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Defining interpretative communities towards climate change: Examining growers of common bean in Latin America

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Abstract
The common bean (*Phaseolus vulgaris L.*) provides numerous ecological, social and nutritional benefits for the rural poor. Varietal uptake, in particular of those which are more heat tolerant, requires rapid adoption of new seeds to replace traditional varieties. However, a number of institutional and household factors, predominantly lack of extension and information, has led to low uptake despite decades of interventions. We focus on growers in Colombia and apply a bespoke questionnaire to 566 households to understand their awareness, experiences and concern towards climatic change. We classify these into four interpretive communities using Latent Class Analysis. Whilst there is a small portion of the sample who claim to be unaffected and unconcerned towards climate change, the remainder identify varying degrees of experience with climatic events. However, this does not directly translate into similar levels of concern towards the future impact of climate change. A multinomial logistic regression finds that concern is driven by a number of factors, but is highest in those farmers who specialise their production. Altitude and distance to markets also appear to have some effect in shaping perceptions of our classes. We conclude that consideration of these interpretative communities offers more information to frame messages and focus effort on those cohorts more likely to change.

Keywords: Latent Class Analysis, Colombia, Climate Change, Farming Communities

1. Introduction

The common bean (Phaseolus vulgaris L.) is an important source of protein for low income households (CIAT, 2008, Gomez *et al*., 2010), provides substantial environmental benefits due to its ability to fix nitrogen in the soil (Giller and Cadisch, 1995, Graham, 2003, Troyo-Diéguez, 2010), and is a major source of income for poor farmers across rural areas in Latin America and Sub-Saharan Africa (Duncan *et al*., 2016, Perez *et al*., 2018, Muoni et al., 2019). In these tropical regions, there are growing threats from weather variability in the form of increasing numbers of dry days or extreme rainfall. More specifically a predicted rise of 2.5°C in the annual mean temperature by 2050 is expected to reduce common bean productivity due to heat stress and an increased prevalence of pests and diseases (Ramirez-Villegas *et al*., 2012, Hershey *et al*., 2013, Eitzinger *et al*., 2014, Eitzinger *et al*., 2018).

Bean growers in developing regions mainly employ labour-intensive and traditional methods. The utilization of technology is less prevalent, which reduces farmers' capacity to adapt to climate change (Ramirez-Villegas *et al*., 2012, Feola *et al*., 2014, Acevedo *et al*., 2016). Accordingly, a major intervention for these growers is the development of bean germplasm and distribution of bean seeds that are both heat and drought resistant but still provide nutritional benefits (Blair, 2003, Muñoz *et al*., 2008, Hershey *et al*., 2013, Atlin *et al*., 2017). However, farmers' voluntary uptake of sustainable technologies, such as these new bean genotypes, depends on a number of socio-economic constraints, such as income and farm size, and institutional barriers such as lack of access to advisory services (Baudoin *et al.*, 2014; Ramborun *et al*., 2020). In addition more internal factors such as attitudes and perceptions of how this technology will support yield growth, resilience to common pests, as well as ease of management are critically important to decision making for these farmers (Mouni et al., 2019; Barnes et al., 2021). In line with this, the farmer's interpretation and experience of climatic changes at the local level has been found to be critical towards this decision making (Islam *et a*l., 2013, Eitzinger *et al*., 2018). The level of concern towards turbulences in weather and how they will effect the farming enterprise are important aspects of how an individual intends to adapt (Niles *et al*., 2015). Capitalising on these perceptions allows information agents to design their communication and engagement strategies to maximize the uptake of technologies, or assess their suitability for specific climatic conditions (Barnes *et al*., 2011, Daxini *et al*., 2019). This is especially important in a developing country context as the public capacity for development support and infrastructure is usually low. This creates a need to support cost-effective interventions for the Government but also for adoption within low income farming households.

Some studies have tended to examine general responses of farmers to climatic change applying both quantitative and qualitative approaches (Gwimbi, 2009, Holloway & Ilbery, 1996, Maddison, 2006, Roncoli, 2006, Ulloa *et al*., 2008, Altschuler *et al*., 2015). Another branch of this work has discovered heterogeneities within farming populations and attempted to classify these in terms of categories or 'types'. Leiserowitz (2005) uses the term 'interpretative communities' to capture these groups of individuals who would share similar beliefs or experiences. These studies have applied a range of methods to identify and understand discrete groups of farmer perceptions towards particular environmental phenomena (Fairweather & Keating, 1990, Davies & Hodge, 2007, Sutherland *et al*., 2011, Barnes and Toma, 2012, Daxini *et al*., 2019). When deriving these farmer typologies most studies have found a sceptical view of climate change, with small pockets of acceptance (Barnes and Toma, 2012, Islam *et al*., 2013). Classifying farmers into types or groups to identify the factors that determine membership to subsequent classifications allows interventions to be more targeted.

Most of the empirical work carried out on farmers' perception of climatic variability in developing countries has been conducted on Asian and African countries (e.g. Maddison, 2007, Gwimbi, 2009, Gbetibouo, 2009), with a paucity of studies focused on Latin America (Roco *et al.*, 2015, Barrucand *et al.*, 2017, Eitzinger *et al.*, 2018). To the best of our knowledge no such exercise of formal classification has been conducted in a Latin American context. Accordingly, the purpose of this paper is to add to the literature on climate perceptions within a low-income farming community in Latin America. We do this by application of a bespoke survey of bean growers in Colombia to establish their perceptions and the motivational characteristics driving these perceptions.

