Climate Change Adaptation: The Case of the Coffee Sector in Nicaragua

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Abstract

This article studies Nicaraguan coffee growers' perceptions on long term changes in climate, the adaptation strategies implemented and its determinants. Using a household level sample, this study estimates probabilistic models where climate change adaptation is explained by household and farm characteristics, perceptions about changes in climate, measurement of exposure to climate change and geographical fixed effects. Results suggest that household age and years of education, number of household members, level of wealth, having received technical assistance, participation in farmer groups, off farm work, perceptions about changes in climate and exposure to climate change, affect the coffee growers' decision to adapt to climate change. However, the magnitude and significance of the effect of these explanatory variables varies across adaptation strategies.

Keywords: Adaptation, Climate Change, Nicaragua, Coffee

Clasification JEL: Q12, Q18, Q54.

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Climatic projections suggest that temperature increases associated with climate change would reduce, keeping agricultural practices an genetic materials constant, Arabica coffee yields and quality in the main coffee producing countries. Ovalle-Rivera et al. (2015) estimated that the acreage with aptitude for growing Arabica coffee would be reduced for all producing countries by 2050, moving the optimal production conditions to areas with higher altitude. Läderach et al. (2010) and Davis et al. (2012) found similar results for Central America and Ethiopia. Jaramillo et al. (2011) predicted that climate change would worsen pest prevalence like “broca” (berry borer) in Eastern Africa.

In spite of the predicted scenarios, the impact of climate change on human welfare in general and on coffee growers in particular, would depend on the adaptation strategies that households, firms and governments would implement. Thus, under the assumption that climate change impacts would not be uncertain and markets would not operate imperfectly, households and firms would adopt strategies to maximize profits under the new climate and market conditions. On the other hand, under uncertain probability of different climate scenarios and their expected consequences, and under imperfect or incomplete functioning markets, farmers and firms reactions to climate change may not be optimal and therefore public policy may have a central role in climate change (Mendelsohn 2012; Zilberman, Zhao and Heiman 2012).

The purpose of this article is to study Nicaraguan coffee growers’ perceptions on climate change in the long run, the adaptation strategies that they have already implemented and the determinants of this adaptation to climate change. In Nicaragua, recent studies have predicted an import impact of climate change over the coffee sector. It is expected that the area with aptitude for growing coffee would be reduced by 16% by 2050 (Läderach et al. 2010). Likewise, Nicaragua is a country with high dependence on coffee production. Coffee is the main export product accounting for 18.2% of total exports and employs directly and indirectly approximately 300,000 workers, representing 53% of the total rural employment and 14% of the national employment (MAGFOR 2013).

This study uses cross sectional data from a national household survey on 1,022 Nicaraguan coffee growers distributed in 266 farm communities and interviewed during the 2013/2014 growing season. Data collected is representative of the main six coffee producing departments of Nicaragua. In order to study climate change adaptation, the sample was stratified by the level of exposure to climate change by 2050 as described by Läderach et al. (2010) and Baca et al. (2014). Additionally, the survey questionnaire included a detailed module on coffee growers' perceptions on climate change during the last 10 years and different adaptation strategies self-reported and implemented by farm households.

In order to understand the determinants of the climate change adaptation, this article uses two standard econometric methods: On one hand, the article employs probabilistic models at household level where climate change adaptation is explained by household and farm characteristics, perceptions about climate change, measurements of exposure to climate change and geographic fixed effects. On the other hand, a multivariate probit model is estimated to explain the adoption of specific strategies (Capellari and Jenkins 2003; Greene 2008). Although these models did not identify the causal effect of these various factors analyzed on adaptation (Foster and Rosenzweig 2010; de Janvry, Dunstan and Sadoulet 2011), model results allow determining household and farm characteristics associated with this adaptation.

Results suggest that 95% of the interviewed households have perceived changes in climate during the last 10 years, which 85% of them have observed changes in temperature, 58%

in the frequency of rains, 54% on the seasonality of rains and 49% in the frequency and intensity of extreme events like drought or flooding. Interestingly, household perceptions on climate variations are consistent with results of articles that analyze climate data for Nicaragua (Gourdji et al. 2015). Regarding to adaptation to perceived changes, 57% of households reported having implemented at least one strategy that include changes in quantities of chemical inputs used, changes in the quantity of hours worked on production fields, investments in productive infrastructure, changes in crops or crop varieties and adoption of soil conservation practices and agroforestry.

Results of the probabilistic univariate model suggest that education, having received technical assistance or agricultural training, household level of wealth and having perceived changes in temperature and frequency of rains are associated positively and significantly with a higher probability to implement at least one adaptation strategy to climate change. These results are consistent with results found by Nhemachena and Hassan (2007), and Gbetibouo (2009) for South Africa, Maddison (2007) for various countries, Deressa et al. (2009), Di Falco, Veronesi and Yesuf (2011) and Di Falco and Veronesi (2013 and 2014) for Ethiopia, Asfaw et al. (2014) for Malawi, Hilasi, Birungi and Buyinza (2011) for Uganda, Below et al. (2012) for Tanzania, Bryan et al. (2013) for Kenya, Yegbemey et al. (2013) for Benin, Roco et al. (2014) for Chile, Huang, Wang and Wang (2015) for China and Piya, Maharjan and Joshi (2013) for Nepal. Additionally, results suggest that the level of exposure to climate change by 2050 does not have a significant effect over the adaptation decision.

Consistently with estimations of the univariate model, results of the multivariate probit suggest that household head age and years of education, number of household members, wealth level, having received technical assistance, participation in farmer groups, off farm work, perception about changes in climate and the exposure to climate change explain the adoption of analyzed strategies. However, the magnitude and significance level of these explanatory variables differ across adaptation strategies.

This article makes contributions to the literature on adaptation to climate change. First, to our knowledge this is the first study that includes in the analysis a measurement of exposure to climate change as covariate, which was measured from future changes on the modelled aptitude of coffee (Läderach et al. 2010). This indicator allow to test whether predicted effects of climate change influence household decisions on adaptation, which is critical for the adopted strategies to be efficient as described by Mendelsohn (2012).

Second, this study uses a representative sample of farmers of one crop (coffee) and specific country (Nicaragua) which overcome aggregation problems described by the current literature on adaptation which limits the ability to derive policy recommendations with clear interpretation and targets. Additionally, given the high vulnerability of the Nicaraguan coffee sector to climate change (Baca et al. 2014; Läderach et al. 2010; Ovalle-Rivera et al. 2015) and the strong climate change already reported in that country (Gourdji et al. 2015), these results are useful to better understand processes of adaptation of farm households to future climate changes.

Survey and Data Description

This study uses a household survey of 1,022 coffee growers located in the six main coffee producing departments of Nicaragua (Estelí, Jinotega, Madriz, Managua, Matagalpa and Nueva Segovia), which represent 87% of total coffee acreage in the country (MAGFOR 2013). It followed a two stage sampling strategy: In the first one, farm communities were selected randomly from the six departments described and, in the second stage, four households were also selected randomly in each farm community.

