Climate Change and the Global Coffee Industry

By

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Abstract

Coffee is a perennial crop that plays an essential role in many emerging countries' economies. It is estimated that the coffee value chain provides a livelihood for about 125 million people worldwide, including 25 million smallholder producers in developing countries (Krishnan, 2017). Coffee farmers, however, have experienced a number of threats in recent decades, including volatile coffee prices and rising production costs. Under the changing climate, additional challenges will be posed to small coffee producers, which may further threaten their economic viability. The most noted effect of climate change is rising temperature, which provides favorable environments for coffee pests and diseases, including coffee berry borer and coffee rust. Climate change also increases the likelihood of extreme weather events such as drought, frost, and flood, and the impact of such events on coffee plantations can be severe, including loss of trees. As such, understanding how this core industry will be impacted by climate change is critically important.

This dissertation investigates the impacts of climate change on coffee production, a critical economic commodity in many developing countries. Through a panel fixed effects econometric modeling approach, this research analyzes how climatic variables such as temperature and precipitation influence coffee yields, particularly focusing on the differential effects dur-

ing various growth stages of coffee plants. This study also utilizes projections from global climate models through the 21st Century to project the impacts of future climatic conditions on coffee yields.

The research estimates a weather-yield response model that captures the heterogeneous weather effects by including variables across critical coffee growth stages such as the blooming, fruit bearing and harvesting phase. The weather variables of interest include growing degree days (GDDs), harmful degree days (HDDs), freezing degree days (FDDs), precipitation, number of dry days, and coefficient of variation of precipitation.

In Brazil, the study reveals pronounced biennial variations in coffee yields, with GDDs positively affecting yields during the blooming stage, whereas HDDs exacerbate yield losses during the same period due to extreme heat. Additionally, my results indicate that prolonged dry periods before the blooming season benefit yields up to a threshold, beyond which yields may be adversely impacted by extended drought conditions. Conversely, in Colombia, coffee yields lack the pronounced biennial variation seen in Brazil. In terms of temperature effects, GDDs during the flowering and harvesting periods positively influence yields, and precipitation during the fruit-bearing stage negatively affects yields .

The dissertation also explores the role of elevation in moderating the impacts of weather variables on coffee production. It finds that in Brazil higher altitudes increase the susceptibility of coffee yields to negative climatic impacts due to the cultivation of different coffee varieties that vary in their response to temperature and moisture levels. In contrast, in Colombia, elevation does not significantly differentiate the impact of climatic variables on coffee yields.

Under IPCC's middle of the road emission scenario, municipalities in most states are projected to see a drop in yield, ranging from 3% to 13% by the end of the century. On the contrary, Municipalities in Mato Grosso do Sul will benefit from the climate change, which would result in a 19% yield increase in the far future. The primary drivers include changes of GDDs and HDDs during blooming and harvesting periods, with mixed effects on future yields.

This dissertation examines the profound and varied impacts of climate change on coffee production in Brazil and Colombia, two of the world's leading coffee producers. The findings underscore the necessity for adaptive strategies tailored to specific regional and varietal characteristics to mitigate the adverse effects of changing climatic conditions. Moreover, these results provide valuable insights that could be extended beyond Brazil and Colombia to understand the broader implications of climate change on coffee-producing regions worldwide.

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Chapter 1

Overview

Over the past few decades, the global climate has undergone continuous changes primarily due to the persistent emission of greenhouse gases (Pachauri et al., 2014). These climatic changes have direct implications for agriculture as temperature and precipitation, key factors for agricultural production, are influenced. As a result, the impact of climate change on agriculture is a matter of significant concern. Climate projections indicate that we can anticipate rising temperatures, altered precipitation patterns, and an increase in the frequency of extreme weather events (Stocker, 2014). These shifts in climate conditions can have varying effects on agricultural productivity, particularly across different cropping systems. For example, annual crop producers often possess a certain level of flexibility in adapting to extreme weather events, as they have the option to adjust their cropping decisions on an annual basis. In contrast, perennial crop producers face challenges in responding to climate fluctuations since their crops, once planted, cannot be easily altered or removed (Salazar-Espinoza et al., 2015).

Among the various perennial crops, coffee holds a crucial position in the economies of many emerging countries. For instance, in Ethiopia, coffee accounted for a significant proportion of the country's total export value in 2021, contributing approximately 26.3% (Observatory of Economic Complexity, 2020). Globally, the coffee value chain is estimated to provide livelihoods for approximately 125 million individuals, including 25 million smallholder producers in developing nations (Krishnan, 2017).

Coffee farmers, unfortunately, have faced numerous challenges in recent decades, including fluctuating coffee prices and escalating production costs. The changing climate poses additional threats to small coffee producers, potentially further jeopardizing their economic sustainability. One of the most significant impacts of climate change on coffee production is the rise in temperatures, which creates favorable conditions for the proliferation of coffee pests and diseases, such as the coffee berry borer and coffee rust (International Coffee Organization, 2019).

Furthermore, climate change amplifies the probability of experiencing extreme weather events. A study conducted by a team of scientists analyzing data from 1982 to 2016 revealed that Brazil had observed an increase in the frequency, duration, intensity, and spatial extent of droughts and heatwaves (Rodrigues et al., 2019). These events pose significant risks to coffee plantations, ranging from short-term yield reductions to long-term consequences like tree loss. The impacts can be multifaceted and encompass various aspects of coffee production and its sustainability.

The primary objective of this dissertation is to assess and project the potential impacts of climate change on coffee-exporting countries. To achieve this objective, several key research questions need to be addressed. First, how do weather variables during each key growing stage affect coffee yields? By analyzing the relationship between weather variables (such as temperature and precipitation) and coffee yields during critical growth stages, we can identify the specific weather factors that impact coffee production and the magnitude of the effect. This approach acknowledges the heterogeneous inter-temporal relationships that are particularly relevant for perennial crops like coffee.

Additionally, this research deepens our understanding of the effects of climate change on coffee yields by incorporating weather variables beyond just average temperature and precipitation. By introducing diverse degree-day variables derived from daily temperature extremes, it provides a detailed evaluation of how adverse weather events, like frost and extreme heat, influence coffee productivity. The study also considers the number of dry days in the critical four-month period preceding blooming, a significant aspect neglected in the existing literature. Importantly, the econometric model developed in my study demonstrates superior out-of-sample prediction power compared to alternative models in the literature.

Third, I control for alternate bearing in order to avoid confounding it with weather shocks and thus generate more precise estimates of the impacts of weather shocks. Alternate bearing refers to the phenomenon where coffee trees produce high yields in one year, followed by lower yields in the next year. Investigating the factors influencing alternate bearing patterns can provide insights into the interplay between climate variability and coffee productivity.

Fourth, what are the heterogeneous effects of weather shocks on coffee yields for municipalities at different elevations? Coffee-growing regions encompass diverse topographies, with variations in elevation playing a crucial role in shaping local climate conditions. Analyzing the heterogeneous effects of weather shocks on coffee yields across different elevations can help us understand the spatial dynamics of climate-change impacts on coffee production.

In this study, I find that in Brazilian coffee regions, temperature indices like growing degree days (GDDs) and harmful degree days (HDDs) play pivotal roles at different growth stages, with GDDs positively affecting yields during the blooming stage, while HDDs cause yield losses during the same period due to extreme heat. Additionally, results indicate that prolonged dry periods benefit yields up to a threshold, beyond which yields may be adversely impacted by extended drought conditions.

Conversely, in Colombia, coffee yields are more consistent year-over-year, lacking the pronounced biennial variation seen in Brazil. This stability is likely due to the unique microclimates and the mitigating effects of a mid-year harvest. In terms of temperature effects, GDDs during the flowering and harvesting periods positively influence yields, while precipitation during the fruit-bearing stage negatively affects yields due to flooding and landslides.

This analysis also allows for heterogeneous impacts of weather variables on yields at higher versus low elevation. In Brazil, elevation significantly modulates environmental effects, with higher altitudes exacerbating the biennial yield variation and the negative impacts of extreme temperatures and precipitation during critical growth stages. The increased susceptibility to these factors at higher altitudes is likely due to the cultivation of different coffee varieties, which vary in their response to temperature and moisture levels. Conversely, in Colombia, the analysis shows that elevation does not markedly differentiate the impact of climatic variables on coffee yield.

I then utilize the estimated coefficients derived from the econometric yield-response model in combination with simulations generated by Global Climate Change models to examine the impacts of climate changes on coffee yields. These models provide projections of future climate scenarios, including changes in temperature, precipitation patterns, and other relevant climatic factors that are included in the yield-response model. By plugging in the values of the projected weather variables from the Global Climate Change models into the yield-response model, I generate forecasts of yields through the end of the current century.

Under the middle-of-the-road emission scenario (SSP245) from the CNRM-CM6-1 model, major coffee growing regions in Brazil are projected to be warmer, with less rainfall, more dry days during the pre-blooming phases, and more variable precipitation during the blooming phase.

Projected climate data is leveraged to forecast coffee yield changes across Brazilian municipalities into future decades. Municipalities in most states are projected to see a drop in yield, ranging from 3% to 13% by the end of the century. On the contrary, Municipalities in Mato Grosso do Sul are predicted to benefit from the climate change, which would result in a 19% yield increase in the far future. The main drivers of changing yields are changes in the number of HDDs during the blooming periods, changes in the number of GDDs during the blooming periods, and changes in the number of HDDs during the harvesting periods. HDDs during the blooming periods consistently contribute to yield reductions across all states. Increases in GDDs during the blooming periods and HDDs during the harvesting periods are projected to have a beneficial impact on yields in the future.

Overall, this dissertation contributes to the literature by: i) offering a flexible and robust model, grounded in agronomic insights, for assessing the relationship between weather variables coffee yields and ii) generating long-run projections of the impacts of climate change on coffee yields in Brazil. These contributions enhance our understanding of the complex interactions between climate change and coffee production and provide valuable insights for policymakers, coffee farmers, and stakeholders in developing strategies to mitigate the potential adverse effects of climate change on the coffee industry.

The remainder of the dissertation is organized as follows. In Chapter 2, I introduce coffee production in each producing region and its features. In the same chapter, I review the plant science literature on how weather conditions during different phases of the growth cycle affect coffee yield. Chapter 3 surveys the existing literature on climate change and agricultural production. Chapter 4 provides an introduction to the methodology for the first-stage analysis in which I estimate an econometric model of the impacts of a range of weather variables on coffee yields. Chapter 5 presents the results of the econometric analysis of coffee production in Brazil and Colombia. In Chapter 6, I compare the predictive power of my model against existing models in the literature. Chapter 7 combines the estimated coefficients from the first stage and climate change projections from major global climate models to project the impact of climate change on coffee production in Brazil. Chapter 8 discusses the limitations of the study and discusses future research opportunities. Chapter 9 is the conclusion of this dissertation.

Chapter 2

Coffee Production around the World

2.1 Coffee Production in the World

The genus *Coffea* encompasses approximately 100 species, but only three species are commercially significant: *C. Arabica* (Arabica coffee), *C. Canephora* (Robusta coffee), and *C. Liberica* (Liberian coffee). Among these, *C. Arabica* is the most important in terms of global coffee production, accounting for 57.4% of total production in the crop year 2023/2024 (International Coffee Organization, 2023).

Coffee production is primarily concentrated within the inter-tropical zone, spanning from approximately 20-25 degrees north latitude in Hawaii to 24 degrees south latitude in Brazil. This distribution is largely influenced by ecological factors such as temperature and humidity, which are conducive to coffee cultivation (DaMatta and Ramalho, 2006).

According to the International Coffee Organization (ICO), there are traditionally 55 coffee-exporting countries. These countries are spread across different regions, with 24 in Africa, 20 in Central and South America, 10 in Asia, and 1 in Oceania. Figure 2.1 shows the coffee exporting countries classified by the ICO. The different color fillings on the map represent the type of coffee varieties each country produces and exports. For instance, green indicates countries that mainly export Arabica coffee, with some smaller amounts of Robusta exports. These exporting countries collectively contribute to more than 96% of global coffee production as of 2022 (International Coffee Organization, 2023).

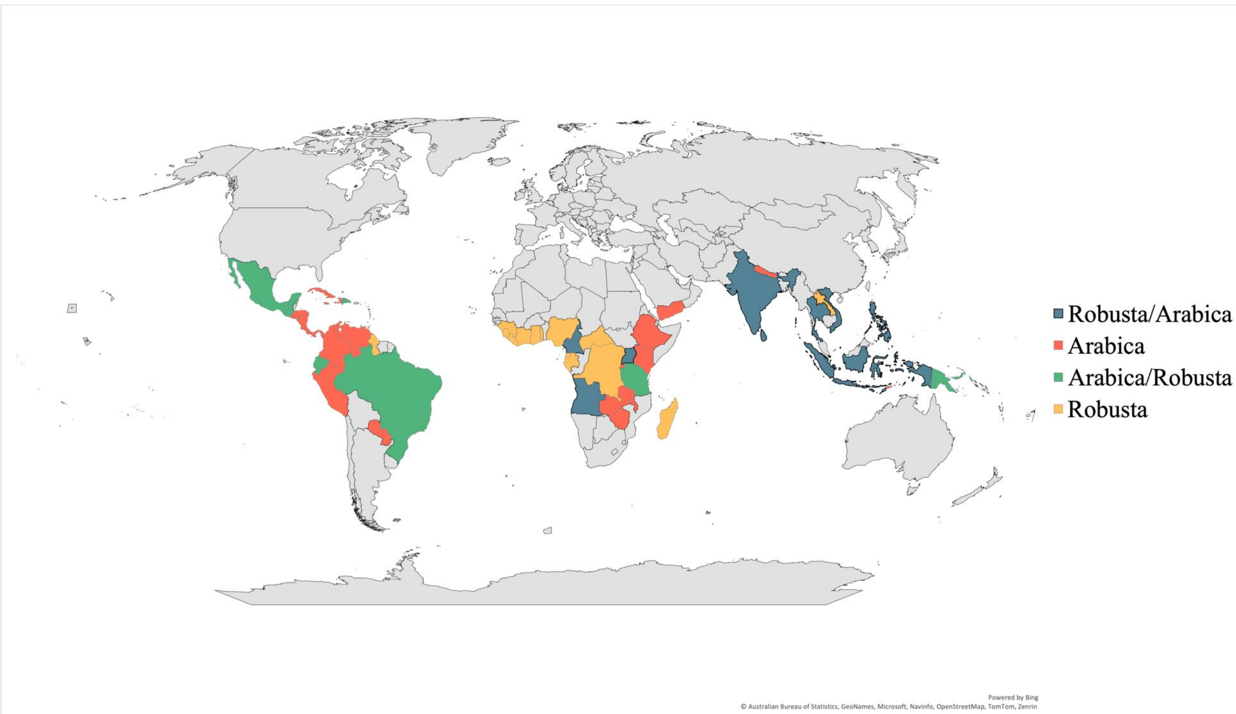


Figure 2.1: Coffee Exporting Countries (International Coffee Organization, 2023)

Africa

Ethiopia holds a significant historical association with coffee, being widely recognized as its birthplace. Coffee cherries were originally harvested from the wild in Ethiopia long before the cultivation of coffee as a crop began in Yemen during the 16th century (Hoffmann, 2014). As the leading coffee producer in Africa for many years, Ethiopia's contribution remains substantial at the global level. During the crop year 2022, Ethiopia is the fifth largest coffee producing country by both volume and area harvested as shown in Table 2.1 and 2.2.

Coffee holds great economic importance in Africa as a key export commodity. In a recent Foreign Agricultural Service (FAS) Global Market Analysis, the federal agency showed that Uganda has been the fourth largest green bean exporting country in the world, after Brazil, Vietnam, and Colombia. In calendar year 2022/2023, 95% of Uganda's coffee production is exported to markets in Europe, Asia, and North America (U.S. Department of Agriculture, Foreign Agricultural Service, 2023). Consequently, revenues generated from coffee exports play a significant role in the national economies of African coffee-producing countries.

Latin America

Across the Atlantic Ocean from the birthplace of coffee, Latin American countries have emerged as major producers for the global market in recent decades. In the crop year 2022/2023, the top ten coffee-producing countries produced a combined total of 109,595 bags of green coffee beans, with five of these countries located in Latin America, accounting for 48% of the total production. Latin America consists of three major coffee-producing regions: Brazil, the Andes, and the Caribbean.

Brazil stands out as the largest coffee producer in the world, contributing approximately 29% of global coffee production during the crop year 2022/2023 (U.S. Department of Agriculture, Foreign Agricultural Service, 2023). The country cultivates both Arabica and Robusta coffee, with Arabica accounting for the majority of its production. Brazil's coffee industry is highly mechanized, and large-scale plantations are common. However, many small-scale farmers also contribute by producing high-quality specialty coffees. Brazilian coffee is known for its mild and nutty flavor profile, and the country is a major supplier to both the specialty and commercial coffee markets.

Colombia ranks as the second-largest coffee producer in Latin America and the third-largest globally. The country is renowned for its high-quality Arabica coffee grown in the Andes Mountains. Colombian coffee is often praised for its bright acidity and sweet, fruity flavor. The coffee industry in Colombia is dominated by small-scale farmers, who frequently belong to cooperatives or associations. These farmers have been actively working to improve the quality of their coffee and increase their presence in the specialty coffee market.

Honduras holds the position of the third-largest coffee producer in Latin America, with an estimated production of 5.35 million bags in the crop year 2022/2023 (U.S. Department of Agriculture, Foreign Agricultural Service, 2023). Like Brazil, Honduras cultivates both Arabica and Robusta coffee, with Arabica being the primary variety. The country has gained recognition for its high-quality specialty coffees, often produced by small-scale farmers. However, the coffee industry in Honduras faces various challenges, including low productivity, pests, diseases, and the impacts of climate change.

Other countries in Latin America, such as Peru, Mexico, Guatemala, Costa Rica, and Nicaragua, also contribute significantly to coffee production. Each of these countries boasts its unique coffee-growing regions and distinct flavor profiles. For example, Peru is known for its organic and fair trade coffees, while Guatemala produces coffees with diverse flavor profiles due to its varied micro-climates.

Asia & Oceania

Although Asia and Oceania's contribution to the global coffee production is relatively smaller compared to Latin American and African countries, the region has a rich history of cultivating the crop. Coffee cultivation in Asia and Oceania began in the 17th century when the Dutch introduced the plant to Indonesia. Today, Asia and Oceania accounts for approximately 30% of global coffee production, with Vietnam, Indonesia, and India being the top coffee-producing countries in the region (International Coffee Organization, 2023).

Vietnam holds the title of the largest coffee producer in Asia and second to Brazil globally. It contributes around 34% of global Robusta coffee production in 2022/2023 crop year. Over the past few decades, the country has experienced significant expansion in coffee cultivation and primarily exports its coffee to Europe and the United States.

Indonesia ranks as the second-largest coffee producer in Asia. The country cultivates both Arabica and Robusta varieties, with coffee plantations spread across the islands of Sumatra, Java, Sulawesi, and Bali. Indonesian coffee is known for its unique flavor profiles, influenced by the diverse growing conditions in different regions. India's coffee production is concentrated in the southern states of Karnataka, Kerala, and Tamil Nadu, with coffee plantations often situated in hilly regions.

