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The Impacts of Climate Change on Farmers and Indigenous Peoples' Consumption: Evidence from Panama

Ambar Lineth Chavez Espinosa
Graduate School of Economics and Management, Tohoku University

Akira Hibiki
Graduate School of Economics and Management, Tohoku University

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The Impacts of Climate Change on Farmers and Indigenous Peoples' Consumption: Evidence from Panama

By AMBAR LINETH CHAVEZ ESPINOSA[1] AND AKIRA HIBIKI[2]

Abstract

Climate change is a significant challenge faced by tropical developing countries. While efforts have been made to support vulnerable socio-economic groups such as farmers and indigenous peoples, little is known about how climate change affects these groups. This paper provides empirical evidence by estimating the impact of weather shocks (high temperature, temperature shock, and flood) on households' total consumption and its components (food and non-food consumption) in Panama. The study aims to explore the heterogeneity of weather shocks' impacts, specifically between households of indigenous and non-indigenous peoples, and farmers and non-farmers, thus contributing to the literature on the effects of belonging to a minority and indigenous group when facing climate change impacts. By combining repeated cross-sectional data from surveys on 17,650 households with gridded climate data and flood events information for the years 1997, 2003, and 2008, the study examines if there are differences in the negative impact due to weather shocks between farmers and non-farmers or indigenous and non-indigenous households. The main findings are as follows: Firstly, higher temperature, temperature shock, and flood reduce consumption and their negative impact on food consumption is smaller than non-food consumption. Secondly, there are significant differences in the negative impact of heavy rain shocks between farmers and non-farmers. Furthermore, there are significant differences in the negative impact of weather shocks (higher temperature, temperature shock, and flood) on non-food consumption between indigenous and non-indigenous households, while there is no significant difference in total consumption and food consumption. Thirdly, the negative impacts of weather shocks on the consumption of poor households are less than those on the consumption of non-poor households. Hence, indigenous households are more vulnerable to climate change than farmers and poor households.

Keywords: Climate change, Indigenous peoples, Farmers, Weather shocks, Consumption, Vulnerability

JEL classification: D13, J15, O10, Q10, Q54

[1] Graduate School of Economics and Management, Tohoku University,
(E-mail: chavez.espinosa.ambar.lineth.s5@dc.tohoku.ac.jp)
[2] Graduate School of Economics and Management, Tohoku University, (E-mail: hibiki@tohoku.ac.jp))

I. Introduction

Tropical developing countries are especially vulnerable to the negative impacts of climate change due to high levels of poverty, inequality, and unfavorable climatic conditions. The frequency of extreme weather events such as floods, storms, and droughts, along with changes in temperature and precipitation patterns, exacerbate the challenges faced by impoverished communities (Nishio, 2021). This study examines the economic implications of climate change on agricultural productivity, with a focus on the impact on indigenous peoples who are among the poorest and most vulnerable to these changes. Discrimination, exploitation, and environmental hazards are some of the challenges faced by indigenous communities who may also be forced to migrate. In Panama, where 12% of the population is indigenous, 96.3% live in poverty, and their way of life and traditions are closely tied to natural resources, making them especially susceptible to the effects of climate change.

Current literature suggests that climate change has a disproportionate impact on low-income groups in various countries, including the African continent. Researchers have examined how farmers and poor households perceive negative trends in their consumption following climate shocks (Azzarri & Signorelli, 2019; Call, et al., 2019). However, these studies tend to focus primarily on poverty as a key factor contributing to climate vulnerability and do not take into account the potential influence of ethnic differences. Likewise, to identify how diversification of crops, investing more time in off-farm jobs, and migration could significantly influence the impact of climate change on poverty dynamics in rural households, Gao & Mills, (2018) analyze the implementation of coping strategies. Furthermore, Amare, et al., (2018) document the use of positive and negative rainfall shocks during the wet season to explain the negative impact on rural household consumption in Nigeria. Nevertheless, the inclusion of temperature shocks and rainfall shocks in either of both seasons could also affect agricultural productivity (Man, 2023).

While previous literature has focused on African countries, it is crucial to consider the unique context of Latin American countries, as they have their own cultural, social, and economic characteristics and a wide variety of weather conditions that may influence the perception of climate change. Despite increasing attention to climate change in Panama, there is no empirical economic study that examines how households respond to temperature and precipitation variations. Panama is an excellent case study as its agricultural sector has a low GDP share but comprises 16% of the country's labor force. Farmers in this sector are particularly vulnerable to weather variations, limiting their ability to invest in new technology and adaptation. Additionally, the most affected ethnic group by poverty in Panama is its indigenous peoples, who face significant social, political, and economic challenges, and rely heavily on agriculture and natural resources.

We contribute to the existing literature by providing empirical evidence on the impacts of the weather shocks (higher temperature, temperature shock, flood, etc.) on consumption and its composition (food consumption and non-food consumption) at the household level, addressing the consumption trade-offs that households make in order to maintain their overall welfare during periods of weather shocks. We especially, focus on the vulnerability of indigenous peoples and farmers to the weather shocks. Our main findings are: Firstly, higher temperatures, temperature shocks, and floods reduce consumption and such negative shock on food consumption is smaller than non-food consumption. Secondly, there are no significant differences in the negative impact of the weather shocks between farmers and non-farmers.

However, there are significant differences in the negative impact (higher temperature, temperature shock, and flood) on non-food consumption between indigenous households and non-indigenous households, while there is no significant difference in total consumption and food consumption. Thirdly, the negative impacts of the weather shocks on the consumption of poor households are less than those on the consumption of non-poor households.

The rest of the paper is organized as follows: Section II presents the socio-economic background of Panama's farmers and indigenous peoples. Section III describes the literature review. Section IV discusses the data and model. Section V presents estimation results. Section VI concludes.

II. Socio-economic background

Panama presents fast economic growth that helps reduce poverty and inequality. Nonetheless, the country was listed as the 4^{th} most unequal in Latin America in 2018. This economic growth can be mainly attributed to three sectors: Construction; Wholesale, Retail, and Repair; and Transport and Communications. And even though agriculture is the second-largest employer in Panama accounting for 16% of the total employment, its share within GDP dropped from 4.6% in 2005 to 2.5% in 2015. Moreover, the demand for non-skilled workers in the construction sector absorbed some of the labor released by agriculture (Hausmann, et al., 2016).

According to the Ministry of Environment of Panama, the variation in precipitation provokes a change in sowing and harvesting periods, meanwhile, the temperature rise helps the propagation of crop pests and diseases. As a result, the food safety of 52% of the rural population is threatened (Ministerio de Ambiente, 2019).

Researchers measure the economic implications of climate change on agricultural productivity at the national or regional level, which also aids in understanding the effects on people's well-being, particularly those living in rural regions. However, climate change affects nations around the world differently, with low-income countries being the most severely impacted. And when examining how climate change is affecting countries with higher inequality levels, it is discovered that the poor and vulnerable people are even more influenced (United Nations, 2016).

Indigenous peoples are particularly sensitive to climate change because they combine several traits that no other socioeconomic group possesses. First, they are among the poorest of the poor, accounting for around 15% of the world's poorest people. Second, 70 million indigenous peoples rely heavily on forests to meet their needs and despite only comprising 5% of the world's population, they are crucial to the sustainability of natural resources, where they safeguard 80% of the planet's biodiversity and 22% of the Earth's surface. Due to their extreme sensitivity to climate change, they encountered a substantial number of challenges, and if forced to migrate, they face the risk of discrimination, exploitation, and environmental hazards in their new locations. Furthermore, indigenous peoples' institutions and rights are usually ignored, which restricts their capacity to engage in decision-making, eliminates their assessments, and prevents them from contributing any viable solutions for boosting their economy. Which in consequence could lead to the loss of their traditional knowledge, practices, and ways of life (International Labour Office, 2017).

There are 7 indigenous groups in the Republic of Panama: The Ngäbe, Buglé, Guna, Emberá, Wounaan, Bri bri, and Naso. According to official statistics, 96.3% of Panama's indigenous population lives in poverty (84.8% in extreme poverty), and as of the 2010 national census, there were 417,559 indigenous peoples or 12% of the nation's overall population. Panama’s indigenous people are mostly located in 5 different regions alongside the country which are denominated as comarcas and comprise 1,7 million hectares. Each of these regions was recognized by different laws based on the constitutional rights of indigenous peoples. Moreover, the religion, traditions, and lifestyle of the indigenous peoples of Panama are highly connected to the use of natural resources. For instance, the main sources of income for the Naso and other indigenous populations in Panama are farming, fishing, and agriculture. Rivers are essential to the Emberá people's way of life and cosmology, whilst the Naso people are leading a massive international movement to protect the biodiverse flora and fauna in the jungle where they have lived for centuries. Additionally, some goods, like cacao, have been used in ceremonies and festivities throughout Central America for thousands of years and are fundamental to their culture and lifestyle (Sarsanedas, 2014).

