Weather Shocks and Food Prices in a Very Diverse Country: Evidence from Colombia*

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Abstract

We estimate the heterogeneous effects of extreme weather shocks on agricultural prices in Colombia. The country is characterized by tropical climate and heterogeneous topography, making its agriculture highly diverse. We estimate two-way fixed effect models based on granular data on wholesale food prices and climate. Results show that local (i.e., municipality-level) events of lack of precipitation mostly affect the prices of non-perennial products (i.e., those with short growing cycle but only one harvest), while global (i.e., country-wide) events of excessive precipitation tend to affect all crops. Our estimates also show that perennial crops (i.e., those with longer growing cycle but more than one harvest) are more resilient to extreme weather events. Last, but not least we conduct a meta-analysis to identify potential mechanisms that help to understand the estimations. By following a Random Tree approach, we find that inadequate access to artificial water sources or over-reliance to credit are relevant mechanisms to understand de effect of weather shocks on increasing food prices, while access to electricity and technical assistance are more likely to be related with resilience from these events.

Keywords: Climate change, extreme weather events, food prices, agriculture, Colombia
JEL Classification: O13, O54, Q10, Q18, Q54

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1 Introduction

Agriculture will be incrementally affected by climate change (IPCC, 2014). This is particularly important for tropical regions, where weather shocks are expected to reduce soil moisture, alter growing period length, damage plant cells, increase sterility, and multiplies invasive weeds species affecting native plants (Hertel and Lobell, 2014, Ortiz-Bobea et al., 2021). Most of the literature that relates the effect of extreme weather events on agricultural production has focused on the impact on crop yields and productivity (Carter et al., 2018, Ortiz-Bobea, 2021). One of the key results of this literature is that the effects of weather shocks are very heterogeneous across regions and crops. Modeling these sources of variation, for instance with panel models, is therefore critical to understanding the effect of weather on agriculture (Carter et al., 2018).

Mechanisms through which weather shocks affect agricultural prices can be differentiated into direct and indirect impacts. The direct impact would be the effect on plant growth and yields on which most of the literature has focused, while the indirect effect is related to farmers inputs' choices usually referred as the adaptation impacts (Burke and Emerick, 2016). The literature on adaptation impacts is relatively recent and shows how farmers by adapting their inputs' choice can reduce the negative impact of climate change. Such literature on adaptation impact focus on 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).

Apart from the mechanisms on the production side (direct and indirect effects above), weather shocks can affect prices by disrupting the trade or access to market along the supply chain (Colon et al., 2021), or with stockholding anticipation through traders' expectations might substantially affects agricultural prices (Letta et al., 2022). Unfortunately, this literature has mainly focused on grains or storable commoditiesm, forgetting the relevance of tubers, fruits, and vegetables in the diet of vulnerable populations in developing countries. Land allocation is particularly affected by climate change in tropical areas where some agricultural activities need to go to higher altitudes to keep current yields. Trade is particularly relevant for tubers, fruits, and vegetables for which lack of cold storage and transportation is highly damaging and increases food loss.

Extreme weather events also affect 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 particularly relevant question in developing countries, where the incidence of food prices on poverty is considerably higher and food inflation tends to be particularly volatile and sensitive to agricultural shocks (Walsh, 2011). Most of the literature studying this phenomenon is based on aggregated, time-series analysis (Abril-Salcedo et al., 2020, González-Molano et al., 2006). Others that use partial and general equilibrium models (Lemoine, 2018) usually work with yearly data frequency and have to make strong assumptions on profit functions and crop prices across states (Carter et al., 2018). While these studies provide useful information at the macroeconomic level, they tend to omit the regional and crop heterogeneity.

In this paper, we address the effect of extreme weather events on food prices, exploiting temporal, geographic, and crop variations of weather events and agricultural production. Our study focuses on Colombia, a country with a enormous geographical and agricultural diversity, where the impact of weather shocks is expected to be highly heterogeneous across such dimensions. We estimate two-way fixed effect models, based on detailed data on food prices in urban areas, information on the origin of the product sold in a given urban area, and weather measures from re-analysis data. This setup allow us to identify the role of local shocks through the estimated coefficients of the model accounting for market and product fixed effects.

Furthermore, we also address the effects of generalized—or global—extreme weather events (i.e., weather episodes across the territory at a given period of time) by regressing the estimated time fixed effects from the local shocks regression models on the national average of the extreme weather events. We take the concept of estimating the impact of global shocks from a literature in international trade and labor markets that implements this methodology to address time-series effects of tariffs on wages and labor relocation (Galiani and Porto, 2010, Cruces et al., 2018).

Our main results indicate the existence of heterogeneity in the impact of precipitation shocks on wholesale food prices. First, we find important effects of local episodes of lack of precipitation on a handful of non-perennial shocks, especially vegetables. On the other hand, global events, especially those of excessive precipitation, have a broader impact among the majority of crops analyzed in this paper, and their estimated effects are greater than those coming from local shocks. Likewise, countrywide events of lack of precipitation are also important to explain the observed increases in food prices, mostly for non-perennial crops. Last, but not least, it is important to note that our estimates provide suggestive evidence on the resilience to droughts of perennial crops. Although we find crop-wide impacts of global events of excessive precipitation, the estimates also show that the estimates of the effect of episodes of lack of precipitation are less likely to be statistically significant for these products.

In addition to the fixed-effect estimates of extreme weather events on food prices, we also conduct a meta-analysis to identify the most relevant observed determinants of increases in food prices. For such that purpose, we run a Random Forest model, that allows us to rank a series of variables, based on their importance on predicting the results from the econometric estimations. The relevance of this methodology relies on the fact that the interactions between food prices and the variables that are put into consideration as predictors may be non-linear.

We use the Colombian Agricultural Census to generate a series of municipality-level variables that account for characteristics that could drive agricultural production (e.g., farm size, access to utilities, technical assistance, credit, distance to wholesale centrals). According to the results, , inadequate access to artificial water sources, over-reliance to credit, access to electricity, or technical assistance are among the key features that help to predict the estimated impacts of weather shocks on food prices, although the signs of their mechanisms vary by type of weather event.

This paper contributes to the literature on the impact of weather shocks on food prices. While most of the previous studies rely on aggregate, time series analysis (Abril-Salcedo et al., 2020, González-Molano et al., 2006), we employ food prices obtained in urban areas and we are also able to trace the production area of the product sold in the cities, which allows us to evaluate how a weather shock in the production area affect food prices. Additionally, we are able to disentangle both local and global (i.e., generalized) events of extreme weather shocks. This is a particularly relevant issue in highly diverse countries, such as Colombia, where there is enormous heterogeneity across climate, geography and crops.

Our results are also related 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). While our estimates mostly reflect short-term effects of weather shocks, they do provide new insights regarding their geographic and crop heterogeneity. Overall, we highlight the importance of accounting for these sources of variation, particularly in very diverse countries, when assessing the potential impacts of climate change.

The remainder of this paper is organized as follows: Section 2 provides background on the weather patterns in Colombian and the main characteristics of agricultural production in the country. Section 3 describes the data, and Section 4 explains the empirical strategy. Section 5 reports the econometric estimations, and, later, in Section 6 we present the Random Forest estimation that allows us to identify the potential mechanisms in which the main results take place. Finally, section 7 concludes.

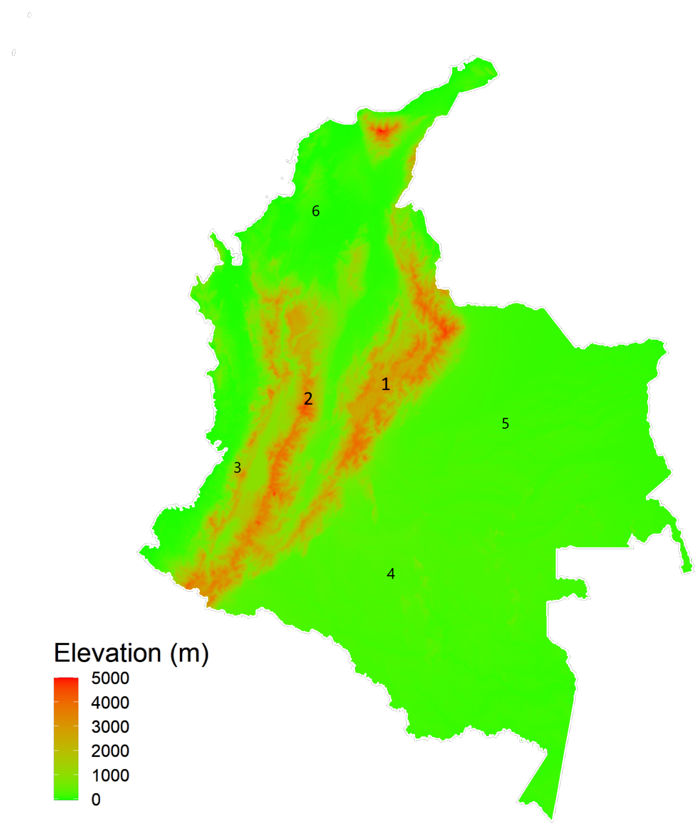
2 Weather and Agriculture in Colombia

Tropical regions are characterized by a low seasonal variability in air temperature, and large variability in rainfall. Additionally, variation in topography can also play an important role in weather, as higher places experience lower average temperatures compared to lands with less altitude. Given its proximity to the Equator, Colombia experiences tropical weather patterns all year long, and its climate is also subject to the differences in altitude throughout the territory. Such characteristics makes the panel approach more adapted to capture the regional effect of weather shocks contrary to time series analysis.

The Colombian topography is composed of three clearly-defined large mountain ranges that run from north to south, in addition to a vast Amazon jungle in the southeast section of the country, the eastern plains known as the Orinoquia, and the savannah by the

Caribbean coast. Figure 1 displays the average altitude for every Colombian municipality, clearly reflecting the three main mountain ranges that later in the South conform the Andes across the continent.

Figure 1
Average altitude in Colombia by municipality



List of regions: 1) East Range, 2) Central Range; 3) West Range; 4) Amazon; 5) Orinoquia; 6) Caribbean. Own calculations. Source: AWS Open Data Terrain Tiles

That variation in altitude reflects differences in precipitation and temperature patterns. Figure 2 displays the correlation between average monthly minimum and maximum temperatures, and monthly precipitation as well for Colombia, during the period 2010–2019.

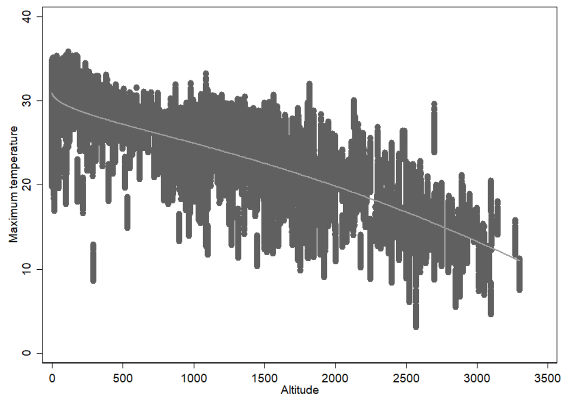
This figure shows a clear negative correlation between (minimum and maximum) temperatures and altitude (panels a and b). With respect to precipitation (panel c), the variance on average monthly precipitation decreases as altitude goes up.

The Southern Oscillation Cycles, known as El Niño and la Niña, are one of the main causes of rainfall shocks in the region (IDEAM, 2000). While these extreme events affect multiple countries, the distribution of the weather shocks can widely vary within a country. Salas-Parra (2020) documents heterogeneous effects of El Niño and la Niña in Colombia. While the impact of La Niña (excessive rainfall) is stronger in the Caribbean, Pacific, and Andean regions, the impact of El Niño (lack of rainfall) is the strongest in the Orinoquia and Amazon regions.