The survey questionnaire had two parts: the first was implemented between October and November 2013 and aimed to collect information regarding the agricultural season between May and August of the same year ("Primera" season in Nicaragua). The second part of the questionnaire, implemented between April and June 2014, targeted to collect data on coffee harvested (November 2013 to February 2014) and the two remaining agricultural seasons: "Postrera" (September-November 2013) and "Apante" (December 2013 – March 2014). Thus data collected correspond to the full agricultural year 2013-2014 and the coffee harvesting of 2014. Questionnaires allowed to collect detailed production information at plot level, household composition data, food security, poverty, agricultural practices, possession of durable goods, access to credit, social capital, adverse events, perceptions about climate change and adaptation strategies implemented.

In order to study adaptation to climate change, the study sample was stratified in such a way that 55% of the included communities were considered to have high exposure to climate change according to the estimations reported by Läderach et al. (2010) and Baca et al. (2014).[1]

[1] Läderach et al. (2010) and Baca et al. (2014) determine the household exposure level using suitability models for coffee, where they combine current climatic data with predicted changes in the same variables between 2020 and 2050. The current information is obtained from WorldClim (www.worldclim.org). Predictions are based on the scenario SRES-A2 and in 19 Global Circulation Models from the el Intergovernmental Panel on Climate Change (IPPC). The current information as well as the predictions were scaled up using the Delta method. In order to predict the suitability for 2050 those authors used the method of Maximum Entropy, calibrating with current climatic data and georeferenced production information. The estimations are based on the assumption that controlling for the climatic conditions, the future and current suitability in a specific area are equal.

Graph 1 shows the current modeled suitability of coffee (large map in the ride side) and by 2050 (large map in the left side) reported by those authors, in addition to the communities included in the study. As shown by the graph, according to the climatic projections and under the assumption that the genetic material and agricultural practices would not change substantially, it is predicted that climate change would reduce significantly the area with suitability for coffee between both periods. From this result, in the study sample design, a community was considered as having high exposure to climate change if its modeled suitability for coffee is a 25% lower than the current suitability.

One of the modules included in the questionnaire was designed to capture perceptions about changes in climate. Concretely, some questions were added in order to know whether coffee growers had observed changes on average temperature and in the rainy season during the last 10 years. 95% of the sample reported having perceived any change in climate. The most generalized perception among interviewed farmers was that temperature had changed (85% of total valid responses), followed by changes in the frequency of rains (58%), changes in the rain seasonality (54%) and changes in the frequency and intensity of extreme events such as drought and floods (49%) (Table 1).

Previous results are consistent with findings in Gourdji et al. 2015, who analyzing a time series of climatic variables for Nicaragua, found that for the period between 1970 and 2007 there was an increase on mean temperature, in the morning range of the temperature, and in the number of dry days. The authors also show evidence of a delay in the beginning of the rains in three agricultural seasons. In spite that data does not suggest that annual levels of precipitation had changed, the increase of the morning temperature and the number of dry days explain the perception about a larger number of adverse events like droughts.

The questionnaire also included questions about strategies implemented by households to face perceived changes in climate. 57% of households reported having adapted in any way. The most implemented strategy among interviewed farmers was the adoption of conservation and agroforestry with 35% of the total valid responses, followed by changes in the number of hours worked in the production plots with the 31%, changes in crops or crop varieties with 14%, changes in the quantities of chemical inputs used (fertilizers, pesticides, etc.) with 8% and investments in productive infrastructure with 6% (Table 1). The reasons given by farmers for not having adapted to climate change were the lack of knowledge on adaptation strategies available (64%), the lack of resources (40%) and not having observed any concrete consequence from the perceived climate changes (6%).

In the reported estimations in the following sections the number of observations corresponds to 882 coffee growers in 232 farm communities. This number differs from the total original sample for two reasons: Frist, 80 farmers rejected to participate or were missing during the second visit (attrition of 7.8%) and secondly, 60 questionnaires had incomplete information in any of the variables included in the adaptation models. In non-reported estimations, several variables qualitatively similar were used but only using information from the first visit, finding in all cases similar results to the ones discussed later in the article. The definition of all variables used in the empirical estimations is detailed in Table A1 of the annex, and the descriptive statistics in Table 1.

Modelling climate change adaptation

Following the literature on technology adoption, this article models the adaptation to climate change as a result of a restricted maximization of farmers expected benefits (or expected utility)

(Foster and Rosenzweig 2010; de Janvry, Dunstan and Sadoulet 2011). It is assumed that a farmer make the decision to adapt to changes in climate if and only if that choice is available and feasible given the resources, market and technology imperfections, and at the same time, provides positive expected benefits (expected utility).

Following de Janvry, Dunstan and Sadoulet (2011), in this artcile the adaptation decision is modelled at the household level as follows:

$$A^j_{hct}(X_{hct}, W_{ct}, U_{hct}, \varepsilon_{hct})$$
$$= \begin{cases} 1 \; si \; E\pi^*\left(X_{hct}, W_{ct}, U_{hct}; A^j_{hct} = 1\right) - E\pi^*\left(X_{hct}, W_{ct}, U_{hct}; A^j_{hct} = 0\right) + \varepsilon_{hct} = \gamma^j_{hct} > 0 \\ 0 \; otherwise \end{cases}. \quad (1)$$

Where A^j_{hct} is a *dummy* that equals to one if household h in community c in period t adopts strategy j, $E\pi^*$ are the expected benefits under each of the possible regimens (A^j_{hct} equals one or zero), γ^j_{hct} is the unobserved expected net benefit, X_{hct} is a vector of observable household characteristics such as education of household head, level of wealth or perceptions about changes in climate, W_{ct} is a vector for community level characteristics such as the level of exposure to climate change, U_{hct} are unobservable variables at household level that affect directly the expected benefits and ε_{hct} is the error that captures deviations of the optimal household behavior.[2]

From (1) it can be derived the following expression that would allow us to estimate household adaptation decisions as follows:

[2] This model specification is similar to a random utility model described in the econometric literature (Greene, 2008 and Cameron and Trivedi, 2005).

$$\gamma_{hct}^{j} = \delta X_{hct} + \theta W_{ct} + U_{hct} + \varepsilon_{hct} = \delta X_{hct} + \theta W_{ct} + \epsilon_{hct}. \ (2)$$

Where ϵ_{hct} is an error composed by U_{hct} and ε_{hct}, δ is a vector of coefficients associated to X_{hct} and θ a vector associated to W_{ct}. Given that γ_{hct}^{j} is unobservable, to estimate coefficients in (2) it is possible to use probabilistic models, in which the adaptation decision A_{hct}^{j} is explained by observable variables. This article uses a probit model for identifying the determinants of having adopted at least one adaptation strategy. This model assumes that the random component of the expected benefit function follows a standard normal distribution (Greene 2008; Train 2009).

As discussed by Nhemachena and Hassan (2007), Teklewold, Kassie and Shiferaw (2013) and Asfaw et al. (2014), the previous methodology might not be adequate to identify factors associated to the individual adaptation strategies described in the previous, given that these factors may be correlated with unobserved factors contained in ϵ_{hct}, which can lead to complementary strategies (positive correlation) o substitutes (negative correlation). Not factoring in the correlation between different decisions may lead to biased and inefficient estimators (Greene 2008).

