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Heterogeneous Effects of Weather Shocks on Food Prices in a Country with Diverse Agriculture*

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Abstract

We study how extreme weather shocks affect food prices in Colombia, a country with exceptional geographic and agricultural diversity. We exploit detailed information on production networks and wholesale prices of 40 crops over a nine-year period, as well as granular rainfall and temperature data, to estimate the local (crop and market-level) and global (countrywide) effects of weather shocks. Our findings reveal that global shocks drive most of the price effects, with local effects remaining small and often statistically insignificant. During El Niño episodes, global high-temperature and low-precipitation shocks are the main drivers of price increases, whereas during La Niña episodes, global high-precipitation and low-temperature shocks dominate. We also find very heterogeneous effects across crops. A machine-learning analysis reveals that this heterogeneity is driven primarily by farm-level characteristics, such as access to electricity, irrigation infrastructure, credit, and technical assistance, rather than by geographic factors. Crucially, the key predictors of price sensitivity differ substantially across shock types, suggesting that effective policies to reduce weather-induced food price volatility must be tailored to the specific risks faced by different crops.

Keywords: Weather shocks, food prices, agriculture, climate change, Colombia.
JEL Classification: O13, O54, Q10, Q18, Q54

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Efectos Heterogéneos de los Choques de Clima sobre los Precios de Alimentos en un País con Agricultura Diversa*

Camilo Bohorquez-Penuela, Leonardo Bonilla-Mejía, Anabelle Couleau, y Alexander Almeida

Resumen

Estudiamos cómo los choques climáticos afectan los precios de los alimentos en Colombia, un país con una excepcional diversidad geográfica y agrícola. Utilizamos información detallada sobre redes de producción y precios mayoristas de 40 cultivos durante un período de nueve años, así como datos de precipitación y temperatura de alta resolución espacial, para estimar los efectos locales (a nivel de cultivo y mercado) y globales (a nivel nacional) de los choques climáticos. Nuestros hallazgos revelan que los choques globales explican la mayor parte de los efectos sobre los precios, mientras que los efectos locales permanecen reducidos y, con frecuencia, no son estadísticamente significativos. Durante los episodios de El Niño, los choques globales asociados con altas temperaturas y baja precipitación constituyen los principales impulsores de los aumentos de precios, mientras que durante los episodios de La Niña predominan los choques globales de alta precipitación y bajas temperaturas. También encontramos una marcada heterogeneidad en los efectos entre cultivos. Un análisis basado en técnicas de aprendizaje de máquinas revela que esta heterogeneidad está determinada principalmente por características a nivel de finca, tales como el acceso a electricidad, infraestructura de riego, crédito y asistencia técnica, más que por factores geográficos. No obstante, estos predictores difieren sustancialmente entre tipos de choques, lo que sugiere que las políticas destinadas a reducir la volatilidad de los precios de los alimentos inducida por el clima deben adaptarse a los riesgos específicos que enfrenta cada cultivo.

Palabras clave: Choques climáticos, precios de alimentos, agricultura, cambio climático, Colombia
Clasificación JEL: O13, O54, Q10, Q18, Q54

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1 Introduction

Agriculture will be increasingly affected by weather shocks and climate change (IPCC, 2014), with potentially important effects on food prices and inflation (Abril-Salcedo et al., 2020, De Winne and Peersman, 2021, Heinen et al., 2019, González-Molano et al., 2006). This is a crucial problem for developing countries, where the incidence of food prices on inflation and poverty is considerably higher (Walsh, 2011). Moreover, tropical countries are expected to experience larger impacts from climate change, including higher temperatures and more volatile rainy seasons, with consequent reductions in soil moisture, alterations in growing period length, and increases in invasive weed species and plant sterility (Hertel and Lobell, 2014, Ortiz-Bobea et al., 2021).

Most of the existing literature on weather shocks and food prices focuses on aggregated price measures, omitting potential variation across regions and crops (González-Molano et al., 2006, Abril-Salcedo et al., 2020, Lemoine, 2018, Carter et al., 2018). The evidence on the direct impact of climate change on crop yields and productivity is mostly based on individual crops, and particularly grains, neglecting the relevance of tubers, fruits, and vegetables in the diet of vulnerable populations in developing countries (Carter et al., 2018, Ortiz-Bobea, 2021). A similar gap exists in studies on indirect effects and adaptation impacts (Burke and Emerick, 2016), as well as alternative mechanisms such as market access disruptions (Colon et al., 2021) and stock-holding anticipation (Letta et al., 2022).[1]

This paper assesses the heterogeneous impact of weather shocks on food prices, focusing on variation across regions and crops. Evidence is based on Colombia, a country with

[1]The literature on adaptation impacts is relatively recent and shows how farmers adapt inputs to attenuate the impact of climate change, including fertilizers and pesticides use (Bareille and Chakir, 2023), acreage adjustments through expansion or crop switching (Cui, 2020), or planting date adjustment (Cui and Xie, 2022, Ahmed et al., 2023).

exceptional geographical and agricultural diversity, where the impact of weather shocks is expected to be highly heterogeneous across both dimensions. We use detailed information on agricultural production and prices from 40 crops sold in 20 wholesale centers, reanalysis weather data, and crop characteristics from an agricultural census. We measure both precipitation and temperature shocks at the municipal level, based on deviations from historical distributions, and compute these shocks by product and market based on baseline supply networks.[2]

In this paper, we estimate the short-term impact on wholesale prices of both local (crop and market-level) and global (countrywide) precipitation and temperature shocks. Our baseline specification jointly estimates these two types of effects within a single regression model that includes, for each crop and wholesale market, the battery of local weather shock variables alongside their nationwide averages, which capture the aggregate weather conditions prevailing across all producing regions of the country in each period. Local and global effects are separately identified because they exploit distinct and orthogonal sources of variation: local effects are identified from cross-sectional differences in weather exposure across crops and markets within each period, while global effects are identified from period-to-period changes in nationwide average weather conditions. Both sets of coefficients are estimated controlling for crop and market fixed effects, which absorb time-invariant differences in price levels and production conditions across products and destinations. As a robustness check, we also implement the two-step procedure of Galiani and Porto (2010) and Cruces et al. (2018), which estimates local effects in a first-stage regression with time fixed effects and recovers global effects by regressing the estimated time fixed effects on nationwide average weather shocks in a second stage. This more saturated specification absorbs yields consistent results.

[2]Hereafter, we refer to *markets* as the 20 main wholesale centers in Colombia, each of which is supplied by a network of crop-producing municipalities. Sections 4 and 5 explain the identification of these networks.

There are three main findings. First, most of the price effects of weather shocks come from global events, while local effects are small and sometimes statistically insignificant. This reflects the importance of El Niño and La Niña phenomena during our study period, which affected vast geographic areas simultaneously and limited the ability of domestic spatial arbitrage to smooth prices. Second, decomposition exercises reveal that global high-temperature and low-precipitation shocks are the primary drivers of price increases during El Niño episodes, whereas global high-precipitation and low-temperature shocks dominate wholesale price spikes during La Niña events. Third, there is significant variation in price effects across crops. We distinguish between perennial crops, those with growing cycles of one year or more that provide multiple harvests without replanting, such as plantain, lulo, and blackberry, and non-perennial crops, which have shorter cycles of three to six months and provide a single harvest, such as potato, tomato, and maize. For non-perennial crops, excessive rainfall drives the largest aggregate price increases, whereas perennial crops exhibit greater vulnerability to extended droughts and extreme low-temperature anomalies.

We further explore the heterogeneous effects across crops with a machine learning analysis that identifies farm-level geographic and technical characteristics that predict crop-level price sensitivity. A key finding is that no single farm characteristic consistently predicts price sensitivity across all weather risks: the set of relevant predictors shifts substantially depending on the type and direction of the shock. For high precipitation shocks, access to electricity and farm size are the strongest predictors, with electricity access negatively associated with price sensitivity. For low precipitation and temperature shocks, the dominant predictors shift toward access to artificial water sources, technical assistance, and distance to market, reflecting the distinct adaptation mechanisms relevant for drought and heat conditions. This finding reinforces the complex cross-crop heterogeneity observed in our aggregate regressions and underscores that effective policies to reduce weather-induced food price volatility must be tailored to the specific risks faced by different crops.

The paper contributes to the literature on the impact of weather shocks on food prices and inflation. While most previous studies rely on aggregate price data or focus on a limited number of crops (González-Molano et al., 2006, Abril-Salcedo et al., 2020, Lemoine, 2018, Carter et al., 2018, Ortiz-Bobea, 2021), we provide new evidence on the heterogeneity of these effects across two key dimensions: geography and crop type. Our results indicate that, even though Colombian agriculture exhibits important geographical and regional variation, price heterogeneity across the geographic dimension remains limited. In contrast, there is substantial heterogeneity across crops, and our machine learning analysis identifies the farm-level characteristics that predict this variation, including access to electricity, irrigation infrastructure, credit, and technical assistance.

The paper is also among the first in the food price literature to jointly estimate the effects of precipitation and temperature shocks on wholesale prices, documenting that temperature shocks constitute an independent and quantitatively important channel of weather-induced price variation, particularly during ENSO episodes. Furthermore, by combining granular production network data with reanalysis weather data, we construct crop- and market-specific exposure measures that reflect the actual geographic structure of each crop's supply network, more accurately capturing the weather conditions experienced by the farms that supply each market than approaches based on the location of wholesale markets alone.

More broadly, our results contribute to the growing literature on the impact of climate change on agriculture (Deschênes and Greenstone, 2007, Dell et al., 2014, Burke and Emerick, 2016, Chen and Gong, 2021), with new evidence from a middle-income tropical country that is underrepresented in this literature. Colombia's exceptional geographic and agricultural diversity, combined with its high exposure to ENSO cycles and the significant share of food in household expenditure among low-income populations, makes it an informative case study for understanding how weather shocks translate into food price volatility in developing tropical economies more broadly. While our estimates reflect short-term effects of weather shocks rather than long-run climate trends, they provide new insights into the heterogeneity of price responses across crops and the farm-level characteristics that mediate them. These findings have direct policy implications: expanding access to electricity, irrigation, credit, and technical assistance may help reduce food price volatility in response to weather shocks, with the most effective interventions depending on the specific weather risks to which different crops are most exposed.

The remainder of this paper is organized as follows. Section 2 presents a conceptual framework that explains the main mechanisms through which weather shocks affect food prices. Section 3 provides background on the weather patterns in Colombia and the main characteristics of agricultural production in the country. Section 4 describes the data and Section 5 explains the empirical strategy. In Section 6 we present and analyze the results, and Section 7 concludes.

2 Conceptual Framework

Weather shocks affect food prices primarily as supply-side disturbances. Extreme rainfall shocks operate through both hydrological and logistical channels: water deficits reduce photosynthesis and impair nutrient uptake, while waterlogging promotes root disease and soil erosion, reducing yields (Lesk et al., 2016). Excessive rainfall may also degrade road infrastructure and disrupt the transport links connecting farms to wholesale markets. Therefore, the resulting logistical bottlenecks amplify production losses before they reach wholesale prices (Colon et al., 2021).

Temperature shocks introduce an additional and partly independent biological channel. Crop yields respond nonlinearly to heat exposure: moderate temperatures may accelerate crop development up to crop-specific optima, but exposure above critical thresholds sharply reduces yields by increasing evapotranspiration, impairing pollination, shortening grain-filling periods, and raising plant respiration costs (Schlenker and Roberts, 2009, **?**). These effects are especially severe when high temperatures coincide with low precipitation, because heat stress increases crop water demand precisely when soil moisture is scarce (Lobell et al., 2011, Carleton and Hsiang, 2016). Low temperature shocks can also reduce supply by delaying planting, damaging seedlings, or affecting flowering and fruit formation, although their relevance depends on crop physiology and altitude-specific agroecological conditions. Consequently, temperature shocks may reinforce the effects of precipitation shocks in some contexts: droughts can become more damaging under extreme heat, while excessive rainfall may be more harmful when followed by high temperatures that increase disease pressure and post-harvest losses. Whether these interactions are quantitatively important is ultimately an empirical question that our additive specification does not directly address, and we leave a full examination of compound shock effects for future work.

Because short-run demand for staple foods is price-inelastic, even modest weather-induced supply contractions can generate disproportionately large price increases (Roberts and Schlenker, 2013). The price response does not need to coincide with the harvest failure. Under the competitive storage model, traders update their expectations about future supply as weather anomalies accumulate during the growing season, so prices can begin rising before harvests are realized (Letta et al., 2022). This expectation channel is particularly relevant for temperature shocks because heat anomalies are often observed during phenological stages that are highly informative about final yields, such as flowering, grain filling, or fruit development. If traders interpret extreme heat, low-temperature events, or compound heat-drought events as signals of future scarcity, wholesale prices may adjust immediately even before physical supply falls. Positive price effects of weather shocks are therefore the expected outcome whenever expected supply contractions are large enough, anticipated early enough, concentrated in important producing areas, and not offset elsewhere in the production network.

Null or negative price effects, however, are equally informative and can arise through a distinct mechanism: spatial arbitrage. Under the law of one price, a weather shock affecting a subset of producing municipalities should exert limited pressure on wholesale prices in an integrated market, because traders in unaffected regions increase shipments to cover the shortfall (Fackler and Goodwin, 2001). The extent of this buffering depends on two factors. First, the geographic concentration of production: crops dispersed across many municipalities are less exposed to correlated shocks, so any single local rainfall or temperature anomaly removes only a small share of national supply and arbitrage closes the gap. Crops concentrated in few producing areas face the opposite risk, i.e., correlated shocks that eliminate a large fraction of supply simultaneously, leaving no unaffected region to compensate. Second, the spatial scope of the shock matters. Local shocks, affecting only the supply network of a single market, can be smoothed through domestic trade. Country-wide shocks, those affecting most or all producing municipalities at once, cannot be arbitraged away domestically and translate more directly into aggregate price increases. This distinction is especially important for temperature shocks, which tend to be spatially correlated over broad areas during heatwaves and El Niño episodes, increasing the probability that several producing regions experience simultaneous yield losses. In contrast, isolated rainfall shocks may be more geographically localized and therefore more susceptible to domestic smoothing.

Negative local price effects may also arise if a shock reduces farm-to-market transport volume, temporarily depressing demand-side pressure at the wholesale level, if quality deterioration lowers prices for affected produce, or if traders substitute toward unaffected goods. These mechanisms predict that heterogeneity in price responses across crops reflects, in large part, differences in the geographic structure of their production networks and in the spatial correlation of the weather shocks to which they are exposed.

Farm-level characteristics further mediate whether a shock that reaches the market translates into a price change, by determining whether producers can partially offset supply losses. Access to artificial water sources, such as irrigation districts, reservoirs, and aqueducts, partially decouples production from precipitation variability and attenuates yield losses during droughts; it can also reduce the damage from heat shocks by allowing producers to satisfy higher crop water requirements under elevated evapotranspiration (Molden, 2013). However, irrigation may be less effective when heat exceeds physiological thresholds or when electricity and pumping constraints limit water access. Access to credit relaxes liquidity constraints when adaptation expenditures are most binding, allowing investment in drought- or heat-tolerant varieties, shade infrastructure, irrigation equipment, pest control, or replanting after crop loss (Karlan et al., 2014). Electricity allows cold storage, water pumping, and refrigeration, limiting post-harvest losses that may rise when high temperatures accelerate spoilage. Farm size conditions the capacity to invest in any of these buffers: smallholder producers face tighter capital constraints and are less able to absorb income shocks (Hertel and Lobell, 2014). Technical assistance may also matter because effective responses to temperature shocks require timely management decisions, including changes in planting dates, cultivar choice, irrigation scheduling, and pest and disease control.

Finally, the biological architecture of the crop itself matters. Perennial crops may maintain deeper root systems and greater soil moisture retention, conferring inherent resilience to rainfall variability that annual crops lack (Basche and Edelson, 2017); however, perennial crops may also be highly vulnerable to heat or cold shocks that affect flowering, fruit set, or long-run plant productivity.

Taken together, these farm and crop characteristics (i.e., farm size, access to credit, electricity, artificial and natural water sources, technical assistance, altitude, distance to markets, number of producing municipalities, and exposure to both precipitation and temperature extremes) generate the cross-crop variation in price resilience that we seek to explain, and provide the basis for the machine learning analysis in Section 6.4.

3 Colombian weather and agriculture

3.1 Geography and weather

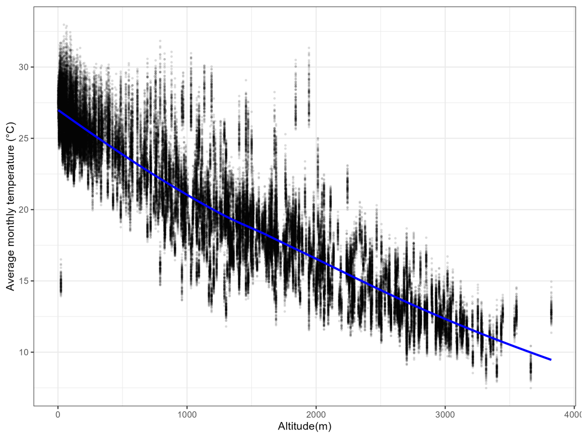
Tropical regions are typically characterized by little seasonal variation but large geographical variation in temperature due to altitude, and by substantial variability in rainfall. Topography can further shape local weather patterns, and Colombia provides a clear example of this interaction. Given its proximity to the Equator, temperature varies relatively little throughout the year. However, there is substantial spatial variation in temperature, largely driven by differences in altitude. Temperatures are systematically lower in the Andean mountain ranges and higher in low-altitude areas, including inter-Andean river valleys, the Amazon region in the southeast, the eastern plains of the Orinoquía, and the Caribbean lowlands and savannas (see Figure A.1 in the Appendix). This geographic pattern is confirmed in Panel a of Figure 1, which shows a strong negative relationship between altitude and average monthly temperature across municipalities.