While Vietnam, Indonesia, and India are the major coffee-producing countries in Asia and Oceania, other countries in the region, such as Papua New Guinea, Mainland China, Taiwan, Laos, Thailand, and Myanmar, also contribute to coffee production, albeit on a smaller scale. These countries often focus on specialty coffee production, catering to niche markets and showcasing unique regional characteristics in their coffee beans. For instance, Thailand became the first Asian country to host the Cup of Excellence (CoE) competition in 2023. Taiwan also held the first ever CoE event - The Best of Taiwan CoE Pilot in the summer of 2023. Hosting the CoE competition not only indicates that these countries are recognized for producing high-quality coffee, but also gives Taiwan and Thailand international exposure, attracting buyers from around the world.

Rank	Country	Production (MT)
1	Brazil	3,172,562
2	Viet Nam	1,953,990
3	Indonesia	794,762
4	Colombia	665,016
5	Ethiopia	496,200
6	Uganda	393,900
7	Peru	352,645
8	India	338,619
9	Honduras	315,490
10	Central African Republic	306,901
11	Guinea	261,645
12	Guatemala	225,500
13	Mexico	181,706
14	Lao People's Democratic Republic	171,000
15	Nicaragua	170,181
16	China, mainland	108,000
17	Costa Rica	79,200
18	Côte d'Ivoire	70,000
19	United Republic of Tanzania	67,200
20	Democratic Republic of the Congo	58,837

Table 2.1: Top 30 Coffee Producing Countries by Production in 2022 (Food and Agriculture Organization of the United Nations, 2023)

Rank	Country	Area Harvested (Ha)
1	Brazil	1,872,511
2	Indonesia	1,285,778
3	Colombia	842,399
4	Central African Republic	761,111
5	Ethiopia	741,850
6	Uganda	727,154
7	Guinea	663,850
8	Viet Nam	655,921
9	Mexico	646,804
10	Côte d'Ivoire	539,000
11	India	438,145
12	Peru	423,854
13	Guatemala	366,865
14	United Republic of Tanzania	263,627
15	Honduras	258,326
16	Nicaragua	163,421
17	Venezuela	160,408
18	Democratic Republic of the Congo	149,614
19	El Salvador	124,795
20	Philippines	112,279

Table 2.2: Top 30 Coffee Producing Countries by Area Harvested in 2022 (Food and Agriculture Organization of the United Nations, 2023)

2.2 Climate and Coffee Production

In this section, I review the plant science literature on how weather conditions during different times of the year affect coffee productivity. First, I summarize different key growth stages during a coffee crop year. Second, I discuss the effects of temperature and precipitation on the production of coffee in general and during each growth stage. Lastly, I emphasize the potential impact of climate change.

Coffee Growth and Production

Coffee is a perennial crop, meaning it does not need to be replanted yearly after harvest. It usually takes a young coffee plant two years to develop its first flower and three years to reach maturity and yield commercial crops. There are two types of growth of a coffee tree. The vegetative growth and reproduction growth. The former develops the root system and branches of a coffee tree. The latter is the repetitive process of coffee cherry development, which is considered to be a more relevant process regarding annual coffee production (DaMatta, Ronchi, et al., 2007;Farah, 2019). The coffee reproduction cycle comprises three main stages: flowering, fruit development, and harvesting.

Flowering is the first and most important physiological process in the reproductive phase. In a normal year, the arrival of the first rain following a prolonged dry period usually breaks the dormancy of flower buds. Anthesis, or blossoming, occurs in this phase, which indicates the beginning of a new growing season (Camargo and Camargo, 2001).

Soon after the blossom, fruit development starts. This process can be summarized by the following five phases (DaMatta, Ronchi, et al., 2007). The *pinhead stage* usually lasts six to ten weeks after the flower opening. The next ten weeks is the *rapid swelling stage*. During this stage, coffee fruits increase rapidly in size. The final size of the fruit is determined in the *stage of suspended and slow growth*, which lasts approximately two weeks. In the next ten weeks, dry matter increases and reaches its maximum level, which is known as the *endosperm filling stage*. The final stage is a 10-week *ripe stage*. During this period, the color of the coffee cherry changes from green to yellow and red. This is the time when growers harvest their crops. The coffee reproduction phases are illustrated in figure 2.2. The last column shows the corresponding months that each event occurs in Brazil's coffee regions.

Coffee production is mainly concentrated in the inter-tropical zone, from $20 - 25°N$ in Hawaii to $24°S$ in Brazil. For non-equatorial producing regions, such as Brazil and Ethiopia, coffee plants follow an annual flowering, fruiting, and harvesting cycle. As for equatorial areas like Colombia, flowering and fruiting might occur multiple times throughout the year,

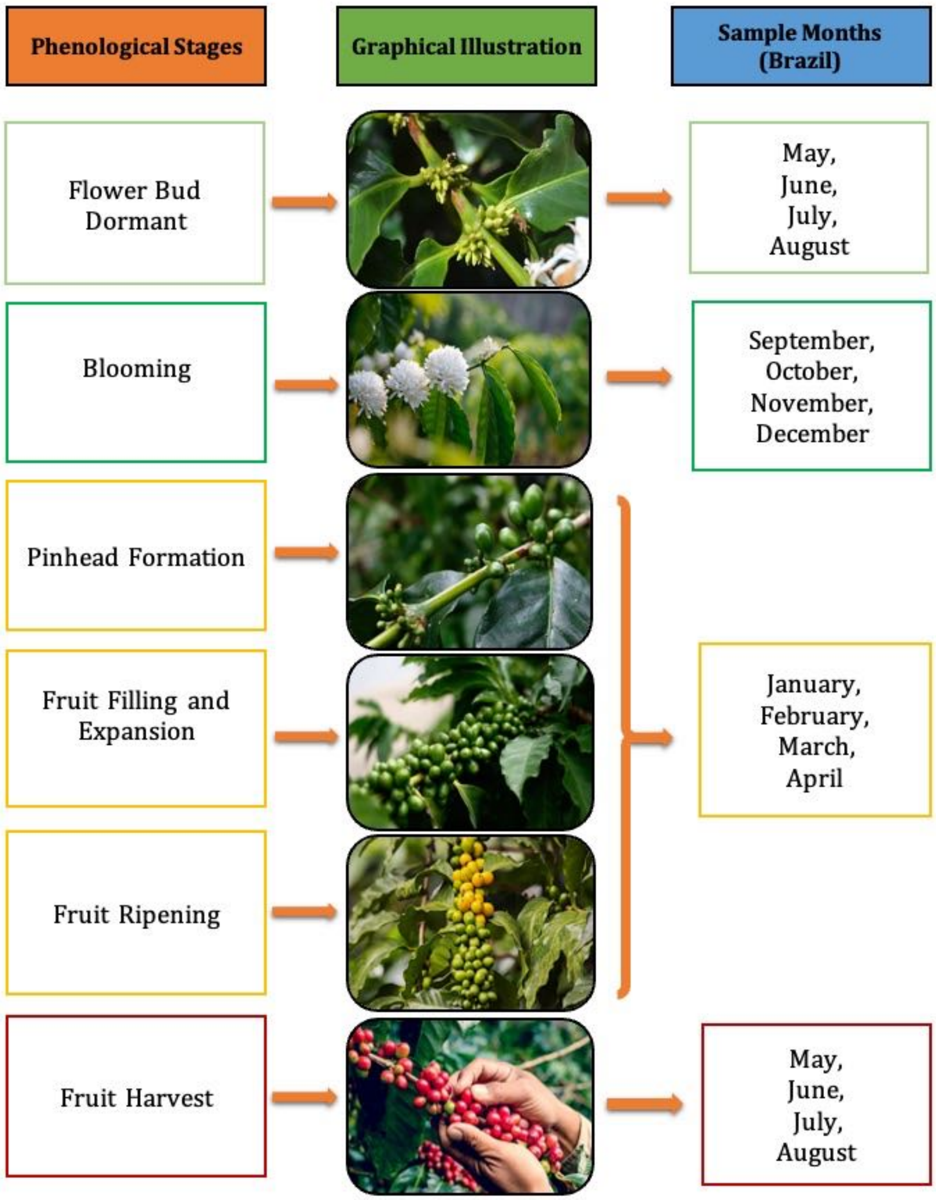


Figure 2.2: Phenological Phases of Coffee

yielding several harvests in a crop year.

Weather and Climate

Favorable temperature is a crucial element to the success of coffee production. The optimum mean annual temperature range for Arabica coffee is $18-21°C$ (Alègre, 1959), while Robusta coffee can sustain under hotter climates. High temperatures during the blooming phase may cause the flower to abort. Excess heat can also accelerate the berry production process during the bean-filling stage, which lowers coffee quality (Camargo, 1985). On the other hand, freezing weather can also damage coffee production. In the winter of 1976, Brazilian coffee producers were hit by a severe frost, causing 30% of their next harvest to be lost (Rohter, 1978). A frost event not only affects the production of coffee in the crop year of occurrence but also causes yield repercussions during the following years due to tree loss and replanting (DaMatta and Ramalho, 2006).

In general, the optimum annual cumulative precipitation for both Arabica and Robusta coffee ranges between 1200 and 1800 mm, while the latter can tolerate more intensive rainfall up to 2000 mm (Alègre, 1959). The seasonal distribution of rainfall also plays a vital role in the growth of coffee trees. For instance, a dry period lasting two to four months is critical for the coffee tree to blossom when the rainy season arrives. If the rainfall is scattered during the flowering season, then uneven flowering is likely to occur, which leads to uneven ripening for the berry. Non-uniform maturation can affect coffee yield and quality (Alvim and Kozlowski, 2013). During the rapid fruit expansion stage, water shortages can limit berry growth, which affects yield and quality as well (DaMatta, Ronchi, et al., 2007).

In addition to the above influences, the adverse effects of water shortages and heavy rainfall can be aggravated if they are coupled with hot temperatures. Drought occurs when rain fails to keep up with potential evapotranspiration, causing water deficits in plants. During 2014 - 2017, a severe drought hit the southeast of Brazil, including the significant coffee-producing region of Minas Gerais. The chronic drought wiped out as much as a third of the coffee crop in some areas in Minas Gerais in 2014, causing the global Arabica price to increase by 50% (Rochas, 2015). On the other hand, a warm and damp climate is also favored by coffee leaf rust, an obligate parasitic fungus that gathers nutrients from the coffee tree. It prevents the plant from photosynthesizing light into energy, causing flowers and fruits to be underdeveloped. Since rust can also damage tree branches, the yield for the next harvest season could also be affected (Nutman et al., 1963).

The most recent AR6 Synthesis Report of the Intergovernmental Panel on Climate Change (IPCC) states that human activities have unequivocally caused global warming, with global surface temperature in 2011-2020 reaching $1.1°C$ above that of 1850 - 1900 (IPCC, 2023). Figure 2.3 illustrates the mean temperature anomaly in the tropics, which also overlaps with the coffee belt, compared to the average annual temperature recorded between 1951 and 1980 (NASA, 2023). Notably, the average annual temperature has been increasing at a steady rate since the early 20th century in the coffee belt. The temperature in 2022 is approximately $0.57°C$ higher than the average temperature recorded from 1951 to 1980. Consequently, as temperatures continue to rise, certain coffee regions may become unsuitable for coffee production in the future. Besides gradual global warming, other adverse climate conditions that are relevant to coffee production are also likely to happen. The IPCC AR6 report conveys that an increase in hot extremes is virtually certain, while an increase in heavy precipitation and an increase in agricultural and ecological drought are likely to happen. Therefore, it is important to understand the effects of weather on coffee production and how climate change could affect the weather in coffee-growing regions.

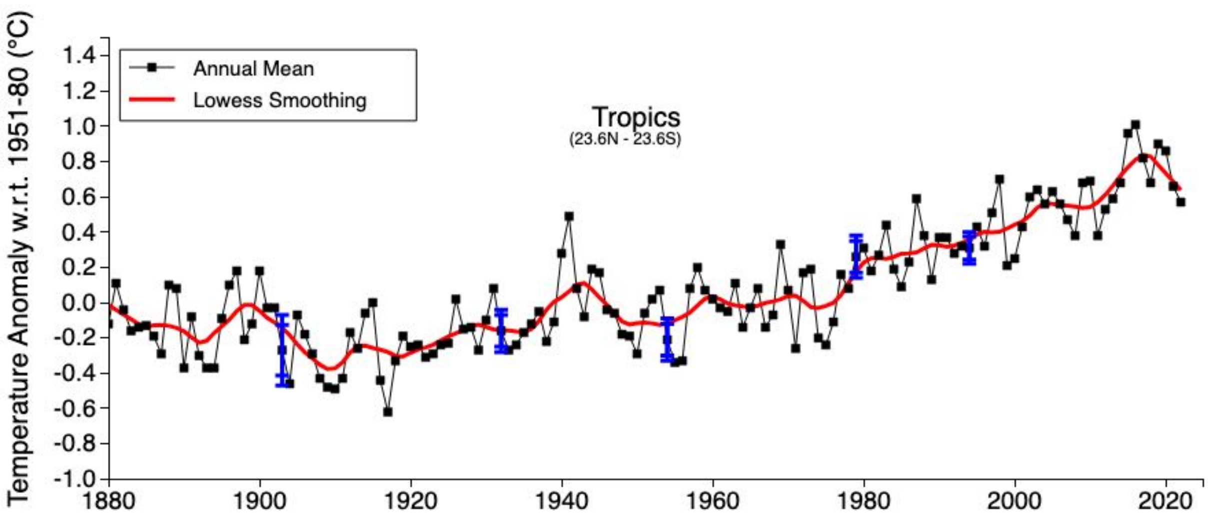


Figure 2.3: Annual Temperature Change vs 1951-1980 in the Tropics (NASA, 2023)

Chapter 3

Review on the Effects of Climate Change on Coffee Production

This chapter provides a review of existing studies that examine the impact of climate change on coffee production. It begins by discussing the broader literature on the effects of climate and weather on agricultural production, with a specific emphasis on the panel fixed effects (FE) approach. The focus then shifts toward the more relevant studies investigating climate change's impacts on coffee production globally.

Climate Change and Agricultural Production

Researchers from various disciplines have conducted extensive studies on the influence of climate change on agriculture. In the agro-physiology literature, researchers have employed experiments and agronomic models to investigate these effects. While experimental analysis can provide precise insights into the biological responses of crops under different climate conditions, it may not fully capture the complexities of real-world human behavior.

In contrast, economists have primarily utilized observational data to understand the impact of climate change on agriculture, taking into account the behavioral responses of individuals. Two main approaches have been adopted in this regard: cross-sectional and panel regression analyses. The cross-sectional approach aims to explain the effect of climate on agricultural outcomes using data from different regions. However, this approach may suffer from biases in identification due to the potential presence of unobserved variables.

To address these issues, researchers have turned to panel regression analysis, which enables control for unobservable time-invariant factors across geographical regions. This approach helps reduce the bias stemming from omitted variables, providing a cleaner identification strategy and more accurate estimation of elasticities.

A seminal study by Schlenker and Roberts (2009) examines the relationship between weather and crop yields for the most valuable crops in the United States. The authors employ a panel of county-level yield data from the USDA and fine-scale weather data spanning the period from 1950 to 2005. They estimate the historical weather-yield relationship using the following regression equation:

$$y_{it} = \int_{\underline{h}}^{\bar{h}} g(h)\phi_{it}(h)dh + \mathbf{z_{it}}\delta + c_i + \epsilon_{it} \tag{3.1}$$

In Equation 3.1, y_{it} represents the outcome of interest, such as crop yield. The term $g(h)$ denotes the non-linear relationship between heat and plant growth. $\phi_{it}(h)$ represents the time distribution of heat over the growing season in county i and year t. Consequently, the integral captures the contribution of heat exposure during the growing season to the yield in that specific year. The control factors, denoted as z_{it}, include a quadratic term for precipitation, quadratic time trends by each state to account for technological change, and c_i, a time-invariant county-fixed effect to control for time-invariant heterogeneity. Finally, ϵ_{it} represents a spatially correlated error term.

This study lays the foundation for subsequent statistical analyses on the impact of climate change on agricultural production. Unlike earlier studies that utilize average weather variables over a month or a year, Schlenker and Roberts combine county-level annual crop yield records with fine-scale daily weather data. This approach allows for the consideration of the entire temperature distribution within each day and each county. The findings reveal nonlinearities in the relationship between weather and yield, consistent with agronomic knowledge indicating that extreme weather events, such as heat exposure above a certain temperature threshold, can have a negative impact on yields.

Similar methodologies have been applied to studies investigating different crops worldwide. These statistical analyses have focused on key annual crops, including investigations into the impacts of climate change on cereal yields in France (Gammans et al., 2017), corn and soybean yields in China (Chen et al., 2016), and rice production in Japan (Kawasaki and Uchida, 2016).

Climate Change and Coffee Production

In the context of perennial crops like coffee, ecologists and climate scientists often employ machine learning techniques such as the maximum entropy (MaxEnt) niche model to predict crop suitability under climate change (Baca et al., 2014; Bunn et al., 2015; Läderach et al., 2017). The crop suitability index provides information on the suitability of growing a crop in a particular location. A limited number of studies have used reduced-form methods to explore the correlation or causal relationship between short-term weather shocks and coffee production and productivity (Gay et al., 2006; Craparo et al., 2015; Rising, 2016). These short-term responses or correlations can then be utilized to project future production and yield changes using weather projections from climate models.

Table 3.1 presents a series of literature that studies the impact of climate change and coffee production using econometric approaches. Gay et al. (2006) demonstrate that coffee production in Mexico significantly responds to mean seasonal temperature changes. They conclude that, given the projected climate change conditions for 2020, coffee production could decline by up to 34% compared to a baseline scenario (1969-1990). According to FAOSTAT, the total coffee production in Mexico in 2020 is 32.7% lower than the average production from 1969-1990 (Food and Agriculture Organization of the United Nations, 2023).

Craparo et al. (2015) suggest that increasing nighttime temperatures are responsible for decreasing coffee yields in Tanzania between 1961 and 2012. By projecting this result into the future, they estimate that every $1°C$ increase in nighttime temperature will result in yield losses of $137 \pm 16.87 kg/ha$, equivalent to 28.5% to 36.4% of the average yield from 1962 to 2013. Using an autoregressive integrated moving average (ARIMA) model, they conclude that average coffee yield will decrease from 24.6% to 44.1% by 2060 without any adaptation strategies.

Most reduced-form studies on the effect of climate variability on coffee yield focus on the impact of weather variation over an entire growing season (Craparo et al., 2015) or a selected window during the growing season (Sachs et al., 2015; Rising, 2016). Rising explores a range of growth periods and concludes that weather variables between December and May have the greatest predictive power in Brazil. Although such specifications provide evidence of the effects of changing weather patterns, such as the negative association between temperature increase and yields, they overlook crucial information regarding the specific impacts of weather at different stages of growth. Neglecting the heterogeneity of weather effects at different stages of plant growth may lead to biased estimates.

In a recent study on climate risks to Brazil's coffee production, Koh et al. (2020) recognize the importance of weather fluctuations across different phenological stages. They find a concave relationship between temperature and yield during the blooming and ripening periods in major coffee-producing states. Despite using monthly average temperature during key growing phases, Koh et al. fail to capture the effect of extreme heat and extreme cold on coffee yield. Most climate change studies on coffee yield focus exclusively on the impact of higher average temperatures (Gay et al., 2006; Craparo et al., 2015). However, extreme weather conditions such as frost can be more damaging to the crop. Frost not only affects the current coffee production cycle but can also take years for the plant to recover from the damage. Extreme frosts can even lead to the complete death of coffee trees (DaMatta and Ramalho, 2006). According to the most recent IPCC Sixth Assessment Report, there is high confidence that the intensity and frequency of hot extremes will increase while that of cold extremes will decrease in most parts of South America (IPCC, 2022). Therefore, it is necessary to consider the impact of both cold and hot extremes in analyzing climate change's impact on coffee production.

