Determinants of vulnerability of bean growing households to climate variability in Colombia

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Abstract

Climate variability largely affects agriculture in the developing world where rainfed agriculture is highly prevalent, and farmers rely on favorable climatic conditions to grow their crops. In Colombia, interannual climate variability can increase human vulnerabilities. Evidence on the vulnerability of farming households to climate variability at the local scale is, however, scarce. Here, we assessed the climate vulnerability and its determinants for a representative sample of 567 bean growing households in Santander, Colombia. We first applied Multiple Correspondence Analysis to calculate a vulnerability index and its components (exposure, sensitivity and adaptive capacity). The vulnerability index is in turn used to classify households into three vulnerability groups, namely, high, medium, and low. We then estimated a Generalized Ordered Probit Model to assess the probability of falling into each vulnerability category according to the household and farm management characteristics. We find that vulnerability is highly variable in the study region, with up to 65 % of households classified as highly vulnerable. Geography, access to agronomic training, crop diversification, the percentage of household members making productive decisions and the gender of the household head are the most important factors determining the probability of being more or less vulnerable.

Keywords:

Vulnerability index, smallholders farmers, Generalized Ordered Probit, climate variability, drought, bush bean

1. Introduction

Climate variability affects agricultural systems across the globe, and especially in the developing world where rainfed agriculture is highly prevalent and farmers rely on favourable climatic conditions to grow their crops (Thornton et al. 2014; Vermeulen et al. 2013; Antwi-Agyei et al. 2012). Estimates suggest that climate variability explains 30-60 % of the observed variations in crop productivity (Ray et al. 2015; Delerce et al. 2016). Year-to-year climate-driven variations in the productivity of crops and livestock can, in turn, significantly affect farm household income, food security, and livelihoods. Furthermore, they can exacerbate vulnerability, especially when adaptive capacity and off-farm income are low (Frelat et al. 2016; Antwi-Agyei et al. 2013; Hahn et al. 2009). Nonetheless, evidence on the vulnerability of farming households to climate variability at the local scale is scarce (Villegas-González et al. 2017; Ruiz Agudelo et al. 2015), in part due to lack of data, and in part due to the multi-dimensional and multi-disciplinary nature of vulnerability, and the difficulties associated with reliably measuring it (O'Brien et al. 2004a; Adger 2006; Wiréhn et al. 2015). In addition to theoretical considerations, challenges exist regarding the differentiation of vulnerability across temporal scales (i.e. climate variability vs. climate change) or as a contextual variable as compared to an outcome (Adger 2006; O'Brien et al. 2007). Section 2 describes the framework we use in this study in light of some of these limitations.

Here, we aim at quantifying the vulnerability of common bean growing households to climate variability across a major common bean growing region of Colombia. Common bean (*Phaseolus vulgaris* L.) is the most important grain legume for direct human consumption, playing a critical role in the food security and nutrition of many rural and urban populations (Beebe 2012; Reichert et al. 2015). In Latin America, the largest bean producer worldwide and where millions of farmers depend on bean production and sale for both food and income (Broughton et al. 2003), some 6.4 million of tons of beans are produced per year in 6.5 million hectares (FAOSTAT 2014). Colombia is the seventh most important bean producer in Latin America (121,698 ha; 149,112 tons), and the fifth most important bean consumer (FAOSTAT 2014). In Colombia, bush bean growing area is concentrated in the department of Santander, followed by Antioquia and Tolima (FENALCE 2017). In these areas, mean bush bean yield remains well below its potential (FENALCE, 2017). Though global and regional studies have analyzed poverty implications of climate change (Hertel et al. 2010), and assess coping strategies to income shocks (Gaviria 2002), no studies quantify farm household vulnerability to climate variability in Colombia. Notably, we contribute understanding on the roles of crop diversification, and farm management, and gender, which are seldom included in vulnerability studies (see Sect. 2 for details).

More specifically, the paper aims to answer the following questions:

- What are the existing degrees of vulnerability to climate variability across a sample of bean growing households from north-eastern Colombia?
- What characterizes different degrees of vulnerability for these households?
- How do intra-household and farm management variables affect the probability of being in a given vulnerability level?

To address these questions, we first measured a number of context- and intra-household-specific variables through a household-level survey of 567 bush bean growing households in the department of Santander (north-eastern Colombia) in 2016. Through literature review and data analysis, we then identified and combined the variables that represented the three components of vulnerability (i.e. exposure, sensitivity and adaptive capacity) into a single Vulnerability Index (*VI*) (see Sect. 2 and Supplementary Text S1). Importantly, in quantifying exposure, we focus on the specific phenological phase of beans. Finally, a multinomial model was applied to the *VI* to assess the influence of intra-household and farm characteristics on the degree of vulnerability. Our analysis, therefore, not only allows understanding and measuring vulnerability, but also determining the propensity of farm households to be classified as highly, moderately, or lowly vulnerable.

2. Specifying a vulnerability framework

The first and most fundamental aspect in quantifying the degree of vulnerability is the choice of a conceptual framework (Reed et al. 2013; Urruty et al. 2016). The most commonly used framework for assessing vulnerability is that of the IPCC, which we adopt here. The IPCC defines vulnerability as '*the degree to which a system is susceptible to injury, damage or harm*', and encompasses three dimensions: exposure, sensitivity and adaptive capacity (Adger 2006; Fraser et al. 2013; IPCC 2014). Exposure to climate variability is the amount of climate variation to which the system is subjected; sensitivity is defined as the degree to which the system is affected (either beneficially or adversely) by climate variability or change; and adaptive capacity is the ability to adjust, to cope with, or benefit from climate variations (Adger et al. 2007; IPCC 2014). While exposure is often defined as a set of biophysical variables (e.g. total rainfall, length or number of drought or heat spells) that characterize the extent of variability or long-term change to which a particular system is subjected (Antwi-Agyei et al. 2012; Cooper and Wheeler 2017), defining indicators to characterize the sensitivity and adaptive capacity of rural households is less straightforward (O'Brien et al. 2004b; Wiréhn et al. 2015).

Most existing applications of the IPCC framework use an index comprised of several indicators related to these dimensions (Cooper and Wheeler 2017; Notenbaert et al. 2013; Abson et al. 2012). Therefore, a major issue when quantifying vulnerability is the choice of context-specific variables to represent different components of vulnerability for the farm-household system (Delaney et al. 2014). Appropriate variable selection facilitates quantification of vulnerability via the application of either a mathematical equation (Simelton et al. 2009; Antwi-Agyei et al. 2012; Parker et al. 2019) or a statistical approach that creates a 'composite' index from a large set of variables (Oijen et al. 2013; Abson et al. 2012; Wiréhn et al. 2015). In either case, an adequate understanding of the factors and conditions that shape vulnerability is required (Ribot 2010; Taylor 2014).

To understand which factors are typically included in vulnerability assessments, we conducted a systematic literature review (Supplementary Text S1 and Table S1). Our review indicates that existing studies seldom consider key intra-household variables on household characteristics (e.g. education level) and crop management but tend to concentrate on contextual variables (e.g. climate, soils, the existence of extension programs or government policies) (Notenbaert et al. 2013). Household and farm characteristics are typically used as indicators of adaptive capacity and access to income, services, and resources as indicators of sensitivity. Household and farm characteristics seen as indicative of adaptive capacity include age, size, dependent members, head sex, education level; access to information, markets, credit, technology and inputs; and number of crops, planted area, and land ownership. Vulnerability studies also use variables related to income and livelihood diversification, and access to services and resources as indicators of sensitivity. These variables typically include migration, access to water, transportation, presence or access to medical services, and climate-related sensitivity indices. Finally, studies rarely (if at all) include large-scale socio-political drivers that may influence vulnerability to climate variability and climate change (Taylor 2014).

3. Materials and methods

3.1 Study area

The study area comprises four bush bean producing municipalities in the department of Santander (Colombia) (Fig. 1). The climate of the study area is defined as tropical savannah (Aw) climate, with Villanueva and Barichara municipalities having frequent water deficit. On the contrary, Curiti and San Gil have the greater recorded precipitation regime, with annual total rainfall (average 1981–2014) of 1,278 mm year^{-1}, distributed in an average 100–150 days. Annual mean temperatures range between 24 and 31 ºC, with February and March being the warmest months (mean temperature 26.9 ºC), and September and October being the coldest months (mean temperature 24 ºC). Interannual climate variability is substantial, especially for precipitation, with years as dry as 786 mm year^{-1} (2015), and as wet as 1,672 mm year^{-1} (1988), with a trend towards drying in the period 1981-2014.

[Figure 1 near here]

Figure 1. Study area and household distribution. Points indicate the household surveys in four municipalities: Barichara, Villanueva, Curiti and San Gil. The municipalities are located in the department of Santander, in the north-east zone of Colombia. The elevation of zone varies between 333-2,240 m.a.s.l., while study households are located specifically in range 1,189-2,240 m.a.s.l.

In Santander, the bush bean is the most important crop in terms of number of producers, and the second after yellow maize regarding area (Blundo Canto et al. 2016). Across the study area, farmers tend to grow more than one crop, in two cropping seasons, one between April and July, and the other between September and December which correspond to the rainy seasons. About 7,000 ha are under cultivation each semester (FENALCE, 2017), with an average cultivated area in bush bean per farm mostly of ca. 1 ha (50 % of farmers), though some farms can be as large as 10 ha (Rios et al. 2017).