To overcome those limitations, this article uses a multivariate probit model (MVP) where it is simultaneously estimated expression (2) for the following five categories: Use of chemical inputs, work on production plots, investments on productive infrastructure, changes in crop or crop varieties and conservation practices and agroforestry. The MVP, that assumes that random components of the expected benefit functions of each strategy j follow a jointly multivariate standard normal distribution, is an improvement of previous adaptation models where each decision is estimated separately. This model was implemented using the STATA routine described by Cappellari and Jenkins (2003) that approximates the multivariate integrals using the simulation model Geweke-Hajivassiliou-Keane (GHK), which has demonstrated to provide unbiased estimation of probabilities, is a continues function and differentiable of the structural model parameters, and is more efficient than other simulation models in the literature.

The estimation of probabilistic models includes variables associated with household characteristics (number of family members, age, gender, years of education and marital status of household head), access to markets and social services (agricultural extension or training, social programs, credit, producer group participation, family members with off farm work and time to reach the municipal capital), level of wealth (index of assets and durable goods, and coffee area), perceptions on climate change in the last 10 years (temperature, frequency of rains, rain seasonality and extreme events) and measurements of exposure to climate change (current and future suitability and changes in suitability by 2050). Additionally, different specifications are reported including fixed effects at department and municipality levels. In all estimations cluster standard error at community level were used, which accounts for potential unobserved factors at this level not included in the estimations and that could generate correlation in the random component of the model.

As highlighted by Foster and Rosenzweig (2000) and de Janvry, Dunstan and Sadoulet (2011) a potential problem with specification (2) is that in order to identify δ and θ consistently, it is needed to assume conditional independence between ϵ_{hct} and the explanatory variables contained in X_{hct} and W_{ct}, something that could not be true if the model excludes a relevant covariate. As robustness check against misspecification, in Table A2 in the annex it is reported the results of a lineal probability model with fixed effects at the community level,[3] which allows checking whether there is an endogeneity problem due to the omission of relevant variables at the community level.[4]

Results

This section starts describing unconditional difference between households who have adapted to perceived climate change and household who have not, then it reports estimations of an adaptation probit model where the dependent variable is a *dummy* that equals to one if the household has implemented at least one adaptation strategy and finally, it reports results of MVP for individual adaptation strategies described previously.

Unconditional Differences

Table 2 reports the unconditional differences between households who have adapted to climate change and those who have not. Results show a clear pattern: households who adapts to climate change, independently of the specific strategy adopted, are those with household head more educated, that have participated in a social program, that belongs to a higher wealth quintile, that owns more land and that have perceived any change in climate. Additionally, it is observed that the proportion of households that have adapted is higher in Matagalpa and lower in Nueva Segovia.

[3] Although ideally a model with fixed effects at this level would have been estimated, given the quantity of parameters to estimate, it was not feasible (Greene, 2008; Cameron and Trivedi, 2005).

[4] Given that in Nicaragua farm communities are usually composed by a relative small number of households in very concentrated geographical areas, the fixed effects at this level may control for unobserved factors like soil quality, access to markets, neighborhood effects, etc. which usually affect the expected benefits associated with the adoption of different technologies and therefore, presents an endogeneity problem in the estimation of (2).

An important result derived from Table 2, reveals that high exposure to climate change is significantly associated only with having worked more in the production plot. In fact, by decomposing that variable into the variables current suitability and suitability for 2050, it is observed that households that have adapted have on average a larger current suitability in coffee, especially those who have adopted strategies associated with the use of chemical inputs (inputs), having worked more in production plots (Work), invested in productive infrastructure (Investment) or having changed crops or crop varieties (Crops). However, the association between the adaptation decisions and the future suitability are no statistically significant in most of the cases.

Although previous results suggest a series of associations between the adaptation decisions and some household characteristics, it is important to consider that the unconditional exercise does not consider the correlation among analyzed variables, including the fact that different adaptation strategies are possibly correlated. In the next section results of the adaptation models that overcome the limitations are reported.

Probit Model of Adaptation

Table 3 presents the marginal effects of the probit model of adaptation, which allows answering the question: What are the determinants of having implemented at least one adaptation strategy to climate change?

In order to evaluate the association between exposure to climate change and adaptation, Table 3 reports two kinds of results: Columns (1)-(3) show results that include measurements of current and 2050 suitability. Oppositely, columns (4)-(6), report estimations that add a *dummy* that equals one if the community where household production plots are located has a high exposure to climate change by 2050. Additionally, as robustness checks both groups of models were estimated with and without municipal and departmental fixed effects. All models included clustered standard errors at community level. The last section of Table 3 shows some goodness of fit measurement, where it is shown an acceptable explicative power given the nature of the data (cross sectional) and the dependent variable (binary), something that is also consistent with the results of the join significance test reported.

Similarly to results reported in Table 2, the estimations of the adaptation model confirm that years of education of household head is positively and significantly associated with household adaptation to climate change. It implies that an additional year of education is associated with a higher probability of having implemented at least one adaptation strategy in 1.2%. Although the marginal effect found is small, given the low level of education of the studied population (3.9 years as shown in Table 1), there is an important margin to promote the adaptation through improvement in household human capital.

As discussed in the previous section, the unconditional analysis could lead to erroneous conclusions if the correlation among different analyzed variables is not accounted for: The case of the variable extension is an example of that situation. As shown in Table 3, having received agricultural extension or participated in agricultural training is associated with a probability of having adapted to a higher climate change in approximately 13%. This result, which is similar to findings of other studies in the topic (Juana, Kahaka and Okurut 2013, Asfaw et al. 2014, Piya, Maharjan and Joshi 2013, Huang, Wang and Wang 2015, Roco et al. 2014), highlights the importance that extension services could have in the adaptation to climate change.

Regarding to household available resources, results suggest that there is a positive and statistically significant relationship between household level of wealth and the adaptation to climate change: being in the highest quintile of the wealth index is associated with a higher probability of having adapted to climate change of 20% compared with being in the first quintile. This result that is also similar to the one found in studies about technology adoption (i.e. Rosenzweig and Binswanger 1993; Langyintuoa and Mungoma 2008), could be explained by the fact that the adoption of different strategies requires investments that are unaffordable for households with lower wealth, which is possibly associated with credit constraints.

From the unconditional analysis in Table 2 it is derived that perceptions about climate change are associated with adaptation to climate change. Consistently, results in Table 3 suggest that having perceived changes in temperature and in rain frequency is associated with a higher probability of having adapted of 23% and 7% respectively. On the other hand, there is no evidence that changes in the rainy season and in the frequency of extreme events explain household adaptation decisions. A plausible explanation for this result is that unlike temperature, the level of precipitation and the occurrence of extreme events in Nicaragua have not had significant changes in the last years (Gourdji et al. 2015), therefore there is higher uncertainty for implementing adaptation strategies to offset these problems.