The alternate bearing effect is another important feature of perennial crops such as coffee (Monselise and Goldschmidt, 1982). The alternate bearing is a pattern of reproduction observed in many fruit and nut trees, such that high-yielding years are followed by low-yielding years. The alternate bearing can pose threats to coffee farmers' livelihoods because fluctu-

Author	Country	Key Results	Notes
Gay et al. (2006)	Mexico (Veracruz)	1. Coffee production responds significantly to mean seasonal temperature change in Mexico. 2. Coffee production could decline up to 34% of the production of a baseline scenario (1969 - 1990).	Time-series analysis
Craparo et al. (2015) Craparo et al. (2021)	Tanzania	Increasing night time temperature could advance harvest date, which results in diminishing coffee yields.	
Sachs et al. (2016) Rising (2016)	Brazil	Higher temperature during December through May are beneficial to coffee yields if it's below 35 degree C.	- Municipality level data - 1990 - 2016 - Panel fixed effects model - The season limits are December through May, which is the main bean-filling stage in Brazil
Koh et al. (2020)	Brazil	1. Temperature during the blooming and fruit ripening periods shows a concave relationship with yields. 2. Precipitation has a monotonically positive relationship with yield. 3. The average yield loss ranged from 9% to 29% since 1974.	- Municipality level data - 1974 - 2017 - Two-way fixed effects model
Ceballos-Sierra and DallErba (2021)	Colombia	1. Mean temperature and precipitation in March exhibits a concave relationship with yields. 2. Productivity over 2041-2060 is expected to increase by 16% in above median elevation regions, and decrease by 8.1% in lower elevation regions.	- Municipality level data - 2007 - 2013 - Sysytem GMM - Accounting for lag yields

Table 3.1: Climate Change and Coffee Production Literature using Econometric Approaches

ating yields can lead to unstable income. Despite the significance of impacting coffee yields, as of today, only one study in the climate change literature has accounted for this dynamic factor in the estimation of coffee production function (Ceballos-Sierra and Dall'Erba, 2021). Ceballos-Sierra and DallErba found a positive relationship between yields in one year and the following year, which contradicts the alternate bearing phenomenon observed in many coffee-producing regions (Bernardes et al., 2012). A possible explanation for their finding is embedded in using a lagged yield variable in the yield-response model. Instead of picking up the biennial bearing effect, it captures the trend that higher yields could lead to higher profits, which are re-invested in the next production cycle.

This dissertation extends the existing body of research on the impact of climate change on coffee production, addressing certain gaps and limitations previously noted in the literature.

Firstly, this study enhances the coffee yield-response model by integrating plant science insights and incorporating weather variables critical to various growing stages. By examining the correlations between weather conditions and coffee yields during these pivotal periods, the research identifies specific climatic factors affecting coffee production and quantifies their impacts. This approach recognizes the heterogeneous inter-temporal relationships that are particularly relevant for perennial crops like coffee.

Moreover, the research expands the scope of analysis beyond mere average temperature and precipitation levels. It introduces a range of degree-day metrics based on daily temperature extremes, offering a nuanced assessment of how adverse weather events, such as frosts and heatwaves, affect coffee yields. Additionally, the study gives attention to the number of dry days in the crucial four months before bloomingan aspect largely overlooked in prior studies. The econometric model developed here shows enhanced predictive accuracy out-of-sample when compared to existing models.

The dissertation also explores the phenomenon of alternate bearing in coffee trees, where cycles of high yield years are followed by low yield years. Understanding the factors that influence these patterns provides valuable insights into how climate variability affect coffee productivity.

Crucially, this study is pioneering in its approach of coupling econometric weather-yield estimations with climate projections from Global Climate Models (GCM) to assess the future impacts of climate change on coffee yields. This holistic approach not only bridges theoretical and methodological gaps but also sets a new precedent for comprehensive climate-related agricultural research.

Chapter 4

Methodology: A Panel Fixed Effect Approach

I model the annual coffee yield as a function of temperature and precipitation at each key growth stage, along with the alternate bearing effect, a systematic linear trend, and other time-invariant factors. There are three key growth stages in a production cycle: (1) Blooming, (2) Fruit-bearing, and (3) Harvesting. The relevant weather variables are growing degree days (GDDs), harmful degree days (HDDs), freezing degree days (FDDs), total precipitation, coefficient of variation of precipitation, and the number of dry days.

The concepts of growing degree days, harmful degree days, and freezing degree days are crucial for understanding temperature's influence on crop development, particularly for coffee. In this study, I adopt the sinusoidal approximation method proposed by Snyder (1985) to calculate these metrics [1]. Their definitions are illustrated in Figure 4.1. TM and

[1] The R code for degree day construction is based on the code written by Professor James Rising, available at: http://www.existencia.org/pro/?p=156

Tm indicate the observed daily maximum and minimum temperatures. TB and Tb represent the upper and lower temperature thresholds, between which coffee trees would gain beneficial heat units for cherry development. For temperatures surpassing the TB (upper threshold), the heat is no longer advantageous for coffee cherry growth. Instead, the excess warmth becomes damaging, contributing to what we term as harmful degree days. On the contrary, any temperature plunging below $0°C$ and its persistence over a given duration is labeled as freezing degree days. This metric serves as an indicator of frosting conditions, which can be detrimental to coffee plants.

The selection of temperature thresholds in Brazil and Colombia follows the proposal by Pedro-Junior et al. (1977) and Jaramillo and Guzmán (1984). They define a minimum temperature of $10°C$ and a maximum temperature of $32°C$ as the optimal lower and upper bounds. Since all temperatures above the upper bound are not beneficial to the growth of coffee cherry, the cumulative temperature over the upper threshold for an approximated time is defined as harmful degree days. I also construct GDDs and HDDs using various thresholds ranging from $30°C$ to $34°C$ for robustness checks. The temperature below $0°C$ for an approximated time is defined as freezing-degree days, which measures the frosting condition.

Based on the plant science literature on coffee phenology discussed in Chapter 2, I propose several hypotheses regarding the impact of weather variations during each growth stage on coffee yields. These hypotheses are summarized in Table 4.1.

Warm temperatures, as quantified by growing degree days, generally support coffee production during the blossoming, fruit-bearing, and harvesting stages. This can be attributed to several factors. First, warm temperatures enhance the rate of photosynthesis - the pro-

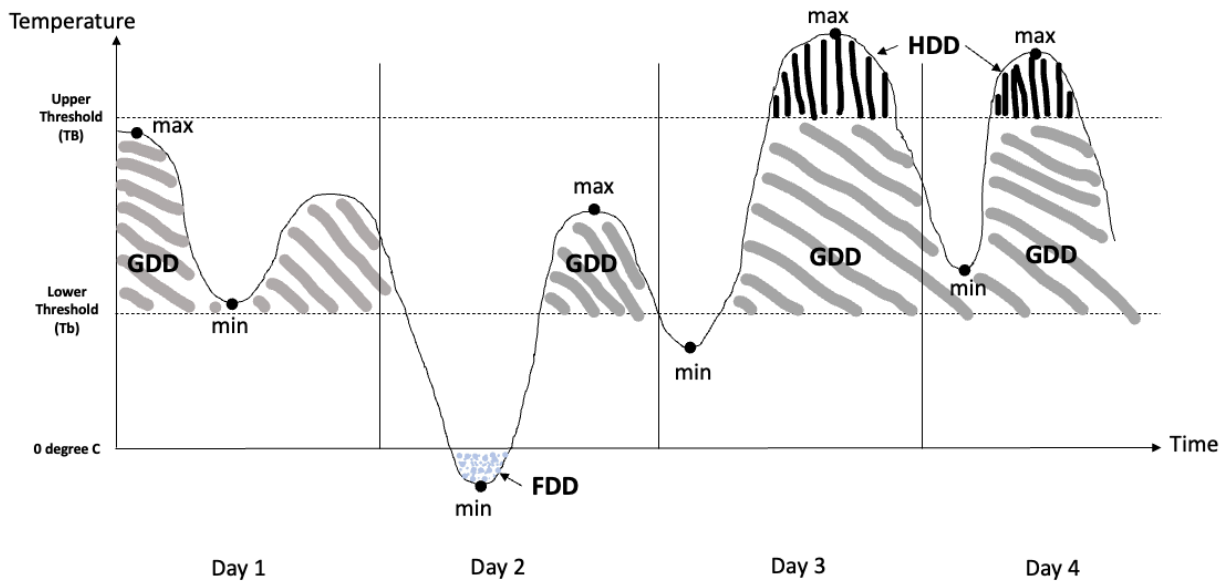


Figure 4.1: Degree Days Definition

cess by which plants convert sunlight into chemical energy, which fuels their growth. This process is more effective in warmer conditions. Second, warm temperatures promote faster fruit development. Following the pollination of coffee flowers, warm temperatures aid the maturation of the coffee cherries (Alègre, 1959).

However, excessive heat can lead to premature flowering, flower abortion, and expedited cherry maturation, resulting in smaller, less flavorful fruits during the fruit-bearing months. Therefore, while GDDs, indicative of warm temperatures, generally foster coffee yields, an overabundance of heat, as captured by harmful degree days, can be detrimental (**camargo1985clima**).

In Brazil, frost is a periodic occurrence during July and August. It damages trees and negatively impacts the yield in the upcoming season, as this period coincides with the floral dormancy period for the next year's crop. However, the effect of extremely low temperatures during the other stages is negligible (DaMatta and Ramalho, 2006).

Precipitation's impact on yields is more ambiguous, varying across all stages except harvesting. During the pre-flowering phase, a period of water stress before flower blooming can be beneficial. The prolonged dry period can induce uniform flowering once rain arrives, which is desirable for maximizing yield potential. While water stress is beneficial for inducing flowering, it's crucial that the trees aren't excessively stressed by drought. Moderate rainfall during this period ensures that the soil remains moist enough for the roots to absorb essential nutrients. A tree that's healthy and well-nourished before the flowering period will be better equipped to produce a larger number of flowers and, subsequently, cherries (Alvim and Kozlowski, 2013; DaMatta, Ronchi, et al., 2007).

Rainfall is needed to initiate bud growth after a dry spell; however, too much rainfall during the blooming stage can knock flowers off the plant, leading to a reduced potential yield. Additionally, continuous wet conditions can promote fungal diseases that affect flowers, like coffee leaf rust. On the other hand, too little rain can lead to incomplete or poor flowering, again reducing the potential yield (DaMatta, Ronchi, et al., 2007).

The fruit-bearing and expansion stage requires a consistent supply of water as the cherries develop. Adequate moisture ensures the cherries fill out and mature properly. Inconsistent rainfall can lead to uneven cherry development. Too much rain can cause cherries to split or become vulnerable to diseases. It can also lead to over-fermentation if cherries fall and remain on the wet ground. Insufficient rain at this stage can cause the cherries to shrivel or not develop fully, leading to a reduction in both yield and quality (DaMatta, Ronchi, et al., 2007).

Finally, dry conditions are preferable during the harvest period. Dry weather makes it easier to pick the cherries and begin the post-harvest processing. Too much rainfall creates conditions conducive to mold growth, disease, and over-fermentation, all of which may increase coffee bean defects (Kath et al., 2021).

	GDD	HDD	FDD	Precip.	Dry Days	Precip.CV
Floral Dormancy ($s = 3, t-1$)			$-$		$+$	
Blossom ($s = 1, t$)	$+$	$-$		$+ -$		$-$
Fruit Development ($s = 2, t$)	$+$	$-$		$+ -$		
Harvest ($s = 3, t$)	$+$	$-$		$-$		

Table 4.1: Hypothesis Table

The relationship between coffee yield and weather for municipality i in year t can be formulated as Equation 4.1. I refer to this equation as the Growth Stage Alternate Bearing Model, which is also the base model of this analysis.

$$y_{it} = \sum_s \sum_j \beta_{sj} X_{ijst} + \sum_j \delta_j W_{ij,s=3,t-1} + \phi \tilde{y}_{i,t-1} + \alpha_i + \tau_{rt} + \epsilon_{it} \tag{4.1}$$

$X \in \{\text{GDD, HDD, Precipitation, Coefficient of Variation of Precipitation}\}$

$W \in \{\text{FDD, Number of Dry Days, (Number of Dry Days)}^2\}$

On the right-hand side of the equation 4.1, X_{ijst} represents the specific weather variable j during the growth stage s in year t for municipality i. The contemporaneous weather variables included in this model are growing degree days, harmful degree days, total precipitation, and the coefficient of variation of precipitation. I also include the dispersion of rainfall during the blossoming stage in the model, namely the coefficient of variation of precipitation, to capture the effect of scattered rainfall on uniform flower blooming. It is calculated as

$$\textit{Coefficient of Variation}_i = \frac{\sigma_i}{\alpha_i},$$

where the numerator is the standard deviation of daily precipitation, and the denominator is the average daily precipitation. The β_{sj} parameter estimates the average marginal effect of weather variable j during stage s on coffee yields within the same production cycle.

The second term, $W_{ij,s=3,t-1}$, accounts for the weather variables from the harvest season of the previous coffee cycle, including freezing degree days, precipitation, and the number of dry days, which is termed as a day with no more than 5 mm total precipitation. It is crucial to consider the weather impacts from this stage because it coincides with the floral dormancy period of the subsequent coffee harvest cycle.

The alternate bearing effect is denoted by ϕ. It is a prevalent dynamic in coffee production and undeniably influences yield variations. This effect oscillates between high and low yields from one year to the next. However, the existing literature provides limited insights into quantifying the alternate bearing impact on coffee using econometric models. Guided by methodologies adopted for other crops, I've implemented a similar estimation strategy. Specifically, I draw inspiration from approaches employed to understand California almond yields (Alston et al., 1995). I have constructed a yield deviation variable, which essentially captures the difference between the yield of the previous year, $y_{i,t-1}$, and the yield two years prior, $y_{i,t-2}$.

$$\tilde{y}_{i,t-1} = y_{i,t-1} - y_{i,t-2}$$

The underlying hypothesis here is intuitive: if the yield of a certain year, represented by the lagged yield, is less than (or greater than) the year before it, it should capture the likelihood of an increase in yield for the upcoming year due to the alternate bearing effect. In the context of equation (4.1), this suggests that the coefficient (ϕ) should bear a negative value. Given the scope of this study and the lack of tree or field-level observations, I have adopted an assumption of spatial synchrony at the municipality level. This assumption posits that there's a degree of alignment in coffee yield trends and patterns across different locales within a municipality (Esmaeili et al., 2020).

The fixed effect at the municipality level controls for time-invariant spatial factors and is estimated by α_i. τ_{rt} is the region-specific linear time trend allowing monotonic productivity shifts in each region due to technology improvements. Accordingly, I specify the area to be state-level and department-level for Brazil and Colombia, respectively. ϵ_{it} is a vector of idiosyncratic shocks that are individual-time specific and uncorrelated with the explanatory variables.

In this panel fixed-effects regression model, I exploit year-to-year anomalies in yield with a state-level trend to identify the weather-yield relationship, therefore the coefficient estimates reflect short-run weather effects on yield that only allow for within-year adaptation.

Chapter 5

An Empirical Study of Latin American Coffee Production

5.1 Study Regions

This section delves into an examination of two major coffee-producing nations: Brazil and Colombia. For the crop year 2019/2020, Brazil took the lead by producing 58.21 million bagseach bag weighing 60 kgconstituting 35.27% of the global output. Colombia trailed, securing the third spot with approximately 14.10 million bags, contributing to 8.5% of the global production volume (International Coffee Organization, 2021). Despite their geographical proximity, Brazil and Colombia display contrasting nuances in their coffee cultivation regions and practices.

Brazil stands out as the most industrialized coffee producer globally. The expansive and flat terrain of its coffee plantations lends itself to bulk harvesting techniques, making mechanical harvesting or strip picking particularly effective in maintaining high yields (Hoffmann, 2014). Figure 5.1 depicts the mean annual production from 1989 to 2018 at the municipal level in Brazil, with darker shades indicating higher annual production. Predominant coffee-producing regions in Brazil encompass southern states such as Minas Gerais, São Paulo, Espírito Santo, and Paraná. In west-central Brazil, the State of Rondônia stands out for its Robusta coffee production. In contrast, Colombia's coffee cultivation exhibits a more scattered pattern. As evident in figure 5.2, coffee production spans numerous municipalities, primarily aligning with the three branches of the Colombian Andes.

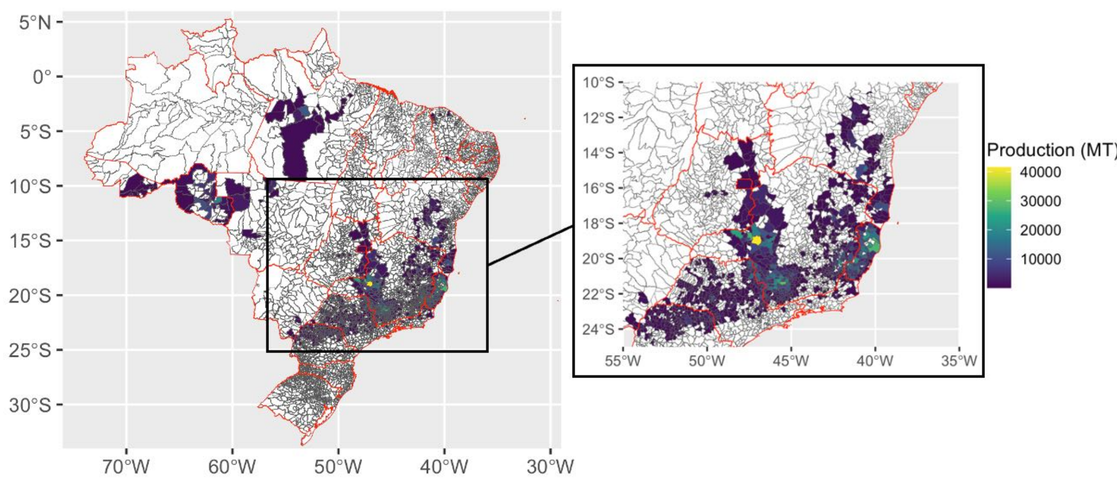


Figure 5.1: Average Annual Production Distribution in Brazil (1989-2018)

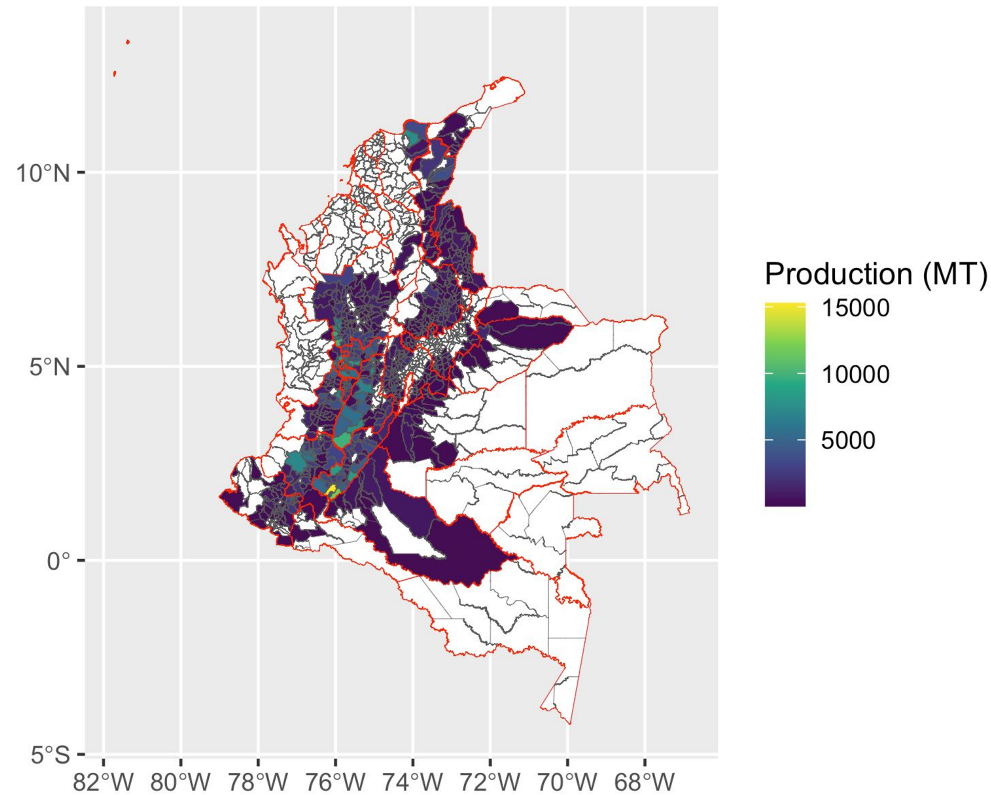


Figure 5.2: Average Annual Coffee Production Distribution in Colombia (2007-2018)

Figure 5.3 illustrates the cumulative coffee production by Brazil's top-producing states from 1989 to 2018. Over the past three decades, Minas Gerais (MG) has consistently led the production charts, producing nearly twice the quantity as Espírito Santo (ES). In contrast, Colombian coffee plantations, predominantly nestled in hilly terrains, operate on a smaller scale (Gonzalez-Perez and Gutierrez-Viana, 2012). As portrayed in Figure 5.4, the disparities in coffee production volumes among Colombia's primary coffee departments are not as marked as in Brazil.