3.2 Household data

A total of 567 households were interviewed, of which 114 (20.1 %) were from Barichara, 145 (25.6 %) from Villanueva, 192 (33.9 %) from Curiti, and 116 (20.5 %) from San Gil. Households responded freely, and under prior informed consent, the duration of the interview was approximately 40 minutes. The municipalities were selected as they are the main bush bean producers in the study area (FENALCE, 2017). The sample is representative of 58% of the total bush bean producers in the four municipalities, according to the Colombian National Agricultural Census carried out in 2014. We used a stratified optimal random sampling strategy across two elevation ranges (1,189–1,538 and 1,539–1,889 m.a.s.l) to account for farmer choice of bean varieties, which depends on elevation (95% confidence). In the stratified optimal random sampling the size of the sample depends on the variance in the variables being studies within the strata. Optimal stratification is beneficial when within-group variability varies widely across groups; in this situation, it is convenient to reduce the sample size of the most homogeneous groups and favor those that are more heterogeneous. Moreover, this allows us to address productivity variation due to elevation, which could affect vulnerability.

Data were collected through Android Devices using ODK-Data Collect. Four local enumerators were required. We performed the data analysis in both Stata (StataCorp 2013) and R (R Core Team 2018) using the FactoMineR library (Lê et al. 2008). The survey was designed to capture information on general household characteristics including size, average age, dependency ratio (ratio of total number of dependent members to the total number of members), and average education level. Household head characteristics included household head age, education level, and sex. Farm characteristics measured through the survey were total area, percentage of area planted with bean, bean yield, and total number of crops grown, access to and use of agro-climatic information, and farmer's perceptions about climate risk and variability, especially with respect to drought. Finally, gender variables included the number of female members working on farm, the number of female members making productive decisions, number of female members working in pre-sowing activities, number of female members working in sowing and control activities, and the number of female members working in harvest and post-harvest activities.

3.3 Climate data

We used precipitation data from the Climate Hazards Infra-red Precipitation with Stations (CHIRPS) database (Funk et al. 2015) for quantifying exposure. CHIRPS is a quasi-global dataset constructed using combining satellite measurements with interpolated precipitation data from weather stations, at a spatial resolution of ~5 km. Daily precipitation data were extracted for each household in the period 2006–2016, and improved by correcting false zeros using the GeoClim software tool (FEWS NET 2017) and observed weather data from four weather stations (Sta. Isabel, Curiti, Zapatoca y el Cucharo) from the IDEAM (Institute of Hydrology, Meteorology, and Environmental Studies) weather station network.

We then used the improved precipitation records to compute the median, maximum, and variability of the maximum number of consecutive dry days (i.e. days with precipitation < 1 mm day^{-1}) for each year, for two key growth periods during the bean season (April - August). The first period corresponds to the time between sowing to the appearance of the third trifoliate leaf (from 1 to 35 days after planting, P1 hereafter), whereas the second period is between pre-flowering to the end of pod-filling (from 36 to 60 days after planting, P2). Both these periods correspond to the times in which the bean crop is most sensitive to water stress. Here, we used the number of consecutive dry days instead of using precipitation values directly, since the number of dry days is often a better indicator of drought-induced crop yield variations (Stern and Cooper 2011; Simelton et al. 2013; Delerce et al. 2016). Using these, we calculated the long-term median, variability (standard deviation), and upper bound (absolute maxima) of the number of consecutive dry days experienced by farmers in the period 2006–2016, separately for each growth period (P1, P2). This yielded three values (median, variability, and a maximum of the number of consecutive dry days 2006–2016) for each household in our sample for P1 and another three values for P2.

3.4 Calculation of the vulnerability index

To perform the vulnerability analysis, we first determined the variables related to the relevant dimensions: exposure, sensitivity and adaptive capacity using data from the household survey and climate data and then we combined the standardized values of the variables through Principal Component Analysis for calculating a single Index. We included all principal components with more than 50% of accumulated variance.

Table 1 shows the complete list of variables used to derive the *VI*, with their expected sign (effect) in relation to the vulnerability level. Based on the data available from the survey and existing literature (see Sect. 2 and Supplementary Text S1 and Table S1), we selected variables related to household and farm characteristics to represent adaptive capacity and variables related to livelihood diversification (and/or income generation) and access to resources and services to represent sensitivity. Since nearly all households own land, we do not include land ownership in the vulnerability index. The three dimensions of vulnerability were thus characterized as follows,

- **Exposure:** we used the variability (standard deviation) and maximum of the number of consecutive dry days 2006–2016 for both P1 and P2 as indicators of exposure. All these variables are expected to have a positive association with the vulnerability level.
- **Sensitivity**: five binary variables were chosen to characterize sensitivity. Three of them are expected to relate positively with vulnerability, namely, whether the household reported: 1) having suffered from drought, 2) drought affecting them more than other events and 3) climate change will high impact their economy. The other two variables, related with the existence of piped aqueduct in the house and whether the household reported precipitation is enough for the crop, are expected to be negatively related with vulnerability.
- **Adaptive capacity:** we used a total of fourteen variables. These describe household composition (size, age), household member characteristics (education levels), farm characteristics (planted area, number of crops, input expenditure), access to transportation and productive assets, and allocation of labour including off-farm[1].

[1] We assume that adaptive capacity is not over-represented because all variables are combined into a single index that is balanced by the variability of the dataset. Furthermore, literature shows that some of the adaptive capacity variables used can also be used as measures of sensitivity (Supplementary Text S1). Future studies could use more comprehensive surveys to ensure inclusion of a greater number of sensitivity factors.

[Table 1 near here]

Building on previous studies that employed a similar vulnerability framework to the one used here (Abson et al. 2012; Opiyo et al. 2014; Lokonon 2017), we calculated the Vulnerability Index (*VI*) through Principal Component Analysis (PCA). Once the factors and their contribution rates to the explained variance have been estimated, we calculated a weighted average for the stages of each main factor based on the importance of the *i*-attribute in the factors (Eq. 1).

$$q_i = \frac{\sum W_i Z_i}{\sum W_i} \tag{1}$$

where W_i is the percentage of explained variance, and Z_i is the value of each component. Finally, an index is calculated for the *j*-observation using the standardized matrix of observations $[\hat{X}]_{ij}$ and the weighing q_i with a reverse logit function (Eq. 2). The construction of the index is objective since the weights are not arbitrarily defined but are established by the explained variance of each factor[2].

$$I_j = \frac{e^{(q_i * [\hat{X}]_{ij})}}{1 + e^{(q_i * [\hat{X}]_{ij})}} \tag{2}$$

Variables that increase vulnerability have a positive correlation with the index, therefore, the higher the index, the more vulnerable the household. We calculated the index for each household in order to explicitly address within municipality heterogeneity. The vulnerability index by municipality is an average of the values of households in each municipality. Finally, we classified the *VI* in terciles across the entire sample of households, so as to represent different vulnerability levels: low (first tercile), medium (second tercile) and high (third tercile). As a result, the most vulnerable households belong to the third

[2] See Supplementary Material Table S3, Table S4, Table S5 and Table S6 for the weight of each dimension in the *VI* and the weight of each variable in each dimension.

tercile, whereas the least vulnerable ones belong to the first. We chose to use terciles as opposed to directly analyzing the *VI* as a continuous variable to reduce potential noise introduced by errors in the survey data, and to facilitate the interpretation of model results (see Sect. 3.5). Our choice of a 3-group classification using terciles ensures a balanced sample across *VI* categories, reduces complexity in the explanatory model (Sect. 3.5) and facilitates interpretation of model results (i.e. as likelihood ratios of being in a given class). However, as a robustness check, we also performed all the analysis of Sect. 3.5 with no classification (i.e. with *VI* as a continuous variable), and using two other classifications: (i) five orderly classes of equal frequency (i.e. quintiles); and (ii) grouping into three classes according to their distance from the mean (one standard deviation above the mean, one standard deviation below the mean, and between one standard deviation above and below the mean).

3.5 Assessing the determinants of vulnerability

As stated above, the second step in the vulnerability analysis is to assess the relationship between the *VI* and household-level variables, to identify determinants of vulnerability in terms of geographic, household, farm and gender characteristics. We used a Generalized Ordered Probit Model given the ordinal nature of the index, as well as the easier interpretation of model coefficients compared to using an Ordinary Least Squares (OLS) regression given that the index is a composite of many variables (see Supplementary Test S2). Moreover, the probit model allowed analyzing all levels of the distribution, including its mean and extremes. Our implementation of probit models follows Greene and Hensher (2008) and Cameron and Trivedi (2005), using Eq. 3 (see Supplementary Text S3 for additional details).

$$y_i{*} = \alpha + \beta' x_i + \varepsilon \tag{3}$$

Where,

$$\begin{aligned} y_i &= 0 \; if \quad y_i^* \le 0 \\ y_i &= 1 \; if \quad 0 < y_i^* \le \mu + \delta' x_i \\ y_i &= 2 \; if \quad y_i^* \ge \mu + \delta' x_i \end{aligned} \tag{4}$$

If the first element is normalized to zero, $\mu_0 = 0$, we obtain the probabilities in Eq. 5.

$$\begin{aligned}
Pr(y=0\,|\,x) &= F(\text{-}a - b'x) = 1 - F(a_0 + b_0'x)\\
Pr(y=1\,|\,x) &= F(m + d'x_i - a - b'x) - F(\text{-}a - b'x) = F(a_0 + b_0'x) - F(a_1 + b_1'x)\\
Pr(y=2\,|\,x) &= F(a + b'x - m - d'x) = F(a_1 + b_1'x)
\end{aligned} \tag{5}$$

Where $\alpha_0 = \alpha$, $\beta_0 = \beta$, $\alpha_0 = \alpha - \mu$, $\beta_1 = (\beta - \delta)$

Therefore, there are different parameter vectors for each result. The specification function is given by Eq. 6.

$$Pr\left(y_i = j\,|\,x_i\right) = F(m_j - b_j`x_i) - F(m_{j\text{-}1} - b_{j\text{-}1}`x_i) \tag{6}$$

Where $F(.)$ is the normal density function, y_i is an ordered and discrete dependent variable, which was defined in Eq. 4, and μ_j is a threshold defined for all individuals in the sample. We use importance weights in the Generalized Ordered Probit Model estimation to include regression weights as the frequency of observation in each municipality.