The paper is structured as follows. The next section outlines the data collection instrument and analysis method. Then results are presented both in terms of the classification of perceptions, but also the drivers of these perceptions. Finally, we discuss implications for local policy and engagement strategies, as well as wider implications for those agencies currently employed in promotion of similar interventions.

2. Data and Statistical Methods

Description of Site

The Santander Department sits within the Andean natural region, located in central Colombia. Figure 1 shows the region chosen for analysis and the location of the farms included in the sample.

Figure 1. Location of study site

Santander's farmers are particularly prone to the weather variations that occur in the Caribbean Sea (Gutierrez, 2015), which affects crops' yields (Ray *et al.*, 2015). Farmers of four municipalities were selected for this study: Barichara, Curití, San Gil and Villanueva. These municipalities represent the largest bush-bean producers in Santander according to the 2014 Colombian Agricultural National Census. This ensured farmers with knowledge on the climatic changes that have occurred to the region were in the sample. These municipalities also have different levels of rainfall according to the IDEAM. Villanueva and Barichara tend to have a water deficit, whereas Curití and San Gil have higher levels of annual rainfall compared to the other two municipalities. Finally, these four municipalities are on the same climatic system and are equally subject to the same regional climatic variations.

Table 1 shows the division of temperature and rainfall within this region using the closest possible weather station data[6]. Splitting these into two sub-samples, covering 2000-2010 and 2011-2017, gives an indication of how the climate may have changed. We choose the recent past to be the decade in which the survey takes place since Colombian weather started to have notorious climatic changes in 2010 (CEPAL, 2012, Corrales *et al.,* 2013) and farmers' climate change perceptions tend to be more influenced by what has occurred in recent production cycles (Pidgeon, 2010, Capstick *et al.*, 2015, Howe, 2018).

Table 1: Maximum and minimum temperatures and rainfall on the study site, 2000-2017

The average maximum temperature and the difference between the daily maximum and minimum temperatures are larger in the period 2011-2017 than in the period 2000-2010. Moreover, there is less average rainfall in the period 2011-2017 than in the period 2000-2010. The standard deviation of the maximum temperature is larger in the period 2011-2017 than in the period 2000-2010. This implies that the period 2000-2010 exhibits a more stable temperature during daytime. This seems to indicate that the largest temperatures and the wettest days took place in the period 2011-2017.

Questionnaire development

[6] See Eitzinger *et al.* (2014) for sources of information about temperature and precipitation levels for the Colombian weather stations.

Capstick *et al.* (2015) outline three dimensions around climate change, namely, i) awareness of climate change, ii) experience with climatic changes, and iii) concern about the negative consequences of future climate change. Accordingly, within our behavioural model acceptance that climate is changing is one of the major steps towards adapting to the phenomena *(*Pinilla *et al*., 2012, Barrucand *et al*., 2017). This defines the interpretive community in which an individual farmer would be identified with and, ultimately, dictates whether they would adopt or not adopt heat tolerant bean varieties. Table 2 shows the specific questions asked around weather perceptions. The aim was to identify, firstly, past experience of hot and cold spells, along with any perturbations around climate phenomena. This is augmented with questions on awareness of climate change, with questions focused on concern, namely towards the climate changing in the future and the economic consequences that may occur for the farmer.

Table 2. Weather perceptions, questions, and responses across the sample

Explaining classifications

Farm size seems to be a common driver of climate perception (Arbuckle *et al.,* 2015, Houser *et al*., 2019), as well as related indicators towards commercial orientation (such as specialisation) (Eitzinger *et al.*, 2018; Barnes et al., 2021) and higher input use (Dresser *et al*., 2011, Niles *et al*., 2016). Ultimately, those with larger farms and larger yields tend to be wealthier, which makes them less sensitive to the marginal effects of climate change. Smaller farm households are more fragile with variances from climate which are more acutely felt within this cohort (Maddison, 2007).

Years of farming experience, educational levels, and age have been found to have varying levels of influence on the perception towards climatic events, with the former being mostly positive and the latter, age, being negatively related (Rao *et al*., 2011, Roco *et al*., 2015, Garcıa de Jalon *et al*, 2013). Gender, whilst an important factor in promoting economic development has not been found significant

Other conditioning factors include altitude of the farm, as higher farms will experience different weather patterns. Within Latin American itself, altitude has been explored as a driver of perception. Farms located at altitudes below 1600 msl[7] are expected to be mostly affected by droughts and lack of rainfall, whereas farms above 1600 msl are expected to receive more torrential rainfall and have more unpredictable seasons and extreme temperature variations (Ramirez-Villegas *et al.*, 2012, Eitzinger *et al.*, 2014).

Distance to urban centres, which offers a route to market are common indicators in development studies (Ndambiri *et al*., 2013, Tesfaye and Seifu, 2016). Farms located further away from their main urban centres are, again, more economically fragile and would therefore be susceptible to climate variances.