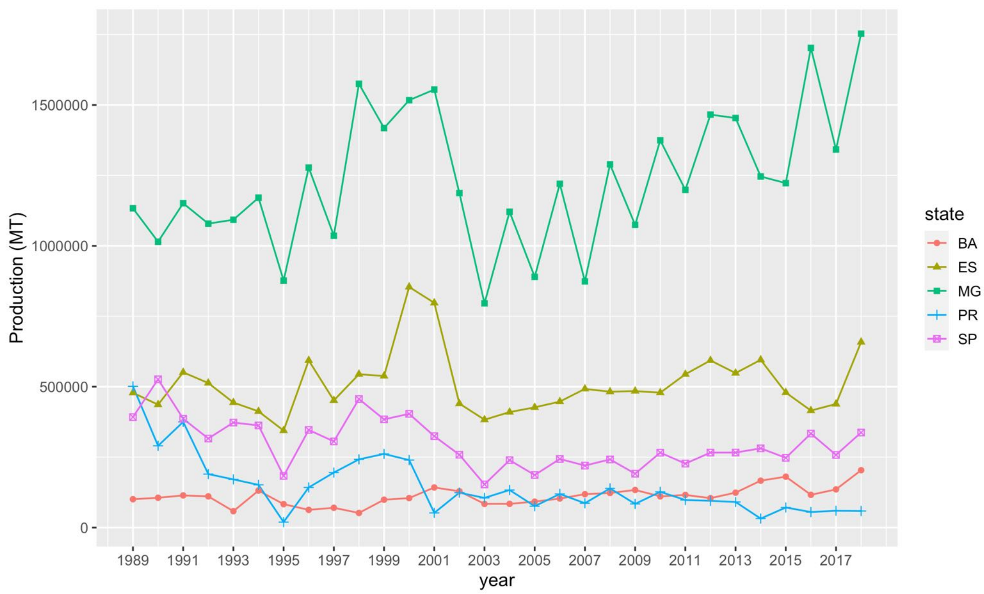


Figure 5.3: Brazil State-Level Production Trend 1989-2018

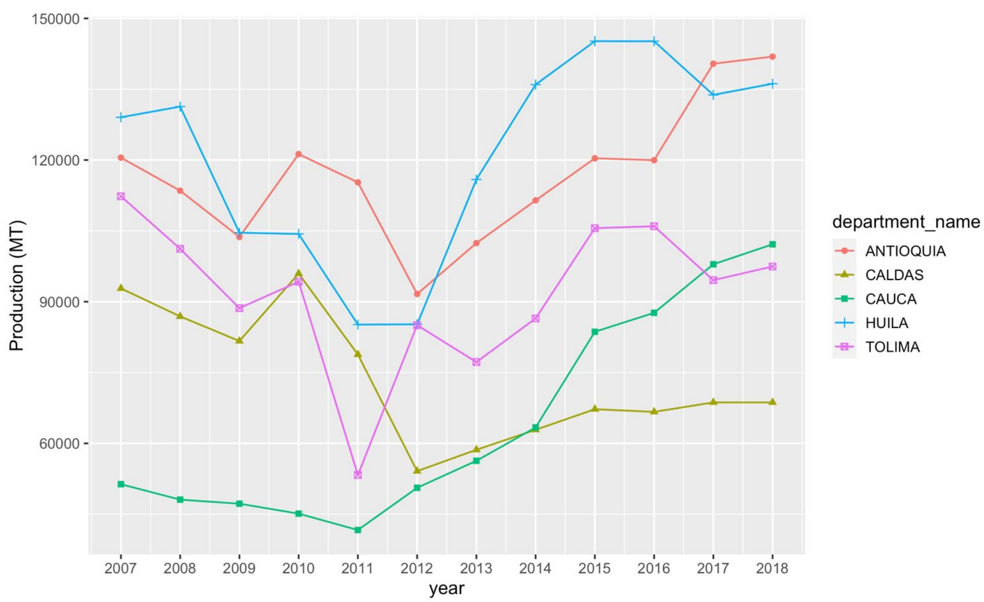


Figure 5.4: Colombia Department-Level Production Trend 2007-2018

Brazil typically has a single annual harvest, primarily spanning June to August. In stark contrast, Colombia, owing to its equatorial position and the influence of the Andes Mountains, undergoes varied harvests contingent on regional rainfall patterns (Kornman, 2018). Figure 5.5 employs different colors to indicate various harvesting times in Colombia. Light green areas, with a single annual harvest between September and December, stand in contrast to the dark green regions where harvests predominantly occur between March and June. Central Colombian regions, benefiting from a bimodal rainfall pattern, generally experience two harvest cycles in a crop year: a primary harvest and a secondary (often smaller) harvest termed the Mitaca. For instance, pink regions like Southern Antioquia undergo a primary harvest from September to December and a Mitaca from April to May. Conversely, orange areas, encompassing most of Tolima's coffee plantations, schedule their primary harvest from March to June and their Mitaca between October and November.

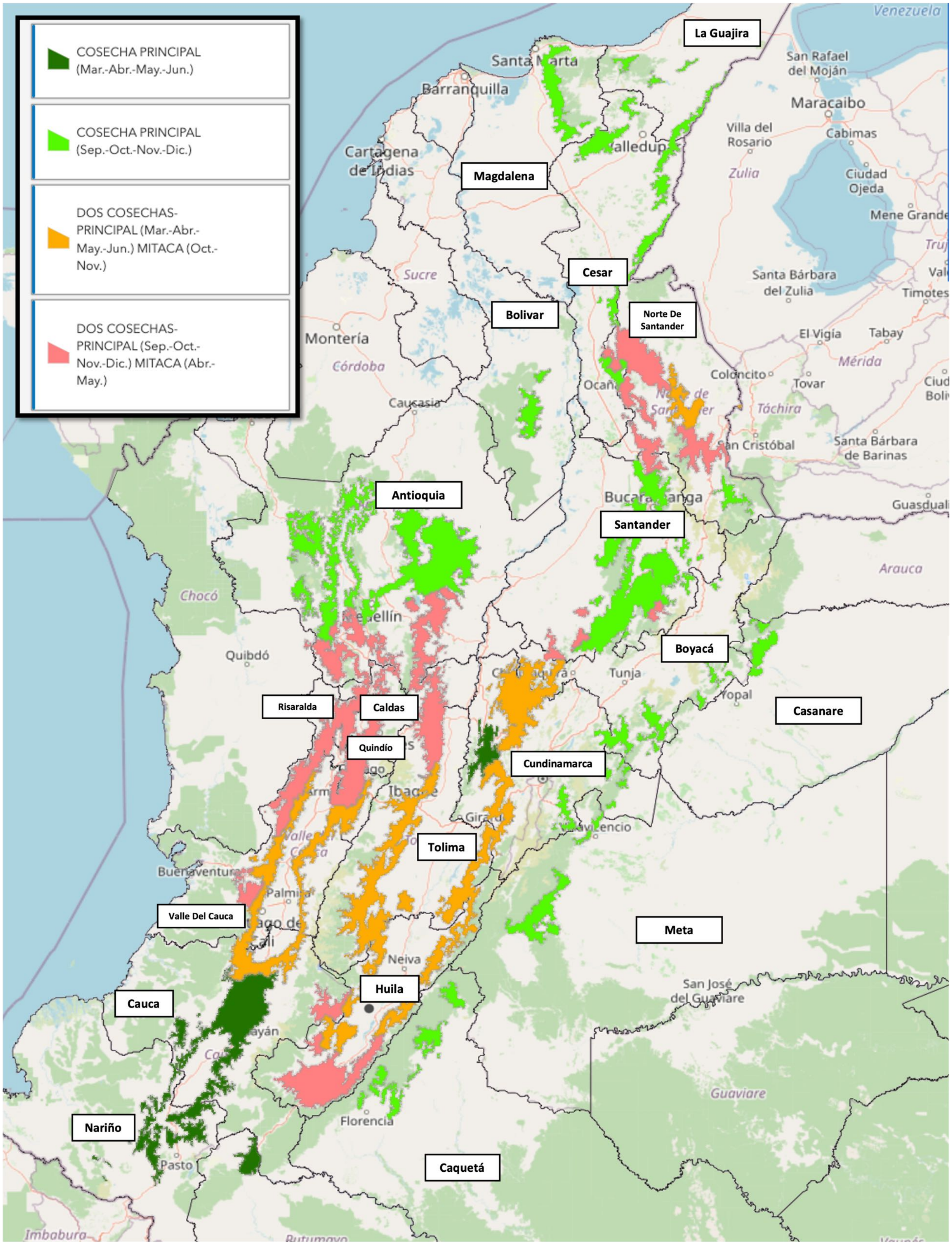


Figure 5.5: Colombia Coffee Harvest Map[1]

5.2 Data

The Brazilian Institute of Geography and Statistics (IBGE)[2] is the primary source for municipality-level coffee production data in Brazil. In Colombia, these data aregathered by the Municipal Agricultural Evaluations (EVA), an arm of the Ministry of Agriculture. My analysis encompasses a span of 39 years of data from Brazil (1980 to 2018) and 11 years from Colombia (2008 to 2018). Both these authoritative bodies track metrics such as production volume, harvested area, and plantation area at the municipality level.

In this analysis, I evaluatehistorical weather and production data from 2103 municipalities in Brazil and 455 in Colombia that contribute to coffee production. To remove the influence of outliers, I have dropped the observations of the first 1% on both tails of the yield distribution, area harvested distribution, and yield distribution. Consequently, the study's lens is specifically focused on balanced panel datasets of 2048 municipalities in Brazil and 451 in Colombia.

It's crucial to understand certain terminologies in this context. The harvest area pertains to the total expanse sown that undergoes harvesting within a crop year. Due to coffee's perennial nature, not every shrub or tree yields harvest every year. For instance, freshly planted saplings usually have a gestation of about three years before they fruit (DaMatta, Ronchi, et al., 2007).

This research prominently focuses on yield, measured in metric tons per hectare (mt/ha). This is computed as the ratio of production volume to the harvest area. It's imperative to

[1] https://federaciondecafeteros.org/wp/coffee-harvest-map/?lang=en
[2] https://sidra.ibge.gov.br/tabela/1613

note that this traditional definition of yield omits potential harvestable zones that remain untouched either because of plant die-off or selective harvesting. Drawing inspiration from Rising's methodology (2016), I introduce an additional metric potential coffee yield in this analysis. This metric is derived by dividing production quantity by the total planted area, serving as a supplementary measure for a robustness check.

The production data are combined with weather data from the Climate Forecast System (CFS). It combines daily information on maximum temperature, minimum temperature, and cumulative precipitation from ground stations and satellites with climate models to create weather estimates at high resolution (Saha et al., 2014). The spatial resolution for temperature is $0.3125° \times 0.3125°$, which is approximately a grid size of 34km by 34km. The spatial resolution for precipitation is $0.5° \times 0.5°$, which is approximately 54km by 54km. I aggregate the gridded historical weather data to the municipality level by averaging over the grids within the municipality.

Since the production patterns are different between Brazil and Colombia, I use climate variables from different months accordingly to account for such variation. In general, the coffee crop calendar can be broadly divided into the following stages: (1) blossoming, (2) fruit development, and (3) harvesting. For major producing regions in southern Brazil, the flowering period begins in August and usually lasts till November. December to April is the period when coffee cherries grow and ripen. The harvest season typically starts in May and can last till August.

In Colombia, part of the producing regions follows the harvest cycle of the northern hemisphere, which harvests the major crop between September and December. Others follow the calendar of the southern hemisphere, with the harvest season ranging from March through

June. Therefore, I distinguish the growing stages based on their cycles. For example, as figure 5.5 illustrates, if the majority of the producing regions in a department harvest between March and June (September and December), then I consider July to October (January to April) as the flowering season, April to August (October to February) as the cherry-filling stage. Table 5.1 shows the departments in each group.

However, the classification does not precisely capture the accurate harvest calendar at the municipality level because municipalities in departments such as Norte de Santander, Huila, Cundinamarca, Tolima, and Valle del Cauca have different harvest times. To correctly model the production seasons in these departments, I overlay the interactive coffee harvest map from the National Federation of Coffee Growers of Colombia website in figure 5.5 onto the departments' maps with municipality boundaries. Therefore, I can identify the true production cycle for each municipality.

Table 5.1: Coffee Harvest Time by Department

	Main Harvest		Second Harvest	
	Sep - Dec	Mar - Jun	Apr - May	Oct - Nov
Bolivar	x			
Boyaca	x			
Caqueta	x			
Casanare	x			
Cesar	x			
La Guajira	x			
Magdalena	x			
Meta	x			
Antioquia	x		x	
Quindio	x		x	
Risaralda	x		x	
Santander	x		x	
Caldas	x		x	
Narino		x		
Cauca		x		x
Norte de Santander*	x		x	
Huila*	x		x	
Cundinamarca*		x		x
Tolima*		x		x
Valle del Cauca*		x		x

Table 5.2: Coffee Growth Stage

	Brazil	Colombia North	Colombia South
Blooming	September to December	January - April	July - October
Fruit-bearing	January to April	May - August	November - February
Harvesting	May to August	September - December	March - June

5.3 Results

Brazil

Table 5.3 presents the summary statistics of pivotal variables for Brazil. Despite omitting extreme observations, Brazil's production scale demonstrates considerable variation. The sample reveals a pronounced alternate bearing effect. The state-level average yield trend, as depicted in figure 5.6, underscores a significant biennial pattern, especially evident in states like Mato Grosso do Sul, Minas Gerais, Paraná, and São Paulo.

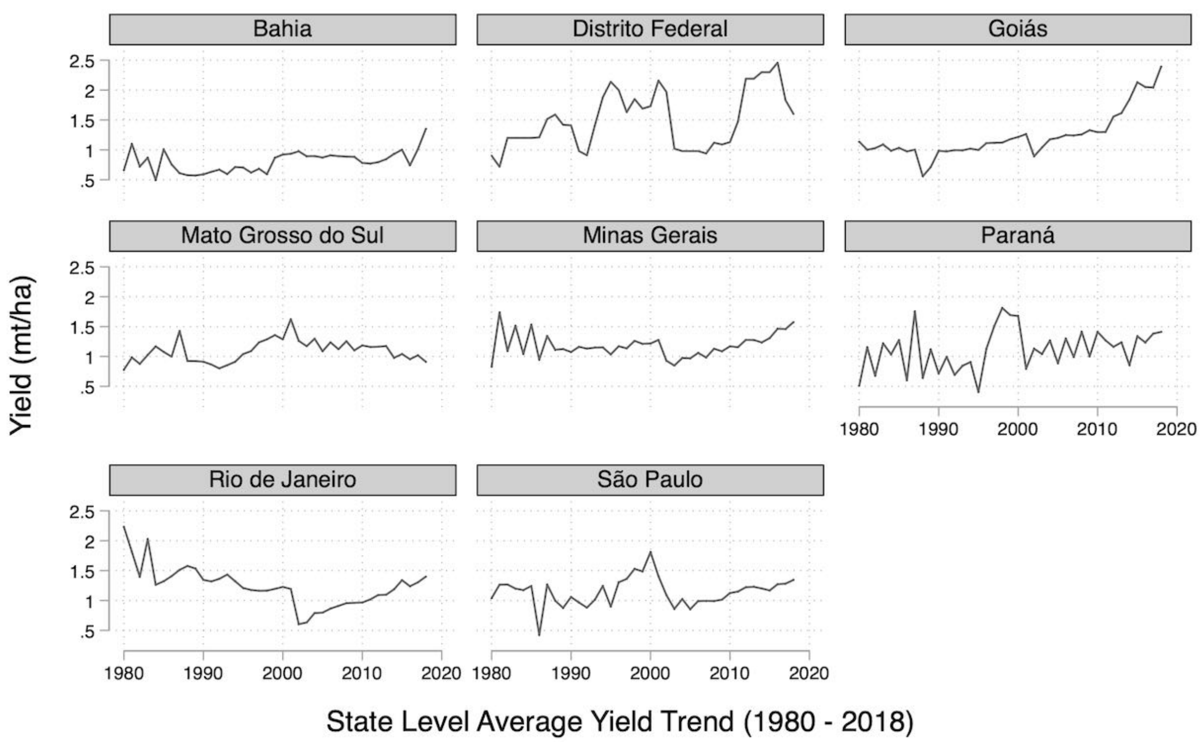


Figure 5.6: Brazil Average Yield Trend by State

The yield deviation variable possesses a mean value in proximity to 0, suggesting a relatively symmetric distribution between "on-years" and "off-years". On average, an "on-year" has a yield that is 0.49 mt/ha higher than the previous year's. At the same time, an "off-year" yield is 0.51 mt/ha short of the prior year's on average.

