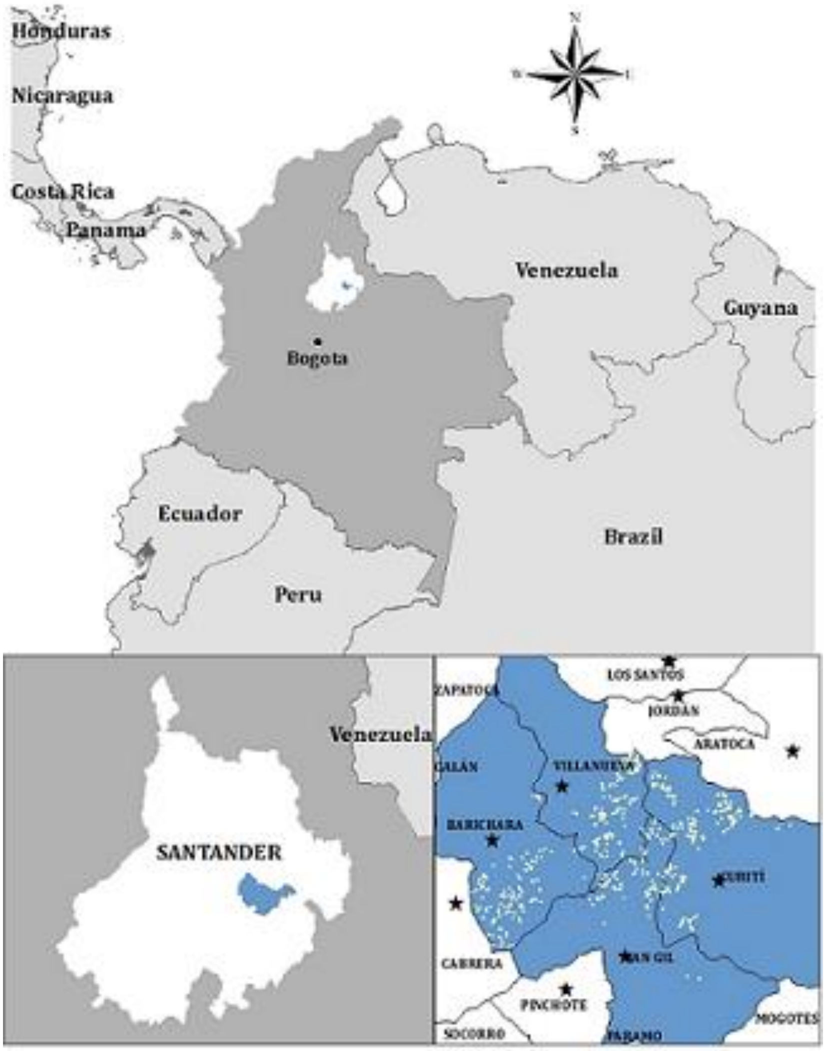

Fig 1: Geographical Distribution of Farms

A.2. *Perceptual Questions*

Table 1: Questions used in the study		
	Awareness of Climate Change	
Variable Name	Question	Answer Options[a]
weather $changed_{young}$	Do you believe today's weather has changed in comparison to how it was when you were a teenager?	1 = if farmer considers that weather has changed (538); 0 = otherwise (28).
weather $changed_7$	How much do you consider that the weather has changed in the last 7 years?	0 = it has not changed (8); 1 = it has changed a little (13); 2 = it changed more or less (49); 3 = it changed a lot (496).
	Experience with Climate Change	
Variable Name	Question	Answer Options[a]
$droughts_7$	Have you experienced droughts in the last 7 years?	1 = if farmer has experienced droughts in the last 7 years (516); 0 = otherwise (50).
$rains_7$	Have you experienced heavy rains in the last 7 years?	1 = if farmer has experienced heavy rains in the last 7 years (38); 0 = otherwise (528).
$temperatures_7$	Have you experienced extreme temperatures in the last 7 years?	1 = if farmer has experienced extreme temperatures in the last 7 years (250); 0 = otherwise (316).
$droughts_{young}$	Have you experienced droughts since you were a teenager?	1 = if farmer has experienced droughts since s/he was a teenager (501); 0 = otherwise (65).
$storms_{young}$	Have you experienced storms since you were a teenager?	1 = if farmer has experienced storms since s/he was a teenager (125); 0 = otherwise (441).
$hailstorms_{young}$	Have you experienced hailstorms since you were a teenager?	1 = if farmer has experienced hailstorms since s/he was a teenager (111); 0 = otherwise (455).
$frosts_{young}$	Have you experienced frosts since you were a teenager?	1 = if farmer has experienced frosts since s/he was a teenager (51); 0 = otherwise (515).
$coldwaves_{young}$	Have you experienced cold waves since you were a teenager?	1 = if farmer has experienced cold waves since s/he was a teenager (49); 0 = otherwise (517).
$heatwaves_{young}$	Have you experienced heat waves since you were a teenager?	1 = if farmer has experienced heat waves since s/he was a teenager (278); 0 = otherwise (288).
unpredictable $seasons_{young}$	Have you experienced unpredictable seasons since you were a teenager?	1 = if farmer has experienced unpredictable seasons since s/he was a teenager (285); 0 = otherwise (281).
	Concern about Future Climate Change	
Variable Name	Question	Answer Options[a]
future weather	How likely is it to you that future weather changes?	0 = s/he does not know (11); 1 = it will not (24); 2 = it is slightly likely (104); 3 = it is very likely (427).