Mitigating some of these influences is access to a water source as a means to minimise impacts from extensive droughts (Niles *et al*., 2016, Ramirez-Villegas *et al*., 2012, Eitzinger *et al*., 2014). Other approaches which will condition some of these effects will be institutional structures, such as access to information services. Institutional structures have also been explored in depth, more in terms of how they can engineer more innovative application towards farming, but access to advisors (Hansen *et al*., 2004, Debela *et al.,* 2015), the supply chains and markets which these farmers operate (Atlin *et al.,* 2017), the social influences of fellow farmers through informal and formal co-operatives have all been found to have an influence on environmental perceptions (Lasco *et al.,* 2016). One of these is access to climatic information and the frequency by which farmers access these (Roco *et al*., 2015).

[7] Meters above sea level (msl).

Table 3: Description of the explanatory variables of climate change perception used

The sample consisted of 566 farmers, who were interviewed during August/September in 2017. Information was collected through face-to-face interviews by the International Center for Tropical Agriculture (CIAT) native speaking researchers, as a means of maximizing response from the selected farmers. The questionnaire and associated consent declarations were approved through CIATs ethical approval process. Farms were selected based on their altitude. Hence, 50% of the sample was below 1600 msl and the other 50% is above 1600 msl. All bean producers around the urban centres of each selected municipality were 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 the town's centre and the most distant one is located at 8.16 km. In addition, transportation costs become a constraining factor for bean production in locations too far away from a 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 were 2 ha or less and only 2% were more than 10 ha. Consequently, this farming community is mainly composed of small landowners with limited land area to diversify production. In turn, bean production is more normally distributed, with the majority obtaining around 800 kg/ha of beans. Some of these farmers have a very productive bean production, obtaining 1600 kg/ha, whereas there are others that only obtain 100 kg/ha. This may occur because they intercrop beans with other crops, which reduce their bean production per ha. This may also occur due to climatic effects on bean production.

Estimation Approach

A latent class analysis (LCA) approach is employed in this study (Lazarsfeld and Henry 1968, Goodman 1974, Hagenaars and McCutcheon, 2002). LCA assumes that there is an underlying latent categorical variable that divides into discrete classes based on a series of measured items, in our case the responses to a set of statements. This classification is performed under the assumption that the number of classes is known *a priori*. In equation 1, let Y_j represent element j of a response Y. An indicator function I equals 1 when the response to variable $j = r_j$ and equals 0 otherwise. Then the probability of observing a particular vector of response is:

$$P(Y = y) = \sum_{c=1}^{C} \gamma_c \prod_{j=1}^{J} \prod_{r_j=1}^{R_j} \rho_{j,r_j|c}^{I(y_j=r_j)}$$

where γ_c is the probability of membership in latent class c and $\rho_{j,r_j|c}^{I(y_j=r_j)}$ is the probability of response r_j to item j, conditional on membership in latent class c. Thus γ parameters represent a vector of latent class membership probabilities which sum up 1 (Lanzer and Rhoades, 2013).

To identify the optimal number of classes or groups in the sample, classes are iteratively added to the model and a typology is performed for each iteration. LCA is based on a maximum likelihood estimation approach, so the optimal number of groups in the sample is that one that minimizes the Bayesian Information Criterion (BIC) (Forster, 2000). We perform LCA for the questions associated to awareness of, experience and concern towards climatic changes. Table 3 shows the resultant identification statistics for the classes for each LCA run from 1 class to 6 classes. The log-likelihood shows a more marginal decrease after four classes. The BIC and AIC is minimised at 4 classes. The BIC is recommended above the AIC as this tends to overestimate the number of classes (Nylund, 2007, Barnes *et al.,* 2013). Accordingly, this seems to point to 4 classes as the optimal solution.

Table 4. Number of classes and the resultant identification of optimal classes

We estimated these classes using the poLCA package (Linzer and Lewis, 2011) in R v.4.01 (R Core Team, 2020). In order to allow convergence, we set the maximum number of iterations to 10,000, we also set the value for starting estimates to run for 3,000 repetitions. This allows the starting values to reach global rather than local maximum of the log-likelihood function.

Once classified, these provide a nominal categorical dependant variable for further exploration for membership of these classes. For this, we use a multinomial logistic regression model to estimate the effect on probabilities which assumes that the dependant variable is discrete, but do not have ordered categories.

3. Results

Characterising Classes

Table 5 shows the percentage response probabilities of the statements around experience, awareness, and concern as a means to profile these classes further. These show the distribution of response across each statement and by class.

Class 1: Marginally affected but unconcerned (n=103, 18%)

This class have experienced drought but is also the most affected by other extreme events, e.g. hailstorms, temperature change and heat waves. This experience has led to the belief that the weather has changed. However, they seem less concerned that in the future the weather will change. They see it as less likely and, if it were to happen, they seem to believe it will have only a low to medium impact.

Class 2: Unaffected and unconcerned (n= 29, 5%)

This is only a small but quite distinct group that have had, relative to other classes, the least levels of experience with most extreme weather events. Only higher temperature changes have a more even distribution within the response probabilities, indicating they have experienced changes in temperature as their main experience of weather change. This class has emerged as having observed fewer changes, thus affecting their awareness. This is also evidenced in terms of concern, where there is a scepticism that changing climate is less likely and that, even if it were to change, that the economic impact would not affect them.

Class 3: Highly affected and concerned (n= 219, 39%)

Class 3 seems to have experienced the most level of droughts compared to other classes, but not experience of wet or other heat related phenomena. Nevertheless, they strongly agree that the weather has changed a lot, perhaps mitigated by the drought experience. These negative experiences show their concern for the future, where they strongly believe weather will change in the future but also that this will have a significant economic impact.