We then fitted the Generalized Ordered Probit Model using the vulnerability level (discrete variable with three categories) as the dependent variable, and 25 independent variables related with geographic, household, demographic, socioeconomic variables as well as farm management factors, agro-climatic information and training (Table 2). These variables were not used to construct the *VI* because their relationship with vulnerability to climate variability is not entirely clear in the literature. Hence, we included them in the probit model to test their relevance as potential vulnerability determinants; that is, to determine the effect of these variables over the probability of belonging to a particular vulnerability level (lower, medium, high) (Notenbaert et al. 2013; Opiyo et al. 2014). We included location (i.e. municipality) as an explanatory variable in order to ensure inclusion of any variables that were not explicitly measured (e.g. soils, governance structures, municipality-specific policies or programs). To avoid duplicity of information in the explanatory variables concerning the set of variables used to construct the *VI* (Table 1), we dropped any variables that were strongly correlated (r > 0.6) with the set of variables in Table 1. Finally, as stated above (see Sect. 3.4), to assess the robustness of our results toward the choice of methods, we conducted two additional analyses. First, we performed an OLS regression on the *VI* as a continuous variable (Supplementary Text S2). Secondly, we fitted the generalized probit models using a 5-group classification with quintiles, and a 3-group classification by distance from the mean (see Sect. 3.4 for details).

[Table 2 near here]

4. Results

4.1 Overview of household characteristics

Table 3 presents general summary statistics for the surveyed sample of households by municipality. Average per-municipality household size ranged from 3 people (Villanueva) to 4 (San Gil) approximately. The population is relatively young, with an average age below 40 years old. Younger and relatively larger households are located in San Gil, as confirmed by a higher dependency ratio, defined as the number of dependents (aged 0-14 and over 65) with respect to the number of members aged 15-64. Conversely, Villanueva has the highest average household age (40.9 years old). In general terms, most household adults across the four municipalities reached about five years of formal education or less. It is noteworthy that the household head is generally above the age average, but below the average education level.

Farms are small (2 ha on average), with the smallest farms located in Barichara (1.06 ha) and the largest ones in San Gil (3.4 ha). The larger farms of San Gil cultivate less bean (63 % area is dedicated to bean) compared to the smaller farms elsewhere (65–98 % area is dedicated to bean). As a result, farms in San Gil grow a greater number of crops (more than two different crops on average), whereas Barichara and Villanueva farmers produce only beans. Besides bush bean, other main crops in the study area are tobacco, coffee, and maize. San Gil farmers also obtain higher bean yields (1.22 ton ha^{-1} in San Gil vs. 0.98–

1.11 ton ha^{-1} elsewhere). Bean yield across the four municipalities is, however, low compared to the yield potential of beans.

[Table 3 near here]

According to respondents, one of every two women actively participate in productive decisions, and more than half the women in the household work on the farm. Approximately 20 % of self-identified household heads are women, with the highest frequency in San Gil (28.4 %), followed by Barichara (21.1 %), Curiti (16.1 %) and Villanueva (14.5 %). The interviewed population in the four municipalities is composed predominantly of farming households, with very low occupation diversification. In fact, about 98 % of male-headed and 67 % of female-headed households reported that their primary occupation is farming. Consistent with that, women more often identify household care as their main occupation (30.3%), against only 0.4% of men (Supplementary Table S2).

4.2 Vulnerability of bean growing households

Our evaluation of the vulnerability index results shows that vulnerability would seem to be concentrated in different portions of the study area. Here, we present the results by municipality. Figure 2 shows the distribution of the vulnerability index terciles[3] in the four municipalities. Villanueva presents the highest frequency of highly vulnerable households (64.8 %). Conversely, the frequency of highly vulnerable households is extremely low in San Gil (1.7 %), where the vast majority of households belong to the low vulnerability tercile (85.3 %). In fact, Villanueva and Barichara, with small farm sizes and virtually entirely dedicated to bean cultivation, have the lowest proportions of farmers in the low vulnerability class. Notably, however, in Barichara, the majority of farmers are in the medium vulnerability class, and about a third are in the high vulnerability class.

[3] The difference between the individuals that are in the margin is not statistically tested since it is not possible to apply a discontinuous regression technique given that the threshold is established somewhat subjectively. On the other hand, a test of difference of means, when considering the tails of the distribution, does not contribute information on the difference of the individuals in the thresholds of each one of the three categories of vulnerability.

[Figure 2 near here]

Figure 2. Municipality composition by Vulnerability Index (VI) terciles. Values in parentheses indicate the mean VI value, varies between 0 and 100. The percentage of households placed in each vulnerability level is shown for municipality and total sample.

Variation in all indicators used to construct the *VI* was generally as expected, as well as statistically different across vulnerability groups (see Supplementary Table S7 and Supplementary Text S4).

4.3 Determinants of vulnerability

In this section, we explore the effect of variables that were not used to construct the vulnerability index measure but that we hypothesize can influence the likelihood of being in a particular vulnerability level, with results being robust toward the choice of model (Supplementary Text S2), and the choice of classification method (Supplementary Table S9). For example, location is not a component of the vulnerability index, but it is possible that it encompasses other non-measured variables such as existence of certain municipality-level policies, or institutions that influence vulnerability. To explore these effects, we Estimated a Generalized Ordered Probit Regression which indicated that 20 variables have a statistically significant effect on the probability of being in a particular household vulnerability level (Table 4, see Supplementary Table S8 for descriptive statistics of these variables). Geography, having received agronomic training, crop diversification, and the percentage of household members making productive decisions are the most important factors determining vulnerability.

[Table 4 near here]

According to the probit model, vulnerability is highly structured across the geographic space. The effect is marked at the municipality level (ascribed by location in one or other municipality), but also within municipalities (ascribed by the distance to populated centers –a proxy of distance to markets). The former (i.e. location in municipality) may indicate the influence of non-measured biophysical (e.g. soils) or socio-economic (e.g. municipality government policies) variables, or cultural differences. Households who live in Villanueva are about 33 % more likely than those in Barichara to be in a high vulnerability group and 52 % less likely to be in the medium vulnerability level. On the other hand, growing beans in San Gil increases the probability to have a low vulnerability level by 54 % and reduces the probability of be highly vulnerable by 21 %, approximately. Within municipalities, we find that more isolated households (i.e. with greater distances to populated centres) are around 3.6 % more likely to be in the most vulnerable class.

Amongst the non-geographic factors that affect vulnerability, we note that access to agro-climatic information increases the likelihood of being highly vulnerable. This result seems counter-intuitive, as it is expected that agro-climatic information and training helps in addressing climate risk. There is a possibility that the information is not suitable due to issues with scale, precision, or transparency (Blundo Canto et al. 2016) or simply due to lack of predictive skill (Esquivel et al. 2018). However, it is possible that access to such information is only occurring recently, mainly by the highly vulnerable households. We note greater frequencies of access in Villanueva and Barichara, which also have more households with greater levels of vulnerability. Further investigation into the type of information that farmers receive, its use and impact is warranted. Access to agronomic training, on the other hand, as expected, reduces the likelihood of being highly vulnerable, and increases the likelihood of being in the low vulnerability class.

There are some other socioeconomic, farm management and gender factors that have a significant effect on the vulnerability level. On-farm diversification also has a substantial effect (16%) on the likelihood of being in the low vulnerability class. Additionally, model results indicate that male-headed households are around 16 % more likely than female-headed households to be in the medium vulnerability class. This result matches the results found by Noterbaert et al. (2013) who indicate the need for interventions and policies that support female-headed households. The marital status of the household head is statistically significant and indicates married household heads are less likely to be in a high vulnerability level (10%).

According to the probit regression, households that are more educated tend to be less vulnerable to climate risk. On the other hand, large numbers of dependents (the elderly and children) increase the probability of being in the most vulnerable group but is not significant. Notenbaert et al. (2013), found that households with many dependent members tend to be more vulnerable and have less adaptive capacity than households where more members can contribute to farm labour or through off-farm income sources. In this regard, households where members have more than one occupation and at least one member has a non-agricultural occupation tend to be less vulnerable. This finding suggests that the more diversified income, the higher their adaptive capacity and lower the probability to be vulnerable to climate risk and is again consistent with Notenbaert et al. (2013). Additionally, our results show that indebted households are more likely to be more vulnerable, perhaps due to narrower debt to income ratios. While it is expected that access to credit decreases vulnerability, actually asking for credit may be an indicator of financial instability or lack of resources for farming.