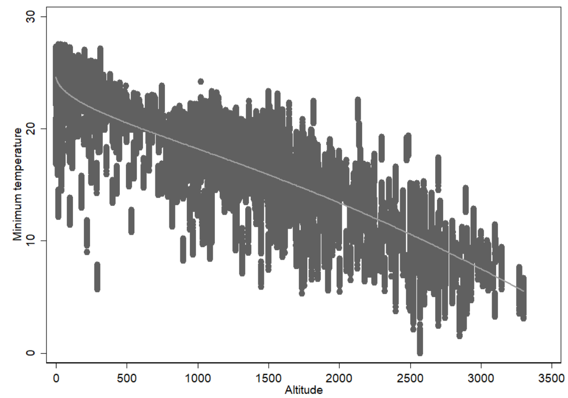
The relationship between climate and topography is also determinant for agricultural production across the Colombian territory, since it also shapes the suitability and adaptability of soil for the production of crops. In the warmest regions of the country (i.e., below 1,000 meters of altitude), the most produced crops or livestock are coconut, banana, plantain, rice, cotton, cacao, sugarcane, cassava, and cattle for meat. Altitudes between 1,000 and 2,000 meters are where coffee, flowers, maize, fruits, and some vegetables are most grown. Finally in higher altitudes (i.e., between 2,000 and 3,000 meters), we can find crops such as potatoes, wheat, barley, cold-climate vegetables, flowers, dairy cattle, and poultry Ramirez-Villegas et al. (2012). Figure 3 displays the mean altitude by groups of (raw and processed) products in 2013 and 2019. In addition to the heterogeneity in average altitude by groups, we observe in most cases an increase in the average altitude between the years of study. Such that increase is particularly marked for tubers, plantains, and vegetables.

Figure 2

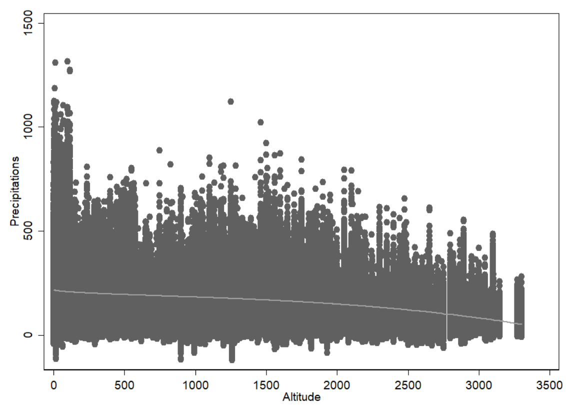
Minimum and maximum temperature (Celsius) by altitude (meters), and precipitation by altitude (meters)



(a) Minimum Temperatures



(b) Maximum Temperatures



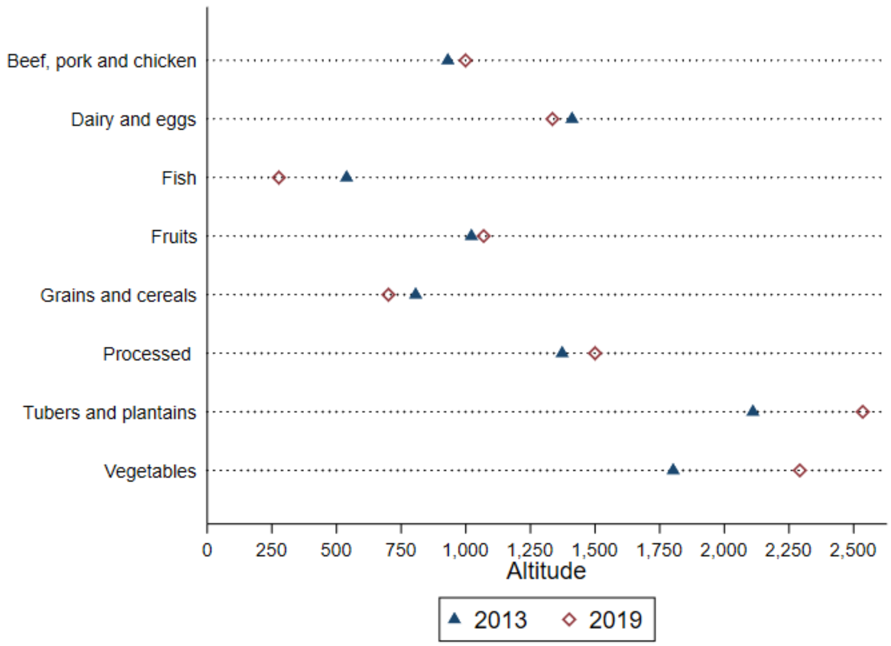
(c) Average Monthly Precipitation

Sources: IDEAM and World Climate

Climate change is expected to increase temperature and the frequency and intensity of Southern Oscillation cycles in Colombia (Bohorquez-Penuela and Otero-Cortés, 2020, Hoyos et al., 2013). Consequently, their effects on crops might be important. 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 most affected regions by droughts will be the Caribbean coast with an acceleration of deserti-

Figure 3

Median Altitude (in meters) for the Production of Food Products in Colombia, 2013 and 2019



Source: SIPSA

fication. Glacier mass is expected to decrease by 80% by 2050, which affects freshwater availability in the Andean regions. These changes will, in turn, increase soil degradation, land instability, and mudslides. The effects on agriculture will depend on the region's topographic and geographic characteristics, as well as the type of crops, and the farm specialization (Ramirez-Villegas et al., 2012, Esquivel et al., 2018, Loboguerrero et al., 2018). Large, highly specialized, farms are expected to be hard hit by extreme shocks due to their lack of diversification (mainly monoculture farms). This is the case of sugarcane in Colombia, which is expected to have a strong yield reduction by 2050 as estimated by the CIAT (Ramirez-Villegas et al., 2012). Small producers, relying on more traditional technology, are particularly vulnerable to climatic variations due to the increase in disease prevalence, yield reductions, and the lack of information and infrastructure (Hertel and Lobell, 2014).

3 Data

We combine data on wholesale prices of agricultural food products and weather in Colombia for the period 2015–2023 from multiple sources. Wholesale 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).[1] SIPSA reports prices of more than 90 different products—crops, animal-based, and processed—on each of the 20 main wholesale markets of the country, and are available on a weekly basis since 2013. In addition to prices, SIPSA also reports quantities delivered to the wholesale centrals, and the municipalities of origin of those deliveries. As we explain in the next section, knowing the origin of the deliveries will be crucial to identify the relevant weather that could have affected the production of crops.

Table A.1 of the appendix lists all products available in SIPSA that we take into consideration for our analysis. To minimize potential bias from our estimations due to data attrition, we kept the products for which we can conform the most balanced panel possible. Also, for products with more than one variety, we kept the one with the most number of observations available. We classify the products according to their corresponding growing cycle (i.e, perennials or non-perennials). [2] This classification is also a central feature to identify the relevant weather that affects crops during the growing cycle. It is important to clarify that SIPSA do not represent the complete dynamics of food supply to wholesale

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

[2]Perennial crops are those whose cycle is usually longer than one year, but provides more than one harvest (i.e., do not require replanting after the first one). On the other hand, non-perennial crops have shorter growing cycle (i.e., between 3 and 12 months), but only provide one harvest.

centrals. These data are not collected on a structured way that ensures full representativeness of the supply of products. According to some informal talks we had with officials from a wholesale central in Colombia, anecdotal evidence indicates that SIPSA data on volumes of products entering the centrals could represent about 70 percent of total volume at any given month.

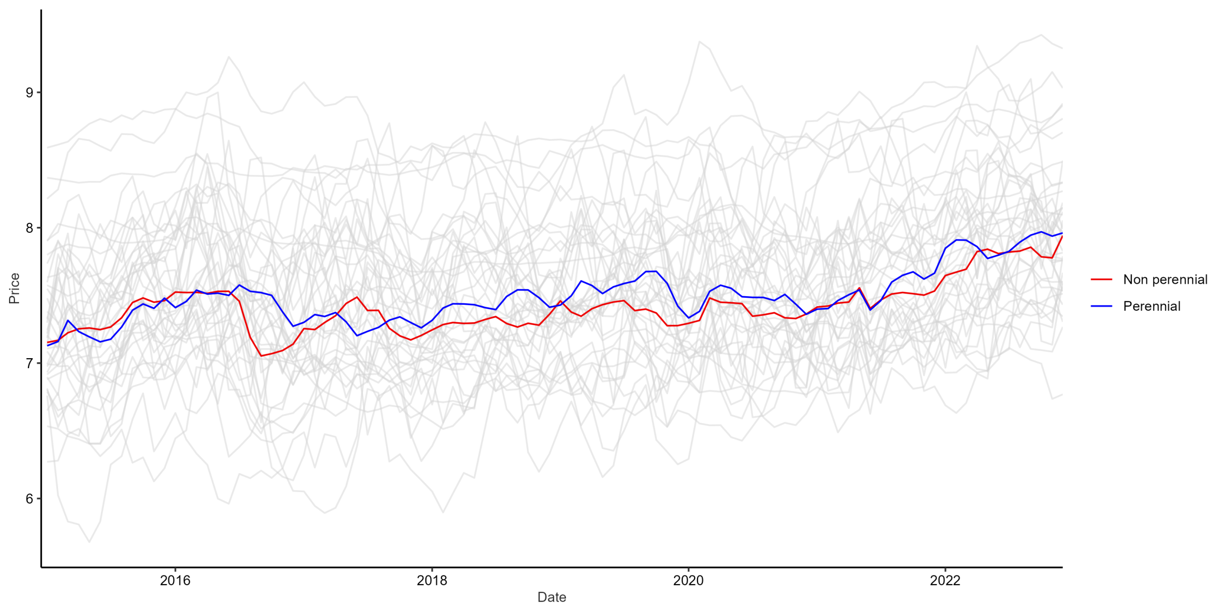
Figure 4 displays the evolution across the period of study of the wholesale central-averaged log prices of all products included in this paper. This graph reveals two important features. First, There is considerable variation in prices across products over time. Second, when aggregating products according to their growing cycle, we observe the trends of log-prices of perennial and non-perennial crops do not greatly vary, but it is possible to observe variance between them across time. Aggregating prices would hide heterogeneity across products and within wholesale centrals. In Figures A.1 and A.2 of the Appendix we present the evolution of prices by products. As seen, even within groups of crops (i.e., non-perennial or perennial), there are substantial differences among prices in terms of trends and variation.

The production of crops in Colombia takes place across the territory, showing important variation by altitude and other relevant geographic characteristics. In Figures A.3 and A.4 of the Appendix we display the origin of the products recorded in SIPSA that are part of our analysis. According to the map, we observe that most of the production of non-perennial crops take place across the mountain ranges of Colombia (with few exceptions like, for example, yucca, that grows by the eastern plains of the Orinoquia region as well as the savannas of the Caribbean coast), while perennial crops display spatial heterogeneity.