Class 4: Affected but less concerned (n=215, 38%)

This class seems to have had a range of experience around weather changes, in terms of both droughts, but also the unpredictability of the seasons. Moreover, they have experienced a spread of experiences, of both heat and cold, and wet related effects. This perhaps explains why they felt the seasons have become more unpredictable. These are also aware that the weather has changed and, like the highly affect class (Class 3), strongly agree with the likelihood that the weather will change. However, they show less concern for the economic impact, feeling that some of the economic effect will be mitigated.

Table 5a: Percentage response probabilities by class, experience of climate events (row percents)

Table 5b. Percentage response probabilities by class, awareness of climate events (row percent)

Table 5c. Percentage response probabilities by class, concern towards of climate events (row percent)

Table 6 shows the defining characteristics in terms of farming household factors, farm biophysical as well as climatic differences across the four classes. Chi-squares are shown for categorical data, and Bartlett's test of Homogeneity of Variances for continuous data (Snedecor and Cochran, 1989) to indicate where there are significant differences.

Class 4 *(Affected but less concerned)* have higher years of education, and, along with Class 2 (*Unaffected and unconcerned)*, are generally younger. Household size for these farmers is fairly constant across the classes, and the head of the household is mostly male, although members of Class 2 have a higher proportion of females as head of households. Significant differences emerge in terms of management techniques, for instance Class 3 (*Highly affected and concerned)* have a significantly high number of users of climatic information compared to the other classes and also the lowest number of members with a water pipe. Class 4 has more members of a local farmer association. Although the level of membership is generally low as a proportion of class membership.

Class 3 are generally smaller farms but reside at a lower altitude to the other classes and, along with Class 4, tend to be further from the market than other classes of farmers. Moreover, Class 3 has a higher percentage of specialisation, that is 95% of this group are growing one crop. The most diverse cropping management emerges from Class 1 (*Marginally affected but unconcerned)* and Class 4, which has the lowest number who monocrop (22%). Class 4 also experiences the most rainfall, compared to other groups, and higher levels of dry days, indicating they are more susceptible to variability within the weather.

Table 6. Characteristics by class, means and standard deviations or percentage of class population

Latent Class Multinomial Logistic Regression

The relationship between characteristics of the system and these perceptual classes are shown in the multinomial logistic regression in Table 7. These were first estimated relative to Class 2, the unaffected and unconcerned class. These are presented as marginal effects to demonstrate both the sign and magnitude of each explanatory variable on the memberships of each class. These show the effect of a 1% increase in each variable, all others being equal, for continuous variables or a discrete change from 0 to 1 for those categorical variables on membership of a particular class. The model fits well, with a significant Wald coefficient, indicating that the model parameters excel the null model, with a reasonable McFadden R^2 of 0.45.

Class 1: Marginally affected but unconcerned

The main positive predictors of membership are altitude, access to a water pipe and less specialisation. This may explain that whilst this class experienced drought and heat spells they were less concerned around the future, as securing irrigation and a diverse cropping portfolio can mitigate some of these effects. For this class there is a negative relationship towards use of climate information. This suggests that they will only be marginally affected by climate change and therefore this limits any information seeking around climate. Moreover, there is a negative relationship with distance. This could indicate that their perceptions are codified by being closer to urban centres, and therefore closer to the markets, than other classes. Farm area has a negative effect, indicating smaller farms are more likely to adopt this interpretation. Hence, whilst they are marginally affected, through a limited palate of weather experiences, this may not be harming them economically more than other classes who are more concerned of the damages from climatic effects.

Class 2: *Unaffected and unconcerned*

Few characteristics influence membership of this class. Nevertheless, the relationship with education is negative. This means less educated farmers will tend to be more unconcerned about climate change, This does seem to support previous work finding a relationship between higher levels of education and concern for climate within farmers(Barnes and Toma, 2012; Muhamad *et al*., 2014). The only other significant indicator is farm size, which is positive. Hence the larger farms tend to have high margins and are less affected by climate turbulence and unpredictability. This would support the contention that this class are the most unconcerned towards climate.

Class 3: Highly affected and concerned

This class is the most concerned around the economic consequences of future climate change. Their apprehension around future weather effects may be driven by experiencing drought and their lack of an accessible water supply, as the water pump variable is negatively related. These farmers are more specialised, focusing mostly on one crop. Accordingly, it demonstrates lack of spreading risk within their cropping portfolio, maybe due to internal biophysical constraints, and hence making them more susceptibility to weather patterns. This class have a positive relationship with accessing climate information which conditions their concerns towards climate. Altitude has a slight but negative effect, which infers that most of these farms are at a lower altitude.

Class 4: Affected but less concerned

This group accepts that climate will change in the future and reiterate previous findings that years of education are positively related to climate concern. However, the lack of concern on the economic effects of climate may be partly explained by the positive effect of farm size, namely these are larger, but more diversified farms. The high level of crop diversity, augmented with a high proportion of farms who have access to a water pipe are able to spread financial risk with a wider cropping portfolio. This perhaps indicates the awareness of farm management strategies to manage at a farm level some of these climatic deviations. In addition, this group has the strongest positive relationship around agrochemical use. This infers a more commercialised farming enterprise, which again may be a way to buffer the economic consequences of climatic change.