The relationship between altitude and precipitation is less clear. Although Panel b of Figure 1 suggests a mildly negative association between altitude and monthly precipitation, the dispersion is considerably larger than in the case of temperature, especially across low-altitude municipalities. This greater variability reflects the fact that rainfall is shaped not only by elevation, but also by regional atmospheric dynamics and exposure to large-scale climate phenomena. In particular, the Southern Oscillation cycles, commonly known as El Niño and La Niña, are among the main sources of rainfall shocks in Colombia. These extreme weather events affect several Latin American countries, but their intensity and spatial distribution can vary substantially within each country. Salas-Parra (2020) documents heterogeneous effects of El Niño and La Niña in Colombia: La Niña episodes, associated with above-average rainfall, tend to have stronger effects in the Caribbean, Pacific, and Andean regions, whereas El Niño episodes, associated with below-average rainfall, tend to affect the Orinoquía and Amazon regions more strongly.

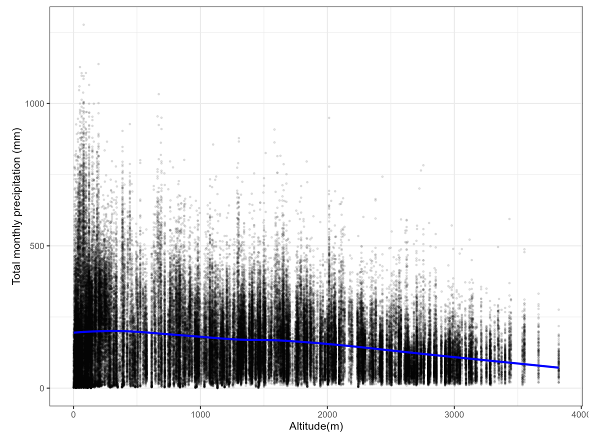
Finally, Panel c of Figure 1 illustrates the relationship between precipitation and temperature. Monthly precipitation initially increases with average temperature, but this association reverses at relatively high temperatures, particularly above approximately 25 degrees Celsius. This non-linear pattern suggests that the warmest municipalities are not necessarily the wettest. The negative segment of the relationship is consistent with conditions in hot and dry areas of the country, such as the Caribbean dry belt — especially La Guajira and parts of Cesar, Magdalena, Atlántico, and Bolívar — as well as dry inter-Andean valleys, including sections of the Magdalena, Cauca, Patía, and Chicamocha valleys. This non-linear relationship between temperature and precipitation further motivates the inclusion of temperature shocks as a separate control in our empirical framework, rather than treating them as a proxy for rainfall anomalies.

Figure 1

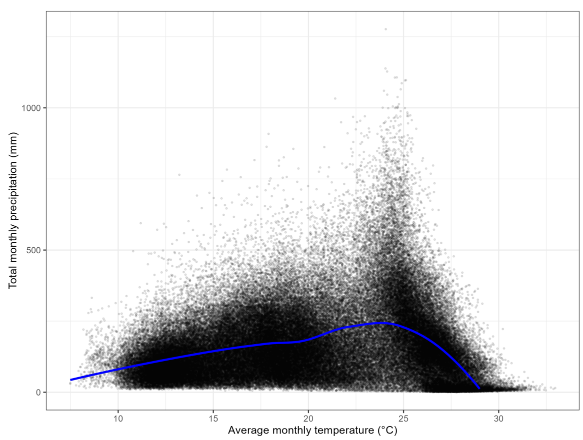
Correlation between altitude, temperature, and precipitation in Colombia, 2013–2022



(a) Altitude and temperature



(b) Altitude and precipitation



(c) Temperature and precipitation

Notes: Each dot represents a municipality-month observation, combining the corresponding variables in each graph for a given municipality and month over the period 2013–2022. Temperature is expressed in degrees Celsius, precipitation in millimeters, and altitude in meters. Blue lines correspond to locally estimated scatterplot smoothing (LOESS) fits.

Sources: Own calculations based on CHIRPS and Copernicus data.

3.2 Agriculture

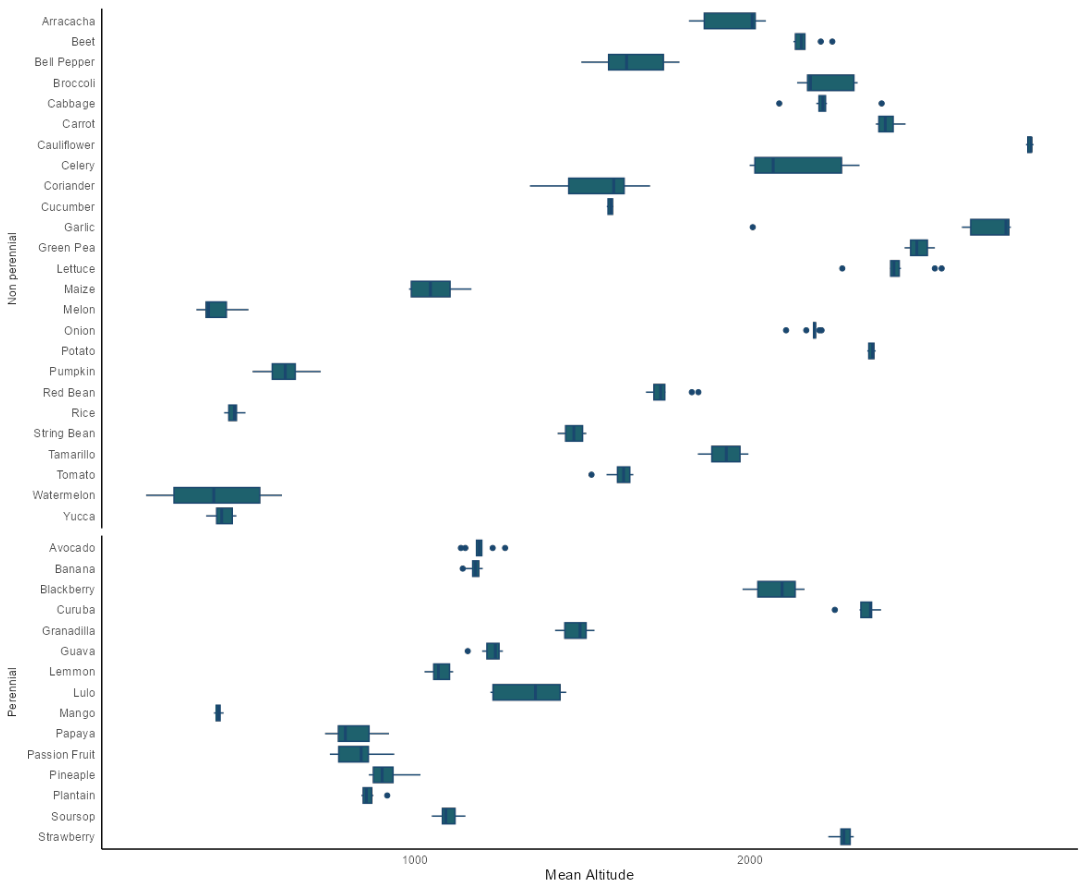
Geography and weather shape the suitability of land for agricultural production. In Colombia, the relationship between altitude and temperature described above creates distinct climate zones known as *thermal floors* (Fischer et al., 2022), each associated with a characteristic set of crops. In the warmest regions of the country (below 1,000 meters), the main crops are coconut, banana, plantain, rice, cotton, cacao, sugarcane, and yucca (cassava). Between 1,000 and 2,000 meters, the most common crops are coffee, maize, fruits, and some vegetables. Above 2,000 meters, it is common to find potatoes, wheat, barley, and cold-climate vegetables (Ramirez-Villegas et al., 2012). The altitude distribution for the crops in our sample, presented in Figure 2, confirms this pattern and illustrates that different crops face systematically different weather conditions depending on their production zone, providing the geographic basis for the heterogeneous price effects we study in this paper.[3]

The crops in our sample differ considerably in their economic relevance and degree of market integration. Several are staple foods that account for a substantial share of household food expenditure, particularly among low-income populations: potato, rice, maize, plantain, and yucca together represent a significant portion of the official food CPI basket. Others, including a wide variety of fruits and vegetables, carry smaller weights in the CPI basket and are consumed more heavily by higher-income households. This distinction matters for interpreting price responses: staple crops tend to face more inelastic demand, amplifying the price impact of supply contractions, while non-staple crops may face greater scope for substitution toward unaffected alternatives. With respect to international trade, most of the fresh fruits and vegetables in our sample are not significantly traded across borders due to perishability and transport costs, making their prices largely determined by domestic supply conditions. For more tradable commodities such as maize and rice, import competition provides an additional buffering mechanism that may attenuate the domestic price response to local weather shocks (Fackler and Goodwin, 2001).

Climate change is expected to increase both the temperature and the frequency and

[3]The geographic distribution of the main crops is presented in Appendix Figures A.2 and A.3.

Figure 2
Altitude Distribution by Crop (2013–2022)



Notes: Each row represents a box-plot of the altitude in meters for each crop producing municipality between 2013 and 2022, weighting by the reported production.

Sources: Own calculations based on SIPSA.

intensity of Southern Oscillation cycles (El Niño and La Niña) in Colombia citepbohorquez2020blame, hoyos2013impact. Ramirez-Villegas et al. (2012) estimate that 79% of crops in Colombia are located in regions which will experience an increase in temperature of 2 to 2.5 degrees Celsius by 2050. The regions most affected by droughts will be the Caribbean coast, with an acceleration of desertification and soil salinization. Glacier mass is expected to decrease by 80% by 2050, affecting freshwater availability in the Andean regions. These changes will, in turn, increase soil degradation, land instability, and mudslides. The potential impacts on agriculture vary across regions' topographic and geographic characteristics, as well as the type of crops and farm size (Ramirez-Villegas et al., 2012, Esquivel et al., 2018, Loboguerrero et al., 2018). Colombia's Nationally Determined Contributions (NDCs) explicitly recognize agriculture as one of the sectors most vulnerable to these changes, highlighting the climatological and hydrological risks faced by producing regions across the country (República de Colombia, 2020). Small producers, relying on more traditional technology, are particularly vulnerable to climate variations due to increases in disease prevalence, yield reductions, and the lack of information and infrastructure (Hertel and Lobell, 2014, Koirala et al., 2022, Hutchins et al., 2025). Large, highly specialized farms may also face greater exposure to extreme shocks due to their lack of diversification, as in the case of monoculture sugarcane operations, which are projected to experience strong yield reductions by 2050 (Ramirez-Villegas et al., 2012).

4 Data and Stylized Facts

We combine detailed information on production networks, wholesale prices, weather conditions, and farm characteristics. Production networks and food prices come from the Agricultural Prices and Supply Information System (SIPSA, by its acronym in Spanish) from the National Department of Statistics (DANE in Spanish).[4] SIPSA reports prices (in COP/kg) for more than 90 different products — crops, livestock products, and processed foods — for each of the 20 main wholesale markets of the country, available on a weekly basis from January 2013 to December 2022. In addition to prices, SIPSA also reports quantities delivered of each crop to the different wholesale centers, as well as the municipalities of origin, allowing us to map the production and distribution networks of the different crops.

To minimize potential bias due to data attrition, we retain the products for which we

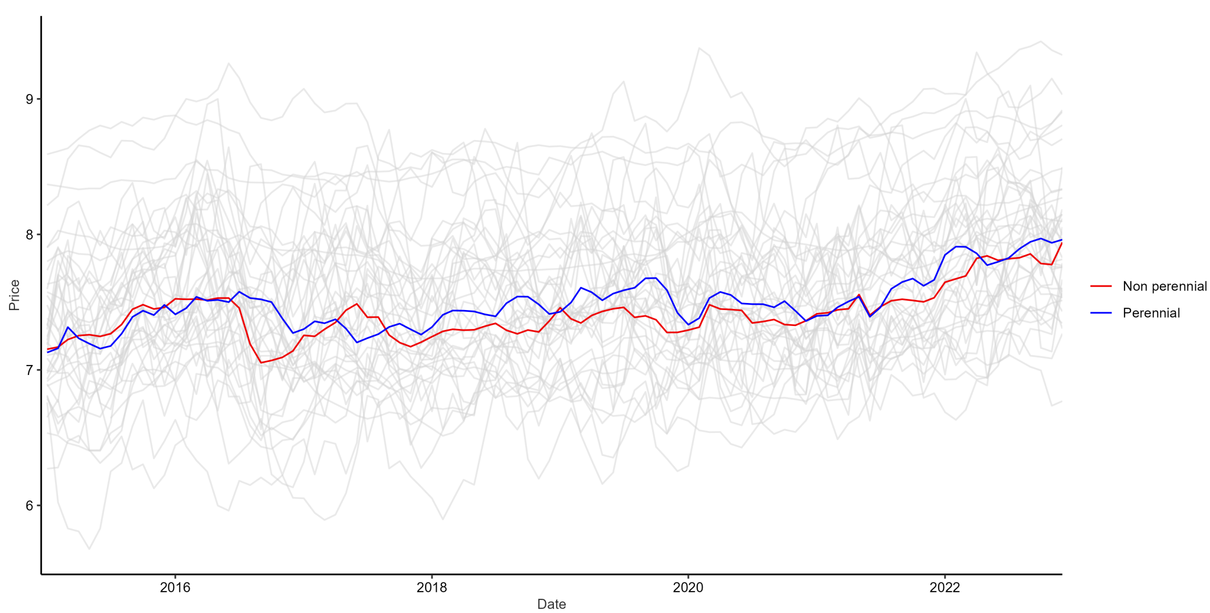
[4]Available at https://www.dane.gov.co/index.php/estadisticas-por-tema/agropecuario/sistema-de-informacion-de-precios-sipsa

can form the most balanced panel possible. For products with more than one variety, we retain the variety with the highest number of available observations. We classify the products according to their corresponding growing cycle (i.e., perennials or non-perennials). Our final sample includes 25 non-perennial crops and 15 perennial crops.[5]

Figure 3 displays the average log prices for all the products studied in this paper.[6] The figure reveals two important features. First, there is considerable variation in prices across products. Second, when aggregating products according to their growing cycle, we observe overall similar trends. Thus, aggregated prices are likely hiding important heterogeneity across products.

Figure 3

Evolution of average prices at wholesale centers (2015-2022)



Notes: All prices are expressed in logs. Grey lines represent the average monthly price of each crop (across wholesale markets). Blue and red lines represent the average price of non-perennial or perennial crops, respectively.

Source: Own Calculations based on SIPSA.

[5]Table A.1 of the Appendix lists the crops by category.

[6]Figures A.4 and A.5 of the Appendix present the prices by crop.

Regarding rainfall, we use data from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) of the Climate Hazards Center at the University of California, Santa Barbara.[7]. CHIRPS specializes in collecting and processing data on precipitation, spanning the area between the latitudes 50°S and 50°N and all longitudes, with a 0.05° level of detail, for the period 1981–present. With respect to temperature, we take information from Copernicus, which processes data on 31km × 31km grids, from 1940 and onward.[8] We use reanalysis data from both sources rather than official information from meteorological stations administered by the Colombian institute of meteorology, to achieve full spatial coverage of the Colombian territory during the period of study. Merging prices and weather information yields a dataset comprising more than 50,000 product-wholesale central-month observations between 2015 and 2022.

We identify episodes of extreme precipitation and temperature (i.e., high or low) by municipality. For this, we begin by computing total monthly precipitation (in mm) and average daily temperature (in °C) for each municipality from the original rasters, for each month of the period 2013–2022. For precipitation, we define high (low) shocks when total monthly rainfall is above the 80th percentile (below the 20th percentile) of the historical distribution for each municipality and calendar month, based on the 1980–2014 period. Panel a of Figure 4 displays the number of municipalities in Colombia that experienced any of these extreme weather episodes at any given month between 2013 and 2022. There are considerably more high rainfall shocks during La Niña periods, and more low rainfall shocks during El Niño. There is also geographic variation in the rainfall shocks. Appendix Figure A.6 presents the number of high and low rainfall shocks by municipality between 2013 and 2022. During the study period, high rainfall shocks are more common in the river valleys and the Amazon region, while low rainfall shocks are more common in the

[7]Available at https://www.chc.ucsb.edu/data/chirps
[8]Available at https://cds.climate.copernicus.eu/

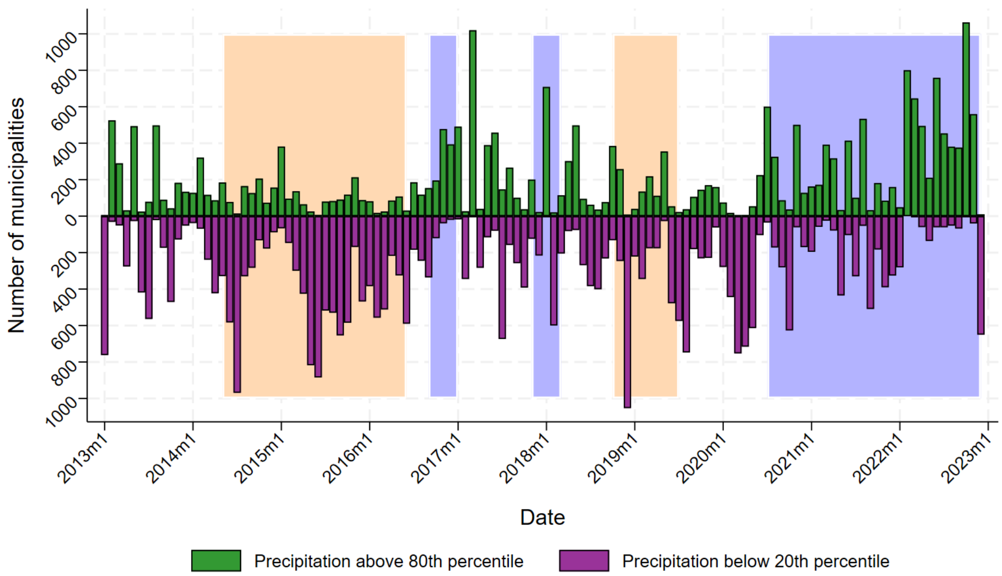
mountains and along both the Caribbean and Pacific coasts.