Regarding weather, we take information from the Climate Hazards Group InfraRed

Figure 4

Evolution of prices (in logs) at wholesale centrals, 2015–2023



Source: SIPSA. Own Calculations

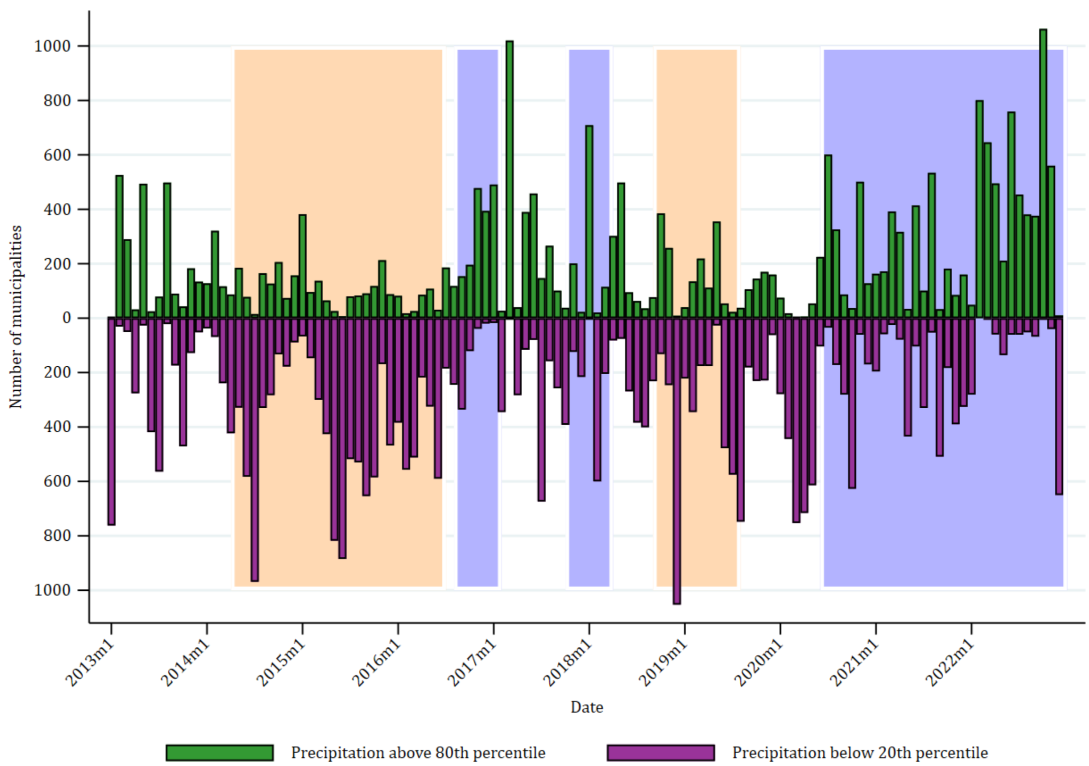
Precipitation with Station data (CHIRPS) of the Climate Hazards Center of UC Santa Barbara.[3]. CHIRPS specializes in collecting and processing data on precipitation, spanning the area between the latitudes 50Â°S and 50Â°N and all latitudes, with a 0.05Â° level of detail, for the period 1981–present. We decide to use re-analysis data like CHIRPS instead of official information from meteorological stations administered by the Colombian institute of meteorology in order to achieve full coverage of the weather for the Colombian territory during the period of study.

In this paper, we are interested in identifying episodes of excessive or lack of precipitation. Therefore, we merge the polygons that represent the Colombian territory with CHIRPS data to calculate monthly precipitation at the municipality level, for the period 2015–2023. Then, we define as an extreme weather event of excessive (lack) precipitation whether the observed monthly rainfall is above (below) the 80th (20th) percentile of the

[3]https://www.chc.ucsb.edu/data/chirps

historical distribution between 1980 and 2014, just before the beginning of the period of study. Figure 5 displays the evolution of the number of municipalities in Colombia that experienced any of these extreme weather episodes at any given month between 2013 and 2022. This graph displays a high correlation between events of extreme (lack) precipitation with la Niña (el Niño) phenomenon.

Figure 5
Incidence of precipitation shocks, 2013–2022



Note: Each bar represents the number of Colombian municipalities that experienced a given precipitation shock art any given month during the period of study. Light red areas denote el Niño episodes, while light blue areas corresponds to la Niña.
Source: CHIRPS

To further explore the geographical variation of the extreme weather events, we plot the total number of events by municipality between 2013 and 2022, reported in Figure A.5

of the Appendix. Panels a and b show the numbers of months with events of excessive and lack of precipitation for each Colombian municipality, respectively. According to the maps, the highest incidence of events of excessive precipitation take place in lower lands of the Amazon region and in between the mountain ranges. On the other hand, episodes of lack of precipitation are more likely to happen in the mountains of the eastern range and some areas of both the Caribbean and Pacific coasts.

4 Empirical strategy

In this section we begin by describing the process for identifying the relevant weather for the different crops we analyze in this paper. Then, we explain the identification strategy that allow us to assess the impact of extreme precipitation events of wholesale food prices.

4.1 Identifying Relevant Weather

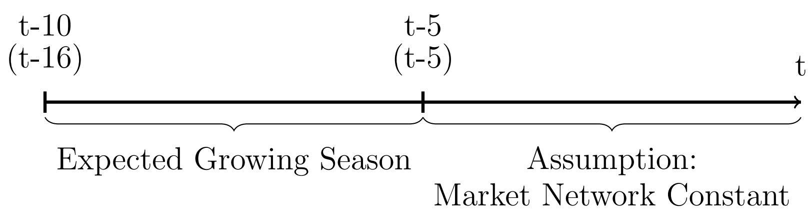
Our final dataset comprises more than 50,000 product-destination city-month observations between the years 2015 and 2022. The greatest challenge in relating climate and prices is to identify the weather that is relevant for each one of the products, given their characteristics (i.e., perennial or non-perennial crop) and the places they were produced.

To achieve this goal, we use SIPSA to identify the origin of the products that arrive to the wholesale centrals. For each crop $i \in I$ (listed in Table A.1 of the Appendix) at time t, we identify a set of producing municipalities M that marketed that product to each wholesale central $j \in J$ (M_{jt}) during its corresponding growing cycle. For non-perennial crops, we consider the period between $t-5$ and $t-10$. For perennial crops, we take into consideration the supply of products from producing municipalities between $t-5$ and

$t - 16$. Then, we calculate the share of each municipality on total supply of crop i to wholesale central j (w_{mjt}) during that period. As described by Figure 6, we identify this time period as the *expected growing season*, and the difference in lengths between perennial and non-perennial crops refer to the expected time between sowing and harvesting for each type. The municipalities we identify for the corresponding expecting growing season for product i that arrived to wholesale central j at month t conform the network of relevant suppliers.

Figure 6

Identification of the Network of Relevant Suppliers



Note: Time period of reference for perennial crops in parentheses.

As described by the timeline displayed in Figure 6, the identification of the expected growing season starts 6 months before the moment the price of crop i is recorded in SIPSA. This is made to avoid any potential endogeneity that could come from weather and, consequently, affect the different distribution networks. Therefore, we assume the market network M_{ij} at time t to be constant in the short term.

After identifying that network, we construct the relevant weather for product i in wholesale center j whose price was registered by SIPSA in month t. For each type of extreme weather event $s \in S =${excessive, lack}, we calculate the weighted proportion of time between t and $t-5$ for which the municipalities that belong to M experienced the corresponding weather shock:

$$\forall i \in I : weather^s_{jt} = \sum_{m \in M_{jt}} C^s_{mt} \times w_{mjt} \tag{1}$$

where C^s_{mt} is the proportion of time during the last 6 months in which those producing municipalities experienced an extreme weather event at any given period t, and w_{mjt} is the share of production of that producing municipality m on the total volume of crop i that arrived to wholesale central j.

4.2 Identification Strategy

Our baseline specification is a two-way fixed effect model that regresses for each product i its price (in logs) at market j and period t, p_{jt}, on the weather shocks that took place on its network of producing municipalities, $weather^s_{jt}$:

$$\forall i \in I : log(p_{jt}) = \sum_{s \in S} \beta_s weather^s_{jt} + \gamma_j + \delta_t + \epsilon_{jt} \tag{2}$$

where $\sum_{s \in S} weather^s_{jt}$ corresponds to the share of time that each relevant producing municipality experienced a given precipitation shock, γ_j is the market fixed effect; δ_t is the period (year-month) fixed effect, and ϵ_{ijt} is a zero-mean error. The β_s coefficients identify the short-term causal effect of the different precipitation shocks. The model includes market fixed effects to account for the unobserved time-unvarying characteristics of each market that may affect prices. We also include period fixed effects that account for common shocks between wholesale centrals, including those related to weather events. Errors are clustered at the product $\times$ market level.

Following Galiani and Porto (2010) and Cruces et al. (2018), we approximate impacts of global episodes of extreme weather events on agricultural prices (that is, the effect of precipitation shocks countrywide rather than local) by recovering the time-fixed effect coefficients from Equation 2 and regressing them on the national average weather shocks:

$$\forall i \in I : \widehat{\delta_t} = \omega + \sum_{s \in S} \alpha_s \overline{weather_t^s} + u_t \tag{3}$$

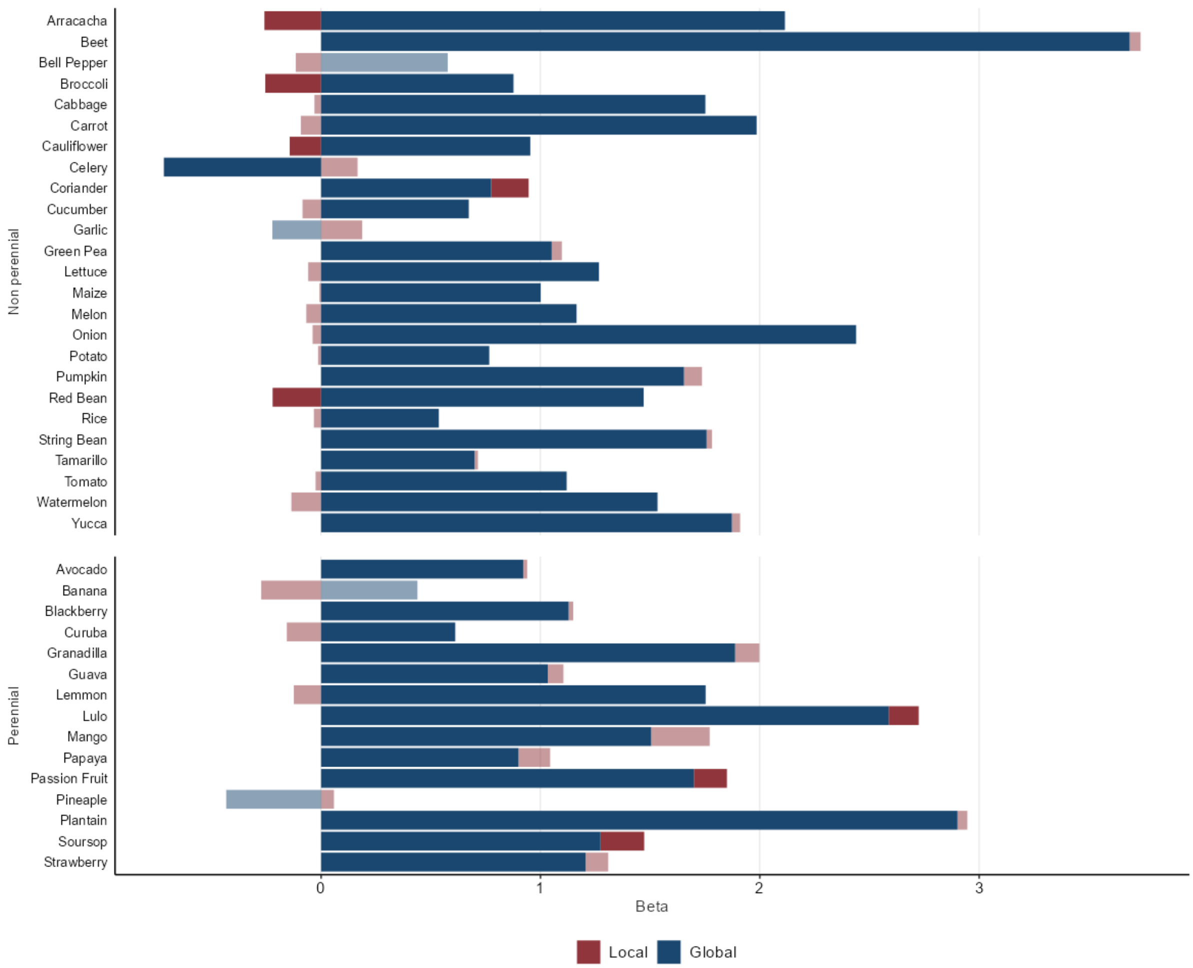
where $\widehat{\delta_t}$ is the estimated period fixed effect. As explained by Galiani and Porto (2010) and Cruces et al. (2018), since the dependent variable is a vector of predicted values, we should estimate the model using Weighted Least Squares (WLS), using as weights the inverse of the estimated variance of the period fixed effects from the estimates of Equation 2 . In Equation 3, the estimated α coefficients capture average effects of countrywide weather shocks s on the variation of wholesale prices.