Table 7. Multinomial logistic model, predictive margins of class membership

4.0 Discussion

Colombia is a particularly prescient example of a tropical country on the edge of climatic changes, but which is also undergoing institutional change. The recent adoption of a green growth strategy, along with mechanisms to support post-agreement transition, showed an ambitious agenda for reform (Villaveces-Izquierdo *et al*., 2016). Whilst the original optimism has eroded (Clerici *et al*., 2020), the rural sector, much like other countries undergoing rapid development, are still an intractable part of the economy, with significant numbers of low income households managing the bulk of the country's natural capital. Legumes have been a consistent focus of aid agencies, given the multiple environmental, nutritional and social goals they address for developing countries (Duncan *et al*., 2016, Perez *et al*., 2018, Muoni et al., 2019). However, uptake has been limited within poor communities due to, for instance the availability of cheap fertiliser (Foyer *et al.,* 2016), extension contacts (Emeana *et al*., 2018; Mulder, 2018), distance to market (Barnes *et al*., 2021) and farm size (Mouni et al., 2019), which means that heat tolerant varieties will be adopted differently and, in some cases, not at all.

An approach to segmenting perceptions is useful for understanding the different responses to how particular problems can be framed in order to maximise engagement with these technologies. This is important as aid budgets, and the underpinning research and advisory services, are under increasing pressures with high profile donor governments to reduce support for the global framework of agricultural research and development[8].

Regardless of the technique applied to identify categories of farmer perceptions the categories, or types, identified tend to range from highly sceptical to acceptance toward prescient environmental problems (Antilla, 2005, Barnes and Toma, 2012, Maibach *et al*., 2011, Daxini *et al*., 2019). We find more nuanced groups, with a small portion of the sample which could be classified as having the classic 'sceptical' perspective. The bulk of the farmers surveyed show varying levels of acceptance driven by their experience and beliefs towards the effects of climate change.

Within Latin America, most studies do find a high level of agreement that the weather is changing (Ulloa *et al.*, 2008, Altschuler *et al.*, 2015, Roco *et al*., 2015), the key issue is agreement towards the driver of these changes and, thus, the level of agency required. Within models of behavioural change, acceptance of the effects of extreme phenomena leads to uptake of management techniques and technologies to adapt to these changes. Against the paucity of work within Colombia itself the general theme is one of acceptance of a changing climate. Pinilla *et al.* (2012) surveyed cocoa and coffee farmers and found that 76% considered that the climate has been changing, and that the clearest evidence is found in the increased levels of precipitation, temperature, and humidity. However, a diversity of responses emerged when farmers were queried on the causes of these perceived changes. Selecting farmers by intervals of elevation, Barrucand *et al.* (2017) found almost unanimous experience of a change in the climate due to more observed precipitation, more heat, and less wind across the different altitudes considered. Altitude itself is a factor contributing to climatic experience (Feola *et al*., 2014, Ramirez-Villegas *et al.,* 2012). Across our classes this is experienced differently and tends to support the notion that if a farm is either above or below 1600 msl it would shape the reaction towards weather changes.

Eitzinger *et al.* (2018) went further by examining weather threats on agricultural livelihood risks in Colombia. They found farmers indicated that failure in crop production and lack of market access as the most significant risks imposed by climate change on their livelihoods. Class 3 (*highly affected and concerned)* seem to be the closest to this, finding they can seek climatic information and adopt more commercial methods of production to mitigate concern towards future climatic changes. For other classes this is less prevalent, driven by less concern. However, what is potentially masked is the agency of the farmers towards climate change. The inference should therefore not be that other farmers in other classes could simply adopt similar approaches but may be constrained by biophysical and spatial access issues to engage fully in these strategies. Nevertheless, a first step is acceptance of the

[8] see for example: https://foreignpolicy.com/2019/08/13/how-to-save-foreign-aid-in-the-age-of-populism-usaid-dfid/

consequences of climate change to enable a more proactive approach to managing the farm to mitigate the negative effects.

One of the factors commonly found in studies in developing countries is market access(Hellin *et al*., 2009, Shiferaw *et al*., 2011; Barnes et al., 2021). Accordingly, distance, is a spatial constraint to changing a system to adapt to climatic changes. Again, only 2 classes indicate this as a significant predictor of class membership. Thus proximity to urban centres, for some of these classes, infers more market access and a softening of perception towards climate change impacts, given the economic opportunities afforded by this access (Ramirez-Villegas *et al.*, 2013).

Seeking and utilising information is another key tranche for creating some agency around climate mitigation. Generally, farmers who are more informed about climatic variations in the short- and long-term and are convinced of the impacts on agricultural production are expected to be more aware of and concerned about climate change. We found access to climate information, including through farmer associations, as having a mixed effect, and therefore dependant on the receiver of the message. This infers that the current information around climate is homogenous and not tailored for the different types operating within this region and sector. Framing would be key, for instance those farms in Class 3 and Class 4 are both accepting of climate change, but only the former is concerned about the future economic effects. Adjusting information across these classes to focus on different effects or highlighting examples of the farm management consequences of weather variation may help to shift awareness further.