Finally, regarding gender dynamics, we note that the hiring of female workers does not affect vulnerability significantly, likely indicating that gender of the hired worker has no direct implication in the production process. On the contrary, the ratio of female and male household members working on farm has a significant impact on the likelihood of being more vulnerable. Notably, our analysis suggests that the greater the percentage of household members making decisions, the more likely it is the household is vulnerable to climate variability. This is especially so for male members making decisions and maybe a result of the difficulty in reaching consensus amongst household decision makers.

5. Discussion

5.1 Vulnerability of bean growing households to climate variability

This paper examines vulnerability to climate variability and the factors affecting it in key common bean producing regions in Colombia. We constructed a vulnerability index using explanatory variables of exposure, sensitivity and adaptive capacity. We find vulnerability to be highly variable, and mostly concentrated in the drier municipalities of Barichara and

Villanueva, where farmers are exposed to considerable climate variability and longer drought spells, have less access to technical assistance, grow beans exclusively and have on average smaller farms. Additionally, there are different vulnerability levels by municipality, offering some insight into how geographic factors such a distance to markets, local climate conditions, and other spatially differentiated variables must be taken into account when attempting to understand the determinants of vulnerability, with implications for policy and practice (see Sect. 5.2). Indeed, our finding that location (i.e. municipality) is an important factor may highlight the importance of variables such as soils, municipality-level governance structures and/or policies, occurrence of pests and diseases, as well as interactions between household characteristics and national- or global-level socio-political and economic variables (Leichenko and O'Brien 2008; Silva et al. 2010; Nielsen and Reenberg 2010), which were not considered here. Future studies could analyze the importance of these variables in determining local-level vulnerability levels.

Studies assessing climate vulnerability in Colombia are scarce and mostly concentrate on climate change timescales. For instance, Ramirez-Villegas et al. (2012) quantified how Colombian agricultural production may be affected by climate change, suggesting that some 10 % of common bean growing areas expect reductions in precipitation and that most growing areas expect increases in annual mean temperature in the range 2–2.5 ºC above historical levels. Eitzinger et al. (2014), focusing on the areas around Bogota, reported that some 20-30 % of climatically suitable common bean area is expected to reduce as a result of climate change. Previous research has also assessed the social causes of vulnerability, including trade and armed conflict (Feola 2013; Feola et al. 2015; Contreras and Contreras 2016). Most of these studies conclude that trade liberalization and armed conflict can further enhance vulnerability by reducing productivity or hindering market competitiveness. This highlights the importance of understanding vulnerability in a broader context, with multiple stressors at various spatial scales (Leichenko and O'Brien 2008; Nielsen and Reenberg 2010; Taylor 2014).

To the knowledge of the authors, however, studies on farmer vulnerability climate variability, and mainly focusing on bean producers, do not exist for Colombia.

Studies in other developing countries support our main finding that vulnerability is highly variable and conditioned by specific climatic variables and household characteristics (e.g. education, income and farm diversification). For instance, Sietz et al. (2012) analyzed Peruvian smallholders' vulnerability and food security through a clustering approach. They found that the cluster with the most vulnerable smallholders exhibits the highest crop failure risk, pronounced livestock constraints, suffer educational deprivation, and have limited or no alternative income sources. Similarly, Notenbaert et al. (2013) suggest that the vulnerability of agro-pastoralists in Mozambique to climate change and variability is influenced by the gender and age of the household head, the ability to save money and access emergency loans. Furthermore, the multi-country study of Wood et al. (2014) reported that African and South Asian farmers' reported changes in farm practices are influenced by access to weather information and participation in social institutions, which ultimately conditions their vulnerability level. Furthermore, our study also highlights important areas of future research. For instance, our finding that access to agro-climatic information in the last 12 months, while somewhat counterintuitive, warrants further investigation as to the reliability and usability of the information being provided, and the capacity of farming households to understand and use it (Selvaraju et al. 2011; Mcnie 2012; Bernardi 2013).

5.2 Implications for science, policy, and practice

A number of implications stem from our work. One of the critical findings of this study relates to the heterogeneity of vulnerability. The vulnerability determinants of farming households are diverse (e.g. location, workforce, and climate). There is a "vulnerability complex" (i.e. many context-dependent variables), which illustrates the importance of policy mechanisms and development interventions that are adequately flexible so as to consider individual household context when attempting to reduce regional vulnerability to climate variability and change. Climate as one of the factors that influences vulnerability might be seen beyond a set of biophysical variables, but part of a constant process of change that involves social organization, technology change and political discourse (Taylor

2014). That is, while vulnerability is experienced at the local level, its causes and solutions can be determined at a variety of scales (from local through to international).

This means that, in addressing vulnerability to climate variability and climate change, a wide range of context socio-economic and political variables must be taken into account (Feola 2013; Ramirez-Villegas and Khoury 2013; Feola et al. 2015). Here, we have analyzed a variety of climate and household characteristics, and have explicitly assessed the roles of crop diversification, and farm management, and gender, in determining vulnerability. Further work remains to be done to understand the influence of socio-political context variables on vulnerability, by using panel datasets (which we did not have here), larger datasets with multiple departments, or by using ethnographic approaches to qualitatively understand other vulnerability determinants (Beveridge et al. 2019). Despite this, our study helps disentangle part of the 'vulnerability complex' at the local scale, contributing to setting priorities for addressing vulnerability.

Based on our analysis, we conclude that climate variability adaptation should be a priority in the study area, with efforts first targeting the most vulnerable areas (Barichara, Villanueva). Such an approach would allow to pilot test most appropriate adaptation measures, which could be prioritize on the basis of a cost benefit analysis. Increased access to up to date technical assistance as well as increased organizational cohesion of farmers are needed (Gutiérrez and Espinosa 2010; Lampis 2013; Feola et al. 2015). While our analysis only targets four municipalities (covering 27% of farmers in Santander, according to the National Agricultural Census, 2014), future studies should assess vulnerability across the whole of Santander and other bean growing areas, in order to better target and expand climate adaptation work, also aiming to understand differences in context-variables at the municipality level. This is especially important Colombia where major changes in agricultural areas are expected as a result of the post-conflict agenda (Aguilar et al. 2015; Gonzalez-Salazar et al. 2017). Our study provides a rigorous approach for assessing vulnerability, and could be the basis of such future assessments.

Ultimately, if vulnerability is to be reduced in these areas, appropriate risk mitigation strategies tailored toward reducing the impact of drought spells need to be devised. The potential benefit of adaptation strategies can be substantial, not only addressing local-scale vulnerability, but also increasing bush bean production and economic output in the Santander department, and in the country. One key mechanism for adaptation is the provision and use of agronomic and climate-related information (e.g. Wood et al., 2014). An important finding of our analysis lies in the difference in the effect between agronomic training and agro-climatic information. While the former has a large positive effect in the likelihood of being in the low vulnerability class, the latter increases the likelihood of being in the high vulnerability class. There are various implications of these results. Foremost, agronomic training can be a lever through which agro-climatic information can be communicated to farmers, so as to enable adaptation. Additionally, it is critical to understand what kinds of agro-climatic information farmers are receiving and whether and how they are using it. For instance, Blundo Canto et al. (2016) reported that issues with scale and reliability of climate predictions, as well as their lack of connection to agricultural activities prevent the use of seasonal and weather forecasts from the Colombian Meteorological Agency (IDEAM). Similarly, Esquivel et al. (2018) reported varying skill in seasonal predictions across major agricultural regions and cropping seasons. Efforts to train farmers to understand climatic predictions (especially drought- related) and connect them to their activities, as well as to provide more locally-relevant and reliable seasonal and weather forecasts will be necessary to adapt bush bean production to climate variability (CIAT-MADR 2015).

Other adaptation strategies could include a combination of diversification at the plot-level, for instance through crop and variety diversification, and at the farm-household level through complementary income generating activities. Baca et al. (2014) discuss the importance of diversification for production risk management in small farming systems, while Lin (2011) shows that diverse levels and types of diversification allow farmers to concomitantly increase resilience and obtain economic benefits. Van Etten et al. (2019) demonstrate how varietal diversification can help small-scale farmers adapt to climate change. In terms of crops, diversification also implies access to suitable germplasm that is climate-adapted, but also fostering and linking formal and informal seed systems (Bellon et al. 2011). At the regional level, technical assistance could be targeted to accompany these diversification strategies and to implement preventive actions to face climate variability and drought (e.g. irrigation, water harvesting, and use of cover crops or residues), including monitoring and early warning systems to orient planting and crop management decisions (Ramirez-Villegas et al. 2012; CIAT-MADR 2015).

The implementation of these strategies will require a concerted effort between public (e.g. Ministry of Agriculture) and private (e.g. FENALCE, the national cereal and legume crop federation, and other local entities) organizations to provide farmers with the technical assistance, economic incentives and inputs to cope with climate variability (Motha 2007; Ramirez-Villegas et al. 2012; Turbay et al. 2014), while also addressing other causes of vulnerability (e.g. armed conflict, political instability, and trade liberalization) (Feola et al. 2015; Contreras and Contreras 2016; Villegas-González et al. 2017).