future economy	the weather actually changes in the future, how much economically impacted will you be?	0 = s/he does not (39); 1 = s/he will not be impacted (19); 2 = s/he will have a low impact (47); 3 = s/he will have a medium impact (118); 4 = s/he will have a large impact (343).
[a] = distribution of answers is in parenthesis.		

A.3. *Regressors Used and their Descriptive Statistics*

Table 2: Description of the explanatory variables of climate change perception used	
Continuous Variables	
Variable	**Explanation**
elevation	Meters above the Sea Level at which farms are located.
distance	Distance (in km) from the farm to municipality's "capital"
farm area	Area of the farm expressed in hectares
bean yield	Kilograms of beans per hectare produced
education	Number of years studied by the individual who responded to the survey
age	Age of the individual who responds to the survey
totalprecsd1	Standard deviation of the number of millimetres of rainfall in the phenological phase 1 (Apr-Jun)
totalprecsd2	Standard deviation of the number of millimetres of rainfall in the phenological phase 2 (Jun-Aug)
dryconsecdayssd1	Standard deviation of the maximum amount of consecutive dry days in growing season 1 (Apr-Jun)
dryconsecdayssd2	Standard deviation of the maximum amount of consecutive dry days in growing season 2 (Jun-Aug)
Discrete Variables	
Variable	**Explanation**
number of crops	Number of crops harvested in the farm
use fungicide	Number of fungicides used by the farmer.
use pesticide	Number of pesticides used by the farmer.
Binary Variables	
Variable	**Explanation**
gender	1 = if responder is a male; 0 = otherwise
aqueduct	1= if farmer has access to water from the municipal aqueduct; 0=Otherwise
climatic info	1=if farmer received climate information from any source; 0 = otherwise
association	1=if farmer belongs to a farmer's association; 0 = otherwise

Table 3: Descriptive Statistics of the Explanatory Variables (N=566)

Variables	Statistical Summary						
	Avg.	Std. Dev	Min.	1st Percentile	Median	3rd Percentile	Max.
elevation (masl)	1581	119	1264	1508	1573	1658	2014
distance (km)	5.13	1.25	2.03	4.27	5.14	5.91	8.16
farm area (ha)	2.02	1.91	0.15	1.00	1.50	2.50	21.00
bean yield/ha	877	306	100	700	800	1100	1600
education (years)	4.52	3.23	0	2	4	5	18
age (years)	48.30	13.81	16	38	48	58	82
dryconsdayssd1	4.38	0.76	3.21	3.63	3.95	5.25	5.77
dryconsdayssd2	2.52	0.33	1.68	2.25	2.43	2.94	2.98
totalprecsd1 (mm)	4.52	0.73	3.22	3.94	4.33	4.66	6.40
totalprecsd2 (mm)	2.29	0.45	1.93	2.06	2.17	2.20	4.04