Another result derived from Table 3 is that measurements of exposure to climate change seem not to be associated with household decisions to adapt, which is the case in both, the estimations in where current and 2050 suitability are included and the estimations where a *dummy* for high exposure to climate change is added. This result could imply that strategies so far implemented by households may not be efficient in the sense described Mendelsohn (2012) and therefore, may create negative consequences over welfare in the long run.

As a robustness check, Table A2 in the annex reports the results of a linear probability model that includes fixed effects at community level. This specification aims to know whether estimations described previously are biased due to omission of relevant factors at community level. As shown, with the exception of the variable for the second quintile of wealth and the perception about changes in the frequency of rains, the majority of results are quantitatively similar to those obtained with the *probit* specification, which reinforce the validity of the previous estimations.

Multivariate Probit Model (MPV) of adaptation of specific strategies

As discussed in the previous section, estimating separate adaptation models for each of the reported adaptation strategies by households could lead to biased and inefficient estimators of parameters of interest (Greene 2008; Teklewold, Kassie and Shiferaw 2013). Tables 4 and 5 present results of the MPV where determinants of different adaptation strategies are modelled jointly. The reported specification includes a *dummy* variable of a high exposure to climate change. Given the frequency of some of the reported strategies, fixed effects variables were not included in order to not affect the convergence of the maximum likelihood function. However, the estimations included clustered standard errors at the community level to control for the spatial correlation of the random term.

Table 5 reports the correlation coefficients of the random components of each implemented adaptation strategies by households. Following Greene (2008) the MVP provides more efficient results if and only if those correlations are jointly different from zero. At the end of Table 5 results of the statistical test for that condition is reported. Test result suggests that different strategies are effectively correlated by unobserved factors and therefore MVP improve the efficiency of the estimation.

Regarding the correlations, Table 5 shows that strategies related to use of chemical inputs, more family work on farm, the investment in productive infrastructure and changes in crop or crop varieties are positively and significantly correlated, which means that are complementary. Oppositely, the use of chemical inputs and the adoption of soil conservation and agroforestry are negatively correlated (substitutes). Additionally, it is found that the adoption of conservation practices is not associated with more family work, with on farm investments or with changes in crop or crop varieties.

Table 4 reports the coefficients of MVP for each of the adaptation strategies. Concretely in (2) it shows results for the use of chemical inputs, in (3) for a greater use of on farm family labor, in (4) for investments in productive investments, in (5) for changes in crops or crop varieties and in (6) for the adoption of soil conservation practices and agroforestry. As a reference, in (1) results for the dummy that equals to one if the household has adapted any adaptation strategy (marginal effects of this model are shown in column (4) of Table 3) are reported. A primer evident result is that the determinants of distinct adaptation strategies differ significantly, which shows the limitations of modelling adaptation as a binary decision without considering the specific strategies implemented (Nhemachena and Hassan 2007; Gbetibouo 2009).

From Table 4 it can be derived that the use of chemical inputs (fertilizers, pesticides, etc.) is more likely having been used as an adaptation strategy by households with less family members, where the household head is married, with at least one member participating in a farmer group, that have perceived changes in the rainy season and that has greater level of wealth. Additionally, the adoption of this strategy is positively and significantly associated with the level of exposure to climate change by 2050, which suggest that households implement this strategy as a mean to maintain crop yields in areas where it is expected a worsen in future yields.

The use of more family labor in production plots is more likely implemented as an adaptation strategy in households that have received extension services, do not participate in farmer groups, do not have greater levels of wealth and that have perceived changes in climate, especially in temperature and occurrence of extreme events. Unlike the use of chemical inputs, the choice of this strategy is negatively and significantly associated with the level of exposure to climate change. A plausible explanation for this finding is that exposure, keeping all other factors constant, disincentive farmers efforts in their production plots which is something suggested by Dalton, Ghosal and Mani (forthcoming) about the effects of the aspirations on poverty.

The probability of having adapted through investments on farm infrastructure is greater for households with a larger number of family members, who have received technical assistance, who have no off farm work, who have perceived changes in frequency of rain or in the occurrence of extreme events, and have greater level of wealth. Regarding the *dummy* variable for exposure, results suggest that there is no association between having implemented that strategy and the level of exposure to climate change, result that is kept when the variables of current suitability and suitability by 2050 are included (these results are not reported in this article).

Regarding changes in crop or crop varieties, results suggest that the probability of having use this adaptation strategy is greater for households with a lower number of family members, who has perceived changes in climate (mainly temperature, frequency of rains and occurrence of extreme events), with greater levels of wealth and with a higher current suitability for coffee (result not reported in this article). On the other hand, the adoption of soil conservation and agroforestry strategies are positively and significantly associated with age (concave relationship) and years of education of the household head, having received technical assistance, belonging to a farmer group and having perceived changes in temperature. Similar to the use of more family on farm labor in productive plots, exposure to climate change does not seem to be associated with the adoption of any of the previous adaptation strategies.

Conclusions

This article estimates univariate and multivariate probit models which explains the adaptation to climate change by household and farm characteristics, perceptions about changes in climate, measurements of exposure to climate change by 2050 and geographic fixed effects.

Results suggest that 95% of interviewed households have perceived changes in climate in the last 10 years, from which 85% have observed changes in temperature, 58% in the frequency rains, 54% in the seasonality of rains and 49% in the frequency and intensity of extreme events like droughts or flooding. Regarding adaptation to perceived changes in climate, 57% of households reported having implemented at least one adaptation strategy that include changes in the quantity of chemical inputs used, changes in family labor used in production plots, investments on production infrastructure, changes in crops or crop varieties and adoption of soil conservation and agroforestry practices.

Results from univariate probit models suggest that education, agricultural technical assistance, level of wealth and having perceived changes in temperature and frequency of rains are positively and significantly associated with a greater probability of having implemented at least one adaptation strategy to climate change. Additionally, results indicate that the level of exposure to climate change by 2050, measured from the modelled suitability for coffee in Läderach et al. (2010) and Baca et al. (2014), has no significant effect on household adaptation to climate change.

Estimations of the multivariate probit model on the other hand, suggest that level of wealth and perceptions about changes in climate are positively associated with the implementation of all adaptation strategies analyzed, with the exception of soil conservation practices and agroforestry. Having received technical assistance is positively associated with a greater family work in production plots and having adopted conservation practices, Years of education and age of household head are positively and significantly associated with the adoption of conservation practices. Finally, there is evidence that the exposure to climate change by 2050 is associated with the use of chemical inputs (positively) and the on farm family work (negatively).

In terms of policy, results suggest that educational programs, from formal education or training or technical assistance to coffee growers, are a channel through which governments could promote adaptation to climate change. Additionally, the fact that level of household wealth are positively and significantly associated with the probability to adapt suggest that in the event of no governmental intervention, climate change could worsen the distribution of income at the social level.