According to the Climate Change Vulnerability Index Report released by the Ministry of Environment of Panama, places with a large indigenous population have a vulnerability value between 0.75 and 1, on a scale from 0 to 1, with 1 being assigned to the most vulnerable locations. This index is derived by taking into account factors such as the degree of poverty, the availability of public services, and infrastructure, as well as environmental and climatic factors like the type of soil, the amount of precipitation, the average temperature, and the frequency of floods and droughts. Most indigenous people live in areas that lack basic infrastructure, have a high concentration of multifaceted poverty, and have enhanced ecological sensitivity, which leads to a limited ability to adapt to climate change (Calderón, et al., 2021).

The Intertropical Convergence Zone, where the Republic of Panama is located, experiences heavy rainfall and high humidity from May to December. Except for the Caribbean basin, where precipitation is frequent nearly all year, the dry season, which lasts from January to April, features significantly less rainfall. The nation's water resources are a significant economic asset. For instance, the optimal operation of the Panama Canal, which contributes around 6% of Panama's GDP, depends on its network of watersheds. Additionally, hydropower accounts for 48% of Panama's electrical production (Perlman & Pava, 2019).

Extreme weather conditions are known to have a negative impact on the economy of Panama. The government reported $102 million in losses in 2016 from drought-related disasters, and $149 million in losses from flood damage in 2010, with the agriculture sector being the most severely impacted. Given the lack of a structure for disaster risk management and land use planning, together with the conditions of fast economic expansion and urbanization since the Panamanian administration of the Panama Canal in 2000, the risk from weather disasters has increased. There were 2717 natural disasters in the Republic of Panama from 1990 to 2013, of which 57% of them were floods, 17% were tropical storms or strong winds, and 15% were landslides. (Gordon, 2014).

III. Literature review

Due to low agricultural productivity in developing nations, the effects of abrupt changes in temperature and precipitation on agricultural activities are particularly important. In developing countries, the majority of farmers lack the necessary financial resources and physical infrastructures, such as an irrigation system, adequate storage space, and farm machinery, therefore their outcomes are largely dependent on weather variations (Call, et al., 2019). This scenario is common in Panama, where only 5% of farmers use technology to enhance their operations according to the 2010 Panama Agriculture Census.

There is an increasing number of studies that address the relationship between climate change and consumption in African countries, where the combination of certain climate conditions and the high presence of poverty has aggravated the climate-induced poverty trap. Azzarri and Signorelli (2019) found that floods in countries of Africa South of the Sahara, negatively affect farmers, more disproportionately smallholders, with a roughly 20% drop in per capita expenditure. In addition, they found that droughts represent a better outcome in West Africa and heat waves seem to be beneficial in Central Africa. On the other hand, some smallholders in Uganda benefit in the short term when they experienced above-average temperatures, although after a decade crop yield declines (Call, et al., 2019). Adaptation strategies are also implemented by some smallholders in Malawi where current and past weather patterns lead households to devote more time to maize cultivation, adopting improved maize seed varieties, while abandoning other potentially more remunerative opportunities elsewhere. They also reduce the application of productivity-enhancing inputs, such as fertilizer in response to adverse weather history (Sesmero, et al., 2017). These results suggest that adaptation and coping mechanisms are not always in the same direction, while some farmers might choose to use more technology and resources to keep producing the same kind of crops, others prefer to produce other varieties of crops which decreases the costs of some inputs.

Letta, et al. (2018) exhibit that one standard deviation rise in temperature anomalies reduces household per-adult total consumption growth by roughly 2.21% using a three-wave household longitudinal dataset encompassing the years 2008 to 2013 in Tanzania. They implement the interaction of weather shocks with poverty to provide insight into the heterogeneous impact of climate change in Tanzania, where most poor households depend on agricultural activities and experience the direct effects of climate change. On the contrary, not all farmers in Panama are poor, and not all the country's poor inhabitants work in agriculture. Hence, our study examines heterogeneity using the interactions between climate variables and dummy variables for agriculture and indigenous households.

Although previous studies by Azzarri and Signorelli (2019) and Letta et al. (2018) have examined the effect of weather shocks on total consumption and food consumption in African countries, the changes in the ratio between food and non-food consumption have not been thoroughly investigated. Our study aims to bridge this gap by exploring the consumption trade-offs that households make to maintain their overall welfare during times of weather shocks.

Previous studies focus on the negative effects experienced in rural areas, even though there is evidence that low-income inhabitants in urban areas of developing countries in Latin America also struggle to cope with climate abnormalities. Desbureaux and Rodella (2019) explored how droughts in metropolitan areas caused harm using data from 78 cities, including Panama City, and they found that droughts have contributed to a decrease in the probability of an active worker being employed, as well as the number of hours worked. They implied that this could be a result of electric shutdowns, due to Latin American countries' high dependence on hydropower, or it can be also explained by the increase in diarrhea, infections, and other conditions that are a consequence of the lack of drinkable water. Additional results also reveal that there was an 8% decrease in labor incomes for informal workers during droughts from 2005 to 2014. This study offers a more comprehensive understanding of the situation in Latin American countries and although there are close socioeconomic similarities among most of these countries, certain individual factors and weather patterns must be taken into account to fully comprehend how extreme weather events affect each country's population.

Our contribution is to understand the importance of preexisting socioeconomic factors such as ethnicity when responding to climate change. We found that being a farmer or belonging to an indigenous group in Panama increases susceptibility to the effects of temperature and precipitation variability. This reveals that contrary to studies done in African countries, poverty itself has little influence on how vulnerable people are to climate change.

IV. Data and Model

A. Data

In this study, we use Panama's Living Standards Measurement Surveys (LSMS) which were collected and administrated by the World Bank and the Ministry of Economics and Finance of Panama. They provide repeated cross-sectional data of 4876 households in the year 1997, 6032 in 2003, and 6742 in 2008. The objective of these surveys was to collect information on living conditions and determine an approximation of the poverty incidence in Panama. The questionnaires did not ask for the ethnicity of the surveyed, however, they ask for the householder's first language, which is a reliable proxy for indigenous ethnicity in this case (Fuentes Cordoba, 2019). After the year 1997, Panama presents several political division changes, for that reason, corregimientos[3] and districts from the years 2003 and 2008 were aggregated to match the political divisions presented in 1997.

In the Living Standard Measurements Surveys, the definition of head of household is: "habitual resident of the house that's recognized as the head by the other members of the house, given by the nature of his/her responsibilities, type of decisions that he/she has to take,

[3] Corregimientos are the administrative subdivisions of districts in Panama.

prestige, relationship within the family, economic reasons, or due to social and cultural traditions”. For that reason, we used household characteristics given their role and influence on the household's social and economic position.