5 Results

In Figure 7 we display the estimated coefficients of β and α from Equations 2 and 3, for events of excessive precipitation. For this type of weather shocks, we observe the predominance of positive effects on prices (i.e., they go up as as the incidence of this event also increases at producing municipalities), for both non-perennial and perennial crops. This result takes place mostly for the global events, which, at the same time, are statistically significant for most coefficients. Moreover, for the majority of crops the estimated coefficient of global events (α) is greater than those from the local events (β). There is only one product for which the estimated coefficient of global precipitation events is negative and significant (celery), and for few of them the corresponding parameter of extreme local events have also the same sign (arracacha, broccoli, cauliflower, and red bean). All of these aforementioned crops are non-perennial.

Figure 7

Estimated coefficients of the impact of local and global extreme weather events of excessive precipitation



Note: Bold bars denote estimated coefficients that are statistically significant at 10% or less. Own Estimates. Sources: SIPSA and CHIRPS.

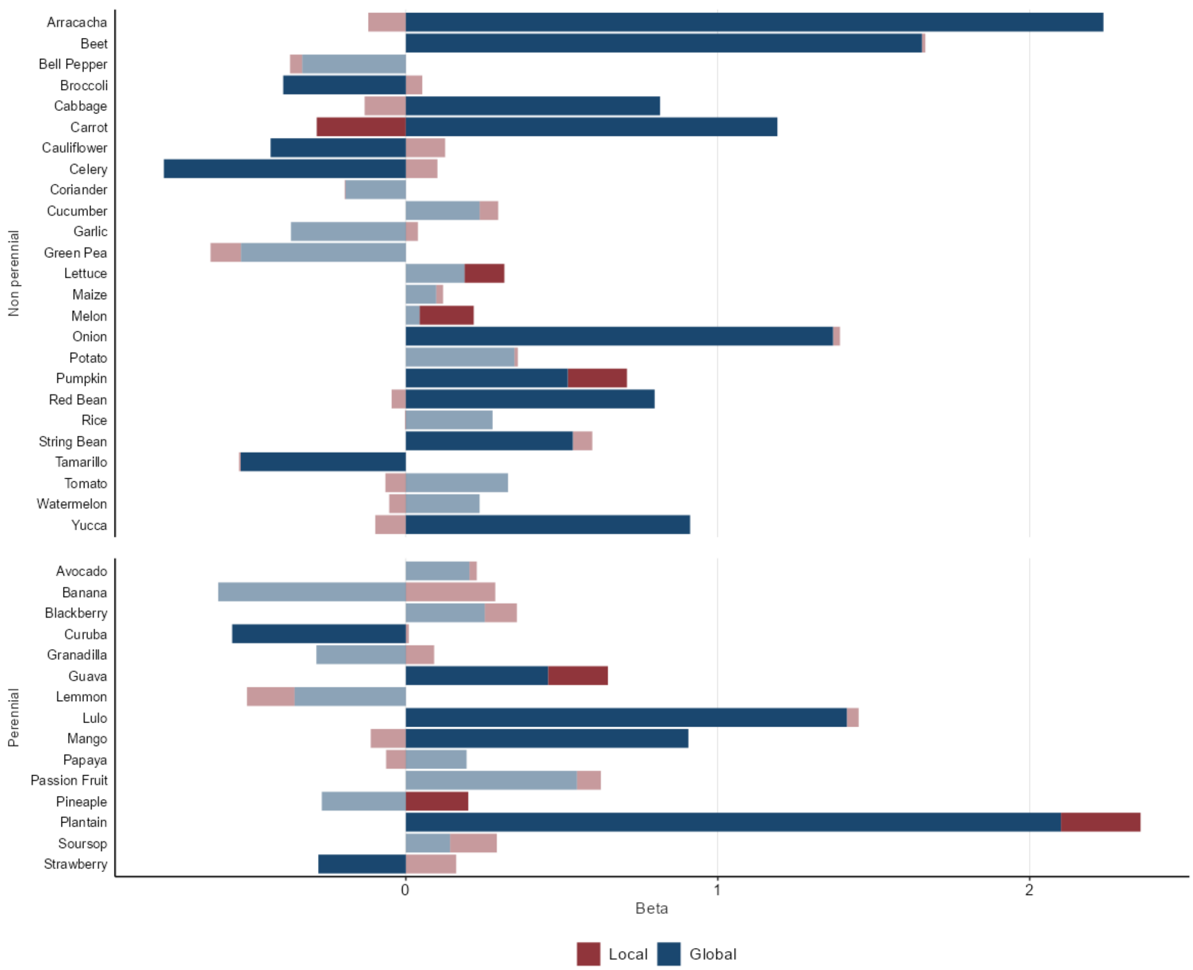
On the other hand, we observe greater heterogeneity on the estimates of the effects of episodes of lack of precipitation, as displayed by Figure 8. For this type of episodes, we find again a predominance of the impacts of global events on food prices, especially for non-perennial crops. Only for a handful of perennial crops (guava, lulo, mango, and plantain), generalized events of lack of precipitation tend to be positive and statistically significant. With respect to the local events, non-perennial crops are more likely to be affected. Unlike the events of excessive precipitation, we find that local episodes of lack of rainfall can have a more important impact on food prices.[4]

In summary, for a geographically diverse country like Colombia, country-wide precipitation shocks are still predominant regarding the effects on food prices. Local events of lack of precipitation tend to be more relevant compared to episodes of excessive precipitation, mostly affecting non-perennial crops, presenting suggestive evidence that perennial crops, as we explained before, are more resilient to droughts.

[4]Tables A.2 to A.5 of the Appendix report the full regression estimates displayed on Figures 7 and 8.

Figure 8

Estimated coefficients of the impact of local and global extreme weather events of lack of precipitation



Note: Bold bars denote estimated coefficients that are statistically significant at 10% or less. Own Estimates. Sources: SIPSA and CHIRPS.

6 Meta-analysis

This section aims to uncover the key determinants driving food price increases, particularly in the context of weather shocks, to reveal the most important mechanisms. Our analysis focuses on a dependent variable represented as a binary outcome, where it takes a value of one if the combined local and global effects are both positive, with at least one of these parameters being statistically significant. To ensure a robust and comprehensive analysis, we employ on data from the 2014 Colombian Agricultural Census (Censo Nacional Agropecuario - CNA) for our feature variables.

We calculate the municipal averages for selected variables from the 2014 Colombian Agricultural Census (Censo Nacional Agropecuario - CNA), including geographic and farm-specific characteristics of municipalities. Geographic attribute is characterized by altitude, while farm characteristics covers factors such as farm size (measured as the area of the production unit), technology access (including availability of electricity, technical assistance, and credit access), and water sources access. Water sources are categorized as natural (including sources such as lakes, rivers, streams, springs, swamps, or wetlands, as well as natural springs with catchment systems) or non-natural (such as reservoirs, dams, ponds, aqueducts, water tankers, and irrigation districts).

Notably, farm area is positively correlated with technical assistance, as larger farms are more likely to receive advisory services aimed at enhancing production efficiency and sustainability. Access to electricity is also positively correlated with technical assistance, reflecting that farms with better infrastructure often attract more support services, which contribute to improved resilience (See Figure A.7 in Appendix).

Additionally, accessibility to central markets is measured in travel time (in hours), calculated using the Google Maps API. Finally, the variable set also includes the number of municipalities producing the same agricultural product. A higher number of municipalities producing the same product is hypothesized to either amplify or mitigate price effects in response to extreme weather shocks, depending on the predominance of global versus local impacts. In Figure A.6 of the Appendix we display maps that show the municipal-level average values of these variables.

6.1 Random Forest Algorithm

The Random Forest model is particularly well-suited for predicting increases in food prices, especially given the complex and nonlinear interactions among predictor variables that influence the effects of weather shocks on food prices. Additionally, the feature importance metrics provided by the random forest algorithm enable the identification and prioritization of the most impactful predictors of food price increases. This enhances the model's interpretability, offering valuable insights that can inform decision-making processes for policymakers and stakeholders.

In our research, we employ the Random Forest machine learning algorithm based on a classification regression tree. The algorithm is built on multiple decision trees, one of the most common ensemble learning method. Its algorithm is based on bagging (also known as Bootstrap AGGregatING). This approach consists in taking several sub-samples of the initial training dataset with bootstrapping (i.e. randomly selects data with replacement). For each of these sub-samples, a decision tree is created. Finally, the combination of all the decision tree building is a 'forest'. The average value of multiple trees is the final result by voting (we say a tree 'votes' for a class when it gives a classification). The purpose of bagging is to lower the model variance of using one single decision tree. The undrawn data will form an Out of Bag (OOB) dataset, which will be used as test sample to evaluate the accuracy of the random forest model and the importance of each feature value.

Utilizing a dataset comprised of 122 sample observations, we construct a random forest model [5], with 10 determinants as independent variables and our constructed dummy as the dependent variable. The dataset is subsequently divided into a training set (70% of the sample) and a test set (30% of the sample). The training set is used to train the random forest model, and the model's accuracy on the test set is employed to assess the impact of determinants on food price increases.

The random forest algorithm developed uses Gini impurity as the default criterion for splitting nodes in classification tasks. Gini impurity measures the "impurity" or disorder within a set of classes, aiming to create splits that increase the purity of nodes by reducing heterogeneity in each successive split.

As a final step, we rank the importance of independent variables in the Random Forest model the Mean Decrease Accuracy. Mean Decrease Accuracy is the mean decrease of accuracy over all out-of-bag cross validated predictions, when a given variable is permuted after training, but before prediction. Feature variables that cause a greater decrease in accuracy are considered more important.

We set the number of trees in the random forest to 500, which controls the total number of trees within the ensemble model. Accuracy stabilizes beyond 150 trees, indicating that 500 trees provide sufficient depth and predictive stability for our analysis. Additionally,

[5] We illustrate the implementation of the random forest in our model in A.8 in the Appendix

we set the minimum size of terminal nodes to one, allowing trees to grow to their natural size without constraints. This setting avoids premature restriction of tree depth, ensuring that the model can capture complex patterns within the data. A higher minimum terminal node size would reduce the tree depth, potentially limiting the model's ability to capture finer data nuances.

6.2 Random Forest Results

This section examines the results of the random forest model regarding variable importance in predicting food price increases after two types of extreme weather shocks: (1) excessive precipitation and (2) lack of precipitation. Key variables such as farm area, access to artificial water sources, access to electricity, technical assistance, and the number of municipalities play critical roles in resilience to these events.

6.2.1 Impact on episodes of excessive precipitation

For events of excessive precipitation, the most influential variables identified were farm area, access to artificial (non-natural) water sources, access to electricity, technical assistance, and the number of municipalities (Figure 9).

Excessive precipitation heightens the risk of erosion and soil degradation (Almagro et al., 2017). Monoculture practices, often linked to large farm areas, are particularly vulnerable to these risks. However, diversified farming can enhance resilience by spreading risk; larger farms with diversified production may absorb losses in part of their output while maintaining minimum production levels.

The access to artificial water sources variable suggests that farms with such access have better water permeability and retention, thus enhancing resilience during heavy rainfall events (Han et al., 2018). However, in Colombia, a large number of municipalities are affected by damaged water services during episodes of flash floods resulting in worsening effect of flooding on production loss (UNGRD, 2023). Such damages might be due to landslides or floods and a lack of maintenance or timely emergency responses. In theAppendix, we assess the direction of the effect by regressing the access to artificial water sources on dummy of price increase if the local or local effect are significant (Table A.6). Results indicate this access tends to increase the prices, making the production more vulnerable when inadequate access to artificial water source is in place.