5.3 Limitations and future work

Here, we have quantified the degree of vulnerability and assessed its determinants. While we have used context-specific data and statistical approaches, limitations arise in our analysis. Foremost, the survey captured only limited information on sensitivity and exposure to climate variability, but sufficient information on adaptive capacity. While over-representation in one of the vulnerability dimensions is unlikely to bias the relative comparisons of vulnerability done here, it is desirable to include similar numbers variables for all vulnerability dimensions. This would allow a more comprehensive assessment of vulnerability. Similarly, as stated earlier, further understanding is required as to socio-political context determinants of vulnerability (see Sect. 5.1–5.2). Additional limitations arise due to possible noise in the household dataset, or in the satellite-derived climate data used to measure exposure. Our analysis generates important evidence on the degree and determinants of vulnerability in bean growing rural households. This evidence, even in a constrained geographic area such as Santander, shows the value of disaggregated analyses, both at the municipality and household levels.

Finally, we believe continued research on vulnerability and its determinants is necessary to generate the evidence and information required to address it. Notably, assessments in other crops and regions of Colombia are necessary to better understand vulnerability to climate variability and its determinants. Such assessments are currently constrained by data availability. Finally, studies that relate vulnerability with food security, and that investigate how gender influences vulnerability are warranted.

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Table 1 Variables used to define the Vulnerability Index (VI)

Variables in index	**Expected sign***
Sensitivity	+
Has suffered drought**	+
Think drought affects more than other events**	+
Think precipitation is enough for crop**	-
Think climate change will high impact HH economy**	+
House have piped aqueduct**	-
Exposure	+
Consecutive dry days (std. dev.), P1	+
Consecutive dry days (std. dev.), P2	+
Consecutive dry days (max), P1	+
Consecutive dry days (max), P2	+
Adaptive Capacity	-
Household size	-
Members in age to work	-
Average household education (years)	-
Household head education (years)	-
Household head age	+
Planted area (% of total)	+
Number of crops	-
Number of assets owned	-
Transportation assets	-
Agricultural Assets	-
Information Assets	-
Number of household members with off farm occupation	-
Agricultural inputs expenditure (per ha)	-
Bush bean income (per ha)	-

*The + (–) sign indicates that a high value in the variable increases (decreases) the level of household vulnerability. These are all based on what is expected, and are not imposed directly onto the analysis.

** Dichotomous variable

Table 2 Summary of the explanatory variables used in the regression model

Variable definition	Units of measurement
Geographic factors	
Municipality Villanueva	1=Yes and 0=No
Municipality Curiti	1=Yes and 0=No
Municipality San Gil	1=Yes and 0=No
Distance to closest populated centre (Km)	km
HHH factors	
HHH sex	1=Man and 0= Female
HHH is married or in consensual union	1=Yes and 0=No
HH demographic factors	
Highest education level of any member	Years
HH Socioeconomic factors	
HH dependency rate	Ratio (dimensionless)
HH members with 2nd occupation	Number of members
Asked for loan in last 12 months	1=Yes and 0=No
Need to collect water at least once a week	1=Yes and 0=No
Information and training	
Anyone in HH received agroclimatic information in last 12 months	1=Yes and 0=No
Anyone in HH received agronomic training in last 12 months	1=Yes and 0=No
Farm management factors	
Total Area	ha
HH have another main crop: coffee, corn or tobacco	1=Yes and 0=No
Hired labour	day ha^{-1}
Intra-household and productivity gender role	
Hired at least one female worker	1=Yes and 0=No
Ratio of women to men family workers (over 14)	Ratio (dimensionless)
HH decision-makers who are woman	%

Table 3 Summary characteristics of surveyed households per municipality

Municipality	Barichara (n=114)		Villanueva (n=145)		Curiti (n=192)		San Gil (n=116)		Total (n=567)	
	20.1%		25.6%		33.9%		20.5%		100.0%	
	Mean	**S.D.**[1]	**Mean**	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**
Household characteristics										
Household size	3.83	1.5	3.48	1.45	3.5	1.4	4.16	1.53	3.7	1.48
HH average age	37.26	15.19	40.87	16.68	38.42	15.49	34.37	14.79	37.98	15.72
HH dependency rate	0.39	0.48	0.34	0.46	0.39	0.56	0.5	0.51	0.4	0.51
HH average education among adult members	5.49	2.42	4.69	2.11	5.4	3.09	5.99	2.26	5.36	2.6
Household head characteristics										
HHH age	47.95	12.31	51.95	13.63	49.08	13.41	46.59	14.53	49.08	13.59
HHH education	4.54	2.86	3.73	2.14	4.85	3.6	4.8	3.03	4.48	3.03
Farm characteristics										
Total area (ha)	1.06	0.9	1.39	1.27	2.22	1.51	3.41	2.8	2.02	1.9
Bean planted area (fraction of total)	0.97	0.12	0.98	0.1	0.65	0.29	0.63	0.28	0.79	0.28
Bean yield (ton ha^{-1})	0.98	0.36	1.07	0.38	1.11	0.4	1.22	0.34	1.1	0.38
Number of crops	1.06	0.24	1.09	0.39	1.68	0.59	2.33	1.26	1.54	0.85
Gender										
Female members working on farm (fraction of total)	0.74	0.4	0.54	0.47	0.55	0.45	0.53	0.45	0.58	0.45

[1] S.D.: standard deviation across the household sample

Table 4 Marginal effects of the Generalized Ordered Probit regression

Tercile	Tercile 1	Tercile 2	Tercile 3
Vulnerability Level	**Low**	**Medium**	**High**
Geographic factors			
Municipality. Villanueva=1	0.017	-0.159***	0.142***
Municipality. Curiti=1	-0.004	0.002	0.002
Municipality. San Gil=1	0.636***	-0.404***	-0.233***
Distance to closest populated centre	-0.076***	0.042***	0.034***
HHH factors			
HHH gender (Male=1)	0.055	0.047	-0.103***
HHH is married/ consensual union. Yes=1	0.215***	-0.076***	-0.139***
HH factors			
Highest education level of any member (years)	0.055***	-0.030***	-0.024***
HH dependency rate	-0.060*	0.033*	0.027*
Anyone in HH received agroclimatic information in last 12 months. Yes=1	0.06	-0.141***	0.080***
Anyone in HH received agronomic training in last 12 months. Yes=1	0.382***	-0.321***	-0.061***
Asked for loan in last 12 months. Yes=1	-0.087***	0.050**	0.037***
Need to collect water at least once at week. Yes=1	-0.067	0.151***	-0.083***
Farm management factors			
Total Area (Ha)	0.071***	-0.063***	-0.009
HH have another main crop (coffee, corn or tobacco). Yes==1	0.395***	-0.214***	-0.181***
Hired labour day (per hectare)	0.001	0.001	-0.002***
Gender factors			
Hired at least one female worker. Yes=1	-0.029	0.016	0.014
Ratio of women to men family workers (over 14)	-0.012	0.007	0.005
Percentage of HH female members making productive decisions	-0.229***	0.126***	0.103***
Percentage of HH male members making productive decisions	-0.614***	0.468***	0.146***
Number		567	
Chi Squared		1477.288	
Log-Likelihood		-819.042	
LRI		0.474	
AIC		1696.084	