Table 1. Summary statistics

Variables	Obs	Mean	SD	Min	Max
Consumption per capita (USD) [4]	17650	2750.28	3019.72	38.80	90159.89
Food consumption per capita (USD)	17588	913.31	711.232	6.49	12512.49
Non-food consumption per capita (USD)	17588	1838.77	2542.06	10.12	81265.46
No. of members per household	17650	4.07	2.46	1	25
Age of householder	17650	48.52	15.81	15	101
Male householder	17650	0.75	0.43	0	1
Householder years of education	17650	8.51	4.56	0	18
Members working per household	17650	1.55	1.09	0	10
Indigenous ethnicity	17650	0.09	0.28	0	1
Works in agriculture	17650	0.22	0.42	0	1
Lives in an urban area	17650	0.53	0.50	0	1
Lives in poverty	17650	0.30	0.46	0	1
Lives in a corregimiento that experienced a flood	17650	0.02	0.14	0	1
Monthly average temperature	17650	25.6	1.61	18.3	29.1
Temperature positive shock[5]	17650	0.11	0.31	0	1
Precipitation positive shock	17650	0.21	0.41	0	1
Precipitation negative shock	17650	0.01	0.11	0	1

Table 1 displays that the number of household members has a maximum of 25 people, this is common among indigenous households, in which a “typical” indigenous household there is an average of two-room with 5-6 members per room. Additionally, the minimum age for householders is 15 years old, there is a small number of cases where householders are less than 18 years old which is Panama’s legal majority of age. Thus, the distribution is mainly concentrated around the mean age. The percentage of indigenous people in the sample is 9%, which is close to the proportion of indigenous people in Panama’s total population during these years (Central Intelligence Agency, 2022). To measure the poverty line each year, LSMS uses consumption as an indirect measure of welfare, weighting total consumption by the regional price index. The general poverty line is calculated based on the extreme poverty line, and people below the extreme poverty line are individuals that can hardly meet their

4 All information for consumption per capita is provided in real value, 2010=100

5 Our study did not include a temperature negative shock variable as no negative temperature shock was observed during the years of analysis when using 1 standard deviation.

minimum calorie requirements even if they spent their entire resources on food consumption. The number of householders that work in the agriculture sector is 22% approximately, which is also not far from the real total population percent that was reported around these years (Hausmann, et al., 2016). Additional summary statistics for subsamples of farmers and indigenous peoples are provided in Appendix Tables A2 and A3.

We obtain climate data from the Climatic Research Unit (CRU) at the University of East Anglia Datasets. Since ground stations and satellite-based datasets have some drawbacks, climate scientists developed different kinds of gridded data products, which are a result of the interpolation among ground stations. Gridded datasets are usually used as a good source of temperature data for economic analysis because they adjust for issues like missing station data and elevation. (Letta, et al., 2018; Sesmero, et al., 2017). Nevertheless, like any other gridded dataset it faces challenges when estimating precipitation. In comparison to temperature, rainfall has a greater spatial variation therefore it is more difficult to interpolate. This issue is very common in middle-income and developing countries because of the lack of stations within a big number of gridded cells, although CRU provides a monthly global average of interpolated gridded temperature and precipitation data of over 4000 weather stations with a spatial resolution of 0.5° latitude by 0.5° longitude. Coordinates of corregimientos were used to link these gridded weather data to households' data. After comparing with other 2 different weather data sources (satellite and ground stations), CRU provided the most consistent and reliable results for this analysis.

To assess the impact of weather on household consumption, we used monthly average temperature data from the year before each survey. We then grouped this data into different temperature bins based on the distribution of monthly average temperatures for each corregimiento during the study period. The temperature bins we used were defined as follows: [18-22.9℃], [23-24.9℃], [25-26.9℃], and [27-29.1℃]. Daily temperatures in Panama can exceed 30 degrees Celsius. However, since we used average monthly temperature data, the maximum monthly temperature was 29.1℃. The frequency of corregimientos experiencing a range of temperatures is presented in Figure A1, as well as the spatial temperature distribution for the study years, shown in Figure A2.

Since previous years' monthly average temperature and precipitation do not necessarily account for historical variations or sudden weather changes. Similarly, to Amare, et al. (2018) we constructed dummy variables for positive and negative weather shocks to capture temperature and precipitation shocks as deviation from the 30-year average as follows:

$$\text{Positive weather shock} = 1 \text{ if } \left(\frac{W_{it-1} - \overline{W}_{it}}{W_i^{SD}}\right) > \sigma$$

$$\text{Negative weather shock} = 1 \text{ if } \left(\frac{W_{it-1} - \overline{W}_{it}}{W_i^{SD}}\right) < -\sigma$$

where W_{it-1} is the previous year's temperature or precipitation during the wet or dry season at the location of household i for year t. $\overline{W}_{it}$ is the historical average of temperature or precipitation during the wet or dry season for 30 years at the location of household i. W_i^{SD} is the standard deviation of temperature and precipitation during the dry or wet season at the location of household i (calculated over 30 years).

A positive weather shock is defined when the monthly average temperature or precipitation of either the wet or dry season of the previous year was (σ) standard deviation above the long-term average of their respective season, while a negative weather shock is defined when the monthly average temperature or precipitation of either the wet or dry season of the previous year was (σ) standard deviation below the long-term average of their respective season. To account for the fact that longer-term changes in temperature can have a more sustained impact on production and consumption, a value of (σ) = 1 is used for temperature shocks, which enables the capture of the effects of gradual temperature changes that are particularly relevant to the agricultural sector. In addition, a value of (σ) = 1.5 is used for precipitation shocks given the higher precipitation variability in tropical countries, thereby allowing for the measurement of the impact of events that could have a severe and immediate effect on agricultural production.

The information for floods used in this study is obtained by DesInventar.net which is a methodological tool that provides inventories for databases of damage, losses, and general effects of disasters. It contains the number of victims, people affected, and damage provoked by floods and other natural disasters in Panama within 1 year before each LSMS was taken (1997, 2003, 2008). To measure the impact of floods on income and consumption, many studies use the frequency of floods within an area without considering if there were people affected or not, accordingly, we first employ the dummy variable for floods being equal to one if any flood happens in a corregimiento without taking into consideration the economic losses or the number of people affected. The definition of people affected in DesInventar.net (2022) is "number of persons who suffer indirect or secondary effects associated with a disaster. These persons, different from "victims", suffer the impact of secondary effects of disasters for reasons such as deficiencies in the provision of public services, the hampering of trade and work, isolation, or their mental health may be affected". Since the purpose of this study is to provide evidence on how floods can affect households' consumption and because the presence of floods doesn't necessarily imply an economic impact on inhabitants of certain areas, in the main results we use a new dummy variable for floods considering the number of people that were affected directly and indirectly, where "Lives in a corregimiento that experienced flood" is equal to one if the flood affected more than 10% of the population that was living in this corregimiento within one year before each LSMS was collected.

Monthly precipitation data may not be sufficient to denote the presence of floods in some regions since multiple criteria such as the total quantity of rainfall over a period of time, the condition of the soil, the lack of vegetation, and the proximity to rivers must also be taken into account. By incorporating a flood dummy variable, we can more accurately examine how heavy rain affects consumption given pre-existing geological conditions of the area.

B. Model

To explore the impact of flood, temperature, and precipitation on total consumption, food consumption, and non-food consumption, we formulate the following equation as the base model.

$$\log(Y_{it}) = \beta_0 + \beta_1 X_{it} + \sum \beta_2 Wbin_{ct}^{b} + \beta_3 F_{it} + \beta_4 TS_{it} + \beta_5 Pns_{it} + \gamma Agri_i + \theta Ind_i + \mu_{dt} + T_c + u_{ict} \quad (1)$$

where Y_{it} denote outcome measures such as total consumption per capita, food consumption per capita, and non-food consumption per capita. In addition, household characteristics such as the number of members, age of the householder, number of members employed, householder education level, and occupation were also included (X_{it}). Bin variables were constructed using monthly average temperature ($Wbin_{ct}^{b}$), while dummy variables were used to indicate whether a household experienced a flood(F_{it}), temperature shock(TS_{it}), negative precipitation shock (Pns_{it}) or was an agricultural household ($Agri_i$) or belonged to an indigenous ethnicity (Ind_i). μ_{dt}, T_c and u_{ict} capture year by district effects, corregimiento fixed effects, and the error term. The inclusion of fixed effects controls for the time-variant heterogeneity across the districts.

Weather bin variables represent the number of months per year that the average temperature of a corregimiento was contained in a temperature band or “bin”. Average monthly temperature bin variables capture the relationship between temperature and consumption per capita. They can provide insights into how consumption per capita responds to variations in temperature across different temperature ranges. Temperature shocks, on the other hand, capture the short-term relationship between temperature and consumption per capita. They represent sudden, unexpected changes in temperature that may have an immediate impact on consumption per capita.

The flood variable captures the event occurrence, whereas a positive precipitation shock indicates a noteworthy deviation from anticipated precipitation levels. Although not a conclusive predictor of flooding, it can signify heavy rainfall events that saturate the soil, leading to instability and a heightened risk of landslides and soil erosion. Conversely, a positive precipitation shock can also signify an increase in the availability of water resources, benefiting industries reliant on water, such as agriculture and hydroelectric power generation.