We define a high (low) temperature shock when the average daily temperature for a given month is above (below) the 80th (20th) percentile of the municipal-level historical distribution. Panel b of Figure 4 shows that high temperature shocks are more frequent during El Niño periods. Low temperature shocks are considerably less frequent and mostly occur during the 2021–2022 La Niña event. In Figure A.6 of the Appendix, we show that low temperature shocks mostly take place in the mountainous regions of the East Range and, to a lesser extent, in some areas of the Colombian Amazon. In contrast, high temperature shocks are more frequent in the Caribbean region.

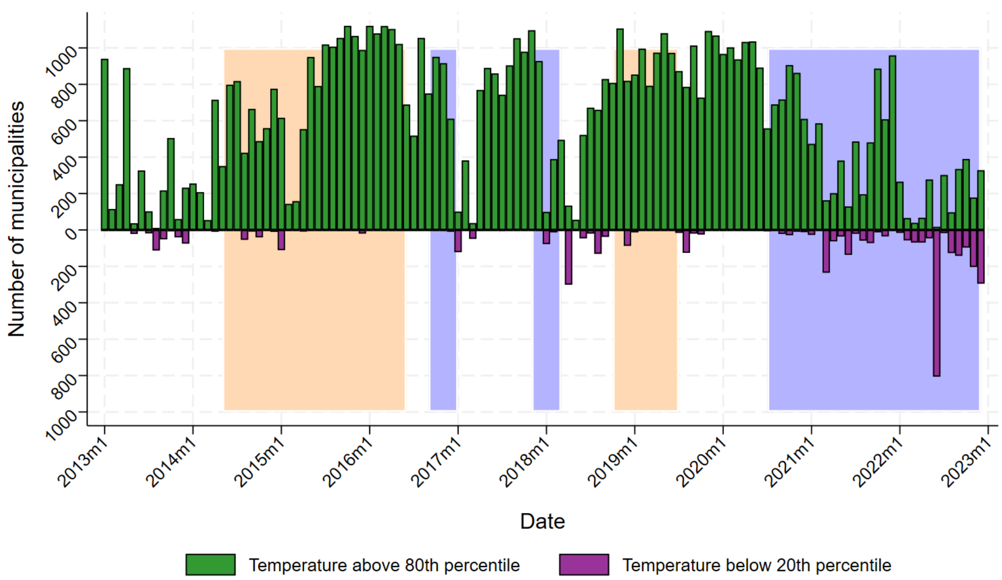
In the final section of the paper we assess which geographic and technical characteristics of the farms drive the heterogeneous effects across crops. For this, we use the 2014 Colombian Agricultural Census (CNA), from DANE, which provides farm-level information on production conditions, infrastructure, and access to resources. For each crop, we compute national averages across producing farms for the following characteristics: altitude, farm size, distance to markets, number of producing municipalities, access to electricity, technical assistance, credit, and natural (different from rainfall) and artificial water sources.[9] Appendix Figure A.11 presents the correlation matrix for these variables. It is worth noting that access to artificial water sources is negatively correlated with access to natural water sources (different from rainfall), but positively correlated with farm size, access to electricity, technical assistance, and credit.

[9]Farm size is measured in hectares. Distance to markets is the driving distance from producing municipalities to wholesale markets recorded in SIPSA, using the Google Maps API, and measured in hours. Natural sources of water, different from rainfall, include lakes, rivers, streams, springs, swamps, wetlands, and natural springs with catchment systems. Artificial sources of water include reservoirs, dams, ponds, aqueducts, water tankers, and irrigation districts.

Figure 4
Municipalities Affected by Weather Shocks in Colombia, 2013–2022



(a) Precipitation shocks



(b) Temperature shocks

Note: Each bar represents the number of Colombian municipalities that experienced a given precipitation shock at any given month during the period of study. Light orange areas denote el Niño episodes, and light blue areas correspond to la Niña.

Source: Own calculations based on CHIRPS and Copernicus data.

5 Empirical strategy

This section presents the empirical methods used in this paper. First, we construct weather shocks that are specific to each crop and wholesale market. Second, we present the estimation strategy used to identify the local and global effects of weather shocks on food prices. Finally, we introduce the machine learning model used to identify the key predictors of heterogeneity in price resilience across crops.

5.1 Crop and market-specific weather shocks

We define crop- and market-specific weather shocks in two steps. First, we construct a baseline production network using data from SIPSA. For each crop i, wholesale market j, and month t, we measure w_{imjt} as the share of the volume sold in market j that comes from producing municipality $m \in M_{ijt}$ during a baseline period that precedes the growing cycle. For non-perennial crops, the baseline period is defined between $t-11$ and $t-6$. For perennial crops, it is defined between $t-17$ and $t-6$. This lagged definition of the production network reduces potential endogeneity concerns arising from weather shocks that may affect the observed distribution of supply across producing municipalities.

In a second step, we define municipality-level weather shocks. In our baseline specification, a high (low) precipitation shock occurs in municipality m and month t when total monthly rainfall is above the 80th percentile (below the 20th percentile) of the historical distribution for that municipality and calendar month, based on the 1980–2014 baseline period. Analogously, a high (low) temperature shock occurs when the average daily temperature in municipality m and month t exceeds (falls below) the 80th (20th) percentile of the corresponding historical distribution. This calendar-month-specific definition ensures that shocks capture genuinely anomalous weather conditions relative to seasonal norms, rather than predictable variation within the year.

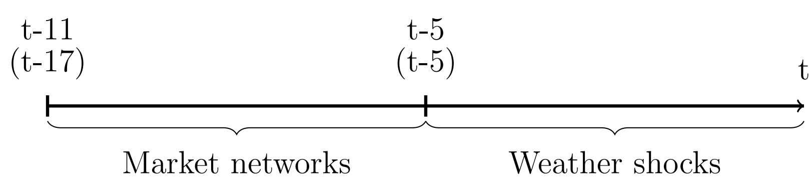
We then aggregate these municipality-level shocks to the crop-market level. For each weather variable $k \in K = \{\text{precipitation}, \text{temperature}\}$ and shock type $s \in S = \{\text{high}, \text{low}\}$, the exposure of crop i in market j at month t over the growing season is defined as:

$$S_{ijt}^{k,s} = \sum_{m \in M_{ijt}} S_{imt}^{k,s} \times w_{imjt} \tag{1}$$

where $S_{imt}^{k,s}$ takes the value of zero if there are no weather shocks of type s and variable k in municipality m between $t-5$ and t, and one if such shocks occur in all months of that window. Figure 5 summarizes the reference periods for the production network and the weather shocks. Since the baseline network weights w_{imjt} are defined between zero and one, so are our final weather shock variables $S_{ijt}^{k,s}$.

Figure 5

Reference Periods for Production Networks and Weather Shocks



Note: The first periods correspond to non-perennial crops and the second ones, in parenthesis, to perennial crops.

An important feature of this construction is that the shock window spans six months preceding each price observation, corresponding to the crop's growing season. This design ensures that the shock variables capture not only the supply effect of realized harvest conditions but also any within-season price updating by traders who observe weather anomalies accumulating during the growing period, as well as residual seasonal patterns in prices that are correlated with weather conditions.

5.2 Local and Global Effects of Weather Shocks

We estimate an OLS model with fixed effects that allows us to identify both local (crop and market-level) and global (countrywide) effects of weather shocks on food prices. The model regresses prices (in logs) of product i at wholesale center j in month t on the battery of market-specific precipitation and temperature shocks defined in Section 5.1:

$$\log(p_{ijt}) = \beta' W_{ijt} + \alpha' \overline{W_t} + \phi_i + \gamma_j + u_{ijt} \tag{2}$$

In Equation 2, the matrix $W_{ijt} = \{S_{ijt}^{k,s}\}_{k \in K, s \in S}$ collects all crop- and market-specific weather shock variables for precipitation and temperature described in the previous section, and the associated coefficient vector β captures their local effects. The coefficients in β can be interpreted as the price impact of moving from a scenario in which no municipality in the local supply network is affected by a given shock to one in which all municipalities are affected. To identify the global effects of weather shocks, we include in Equation 2 the nationwide average of each shock variable, computed across all producing municipalities in the country. These country-wide average shocks are collected in $\overline{W_t}$, and the associated coefficients in α capture the corresponding global effects.

Local and global effects are separately identified because they operate through distinct and orthogonal sources of variation. Local effects are identified from cross-sectional differences in weather exposure across products and markets within a given period. In contrast, the identifying variation for global effects comes exclusively from the time-series dimension, that is, from period-to-period changes in nationwide average weather shocks. The causal interpretation of the global effects rests on the exogeneity of weather at the aggregate level, which is grounded in the fact that nationwide weather patterns are determined by large-scale meteorological phenomena, such as El Niño and La Niña cycles, that are independent of market conditions or economic decisions. While ENSO episodes have some degree of predictability at seasonal horizons, their local intensity and spatial distribution within Colombia are substantially heterogeneous and uncertain ex ante (**?**Salas-Parra, 2020), which is the variation that identifies our local effects. Furthermore, the six-month lag structure of the shock window implies that any anticipatory response to ENSO forecasts would have to occur more than six months before harvest, a horizon at which forecast skill for within-country weather distribution is substantially limited. To the extent that some residual anticipation remains, our estimates should be interpreted as conservative lower bounds on the total price effect of weather anomalies.

In Equation 2, we control for crop and market fixed effects (ϕ_i and γ_j, respectively), which account for time-invariant unobserved characteristics of crops and markets. Errors are clustered at the product-market level. Since we require a comparable sample across crops, and some observations are lost due to the construction of baseline networks and weather shock variables, the estimation sample begins in January 2015.

In an alternative specification, we re-estimate Equation 2 with weights derived from the official CPI basket of the Colombian Department of Statistics. Although our prices are measured at the wholesale level, this reweighting approximates the aggregate inflationary impact of weather shocks as perceived by the average consumer, by assigning greater importance to products with larger shares in household food expenditure. This connects our disaggregated estimates to the existing time-series literature on weather shocks and food price inflation in Colombia (González-Molano et al., 2006, Abril-Salcedo et al., 2020), which focuses on CPI-based aggregate price measures. We acknowledge that the wholesale-retail distinction is a limitation of this approach, and we therefore present the CPI-weighted results as a complementary specification rather than as our baseline.

As an additional robustness check, we estimate a more saturated two-step specification, which includes time fixed effects. These time fixed effects absorb all common variation across periods, including macroeconomic trends, aggregate price dynamics, and residual seasonal patterns in prices that are common across crops and markets:

$$\log(p_{ijt}) = \beta' W_{ijt} + \phi_i + \gamma_j + \delta_t + \epsilon_{ijt} \tag{3}$$

The global effects are then estimated in a second step following Galiani and Porto (2010) and Cruces et al. (2018), by recovering the estimated time fixed effects from Equation 3 ($\widehat{\delta_t}$) and regressing them on the nationwide average weather shocks, weighted by product sales across markets:

$$\widehat{\delta_t} = \omega + \alpha' \overline{W_t} + u_t \tag{4}$$

The α coefficients capture the global effects of weather shocks, that is, the impact of nationwide extreme weather shocks on the aggregate variation in wholesale prices that is common across all products and markets in a given period. Since these are generated regressors, we estimate Equation 4 by Weighted Least Squares (WLS), using the inverse of the estimated variance of the time fixed effects as weights (Galiani and Porto, 2010).

To assess heterogeneous effects across crops, we re-estimate Equation 2 separately for each product, omitting the crop fixed effect since the regression is run on a single crop at a time. In these crop-level regressions, errors are clustered at the market level.

5.3 Crop-level PriceSensibility

The final section of the paper explores heterogeneity in the impact of weather shocks on prices across crops using machine learning methods to identify key factors driving these differences. We begin by constructing an indicator variable that reflects the price sensibility to weather shocks of each crop. Specifically, this indicator equals one if the sum of the local and global effects for each type of shock $S^{k,s}$ is positive and at least one of them is statistically significant, and zero otherwise. A crop is considered price sensible to weather shocks if this variable equals one.

We then use a Random Forest classification model to identify farm-level characteristics that predict price resilience.[10] This model is particularly well-suited for this task due to its ability to handle complex, nonlinear relationships among predictors. Unlike parametric approaches, Random Forest does not impose restrictive functional forms, making it suitable for identifying key determinants of food price responses to weather shocks. Additionally, its built-in feature importance metrics allow us to systematically assess which factors contribute most to price variations.

We train the model using 10 geographic and technical characteristics of farms as predictors. These characteristics are drawn from the 2014 Agricultural Census and were selected from a broader set of candidate variables to capture distinct dimensions of farm and crop

[10] Random Forest is an ensemble learning method based on multiple decision trees, where each tree is trained on a bootstrapped subsample of the dataset. Bagging (bootstrap aggregating), introduced by Breiman (2001), reduces variance by averaging predictions across trees, mitigating overfitting. The model aggregates individual tree classifications via majority voting, while Out-of-Bag (OOB) samples—data points not included in individual bootstrap samples—are used to evaluate predictive accuracy. The implementation details of the Random Forest model are illustrated in Appendix Figure A.12.

heterogeneity, including infrastructure access, market integration, financial capacity, agronomic characteristics, and geography, while minimizing redundancy arising from high pairwise correlations among the full candidate set (see Appendix Figure A.11). The retained characteristics and the mechanisms through which they may mediate price sensitivity to weather shocks are discussed in Section 2. We split the data into a training set (70%) and a test set (30%). The model's performance on the test set provides an estimate of its predictive accuracy and the relative contribution of different factors to food price fluctuations. The algorithm applies Gini impurity to split nodes, prioritizing variables that yield the highest reduction in impurity at each step. To quantify variable importance, we compute the Mean Decrease Accuracy (MDA), which measures the decline in classification accuracy when a given predictor is randomly permuted. Higher MDA values indicate stronger predictive power. We set the number of trees in the forest to 500, ensuring model stability, as accuracy plateaus beyond 150 trees. The minimum terminal node size is set to one, allowing the trees to fully capture the underlying patterns in the data without premature pruning.

6 Results

6.1 Local and global effects

We begin our analysis by examining the average effect of extreme weather shocks on perennial and non-perennial crops. To do so, we split the sample by growing cycle and estimate Equation 2, controlling for crop and market fixed effects. Columns 1 and 3 of Table 1 present unweighted estimates, while columns 2 and 4 weight products based on their share in the CPI basket.

Across all specifications—whether weighted or unweighted, and for both perennial and non-perennial crops, global effects consistently dominate local effects. While local effects are often small, sometimes statistically insignificant, or even negative, global effects are positive, significant, and substantially larger in magnitude. These results indicate that, even though there is substantial geographic and regional variation across crops and production networks, local shocks have a relatively small effect on prices. The dominance of the global effects reflects the key role that El Niño and La Niña played in weather regimes during the estimation period. In fact, there were 29 months of El Niño and 42 months of La Niña between 2015 and 2022, with a large number of municipalities affected in each case, leaving little room for local effects to play a significant role (Figure 4). The relatively small local effects could also reflect some degree of market integration: price effects of a weather shock may be mitigated when markets are sufficiently integrated and producers from unaffected regions are able to cover the missing supply.