Finally, article estimations show that adaptation to climate change seems to not be associated in general with the exposure of households to climate change which may have various explanations. First, households may have reacted to perceived changes so far in climate which would denote that observed adaptation is reactive and no proactive in the terminology of

Zilberman, Zhao and Heiman (2012), being the last kind of adaptation important to face phenomena of slow development like climate change. Secondly, information about which areas would be more likely affected by climate change seems to have no reached households or could not have been able to be used in a practical way. In any case, the lack of association between exposure and adaptation could imply that strategies implemented so far by households are not efficient as described by Mendelsohn (2012) and therefore long term consequences could have a negative welfare effect.

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Table 1: Descriptive Statistics

	Total		Adaptation=1		Adaptation=0	
	Mean	SD	Mean	SD	Mean	SD
Adaptation to perceived changes in climate						
Adaptation	0.57	0.50	1.00	0.00	0.00	0.00
Inputs	0.08	0.27	0.13	0.34	0.00	0.00
Work	0.31	0.46	0.55	0.50	0.00	0.00
Investment	0.06	0.23	0.10	0.30	0.00	0.00
Crop/variety	0.14	0.35	0.25	0.43	0.00	0.00
Conservation	0.33	0.47	0.59	0.49	0.00	0.00
Household and Farm Characteristics						
Male	0.88	0.32	0.90	0.30	0.86	0.34
Age	50.62	13.90	50.34	13.24	50.98	14.73
Marital status	0.63	0.48	0.65	0.48	0.61	0.49
Education	3.89	3.62	4.34	3.72	3.31	3.40
Household size	5.23	2.13	5.20	2.08	5.28	2.20
Extension	0.33	0.74	0.32	0.72	0.35	0.76
Social program	0.37	0.48	0.44	0.50	0.27	0.44
Off farm work	0.28	0.45	0.30	0.46	0.25	0.43
Credit	0.42	0.49	0.45	0.50	0.38	0.49
Producer group	0.67	0.47	0.71	0.45	0.62	0.49
Wealth quintile 1	0.20	0.40	0.19	0.39	0.21	0.41
Wealth quintile 2	0.20	0.40	0.18	0.39	0.23	0.42
Wealth quintile 3	0.20	0.40	0.24	0.43	0.16	0.37
Wealth quintile 4	0.20	0.40	0.22	0.41	0.18	0.38
Wealth quintile 5	0.20	0.40	0.24	0.43	0.15	0.36
ln(coffee area)	0.74	0.95	0.81	0.93	0.64	0.98
Time to municipality	37.86	30.20	36.07	27.02	40.18	33.79
Perceptions about climate change in the last 10 years						
Changes in climate	0.95	0.21	1.00	0.00	0.90	0.31
Temperature	0.85	0.36	0.92	0.27	0.75	0.43
Frequency in rains	0.58	0.49	0.62	0.49	0.52	0.50
Rain seasonality	0.54	0.50	0.58	0.49	0.49	0.50
Extreme events	0.49	0.50	0.54	0.50	0.43	0.50
Exposure to climate change						
Current suitability	0.54	0.09	0.55	0.09	0.54	0.09
Suitability 2050	0.24	0.23	0.25	0.23	0.22	0.23
High exposure	0.55	0.50	0.53	0.50	0.58	0.49
Geographic location						
Estelí	0.07	0.26	0.08	0.28	0.06	0.24
Jinotega	0.24	0.43	0.23	0.42	0.26	0.44
Madriz	0.13	0.34	0.13	0.33	0.13	0.34
Managua	0.01	0.12	0.01	0.09	0.02	0.15
Matagalpa	0.28	0.45	0.32	0.47	0.23	0.42
Nueva Segovia	0.26	0.44	0.23	0.42	0.30	0.46
Observations	*882*		*499*		*383*	

Note: Variables definitions are in Table A1 in the annex. SD refers to standard deviation.

Table 2: Mean Differences between households that have adopted and those that have not due to changes in climate

	(1) Adaptation=0	(2) Adaptation=1	(3) Inputs	(4) Work	(5) Investment	(6) Crops	(7) Conserv.
Household and farm characteristics							
Male	0.86	0.9	0.91	0.92**	0.86	0.92*	0.88
Age	50.98	50.34	48.15	49.24*	50.08	50.02	51.14
Marital Status	0.61	0.65	0.76**	0.66	0.71	0.69*	0.64
Education	3.31	4.34***	5.25***	4.29***	4.94**	4.72***	4.37***
Household size	5.28	5.2	4.93	5.29	5.69	5.07	5.13
Extension	0.35	0.32	0.33	0.34	0.18**	0.43	0.32
Social program	0.27	0.44***	0.43**	0.45***	0.59***	0.45***	0.45***
Off farm work	0.25	0.3*	0.31	0.32**	0.39**	0.29	0.3
Credit	0.38	0.45**	0.52**	0.49**	0.47	0.44	0.46**
Producer group	0.62	0.71**	0.79***	0.66	0.71	0.65	0.76***
Wealth quintile 1	0.21	0.19	0.12*	0.19	0.18	0.16	0.17
Wealth quintile 2	0.23	0.18	0.13*	0.19	0.18	0.19	0.16**
Wealth quintile 3	0.16	0.24**	0.19	0.22*	0.16	0.19	0.25**
Wealth quintile 4	0.18	0.22	0.27	0.22	0.27	0.25*	0.2
Wealth quintile 5	0.15	0.24***	0.39***	0.27***	0.37**	0.3**	0.23**
ln(coffee area)	0.64	0.81**	0.96**	0.82**	0.93**	0.91**	0.84**
Time to municipality	40.18	36.07*	36.34	35.79*	36.54	33.26**	36.02
Perceptions about climate change in the last 10years							
Temperature	0.75	0.92***	0.94***	0.95***	0.94***	0.94***	0.92***
Frequency of rains	0.52	0.62**	0.63*	0.65***	0.78***	0.71***	0.61**
Rain seasonality	0.49	0.58**	0.76***	0.64***	0.71**	0.69***	0.58**
Extreme events	0.43	0.54**	0.81***	0.62***	0.78***	0.66***	0.5*

Table 2: Mean Differences between households that have adopted and those that have not due to changes in climate (Continuation)

	(1) Adaptation=0	(2) Adaptation=1	(3) Inputs	(4) work	(5) Investment	(6) Crops	(7) Conserv.
			Exposure to climate change				
Current suitability	0.54	0.55	0.56**	0.56*	0.56*	0.56*	0.54
Suitability 2050	0.22	0.25	0.21	0.28**	0.24	0.25	0.24
High exposure	0.58	0.53	0.66	0.48**	0.55	0.54	0.54
			Geographic location				
Estelí	0.06	0.08	0.03	0.14**	0.1	0.09	0.06
Jinotega	0.26	0.23	0.24	0.33*	0.24	0.29	0.15***
Madriz	0.13	0.13	0.01***	0.08*	0.12	0.07**	0.18*
Managua	0.02	0.01	0.01	0.01	0*	0*	0.01
Matagalpa	0.23	0.32**	0.57***	0.3**	0.43**	0.35**	0.34**
Nueva Segovia	0.30	0.23**	0.13***	0.15***	0.12***	0.2**	0.26