Varietal switching is slow in most developing countries due to lack of market access or a non-competitive private sector with no incentive to develop new varieties (Atlin et al., 2017). These authors recognise the need to change the institutional structures of plant breeding and delivery of new varieties to keep pace with the changing climate. They argue that this could be achieved by convincing farmers through endorsement and aggressive demonstrating and promoting these varieties by aid agencies. We would argue that a further constraint to adoption, where we operate in a voluntary system of market activity, would be understanding the behavioural differences within these farmers, which are formed through current biophysical and economic constraints but also experience of past varieties and their performance under variable climate conditions.

5. Conclusions

The promotion of heat tolerant varieties of common bean will be a significant pillar to sustaining agricultural production within tropical agricultural systems(Beebe et al., 2011), as these regions are predicted to be the most affected by climatic change in the coming decades (Ramirez-Villegas *et al*., 2012; Eitzinger *et al*., 2018). Colombia provides a pertinent example of a tropical farming system which has limited extension capacity and a high level of low income farming households. The socio-economic and biophysical constraints experienced by these households, such as limited market access and low levels of education, lead to limited capacity to adapt.

We find within a common producer group and within a single region a diversity of perceptions and a range of concerns towards climate change and its economic effects. These will effect the priority given within decision-making towards heat-tolerant varieties. Accordingly, to ensure a transition to more sustainable agriculture these concerns and perceptions provide a way to frame messages to engage varietal uptake.

Consideration of farmer perceptions offers more information to frame messages and direct resources effectively as aid agencies and Governments are under financial pressures. For our classes an overall engagement plan can be created to support adoption of heat tolerant beans but this would have differing frames to target support towards a particular segment's concern. Clearly, the way in which adoption of these varieties mitigates the impact of climate change will appeal to Class 3 (Highly affected and concerned), whereas this would not be

effective with Class 2 (Not affected and unconcerned). Indeed as this class only merits a small part of the population (around 5%) and, given the costs of trying to engage this cohort, there is an argument to ignore this group to focus effort on those groups more likely to shift practices. Resources saved would then focus on the more concerned groups to enable a more effective impact for uptake.
Moreover bundling information could offer benefits for engagement. For Class 4 *(Affected but less concerned) and Class 1 (Marginally affected but unconcerned)* packages which promote access to climate information could be supported alongside adoption of heat tolerant beans. Accordingly, focusing on recent experiences of climate change should provide a gateway to more engagement within some of these cohorts to enable a more rapid uptake of heat tolerant varieties.

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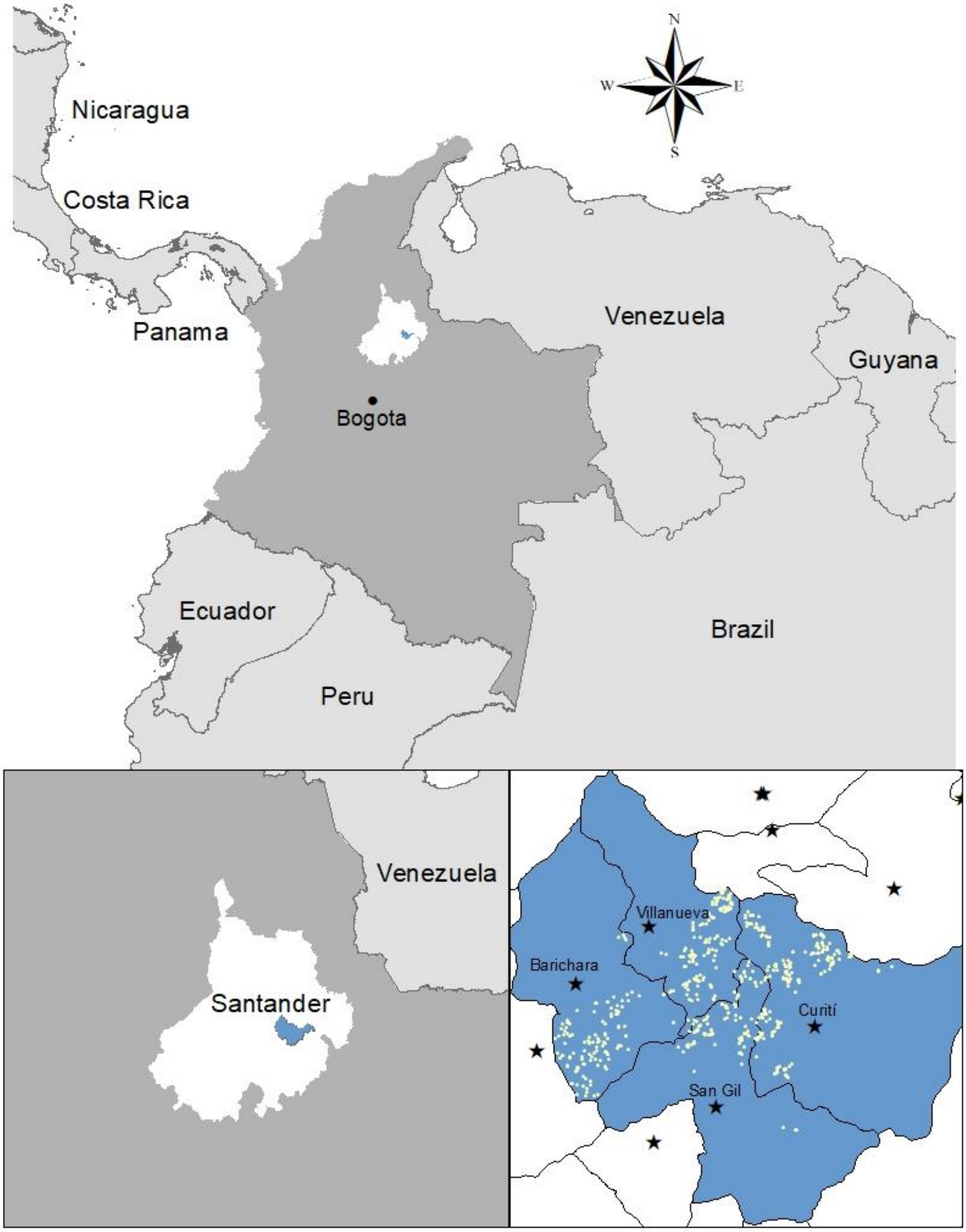