Access to electricity and technical assistance are also critical, as they support rapid recovery and pest control in high-humidity conditions. Electricity enables refrigeration to prevent post-harvest losses and access to real-time weather and market information. Technical assistance offers training on sustainable practices and pest control, aiding in recovery. These resources enable faster responses than credit access, which serves primarily for medium- to long-term recovery. Regression results in Appendix (Table A.6) confirm the positive role of these variables in mitigating post-flood losses.

The number of municipalities variable shows limited influence, as events of excessive precipitation often impact multiple municipalities simultaneously, diminishing local supply buffers. Consequently, heavy rainfall's impact on food prices stems largely from widespread disruptions rather than isolated local effects (see Figure 7).

6.2.2 Impact on episodes of lack of precipitations

Key variables driving products price increases due to lack of precipitation events includes access to credit, type of crop (permanent or transitory), number of municipalities, and access to artificial water sources. Variables with lesser importance were altitude, farm area, access to electricity, technical assistance, and distance to market.

Access to credit primarily facilitates medium- and long-term recovery by financing investments in drought-resistant crops, irrigation systems, and other adaptation strategies. However, over-reliance on credit without immediate recovery mechanisms can increase vulnerability, especially if farmers face repayment challenges (Li et al., 2024).

Perennial crops provide higher resilience to droughts than non-perennials, making crop type an essential factor in predicting price stability under low-precipitation conditions (Basche and Edelson, 2017). Regression results in Appendix (Table A.6) support the significant role of crop type in enhancing resilience during droughts.

The number of municipalities is another important factor, as regions unaffected by drought can buffer local price increases, ensuring a stable supply from unaffected areas. As for the case of excessive precipitation events, this variable played a minor role.

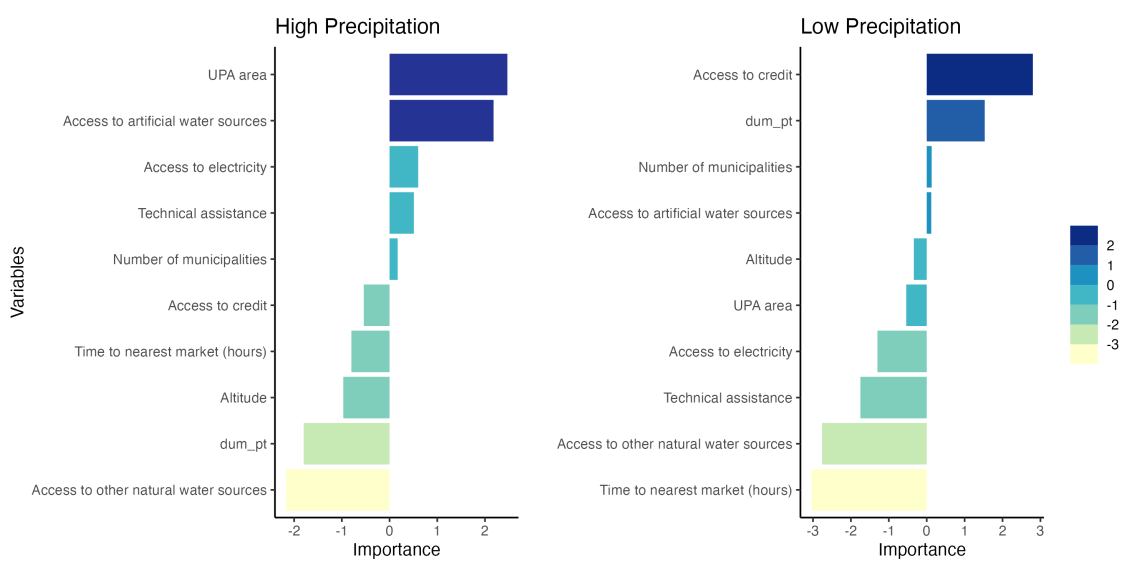
Availability of artificial water sources significantly reduces the impact of droughts on food prices, underscoring its importance as a resilience factor during low-precipitation events (Molden, 2013). While it has a relative minor importance in our results, it might be redundant with access to credit feature variable which provides a more holistic approach in terms of past adaptation to drought events.

These results provides valuable insights into the drivers of food price increases following extreme weather events, highlighting the importance of farm area, access to artificial water sources, electricity, technical assistance, and regional reach. These variables, in varying degrees, significantly influence the resilience of agricultural production under both excessive precipitation and drought conditions, offering crucial information for designing targeted interventions.

From a policy perspective, this analysis underscores the importance of strengthening rural infrastructure, particularly in artificial water systems, and providing technical assistance to farms. Investment in these areas could mitigate the adverse effects of extreme weather on food prices, promoting stability in vulnerable communities. Additionally, fostering credit systems geared toward climate adaptation and promoting diversified cropping systems can enhance resilience, supporting farmers in both the short and long term.

Figure 9

Variable importance ranking from the Random Forest



7 Conclusions

The accelerating pace of climate change is not only represented by increasing temperatures but also by winding precipitation regimes, in terms of incidence and temporal and spatial variation as well. In developing countries, in which most farmers lack of enough production technologies (i.e., irrigation, drainage, machinery, technical assistance), unstable weather conditions can affect their production decisions and, consequently, the outcomes. Under these circumstances, it is likely to observe increases in food prices after the occurrence of extreme weather events, with subsequent consequences on households' well being, especially the poorest and vulnerable.

In this paper we address the effects of precipitation shocks on wholesale food prices in Colombia, a tropical developing country with enormous geographical and climate variation, allowing the production of different crops throughout the territory. To address such that diversity, our empirical strategy is threefold: first, we estimate two-way fixed effect models to estimate the effect of local (i.e., municipality level) precipitation shocks on prices. Then, we approximate the impact of global (i.e., countrywide level) events by recovering the period fixed effects from the TWFE estimates and regress them on aggregate measures of precipitation shocks. Our findings highlight the importance of global events, especially those of excessive precipitation, on explaining the observed increases in prices, whereas local events of lack of precipitation have an impact on some non-perennial crops. These results provide suggestive evidence of resilience of perennial crops on droughts.

Our regression estimates present evidence on the impacts of precipitation shocks on wholesale prices, but are not indicative of the potential mechanisms in which such that relationship takes place. Therefore, the last step of our empirical strategy consists of conducting a meta-analysis to understand which geographic, topographic, environmental, and infrastructure characteristics could explained the results we obtain with the econometrics. After running the Random Forest model, we find that inadequate access to artificial sources of water and over-reliance on credit are good predictors of the estimated effects of weather shocks on food prices. On the other hand, access to electricity and technical assistance tend to be related with resilience. Both the econometric estimations and the subsequent meta-analysis aim to provide insightful discussions around policies for addressing both mitigation and adaptation effects of climate change for agricultural producers.

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Appendix

Table A.1
List of Products

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

Table A.2

Effects of local extreme weather events on wholesale prices of non-perennial crops

	Precipitation above 80th percentile	Precipitation below 80th percentile	R-squared	Observations
Arracacha	-0.258**	-0.120	0.876	1151
	(0.0924)	(0.0772)		
Beet	0.0135	0.139***	0.930	1256
	(0.0498)	(0.0110)		
Broccoli	0.0482	0.0638	0.884	1117
	(0.316)	(0.865)		
Cabbage	-0.255***	0.0526	0.750	1363
	(0.0546)	(0.0403)		
Carrot	0.000364	0.212	0.915	1441
	(-0.0304)	(-0.132)		
Cauliflower	0.102	0.0790	0.885	1135
	(0.770)	(0.111)		
Celery	-0.0924	-0.286***	0.812	1293
	(0.0850)	(0.0637)		
Coriander	0.290*	0.000227	0.757	1398
	(-0.143)	(0.126)		
Cucumber	0.0764	0.0919	0.865	1407
	(0.0820)	(0.192)		
Garlic	0.166	0.101	0.792	1302
	(0.135)	(0.0889)		
GreenPea	0.235	0.270***	0.928	1207
	(0.171)	(-0.00305)		
Lettuce	0.0866	0.111	0.889	1439
	(0.0632)	(0.978)		
Maize	-0.0847	0.0595	0.733	1330
	(0.0490)	(0.0695)		
Melon	0.100	0.402***	0.784	1222
	(0.187)	(0.0387)		
Onion	0.120	0.0804	0.885	1411
	(0.135)	(0.636)		
Pepper	0.0464	-0.0977	0.824	1411
	(0.0426)	(0.0851)		
Potato	0.294***	0.269*	0.925	1447
	(-0.0589)	(0.128)		
Pumpkin	0.0535	0.0432***	0.736	1307
	(0.285)	(0.00784)		
RedBean	-0.00764	0.0222	0.822	1264
	(0.108)	(0.0658)		
Rice	0.944***	0.739***	0.943	1275
	(-0.0675)	(0.174)		
StringBean	0.0532	0.0616***	0.813	1411
	(0.223)	(0.0123)		
Tamarillo	-0.0388	0.0224	0.892	1402
	(0.0554)	(0.124)		
Tomato	0.492***	0.859***	0.896	1165
	(-0.116)	(-0.0393)		
Watermelon	0.0947	0.0859	0.792	1157
	(0.237)	(0.652)		
Yucca	-0.0139	0.0111	0.904	1397
	(0.0646)	(0.0609)		

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Note: Each row corresponds to the estimates of Equation 2 for each one of the products $i \in I$ listed in the first column.
Own estimations. Sources: CHIRPS and SIPSA.

Table A.3

Effects of global extreme weather events on wholesale prices of non-perennial crops

	Precipitation above 80th percentile	Precipitation below 80th percentile	R-squared	Observations
Arracacha	0.727	0.979**	0.0516	96
	(0.551)	(0.318)		
Beet	0.190	0.00273	0.240	96
	(2.217)	(0.626)		
Broccoli	0.520***	0.376***	0.333	96
	(0.0000479)	(0.0989)		
Cabbage	0.542**	-0.600***	0.135	96
	(0.180)	(0.150)		
Carrot	0.00330	0.000132	0.0809	96
	(1.708)	(0.699)		
Cauliflower	0.380***	0.294***	0.411	96
	(0.0000201)	(0.0193)		
Celery	1.274***	0.686*	0.0286	96
	(0.355)	(0.300)		
Coriander	0.000543	0.0244	0.243	96
	(0.701)	(-0.544)		
Cucumber	0.175***	0.116***	0.0325	96
	(0.000126)	(0.00000894)		
Garlic	-0.00410	-0.260	0.0169	96
	(0.199)	(0.186)		
GreenPea	0.984	0.164	0.219	96
	(0.754)	(-0.168)		
Lettuce	0.218***	0.196	0.106	96
	(0.000833)	(0.393)		
Maize	0.466	0.0654	0.233	96
	(0.317)	(0.229)		
Melon	0.144	0.776*	0.355	96
	(-0.384)	(-0.332)		
Onion	0.361	0.247	0.0939	96
	(0.291)	(0.182)		
Pepper	1.162***	-0.216	0.127	96
	(0.318)	(0.295)		
Potato	0.000426	0.465***	0.00113	96
	(0.680)	(-0.0555)		
Pumpkin	0.337***	0.218	0.416	96
	(0.0467)	(0.800)		
RedBean	1.166***	0.322*	0.161	96
	(0.228)	(0.163)		
Rice	0.00000172	0.0503	0.0427	96
	(0.883)	(-0.150)		
StringBean	0.188***	0.151	0.251	96
	(0.00000924)	(0.324)		
Tamarillo	1.245**	0.487	0.253	96
	(0.419)	(0.305)		
Tomato	0.00379	0.113	0.137	96
	(0.614)	(-0.326)		
Watermelon	0.433**	0.273	0.185	96
	(0.159)	(0.236)		
Yucca	0.0620	-0.0515	0.0515	96
	(0.456)	(0.360)		

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Note: Each row corresponds to the estimates of Equation 3 for each one of the products $i \in I$ listed in the first column.
Own estimations. Sources: CHIRPS and SIPSA.