Note: Column (1) shows the mean for households that have no implemented any adaptation strategy (383), column (2) for those who at least implemented one strategy (499), column (3) for those who increase chemical input use (67), column (4) for those who has worked more in the production plots (276), column (5) for those who have invested in productive infrastructure (51), column (6) for those who have changed crops or varieties (125) and column (7) for those who have adopted conservation practices or agroforestry (294). The high exposure to climate change was built as a dummy variable equals to one if the change in suitability for 2050 is less than -0.25. The univariate tests were implemented through a regression model with cluster standard errors at the community level. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Probit Models of Adaptation

VARIABLES	(1)	(2)	(3)	(5)	(6)	(7)
		Adaptation variables			*Dummy high exposure*	
Male	0.012	0.018	0.022	0.011	0.018	0.023
	(0.055)	(0.055)	(0.053)	(0.054)	(0.055)	(0.053)
Age	0.000	0.000	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Marital status	0.006	0.002	0.015	0.005	0.002	0.015
	(0.033)	(0.033)	(0.034)	(0.033)	(0.033)	(0.034)
Education	0.012**	0.012**	0.011**	0.011**	0.012**	0.011**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Household size	-0.008	-0.008	-0.007	-0.008	-0.008	-0.007
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Extension	0.128***	0.130***	0.145***	0.130***	0.131***	0.144***
	(0.035)	(0.034)	(0.034)	(0.035)	(0.034)	(0.034)
Social program	0.046	0.031	0.043	0.048	0.031	0.043
	(0.037)	(0.037)	(0.038)	(0.037)	(0.037)	(0.038)
Off farm work	-0.016	-0.014	-0.015	-0.017	-0.014	-0.014
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Credit	0.005	0.013	0.007	0.005	0.013	0.007
	(0.032)	(0.032)	(0.031)	(0.033)	(0.032)	(0.031)
Producer group	0.043	0.039	0.029	0.044	0.040	0.028
	(0.034)	(0.034)	(0.035)	(0.034)	(0.034)	(0.034)
Wealth quintile 2	0.096**	0.098**	0.101**	0.094*	0.097**	0.101**
	(0.048)	(0.048)	(0.048)	(0.048)	(0.048)	(0.048)
Wealth quintile 3	0.212***	0.214***	0.222***	0.211***	0.213***	0.222***
	(0.045)	(0.046)	(0.045)	(0.045)	(0.046)	(0.045)
Wealth quintile 4	0.155***	0.156***	0.162***	0.152***	0.154***	0.162***
	(0.048)	(0.050)	(0.049)	(0.049)	(0.050)	(0.049)
Wealth quintile 5	0.202***	0.197***	0.200***	0.200***	0.196***	0.200***
	(0.052)	(0.055)	(0.054)	(0.053)	(0.055)	(0.054)

Table 3: Probit Models of Adaptation (Continuation)

VARIABLES	(1)	(2)	(3)	(5)	(6)	(7)
		Adaptation variables			*Dummy high exposure*	
ln(coffee area)	-0.021	-0.014	-0.011	-0.019	-0.014	-0.011
	(0.019)	(0.019)	(0.018)	(0.019)	(0.019)	(0.019)
Time to municipality	-0.000	-0.000	0.000	-0.000	-0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Temperature	0.245***	0.231***	0.227***	0.245***	0.232***	0.227***
	(0.050)	(0.050)	(0.049)	(0.050)	(0.050)	(0.049)
Frequency of rains	0.075**	0.076**	0.066**	0.074**	0.075**	0.066**
	(0.032)	(0.031)	(0.032)	(0.032)	(0.031)	(0.032)
Rain seasonality	0.029	0.019	0.039	0.028	0.018	0.040
	(0.033)	(0.033)	(0.034)	(0.032)	(0.033)	(0.034)
Extreme events	0.050	0.042	0.046	0.051	0.042	0.046
	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)
Current suitability	0.101	0.078	-0.012	-	-	-
	(0.208)	(0.214)	(0.239)			
Suitability 2050	0.016	0.002	-0.034	-	-	-
	(0.077)	(0.079)	(0.098)			
High exposure	-	-	-	-0.016	-0.009	0.004
				(0.033)	(0.033)	(0.038)
Observations	882	882	882	882	882	882
Department fixed effect	NO	YES	NO	NO	YES	NO
Municipal fixed effect	NO	NO	YES	NO	NO	YES
Pseudo R-square	0.109	0.118	0.144	0.109	0.118	0.127
Chi2	120.0	114.5	118.6	119.5	113.2	119.6
Pr > Chi2	0	0	0	0	0	0

Note: The dependent variable is a dummy that equals 1 if the household has implemented at least one adaptation strategy to climate change. The high exposure to climate change was built as a dummy that equals one if the change in suitability by 2050 is less than -0.25. Age was introduced in level and quadratic forms. Marginal effects of the Probit model are reported. Clusters standard error at community level in parenthesis, *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Multivariate Probit Model for Individual Adaptation Strategies

VARIABLES	(1) Adaptation	(2) Inpus	(3) Work	(4) Invesment	(5) Crops	(6) Conserv.
Male	0.033	-0.027	0.242	-0.220	0.166	-0.111
	(0.156)	(0.248)	(0.157)	(0.228)	(0.204)	(0.155)
Age	0.034	-0.038	0.006	-0.012	0.016	0.051**
	(0.021)	(0.029)	(0.023)	(0.039)	(0.027)	(0.023)
Age squared	-0.000*	0.000	-0.000	0.000	-0.000	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Marital status	0.015	0.334**	0.037	0.076	0.068	0.034
	(0.096)	(0.165)	(0.105)	(0.180)	(0.126)	(0.100)
Education	0.033**	0.021	0.005	0.024	0.019	0.030**
	(0.014)	(0.020)	(0.014)	(0.022)	(0.017)	(0.014)
Household size	-0.023	-0.073**	-0.000	0.067*	-0.045*	-0.036
	(0.022)	(0.032)	(0.023)	(0.034)	(0.027)	(0.023)
Extension	0.369***	0.028	0.235**	0.476***	0.186	0.213**
	(0.100)	(0.146)	(0.107)	(0.155)	(0.115)	(0.097)
Social program	0.137	0.060	0.138	0.166	0.010	0.088
	(0.107)	(0.153)	(0.101)	(0.155)	(0.116)	(0.103)
Off farm work	-0.050	0.045	0.015	-0.318***	0.118	-0.025
	(0.060)	(0.095)	(0.058)	(0.103)	(0.077)	(0.061)
Credit	0.014	0.086	0.125	-0.135	-0.080	0.042
	(0.093)	(0.144)	(0.102)	(0.158)	(0.120)	(0.096)
Producer group	0.125	0.279*	-0.220**	-0.178	-0.143	0.288***
	(0.096)	(0.148)	(0.107)	(0.174)	(0.120)	(0.099)
Wealth quintile 2	0.279*	1.062***	0.395**	0.943**	0.455**	-0.126
	(0.149)	(0.373)	(0.164)	(0.379)	(0.196)	(0.146)
Wealth quintile 3	0.639***	1.463***	0.514***	0.945***	0.527***	0.233
	(0.153)	(0.377)	(0.164)	(0.366)	(0.193)	(0.151)
Wealth quintile 4	0.454***	1.575***	0.552***	1.178***	0.623***	-0.048
	(0.155)	(0.388)	(0.174)	(0.372)	(0.209)	(0.164)
Wealth quintile 5	0.603***	1.894***	0.737***	1.460***	0.717***	0.045
	(0.174)	(0.400)	(0.190)	(0.379)	(0.216)	(0.171)