Significance levels: * p<0.10, ** p<0.05, *** p<0.01

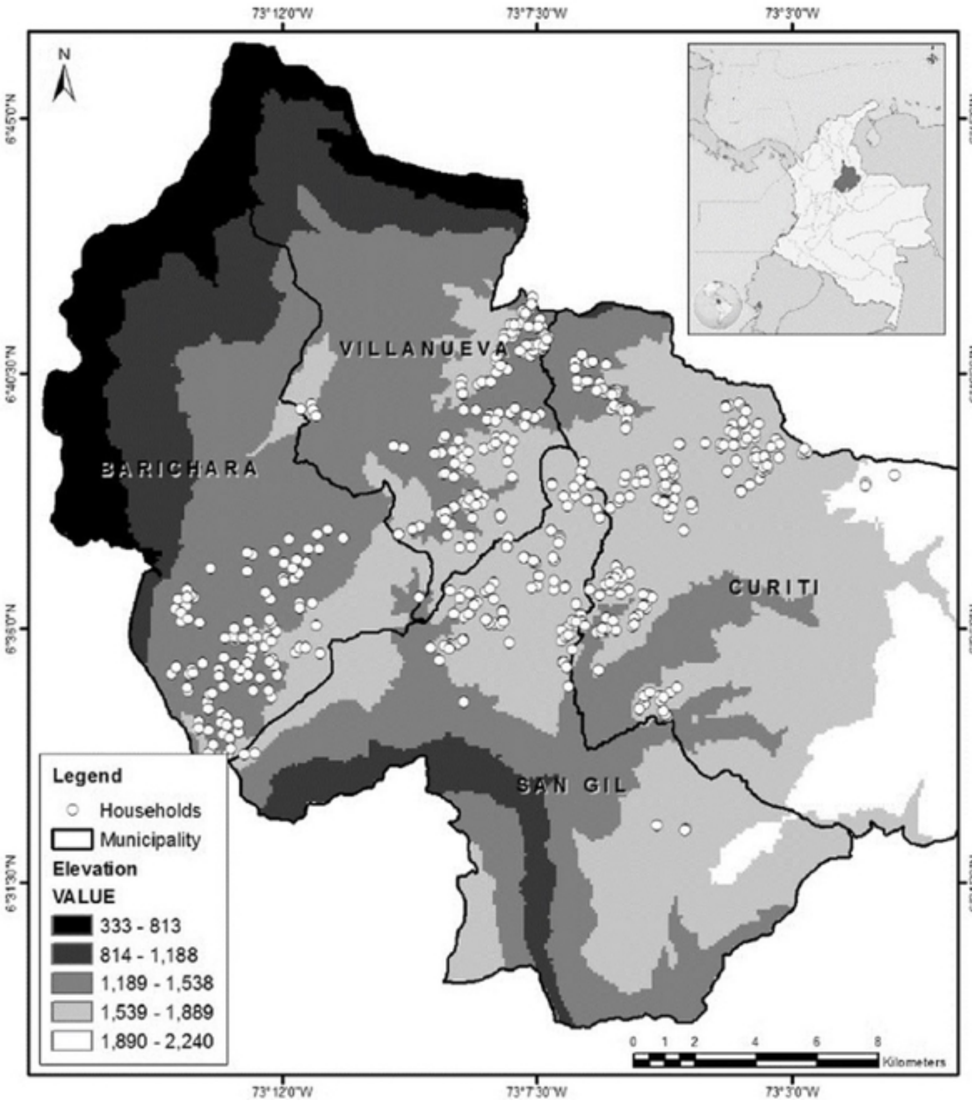

Figure 1 Study area and household distribution. Points indicate the household surveys in four municipalities: Barichara, Villanueva, Curiti and San Gil. The municipalities are located in the department of Santander, in the north-east zone of Colombia. The elevation of zone varies between 333-2.240 m.a.s.l., while study households are located specifically in range 1.189-2.240 m.a.s.l.

50x56mm (300 x 300 DPI)

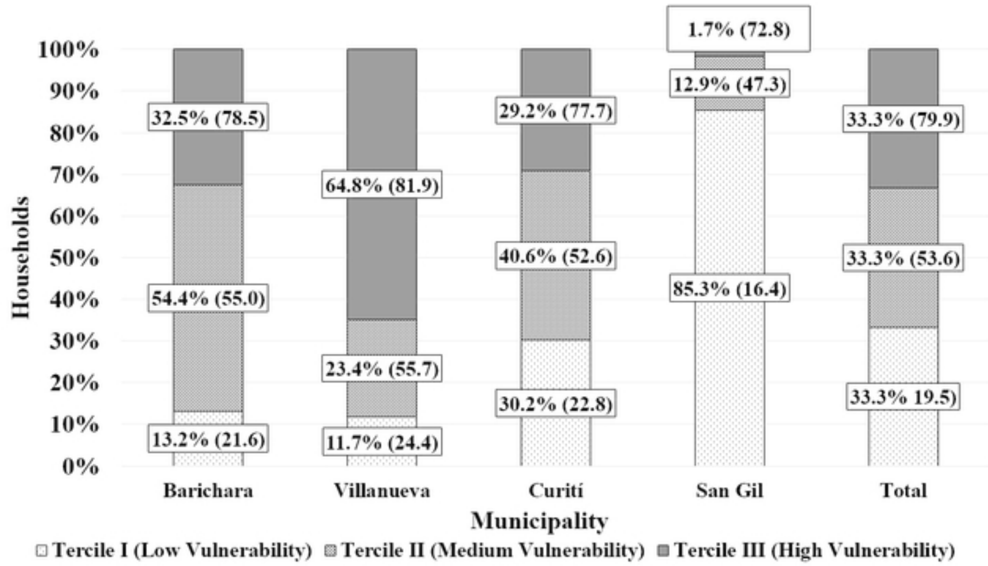

Figure 2. Municipality composition by Vulnerability Index (VI) terciles. Values in parentheses indicate the mean VI value, varies between 0 and 100. The percentage of households placed in each vulnerability level is shown for municipality and total sample.

53x30mm (300 x 300 DPI)

Supplementary Material

Supplementary Text S1 – Literature review to identify sensitivity and adaptive capacity indicators

In order to identify those variables that were most useful in characterizing sensitivity and adaptive capacity, a systematic literature review was conducted. Based on these results, we establish our final choice of variables for analysis (see Sect. 2 and 3.4, main text).

The studies were identified through Google Scholar™, using the search terms "climate", "vulnerability", and "households". A total of 9 published studies were identified that use IPCC's climate vulnerability framework. The studies as well as the variables they use to characterize sensitivity and adaptive capacity are listed in Supplementary Table S1. In general, the variables commonly used to define household adaptive capacity and sensitivity to climate events are clearly distinct, with the exception of household composition and land ownership (also see Sect. 2 of the main text).

One challenge in variable selection and specification is that different researchers may categorize indicator variables in different ways. Household composition and land ownership, for example, can be used to characterize both sensitivity and adaptive capacity. Household composition was included as a measure of adaptive capacity by Opiyo et al. (2014) and Lokonon (2017) and, contrastingly, as a measure of sensitivity by Baca et al. (2014). Land ownership was included as a measure of adaptive capacity by Opiyo et al. (2014) but as a measure of sensitivity by Baca et al. (2014). Both variables can arguably be included in either dimension of vulnerability. For instance, households with many dependent members can be highly sensitive if those members could suffer more via lack of food, water or care (Notenbaert et al. 2013). On the other hand, households with many dependent members tend to show less adaptive capacity since the workload and responsibility for adapting is concentrated in one single or only a few household members (Notenbaert et al. 2013).

Supplementary Text S2 – Ordinary Least Squares (OLS) regression

First, we adopted the Ordinary Least Square method (OLS) using the following equation:

$$y_i = \alpha + \beta' x_i + \varepsilon$$

where x_i is a set of household-level variables, y is the *VI* and ε is the error term. Results of the OLS model are shown in Table A1.

Table A1 – OLS regression results

Variables / Vulnerability Level	OLS Regression
Geographic factors	
Municipality. Villanueva=1	7.982**
Municipality. Curiti=1	-0.855
Municipality. San Gil=1	-21.471***
Distance to closest populated centre	1.496*
HHH factors	
HHH gender (Male=1)	-0.544
HHH is married/ consensual union. Yes=1	-6.174**
HH factors	
Highest education level of any member (years)	-1.831***
HH dependency rate	1.637
Anyone in HH received agroclimatic information in last 12 months. Yes=1	3.258*
Anyone in HH received agronomic training in last 12 months. Yes=1	-8.449**
Asked for loan in last 12 months. Yes=1	3.108*
Need to collect water at least once at week. Yes=1	-3.509
Farm management factors	
Total Area (Ha)	-0.945*
HH have another main crop (coffee, corn or tobacco). Yes==1	-13.115***
Hired labour day (per hectare)	-0.114*
Gender factors	
Hired at least one female worker. Yes=1	0.063
Ratio of women to men family workers (over 14)	-2.113
Percentage of HH female members making productive decisions	7.596***
Percentage of HH male members making productive decisions	16.342***
Number	567
R-squared	0.6674
Degrees of fredom	92.78

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

OLS regression results indicate that most variables have a statistically significant effect on the *VI*. In particular, we found a positive and statistically significant effect of being in the municipality of Villanueva, the distance to the closest populated center, the receiving information about agroclimatic issues, and the percentage of female and male members in the households making decision about production. Being in the municipality of San Gil, having a married household head, having higher level of education, having received an agronomic training in the past 12 months, total areas in hectares, and hired labour per day has a negative and statistically significant effect on the *VI*.

However, through the OLS method we can learn something about the direction of the coefficient but not regarding the magnitude of the effect, as coefficients cannot be easily interpreted[1]. For this reason, we transformed the index into a categorical variable in three different ways: the first one is to divide the *VI* into three ranges of $\pm$ a standard deviation around the mean. The second one was to split the *VI* into quintiles. The third one correspond to the terciles of the *VI*. Then we estimated a Generalized Ordered Probit Regression with the three different categorical variables (see supplementary material Table S10). We found that the vulnerability values near the threshold between two categories did not introduce noise or bias in our results, in terms that the most of the variables coincide among the models in statistical significance and direction of the effect. Then we choose the model where the dependent variable is the *VI* divided into terciles for explaining our results since its results coincide with both the alternatives Generalized Ordered Probit estimations and with the OLS regression. The model

The OLS method allows us to look at the mean values, while we are interested in understanding what happens across of the distribution. Furthermore, the coefficient of the OLS is of difficult interpretation, since the dependent variable is an index composed of several variables.

[1] Due to the normalization process over the overall index, the coefficients can be interpreted as the effect of an increase of 1 standard deviation of the regressor on the VI index.

Supplementary Text S3 – the parallel regressions assumption and the Brant test

The parallel regressions assumption departs from the specification of discrete ordered choice model (Long, 1997) (Eq. 1).

$$\Pr(y \geq J \mid x_i) = F(\mu_j - \beta' x_i);\ j = 1,\ldots, J-1 \tag{1}$$

Differentiating (1), we have:

$$\partial \Pr[y_i \leq j \mid x_i] / \partial x_i = -f^*(\mu_i - \beta x_i)\beta \tag{2}$$

This is defined as a set of binary choice models by with the same slope vector β. Fixing the probability at $P = P^*$ for any outcome, by monotonicity of the normal density function, it follows that $f(\mu_i - \beta x_i)$ is fixed at f^*. It means that for a particular choice the probability is:

$$\partial \Pr[y_i \leq j \mid x_i] / \partial x_i = f^* \beta = \partial \Pr[y_i \leq m \mid x_i] / \partial x\ ,\ m = 0,\ldots, J\ ,$$

Where f^* is the same for all J, that is, a multiple of the same β. This intrinsic characteristic is called “Parallel regression assumption” (Greene and Hensher, 2010).