Table 5.3: Summary Statistics (Brazil)

VARIABLES	N	mean	sd	min	max
Harvested Area (ha)	54428	927.00	1660.26	3.00	11315.00
Quantity Produced (mt)	54428	1078.97	2070.86	3.00	13440.00
Yield (mt/ha)	54428	1.12	0.58	0.01	3.48
Yield Deviation	51858	0.00	0.64	-7.65	12.05
Yield Deviation (+)	19517	0.49	0.55	0	12.05
Yield Deviation (-)	18515	-0.51	0.55	-7.65	0
Elevation (m)	54428	608.78	233.459	2.98	1378.71
GDD/1000 - Blooming	54428	1.67	0.25	0.94	2.41
GDD/1000 - Fruit Bearing	54428	1.57	0.23	0.98	2.32
GDD/1000 - Harvesting	54428	1.20	0.24	0.57	2.13
HDD - Blooming	54428	31.73	44.03	0.00	404.19
HDD - Fruit Bearing	54428	9.14	21.08	0.00	249.87
HDD - Harvesting	54428	2.23	4.77	0.00	105.41
FDD - Pre-blooming	54428	0.26	1.17	0.00	21.27
Rainfall (mm) - Blooming	54428	638.86	330.25	11.48	2298.75
Rainfall (mm) - Fruit Bearing	54428	811.63	364.09	19.20	2460.20
Rainfall (mm) - Harvesting	54428	156.83	111.43	1.32	1048.25
Number of Dry Days - Pre-blooming	54428	115.35	6.08	73.00	123.00
Precipitation CV - Blooming	54428	2.18	0.69	0.83	8.27
Number of municipalities	2048				
Year	1980-2018				
Blooming	September to December				
Fruit Bearing	January to April				
Harvesting	May to August				
Pre-blooming	May to August of previous year				

Growing degree days (GDDs) quantify the cumulative warmth favorable for plant growth, specifically accounting for temperature units between 10 and 32°C. Across various coffee growth stagesnamely blooming, fruit-bearing, and harvestingthe average GDD values stand at 1670, 1570, and 1200, respectively.

In contrast, harmful degree days (HDDs) represent the cumulative exposure to extreme temperatures exceeding 32°C. These extreme temperatures are mostly seen in the blooming phase of the coffee production stages.

The freezing degree days (FDDs) gauge the cumulative exposure to temperatures below 0řC, which predominantly occurs during the pre-blooming phase of coffee growth. As illustrated in Figure 5.7, the FDDs for each municipality are showcased annually for the period from 1980 to 2018. Although the average FDD value is relatively low at 0.25, particularly severe frosts, typically associated with FDD values above 10, were recorded in specific years such as 1981, 1988, 1994, and 2000 (Coffee Research Institute, 2006; Reuters, 1994; Larry Rohter, 1978).

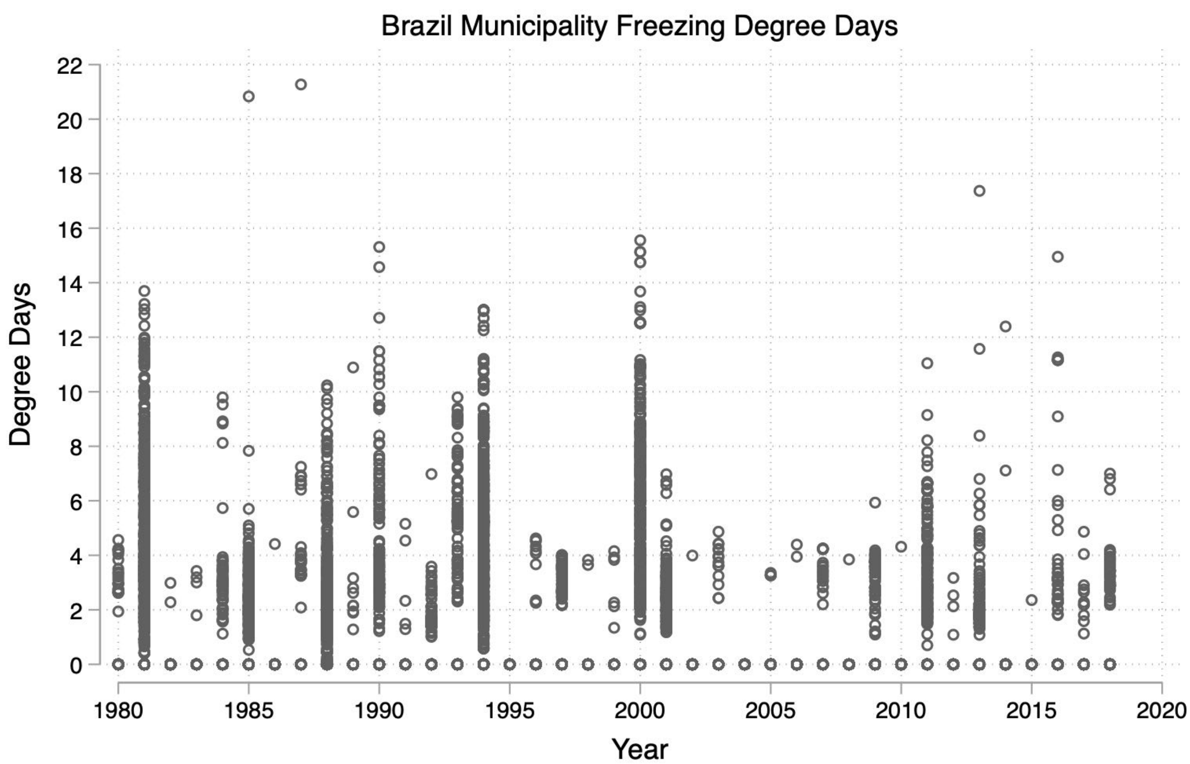


Figure 5.7: Brazil Municipality Freezing Degree Days Trend

In Brazil's predominant coffee regions, precipitation exhibits a distinct seasonal pattern.

The months from May to August constitute the dry season, during which municipalities experience an average total rainfall of merely 157.25 mm. September typically heralds the onset of the wet season, which often extends until April of the subsequent year. Figure 5.8 illustrates the distribution of total precipitation across these distinct stages.

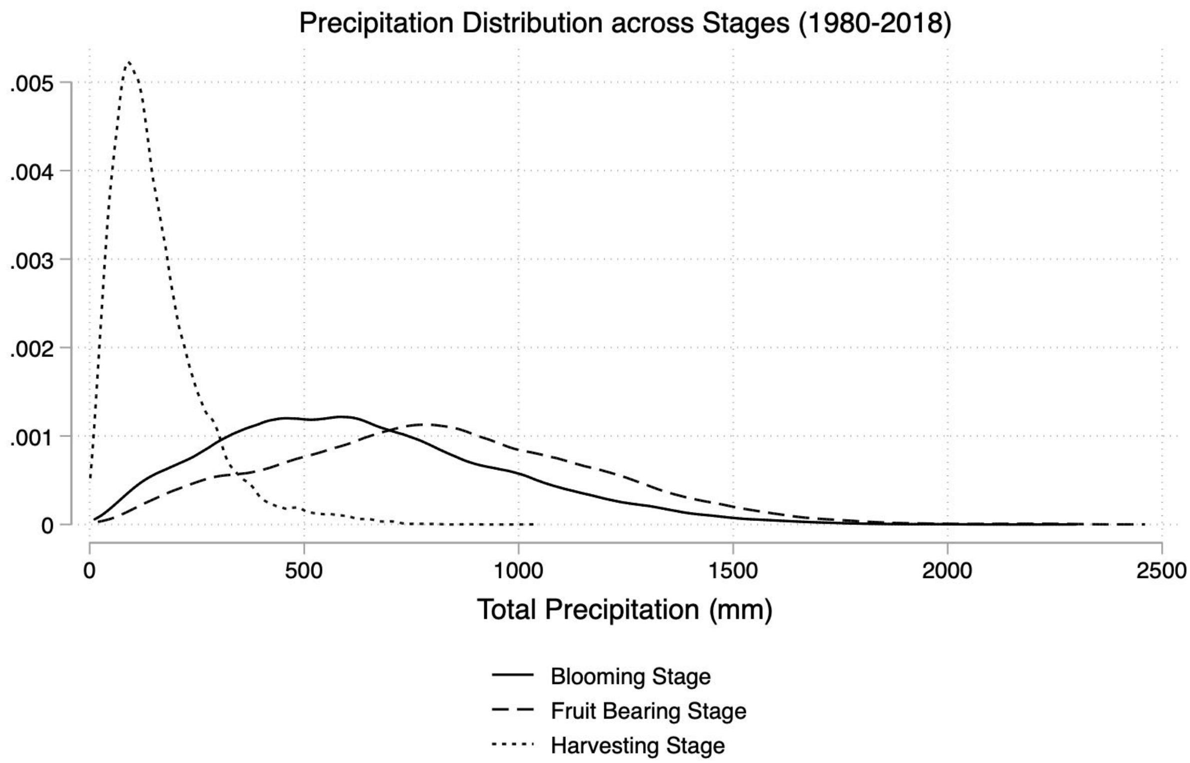


Figure 5.8: Brazil Precipitation Distribution across Stages

In addition to total precipitation, the effect of water on coffee growth can be gauged by considering two other significant dimensions: the number of dry days during the pre-blooming stage and the variability of rainfall during the blooming period. Figure 5.9 captures the number of dry days in the pre-blooming phase. In a typical year, over 90% of the days between May and August register precipitation levels of less than 5 mm. The variability of total precipitation, as expressed by the coefficient of variation, with an average of 2.18 and a standard deviation of 0.69.

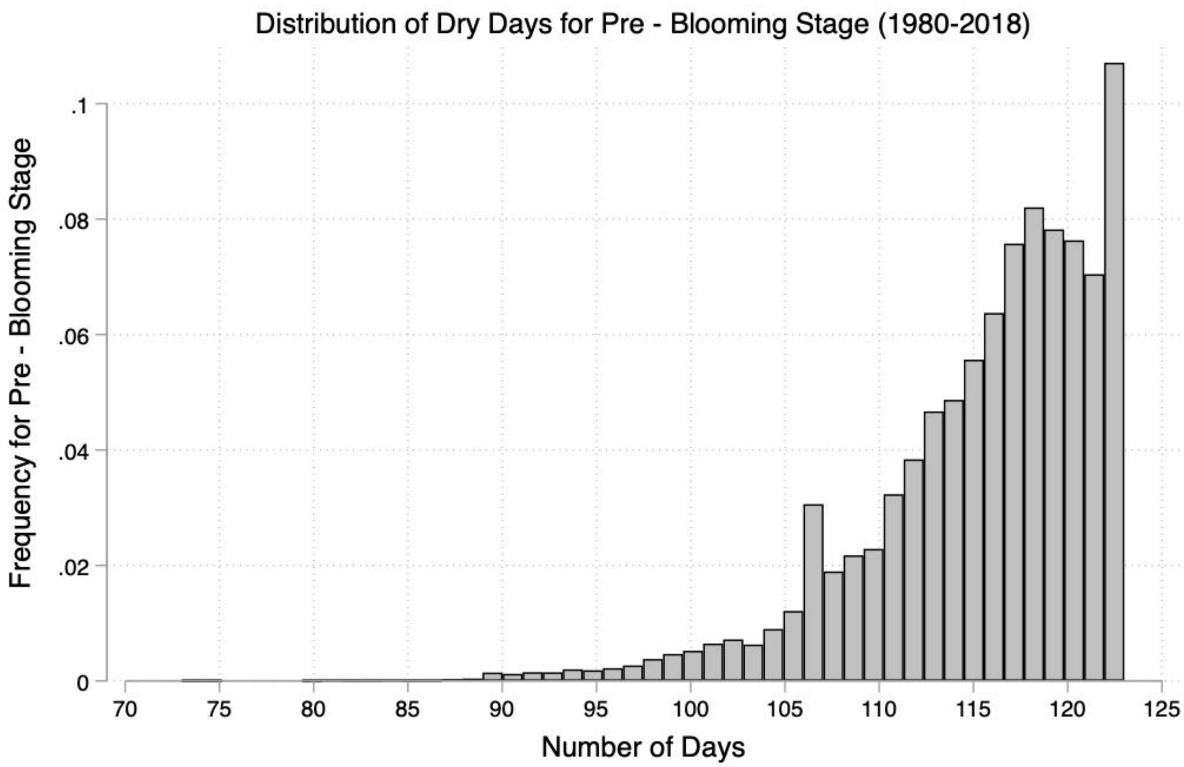


Figure 5.9: Brazil Number of Dry Days Distribution across Stages

Table 5.4 presents the results of the Growth Stage Alternate Bearing regression. The first column lists the variable names, the second provides the coefficient estimates, and the third represents the elasticity of each variable in the model when evaluated at the mean.

For clarification, the elasticity for the initial term of equation 4.1 is defined as:

$$elasticity = \frac{\Delta y}{\Delta X} \times \frac{\bar{X}}{\bar{y}} = \hat{\beta} \times \frac{\bar{X}}{\bar{y}},$$

where $\bar{X}$ is the mean of the specific weather variable, $\bar{y}$ represents the average yield across all observations, and $\hat{\beta}$ is the coefficient estimate.

As anticipated, the coefficient on lagged yield deviation is significantly negative, signaling a prominent biennial pattern in coffee yield across Brazil's coffee-producing regions. Nevertheless, the magnitude of this effect remains relatively modest. On average, an "on-year" produces 0.49 mt/ha more than the previous year. If the yield deviation is increased by 100%, then yield from the current harvest will be 0.6% lower solely due to the alternate bearing effect. Conversely, the "off-year" impact is of an equivalent magnitude but in the opposite direction.

One plausible rationale for this subdued biennial effect pertains to the inherent heterogeneity among coffee plants spanning different cultivars and varieties. Recent studies from Brazil highlight that certain coffee plants can consistently sustain stable yields over consecutive years. Alternatively, some plants might exhibit high yields for a span of two years, followed by a diminished yield in the third year (Vieira Junior et al., 2019). Lacking precise data at the tree or variety level, our analysis can only capture the overarching pattern across various municipalities rather than pinpointing the true alternate bearing effect.

Interestingly, only the growing degree days (GDDs) during the flower blooming period, spanning from September to December, shows a positive influence on the current year's yield. This is evidenced by an elasticity of 0.27 at the mean GDD value of 1670. This suggests that, when all other factors are held constant at their mean values, a 10% rise in GDDs translates to an increase in yield by 2.7%.

Conversely, the cumulative warm temperatures during both the fruit-bearing stage (January to April) and the harvesting stage (May to August) negatively impact the yield. Specifically, a 10% increase in GDDs during the fruit-bearing phase correlates with a yield reduction of 1.9%. Similarly, the same increase in GDDs during the harvest season is associated with

Table 5.4: Brazil Model

	coefficients	elasticity (mean)
Yield Deviation	-0.014**	if >0: -0.006**
		if <0: 0.006**
	(0.0057)	(0.026)
GDD/1000 - Blooming	0.17***	0.27***
	(0.031)	(0.047)
GDD/1000 - Fruit Bearing	-0.13***	-0.19***
	(0.045)	(0.065)
GDD/1000 - Harvesting	-0.25***	-0.27***
	(0.033)	(0.037)
HDD - Blooming	-0.0017***	-0.055***
	(0.00014)	(0.0048)
HDD - Fruit Bearing	-0.00025	-0.0024
	(0.00024)	(0.0023)
HDD - Harvesting	0.012***	0.025***
	(0.0011)	(0.0022)
FDD - Pre-blooming	-0.018***	-0.0045***
	(0.0025)	(0.00070)
Rainfall - Blooming (m)	0.092***	0.052***
	(0.012)	(0.0069)
Rainfall - Fruit Bearing (m)	0.081***	0.059***
	(0.011)	(0.0081)
Rainfall - Harvesting (m)	-0.15***	-0.022***
	(0.028)	(0.0041)
Number of Dry Days - Pre-blooming	0.096***	10.2***
	(0.011)	(1.14)
Number of Dry Days - Pre-blooming ^{2}	-0.00046***	-5.57***
	(0.000049)	(0.60)
Precipitation CV - Blooming	0.023***	0.046***
	(0.0044)	(0.0087)
Constant	-3.82***	
	(0.60)	
Linear State Trend	BA(+), DF(+), GO(+), MG(-), MS(+), PR(+), RJ(-), SP(-)	
Observations	50796	
Adjusted R^2	0.276	
FE	Municipalities	

Standard errors in parentheses

* p<.1, ** p<.05, *** p<.01

a yield decline of 2.7%.

One thing to note is the positive correlation between the GDD and HDD variables, as shown in Figure 5.10 When predictor variables exhibit high correlation, it can distort both the sign and magnitude of regression coefficients. Notably, in this study, GDDs during the fruit-bearing stage are highly correlated with HDDs over the same time frame. A surge in HDDs naturally corresponds to greater GDDs. Consequently, the observed coefficient may not purely represent the singular effect of GDDs on coffee yield.

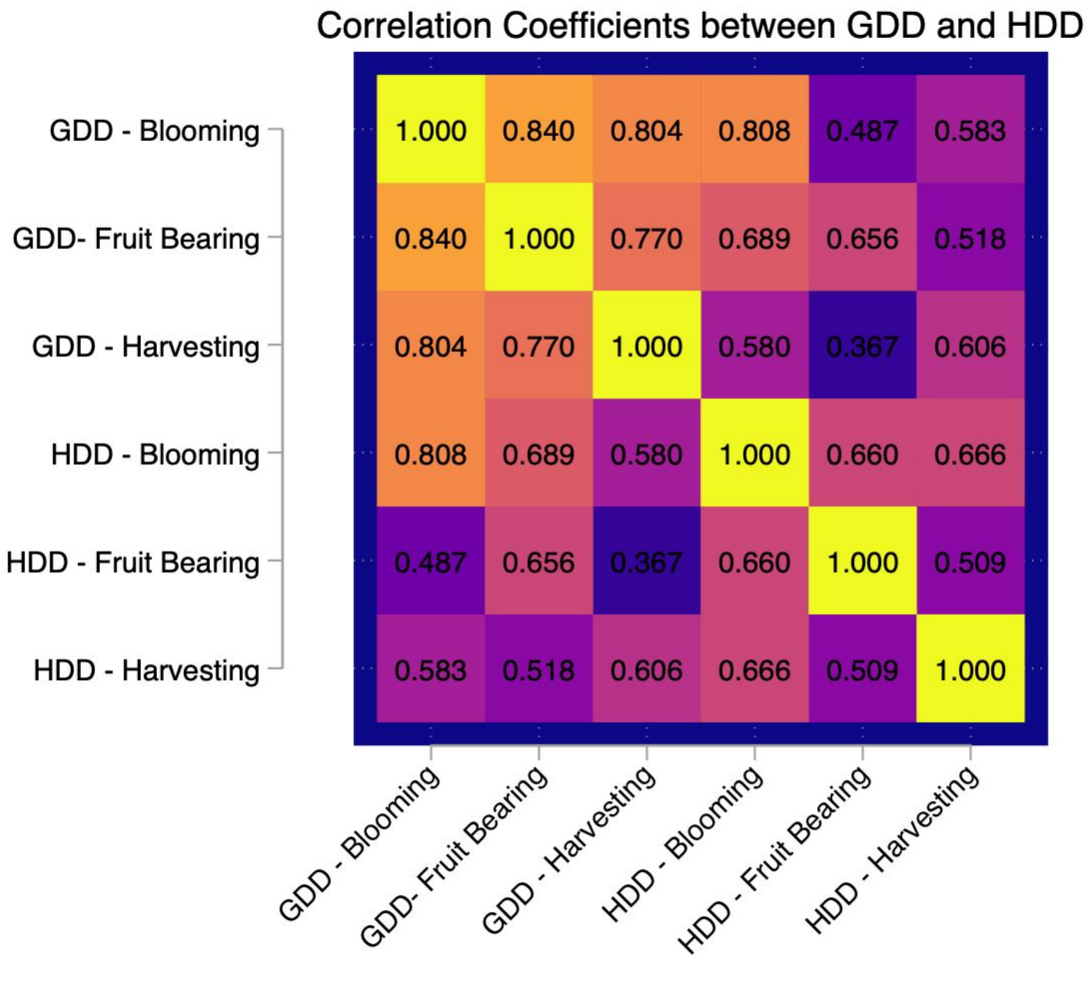


Figure 5.10: Correlation Coefficients between GDDs and HDDs in Brazil

Furthermore, extreme heat exhibits heterogeneous effects on yield across growth stages.