When evaluating the total average impact (the sum of local and global effects) by type of shock, clear patterns emerge that are consistent across both unweighted and CPI-weighted specifications. For non-perennial crops, excessive rainfall consistently exerts a greater total average impact on prices than low rainfall. For instance, in the unweighted estimation, the total effect of high precipitation shocks is 0.834 log points ($-0.001+0.835$), far outweighing the total effect from low precipitation shocks (0.225). These results are consistent with the conceptual framework presented in Section 2. From an agronomic standpoint, excessive rainfall leads to waterlogging, which promotes root disease, accelerates soil erosion, and directly reduces yields. Economically, extreme rainfall can disrupt the logistics infrastructure connecting farmers with markets. In Colombia, the road network is essential for transporting crops across the country (Ayala-García et al., 2026), and it is highly vulnerable to weather-induced landslides that lead to frequent closures, impeding

Table 1
Local and Global Effects of Weather Shocks on Prices of Non-Perennial and Perennial Crops

	Non-Perennial		Perennial	
	Unweighted	CPI weighted	Unweighted	CPI weighted
Precipitation above 80th percentile	-0.001	-0.096**	0.279***	0.215**
	(0.056)	(0.043)	(0.085)	(0.091)
Precipitation below 20th percentile	-0.099**	-0.072	0.213**	0.397***
	(0.045)	(0.063)	(0.077)	(0.121)
Temperature above 80th percentile	-0.186***	-0.123**	-0.146**	-0.122*
	(0.056)	(0.049)	(0.052)	(0.059)
Temperature below 20th percentile	-0.042	0.024	-0.241	-0.509**
	(0.046)	(0.055)	(0.160)	(0.196)
Avg. Precipitation above 80th percentile	0.835***	0.938***	0.276*	0.111
	(0.093)	(0.078)	(0.133)	(0.128)
Avg. Precipitation below 20th percentile	0.324***	0.299***	0.216**	0.076
	(0.058)	(0.081)	(0.086)	(0.120)
Avg. Temperature above 80th percentile	0.316***	0.373***	0.253***	0.318***
	(0.067)	(0.046)	(0.066)	(0.069)
Avg. Temperature below 20th percentile	1.350***	1.130***	4.776***	6.712***
	(0.101)	(0.078)	(0.324)	(0.333)
R-squared	0.716	0.622	0.707	0.714
No. Observations	32,708	303,398	17,860	129,344

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Each column corresponds to a separate estimation of Equation 2. The estimation period is 2015–2022. Weighted regressions use official CPI weights. Errors (in parentheses) are clustered at the product and market level.
Sources: Own Estimates based on CHIRPS, Copernicus, DANE, and SIPSA.

product distribution and driving up prices.

For perennial crops, we find the opposite: the total average effect of high precipitation shocks is smaller than that of low rainfall (0.429 vs. 0.555 log points in the unweighted estimations). While perennial crops are more resilient to standard water variability during the production cycle, extreme low-precipitation events can severely affect production by reducing photosynthesis and nutrient uptake. Beyond the agronomic channel, economic mechanisms also play an important role: harvesting perennial crops requires multi-period investments that are typically more costly than those for non-perennial crops. Extended periods of low precipitation directly affect plant productivity and, consequently, farmers and traders may update their expectations about future supply, leading to higher prices.

With respect to temperature, the magnitude and significance of both high and low temperature shocks reveal important dimensions of climate vulnerability across crop types. For high temperature shocks, results show consistent positive average price effects (0.130 log points for non-perennials and 0.107 for perennial crops in the unweighted models). As discussed in Section 2, crop yields respond non-linearly to heat exposure: temperatures exceeding critical thresholds sharply reduce yields by increasing evapotranspiration, impairing pollination, shortening grain-filling periods, and raising plant respiration costs, with direct consequences for food prices.

However, low temperature shocks generate an even larger price response, particularly for perennial crops, with a total average effect of 4.535 log points, compared to 1.308 for non-perennial crops. As shown in Figure 4, low temperature shocks were rare during our study period, occurring mostly toward the end of the 2021–2022 La Niña episode. This relative rarity may amplify their estimated price effects, as the few affected periods coincided with a large and geographically concentrated cold event.

We also compare the estimates from Table 1 with those from the two-step approach described in Section 5, reported in Table A.2 of the Appendix. Both approaches yield very similar estimates in terms of magnitude and sign, with differences confined to marginal shifts in statistical significance. The finding that global weather effects drive the bulk of observed price fluctuations remains consistent across both methods.

The regression estimates of Equation 2 are robust to different thresholds for the identification of weather shocks. Figure A.7 of the Appendix displays the coefficients for local and global effects on non-perennial and perennial crops using alternative threshold pairs for high and low shocks, respectively (95th–5th, 90th–10th, 85th–15th, 75th–25th, 70th–30th). Global effects consistently dominate local effects at all thresholds, confidence intervals are wider when using more extreme thresholds (e.g., the 95th and 5th percentiles), and the magnitudes and direction of the effects remain stable.

6.2 Crop Heterogeneity

We further explore heterogeneity in price effects across crops in Figures 6 and 7, which present the local and global price effects of weather shocks for each of the 40 crops studied. Consistent with the findings in Table 1, the crop-level estimates confirm that global shocks (represented by the blue bars) dominate the local ones (represented by the red bars) and that wholesale price responses vary considerably across products. For precipitation (Figure 6), the global effect of excessive rainfall is highly significant and particularly large for non-perennial crops such as beet and onion, where global effects exceed 2 and 3 log points, respectively. Low rainfall shocks yield positive and statistically significant global effects for crops such as arracacha and beet, with impacts between 1 and 2 log points. Crops like onion and lemon also display large global effects, partially offset by negative and significant local effects.

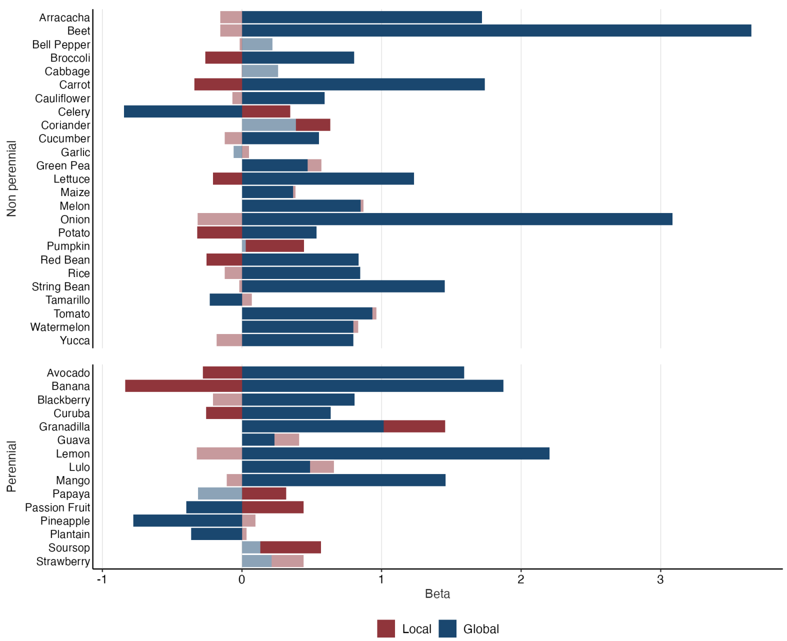
Temperature shocks generate additional cross-crop heterogeneity. While high-temperature shocks exert a moderately positive aggregate effect across most products, low-temperature events trigger extreme price spikes. As displayed in Figure 7, the largest global effects for low temperatures are not necessarily found in high-altitude crops, but rather in specific perennials such as plantain and pineapple, for which the corresponding estimates are exceptionally large and statistically significant.

This crop-level variation explains the relative differences between the unweighted and CPI-weighted regressions in Table 1. The weighted effects on perennial crops are substantially larger than the unweighted ones, driven by the extreme estimated impacts on plantain, a highly relevant staple in the CPI basket. In contrast, unweighted estimates are larger for non-perennial crops because staple grains and tubers such as maize and rice exhibit relatively smaller price responses to weather shocks, dampening the CPI-weighted averages.

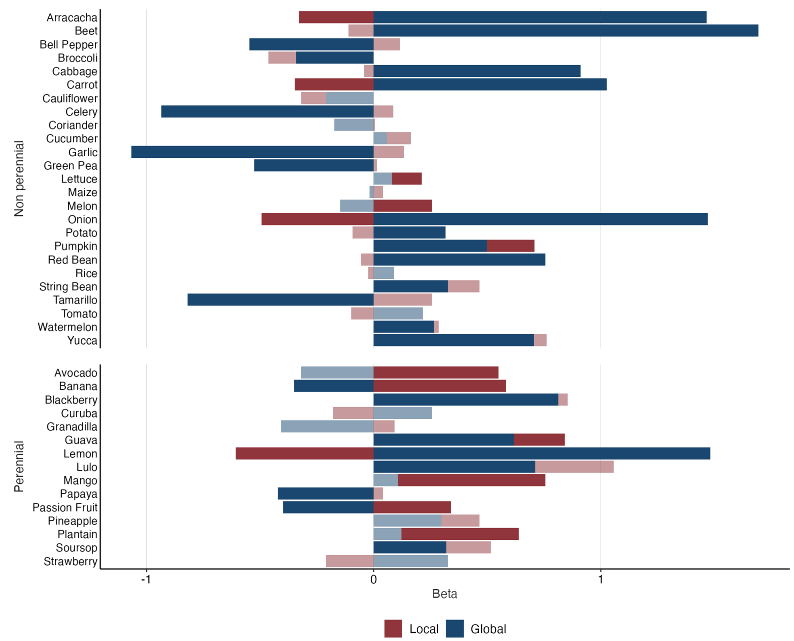
Our main results are robust to defining extreme weather events using the 10th and 90th percentiles of the historical distributions, as presented in Appendix Figures A.8 and A.9. The direction of the effects remains broadly consistent, with minor differences in magnitude or statistical significance, both in the overall estimates and in the crop-specific results.

Figure 6

Local and Global Effects of Precipitation Shocks by Crops



(a) High Precipitation Shocks



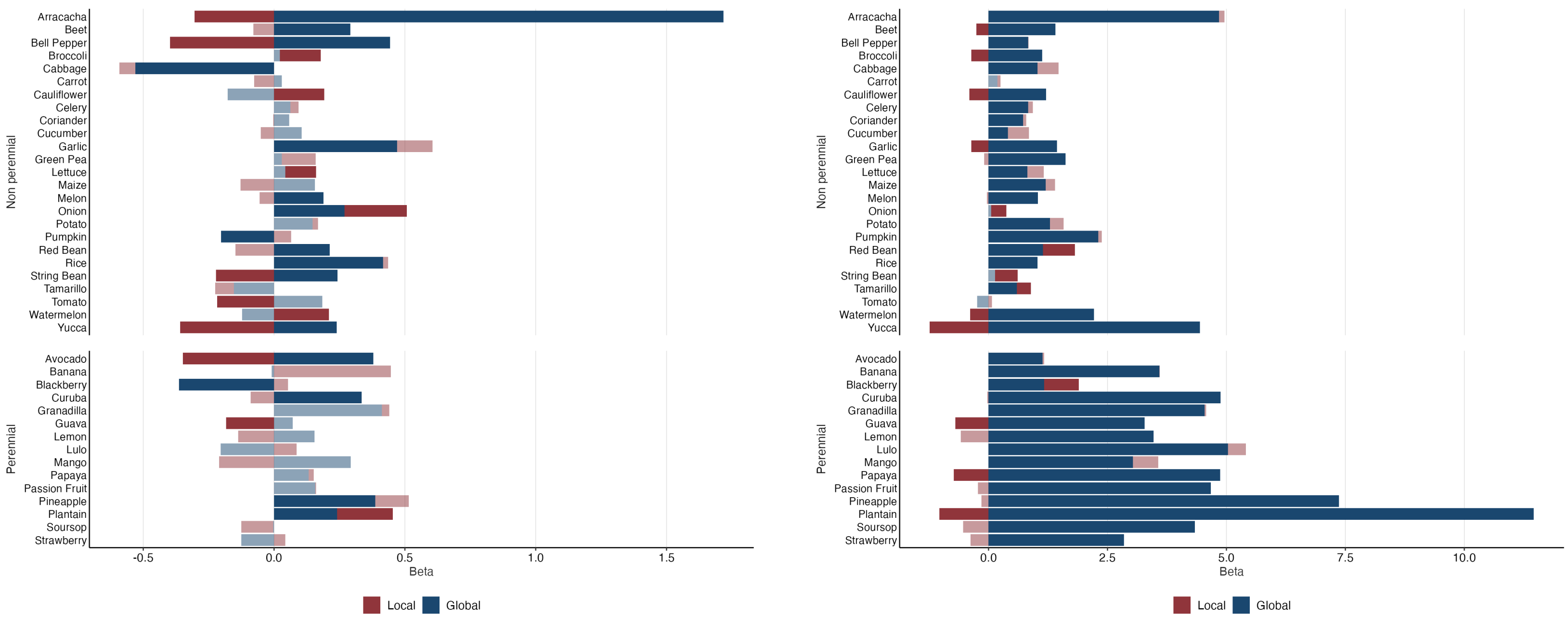
(b) Low Precipitation Shocks

Note: Each bar adds the local (red) and global (blue) effects of precipitation shocks. Bold bars denote estimated coefficients that are statistically significant at 10% or less.

Sources: Own Estimates based on CHIRPS, Copernicus, and SIPSA.

Figure 7

Local and Global Effects of Temperature Shocks by Crops



(a) High Temperature Shocks

(b) Low Temperature Shocks

Note: Each bar adds the local (red) and global (blue) effects of temperature shocks. Bold bars denote estimated coefficients that are statistically significant at 10% or less.

Sources: Own Estimates based on CHIRPS, Copernicus, and SIPSA.

6.3 Contribution of Weather Shocks to Wholesale Price Variation

The crop-level estimates presented above document substantial heterogeneity in the price effects of weather shocks across products and shock types. To quantify how much of the *observed* month-to-month variation in wholesale prices can be attributed to each type of shock, we perform a back-of-the-envelope decomposition. This exercise translates the estimated coefficients from Equation 2 into time-varying contributions by combining them with the observed changes in shock incidence over the study period. Specifically, for each weather variable k and shock type s, the contribution to the observed change in wholesale prices at month t is defined as:

$$cont\left(S_t^{k,s}\right) = \beta^{k,s} \times \Delta\overline{S_t^{k,s}} \tag{5}$$

where $\beta^{k,s}$ is the estimated coefficient for variable $k \in \{\text{precipitation}, \text{temperature}\}$ and shock type $s \in \{\text{high}, \text{low}\}$ from Equation 2, and $\Delta\overline{S_t^{k,s}}$ is the observed month-to-month change in the share of producing municipalities experiencing that shock. Summing these contributions across all eight shock variables at each point in time yields a decomposition of the predicted price variation attributable to weather, which can be compared against the observed wholesale price index to assess the overall explanatory power of weather shocks during key episodes such as El Niño and La Niña periods.

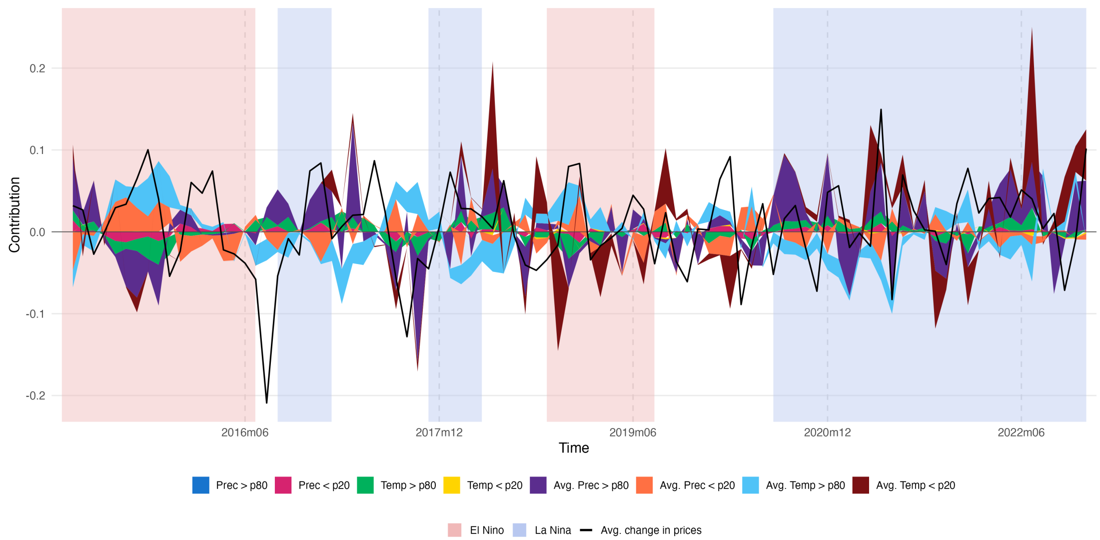
Figure 8 displays the evolution of the average contribution of each weather shock to the observed changes in prices for both non-perennial and perennial crops. Both panels show that the importance of each shock type, whether local or global, varies over time and that global effects remain the dominant contributors relative to local ones. During El Niño episodes (denoted by light red shading), global low-precipitation and high-temperature shocks are the main contributors to observed price increases, while global high-precipitation and low-temperature shocks exert a negative contribution. The opposite pattern emerges during La Niña episodes (light blue shading), especially the 2020–2022 event, during which global high-precipitation and low-temperature shocks make the largest positive contributions to price changes. In contrast, high-temperature shocks act as negative contributors during these periods.[11]

To connect these findings with the crop-level heterogeneity documented in the previous subsection, we calculate for each product the average shock contribution across all months in which El Niño or La Niña episodes occurred during our study period, as displayed in Figure 9. While the aggregate patterns described above hold on average, the figure reveals substantial heterogeneity in the composition of contributions across crops.