Brant (1990) approaches the parallel regressions issue through the proportional odd test in which implies the null hypothesis is equivalent to $Ho: \beta_1 = \beta_2 \ldots = \beta_{J-1}$ implying that $\Pr(y \geq j| x_i) = \phi(\beta_{0j} - \beta' x_i)$ where $\beta_{0j} = \beta_0 - \mu_j$ y ϕ is the normal density function. The slope vector β_j must be the same in each equation. This specification implies that J-1 binary choice models can be estimated at the same time. Each with its own constant term and the same slope vector. So, the null hypothesis is equivalent to:

$$H_0: \beta_q - \beta_1 = 0, q = 2,\ldots, J-1$$

Which can be summarized as:

$H_0: R\beta^* = 0$, Where

$$R = \begin{bmatrix} I & -I & 0 & \dots & 0 \\ I & 0 & -I & \dots & 0 \\ \dots & \dots & \dots & \dots & \dots \\ I & 0 & 0 & \dots & -I \end{bmatrix} \quad \beta^* = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \dots \\ \beta_k \end{bmatrix} \quad C = \begin{bmatrix} 0 \\ 0 \\ \dots \\ 0 \end{bmatrix}$$

The Wald statistic follows a chi-squared distribution and is defined as:

$$\chi^2\left[(J-1)K\right] = (R\hat{\beta}^*)'\left[R \times Asy.Var\left[\hat{\beta}^*\right]R'\right]^{-1}(R\hat{\beta}^*)$$

Where $\hat{\beta}^*$ is obtained from the individual estimator of binary probit of β (without a constant term). Using the results of the Brant test or the results of parallel odds ratio, the asymptotic variance and covariance matrix is defined as:

$$Est.Cov.Asy\left[\beta_i, \beta_j\right] = \left[\sum_{i=1}^{n} \hat{\Phi}_{ij}(1-\hat{\Phi}_{ij})x_i x'_i\right]^{-1}\left[\sum_{i=1}^{n} \hat{\Phi}_{im}(1-\hat{\Phi}_{ij})x_i x'_i\right]\left[\sum_{i=1}^{n} \hat{\Phi}_{im}(1-\hat{\Phi}_{im})x_i x'_i\right]^{-1}$$

And $\hat{\Phi}_{ij} = \Phi(\hat{\beta}_{0j} - \hat{\beta}' x_i)$.

If the null hypothesis of the Parallel Regressions Assumption test is accepted the Ordered Probit Model should not be estimated, as it could be a result of (i) wrong specification of the latent variable; (ii) negative probabilities, heteroscedasticity of errors; and (iii) a wrong specification of the latent variable distribution (i.e. the variable does not follow a logistic or normal distribution). On the other hand, if the null hypothesis is rejected, a generalized ordered probit should be estimated (Greene and Hensher, 2010).

In our particular case, the null hypothesis of the Parallel Regressions Assumption was rejected, which means we can indeed estimate the generalized ordered probit model.

Table S1 Variables identified in the literature as determinants of adaptive capacity (A) and sensitivity (S). Bold text is used indicate variables that overlap between dimensions across studies. HH: household.

Variable/Dimension	**Agrawal (2010)**	**Anderson et al. (2010)**	**Harvey et al. (2014)**	**Baca et al. (2014)**	**Huai (2016)**	**Lokonon (2017)**	**Opiyo et al. (2014)**	**Byrne (2014)**	**Nelson et al. (2002)**	**Our index**
Water storage/irrigation	A		A	A						
HH age/ HH head age						A	A			A
HH size							A			A
HH composition / dependent members				**S**		**A**	**A**			**A**
HH head sex							A			
HH education level				A			A			A
HH head [highest] education level						A	A	A		A
Training	A		A	A						A
Assets/ Productive technology	A			A	A	A		A		A
Access to information	A	A	A				A	A		
Access/ Distance to market	A					A	A	A		A
Agriculture income					A	A	A	A		A
Occupational diversification	A	A	A	A			A			A
Alternative crops	A									A
Planted area						A				A
Production costs (inputs)					A	A				A
Access to inputs	A							A		
Access and management of natural resources				A						
Land ownership				**S**			**A**			
Agricultural insurance	A		A		A					A
Affiliation to organizations		A		A			A	A		A
Access to credit		A	A	A			A			
Migration				S					S	
Water access				S					S	
Transportation				S						
Medical services				S						
Soil moisture deciles-based drought index					S					S
Whether or not the HH suffered climate events						S	S			S

Table S2 Summary characteristics of household heads in the surveyed sample of households

Municipality	**Barichara**		**Villanueva**		**Curiti**		**San Gil**		**Total**	
HHH gender	**Male**	**Female**	**Male**	**Female**	**Male**	**Female**	**Male**	**Female**	**Male**	**Female**
% of sample	78.9%	21.1%	85.5%	14.5%	83.9%	16.1%	71.6%	28.4%	80.8%	19.2%
	Perc.	**Perc.**	**Perc.**	**Perc.**	**Perc.**	**Perc.**	**Perc.**	**Perc.**	**Perc.**	**Perc.**
HHH occupation										
Farmer	98.9%	58.3%	95.2%	57.1%	98.8%	71.0%	98.8%	75.8%	97.8%	67.0%
Housewife	1.1%	41.7%	0.8%	38.1%	0.0%	25.8%	0.0%	21.2%	0.4%	30.3%
Other	0.0%	0.0%	4.0%	4.8%	1.2%	3.2%	1.2%	3.0%	1.7%	2.8%

Table S3 Weights of factor in multivariate analysis on adaptive capacity

Adaptive Capacity	Sign in index	Weight in index
Number of assets owned	-	0.196
Agricultural Assets	-	0.167
Household size	-	0.140
Members in age to work	-	0.135
Transportation assets	-	0.120
Information Assets	-	0.103
Number of crops	-	0.101
Number of household members with off farm occupation	-	0.100
Agricultural inputs expenditure (per ha)	-	0.033
Average household education (years)	-	0.017
Bush bean income (per ha)	-	0.012
Household head age	+	0.002
Household head education (years)	-	-0.048
Planted area (% of total)	+	-0.078

Table S4 Weights of factor in multivariate analysis on sensitivity

Sensitivity	Sign in index	Category	Weight in index
Think climate change will high impact HH economy*	+	No	-0.216
		Yes	0.140
House have piped aqueduct*	-	No	0.011
		Yes	-0.006
Think precipitation is enough for crop*	-	No	0.130
		Yes	-0.201
Has suffered drought*	+	No	-0.594
		Yes	0.057
Think drought affects more than other events*	+	No	-0.404
		Yes	0.082

Table S5 Weights of factor in multivariate analysis on exposure

Exposure	Sign in index	Weight in index
Consecutive dry days (std. dev.), P1	+	0.256
Consecutive dry days (std. dev.), P2	+	0.246
Consecutive dry days (max), P1	+	0.265
Consecutive dry days (max), P2	+	0.233

Table S6 Weights of factor in multivariate analysis on vulnerability

Vulnerability	Sign in index	Weight in index
Exposure index	+	0.582
Sensitivity index	+	0.540
Adaptive capacity index	-	-0.122

Table S7 Summary statistics of vulnerability index components by tercile

Vulnerability level	Tercile 1 Low vulnerability			Tercile 2 Medium vulnerability			Tercile 3 High vulnerability			K-Wallis Test[1]
	Mean	Std. Dev.	Median	Mean	Std. Dev.	Median	Mean	Std. Dev.	Median	
Exposure										
Consecutive dry days (median), P1	10.77	0.61	11	10.88	1.02	11	11.97	1.53	13	75.18***
Consecutive dry days (median), P2	6.11	0.36	6	6.34	0.6	6	6.38	0.94	6	23.25***
Consecutive dry days (std. dev.), P1	3.78	0.4	3.63	4.26	0.71	3.95	5.1	0.41	5.25	264.54***
Consecutive dry days (std. dev.), P2	2.28	0.18	2.18	2.45	0.26	2.42	2.83	0.25	0.94	268.89***
Consecutive dry days (max), P1	17.33	1.74	17	19.6	2.7	19	22.61	1.47	23	294.23***
Consecutive dry days (max), P2	10.12	0.48	10	10.61	0.56	11	11.08	0.39	11	251.84***
Adaptive Capacity										
HH size	4.39	1.33	4	3.58	1.43	4	3.12	1.38	3	74.88***
Members in age to work	3.3	1.28	3	2.63	1.24	2	2.24	1.23	2	61.06***
Average HH education (years)	6.61	2.26	6.5	5.4	2.82	5	4.05	1.99	3.57	109.24***
HHH education (years)	5.05	3.21	5	4.66	3.22	4	3.39	2.58	3	43.98***
HHH age	46.15	12.87	45	48.24	13.14	48	52.85	13.93	54	27.13***
Planted area (% of total)	0.63	0.28	0.52	0.8	0.27	1	0.96	0.17	1	133.45***
Number of assets in HH	8.04	1.76	8	6.99	1.22	7	6.46	1.04	7	98.99***
Transportation assets	0.58	0.66	0	0.36	0.52	0	0.1269	0.35	0	62.7***
Agricultural Assets	1.43	0.92	1	0.86	0.53	1	0.89	0.33	1	70.2***
HH members with 2nd non-agricultural occupation	0.35	0.6	0	0.053	0.22	0	0.02	0.14	0	77.87***
Number of different occupations in HH	1.47	0.66	1	1.11	0.34	1	1.05	0.22	1	86.47***
Inputs expenditure ($USD)	197.41	78.59	190.16	189.45	78.33	183.6	142.51	86.96	118.0	65.23***
Bean derived income (total) ($USD)	2095.9	1881.9	1573.8	1340.8	1346.5	944.3	1242.8	1404.9	872.1	45.17***
Bean derived income (per hectare) ($USD)	1184.3	415.6	1178.1	1112.5	423.1	1082.0	1036.1	365.3	997.4	12.27***
Sensitivity (qualitative variables)	**Freq.**			**Freq.**			**Freq.**			**Chi2[2]**
Have Suffered Drought. Yes==1	81.5%			94.2%			97.9%			34.78***
Think drought affect more than other events. Yes==1	68.3%			85.7%			95.2%			50.33***

[1] A Kruskal-Wallis (Chi-squared) test is used for continuous (discrete) variables to test for differences between vulnerability classes. *** indicates statistically significant differences at 1 %, ** indicates significant at 5 %, and * at 10 %.