Table 4: Multivariate Probit Model for Individual Adaptation Strategies (Continue)

VARIABLES	(1) Adaptation	(2) Inputs	(3) Work	(4) Investment	(5) Crops	(6) Conserv.
ln(coffee area)	-0.001	0.002	-0.001	0.002	-0.003	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Time to municipality	-0.055	-0.083	-0.088	-0.101	-0.023	0.025
	(0.054)	(0.097)	(0.061)	(0.087)	(0.067)	(0.057)
Temperature	0.679***	0.217	0.756***	0.037	0.485**	0.532***
	(0.144)	(0.264)	(0.166)	(0.281)	(0.190)	(0.174)
Frequency of rains	0.212**	0.154	0.258***	0.600***	0.381***	0.079
	(0.090)	(0.143)	(0.093)	(0.163)	(0.122)	(0.092)
Rain seasonality	0.080	0.305**	0.203**	0.154	0.239*	0.063
	(0.093)	(0.154)	(0.090)	(0.165)	(0.125)	(0.100)
Extreme events	0.146	0.677***	0.368***	0.650***	0.403***	-0.039
	(0.093)	(0.145)	(0.088)	(0.175)	(0.115)	(0.102)
High exposure	-0.047	0.323**	-0.226**	-0.010	-0.021	0.012
	(0.095)	(0.133)	(0.102)	(0.136)	(0.103)	(0.092)
Observations	882	882	882	882	882	882
Repetitions	-	100	100	100	100	100
Pseudo R-squared	0.109	-	-	-	-	-
Chi2 (global significance test)	119.5	842.2	842.2	842.2	842.2	842.2
Pr > Chi2	0	0	0	0	0	0
Chi2 (All ρ equal zero)	-	183.3	183.3	183.3	183.3	183.3
Pr > Chi2	-	0	0	0	0	0

Note: The dependent variable in column (1) is a dummy equals to 1 if household has implemented at least one adaptation strategy to climate change, column (2) if has changed the use of chemical inputs, column (3) if has worked more in production plots, column (4) if has invested in productive infrastructure, column (5) if has changes crop or varieties and column (6) if has adopted conservation practices or reforested. High exposure to climate change was built as a dummy that equals one if the change in suitability by 2050 is lower than -0.25. Coefficients of a Probit model are reported in Column (1) and for a multivariate probit in columns (2)-(6). Clustered standard errors at community level in parenthesis; *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Correlations Matrix of the Multivariate Probit Model of Adaptation

	Inputs	Work	Investment	Crops
Work	0.492***			
	(0.090)			
Investment	0.497***	0.485***		
	(0.113)	(0.094)		
Crops	0.536***	0.788***	0.385***	
	(0.101)	(0.081)	(0.088)	
Conservation	-0.154*	-0.041	-0.062	-0.115
	(0.087)	(0.057)	(0.088)	(0.073)

Note: Correlations come from specification reported in columns (2)-(6) of Table 4. The test that all correlations are equal to Zero is equal to $\chi^2(10) = 183.3$ with a p value associated to less than 0.01. N=882.

Table A1: Definition of Variables

Variable name	Definition
Adaptation to perceived changes in climate	
Adaptation	1 if household has implemented at least one strategy
Inputs	1 if household has used more chemical inputs
Work	1 if household has worked more in the production plots
Investment	1 if household has invested in productive infrastructure
Crop	1 if household has changed crop or crop variety
Conservation	1 if household adopted conservation practices/ has reforested
Household and farm characteristics	
Male	Male household head
Age	Age of household head
Marital status	Married household head
Education	Years of education of household head
Household size	Household size
Extension	1 if received extension or trainings on agricultural practices
Social Program	1 household has participated in any social program
Off farm work	Number of family members that work off farm
Credit	1 household applied for credit
Producer group	1 household had Access to producer groups
Wealth quintile 1	Household in the first quintile in the poverty index
Wealth quintile 2	Household in the second quintile in the poverty index
Wealth quintile 3	Household in the third quintile in the poverty index
Wealth quintile 4	Household in the fourth quintile in the poverty index
Wealth quintile 5	Household in the last quintile in the poverty index
ln(coffee)	Logarithm of coffee area (ha)
Time to municipal capital	Time in minutes to reach the nearest municipal capital
Perceptions about climate change in the last 10 years	
Changes in climate	1 household has perceived changes in climate
Temperature	1 if perceived changes in temperature
Frequency in rains	1 if perceived changes in frequency in rains
Rain seasonality	1 if perceived changes in rain seasonality
Extreme events	1 if perceived changes in the frequency of extreme events
Exposure to climate change	
Current suitability	Current Suitability for coffee
Suitability 2050	Suitability for coffee in 2050
High exposure	High exposure to climate change (change in suitability < -.25)

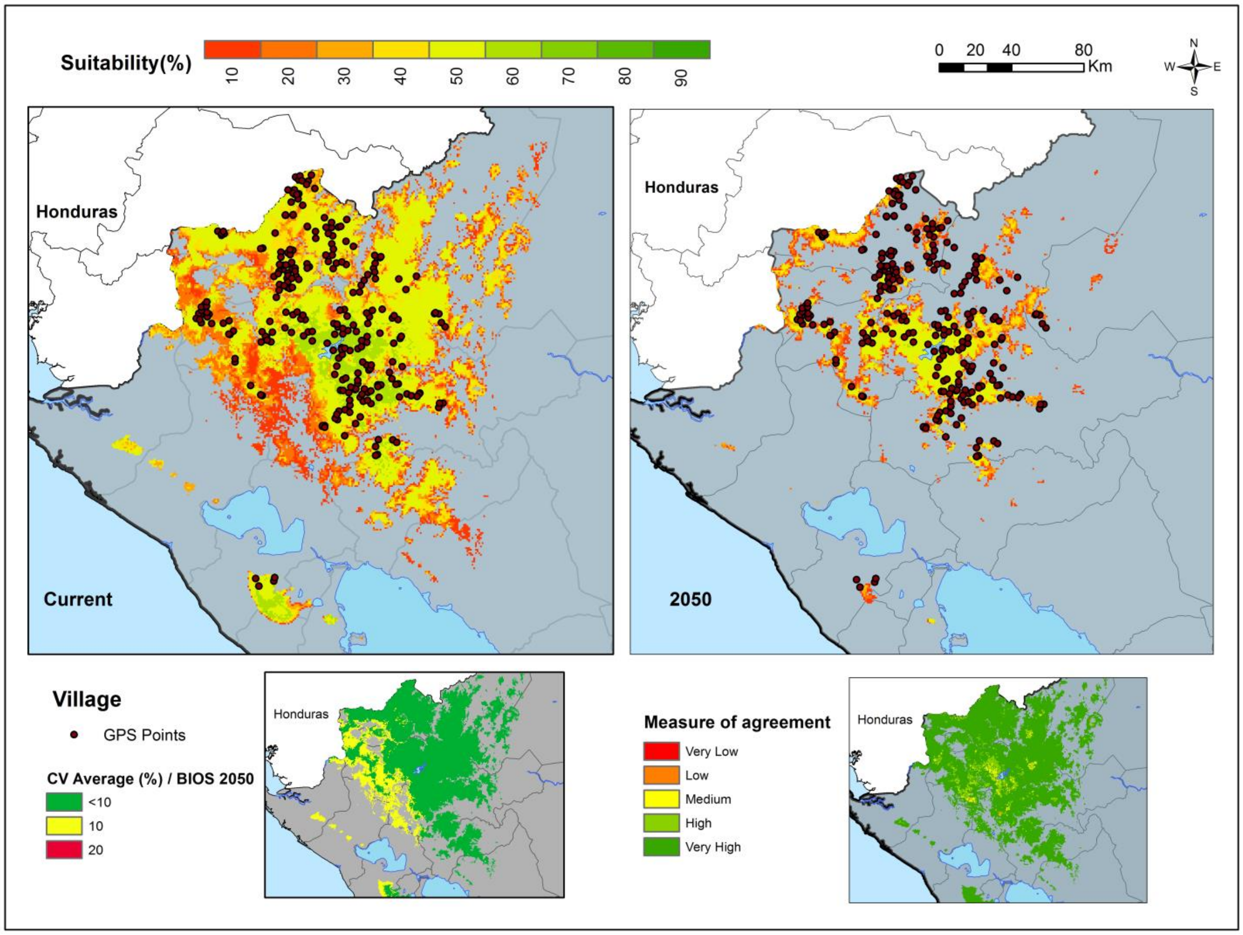
Table A2: Lineal Probability Models of Adaptation