Variables	Number of Pesticides or Fungicides Used or Number of Crops Grown						
	1	2	3	4	5	6	7
number of crops	349	159	38	14	3	2	1
use fungicide	452	112	2	-	-	-	-
use pesticide	163	167	235	1	-	-	-

Variables	Possible Answers	
	0	1
Gender	140	426
Aqueduct	146	420
climatic info	282	284
Association	454	112

A.4. Latent Class Analysis

Table 4: BIC Values for the latent classes

Number of classes	Awareness	Experience	Concern	Combined
2	791.17	4314.23	1912.63	2769.99
3	810.3	4229.71	1895.66	2713.84
4	825.1	4213.93	1887.44	2720.86
5	822.96	4226.47	1889.46	2751.63
6	834.55	4247.75	1929.14	2768.18
7	840.62	4250.89	1938.02	2780.45
8	896.69	4279.09	1966.56	2799.57

Table 5: Class membership and answer distributions (percentage of farmers) (heat map)

Variables	*Categories of the Answers*[a]																			
	0	1	2	3	4	0	1	2	3	4	0	1	2	3	4	0	1	2	3	4
Awareness	Class 1 (N = 526)					Class 2 (N = 40)					Class 3 (NA)					Class 4 (NA)				
weather changed$_7$	0	0	8.9	91.1		20	32.5	5	42.5											
weather changed$_{young}$	0	100				70	30													
Experience	Class 1 (N = 70)					Class 2 (N = 40)					Class 3 (N = 222)					Class 4 (N = 234)				
droughts$_7$	8.6	91.4				52.5	47.5				9.9	90.1				0.4	99.6			
rains$_7$	78.6	21.4				97.5	2.5				90.1	9.9				100	0			
temperatures$_7$	24.3	75.7				22.5	77.5				26.1	73.9				99.2	0.8			
droughts$_{young}$	4.3	95.7				100	0				5.9	94.1				3.9	96.1			
storms$_{young}$	0	100				92.5	7.5				76.6	23.4				100	0			
hailstorms$_{young}$	15.7	84.3				100	0				77	23				99.6	0.4			
frosts$_{young}$	88.6	11.4				100	0				80.6	19.4				100	0			
coldwaves$_{young}$	47.1	52.9				97.5	2.5				95.1	4.9				100	0			
heatwaves$_{young}$	14.3	85.7				77.5	22.5				9	91				97	3			
unpredictable seasons$_{young}$	30	70				65	35				3.2	96.8				97	3			
Concern	Class 1 (N = 43)					Class 2 (N = 76)					Class 3 (N = 343)					Class 4 (N = 104)				
future weather	25.6	55.8	4.7	13.9		0	0	0	100		0	0	0	100		0	0	98.1	1.9	
future economy	90.7	0	0	4.7	4.6	0	0	0	100	0	0	3.8	0	0	96.2	0	5.8	45.2	38.5	10.5
Combined	Class 1 (N = 27)					Class 2 (N = 303)					Class 3 (N = 236)					Class 4 (NA)				
Class of Awareness		0	100		0		97.7	2.3				97.5	2.5							
Class of Experience		0	81.5	0	0		21.5	3	0	75.5		2.1	3.8	94.1	0					
Class of Concern		51.9	3.7	18.5	51.9		4.3	11.2	83.8	0.7		6.8	17.4	35.6	40.3					

a = These categories are the codification provided to farmers' answers to the perceptual questions presented in Table A.1. For the combined case, these numbers

A.5. *Results of the Multinomial Logistic Regression Model*

Table 6: Relative Risk Ratios of the Logistic Regression for Class Membership per Type of Perceptual Question