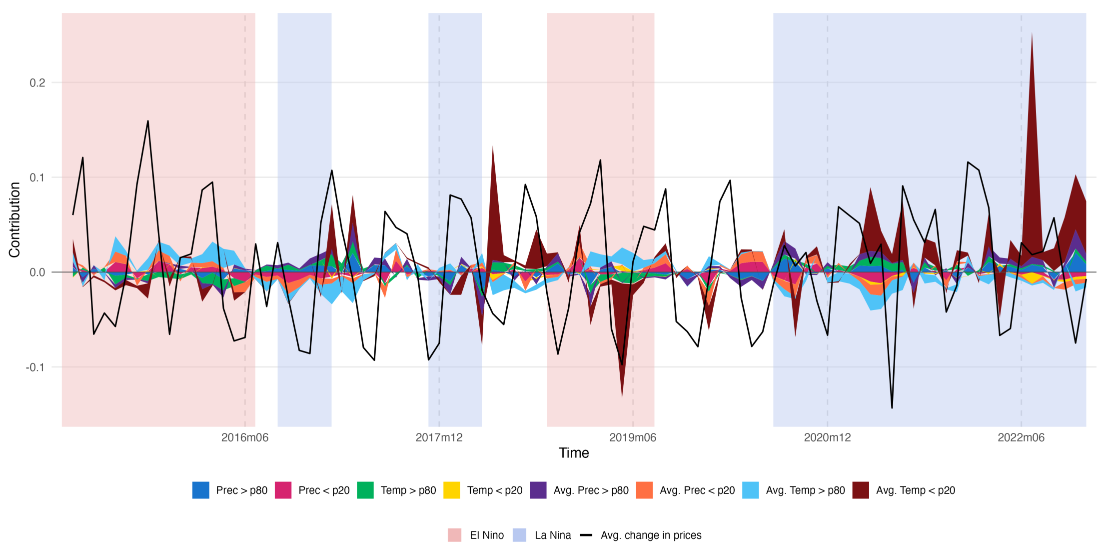
During El Niño episodes (Panel a), global high-temperature shocks (dark red bars) are the dominant positive contributor for most crops, but their relative importance varies considerably. For several non-perennial crops such as arracacha, garlic, and onion, the total predicted contribution is notably large and positive, driven by a combination of global temperature and precipitation shocks. In contrast, crops like cabbage and yucca display large negative local precipitation contributions that partially or fully offset the positive global effects, resulting in muted or even negative net contributions. For perennial crops during El Niño, the pattern is more homogeneous: global high-temperature shocks dominate across nearly all products, with smaller and more variable contributions from precipitation shocks.

[11] These results are consistent with the CPI-weighted estimates, as displayed in Figure A.10 of the Appendix.

Figure 8
Climate Contributions to Average Price Changes, 2015–2022



(a) Non-perennial Crops



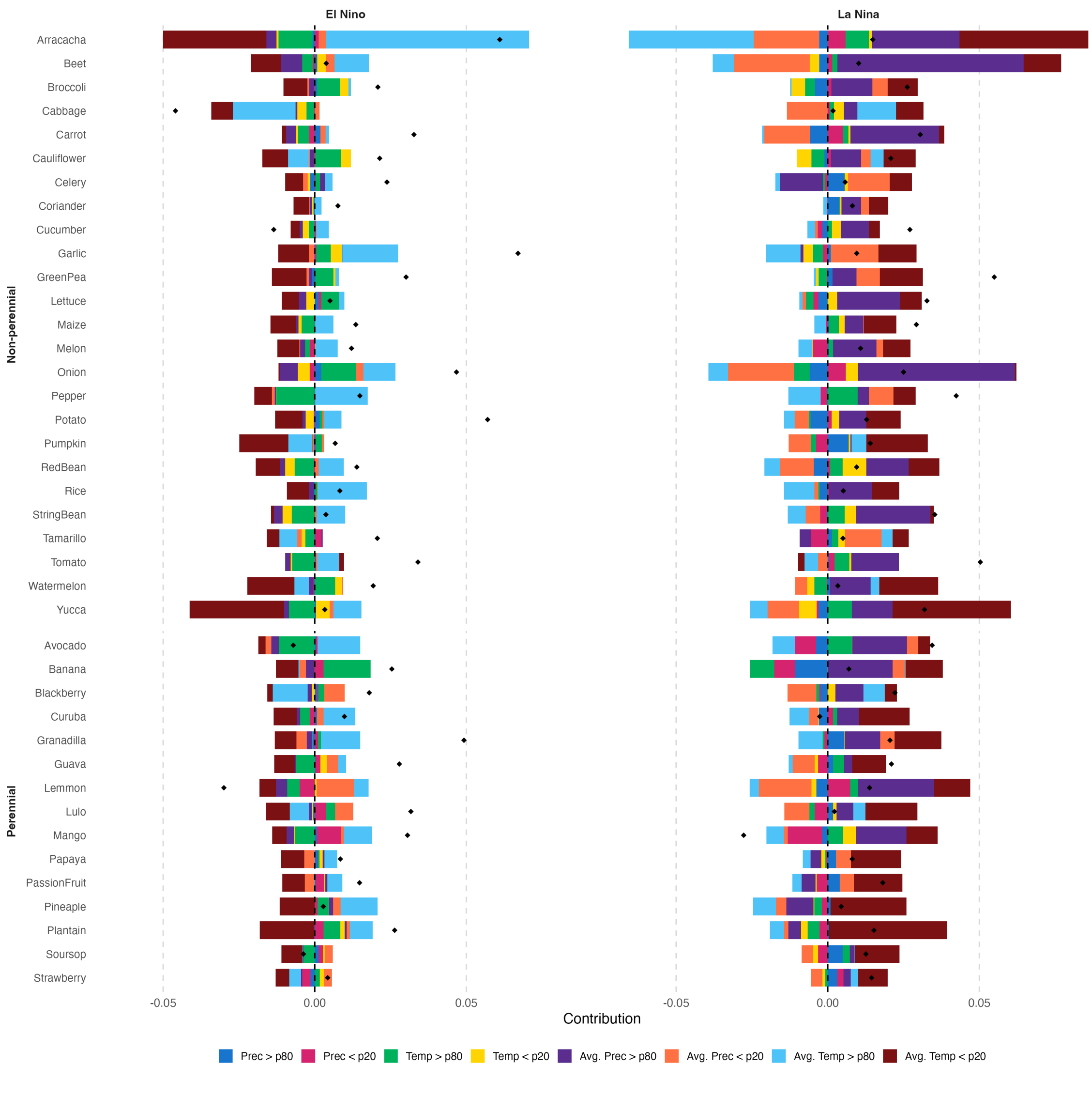
(b) Perennial Crops

Note: The colored areas represent the estimated contributions of local and average precipitation and temperature shocks to monthly changes in average prices. The black line represents the observed monthly change in average prices. Light orange areas identify El Niño episodes, and light blue areas correspond to La Niña episodes.

Source: Own estimates based on CHIRPS, Copernicus, DANE, and SIPSA.

During La Niña episodes (Panel b), the composition of contributions shifts markedly, and cross-crop heterogeneity is even more pronounced. Global low-temperature shocks (dark red bars) and global high-precipitation shocks (light blue bars) are the primary drivers of price increases for most crops, but their relative importance differs sharply across products. Among non-perennial crops, global high-precipitation shocks tend to dominate for products such as arracacha, onion, and yucca, where total contributions are among the largest observed in the sample. For perennial crops, global low-temperature shocks play a comparatively larger role, consistent with the heightened sensitivity of perennials to cold episodes discussed above. Notably, the diamond markers — representing the average observed change in prices — align closely with the total predicted contributions for most crops, suggesting that weather shocks account for a meaningful share of the price variation observed during ENSO episodes.

Figure 9
Average Contributions of Climate Shocks to Price Changes by Crop Across All El Niño and La Niña Episodes



Note: Bars show the average contribution of local and aggregate precipitation and temperature shocks to monthly price changes for each crop, averaging across all months classified as El Niño or La Niña episodes. Positive (negative) values indicate positive (negative) contributions to price changes. Black diamonds denote the observed average monthly price change for each crop during the corresponding episode. Crops are grouped into perennial and non-perennial categories. *Sources:* Own estimates based on CHIRPS, Copernicus, DANE, and SIPSA.

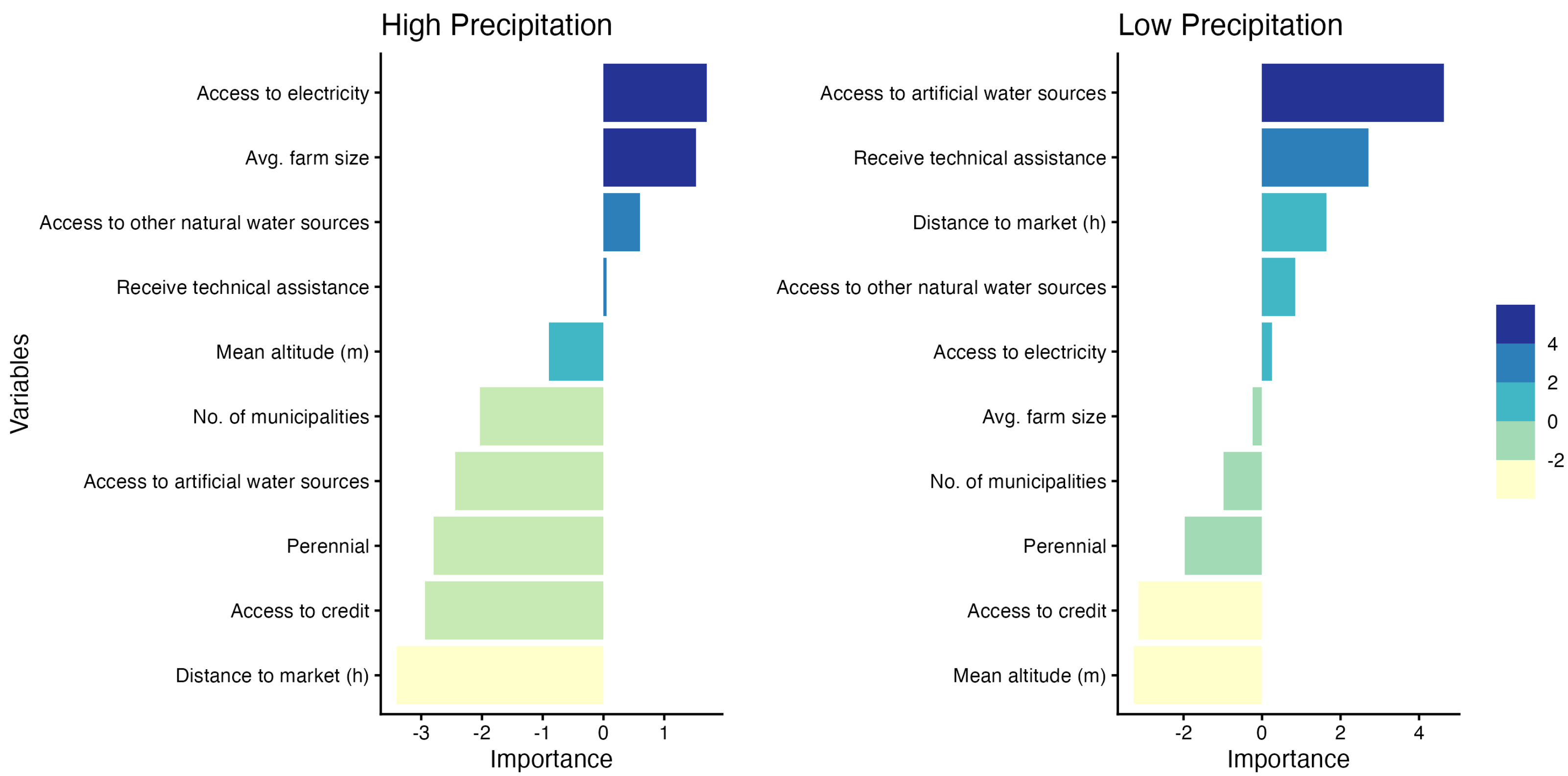
6.4 Crop-Level Price Sensitivity

We showed that there is substantial variation in price sensitivity across crops. To further explore this, we assess which farm-level characteristics best predict this heterogeneity using a Random Forest model, as described in Section 5.3. Figures 10 and 11 present the variable importance rankings for precipitation and temperature shocks, respectively. The rankings capture the predictive power of each variable but are not informative about the direction of the relationship. To assess the sign of each effect, we examine the pairwise correlations between farm characteristics and the crop-level estimated price effects, reported in Appendix Table A.3.

For high precipitation shocks, access to electricity and average farm size are by far the two most important predictors, with the remaining variables contributing little to the classification. Access to electricity is negatively correlated with price sensitivity, indicating that crops produced on farms with better electricity access tend to exhibit smaller price responses to excessive rainfall. This is consistent with the role of electricity in enabling water pumping, drainage, and cold storage that limit harvest and post-harvest losses during flood events (Mendelsohn, 2012). Farm size is weakly positively correlated with price sensitivity for this shock type, suggesting that larger farms are not necessarily better buffered against excessive rainfall — possibly because larger, more specialized operations face greater exposure when flood events affect their concentrated production areas. Access to natural water sources is also negatively correlated with price sensitivity, consistent with the idea that farms located near rivers and lakes have better drainage capacity during high rainfall episodes.

Figure 10

Farm Characteristics and Price Resilience: Variable Importance Rankings for Precipitation Shocks



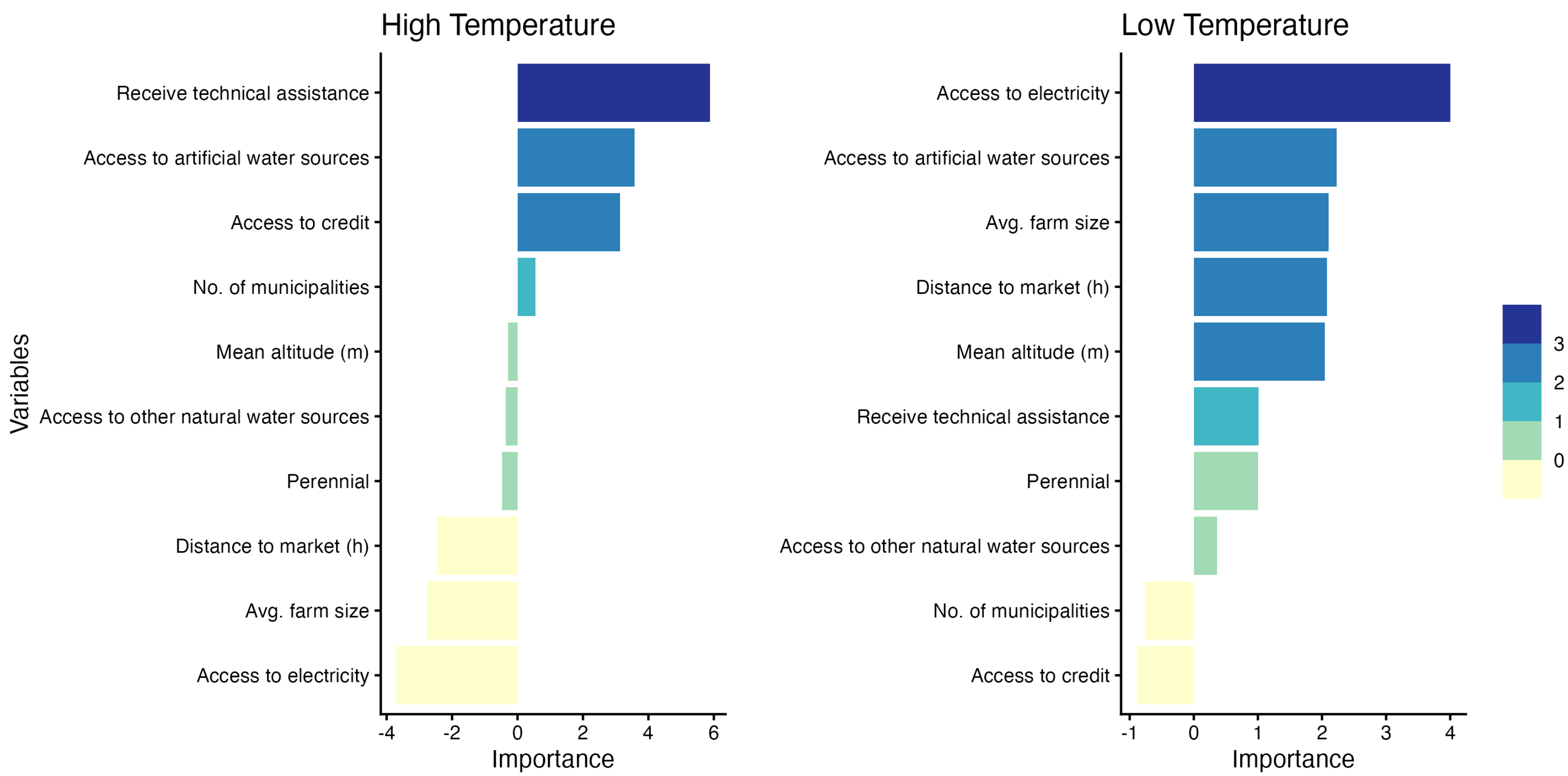
Notes: The figure reports the variable importance rankings from the Random Forest models for the crop resilience indicator based on high and low precipitation shocks, as defined in Section 5.3.

Sources: Own estimations based on DANE, Google API, Open Data Terrain Tiles, and SIPSA.

For low precipitation shocks, the ranking shifts considerably. Access to artificial water sources emerges as the strongest predictor, followed by technical assistance and distance to markets. All three are positively correlated with price sensitivity. The positive correlation with artificial water sources may reflect that irrigation-dependent crops tend to be produced in areas where rainfall deficits are more consequential for yields, so that even with irrigation access, severe drought events generate meaningful supply contractions that translate into price increases. Technical ssistance and distance to market being positively associated with price sensitivity is consistent with the idea that crops requiring more intensive management and originating in more remote areas face greater exposure to logistical disruptions during dry periods (Di Falco et al., 2011).