We use consumption as our dependent variable because it can account for individuals’ welfare differences. While income estimations sometimes are not provided for informal workers or for those who rely on subsistence agriculture. Consumption measurements provided by the LSMS account for the annual consumption of food (both purchased and non-purchased, including self-consumption), housing (using an imputed value for self-owned housing), durable consumer goods, consumer goods, and service expenses, basic services (such as water, gas, and electricity), as well as health and education expenditures.

$$\log(Y_{it}) = \delta_0 + \sum \delta_1 Wbin_{ct}^{b} \times \pi_i + \sum \delta_2 Wbin_{ct}^{b} + \delta_3 F_{it} \times \pi_i + \delta_4 F_{it} + \delta_5 TS_{it} \times \pi_i + \delta_6 TS_{it} + \delta_7 Pns_{it} \times \pi_i + \delta_8 Pns_{it} + \delta_9 X_{it} + \gamma \pi_i + \mu_{dt} + T_c + u_{ict} \quad (2)$$

For alternative specification to capture the heterogenous effect of flood and weather variables by minority/non-minority and farmer/non-farmer, we used interaction terms of the dummy variable of interest (farmer, indigenous or poor), π_i, with the weather variables in equation (2).

V. Results

The baseline estimates from equation (1) are reported in Table 2. We find that temperatures between 27°C and 29.1°C have a significant negative influence on households' total consumption per capita, food consumption per capita, and non-food consumption per capita by 3.8 %, 4.4 %, and 3.3 %, respectively. Temperature shocks are significant with a negative sign for total consumption per capita and non-food consumption per capita, while it is not significant for food consumption per capita. They reduce non-food consumption to avoid a decrease in food consumption since food is more important than non-food. On the other hand, floods are significantly negative for total consumption per capita, food consumption per capita, and non-food consumption per capita. It should be noted that the negative impact on non-food consumption per capita is larger than food consumption per capita. Households reduce their non-food consumption to lessen the negative impact on food consumption due to flood shocks, similar to temperature shocks. However, due to the larger negative impact of flood shocks on food consumption, households are unable to fully offset its effects despite reducing their non-food consumption.

Table 2. Effect of climate change on households' consumptions

	Log total consumption per cap (USD)	Log food consumption per cap (USD)	Log non-food consumption per cap (USD)
Bin temperature 23°_24.9°C	-0.0044	-0.0071	-0.0097
	(0.0094)	(0.0097)	(0.0113)
Bin temperature 25°_26.9°C	-0.0080	-0.0082	-0.0113
	(0.0067)	(0.0072)	(0.0079)
Bin temperature 27°_29.1°C	-0.0386***	-0.0441***	-0.0334***
	(0.0100)	(0.0104)	(0.0122)
Temperature shock	-0.1503*	-0.0602	-0.2553***
	(0.0794)	(0.0781)	(0.0978)
Precipitation negative shock	0.0022	0.0683	-0.0815
	(0.1419)	(0.1260)	(0.1780)
Lives in a town that experienced a flood	-0.1916***	-0.1047**	-0.2553***
	(0.0484)	(0.0500)	(0.0582)
Farmer	-0.0410*	-0.0258	-0.0802***
	(0.0222)	(0.0222)	(0.0279)
Indigenous	-0.2790***	-0.1916***	-0.3935***
	(0.0235)	(0.0257)	(0.0286)
No. of members per household	-0.1597***	-0.1334***	-0.1788***
	(0.0025)	(0.0026)	(0.0030)
Male householder	0.1078***	0.0953***	0.1114***
	(0.0103)	(0.0106)	(0.0124)
Age of householder	0.0249***	0.0124***	0.0323***

	(0.0015)	(0.0016)	(0.0019)
Age of householder^2	-0.0002***	-0.0001***	-0.0002***
	(0.00001)	(0.00001)	(0.00001)
Householder years of education	0.0483***	0.0242***	0.0645***
	(0.0013)	(0.0013)	(0.0016)
Members working per household	0.0751***	0.0473***	0.0957***
	(0.0050)	(0.0049)	(0.0060)
Lives in an urban area	0.1978***	0.1161***	0.2555***
	(0.0162)	(0.0167)	(0.0201)
Observations	17650	17588	17588
R-squared	0.704	0.525	0.724
Adjusted R-squared	0.695	0.510	0.716
F	72.32***	32.5***	87.20***
df_m	541	541	541

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

Table 3 presents the findings on the heterogeneous impacts between farmers and non-farmers. The analysis indicates that temperature shocks and flood variables have a significant negative effect, while their interaction terms with the farm's dummy variable are insignificant. Our results show that floods decrease total consumption, food consumption, and non-food consumption, but we do not observe any statistical differences in the impacts between farmers and non-farmers. Notably, the negative impacts on total consumption and non-food consumption are larger than those on food consumption because of the same reason as is in the case of Table 2. The bin variable of 27~29.1 ℃ is significant with the negative sign. This indicates that higher prices caused by a reduction in crop production due to higher temperature reduces not only food consumption but also non-food and total consumption. It is worth mentioning that the interaction terms of this bin variable with the farmer's dummy variable for food expenditure are significantly positive indicating that such an impact on the farmer's food expenditure is smaller. This could be due to a variety of factors, such as greater access to food through agricultural production, the ability to store food for longer periods, and the decreased sales of their crop production to consume them by themselves.

Table 3. Heterogenous effects of climate change (farmers and non-farmers)

	Log total consumption per cap (USD)	Log food consumption per cap (USD)	Log non-food consumption per cap (USD)
Bin temperature 23°_24.9°C	-0.0003	-0.0050	-0.0028
	(0.0095)	(0.0098)	(0.0114)
Farmer # Bin temperature 23°_24.9°C	-0.0163***	-0.0081	-0.0258***
	(0.0062)	(0.0066)	(0.0075)
Bin temperature 25°_26.9°C	-0.0056	-0.0068	-0.0068
	(0.0069)	(0.0074)	(0.0081)
Farmer # Bin temperature 25°_26.9°C	-0.0056	-0.0040	-0.0101**
	(0.0039)	(0.0041)	(0.0048)
Bin temperature 27°_29.1°C	-0.0401***	-0.0487***	-0.0295**
	(0.0103)	(0.0107)	(0.0124)

Farmer # Bin temperature 27°_29.1°C	0.0059	0.0155***	-0.0088
	(0.0059)	(0.0060)	(0.0073)
Temperature shock	-0.1591**	-0.0746	-0.2552**
	(0.0811)	(0.0800)	(0.0998)
Farmer # Temperature shock	0.0291	0.0310	0.0051
	(0.0334)	(0.0331)	(0.0417)
Precipitation negative shock	0.0059	0.0603	-0.0480
	(0.1485)	(0.1290)	(0.1897)
Farmer # Precipitation negative shock	-0.0256	-0.0170	-0.0840
	(0.0750)	(0.0741)	(0.0964)
Lives in a town that experienced a flood	-0.1926***	-0.0961*	-0.2530***
	(0.0492)	(0.0499)	(0.0600)
Farmer # Lives in a town that experienced a flood	0.0158	-0.0467	0.0062
	(0.0829)	(0.0978)	(0.0998)
No. of members per household	-0.1599***	-0.1336***	-0.1791***
	(0.0025)	(0.0026)	(0.0030)
Male householder	0.1079***	0.0953***	0.1116***
	(0.0103)	(0.0106)	(0.0124)
Age of householder	0.0248***	0.0124***	0.0323***
	(0.0015)	(0.0016)	(0.0019)
Age of householder^2	-0.0002***	-0.0001***	-0.0002***
	(0.00001)	(0.00001)	(0.00001)
Householder years of education	0.0483***	0.0242***	0.0645***
	(0.0013)	(0.0013)	(0.0016)
Members working per household	0.0754***	0.0476***	0.0960***
	(0.0050)	(0.0049)	(0.0060)
Lives in an urban area	0.2000***	0.1182***	0.2582***
	(0.0162)	(0.0167)	(0.0201)
Observations	17650	17588	17588
R-squared	0.705	0.526	0.725
Adjusted R-squared	0.695	0.511	0.716
F	71.61***	32.29***	86.09***
df_m	547	547	547

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

Table 4 presents the results of the analysis of the heterogeneous impacts between indigenous and non-indigenous households. The results for the effects of temperature shocks and flood are similar to those in Table 3, indicating that they significantly reduce consumption and that there is no difference between indigenous households and non-indigenous households except for the impact of temperature shock on non-food consumption. Since indigenous households are generally poor, the share of their food consumption is higher. This is why they reduce non-food consumption to avoid a reduction in food consumption. We also find that the bin variable of 27~29.1°C is significantly negative for all types of consumption and the interaction term of the bin variable with the indigenous dummy variable is insignificant for food consumption but significantly negative for non-food consumption. This is because indigenous households are likely to reduce non-food consumption to avoid a reduction in food consumption as is in the case of temperature shock. Interestingly, precipitation negative shock capturing the impact of drought is not significant but the interaction term of the shock with the indigenous dummy variable for non-food is significantly negative only for non-food consumption but not for other consumption. This may be because indigenous households cannot adapt to the drought because of a lack of financial resources to mitigate its negative impact.