Notably, during both the blooming and fruit-bearing stages, the beneficial impact of elevated temperatures on yields diminishes when temperatures consistently exceed $32°C$. The detrimental effects of intense heat during the blooming phase are more pronounced than those during the fruit-bearing period. In a typical year, an increase of the HDD from 31.73 to 63.46 (essentially doubling it) can lead to a notable 5.5% decline in yield. However, the coefficient for HDD during the fruit-bearing stage appears statistically insignificant, suggesting no discernible impact on yield during this stage.

Regarding the harvesting phase, the data indicate that warmer days might actually be advantageous for coffee yields, as evidenced by a positive elasticity of 0.025. In Brazil's primary coffee-growing regions, the harvesting season commences during the year's cooler months. During this quarter, the recorded average maximum temperature across the sample oscillates between $25°C$ and $27°C$, while the average minimum fluctuates between $13°C$ and $14°C$. This observed positive coefficient for HDD in the harvesting period might be explained by the possibility that elevated temperatures create optimal conditions for both harvesting and subsequent post-harvest practices, such as drying.

The coefficient estimates display a significant negative effect between frosts during the early period of the coffee cycle and the coming yield, with an elasticity of -0.0043 evaluated at the mean. On an average year, the FDD during the pre-blooming period is 0.26, which is a small number. The daily minimum temperature rarely drops below $0°C$ in these months. From 1980-2018, only 18 days have recorded subzero temperatures in my sample. Yet, it's important to note that when an intense cold snap does strike, the FDD can surge by well over 500%. For instance, if the FDDs were to rise from their mean value of 0.26 to the maximum of 21.27, the consequential impact on yield could be as substantial as a decline of

-36.4%.

The relationship between total precipitation during each growth stage and yields displays varied dynamics. During both the flowering and fruit-bearing stages, increased cumulative precipitation appears beneficial, with elasticities of a roughly similar magnitude. However, excessive rainfall during the harvesting phase tends to be detrimental to yields in Brazil's coffee-producing regions. Elevated precipitation levels during this time, when the coffee cherries are ripe and ready for harvest, can foster mold or fungal growth, leading to defects in the coffee beans. Additionally, increased rainfall can heighten the risk of mold development during the coffee cherry drying process (Kath et al., 2021).

During the dry and cold pre-flowering period, I include the number of dry days in both linear and quadratic terms to capture the effect of water stress on coffee flowering for the coming production year. The positive coefficient on the linear term and the negative sign on the quadratic term suggest that a prolonged dry period is beneficial for yield. Nevertheless, if drought conditions intensify excessively, yields might suffer adversely.

Figure 5.11 shows this non-linear relationship, charting the correlation between the number of dry days in the pre-blooming phase and the subsequent coffee yield. The two dashed lines on each end indicate the minimum (73) and maximum (123) amount of dry days in the sample. The optimal amount of dry days during the 4-month span is 104 days. Exceeding this threshold of dry days could disrupt the blooming process, thereby influencing the impending harvest adversely.

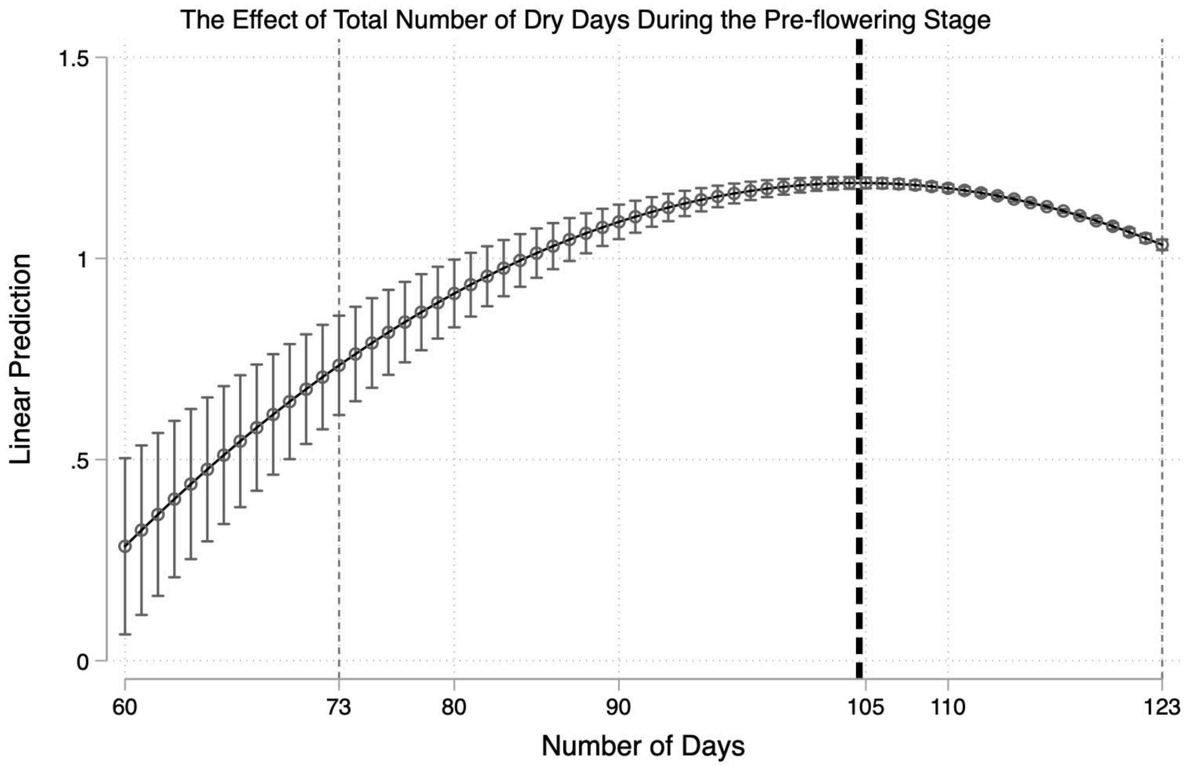


Figure 5.11: The effect of total number of dry days during the pre-flowering stage in Brazil

The coefficient of variation for precipitation gauges the variability of daily rainfall. Its positive and significant coefficient suggests that erratic rainfall distribution is more favorable than a consistent pattern during the blooming phase. At first glance, this outcome seems counter-intuitive, as uniform precipitation patterns typically foster synchronized flower blossoming, leading to the uniform ripening of berries.

However, another dimension to consider is how precipitation variability might influence the application of fertilizers during the flowering period. Guo and Chen (2022) observed that rainfall variability significantly bolsters farmers fertilizer application rates on maize in China. Notably, their research underscores that irregular rainfall patterns exert a more pronounced impact on fertilizer usage in hilly and mountainous terrains. This setting parallels the topographical conditions of coffee plantations in Brazil, offering a potential explanation for the observed findings.

Colombia (2008-2018)

Table 5.5 presents the summary statistics of key variables for Colombia. I also present key metrics of Colombia North and Colombia South separately in Table 5.6 and 5.7. In the Colombia sample, I define the production cycle as north or south for each municipality based on the information provided by Federación Nacional de Cafeteros de Colombia, which is also shown in table 5.1.

The average harvested area and production quantity per municipality is 1280.50 hectares and 1229.38 metric tons, which are greater than that of Brazil's. However, The standard deviation and the maximum observation for both metrics are smaller than that of producing regions in Brazil. Average yield is less than one metric ton per hectare, which may reflect the challenging growing conditions or smallholder farm dominance.

Contrary to the patterns observed in Brazil, the data from Colombia for the years 2007-2018, as illustrated in figure 5.12, do not display an alternating production cycle at the state level. This could be attributed to the unique micro climates prevalent in various Colombian coffee-growing regions, coupled with the occurrence of the mitaca, or mid-year crop. These factors are likely instrumental in diminishing the impact of alternate bearing, a phenomenon common in coffee production where years of high yield are typically followed by years of lower yield.

Growing degree days (GDD) and harmful degree days (HDD) for different stages of coffee growth are given, with blooming and fruit-bearing stages requiring more thermal units compared to harvesting, highlighting the thermal demands of coffee development.

Total rainfall exhibits a much less obvious seasonality pattern comparing to Brazil. The highest average rainfall occurs during the harvesting stage, which is September to December in municipalities following the northern hemisphere cycle

Table 5.5: Summary Statistics (Colombia)

VARIABLES	N	mean	sd	min	max
Harvested Area (ha)	4780	1280.50	1435.35	15.00	8234.59
Quantity Produced (mt)	4780	1229.38	1503.63	13.00	8180.77
Yield (mt/ha)	4780	0.87	0.27	0.06	1.56
Yield Deviation	4357	0.00	0.23	-1.91	2.47
Yield Deviation (+)	2678	0.12	0.16	0	2.47
Yield Deviation (-)	1679	-0.20	0.18	-1.91	0
Elevation (m)	4575	1655.49	563.06	277.85	2864.68
GDD/1000 - Blooming	4780	1.12	0.45	0.05	2.28
GDD/1000 - Fruit Bearing	4780	1.08	0.45	0.09	2.32
GDD/1000 - Harvesting	4780	1.09	0.44	0.04	2.24
HDD - Blooming	4780	4.68	18.31	0.00	239.08
HDD - Fruit Bearing	4780	3.91	16.98	0.00	225.22
HDD - Harvesting	4780	3.02	11.81	0.00	172.88
FDD - Pre-blooming	4780	0.14	1.83	0.00	46.64
Rainfall (mm) - Blooming	4780	770.95	695.63	3.78	4436.98
Rainfall (mm) - Fruit Bearing	4780	878.77	787.52	0.50	5045.16
Rainfall (mm) - Harvesting	4780	1015.26	819.39	6.00	5494.08
Number of Dry Days - Pre-blooming	4780	74.84	32.69	0.00	122.00
Precipitation CV - Blooming	4780	1.78	0.89	0.55	8.63
Number of municipalities	451				
Year	2007-2018				
Stage 1 (flowering)	N:January to April | S: July to October				
Stage 2 (fruit-bearing)	N:May to August | S: November to February				
Stage 3 (harvesting)	N:September to December | S: March to June				

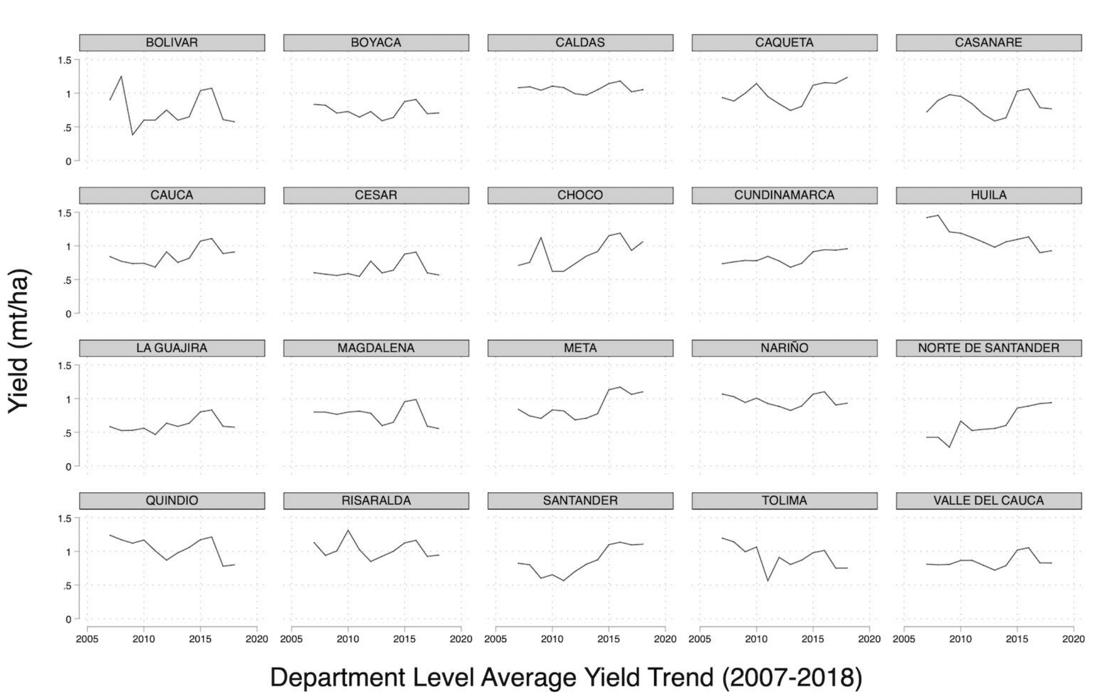


Figure 5.12: Department Annual Yield Trend in Colombia (2007-2018)

Table 5.6: Summary Statistics (Colombia North)

VARIABLES	N	mean	sd	min	max
Harvested Area (ha)	2662	1245.98	1423.91	15.00	8050.27
Quantity Produced (mt)	2662	1207.24	1525.10	13.00	8180.77
Yield (mt/ha)	2662	0.86	0.28	0.12	1.56
Yield Deviation	2431	0.00	0.24	-1.91	2.47
Yield Deviation (+)	1513	0.13	0.18	0	2.47
Yield Deviation (-)	918	-0.20	0.20	-1.91	0
Elevation (m)	2457	1647.43	608.62	277.85	2864.68
GDD/1000 - Blooming	2662	1.16	0.46	0.15	2.28
GDD/1000 - Fruit Bearing	2662	1.18	0.48	0.17	2.32
GDD/1000 - Harvesting	2662	1.13	0.45	0.13	2.24
HDD - Blooming	2662	7.05	23.01	0.00	239.08
HDD - Fruit Bearing	2662	6.20	21.99	0.00	225.22
HDD - Harvesting	2662	4.10	14.13	0.00	172.88
FDD - Pre-blooming	2662	0.25	2.44	0.00	46.64
Rainfall (mm) - Blooming	2662	801.59	657.47	6.51	3974.03
Rainfall (mm) - Fruit Bearing	2662	850.33	740.83	1.40	5045.16
Rainfall (mm) - Harvesting	2662	995.83	732.86	23.10	5039.51
Number of Dry Days - Pre-blooming	2662	77.29	30.44	0.00	121.00
Precipitation CV - Blooming	2662	1.69	0.83	0.55	6.22
Number of municipalities	253				
Year	2007-2018				
Stage 1 (flowering)	January to April				
Stage 2 (fruit-bearing)	May to August				
Stage 3 (harvesting)	September to December				

Table 5.7: Summary Statistics (Colombia South)

VARIABLES	N	mean	sd	min	max
Harvested Area (ha)	2118	1323.90	1448.78	19.79	8234.59
Quantity Produced (mt)	2118	1257.21	1476.07	14.40	8118.80
Yield (mt/ha)	2118	0.88	0.25	0.06	1.56
Yield Deviation	1926	-0.01	0.21	-0.90	1.00
Yield Deviation (+)	1165	0.11	0.14	0	1
Yield Deviation (-)	761	-0.19	0.17	-0.9	0
Elevation (m)	2118	1664.84	505.06	619.73	2745.15
GDD/1000 - Blooming	2118	1.07	0.41	0.05	2.23
GDD/1000 - Fruit Bearing	2118	0.96	0.38	0.09	2.02
GDD/1000 - Harvesting	2118	1.04	0.41	0.04	2.13
HDD - Blooming	2118	1.69	8.69	0.00	131.51
HDD - Fruit Bearing	2118	1.04	5.27	0.00	107.14
HDD - Harvesting	2118	1.67	7.79	0.00	106.69
FDD - Pre-blooming	2118	0.01	0.26	0.00	9.59
Rainfall (mm) - Blooming	2118	732.44	739.17	3.78	4436.98
Rainfall (mm) - Fruit Bearing	2118	914.51	841.36	0.50	4580.93
Rainfall (mm) - Harvesting	2118	1039.67	916.24	6.00	5494.08
Number of Dry Days - Pre-blooming	2118	71.75	35.07	0.00	122.00
Precipitation CV - Blooming	2118	1.90	0.96	0.57	8.63
Number of municipalities	198				
Year	2007-2018				
Stage 1 (flowering)	July to October				
Stage 2 (fruit-bearing)	November to February				
Stage 3 (harvesting)	March to June				

Table 5.8: Colombia Model

	coefficients	elasticity (mean)
Yield Deviation	0.24***	if > 0: 0.04***
		if < 0: -0.05***
GDD/1000 - Blooming	0.26***	0.38***
	(0.047)	(0.069)
GDD/1000 - Fruit Bearing	-0.15	-0.22
	(0.10)	(0.16)
GDD/1000 - Harvesting	0.14**	0.21**
	(0.070)	(0.10)
HDD - Blooming	0.00075*	0.0037*
	(0.00044)	(0.0022)
HDD - Fruit Bearing	-0.00076	-0.0035
	(0.00075)	(0.0034)
HDD - Harvesting	0.0017**	0.0053**
	(0.00083)	(0.0026)
FDD - Pre-blooming	0.00098	0.00021
	(0.0038)	(0.00079)
Rainfall - Blooming (m)	-0.017	-0.022
	(0.016)	(0.022)
Rainfall - Fruit Bearing (m)	-0.097***	-0.10***
	(0.018)	(0.020)
Rainfall - Harvesting (m)	0.071***	0.099***
	(0.013)	(0.018)
Number of Dry Days - Pre-blooming	-0.00088	-0.095
	(0.00083)	(0.089)
Number of Dry Days - Pre-blooming ^{2}	-0.0000031	-0.030
	(0.0000057)	(0.053)
Precipitation CV - Blooming	0.0086	0.021
	(0.0081)	(0.019)
Constant	0.57***	
	(0.066)	
Linear Department Trend	Bolivar(+), Boyaca(+), Caldas(+), Caqueta(+), Casanare(+), Cauca(+), Cesar(+), Choco(+), Cundinamarca(-), Huila(+), La Guajira(+), Magdalena(+), Meta(+), Nariño(-), N.de Santander(+), Quindio(-), Risaralda(-), Santander(+), Tolima(-), Valle del Cauca(+)	
Observations	4298	
Adjusted R^2	0.557	
FE	Municipalities	

Standard errors in parentheses
* p<.1, ** p<.05, *** p<.01

The regression results for Colombian coffee yields are presented in Table 5.8. Contrary to the results obtained from Brazil, there is no evidence of alternate bearing in Colombian coffee yields. Instead, the data suggest a slight but positive correlation between yield deviations from the previous year and the current year's yields. This observation aligns with findings by Ceballos-Sierra and Dall'Erba (2021), who attributed such positive relationships to the reinvestment of higher profits derived from improved yields. Notably, their analysis did not incorporate a time trend to capture this effect. In contrast, my model includes a linear time trend at the departmental level to explore the presence of any monotonic trends in yields. Given that Colombia experiences two main harvests annually, capturing the alternate bearing effect is challenging. This biannual cycle could dampen the alternate bearing effects, as the impact of a poor harvest may be offset by a subsequent better one within the same year, thus stabilizing yield fluctuations. This interpretation is supported by visualization depicted in Figure 5.12 at the departmental level.