For high temperature shocks, technical assistance is the dominant predictor by a wide margin, followed by access to artificial water sources and access to credit. Technical assistance is negatively correlated with price sensitivity, suggesting that crops produced on farms with access to agronomic advisory services tend to be less affected by heat episodes. This is consistent with the role of technical assistance in enabling timely management responses to heat stress, including adjustments in planting dates, crop choice, and pest and disease control (Di Falco et al., 2011). In contrast, access to artificial water sources and credit are both positively correlated with price sensitivity for this shock type, which may reflect the fact that irrigation-intensive and credit-dependent crops tend to be produced in lowland areas with greater heat exposure, where temperature anomalies above physiological thresholds generate the largest supply contractions. Number of producing municipalities is negatively correlated with price sensitivity, consistent with the spatial arbitrage mechanism: crops whose production is geographically dispersed are less vulnerable to correlated heat shocks, as supply from unaffected regions can offset losses in affected ones (Fackler and Goodwin, 2001).

Figure 11
Farm Characteristics and Price Resilience: Variable Importance Rankings for Temperature Shocks



Notes: The figure reports the variable importance rankings from the Random Forest models for the crop resilience indicator based on high and low temperature shocks, as defined in Section 5.3.
Sources: Own estimations based on DANE, Google API, Open Data Terrain Tiles, and SIPSA.

For low temperature shocks, distance to market is the strongest positive predictor, followed by access to artificial water sources and farm size, while electricity and altitude show weak negative correlations with price sensitivity. However, these results should be interpreted with caution. As documented in Section 4, low temperature shocks were rare during the study period, occurring mostly toward the end of the 2021–2022 La Niña episode. Moreover, our estimations indicate that the large majority of crops in our sample are sensitive to this shock type (Figure 7), leaving little variation in the outcome variable for the Random Forest to exploit. The importance rankings for low temperature shocks are therefore less informative than those for other shock types, and the correlations with farm characteristics are correspondingly weak and imprecisely measured.

Taken together, the results across all four shock types reveal an important cross-cutting pattern: no single farm characteristic consistently predicts price sensitivity in the same direction across all weather risks. Access to artificial water sources, for instance, is negatively associated with price sensitivity for high precipitation shocks but positively associated for low precipitation and temperature shocks, reflecting the context-dependence of irrigation infrastructure as an adaptation tool. This finding underscores that policies designed to reduce food price volatility must account for the specific weather risks to which different crops are most exposed, rather than relying on a single set of across-the-board interventions.

7 Conclusions

This paper assesses the impact of weather shocks on food prices in Colombia, a tropical country with highly heterogeneous geography and agriculture. We exploit detailed information on production networks and wholesale prices of 40 crops sold in 20 wholesale centers, as well as granular data on both rainfall and temperature. We begin our analysis by estimating the local and countrywide (global) effects of high and low precipitation and temperature shocks on prices. There are three main findings. First, the estimated global effects are consistently larger than local ones in both magnitude and statistical significance, reflecting the key role of El Niño and La Niña phenomena during the study period and the limited ability of domestic spatial arbitrage to smooth prices when shocks affect all producing regions simultaneously. Second, historical decompositions reveal that global high-temperature and low-precipitation shocks are the primary drivers of price increases during El Niño episodes, whereas global high-precipitation and low-temperature shocks dominate wholesale price spikes during La Niña events. Third, there is important heterogeneity in the impact of weather shocks across crops. For non-perennial crops, excessive rainfall drives the largest aggregate price increases, whereas perennial crops exhibit greater vulnerability to extended droughts and extreme low-temperature anomalies.

We further assess the drivers of price sensitivity variation across crops using machine learning methods. Specifically, we estimate Random Forest models to identify which geographic and technical farm characteristics best predict crop-level price sensitivity to different weather shocks. A key finding is that no single farm characteristic consistently predicts price sensitivity across all shock types: access to electricity and farm size are the dominant predictors for high precipitation shocks, while access to artificial water sources and technical assistance are more relevant for low precipitation and temperature shocks.

Our results provide new insights on the heterogeneous impacts of weather shocks on food prices, highlighting that variation across crops is more important than variation across geography. The finding that key predictors of price sensitivity differ substantially across shock types demonstrates that no single farm characteristic consistently buffers against all weather risks. These results have direct implications for public policy: interventions aimed at reducing weather-induced food price volatility must account for the specific risks to which different crops are exposed, rather than relying on a single set of across-the-board measures. As climate change increases the frequency and intensity of extreme weather events in Colombia (Bohorquez-Penuela and Otero-Cortés, 2020, Hoyos et al., 2013), the heterogeneous price effects documented in this paper are likely to become more economically significant, underscoring the urgency of targeted adaptation policies for the agricultural sector.

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Appendix

Table A.1
Crop Classification

Perennial Crops			
Fruits		**Plantains**	
Avocado	Lemmon	Plantain	
Banana	Lulo		
Blackberry	Mango		
Curuba	Papaya		
Granadilla	Passion fruit		
Guava	Pineapple		
Soursop			
Strawberry			

Non-perennial Crops			
Cereals and grains	**Fruits**	**Roots and tubers**	**Vegetables**
Maize	Melon	Arracacha	Beet
Red bean	Tamarillo	Potato	Bell pepper
Rice	Watermelon	Yucca	Broccoli
			Cabbage
			Cauliflower
			Celery
			Coriander
			Garlic
			Green Pea
			Lettuce
			Onion
			Pumpkin
			Tomato

Source: SIPSA

Table A.2

Local and Global Effects of Weather Shocks on Prices of Non-Perennial and Perennial Crops: Two-step Estimation

a. Non-perennial Crops				
	Local Effects		Global Effects	
	Unweighted	CPI weighted	Unweighted	CPI weighted
Precipitation above 80th percentile	-0.013	-0.088**	1.007***	0.969***
	(0.047)	(0.036)	(0.236)	(0.231)
Precipitation below 20th percentile	-0.091*	-0.041	0.371***	0.342***
	(0.046)	(0.047)	(0.125)	(0.110)
Temperature above 80th percentile	-0.187***	-0.148***	0.410***	0.436***
	(0.044)	(0.040)	(0.092)	(0.082)
Temperature below 20th percentile	-0.086*	0.001	1.645***	1.462***
	(0.043)	(0.050)	(0.336)	(0.371)
R-squared	0.752	0.691	0.431	0.364
No. Observations	32,708	32,708	96	96

b. Perennial Crops				
	Local Effects		Global Effects	
	Unweighted	CPI weighted	Unweighted	CPI weighted
Precipitation above 80th percentile	0.275***	0.218***	0.551	0.444
	(0.052)	(0.058)	(0.358)	(0.459)
Precipitation below 20th percentile	0.223**	0.384***	0.312	0.390
	(0.087)	(0.119)	(0.225)	(0.258)
Temperature above 80th percentile	-0.140**	-0.137**	0.406***	0.452***
	(0.056)	(0.057)	(0.138)	(0.141)
Temperature below 20th percentile	-0.264**	-0.468***	5.771***	8.060***
	(0.115)	(0.122)	(0.916)	(0.994)
R-squared	0.758	0.769	0.504	0.557
No. Observations	17,860	17,860	96	96

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$. For local effects, for each type of crop (i.e., non-perennial or perennial crops), each column corresponds to a separate estimation of Equation 3. For global effects, each column for each type of crop relates to the estimation of Equation 4. The estimation period is 2015-2022. Weighted regressions use official CPI weights. Standard errors (in parentheses) are clustered at the product and market level.

Sources: Own Estimates based on CHIRPS, Copernicus, DANE, and SIPSA.

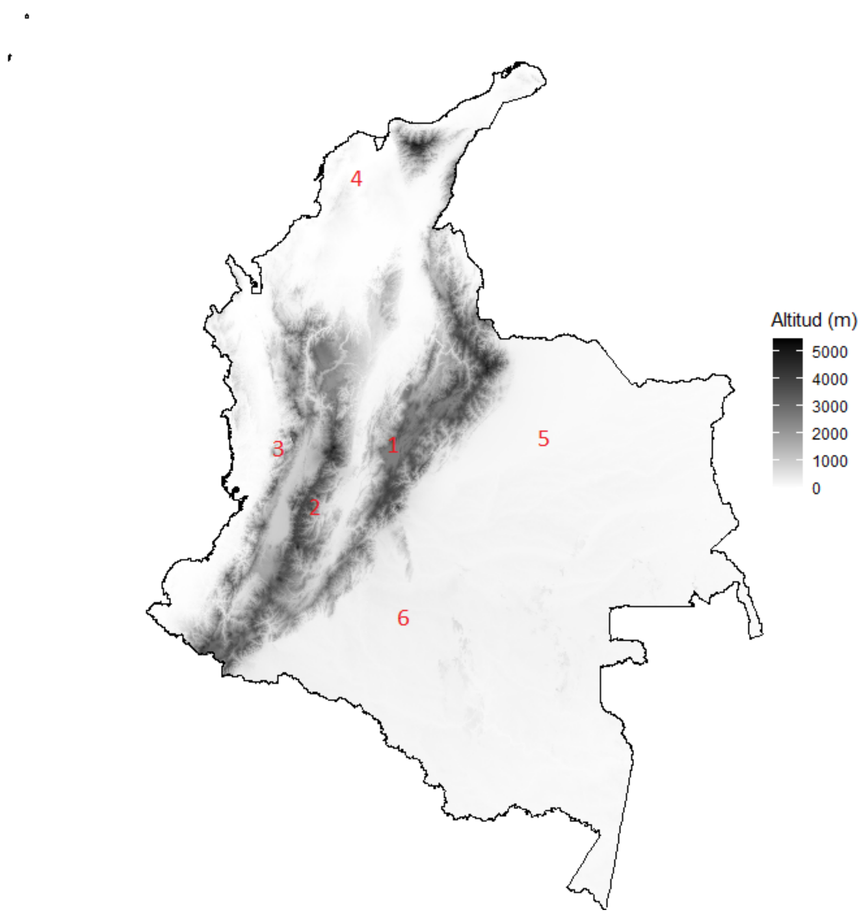
Table A.3

Correlations Between Local and Global Effects of Weather Shocks and Crop Characteristics

	Precipitation shock		Temperature shock	
	High	Low	High	Low
Mean altitude (m)	-0.164	-0.244	0.118	-0.153
Distance to market (h)	0.139	0.100	0.046	0.167
# producing municipalities	0.162	0.116	-0.406	-0.177
Avg. farm size (ha)	0.060	-0.053	0.095	0.063
Access to other natural water sources	-0.100	-0.103	-0.088	-0.111
Access to artificial water sources	0.076	0.064	0.260	0.052
Access to electricity	-0.154	0.116	0.005	-0.066
Receives technical assistance	0.135	0.095	-0.168	0.045
Access to credit	0.087	-0.055	0.099	0.058

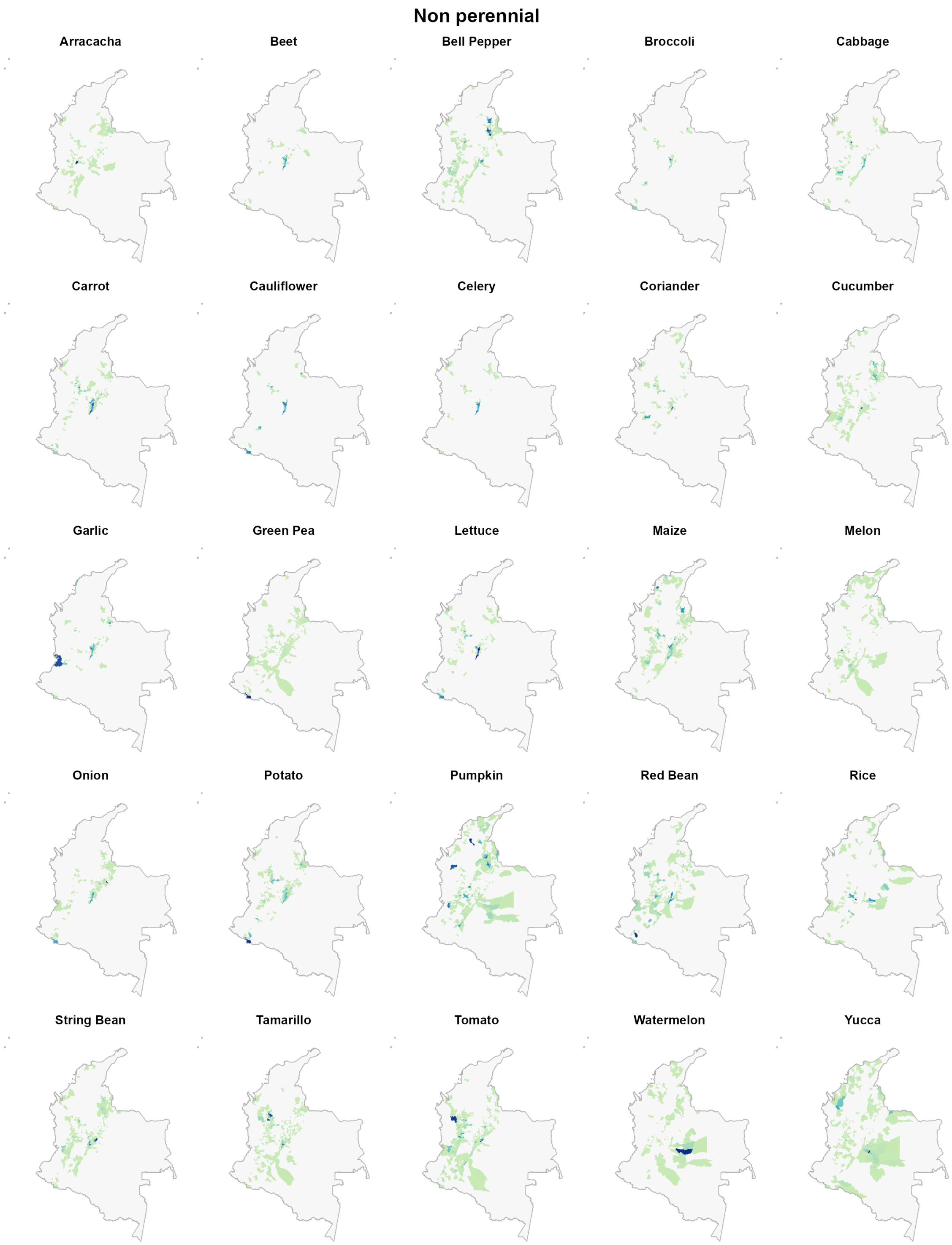
Note: The value of each one of the farm-level characteristics correspond to the average over all producing municipalities that produced each crop listed in Table A.1 during the period of study (2015–2022).
Sources: 2014 Colombian Agricultural Census and SIPSA.

Figure A.1
Elevation Map of Colombia



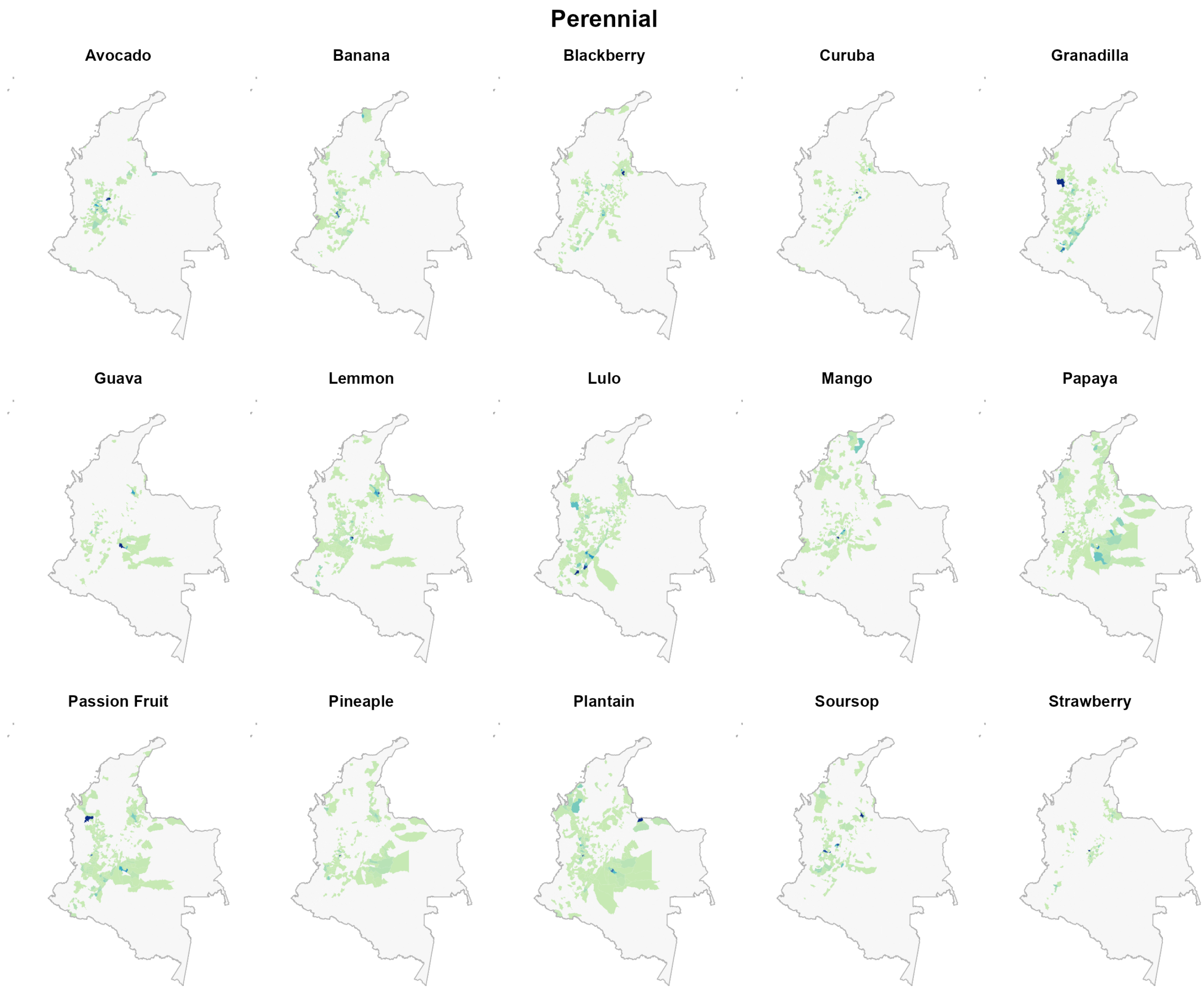
Note: Sources: Own Estimates based on CHIRPS, DANE, and SIPSA.