We examined the effect of heavy rainfall by substituting our flood variable with a precipitation positive shock in Tables A1 and A2. The results demonstrate that farmers experience larger negative impacts on their consumption, while indigenous peoples do not show any significant differences in the impact of heavy rainfall.

Table 4. Heterogenous effects of climate change (indigenous and non-indigenous peoples)

	Log total consumption per cap (USD)	Log food consumption per cap (USD)	Log non-food consumption per cap (USD
Bin temperature 23°_24.9°C	-0.0009	-0.0088	0.0001
	(0.0098)	(0.0100)	(0.0116)
Indigenous # Bin temperature 23°_24.9°C	-0.0328***	-0.0194	-0.0512***
	(0.0120)	(0.0127)	(0.0152)
Bin temperature 25°_26.9°C	-0.0074	-0.0118	-0.0058
	(0.0070)	(0.0075)	(0.0083)
Indigenous # Bin temperature 25°_26.9°C	0.0029	0.0113*	-0.0075
	(0.0061)	(0.0068)	(0.0074)
Bin temperature 27°_29.1°C	-0.0361***	-0.0474***	-0.0231*
	(0.0104)	(0.0107)	(0.0125)
Indigenous # Bin temperature 27°_29.1°C	-0.0163	-0.0005	-0.0338**
	(0.0125)	(0.0128)	(0.0154)
Temperature shock	-0.1343*	-0.0601	-0.2023**
	(0.0807)	(0.0793)	(0.0994)
Indigenous # Temperature shock	-0.0243	0.0293	-0.1411**
	(0.0537)	(0.0570)	(0.0662)
Precipitation negative shock 1.5	0.0076	0.0709	-0.0668
	(0.1419)	(0.1259)	(0.1784)
Indigenous # Precipitation negative shock 1.5	-0.0840	-0.1064	-0.3061**
	(0.1187)	(0.1297)	(0.1454)
Lives in a town that experienced a flood.	-0.1921***	-0.1156**	-0.2303***
	(0.0479)	(0.0491)	(0.0586)
Indigenous # Lives in town that experienced flood	0.0115	0.0577	-0.0958
	(0.0905)	(0.1075)	(0.1020)
No. of members per household	-0.1599***	-0.1334***	-0.1793***
	(0.0025)	(0.0026)	(0.0030)
Male householder	0.1073***	0.0949***	0.1108***
	(0.0103)	(0.0106)	(0.0124)
Age of householder	0.0249***	0.0124***	0.0323***

	(0.0015)	(0.0016)	(0.0019)
Age of householder^2	-0.0002***	-0.0001***	-0.0002***
	(0.00001)	(0.00001)	(0.00001)
Householder years of education	0.0484***	0.0241***	0.0647***
	(0.0013)	(0.0013)	(0.0016)
Members working per household	0.0755***	0.0474***	0.0967***
	(0.0050)	(0.0049)	(0.0060)
Lives in an urban area	0.1999***	0.1160***	0.2609***
	(0.0162)	(0.0167)	(0.0201)
Observations	17650	17588	17588
R-squared	0.705	0.526	0.725
Adjusted R-squared	0.695	0.510	0.716
F	71.71***	32.16***	87.13***
df_m	547	547	547

Robust standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. District, year, district x year fixed effects, and corregimiento fixed effects are included

In our study, we aimed to investigate whether poverty is the primary determinant of vulnerability to climate change. We used interaction terms of a poverty dummy variable with weather variables to evaluate the heterogeneous effects of weather on poverty. Our results, presented in Table 5, demonstrate that poor households with temperature shocks have a smaller negative impact on total and food consumption compared to Letta et al.'s (2018) study. However, the negative impact of precipitation shocks is larger on poor households, similar to what we found in Table 4. Since our poverty dummy variable reflects the effect perceived by poor farmers and indigenous peoples, we further analyzed the impact of climate change on non-farmers and non-indigenous households in Table A3. This allows us to account for the impact on households that do not directly depend on agricultural activities. The results show that these households do not have significant impacts from monthly temperature variations. Temperature shocks have a significant negative impact on non-agricultural non-indigenous households' consumption, plausibly due to higher food prices making it more difficult to afford sufficient quantities of food and other goods. However, poor households experience less negative impact from temperature shocks and floods than non-poor individuals, possibly due to some poor households having greater access to government assistance for severe floods and food fairs in their communities when prices increase. Overall, our study suggests that poverty in Panama does not necessarily render individuals vulnerable to temperature variations, and negative precipitation shocks do not seem to have a significant negative impact on consumption, contrary to previous literature's suggestions.

TABLE 5. Heterogenous effects of climate change (poor and non-poor)

	Log total consumption per cap (USD)	Log food consumption per cap (USD)	Log non-food consumption per cap (USD)
Bin temperature 23°_24.9°C	-0.0058	-0.0119	-0.0077
	(0.0081)	(0.0090)	(0.0101)
Poor # Bin temperature 23°_24.9°C	-0.0025	0.0070	-0.0135**
	(0.0046)	(0.0059)	(0.0059)
Bin temperature 25°_26.9°C	-0.0119**	-0.0136**	-0.0148**

	(0.0057)	(0.0066)	(0.0071)
Poor # Bin temperature 25°_26.9°C	0.0025	0.0076**	-0.0024
	(0.0026)	(0.0033)	(0.0034)
Bin temperature 27°_29.1°C	-0.0346***	-0.0434***	-0.0255**
	(0.0085)	(0.0094)	(0.0108)
Poor # Bin temperature 27°_29.1°C	0.0071*	0.0148***	-0.0037
	(0.0041)	(0.0049)	(0.0053)
Temperature shock	-0.1196*	-0.0617	-0.1784**
	(0.0639)	(0.0664)	(0.0878)
Poor # Temperature shock	0.0422*	0.0819***	-0.0188
	(0.0238)	(0.0273)	(0.0327)
Precipitation negative shock	0.0259	0.1244	0.0250
	(0.1057)	(0.1022)	(0.1436)
Poor # Precipitation negative shock	-0.0998*	-0.1292*	-0.2383***
	(0.0600)	(0.0660)	(0.0847)
Lives in town that experienced flood=1	-0.1966***	-0.1118**	-0.2413***
	(0.0427)	(0.0468)	(0.0540)
Poor # Lives in town that experienced flood	0.0446	0.0492	-0.0054
	(0.0485)	(0.0605)	(0.0662)
No. of members per household	-0.1080***	-0.0889***	-0.1215***
	(0.0021)	(0.0024)	(0.0026)
Male householder	0.0718***	0.0657***	0.0694***
	(0.0091)	(0.0097)	(0.0111)
Age of householder	0.0168***	0.0057***	0.0234***
	(0.0013)	(0.0015)	(0.0016)
Age of householder^2	-0.0001***	-0.00001***	-0.0002***
	(0.00001)	(0.00001)	(0.00001)
Householder years of education	0.0364***	0.0138***	0.0518***
	(0.0011)	(0.0012)	(0.0014)
Members working per household	0.0439***	0.0207***	0.0615***
	(0.0041)	(0.0043)	(0.0051)
Lives in an urban area	0.1179***	0.0459***	0.1732***
	(0.0135)	(0.0149)	(0.0173)
Observations	17650	17588	17588
R-squared	0.783	0.612	0.786
Adjusted R-squared	0.776	0.599	0.779
F	112.93***	48.82***	115.42***
df_m	546	546	546

Robust standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. District, year, district x year fixed effects, and corregimiento fixed effects are included.