Table A.4

Effects of local extreme weather events on wholesale prices of perennial crops

	Precipitation above 80th percentile	Precipitation below 80th percentile	R-squared	Observations
Avocado	0.0181	0.0237	0.915	1157
	(0.0702)	(0.0808)		
Banana	0.800**	0.773**	0.852	1056
	(-0.273)	(0.287)		
Blackberry	0.167	0.176	0.864	1398
	(0.125)	(0.126)		
Curuba	0.0207	0.103	0.766	1050
	(0.0708)	(0.0765)		
Granadilla	0.773***	0.193***	0.869	1111
	(-0.156)	(0.00962)		
Guava	0.106	0.0968	0.758	1186
	(0.162)	(0.922)		
Lemmon	0.111	0.0907	0.885	1179
	(0.117)	(0.0841)		
Lulo	0.358***	0.298	0.942	1388
	(0.0714)	(0.192)		
Mango	0.0964	0.0629***	0.891	1174
	(0.470)	(0.00801)		
Papaya	-0.124	-0.153	0.798	1125
	(0.195)	(0.0996)		
PassionFruit	0.533***	0.147***	0.866	1370
	(0.137)	(0.0378)		
Pineaple	0.0574*	0.0497	0.828	1135
	(0.0277)	(0.456)		
Plantain	0.267	-0.112	0.880	1392
	(0.155)	(0.0717)		
Soursop	0.104	0.136*	0.836	1047
	(0.144)	(-0.0632)		
Strawberry	0.0908	0.0735	0.703	1092
	(0.132)	(0.402)		

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Note: Each row corresponds to the estimates of Equation 2 for each one of the products $i \in I$ listed in the first column.
Own estimations. Sources: CHIRPS and SIPSA.

Table A.5

Effects of global extreme weather events on wholesale prices of perennial crops

	Precipitation above 80th percentile	Precipitation below 80th percentile	R-squared	Observations
Avocado	0.921**	0.204	0.0952	90
	(0.350)	(0.354)		
Banana	0.0101	0.567	0.250	90
	(0.439)	(-0.602)		
Blackberry	0.464	0.377***	0.117	96
	(0.347)	(0.115)		
Curuba	1.129**	0.253	0.273	96
	(0.416)	(0.384)		
Granadilla	0.00796	0.512	0.399	96
	(0.612)	(-0.557)		
Guava	0.329***	0.228***	0.111	90
	(0.0663)	(0.0165)		
Lemmon	1.887***	-0.287	0.153	96
	(0.454)	(0.337)		
Lulo	0.0000722	0.397	0.226	96
	(1.033)	(0.456)		
Mango	0.359***	0.248***	0.0555	96
	(0.00499)	(0.0698)		
Papaya	1.753*	-0.357	0.105	96
	(0.748)	(0.713)		
PassionFruit	0.0212	0.618	0.174	96
	(2.588)	(1.414)		
Pineaple	0.432***	0.325***	0.0103	96
	(4.01e-08)	(0.0000343)		
Plantain	1.505*	0.906*	0.131	96
	(0.605)	(0.390)		
Soursop	0.0147	0.0225	0.382	96
	(0.900)	(0.195)		
Strawberry	0.417***	0.355	0.549	96
	(0.0337)	(0.584)		

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Note: Each row corresponds to the estimates of Equation 3 for each one of the products $i \in I$ listed in the first column.
Own estimations. Sources: CHIRPS and SIPSA.

Table A.6

Regression results of meta-analysis for high precipitation shocks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Access to other natural water sources	-0.184	-0.272	-0.154	-0.201					0.422	0.310	0.621	0.645
	(0.510)	(0.535)	(0.478)	(0.521)					(0.659)	(0.662)	(0.563)	(0.628)
Access to other non-natural water sources					0.584	0.619	0.840*	0.816*	0.857	0.808	1.263**	1.246**
					(0.408)	(0.455)	(0.427)	(0.455)	(0.638)	(0.653)	(0.549)	(0.576)
Mean altitude (m)		-0.000		-0.000		-0.000		-0.000		-0.000		-0.000
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
No. municipalities		0.000		-0.000		0.000		0.000		0.000		-0.000
		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)
Avg. time (h)		-0.030		-0.028		-0.026		-0.019		-0.020		-0.004
		(0.040)		(0.034)		(0.038)		(0.030)		(0.036)		(0.030)
Access to electricity			-0.727	-0.705			-1.024*	-0.980*			-1.055**	-1.049**
			(0.531)	(0.514)			(0.509)	(0.484)			(0.491)	(0.495)
Receive technical assistance			0.930	0.843			0.954*	0.899			1.004*	0.958
			(0.557)	(0.612)			(0.505)	(0.602)			(0.509)	(0.598)
Access to credit			0.035	0.109			-0.114	-0.057			-0.181	-0.189
			(0.557)	(0.556)			(0.514)	(0.517)			(0.489)	(0.509)
Avg. farm size			-0.092	-0.090			-0.114	-0.118			-0.131	-0.129
			(0.132)	(0.184)			(0.119)	(0.178)			(0.121)	(0.187)
Avg. farm size squared			0.006	0.006			0.008	0.008			0.009	0.008
			(0.011)	(0.016)			(0.010)	(0.015)			(0.010)	(0.016)
= 1 if perennial			-0.063	-0.078			-0.036	-0.043			-0.042	-0.065
			(0.128)	(0.125)			(0.126)	(0.123)			(0.127)	(0.123)
R-squared	0.005	0.022	0.132	0.149	0.054	0.069	0.212	0.219	0.068	0.075	0.241	0.245
No. Observations	45	45	45	45	45	45	45	45	45	45	45	45

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.7

Regression results of meta-analysis for low precipitation shocks

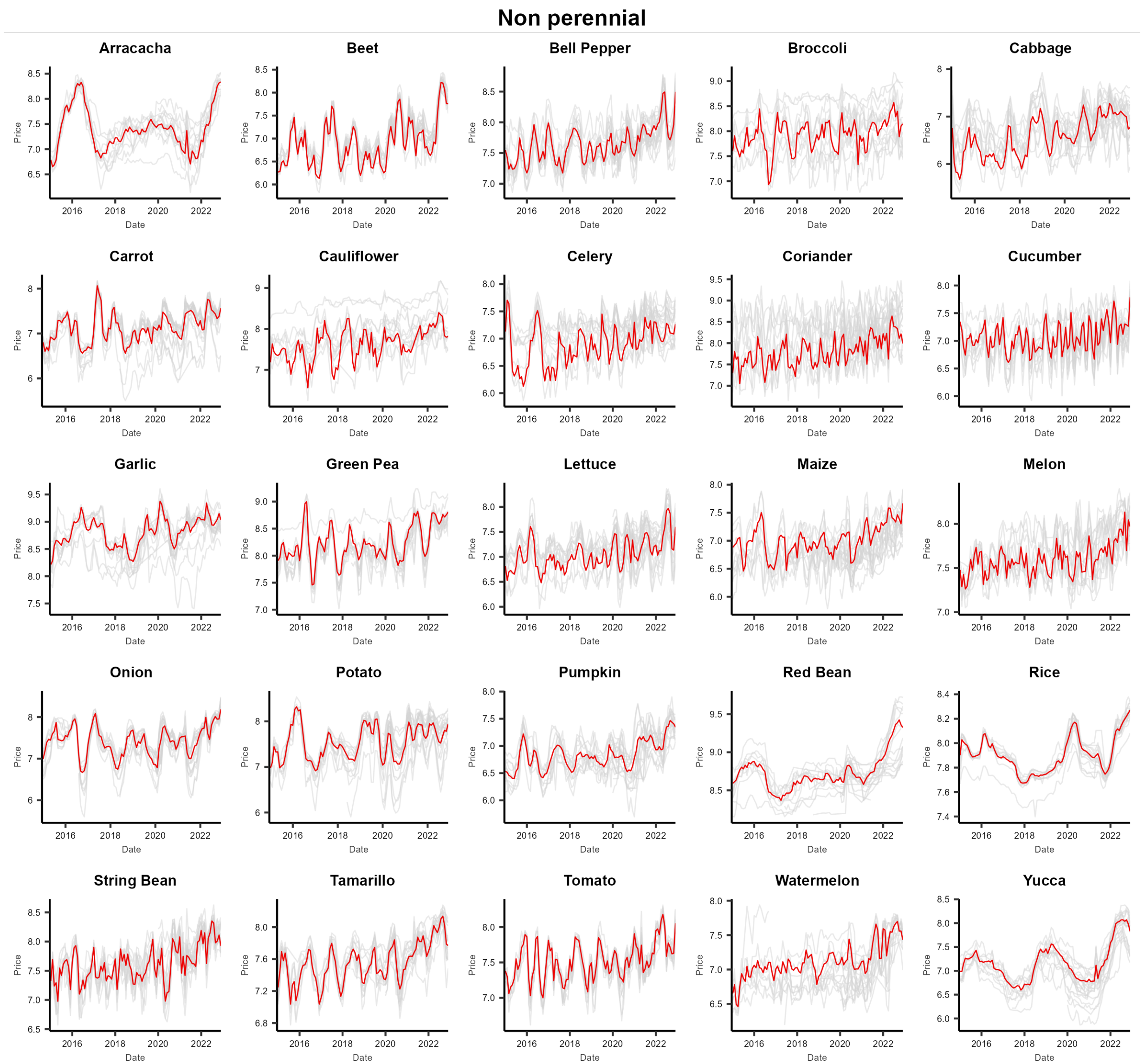
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Access to other natural water sources	-0.161	-0.217	-0.254	0.071					-0.194	-0.312	0.014	0.438
	(0.480)	(0.555)	(0.510)	(0.527)					(0.681)	(0.762)	(0.811)	(0.760)
Access to other non-natural water sources					0.078	0.058	0.427	0.249	-0.047	-0.132	0.436	0.542
					(0.459)	(0.509)	(0.486)	(0.510)	(0.648)	(0.682)	(0.804)	(0.741)
Mean altitude (m)		-0.000		-0.000**		-0.000		-0.000**		-0.000		-0.000**
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
No. municipalities		-0.000		-0.001		-0.000		-0.001		-0.000		-0.001
		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)		(0.002)
Avg. time (h)		-0.023		0.012		-0.019		0.012		-0.025		0.023
		(0.042)		(0.044)		(0.038)		(0.046)		(0.043)		(0.047)
Access to electricity			-0.000	0.123			-0.113	0.021			-0.114	-0.026
			(0.565)	(0.579)			(0.572)	(0.596)			(0.579)	(0.617)
Receive technical assistance			0.289	-0.065			0.313	-0.055			0.314	-0.015
			(0.673)	(0.617)			(0.683)	(0.617)			(0.693)	(0.639)
Access to credit			-1.221*	-1.541**			-1.294*	-1.581**			-1.295*	-1.670***
			(0.671)	(0.614)			(0.673)	(0.619)			(0.683)	(0.611)
Avg. farm size			0.027	-0.027			0.013	-0.036			0.013	-0.043
			(0.166)	(0.191)			(0.164)	(0.191)			(0.167)	(0.192)
Avg. farm size squared			-0.007	-0.007			-0.007	-0.006			-0.007	-0.006
			(0.014)	(0.017)			(0.014)	(0.017)			(0.014)	(0.017)
= 1 if perennial			-0.327*	-0.487***			-0.320*	-0.467***			-0.320*	-0.482***
			(0.172)	(0.168)			(0.173)	(0.165)			(0.178)	(0.172)
R-squared	0.002	0.009	0.163	0.269	0.001	0.006	0.171	0.273	0.002	0.010	0.171	0.281
No. Observations	45	45	45	45	45	45	45	45	45	45	45	45