Regressors	Comparison Class/Base Class[c]												
	Awareness[a]	Experience						Concern					
	2/1[b]	2/1	3/1	4/1	3/2	4/2	4/3	2/1	3/1	4/1	3/2	4/2	4/3
education	0.84 (0.03)	0.91 (0.25)	0.96 (0.47)	0.90 (0.15)	1.06 (0.45)	0.99 (0.89)	0.94 (0.29)	1.11 (0.16)	1.06 (0.40)	1.03 (0.75)	0.95 (0.27)	0.92 (0.16)	0.97 (0.53)
gender	0.59 (0.19)	0.52 (0.19)	1.04 (0.92)	0.84 (0.70)	2.00 (0.09)	1.60 (0.31)	0.80 (0.55)	1.09 (0.84)	1.78 (0.13)	2.88 (0.03)	1.63 (0.10)	2.64 (0.02)	1.62 (0.21)
age	0.97 (0.09)	0.97 (0.09)	0.98 (0.07)	0.99 (0.44)	1.01 (0.68)	1.02 (0.29)	1.01 (0.36)	1.02 (0.29)	1.01 (0.55)	1.02 (0.29)	0.99 (0.39)	1.00 (0.97)	1.01 (0.41)
elevation	1.00 (0.71)	1.00 (0.18)	1.01 (0.00)	0.99 (0.00)	1.01 (0.03)	0.99 (0.00)	0.98 (0.00)	1.00 (0.77)	0.99 (0.01)	1.01 (0.00)	0.99 (0.00)	1.01 (0.00)	1.01 (0.00)
distance	0.87 (0.42)	0.75 (0.19)	0.72 (0.06)	1.16 (0.46)	0.96 (0.82)	1.55 (0.03)	1.62 (0.00)	1.23 (0.26)	1.53 (0.01)	0.82 (0.30)	1.25 (0.08)	0.66 (0.02)	0.53 (0.00)
aqueduct	2.86 (0.07)	0.62 (0.36)	1.30 (0.53)	0.31 (0.01)	2.11 (0.11)	0.50 (0.17)	0.24 (0.00)	0.66 (0.43)	0.89 (0.80)	1.66 (0.40)	1.35 (0.36)	2.52 (0.07)	1.87 (0.17)
climatic info	0.48 (0.09)	1.37 (0.52)	0.63 (0.21)	3.70 (0.00)	0.46 (0.06)	2.70 (0.03)	5.86 (0.00)	1.64 (0.27)	1.80 (0.13)	0.61 (0.30)	1.10 (0.76)	0.37 (0.01)	0.34 (0.00)
bean yield	1.14 (0.02)	1.06 (0.41)	1.00 (0.94)	1.03 (0.63)	0.94 (0.28)	0.97 (0.68)	1.04 (0.49)	1.10 (0.17)	1.02 (0.8)	1.02 (0.79)	0.93 (0.09)	0.93 (0.19)	1.00 (0.95)
farm area	1.08 (0.40)	1.25 (0.09)	1.17 (0.14)	1.12 (0.45)	0.94 (0.47)	0.90 (0.46)	0.96 (0.75)	0.83 (0.14)	0.90 (0.27)	0.77 (0.05)	1.08 (0.40)	0.92 (0.52)	0.86 (0.14)
number of crops	0.62 (0.16)	0.51 (0.04)	0.76 (0.17)	0.39 (0.01)	1.49 (0.18)	0.77 (0.49)	0.51 (0.03)	3.45 (0.01)	3.51 (0.01)	3.43 (0.01)	1.02 (0.92)	1.00 (0.99)	0.98 (0.92)
association	0.79 (0.61)	0.39 (0.06)	0.47 (0.04)	0.16 (0.00)	1.21 (0.67)	0.42 (0.15)	0.35 (0.04)	2.77 (0.09)	1.76 (0.29)	1.11 (0.86)	0.64 (0.20)	0.40 (0.04)	0.63 (0.24)
use fungicide	0.60 (0.31)	0.36 (0.09)	0.93 (0.85)	0.34 (0.05)	2.55 (0.08)	0.94 (0.92)	0.37 (0.03)	0.83 (0.75)	1.32 (0.59)	3.52 (0.02)	1.60 (0.27)	4.26 (0.00)	2.67 (0.01)
use pesticide	0.91 (0.69)	1.00 (0.99)	0.96 (0.83)	1.52 (0.11)	0.96 (0.86)	1.52 (0.13)	1.59 (0.03)	0.92 (0.78)	1.20 (0.44)	0.81 (0.45)	1.30 (0.16)	0.88 (0.58)	0.67 (0.05)
dryconsdayssd1	1.35 (0.46)	0.77 (0.58)	1.27 (0.50)	1.24 (0.61)	1.65 (0.23)	1.60 (0.29)	0.97 (0.93)	1.75 (0.21)	1.14 (0.72)	2.23 (0.10)	0.65 (0.18)	1.27 (0.60)	1.95 (0.07)
dryconsdayssd2	0.05 (0.00)	7.69 (0.14)	17.35 (0.01)	92.20 (0.00)	2.26 (0.45)	11.98 (0.02)	5.31 (0.02)	0.70 (0.72)	1.35 (0.71)	0.49 (0.51)	1.92 (0.36)	0.70 (0.73)	0.36 (0.23)
totalprecsd1	0.86 (0.60)	0.69 (0.23)	0.73 (0.18)	0.66 (0.16)	1.05 (0.88)	0.95 (0.87)	0.90 (0.73)	0.69 (0.25)	0.99 (0.97)	0.60 (0.20)	1.44 (0.08)	0.88 (0.71)	0.61 (0.11)
totalprecsd2	2.10 (0.11)	0.26 (0.04)	0.16 (0.00)	0.05 (0.00)	0.61 (0.39)	0.21 (0.01)	0.34 (0.01)	1.58 (0.34)	0.77 (0.54)	1.29 (0.66)	0.49 (0.02)	0.82 (0.68)	1.68 (0.24)
N	566	566						566					
R^2	0.1766	0.4326						0.2371					
LR chi2	51.05	576.91						289.91					
Prob > chi2	0.0001	0						0					