VI. Conclusion

The empirical evidence on the vulnerability of indigenous and farmer households is important to consider effective solutions. Indigenous peoples of Panama who depend heavily on agriculture view the effects of climate change differently from other socioeconomic groups. They are one of the groups in Panama most at risk from climate change due to their cultural dependence on natural resources, lack of government support, and several social adversities. Also, farmers encounter numerous difficulties while attempting to adapt to and execute the usage of technology at a time when agricultural productivity is continuously declining and preventing them from escaping the poverty cycle. However, few previous studies have discussed these issues. Therefore, in this study, we explore how the weather shocks (temperature shock, precipitation shock, flood, etc.) affect consumption and its composition (total consumption, food consumption, and non-food consumption) and how heterogenous the impact of the shocks is between farmers and non-farmers, indigenous people and non-indigenous people, and poor household and non-poor households.

Our main findings are threefold. Firstly, higher temperatures, temperature shock, and floods reduce consumption and such negative shock on food consumption is smaller than non-food consumption. This is because households try to mitigate the negative impact on food consumption by reducing non-food consumption since food is more important. Secondly, there is no significant difference in the negative impact of the weather shocks between farmers and non-farmers. However, there are significant differences in the negative impact (higher temperature, temperature shock, and flood) on non-food consumption between indigenous households and non-indigenous households, while there is no significant difference in total consumption and food consumption. This may occur since indigenous households, who are poorer, would like to shield their food consumption by reducing non-food consumption more. Therefore, indigenous households are vulnerable to weather shocks, though farmer's households are not. Thirdly, the negative impacts of the weather shocks on the consumption of poor households are less than those on the consumption of non-poor households. This is likely to be because of the financial support from the government which targeted poor households' functions effectively.

From the above evidence, indigenous households are more vulnerable to climate change than farmers and poor households. Therefore, more attention should be paid to indigenous households for public support to reduce the risk of climate change.

References

Amare, M., Jensen, N. D., Shiferaw, B. & Denno Cissé, J., 2018. Rainfall shocks and agricultural productivity: Implication for rural household consumption. *Agricultural Systems*, Volume 166, pp. 79-89.

Azzarri, C. & Signorelli, S., 2019. Climate and poverty in Africa South of Sahara. *World Development 125.*

Calderón, A., Francisco, N. & López, R., 2021. *Índice de Vulnerabilidad al Cambio Climático de la República de Panamá,* s.l.: Ministerio de Ambiente.

Call, M., Gray, C. & Jagger, P., 2019. Smallholder responses to climate anomalies in rural Uganda. *World Development 115,* pp. 132-144.

Central Intelligence Agency, 2022. *The World Factbook, Panama.* [Online]
Available at: https://www.cia.gov/the-world-factbook/countries/panama/
[Accessed 2022].

Dell, M., Jones, B. F. & Olken, B. A., 2014. What do we learn from the weather? The new climate-economy literature. *Journal of Economic Literature 52(3),* pp. 740-798.

Desbureaux, S. & Rodella, A.-S., 2019. Drought in the city: The economic impact of water scarcity in Latin. *World Development 114,* pp. 13-27.

Gao, J. & Mills, B. F., 2018. Weather Shocks, Coping Strategies, and Consumption Dynamics in Rural Ethiopia. *World Development,* Volume 101, pp. 268-283.

Gordon, C., 2014. *Caracterización de la ocurrencia e impacto por desastres de origen natural en Panamá. 1990-2013,* Panama: Universidad Santa María la Antigua.

Guerra, J., 2020. *Pobreza e Indigencia por ingreso,* Panama: Panama's Ministry of Economics and Finance.

Hausmann, R., Espinoza, L. & Santos, M. A., 2016. *Shifting Gears: A Growth Diagnostic of Panama,* s.l.: Working Papers, Center for International Development at Harvard University.

International Labour Office, 2017. *Indigenous peoples and climate change*, Geneva: International Labour Organization.

Letta, M., Montalbano, P. & Tol, R. S., 2018. Temperature shocks, short-term growth, and poverty thresholds. *World Development 112,* pp. 13-32.

Macchi, M. et al., 2008. *Indigenous and Traditional Peoples and Climate Change, Issues Paper,* s.l.: International Union for Conservation of Nature.

Man, L., 2023. Adaptation to expected and unexpected weather fluctuations: Evidence from Bangladeshi smallholder farmers. *World Development,* Volume 161, p. 106066.

Ministerio de Ambiente, 2019. *Tercera Comunicación Nacional de Panamá sobre cambio climático,* s.l.: UNDP.

Natura, 2017. *Adapting to climate change through integrated water management in Panama,* Washington: Adaptation Fund.

Nishio, A., 2021. *When poverty meets climate change: A critical challenge that demands cross-cutting solutions. World Bank Blogs.* [Online]
Available at: https://blogs.worldbank.org/climatechange/when-poverty-meets-climate-change-critical-challenge-demands-cross-cutting-solutions
[Accessed 2022].

Pearce, F., 2021. *Forest Defenders: A Panamanian Tribe Regains Control of Its Lands.* [Online]
Available at: https://e360.yale.edu/features/forest-defenders-a-panamanian-tribe-regains-control-of-its-lands
[Accessed 24 October 2022].

Perlman, G. & Pava, P., 2019. *Diversificación de la matriz energética de Panamá,* Panama: Centro de Incidencia Ambiental de Panamá (CIAM).

Sarsanedas, J., 2014. *Reflections from the Ngäbe-Buglé region: Food security or food sovereignty?* [Online]
Available at: https://www.envio.org.ni/articulo/4942
[Accessed 24 October 2022].

Sesmero, J., Ricker-Gilbert, J. & Cook, A., 2017. How do African farm households respond to changes in current and past weather patterns? A structural panel data analysis from Malawi. *American Journal of Agricultural Economics 100(1),* pp. 115-144.

Taraz, V., 2018. Can farmers adapt to higher temperatures? Evidence from India. *World Development,* Volume 112, pp. 205-219.

United Nations Office for disaster risk reduction, n.d. *UNDRR DesInventar.* [Online]
Available at: https://www.desinventar.net/
[Accessed 2022].

United Nations, 2016. *World Economic and Social Survey, Climate Change Resilience,* New York: United Nations.

Wetlands International, 2019. *Living with water & wetlands: flood risk reduction in Panama City.* [Online]
Available at: https://www.wetlands.org/casestudy/living-water-wetlands-flood-risk-reduction-panama-city/
[Accessed 14 November 2022].

World Bank, 2022. *Data Bank World Development Indicators.* [Online]
Available at: https://databank.worldbank.org/source/world-development-indicators
[Accessed 2022].

VII. Appendix

Table A1. Heterogenous effects of climate change (farmers and non-farmers)

	Log total consumption per cap (USD)	Log food consumption per cap (USD)	Log non-food consumption per cap (USD)
Bin temperature 23°_24.9°C	-0.0005	-0.0048	-0.0026
	(0.0096)	(0.0099)	(0.0114)
Farmer # Bin temperature 23°_24.9°C	-0.0132**	-0.0046	-0.0228***
	(0.0063)	(0.0067)	(0.0076)
Bin temperature 25°_26.9°C	-0.0068	-0.0082	-0.0080
	(0.0069)	(0.0074)	(0.0082)
Farmer # Bin temperature 25°_26.9°C	-0.0054	-0.0030	-0.0098**
	(0.0040)	(0.0041)	(0.0048)
Bin temperature 27°_29.1°C	-0.0423***	-0.0502***	-0.0321***
	(0.0103)	(0.0107)	(0.0124)
Farmer # Bin temperature 27°_29.1°C	0.0101*	0.0203***	-0.0047
	(0.0060)	(0.0061)	(0.0075)
Temperature shock	-0.1578*	-0.0638	-0.2438**
	(0.0815)	(0.0802)	(0.1014)
Farmer # Temperature shock	0.0112	0.0054	-0.0121
	(0.0344)	(0.0344)	(0.0428)
Precipitation negative shock	-0.0054	0.0691	-0.0333
	(0.1504)	(0.1305)	(0.1946)
Farmer # Precipitation negative shock	-0.0599	-0.0582	-0.1222
	(0.0752)	(0.0746)	(0.0967)
Precipitation positive shock	-0.0548**	-0.0145	-0.0477
	(0.0273)	(0.0267)	(0.0338)
Farmer # Precipitation positive shock	-0.0648**	-0.0946***	-0.0644*
	(0.0280)	(0.0289)	(0.0351)
All controls	YES	YES	YES
Observations	17650	17588	17588
R-squared	0.705	0.526	0.725
Adjusted R-squared	0.695	0.511	0.716
F	71.45***	32.28***	85.72***

Robust standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. District, year, district x year fixed effects, and corregimiento fixed effects are included. These results include a precipitation positive shock variable instead of a flood dummy variable.