Figure A.2
Spatial Distribution of Non-perennial Crops, 2015–2023



Source: Own calculations based on SIPSA.

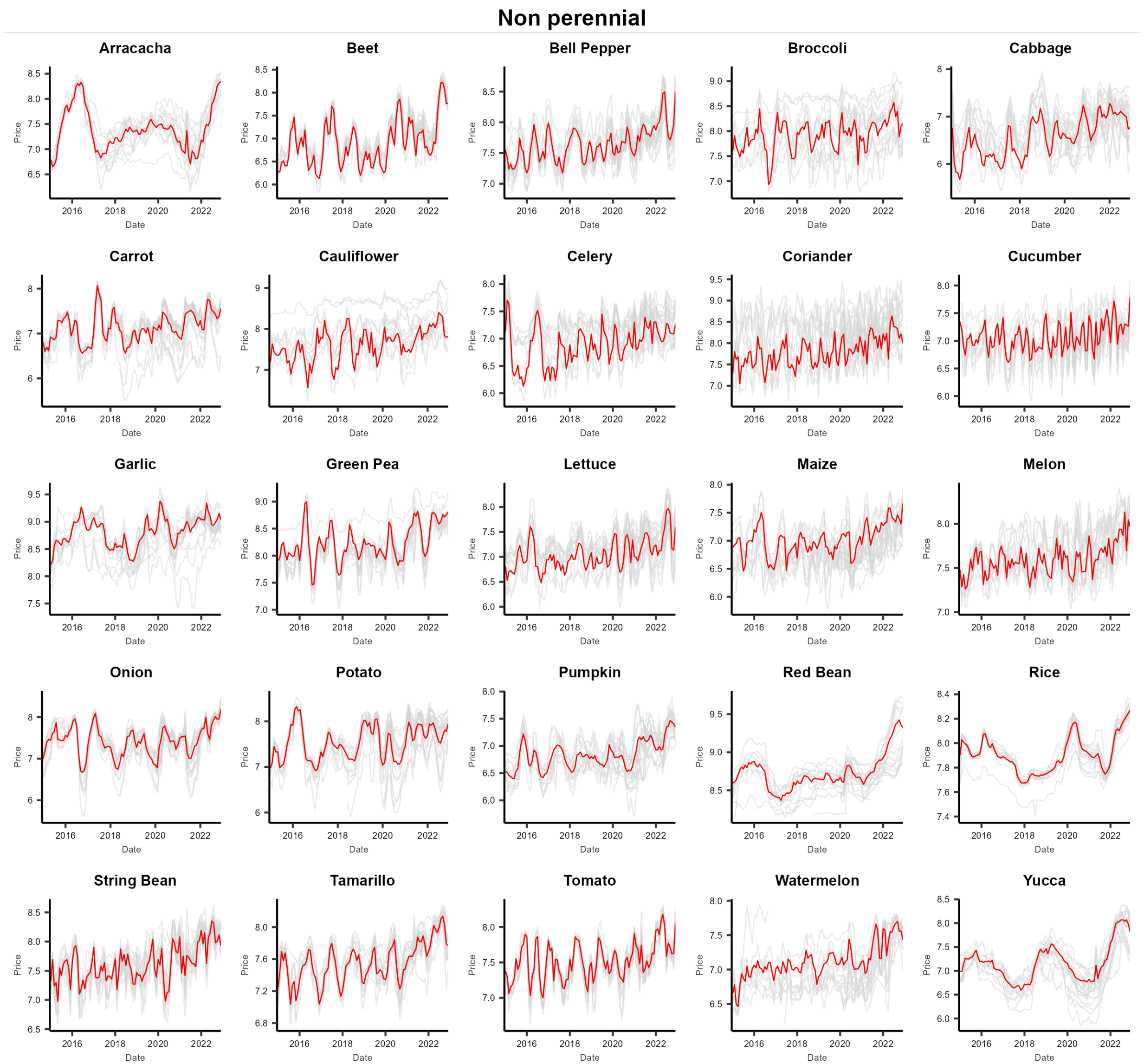
Figure A.3
Spatial Distribution of Perennial Crops, 2015–2023



Source: Own calculations based on SIPSA.

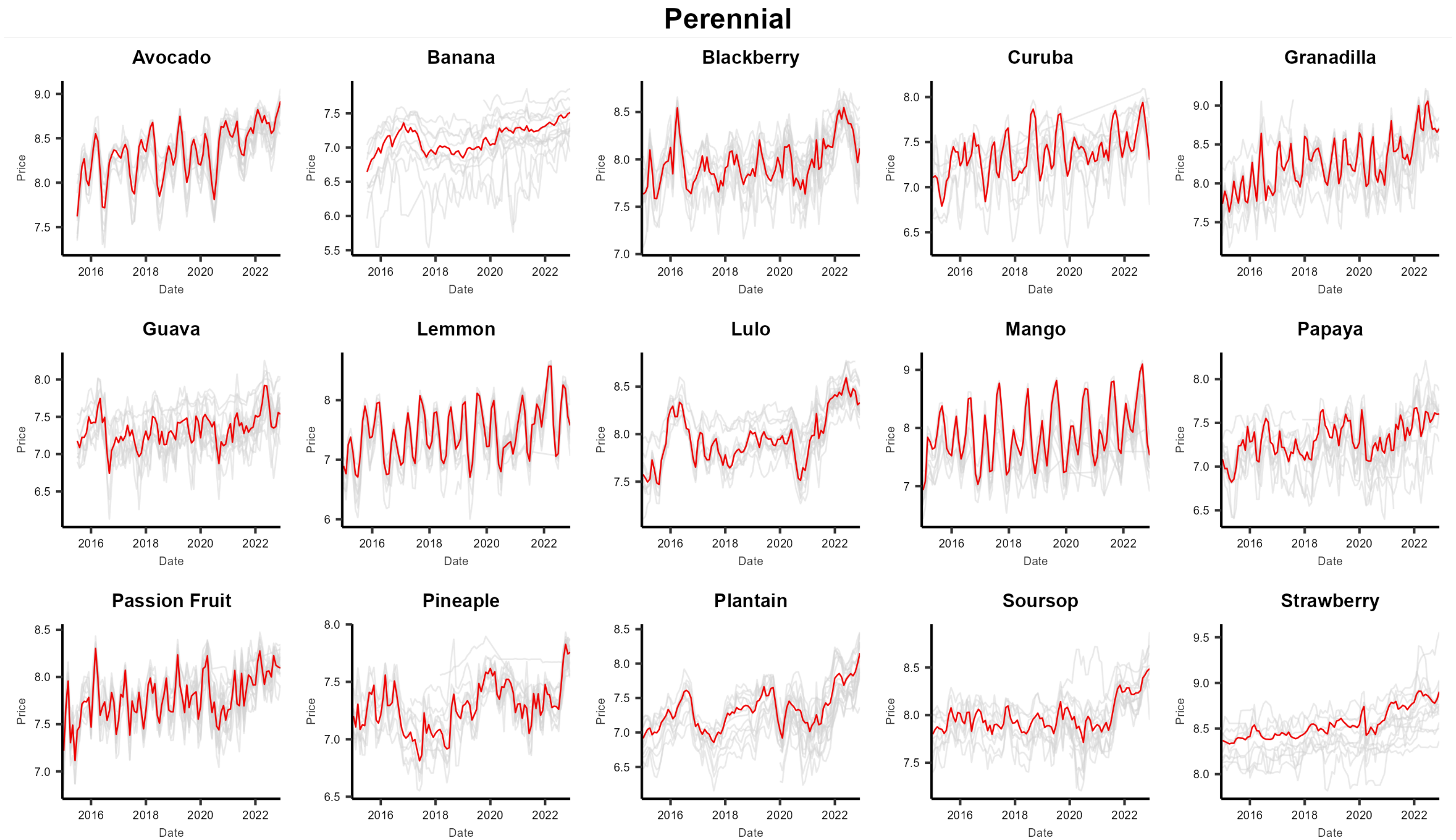
Figure A.4

Average Prices (in logs) of Non-perennial Crops, 2015–2023



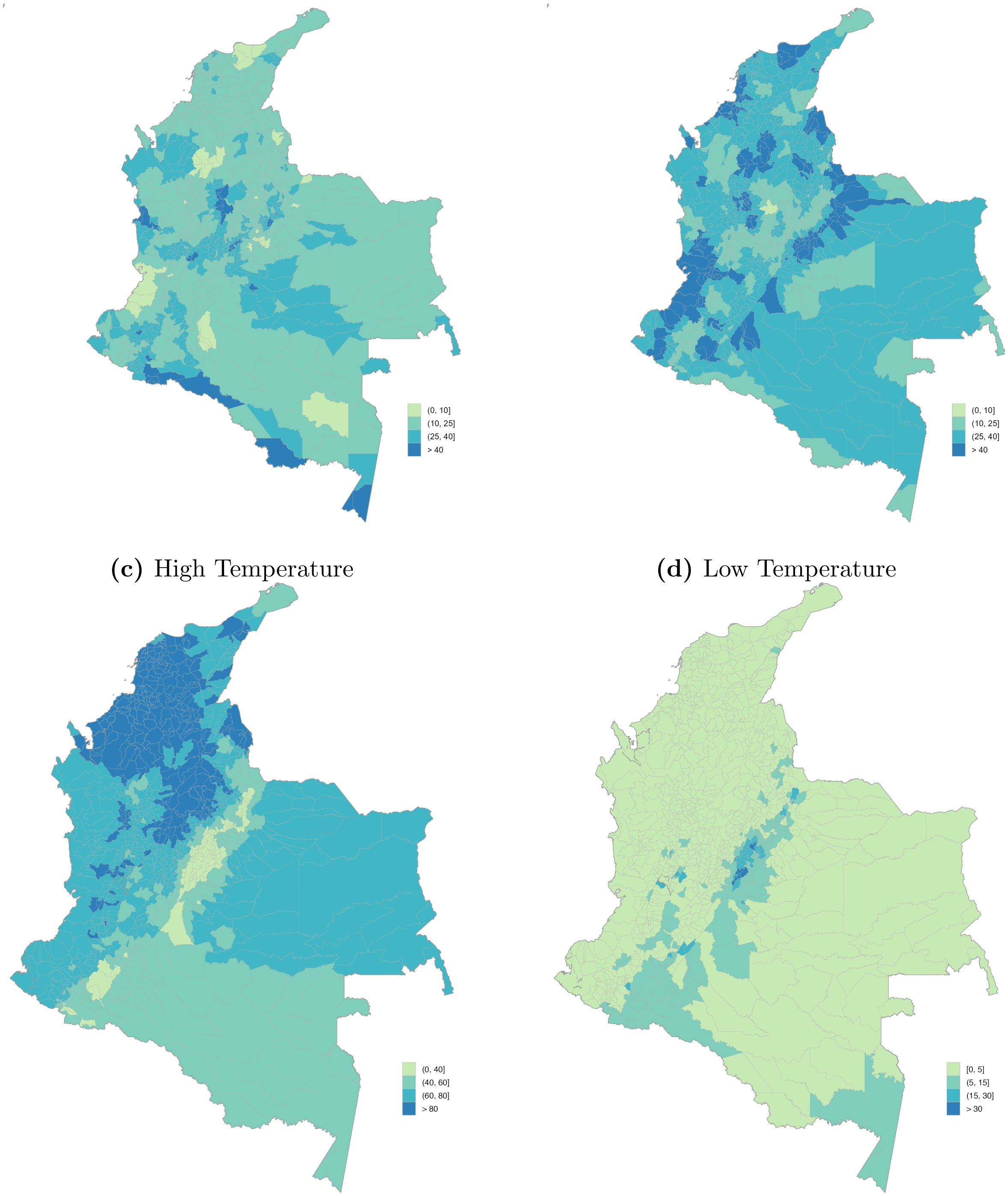
Source: Own calculations based on SIPSA.

Figure A.5
Average Prices (in logs) of Perennial Crops, 2015–2023



Source: Own calculations based on SIPSA.

Figure A.6
Number of Climate Shocks by Municipality, 2013–2022



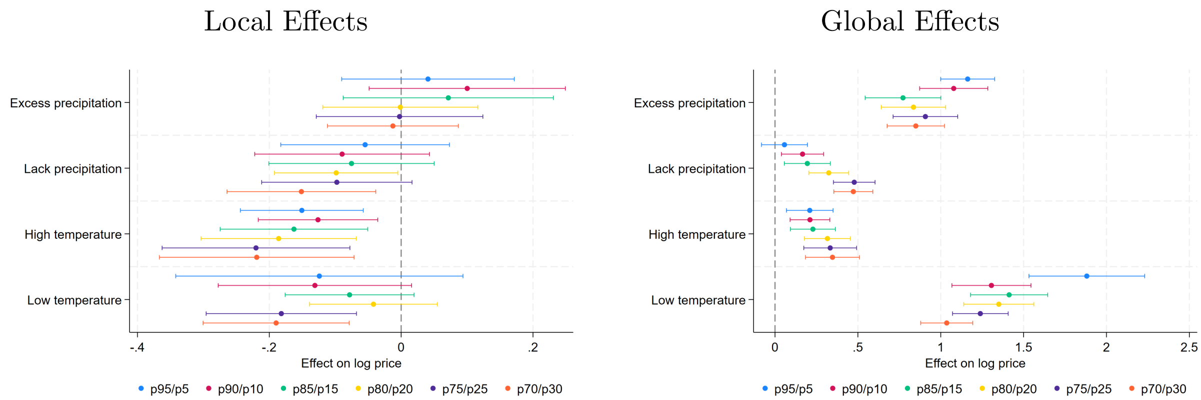
(a) High Precipitation
(b) Low Precipitation
(c) High Temperature
(d) Low Temperature

Source: Own calculations based on CHIRPS (precipitation) and Copernicus (temperature).

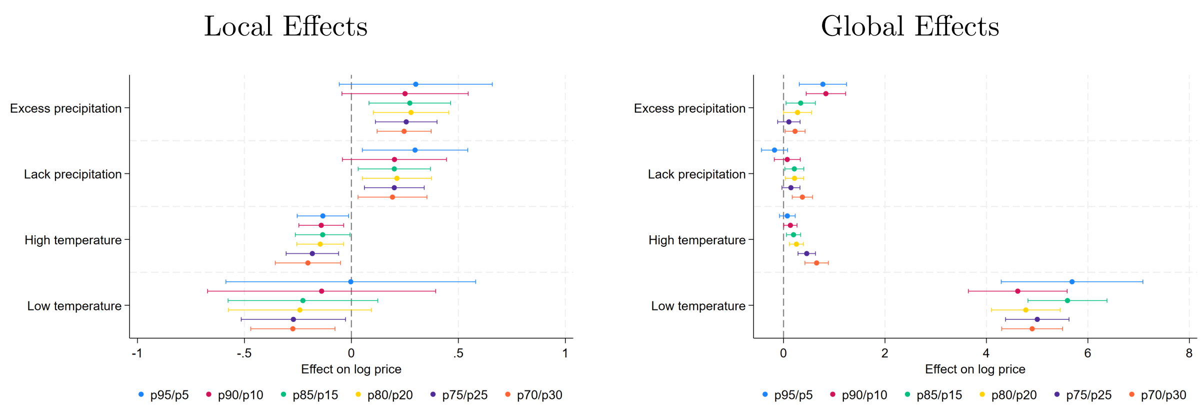
Figure A.7

Local and Global Effects of Weather Shocks, Alternative Thresholds

(a) Non-perennial Crops



(b) Perennial Crops

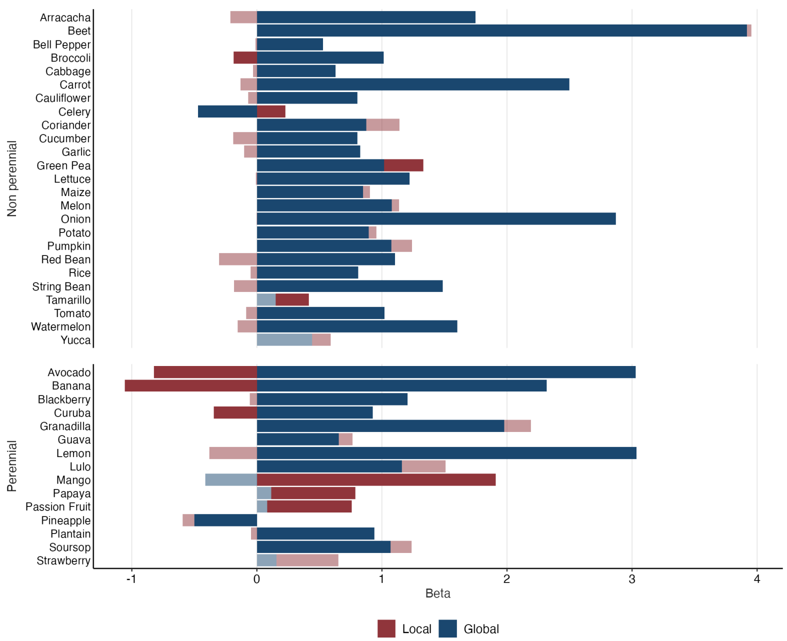


Each pair of percentiles indicates the thresholds used for high shocks and low shocks, respectively, at the same regression model (e.g., the pair p95/p5 corresponds to p95 for high precipitation and temperature shocks, whereas p5 for low precipitation and temperature shocks). Confidence intervals estimated at 5% significance level.