[a] p-values are in parenthesis.
[b] Light gray represents coefficients statistically significant at 5% and dark gray represents coefficients statistically significant at 1%.
[c] The inverse RRR's (i.e., 1/2 for instance) are obtained by dividing 1 by the coefficients on the table and the p-values are the same.

[1] masl = meters above sea level

[2] Centro Internacional de Agricultura Tropical (CIAT).

[3] See https://ciat.cgiar.org/what-we-do/breeding-better-crops/beans/.

[4] We computed Cronbach's alpha for all 14 perceptual questions together and for each group of variables to test for internal reliability of the instruments used. The scale reliability coefficients are: 0.6303 (using all variables), 0.3314 (using awareness variables only), 0.7391 (using experiential variables only), and 0.7287 (using concern variables only). A rule of thumb for a good internal reliability is to have a value of Cronbach's alpha between 0.6 and 0.9 (Tavakol and Dennick, 2011). As a result, all Cronbach's alphas indicate a good internal reliability of the instruments used, except for the case in which only variables that capture awareness of climate change are used. A low value of alpha may be the result of a low number of questions, low correlation between variables, or heterogeneous constructs. As the two variables that capture awareness are very similar constructs and are highly correlated, a low alpha in this case seems to indicate a low number of questions in the test. As a result, we will continue using both questions to measure awareness of climate change since they are not perfectly correlated and provide complementary insights of farmers' awareness of climate change in this region.

[5] There are 2 possible answers for the question associated to $\textit{weather changed}_{young}$ and 4 possible answers for the question associated to $\textit{weather changed}_{7}$.

[6] For the cases in which there are more than 566 possible groups, the maximum number of groups in Y can only be 566 since, in this case, there would be 566 answers, one per farmer.

[7] The multinomial logistic regression model is employed because farmers' answers to the perceptual questions are independent from each other, which signifies that, a priori, latent variables are not expected to exist affecting class membership identification. If this phenomenon existed, such as in the case of revealed-preferences regression problems, a more sophisticated regression approach should be employed to deal with these latent variables since their presence generate that the residuals of the multinomial logistic regression model become autocorrelated (Louviere *et al.*, 2000).