Table A2. Heterogenous effects of climate change (indigenous and non-indigenous peoples)

	Log total consumption per cap (USD)	Log food consumption per cap (USD)	Log non-food consumption per cap (USD)
Bin temperature 23°_24.9°C	-0.0012	-0.0089	-0.0006
	(0.0098)	(0.0100)	(0.0117)
Indigenous # Bin temperature 23°_24.9°C	-0.0301**	-0.0180	-0.0473***
	(0.0119)	(0.0127)	(0.0152)
Bin temperature 25°_26.9°C	-0.0083	-0.0125*	-0.0076
	(0.0071)	(0.0075)	(0.0083)
Indigenous # Bin temperature 25°_26.9°C	0.0019	0.0106	-0.0071
	(0.0060)	(0.0067)	(0.0073)
Bin temperature 27°_29.1°C	-0.0378***	-0.0482***	-0.0259**
	(0.0103)	(0.0107)	(0.0125)
Indigenous # Bin temperature 27°_29.1°C	-0.0109	0.0029	-0.0260*
	(0.0127)	(0.0130)	(0.0157)
Temperature shock	-0.1452*	-0.0653	-0.2113**
	(0.0816)	(0.0797)	(0.1017)
Indigenous # Temperature shock	-0.0454	0.0090	-0.1607**
	(0.0539)	(0.0570)	(0.0663)
Precipitation negative shock	-0.0035	0.0772	-0.0624
	(0.1453)	(0.1285)	(0.1847)
Indigenous # Precipitation negative shock	-0.1399	-0.1465	-0.3814***
	(0.1204)	(0.1319)	(0.1474)
Precipitation positive shock	-0.0576**	-0.0211	-0.0524
	(0.0268)	(0.0262)	(0.0334)
Indigenous # Precipitation positive shock	-0.0750	-0.0632	-0.1159
	(0.0638)	(0.0680)	(0.0783)
All controls	YES	YES	YES
Observations	17650	17588	17588
R-squared	0.704	0.526	0.725
Adjusted R-squared	0.695	0.510	0.716
F	71.69***	32.23***	86.96***

Robust standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. District, year, district x year fixed effects, and corregimiento fixed effects are included. These results include a precipitation positive shock variable instead of a flood dummy variable.

Table A3. Heterogenous effects of climate change (poor and non-poor)

	Log total consumption per cap (USD)	Log food consumption per cap (USD)	Log non-food consumption per cap (USD)
Bin temperature 23°_24.9°C	-0.0012	-0.0081	-0.0012
	(0.0134)	(0.0147)	(0.0153)
Poor # Bin temperature 23°_24.9°C	-0.0019	0.0066	-0.0082
	(0.0060)	(0.0084)	(0.0075)
Bin temperature 25°_26.9°C	-0.0054	-0.0037	-0.0085
	(0.0120)	(0.0135)	(0.0134)
Poor # Bin temperature 25°_26.9°C	0.0024	0.0064	-0.0015
	(0.0034)	(0.0048)	(0.0042)
Bin temperature 27°_29.1°C	-0.0111	-0.0259	0.0024
	(0.0154)	(0.0173)	(0.0177)
Poor # Bin temperature 27°_29.1°C	0.0037	0.0084	-0.0010
	(0.0054)	(0.0070)	(0.0067)
Temperature shock	-0.2766***	-0.2547**	-0.3193***
	(0.1001)	(0.1135)	(0.1226)
Poor # Temperature shock	0.0794**	0.0904**	0.0778*
	(0.0322)	(0.0398)	(0.0421)
Precipitation negative shock	-0.1459	-0.0250	-0.2994
	(0.1526)	(0.1216)	(0.2223)
Poor # Precipitation negative shock	-0.0009	-0.0688	0.0326
	(0.0973)	(0.1054)	(0.1497)
Lives in town that experienced flood=1	-0.1785***	-0.0702	-0.2306***
	(0.0484)	(0.0513)	(0.0617)
Poor # Lives in town that experienced flood=1	0.1884***	0.2431***	0.0832
	(0.0591)	(0.0741)	(0.0890)
Observations	13028	12981	12981
R-squared	0.692	0.495	0.691
Adjusted R-squared	0.680	0.474	0.679

Robust standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Results are provided excluding farmers and indigenous peoples.

Table A4. Summary statistics (Farmers)

Variables	Obs	Mean	SD	Min	Max
Consumption per cap (USD)	3942	1361.	1608.99	38.80	28312.11
Food consumption per cap (USD)	3932	625.02	510.94	12.63	5630.75
Non-food consumption per cap (USD)	3932	734.75	1291.02	10.47	27686.11
No. of members per household	3942	4.68	3.0	1	24
Age of householder	3942	48.83	14.91	16	95
Male householder	3942	.95	0.20	0	1
Householder's years of education	3942	5.39	3.46	0	18
Members working per household	3942	1.82	1.13	0	10
Indigenous ethnicity	3942	0.21	0.41	0	1
Lives in an urban area	3942	0.07	0.26	0	1
Lives in poverty	3942	0.62	0.48	0	1
Lives in a corregimiento that experienced a flood	3942	0.02	0.13	0	1
Monthly average temperature 1 year	3942	25.27	2.04	18.3	29.1
Temperature positive shock	3942	0.19	0.39	0	1
Precipitation positive shock	3942	0.27	0.44	0	1
Precipitation negative shock	3942	0.03	0.17	0	1

Table A5. Summary statistics (indigenous peoples)

Variables	Obs	Mean	SD	Min	Max
Consumption per cap (USD)	1520	725.69	856.15	38.80	12921.52
Food consumption per cap (USD)	1513	384.18	368.55	11.35	3706.41
Non-food consumption per cap (USD)	1513	339.06	580.21	10.12	10638.11
No. of members per household	1520	6.97	3.77	1	25
Age of householder	1520	45.76	14.11	16	90
Male householder	1520	.84	0.36	0	1
Householder years of education	1520	4.31	4.33	0	18
Members working per household	1520	2.06	1.48	0	10
Works in agriculture	1520	0.55	0.49	0	1
Lives in an urban area	1520	0.15	0.35	0	1
Lives in poverty	1520	0.86	0.34	0	1
Lives in a corregimiento that experienced a flood	1520	0.04	0.18	0	1
Av. monthly temperature 1 year	1520	24.43	2.50	18.3	28.7
Temperature positive shock	1520	0.25	0.43	0	1
Precipitation positive shock	1520	0.19	0.39	0	1
Precipitation negative shock	1520	0.07	0.25	0	1

Figure A1. Frequency of monthly average temperature by corregimientos in 3 years period.