Fig 1: Geographical Distribution of Farms

Table 1: Maximum and minimum temperatures and rainfall on the study site, 2000-2017

Statistics		**Maximum Temperature (°C)**		**Minimum Temperature (°C)**		**Difference between Maximum and Minimum Temperatures (°C)**		**Rainfall (mm)**	
		2000-2010	**2010-2017**	**2000-2010**	**2010-2017**	**2000-2010**	**2010-2017**	**2000-2010**	**2010-2017**
Mean		25.62	26.39	18.62	18.67	7.00	7.72	3.52	3.06
Standard deviation		1.46	1.51	0.78	0.78	1.36	1.48	9.46	8.75
Maximum		30.60	31.80	21.30	21.60	12.60	13.20	117.20	147.60
Minimum		19.60	20.00	15.80	16.00	1.70	2.40	0.00	0.00
means	*t-test value*	-20.12		-2.29		-19.689		2.02	
	p-value	***		*		**		*	
standard deviations	*f-test value*	0.92		1.01		0.85		1.17	
	p-value	*		-		***		***	

*** p < 0.001, ** p < 0.05, * p < 0.01

Table 2. Weather perceptions, questions and responses across the sample^

Variable Name	Question	Answer Options
weather	*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).
droughts	*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	*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).
temperature	*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).
storms	*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	*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	*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).
cold waves	*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).
heat waves	*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	*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).
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	*Assume the weather actually changes in the future, how much economically impacted will you be?*	0 = s/he does not know (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).

^ distribution of answers is in parenthesis.

Table 3: Description of the explanatory variables of climate change perception used

Variable	Explanation	Mean	SD	Min.	Max.
distance	*Distance (in km) from the farm to municipality's capital*	5.13	1.25	2.03	8.16
farm area	*Area of the farm expressed in hectares*	2.02	1.91	0.15	21.00
bean yield	*Kilograms of beans per hectare produced*	877	306	100	1600
education	*Number of years studied by the individual who responded to the survey*	4.52	3.23	0	18
age	*Age of the individual who responds to the survey*	48.30	13.81	16	82
		0		**1**	
altitude	*Dummy variable indicating altitude of farm. 1= above 1600 msl, 0 = below 1600 msl*	343		223	
gender	*1 = if responder is a male; 0 = otherwise*	426		140	
wpipe	*1= if farmer has access to water from the municipal aqueduct; 0=Otherwise*	420		146	
climatic info	*1=if farmer received climate information from any source; 0 = otherwise*	284		282	
association	*1=if farmer belongs to a farmer's association; 0 = otherwise*	112		454	
		1	**2**	**>=3**	
number of crops	*Number of crops grown on the farm*	349	159	58	
		0	**1**	**>=2**	
agrochem	*Use of insecticides/fungicides*	153	137	276	

Table 4. Number of classes and the resultant identification of optimal classes

Classes	log-likelihood	BIC	AIC
1	-4038.5	8210.2	8231.2
2	-3407.3	7087.1	7130.1
3	-3190.1	6792.2	6857.2
4	**-3051.2**	**6653.8**	**6740.8**
5	-2986.7	6664.2	6773.2
6	-2937.6	6705.6	6836.6

BIC: Bayesian Information Criterion; AIC: Akaike Information Criterion

Table 5a: Percentage response probabilities by class, experience of climate events (row percents)

	Drought		*Rains*				*Storms*		*Hailstorms*	
	No	Yes	No	Yes			No	Yes	No	Yes
class 1:	10%	90%	98%	2%			83%	17%	70%	30%
class 2:	28%	72%	100%	0%			100%	0%	100%	0%
class 3:	0%	100%	100%	0%			100%	0%	100%	0%
class 4:	14%	86%	83%	17%			50%	50%	63%	37%
	Frosts		Cold waves		Heat waves		Unpredseasons		Temperatures	
	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
class 1:	68%	32%	97%	3%	11%	89%	4%	96%	28%	72%
class 2:	100%	0%	100%	0%	97%	3%	100%	0%	45%	55%
class 3:	100%	0%	100%	0%	97%	3%	99%	1%	99%	1%
class 4:	92%	8%	78%	22%	17%	83%	15%	85%	26%	74%

Table 5b. Percentage response probabilities by class, awareness of climate events (row percent)