Supplementary Text S4 – Description of Table S7: Vulnerable households are characterized by being exposed to a higher number of consecutive dry days especially during the first growth period analysed (P1, from sowing to third tri-foliate leaf). Notably, vulnerable households also experience greater interannual variations in the number of consecutive dry days in P1, but considerably less variation than other households in P2 (from pre-flowering to end of pod-filling). This would be expected since it is during sowing and crop establishment (i.e. throughout P1) that drought can cause crop failure and lead to vulnerability. Consistent with the biophysical exposure to drought, some 95 % households in the high vulnerability class perceive drought as the most important factor affecting their production (vs. 81 % in the low vulnerability class), and almost all of them reported having experienced drought in the two seasons before the survey.

Households in the high vulnerability class also appear to have lower family labour availability, they are less educated, and the household head is older compared to the other two classes. Importantly, they tend to practice monoculture, have greater proportions of farm area under crops, and do not belong to agricultural organizations. The latter is especially important as it likely means they have less access to improved seed and technical assistance. Conversely, the least vulnerable households appear to be wealthier in terms of household and productive assets and more educated. These households are also characterized by having more members with an off-farm occupation. Therefore they are slightly more diversified in their income sources. This diversification is paralleled regarding crops, as the majority of households in the low vulnerability class grow more than one crop. They also more often belong to a farmer organization, and invest more in their crops, both of which may contribute to higher yields, yield stability, and therefore lower vulnerability.

Bean-derived total income is lowest for the households in the high vulnerability class, which is likely a result of lower overall income. Bean income per hectare is also the lowest for this group of farmers, likely due to lower yield as a result of less use of inputs, less access to technology and technical assistance, and less favourable climatic conditions.

Table S8 Descriptive statistics of vulnerability determinants

Municipality	Barichara		Villanueva		Curití		San Gil		Total	
N	(n=114)		(n=145)		(n=192)		(n=116)		(n=567)	
Continuous variables	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Geographic factors										
Distance to closest populated centre	5.11	1.51	4.75	1.01	5.13	1.33	5.63	0.86	5.13	1.25
HH factors										
Highest education level of any member (years)	8.11	3.6	6.79	3.2	7.67	4.13	8.56	3.07	7.72	3.64
HH dependency rate	0.39	0.48	0.34	0.46	0.39	0.56	0.5	0.51	0.4	0.51
Farm factors										
Total area (ha)	1.06	0.9	1.39	1.27	2.22	1.51	3.41	2.8	2.02	1.9
Hired labour day (per hectare)	23.79	9.8	21.29	14.77	16.66	15.32	20.36	13.6	20.03	14.09
Gender Factors										
Ratio of women to men family workers (over 14)	0.73	0.47	0.64	0.69	0.6	0.54	0.6	0.6	0.64	0.58
Percentage of HH female members making productive decisions	0.46	0.4	0.51	0.43	0.6	0.36	0.41	0.39	0.51	0.4
Percentage of HH male members making productive decisions	0.69	0.3	0.73	0.3	0.73	0.31	0.55	0.34	0.68	0.32

Categorical variables	Percentage				
	Barichara	**Villanueva**	**Curití**	**San Gil**	**Total**
HHH factors					
HHH gender (Male=1)	78.95%	85.52%	83.85%	71.55%	80.78%
HHH is married/ consensual union. Yes=1	78.95%	88.28%	86.98%	85.34%	85.36%
HH factors					
Anyone in HH received agroclimatic information in last 12 months. Yes=1	71.05%	56.55%	36.98%	43.97%	50.26%
Anyone in HH received agronomic training in last 12 months. Yes=1	7.02%	3.45%	4.69%	18.10%	7.58%
Asked for loan in last 12 months. Yes=1	91.23%	62.76%	63.02%	59.48%	67.90%
Need to collect water at least once a week. Yes=1	78.95%	1.38%	5.73%	29.31%	24.16%
Farm management factors					
HH have another main crop (coffee, corn or tobacco). Yes==1	6.14%	4.83%	61.46%	64.66%	36.51%
Hired at least one female worker. Yes=1	27.19%	20.69%	13.54%	52.59%	26.10%

Table S9 Check of robustness for the probit model by using alternative classification methods for the *VI*

Variables / Vulnerability Level	Quintiles Quintile 1 Low	 Quintile 2 Medium low	 Quintile 3 Medium	 Quintile 4 Medium high	 Quintile 5 High	Ranges around the mean[1] Class 1 Low	 Class 2 Medium	 Class 3 High
Geographic factors								
Municipality. Villanueva=1	0.061	-0.214***	-0.039	0.146***	0.046**	-0.106***	0.057***	0.049*
Municipality. Curiti=1	0.117**	-0.106*	-0.061	0.057	-0.007	-0.122**	0.158***	-0.036**
Municipality. San Gil=1	0.501***	0.066***	-0.267***	-0.262***	-0.039***	0.314***	-0.208***	-0.105***
Distance to closest populated centre	0.009	-0.119***	0.057***	0.045***	0.009***	-0.022*	0.001	0.021***
HHH factors								
HHH gender (Male=1)	-0.027	0.073*	0.010	-0.027	-0.028**	-0.052	0.104***	-0.052***
HHH is married/ consensual union. Yes=1	0.095***	0.088***	-0.055***	-0.108***	-0.019**	0.116***	-0.054***	-0.063***
HH factors								
Highest education level of any member (years)	0.023***	0.026***	-0.011**	-0.032***	-0.006***	0.037***	-0.025***	-0.012***
HH dependency rate	-0.017	-0.010	0.011	0.014	0.002	0.010	-0.007	-0.003
Anyone in HH received agroclimatic information in last 12 months. Yes=1	0.086***	-0.100**	-0.118***	0.115***	0.017***	0.085***	-0.140***	0.056***
Anyone in HH received agronomic training in last 12 months. Yes=1	0.303***	0.021	-0.181***	-0.130***	-0.012***	0.376***	-0.352***	-0.024*
Asked for loan in last 12 months. Yes=1	-0.029	-0.017*	0.019	0.024*	0.003	-0.048**	0.033**	0.014**
Need to collect water at least once at week. Yes=1	-0.059**	0.045	0.003	0.022	-0.010**	-0.129***	0.177***	-0.048***
Farm management factors								
Total Area (Ha)	0.020***	0.044***	-0.049***	-0.009	-0.006***	0.033***	-0.022***	-0.011***
HH have another main crop (coffee, corn or tobacco). Yes==1	0.164***	0.179***	-0.085**	-0.240***	-0.018***	0.244***	-0.166***	-0.079***
Hired labour day (per hectare)	0.001	0.000	0.001	-0.003***	0.000	0.002**	-0.001**	-0.001**
Gender factors								
Hired at least one female worker. Yes=1	-0.021	0.069	-0.109**	0.059*	0.001	0.021	-0.014	-0.006
Ratio of women to men family workers (over 14)	-0.041*	-0.016	0.048	0.000	0.008**	-0.039**	0.026**	0.012*
Percentage of HH female members making productive decisions	-0.157***	-0.098***	0.104***	0.133***	0.018***	-0.167***	0.113***	0.054***

Variables / Vulnerability Level	Quintiles: Quintile 1 Low	Quintile 2 Medium low	Quintile 3 Medium	Quintile 4 Medium high	Quintile 5 High	Ranges around the mean[1]: Class 1 Low	Class 2 Medium	Class 3 High
Percentage of HH male members making productive decisions	-0.258***	-0.161***	0.170***	0.219***	0.030***	-0.248***	0.169***	0.080***
Number	567					567		
Chi Squared	1145.896					727.113		
Log-Likelihood	-1409.75					-807.283		
LRI	0.385					0.459		
AIC	2937.509							

* p<0.10, ** p<0.05, *** p<0.01; [1] Classes are defined as follows: class 1 contains all households with *VI* less than the mean *VI* minus one standard deviation of the entire sample; class 2 contains all households with *VI* between one standard deviation below and one standard deviation above the mean *VI* of the entire sample; and class 3 contains all households with *VI* greater than the mean *VI* plus one standard deviation of the entire sample.

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