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

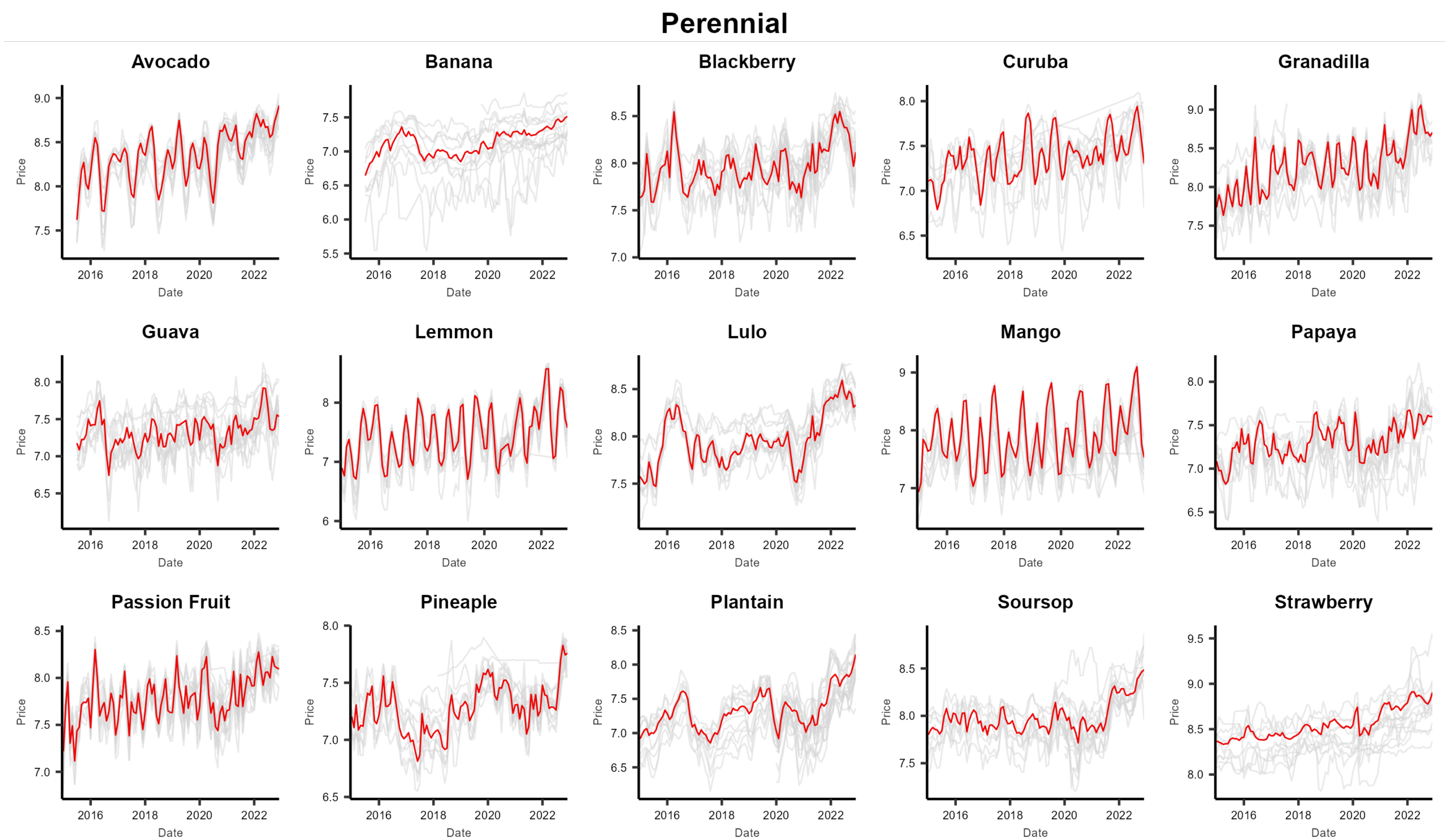
Figure A.1

Evolution of prices (in logs) of non-perennial crops, 2015–2023



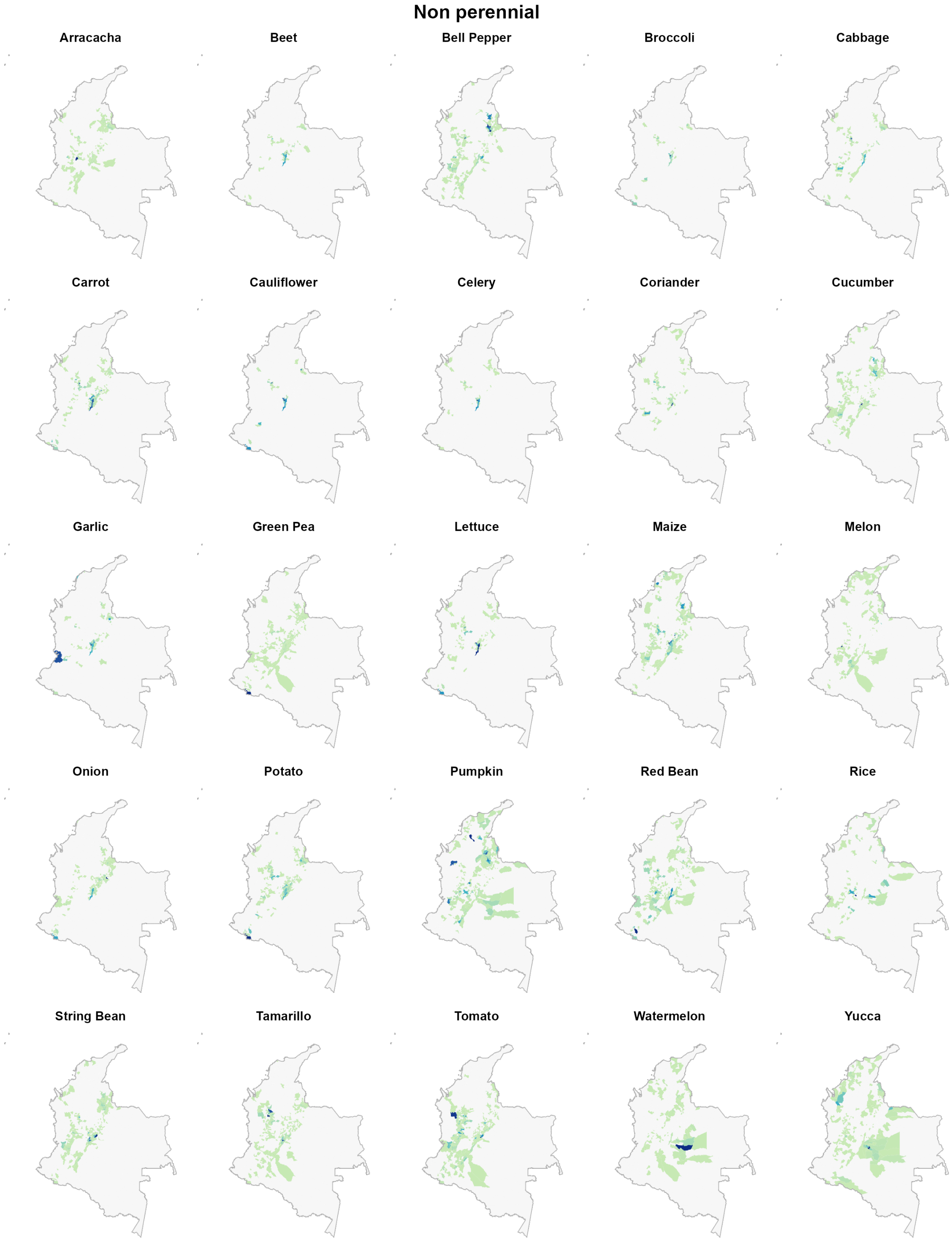
Source: SIPSA

Figure A.2
Evolution of prices (in logs) of perennial crops, 2015–2023



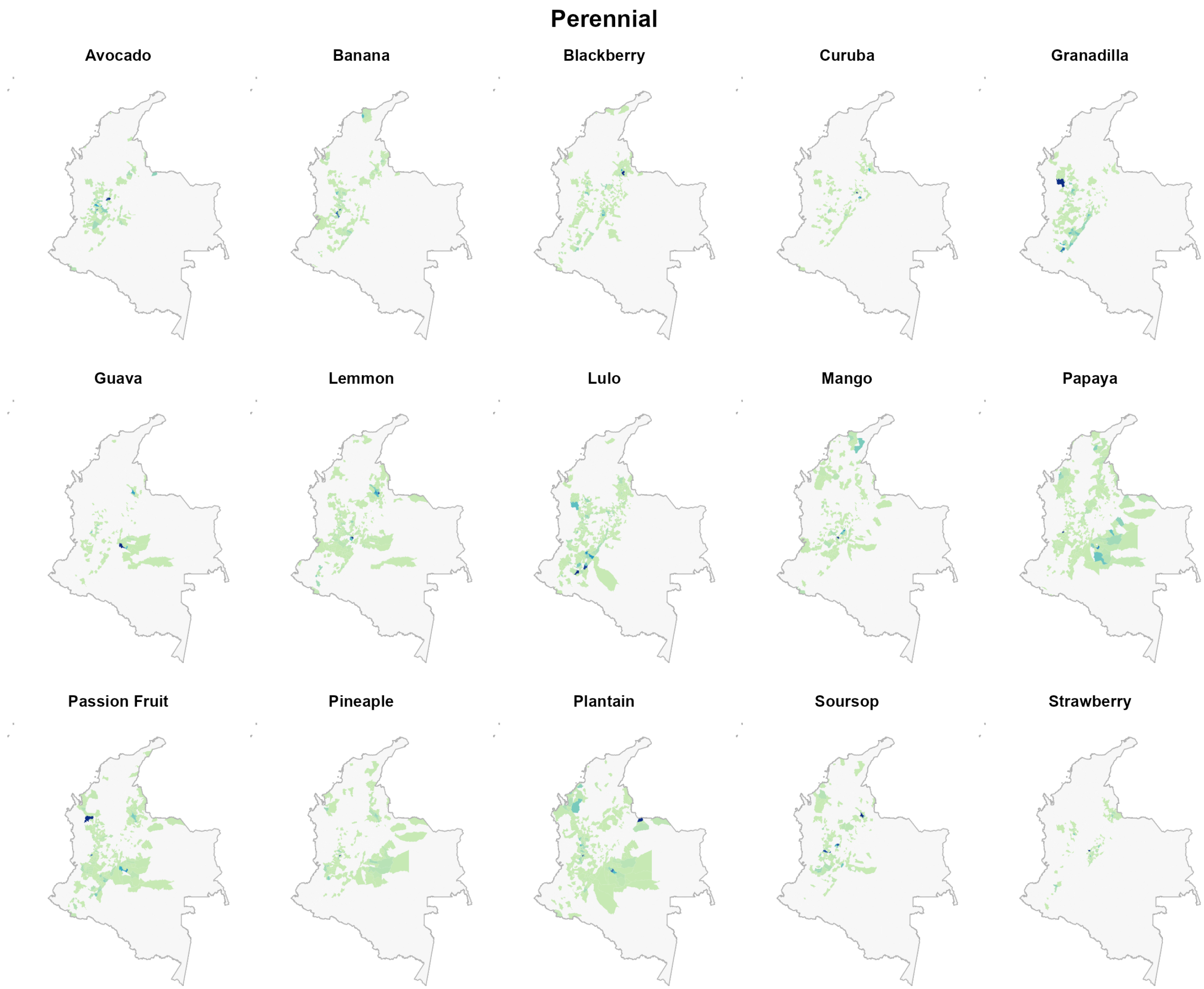
Source: SIPSA

Figure A.3
Distribution of non-perennial crops based on producing municipalities



Source: SIPSA

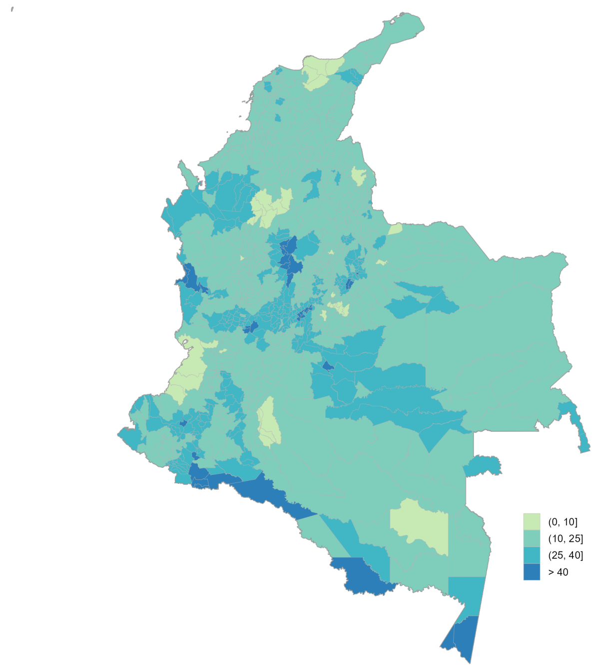
Figure A.4
Distribution of perennial crops based on producing municipalities