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Variables of adaptation			*Dummy high exposure*			-
Male	0.019	0.023	0.030	0.018	0.023	0.030	0.064
	(0.055)	(0.054)	(0.055)	(0.055)	(0.054)	(0.055)	(0.065)
Age	0.000	0.000	0.000	0.000	0.000	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Marital status	0.006	0.002	0.013	0.006	0.002	0.013	-0.007
	(0.034)	(0.034)	(0.035)	(0.034)	(0.034)	(0.035)	(0.041)
Education	0.012**	0.012**	0.011**	0.011**	0.012**	0.011**	0.013**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
Household size	-0.008	-0.008	-0.007	-0.008	-0.008	-0.007	-0.015
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)
Extension	0.130***	0.131***	0.148***	0.131***	0.132***	0.147***	0.172***
	(0.035)	(0.035)	(0.036)	(0.035)	(0.035)	(0.036)	(0.043)
Social program	0.046	0.032	0.041	0.047	0.032	0.041	0.039
	(0.038)	(0.038)	(0.039)	(0.037)	(0.038)	(0.039)	(0.046)
Off farm work	-0.017	-0.014	-0.014	-0.018	-0.015	-0.013	-0.026
	(0.021)	(0.022)	(0.022)	(0.021)	(0.022)	(0.022)	(0.025)
Credit	0.003	0.011	0.003	0.003	0.010	0.003	0.013
	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.032)	(0.040)
Producer group	0.043	0.040	0.032	0.045	0.041	0.032	0.042
	(0.035)	(0.035)	(0.037)	(0.035)	(0.035)	(0.036)	(0.044)
Wealth quintile 2	0.101*	0.104*	0.107*	0.098*	0.103*	0.108*	0.080
	(0.054)	(0.055)	(0.056)	(0.054)	(0.055)	(0.056)	(0.061)
Wealth quintile 3	0.229***	0.231***	0.241***	0.228***	0.230***	0.241***	0.255***
	(0.054)	(0.055)	(0.056)	(0.054)	(0.055)	(0.056)	(0.065)
Wealth quintile 4	0.169***	0.170***	0.176***	0.166***	0.168***	0.176***	0.178***
	(0.055)	(0.057)	(0.057)	(0.055)	(0.057)	(0.057)	(0.069)
Wealth quintile 5	0.219***	0.214***	0.218***	0.217***	0.212***	0.219***	0.198**
	(0.061)	(0.065)	(0.065)	(0.062)	(0.065)	(0.065)	(0.078)

Table A2: Lineal Probability Models of Adaptation (Continue)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Variables of adaptation			*Dummy high exposure*		-
ln(coffee area)	-0.022	-0.016	-0.011	-0.021	-0.015	-0.012	0.002
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.024)
Time to municipality	-0.000	-0.000	0.000	-0.000	-0.000	0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Temperature	0.240***	0.228***	0.218***	0.240***	0.228***	0.218***	0.206***
	(0.049)	(0.049)	(0.048)	(0.048)	(0.049)	(0.048)	(0.057)
Frequency of rains	0.075**	0.074**	0.066**	0.074**	0.074**	0.066**	0.010
	(0.032)	(0.032)	(0.033)	(0.032)	(0.032)	(0.033)	(0.036)
Rain seasonality	0.029	0.019	0.038	0.028	0.018	0.038	0.032
	(0.033)	(0.034)	(0.035)	(0.033)	(0.034)	(0.035)	(0.041)
Extreme events	0.051	0.044	0.047	0.052	0.045	0.047	0.027
	(0.033)	(0.034)	(0.034)	(0.033)	(0.034)	(0.034)	(0.038)
Current suitability	0.107	0.088	0.006	-	-	-	-
	(0.220)	(0.225)	(0.261)				
Suitability 2050	0.020	0.002	-0.031	-	-	-	-
	(0.078)	(0.081)	(0.100)				
High exposure	-	-	-	-0.018	-0.011	0.003	-
				(0.034)	(0.034)	(0.039)	
Observations	882	882	882	882	882	882	882
Fixed effects at department	NO	YES	NO	NO	YES	NO	NO
Fixed effects at municipality	NO	NO	YES	NO	NO	YES	NO
Fixed effects at community	NO	NO	NO	NO	NO	NO	YES
R-squared	0.141	0.151	0.181	0.141	0.151	0.181	0.127
F	8.017	7.366	7.152	8.354	7.597	7.186	6.220
Pr > F	0	0	0	0	0	0	0

Note: The dependent variable is a dummy equals to 1 if the household has implemented at least one adaptation strategy to climate change. High exposure to climate change was built as a dummy equals to one if the change in suitability by 2050 is lower than -0.25. Marginal effects of the linear probability model are reported. Age was introduced in level and quadratic forms. Clustered standard error at community level in parenthesis, *** p<0.01, ** p<0.05, * p<0.1.



Graph 1: Predictions of the relative adaptation of coffee for Nicaragua in 2010 (current) and 2050 (large map), coefficient of variation (CV, small map to the left), consistency between models (small map to the right) and location of communities included in the sample. Map built from estimations described in Läderach et al. (2010) and Baca et al. (2014) and the GPS coordinates in the visited communities during field work.