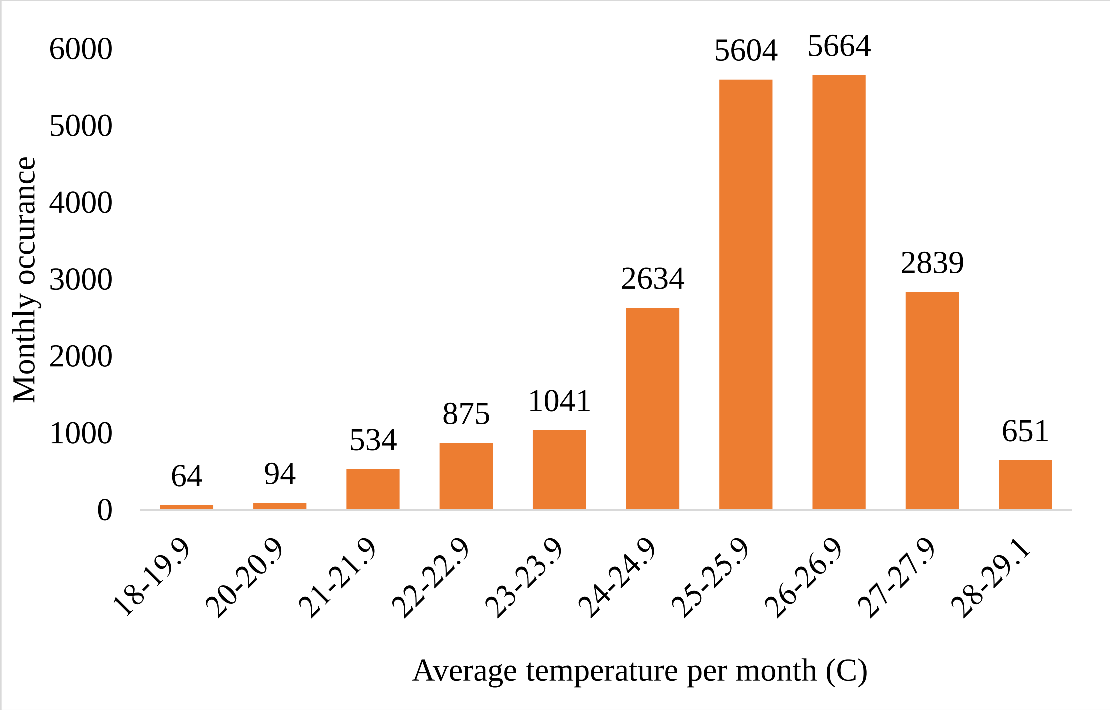
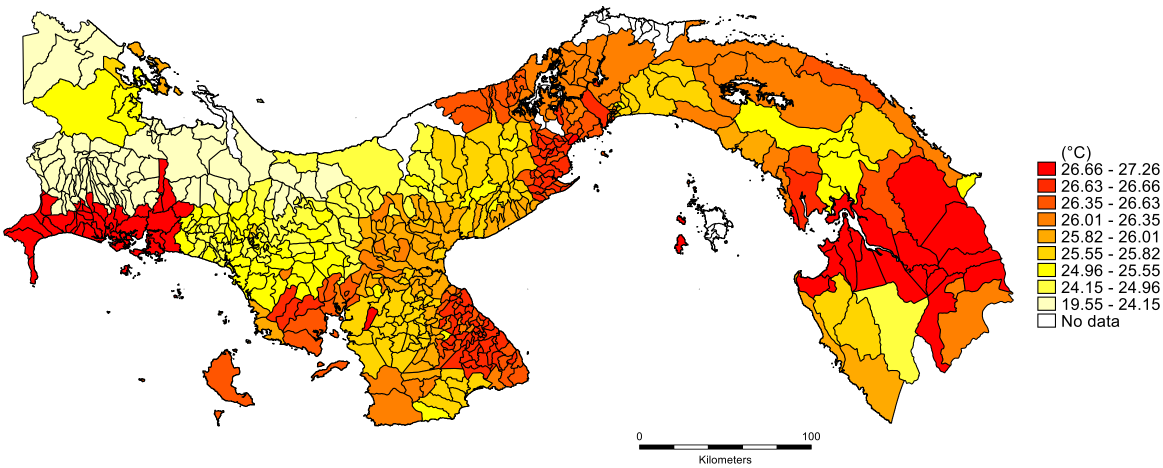


Figure A2. Annual average temperature (°C) years 1997, 2003, and 2008, in each corregimiento.



Note: 631 corregimientos are considered based on Panama's 2010 census.

Figure A3. Frequency of floods in years 1997, 2003, and 2008 by the proportion of people affected in each corregimiento.

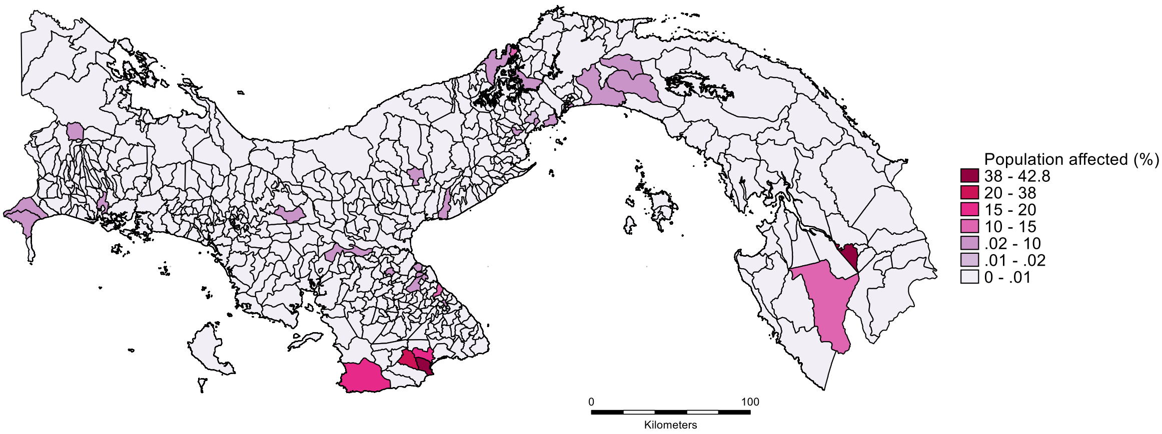


Figure A4. Percentage of farmer households by corregimiento (LSMS's 1997, 2003,2008)

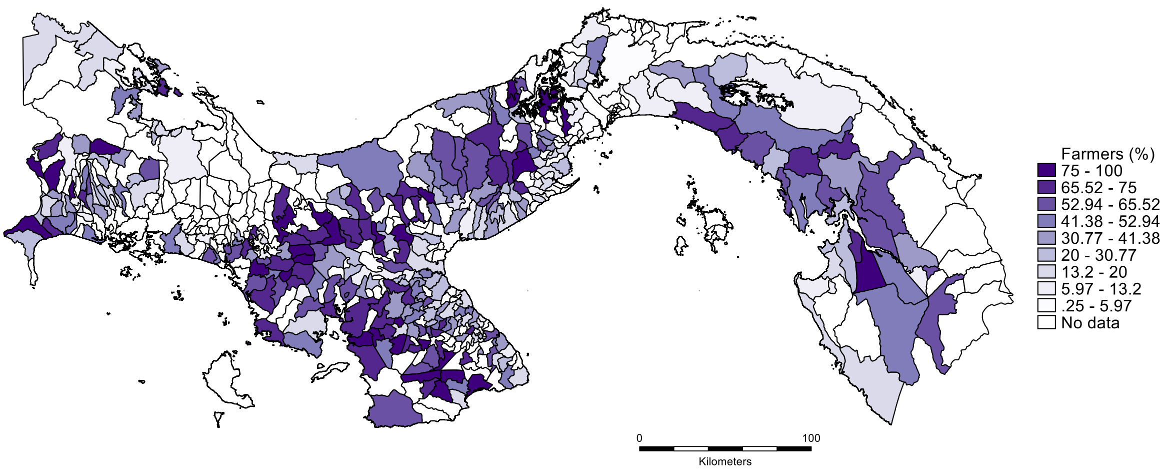


Figure A5. Percentage of indigenous households by corregimiento (LSMS's 1997, 2003,2008)

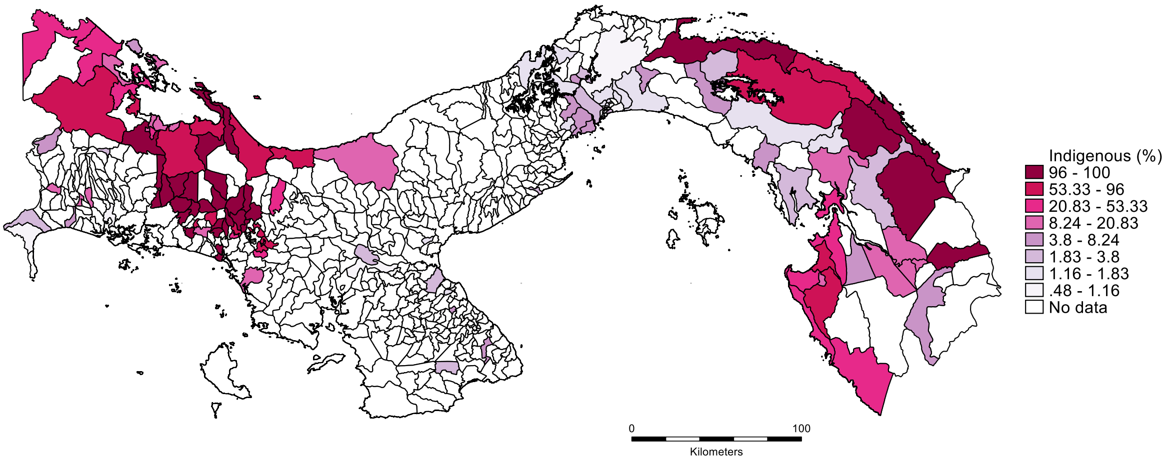


Figure A6. Percentage of poor households by corregimiento (LSMS's 1997, 2003,2008)