	How much do you consider that the weather has changed in the last 7 years				*Do you believe today's weather has changed in comparison to how it was when you were a teenager?*	
	Not Changed	Changed a little	Changed somewhat	Changed a lot	No	Yes
Class 1:	0%	2%	17%	81%	0%	100%
Class 2:	14%	21%	7%	59%	97%	3%
Class 3:	0%	1%	2%	98%	0%	100%
Class 4:	2%	2%	12%	85%	0%	100%

Table 5c. Percentage response probabilities by class, concern towards of climate events (row percent)

	How likely is it to you that future weather changes?				*How much economically impacted will you be?*				
	Don't know	Not at all	Slightly likely	Very likely	Don't know	Not At All	Low impact	Medium impact	Large impact
class 1:	4%	11%	83%	3%	15%	3%	42%	36%	3%
class 2:	7%	31%	28%	35%	41%	10%	7%	14%	28%
class 3:	2%	2%	0%	96%	4%	0%	1%	9%	86%
class 4:	1%	0%	5%	95%	1%	6%	0%	26%	67%

Table 6. Characteristics by class, means and standard deviations or percentage of class population

Variable	*Class 1 : Marginally affected but unconcerned* (n=103)		*Class 2: Unaffected and unconcerned* (n=29)		*Class 3: Highly affected and concerned* (n=219)		*Class 4: Affected but less concerned* (n=215)		sig.
	mean	sd	mean	sd	mean	sd	mean	sd	
Education(years)	4.1	*3.1*	3.9	*2.3*	4.0	*2.7*	5.3	*3.7*	** (b)
Age (years)	51.1	*12.6*	45.9	*15.3*	49.3	*13.9*	46.3	*13.8*	* (b)
Household Size (n)	3.4	*1.5*	3.6	*1.4*	3.7	*1.5*	3.9	*1.5*	- (b)
Gender (%male)	86%		66%		73%		74%		* (a)
Use climate information (%)	18%		28%		82%		36%		*** (a)
Water pipe installed (%)	94%		90%		61%		76%		*** (a)
Member of a farmer association	14%		21%		6%		37%		*** (a)
Altitude (msl)	1,693	*103*	1,583	*120*	1,497	*76*	1,612	*102*	*** (b)
Distance (km)	4.7	*1.0*	4.7	*1.0*	5.4	*1.4*	5.1	*1.1*	*** (b)
Farm size (ha)	2.0	*1.2*	2.0	*1.2*	1.3	*1.4*	2.8	*2.3*	*** (b)
Number who monocrop (%)	36%		62%		95%		22%		*** (a)
Maximum amount of consecutive dry days in the phenological phase 1	30.7	*2.8*	27.6	*2.4*	27.2	*2.9*	28.2	*2.6*	- (b)
Maximum amount of consecutive dry days in the phenological phase 2	15.0	*0.3*	15.0	*0.4*	14.5	*0.4*	15.1	*0.7*	*** (b)
Total rainfall in the phenological phase 1 (mm)	6,629	*327*	6,885	*477*	6,899	*871*	7,067	*665*	*** (b)
Total rainfall in the phenological phase 2 (mm)	8,413	*272*	8,717	*375*	8,806	*632*	8,891	*601*	*** (b)

(a) *chi*^{2} , (b) Bartlett's test of Homogeneity of Variances

*** p < 0.001, ** p < 0.05, * p < 0.01.

Table 7. Results of the latent class logistic regression (marginal effects)

	Class 1 *Marginally affected but unconcerned*		Class 2 *Unaffected and unconcerned*		Class 3 *Highly affected and concerned*		Class 4 *Affected but less concerned*	
	Marginal effect	***s.e.***	***Marginal effect***	***s.e.***	***Marginal effect***	***s.e.***	***Marginal effect***	***s.e.***
education	-0.003	0.004	-0.008 *	0.004	-0.009 *	0.004	0.020 ***	0.005
gender	0.064	0.035	-0.027	0.019	0.009	0.027	-0.046	0.039
age	0.001	0.001	-0.001	0.001	0.001	0.001	0.000	0.001
altitude	0.240 ***	0.027	0.006	0.018	-0.231 ***	0.030	-0.015	0.036
distance	-0.056 ***	0.013	-0.012	0.007	0.050 ***	0.010	0.018	0.014
wpipe	0.150 ***	0.041	0.028	0.028	-0.099 ***	0.028	-0.080	0.042
climatic info	-0.051	0.029	-0.019	0.021	0.181 ***	0.019	-0.111 **	0.034
bean yield	-0.003	0.004	0.005	0.003	0.002	0.005	-0.005	0.006
farm area	-0.022 *	0.011	0.009 *	0.005	-0.018	0.010	0.030 **	0.011
number of crops *(reference category = 1)*								
2	0.114 **	0.040	0.003	0.040	-0.333 ***	0.059	0.216 ***	0.060
3+	-0.073	0.055	-0.036	0.030	-0.190 **	0.070	0.299 ***	0.083
association	-0.083 *	0.033	0.011	0.020	-0.154 ***	0.040	0.225 ***	0.040
agrochem *(reference category = 0)*								
1	0.027	0.044	0.031	0.033	0.064	0.039	-0.122 *	0.053
2+	0.038	0.028	0.004	0.022	0.034	0.035	-0.076	0.042
N	566							
Wald Chi^2	194.45^{***}							
Log-Liklihood	-378.84							
McFadden R^2	0.441							

* 0.05, ** 0.01, *** 0.001

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