Growing degree days (GDDs) during the flowering and harvesting seasons show significant positive effects on yields. Specifically, a 10% increase in GDDs corresponds to an approximate yield increase of 3.8% during the flowering period and 2.1% during the harvesting stage. However, GDDs during the fruit-bearing period do not appear to influence productivity.

In terms of harmful degree days during the flowering and harvesting periods, the estimated impacts on yields are positive but minimal. A 10% increase in GDDs leads to a yield increase of merely 0.037% during the flowering period and 0.053% during the harvesting stage, which is effectively negligible. Furthermore, exposure to extreme heat during the fruit-bearing period does not significantly affect coffee yields in Colombia.

Precipitation during the fruit-bearing stage has a detrimental effect on yield, with a 10% increase in total precipitation leading to a roughly 1% decrease in yield. This negative impact is likely due to flooding and landslides, common issues in many Colombian coffee-growing regions when extreme rainy events occur (U.S. Department of Agriculture, Foreign Agricultural Service, 2012).

Conversely, during the harvesting season, a 10% increase in rainfall slightly enhances coffee yields by almost 1%. This finding is somewhat contradictory to the Brazilian data, where increased rainfall typically hampers the coffee harvesting process and subsequently reduces yields. Since many coffee producing regions in Colombia do not have a distinct dry season and wet season, the growing stages for coffee plants in different coffee plantations within a municipality can vary. It is difficult to match the exact phenological stages with different months of a year. It is normal that even within a plantation, some trees are ready to be harvested while some others are ready to bloom for the next crop. Therefore, the estimation results might be biased.

5.4 Heterogeneity Across Elevation

Elevation plays a pivotal role in influencing coffee's quality and taste profile. As one ascends in elevation, the prevailing temperatures tend to drop. This cooler environment ensures that the coffee beans retain a richer concentration of sugars and nutrients, which significantly impacts their flavor (Wilson, 2018). Moreover, altitude serves as a reliable indicator of the specific coffee variety cultivated in a region. For example, Robusta coffee predominantly thrives at lower altitudes, generally between 200 and 800 meters, while Arabica coffee prefers higher terrains above 600 meters.

According to the Sustainable Coffee Institute [3] (2018), coffee-producing regions can be

[3] https://www.upi.com/Archives/1981/07/28/Brazilian-frost-less-damaging-than-1975/4715365140800/

categorized into three groups: low-elevation (below 900 m), mid-elevation (900 m to 1200 m), high-elevation (1200m to 1500m), and very high-elevation (1500 m and above).

To determine the average elevation of coffee-producing municipalities, I employed the Terrain Base elevation dataset (5 Arc-minute) sourced from the National Center for Atmospheric Research. Using a gridded map, I computed the elevation for each municipality based on an area-weighted average. I show the elevation distribution map in both the Brazil and Colombia municipalities in figures (5.13) and (5.14).

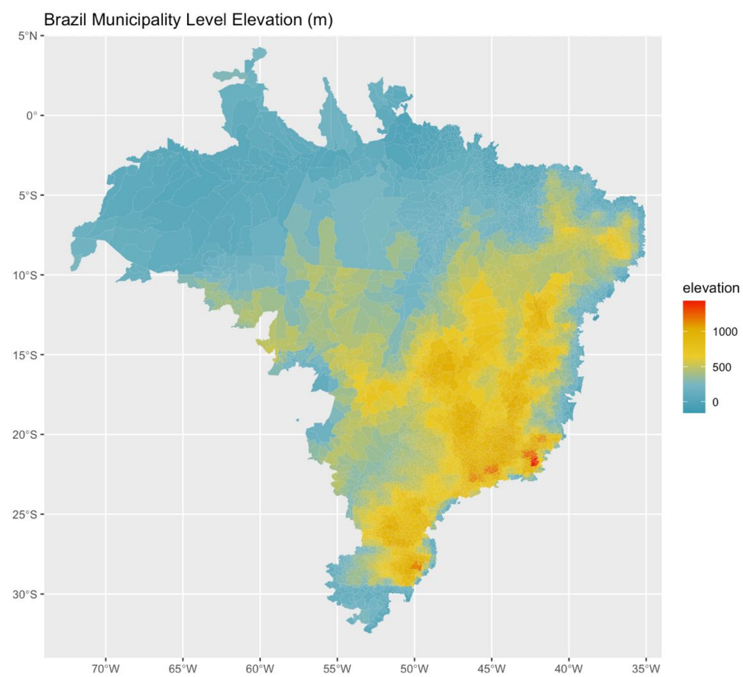


Figure 5.13: Brazil Municipality Elevation

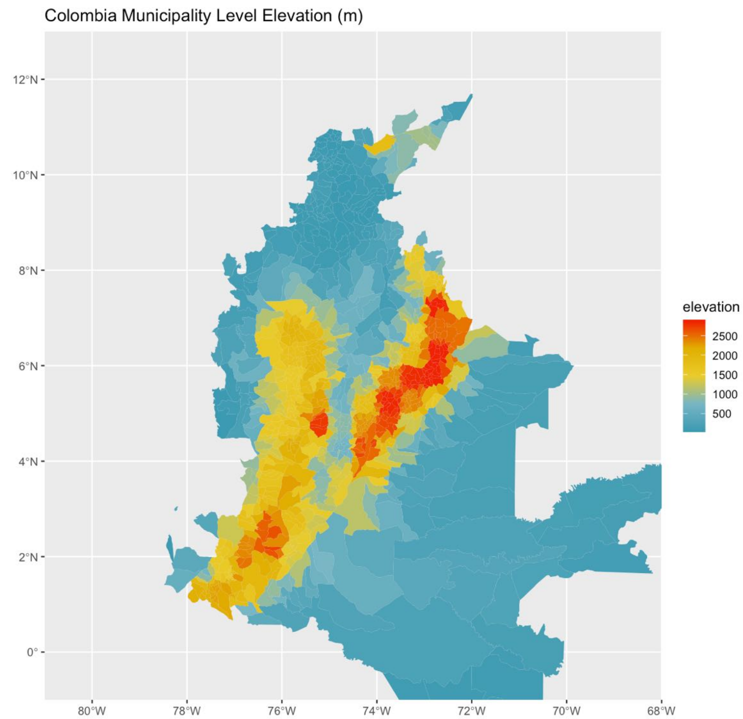


Figure 5.14: Colombia Municipality Elevation

Brazil

To ensure the elevation's accuracy, I cross-referenced the area-weighted average value with the city elevations provided by The Brazilian Institute of Geography and Statistics for each municipality. Any municipalities displaying significant discrepancies in their values (for instance, a 90% difference in absolute terms) were further scrutinized using Google Earth. The elevation distribution for the Brazilian municipalities under study is illustrated in Figure 5.15.

Within the Brazilian sample, coffee-producing municipalities have an average elevation

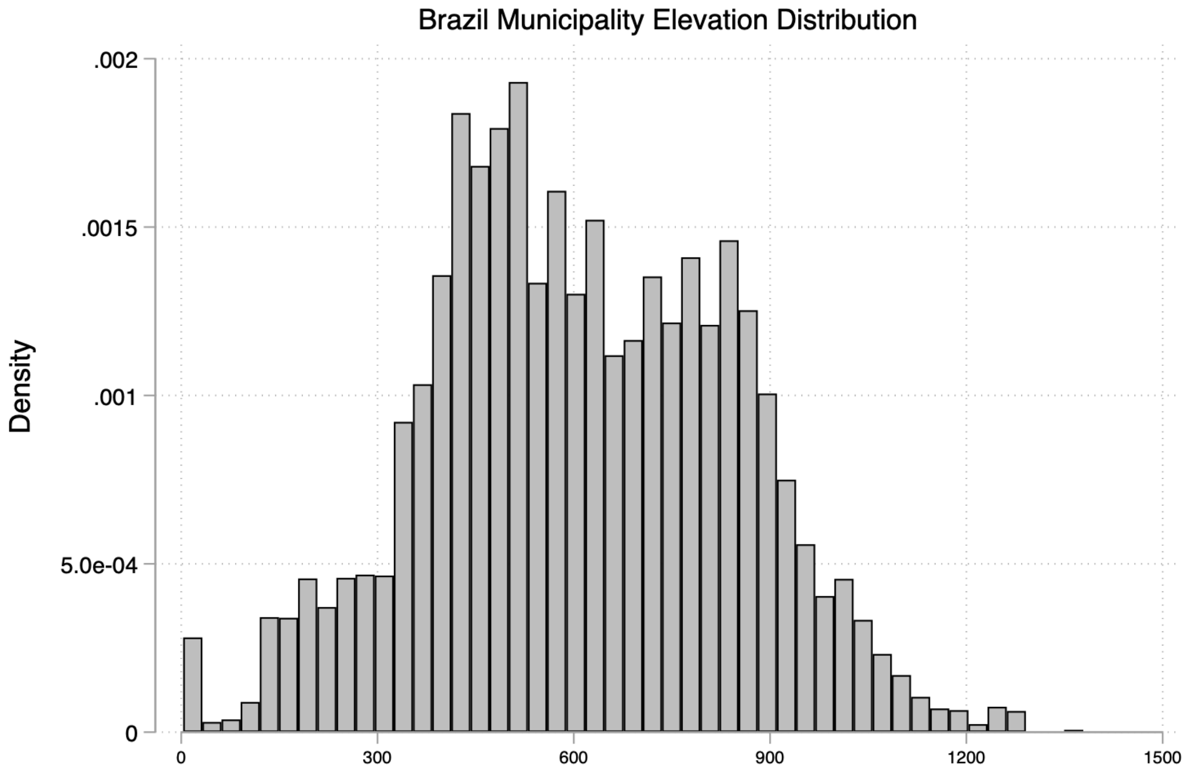


Figure 5.15: Sample Municipality Elevation Distribution in Brazil

of 609m. Topping the list is Bom Repouso in the state of Minas Gerais at an altitude of 1378.7m. Consequently, I set 600m as the threshold, differentiating low-land municipalities from their high-land counterparts.

The variations in the effects of weather conditions on coffee yield between low-land and high-land municipalities are presented in Table 5.9. Notably, the phenomenon of alternate bearing, or biennial variation in yield, is more pronounced in areas of higher elevation. Additionally, the adverse effects of extreme heat during both the fruit-bearing stage, as well as the impact of precipitation during the blooming and harvesting periods, intensify with elevation.

One plausible explanation for these variations stems from the differing primary coffee varieties cultivated at different altitudes. Typically, Robusta coffee is cultivated at lower elevations, whereas Arabica primarily flourishes in regions elevated above 600m (World Coffee Research, 2023). The Robusta plant is renowned for its resilience, exhibiting a heightened resistance to pests and diseases, and boasting an enhanced tolerance to warmer, more humid climates compared to its Arabica counterpart. As a result, the regression analyses for the two elevation-based sub-samples suggest that coffee cultivation in regions elevated above 600m is more susceptible to the adverse impacts of rising temperatures during the blooming and fruit-bearing stages, as well as the increased humidity during harvest. Interestingly, the detrimental effects of freezing degree days are marginally more pronounced in low-land areas as opposed to the highlands.

Table 5.9: Elevation Heterogeneous Model - Brazil

	Low ($\leq 600m$)	High ($> 600m$)	p-Value	Significant?
Yield Deviation	-0.00045	-0.027***	0.018	Yes
	(0.0070)	(0.0089)		
GDD/1000 - Blooming	0.21***	0.19***	0.783	No
	(0.049)	(0.040)		
GDD/1000 - Fruit Bearing	-0.17**	-0.079	0.331	No
	(0.067)	(0.061)		
GDD/1000 - Harvesting	-0.29***	-0.20***	0.167	No
	(0.042)	(0.054)		
HDD - Blooming	-0.0019***	-0.0023***	0.237	No
	(0.00017)	(0.00031)		
HDD - Fruit Bearing	-0.00015	-0.0016***	0.007	Yes
	(0.00027)	(0.00048)		
HDD - Harvesting	0.014***	0.0065***	0.006	Yes
	(0.0012)	(0.0024)		
FDD - Pre-blooming	-0.018***	-0.014***	0.434	No
	(0.0034)	(0.0036)		
Rainfall- Blooming (m)	0.038**	0.12***	0.001	Yes
	(0.017)	(0.017)		
Rainfall - Fruit Bearing (m)	0.096***	0.064***	0.155	No
	(0.016)	(0.016)		
Rainfall- Harvesting (m)	-0.083**	-0.24***	0.007	Yes
	(0.035)	(0.047)		
Number of Dry Days - Pre-blooming	0.11***	0.046**	0.009	Yes
	(0.014)	(0.021)		
Number of Dry Days - Pre-blooming ^{2}	-0.00053***	-0.00024**	0.008	Yes
	(0.000064)	(0.000093)		
Precipitation CV - Blooming	0.033***	0.0081	0.008	Yes
	(0.0055)	(0.0075)		
Constant	-4.68***	-1.05		
	(0.79)	(1.17)		
Observations	25854	24942		
Adjusted R^2	0.225	0.297		
State Trend	Linear			
FE	Municipality			

Standard errors in parentheses
* p<.1, ** p<.05, *** p<.01

Colombia

The elevation distribution for the Colombia municipalities in the sample is shown in Figure 5.16. Coffee-producing municipalities have an average elevation of 1655.5m, which is much higher than the altitude of Brazil coffee producing municipalities. The municipality with the highest altitude is Onzaga in the department of Santander at 2864.7m. Hatonuevo of La Guajira is recorded with the lowest elevation of 277.85m. I use 1500m as the threshold, differentiating coffee grown in very high altitude level from relatively lower-land.

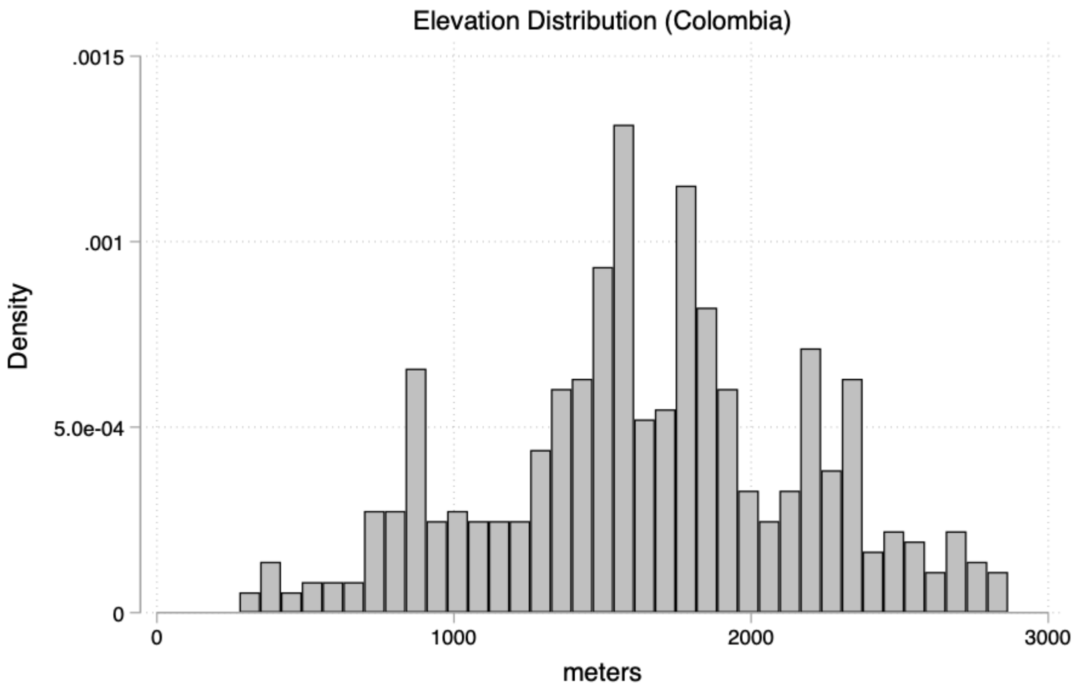


Figure 5.16: Municipality Elevation Distribution in Colombia

Our analysis suggests that contrary to expectations, the effects of weather conditions on coffee yield are not significantly different between municipalities above and below 1500m. In Table 5.10, the only variable that has a distinct effect between municipalities above and below 1500m is the coefficient of variation of precipitation. Scattered rainfall during blooming phase has a positive effect on yields if the elevation is no higher than 1500m. One possible explanation is that at lower elevations, where temperatures are relatively higher, coffee plants may be more responsive to variations in rainfall, benefiting from scattered

Table 5.10: Elevation Heterogeneous Model - Colombia

	Low ($\leq 1500m$)	High ($> 1500m$)	p-Value	Significant?
Yield Deviation	0.240***	0.238***	0.971	No
	(0.028)	(0.018)		
GDD/1000 - Blooming	0.257***	0.280***	0.820	No
	(0.086)	(0.056)		
GDD/1000 - Fruit Bearing	-0.220	-0.144	0.729	No
	(0.182)	(0.122)		
GDD/1000 - Harvesting	0.261**	0.141*	0.434	No
	(0.128)	(0.085)		
HDD - Blooming	0.00083	0.00091	0.926	No
	(0.00060)	(0.00066)		
HDD - Fruit Bearing	-0.00080	-0.00092	0.928	No
	(0.00099)	(0.00089)		
HDD - Harvesting	0.0029**	0.00054	0.131	No
	(0.0013)	(0.00088)		
Rainfall - Blooming (m)	-0.039*	-0.0060	0.282	No
	(0.023)	(0.021)		
Rainfall - Fruit Bearing (m)	-0.067**	-0.121***	0.111	No
	(0.026)	(0.021)		
Rainfall - Harvesting (m)	0.049**	0.089***	0.144	No
	(0.022)	(0.016)		
Number of Dry Days - Pre-blooming	-0.0010	-0.0010	0.983	No
	(0.0013)	(0.0010)		
Number of Dry Days - Pre-blooming ^{2}	-0.0000063	-0.00000073	0.641	No
	(0.0000096)	(0.0000070)		
Precipitation CV - Blooming	0.033**	-0.0032	0.041	Yes
	(0.015)	(0.0090)		
Observations	1466	2832		
Adjusted R^2	0.582	0.557		
State Trend	Linear			
FE	Municipality			

Standard errors in parentheses
* p<.1, ** p<.05, *** p<.01

showers that alleviate water stress. In higher elevations, the cooler climate naturally reduces water stress, making plants less responsive to short-term changes in rainfall patterns.

5.5 Summary

The empirical results from Brazil indicate significant biennial variation in coffee yields. This pattern is particularly pronounced in key states like Mato Grosso do Sul, Minas Gerais, Paraná, and São Paulo. The alternate bearing effect is further examined through the negative coefficient on lagged yield deviation in the regression results, suggesting a modest but significant impact on yield variations across Brazilian coffee regions. Additionally, temperature indices like growing degree days (GDDs) and harmful degree days (HDDs) play crucial roles across different coffee growth stages, with GDDs positively influencing yields during the blooming stage while HDDs have a heterogeneous impact across stages, particularly exacerbating yield losses during the blooming phase due to extreme heat.