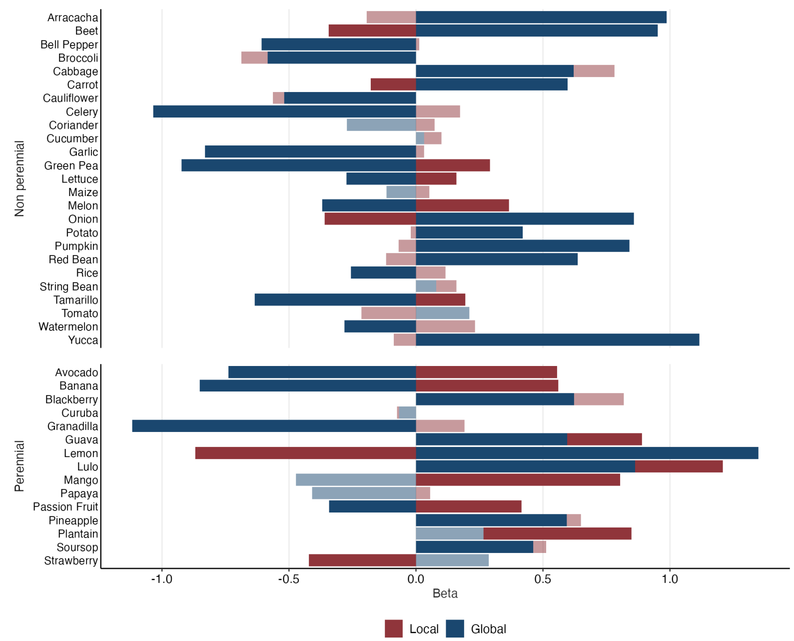
Source: Own calculations based on CHIRPS (precipitation) and Copernicus (temperature).

Figure A.8

Local and Global Effects of Precipitation Shocks by Crops, Percentiles 10 and 90



(a) High Precipitation Shocks



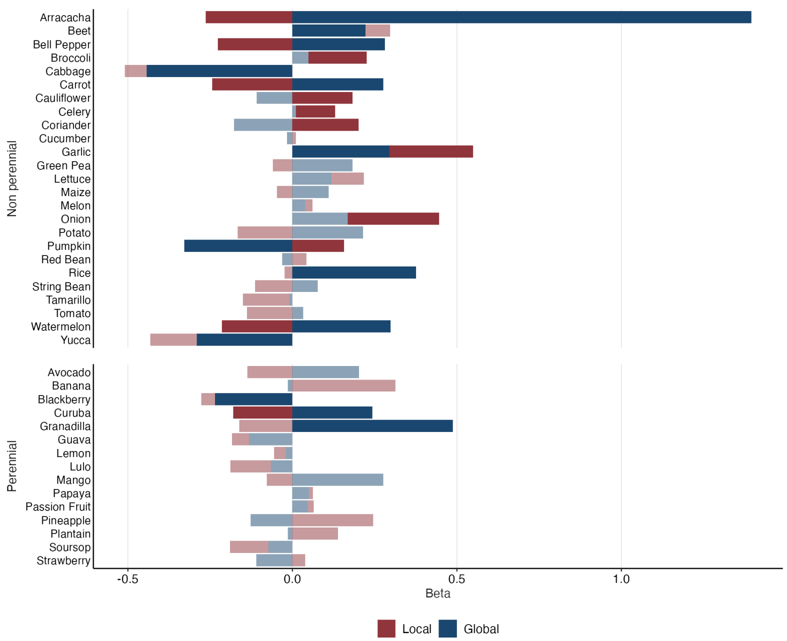
(b) Low Precipitation Shocks

Note: Each bar adds the local (red) and global (blue) effects of precipitation shocks. Bold bars denote estimated coefficients that are statistically significant at 10% or less.

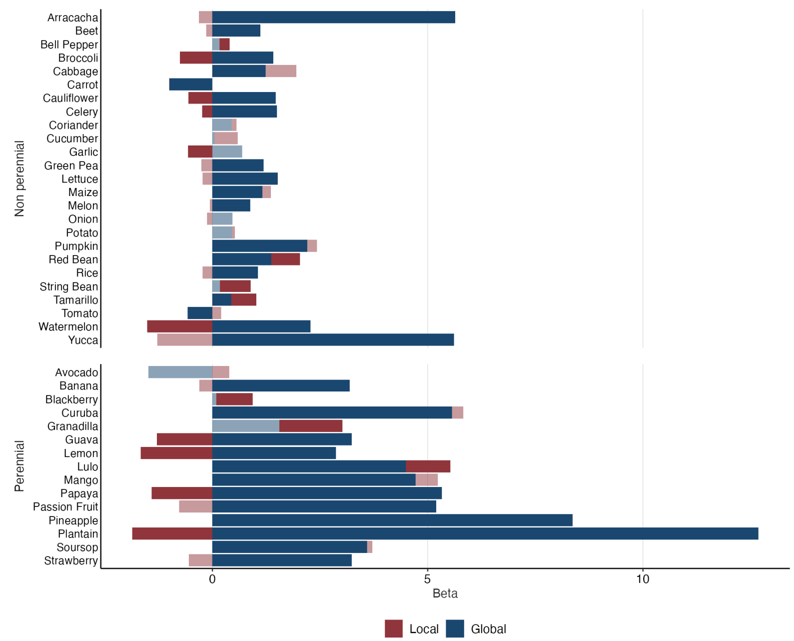
Sources: Own Estimates based on CHIRPS, Copernicus, and SIPSA.

Figure A.9

Local and Global Effects of Temperature Shocks by Crops, Percentiles 10 and 90



(a) High Temperature Shocks

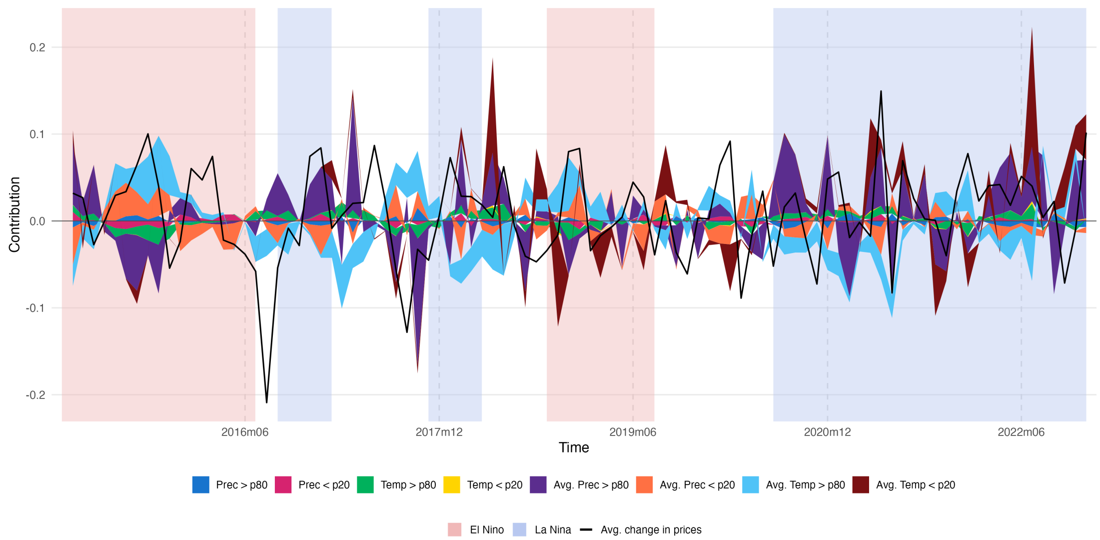


(b) Low Temperature Shocks

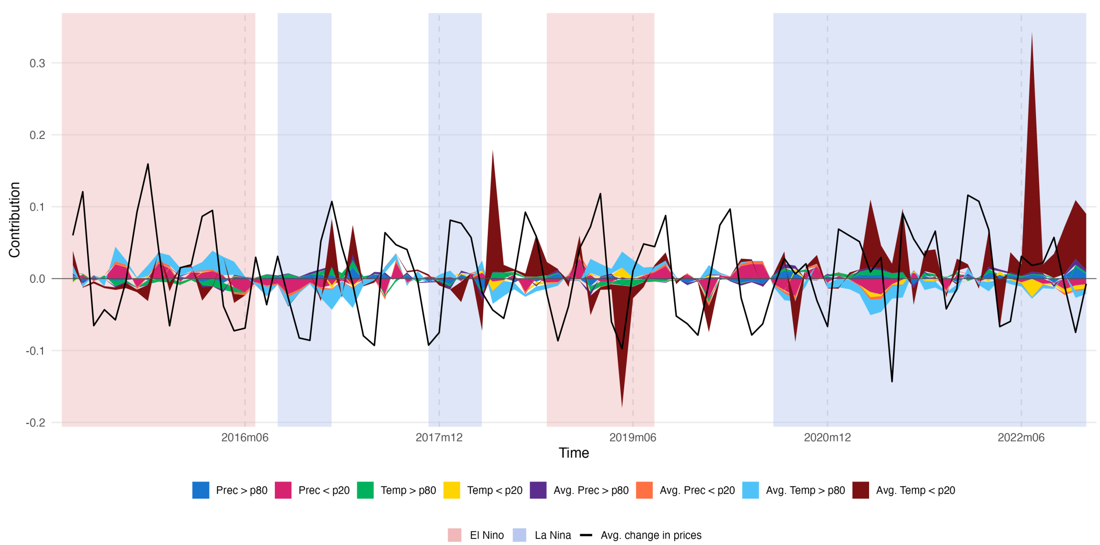
Note: Each bar adds the local (red) and global (blue) effects of temperature shocks. Bold bars denote estimated coefficients that are statistically significant at 10% or less.

Sources: Own Estimates based on CHIRPS, Copernicus, and SIPSA.

Figure A.10
Climate Contributions to Average Price Changes, 2015–2022 (CPI-weighted estimates)



(a) Non-perennial Crops



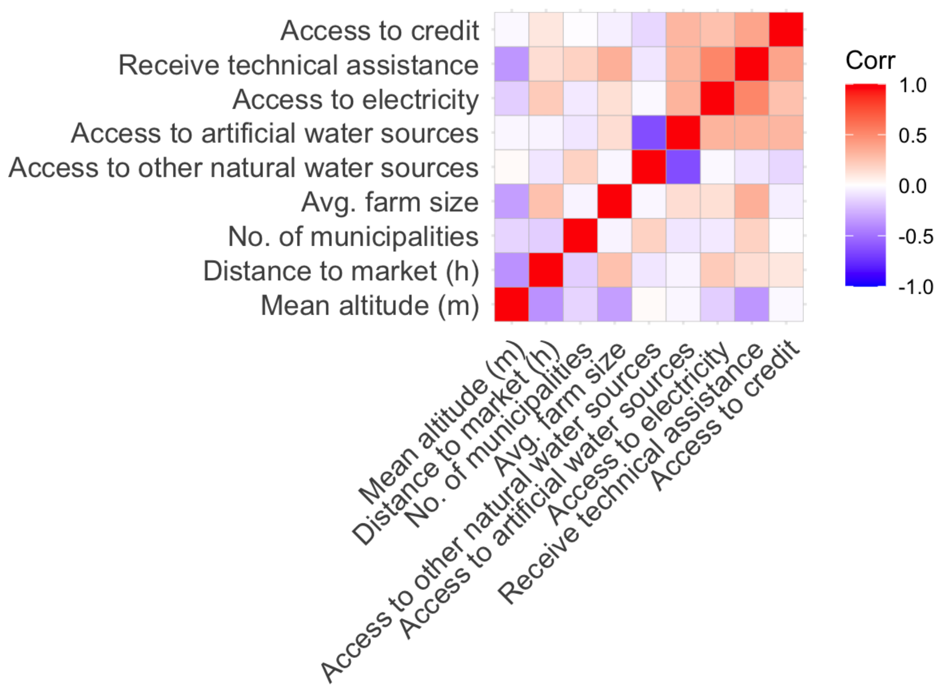
(b) Perennial Crops

Note: The colored areas represent the estimated contributions of local and average precipitation and temperature shocks to monthly changes in average prices. The black line represents the observed monthly change in average prices. Light orange areas identify El Niño episodes, and light blue areas correspond to La Niña episodes.

Source: Own estimates based on CHIRPS, Copernicus, DANE, and SIPSA.

Figure A.11

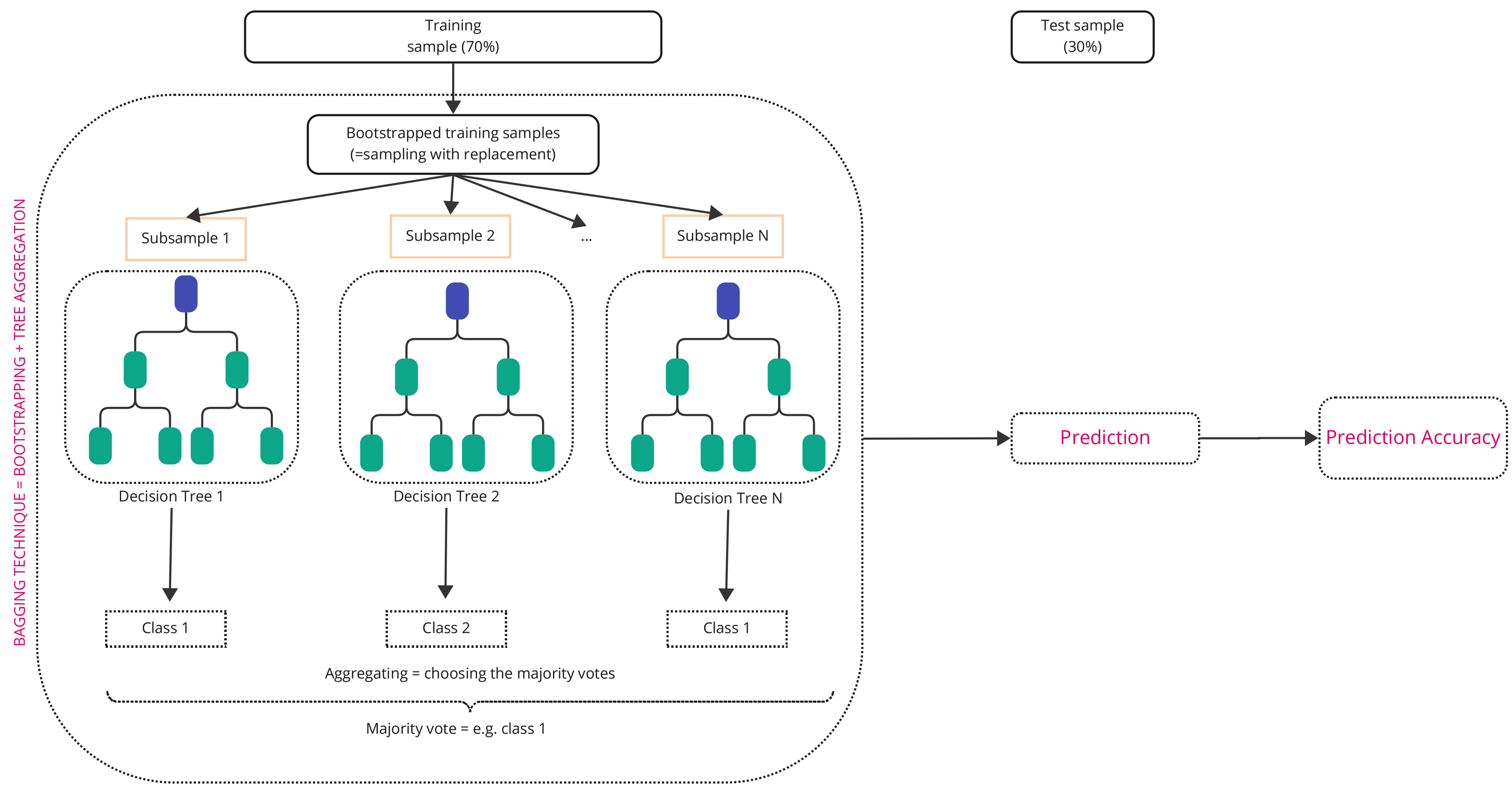
Correlation Matrix of Farm Characteristics (by crop)



Sources: Own estimations based on DANE, Google API, and Open Data Terrain Tiles.

Figure A.12

Description of the Random Forest Model



Classes: *class 1* = price increase is positive and global or local effect is significant, *class 2* = otherwise
Number of trees = 500
Minimum size of terminal node = 1