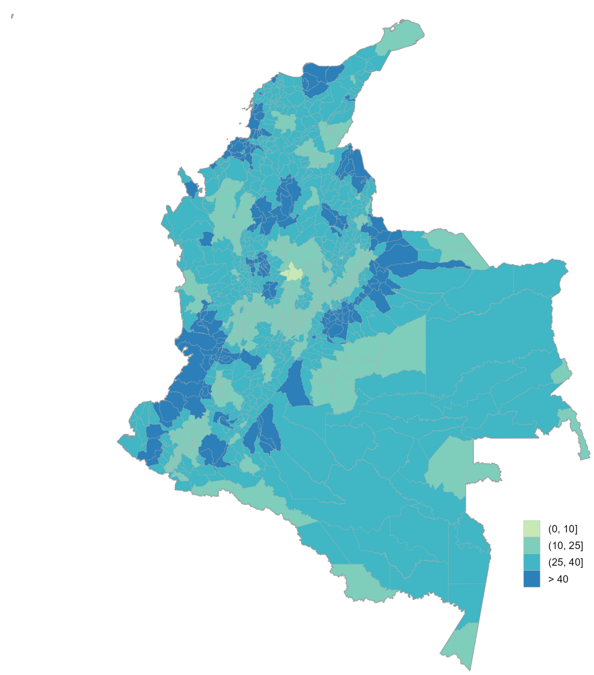
Source: SIPSA

Figure A.5
Number of extreme precipitation events by Municipality, 2013–2022

(a) Excessive precipitation



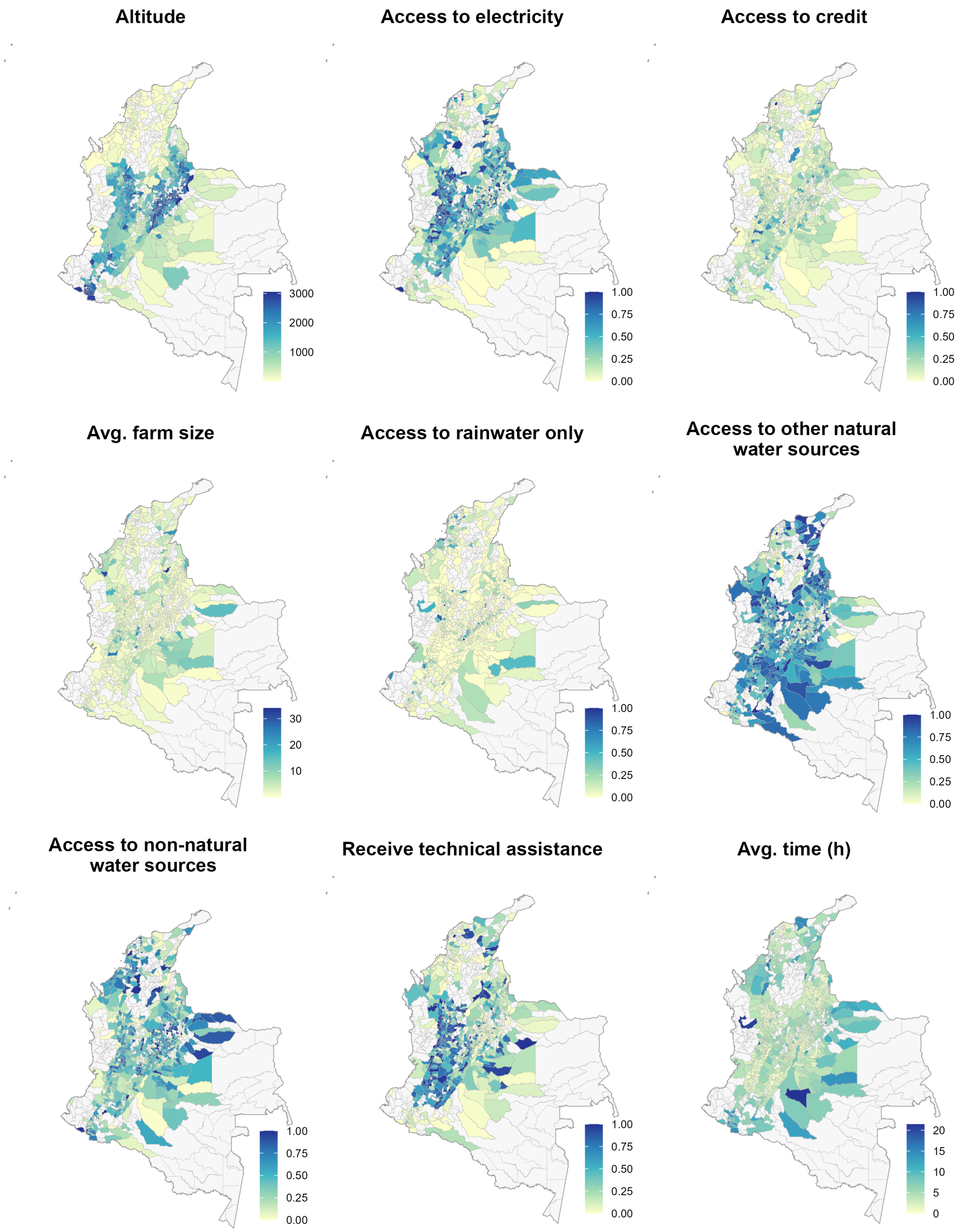
(b) Lack of precipitation



Source: CHIRPS

Figure A.6

Municipal averages for selected characteristics used for Meta-analysis



Source: 2014 Colombian Agricultural Census (CNA) and Google Drive API. Own calculations.

Figure A.7
Correlation matrix of the features variables

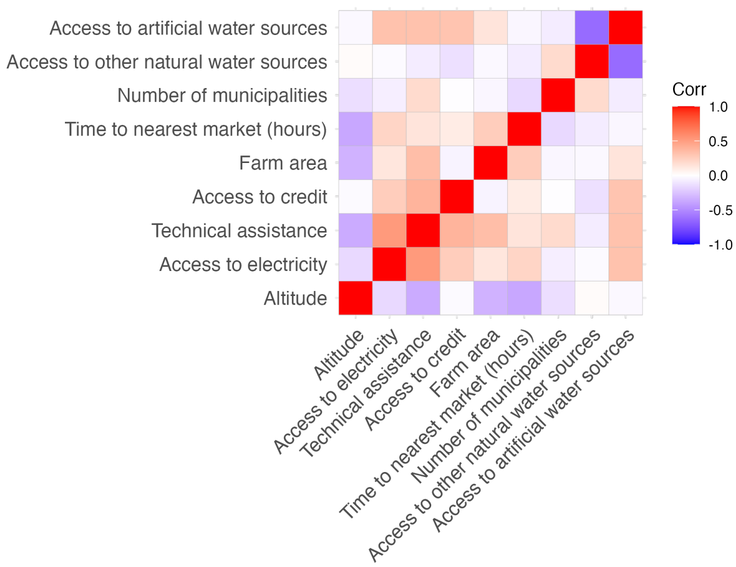
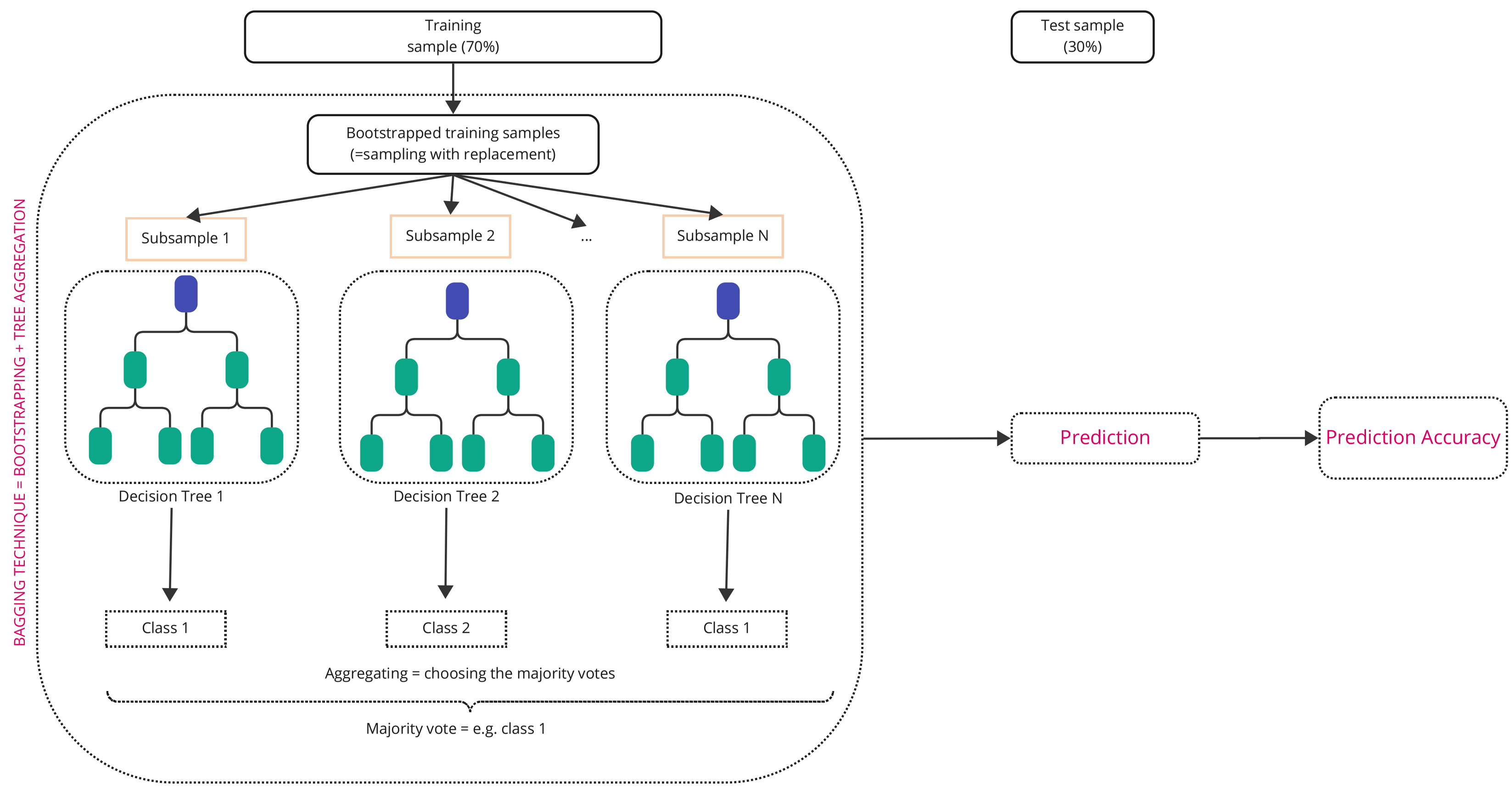


Figure A.8
Random Forest Model



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