Furthermore, precipitation patterns reveal a strong seasonal influence. A prolonged dry period is found to be beneficial for yield. However, yield could be adversely affected if drought condition extends beyond 105 days.

The empirical results also emphasize the role of elevation in modulating these estimated effects, where higher altitudes exacerbate the biennial yield variation and the negative impacts of extreme temperatures and precipitation during critical growth stages.

In Colombia, the empirical analysis reveals that coffee yields do not exhibit the pronounced biennial variation observed in Brazil. Instead, yields appear more consistent year over year, which may be due to Colombia's unique coffee-growing conditions that include varied micro climates and the presence of a mid-year harvest, mitigating the impacts of alternate bearing. This consistency is highlighted by the slight positive correlation found between yield deviations from one year to the next, suggesting that favorable conditions in one year can beneficially influence the subsequent year's production.

Growing degree days (GDDs) during the flowering and harvesting periods show significant positive effects on yields, with a notable yield increase corresponding to rises in GDDs during these critical growth stages. This suggests that warmer conditions during blooming and harvesting are conducive to higher coffee yields, which contrasts with the negative impact of excessive warmth during these stages observed in Brazil. Moreover, harmful degree days (HDDs), reflecting exposure to extreme heat, do not significantly affect yields in Colombia.

Precipitation during the fruit-bearing stage negatively impacts yields, which could be attributed to the issues of flooding and landslides during heavy rainfallscommon occurrences that disrupt coffee production in the region. Interestingly, increased rainfall during the harvesting season enhances coffee yields by a small magnitude, which is contrary to the typical expectations where rain could delay harvesting activities. This anomaly might be due to Colombia's diverse elevation and lack of a clear wet or dry season, allowing coffee plants at various growth stages to benefit from increased moisture during what would traditionally be the harvesting period.

Chapter 6

Predictive Power

One of the primary contributions of this study is the improved econometric modeling of coffee yield. In this chapter, I compare my proposed model with existing yield response models in the literature. Among the significant climate and coffee studies listed in Table 3.1, I focus my comparison on Koh et al. (2020) and Sachs et al. (2015) because they also examine climate change's impacts on Brazilian coffee production.

First, I present the Brazil regression results using each of these models. Sachs et al. (2015) suggest that the most relevant weather variables are growing degree days, harmful degree days, average minimum temperature, and the total rainfall during the fruit-bearing stage of a crop year in Brazil, which is from December to May. I present their model with a linear time trend and no quadratic rainfall for consistent comparison to the specification of my model.

$$Y_{it} = \beta_0 + \beta_1 GDD_{it} + \beta_2 HDD_{it} + \beta_3 AvgMin_{it} + \beta_4 Precip_{it} + \mu_i + STATE \times TREND_{linear} + \epsilon_{it} \quad (6.1)$$

Coefficients estimated by equation (6.1) are displayed in Table 6.1. The main takeaway from this specification is that temperature during the fruit ripening period exhibits a non-linear effect on yield. With a temperature below $33°C$, an additional degree day has a insignificant positive impact on yield. If the temperature is above the threshold, then the effect of one extra degree day on yield is negative. The results are relatively consistent with the estimation results from the Growth Stage Alternate Bearing regression shown in Table 5.4. However, the estimated effects of HDD and precipitation during the fruit-bearing stage are greater in the Sachs' style model. Notably, the Growth Stage Alternate Bearing Model proposed in this study offers a more nuanced analysis of the weather-yield relationship across key coffee-growing stages by providing distinct coefficient estimates for the GDDs, HDDs and precipitation during the blooming, fruit-bearing, and harvesting periods. This granular approach allows for the assessment of how temperature and rainfall variations at specific developmental stages of coffee cultivation impact yield. Moreover, the inclusion of variables for both the number of dry days and the freezing degree day (FDDS) during the pre-blooming phase further refines the analysis by looking outside the lens of the current crop year.

Table 6.1: Brazil Model - Sachs et al.

	Coefficients	Elas.
GDD (1000 units)	0.011	0.023
	(0.042)	(0.087)
HDD (1000 units)	-1.73***	-0.016***
	(0.21)	(0.0019)
Monthly Minimum Temperature (c)	-0.057***	-0.90***
	(0.0099)	(0.16)
Rainfall (m)	0.15***	0.15***
	(0.013)	(0.014)
BA × trend	0.0059***	
	(0.0018)	
DF × trend	0.020***	
	(0.00015)	
GO × trend	0.022***	
	(0.0040)	
MG × trend	-0.0024***	
	(0.00086)	
MS × trend	-0.00014	
	(0.0047)	
PR × trend	0.0028***	
	(0.00089)	
RJ × trend	-0.024***	
	(0.0039)	
SP × trend	0.00017	
	(0.00084)	
Constant	1.94***	
	(0.12)	
Observations	50796	
Adjusted R^2	0.268	
State Trend	Linear	
FE	Municipality	

Standard errors in parentheses
* p<.1, ** p<.05, *** p<.01

Koh et al. (2020), on the other hand, aggregated weather observations at the municipality level for each developmental stage, which is a method analogous to the Growth Stage Alternate Bearing Model in this study. The authors separate the blooming (September to

November), fruit ripening (December to May), and harvesting (June to August) periods. Relevant regressors are the average monthly temperature and average monthly precipitation during each period as shown in equation (6.2). I do not perform log transformation, or include the precipitation square terms and the year fixed effects in this replication for better model comparison.

$$
\begin{aligned}
Y_{it} = \beta_0 + \sum_{s=1}^{3} \beta_s Tmp_{sit} + \beta_s {Tmp_{sit}}^2 + \phi_s Precipitation_{sit} \\
+ \mu_i + STATE \times TREND_{linear} + \epsilon_{it} \quad (6.2)
\end{aligned}
$$

Table 6.2: Brazil Model - Koh et al.

	Coefficients	Elas.
Temp.Blooming	0.094***	1.99***
	(0.028)	(0.59)
Temp.Blooming^2	-0.0021***	-1.05***
	(0.00060)	(0.30)
Temp.Fruit Bearing	0.24***	5.03***
	(0.050)	(1.02)
Temp.Fruit Bearing^2	-0.0048***	-2.23***
	(0.0011)	(0.50)
Temp.Harvesting	0.17***	2.92***
	(0.047)	(0.81)
Temp.Harvesting^2	-0.0051***	-1.64***
	(0.0013)	(0.41)
Precip.Blooming	0.00066***	0.096***
	(0.000045)	(0.0066)
Precip.Fruit Bearing	0.00050***	0.093***
	(0.000044)	(0.0081)
Precip.Harvesting	-0.00087***	-0.032***
	(0.00011)	(0.0042)
BA × trend	0.0060***	
	(0.0018)	
DF × trend	0.020***	
	(0.00027)	
GO × trend	0.023***	
	(0.0042)	
MG × trend	-0.0026***	
	(0.00089)	
MS × trend	0.0032	
	(0.0047)	
PR × trend	0.0045***	
	(0.00090)	
RJ × trend	-0.025***	
	(0.0039)	
SP × trend	0.00027	
	(0.00086)	
Constant	-4.52***	
	(0.64)	
Observations	50796	
Adjusted R^2	0.268	
State Trend	Linear	
FE	Municipality	

Standard errors in parentheses

* p<.1, ** p<.05, *** p<.01

The coefficients of Koh style model are shown in Table (6.2). Their results suggest concave relationships between temperature and yield across growth stages, with the strongest effect appeared during December to May. These results are consistent with coefficients estimate of the Growth Stage Alternate Bearing Model except for the harvesting temperature effect. Despite evaluating weather effects in different critical growing phases, Koh style model fails to estimate the effect of extreme heat and extreme cold on coffee yield, which is captured by the inclusion of harmful degree days and freezing degree days in my analysis.

A conventional method of evaluating predictive power is using the k-fold cross-validation approach (Stone, 1974). This method first divides the dataset into several mutually exclusive subsets. Each subset serves sequentially as the validation set while the others form the training set. However, this common approach may not adequately address the time-series nature inherent in panel data, especially when observations are not independent but are rather sequential and linked across time.

To overcome this issue, I utilize a recent user developed Stata package XTOOS to evaluate the out-of-sample predictive accuracy of various panel-data models concerning their time-series dimensions (Ruiz, 2019). XTOOS addresses this by allowing for a more nuanced validation approach that respects the temporal structure within the data. This method is particularly relevant for agricultural data, where yield measurements from the same location across consecutive years are not independent events but are influenced by overlapping factors such as climatic conditions and soil fatigue.

The temporal validation strategy used in XTOOS involves partitioning the data into a sequence of time periods rather than arbitrary cross-sectional divisions. This means that the model's ability to predict future outcomes can be tested more realistically by training on past data and testing on future data. Such an approach is crucial for models intended to predict agricultural outcomes, where the goal is often to forecast future yields based on past data. The out-of-sample testing conducted using XTOOS provides a robust measure of how the models might perform in real-world scenarios, where predictions are made for future growing seasons. It assesses the models' robustness and reliability

In my evaluation, I partitioned the data into two subsets: an initial training set encompassing data points from 1980 to 2012, and a testing set containing data from 2013 to 2018. The models were trained using the in-sample dataset. Then the estimated model coefficients were used to predict the dependent variableyield for municipality i in year $t$in the out-of-sample periods. Subsequently, the out-of-sample periods were progressively shortened by a year, with the estimation and forecasting process repeated until all years were accounted for. The prediction accuracy was assessed using the Root Mean Square Error (RMSE) given by:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(yield_{it} - yi\hat{e}ld_{it})^2}.$$

This metric gauges the differences between predictions and actual values, quantifying the average prediction error while accounting for both underestimations and overestimations.

Table 6.3 details the RMSE for each forecasting iteration, as well as the weighted average RMSE for every model. For instance, the 2012 row indicates that the last in-sample year was 2012 for that specific out-of-sample prediction. Similarly, the table's final row displays the RMSE for each model when the data spans from 1980 to 2017, predicting yields for 2018. The average RMSE is weighted according to the count of out-of-sample observations. Lower RMSE values indicate better performance since RMSE measures the average magnitude of the errors between predicted and observed values, with lower values indicating better fit.

	RMSE (Out of Sample)			N
Year	Xiao's Model	Sachs' Model	Koh's Model	
2012	0.5178	0.5181	0.5228	6117
2013	0.5196	0.5212	0.5269	4899
2014	0.5170	0.5167	0.5199	3780
2015	0.5224	0.5244	0.5268	2747
2016	0.5404	0.5384	0.5400	1754
2017	0.5520	0.5426	0.5526	858
Average	0.5222	0.5223	0.5266	

Table 6.3: Out of Sample Evaluation According to Last In-Sample Year (2012-2017)

The first column of Table 6.3 shows the RMSE of the Growth Stage Alternate Bearing Model (Xiao's Model), while the second and third column display RMSEs from the Sachs and Koh type model. The outcomes reveal that the model used in this analysis exhibits a performance comparable to other established models in the literature, signifying its robustness and reliability in forecasting. Notably, the Growth Stage Alternate Bearing Model of this study distinguishes itself by specifically accounting for the nuanced impacts of growth stage-specific weather conditions and the effects of temperature extremes on coffee yield. This is particularly captured through the incorporation of harmful degree days and freezing degree days in the analysis, which are critical factors in agricultural forecasting. By including such detailed meteorological variables, Xiao's model not only provides predictions of yield but also offers valuable insights into the agronomic implications of climate variability. The weighted average RMSE further underscores this model's capability to balance accuracy with specialized focus, making it a potentially invaluable tool for researchers and practitioners interested in the intricate dynamics between weather patterns and coffee yields.

Chapter 7

Assessment of the Impact of Climate Change on the Global Coffee Industry

After establishing the causal relationship between coffee yield and weather patterns, the next step is to use these findings to forecast the potential impacts of climate change. The projected consequences of climate change hold significant implications for devising effective policies and adaptation strategies, particularly in helping coffee farmers navigate the uncertainties associated with shifting climatic conditions. This section presents a comprehensive overview of the key component employed in this exercise, namely the outputs of the Global Climate Models, as well as a road map outlining the methodology for projecting the global climate effects on coffee yields using the estimated yield-response model.

7.1 Introduction to Global Climate Models

Climate models serve as mathematical representations of our understanding of the complex climate system (Hsiang and Kopp, 2018). In contemporary climate studies Global Climate Models, also known as General Circulation Models (GCMs), have gained widespread recognition. At their core, GCMs comprise a collection of differential equations that capture the fundamental laws governing the behavior of fluids, such as the atmosphere and oceans.

The Coupled Model Intercomparison Project (CMIP) serves as an international initiative aimed at comparing and evaluating the performance of global climate models. It involves collaboration among many climate modeling centers worldwide. Its primary objective is to enhance our understanding of the earth's climate system and its response to various factors, including greenhouse gas emissions, solar radiation, and land-use changes. CMIP provides a standardized framework that enables climate modeling centers worldwide to share their data and results in a consistent format, fostering scientific collaboration and advancing climate research. The most recent phase of this project, CMIP6, was launched in 2016 (Eyring et al., 2016).

Under CMIP6, global climate projections are generated at different temporal and geographical resolutions until 2100. Each climate model within the project also produces projections based on various future climate scenarios known as the Shared Socioeconomic Pathways (SSPs). The SSPs are a set of scenarios that depict different potential trajectories for global socio-economic development, population growth, and energy usage (Riahi et al., 2017). The SSPs are categorized as SSP1 to SSP5, representing a range of possible future human activity and economic development-related drivers of climate change (IPCC, 2023). SSP1 represents a sustainable trajectory associated with low greenhouse gas emissions, and low challenges to mitigate and adapt to the changing climate. SSP2 is the middle of the road scenario, under which the world is assumed to follow a social and economic path similar to historical patterns. SSP3 is considered a "rocky road" scenario, in which regional conflicts make mitigation and adaptation to climate change very challenging. SSP4 pictures a divided path globally. With this scenario, challenges to mitigation are low but to adaptation are high. SSP5 assumes relatively high levels of greenhouse gas emissions due to due to continued reliance on fossil fuels, and low challenges to adaptation resulting from technological development and more integrated global markets.

For each SSP scenario, there are sub-scenarios representing different Representative Concentration Pathways (RCP). RCP-based sub-scenarios indicate the level of radiative forcing (in W/m^2) that occurs in 2100 resulting from the corresponding scenario. Radiative forcing is a way to quantify how different factors, like greenhouse gases, can change the amount of energy that enters or leaves Earth's atmosphere. [1] Essentially, it measures how these factors can heat up or cool down the planet. Table 7.1 lists the SSPs and their corresponding assumptions.

[1]For example, RCP2.6 pathway is characterized by a radiative forcing level that peaks at approximately $3W/m^2$ before 2100 and then declines to $2.6W/m^2$ by 2100. It represents a scenario where stringent mitigation measures are implemented to limit the increase in global mean temperature to well below $2°C$ above pre-industrial levels by the end of the century.

Shared Socioeconomic Pathways		Sub Scenarios	Assumptions
SSP 1	Sustainability	1.9	Rapid and deep reduction in greenhouse gas emissions.
		2.6	Sustained and ambitious reduction in greenhouse gas emissions.
SSP 2	Middle of the Road	4.5	Moderate levels of greenhouse gas emissions.
		6.0	Assumes a middle-of-the-road scenario with intermediate levels of greenhouse gas emissions.
		7.0	Assumes a scenario with higher levels of greenhouse gas emissions than SSP2-4.5.
SSP 3	Regional Rivalry	7.0	High levels of greenhouse gas emissions.
		7.9	Even higher levels of greenhouse gas emissions than SSP3-7.0.
SSP 4	Inequality	3.4	Moderate levels of greenhouse gas emissions.
		6.0	A scenario with higher levels of greenhouse gas emissions than SSP4-3.4.
SSP 5	Fossil-fuel Development	8.5	Very high levels of greenhouse gas emissions.
		3.4-OS	Some level of negative emissions technologies will be available in the future.

Table 7.1: Shared Socio-Economic Pathways (IPCC, 2023)

The IPCC AR6 Synthesis Report has chosen primary future scenarios for climate change, which include SSP1-1.9, SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5. (IPCC, 2023). SSP1-1.9 and SSP1-2.6 have greenhouse gas emissions declining to net zero around 2050 and 2070, respectively, followed by different levels of net negative CO_2 emissions. SSP2-4.5 follows the moderate emission trajectory, which has CO_2 emissions sustaining around current levels until 2050. SSP3-7.0 and SSP5-8.5 are the two high emissions scenarios. In this analysis, I center my projection around the intermediate greenhouse Gas emissions scenario (SSP2-4.5). Evaluation with other scenarios mentioned in the IPCC AR6 Synthesis Report are presented in the Appendix.

Among all the Climate models available via the CMIP6 platform, CNRM-CM6-1 and CNRM-CM6-1-HR are selected as the main Global Climate Models of interest for three reasons.[2] First, the CNRM-CM6-1 and CNRM-CM6-1-HR models are among the best GCMs in simulating daily maximum temperature and minimum temperature. Di Virgilio et al. (2022) compared model output from 39 GCMs with daily data against observed data in Australia. They concluded that CNRM-CM6-1 and CNRM-CM6-1-HR show consistently good performance in matching daily maximum and minimum temperature observations.

[2]Forecasting results using other GCMs are included in the appendix for robustness checks.

Second, CNRM-CM6-1 and CNRM-CM6-1-HR perform well in projecting precipitation in Brazil. de Medeiros et al.(2022) evaluated 8 precipitation climate indices, including total precipitation and consecutive dry days, using 40 different GCMs across CMIP3, CMIP5 and CMIP6. Their results showed that CNRM-CM6-1 and and CNRM-CM6-1-HR are two of the top 3 performing models for the Southeast and South regions in Brazil, which overlaps the coffee producing regions in my study. Lastly, the CNRM-CM6-1-HR has the highest-resolution among all models of the CMIP6. It has a resolution of 0.5×0.5 or $50km \times 50km$, which provides more weather heterogeneities among coffee producing municipalities.

7.2 Methodology

To facilitate the analysis, I aggregated the gridded data, such as daily maximum temperature, daily minimum temperature, and daily total precipitation, from the projection of the CNRM-CM6-1 model to the municipality level from 2051 to 2100 using area-weighted average. These aggregated data are then used to calculate key metrics at the municipality level during different crucial coffee growing phases. In order to match the yield response model, these metrics include growing degree days (GDDs), harmful degree days (HDDs), freezing degree days (FDDs), total precipitation, consecutive dry days and precipitation coefficient of variation.

I use the coefficient estimates from the Growth Stage Alternate Bearing model to project coffee yields in Brazilian municipalities to the end of the 21 century. I generate projected yields by plugging in the key weather variables aggregated from the output of Global Climate

Models to the following yield projection equation:

$$\hat{y}_{it} = \sum_s \sum_j \hat{\beta}_{sj} w_{ijst} + \hat{\mu}_i \tag{7.1}$$

where $\hat{y}_{it}$ denotes the predicted yield for municipality i in year t, w_{js} denotes vectors encompassing critical weather variables j in each stage s. [3] The coefficients $\hat{\beta}_{sj}$ are the parameter estimates from the yield response model and represent the impacts of weather conditions on coffee yields. The term $\hat{\mu}_i$ represents the estimated fixed effects for municipality i, which acts as an intercept shifter.

The impact of climate change on coffee yield for time period T is defined as the difference between the average predicted yield given climate change and the average predicted yield in municipality i assuming no climate change. The impact of climate as defined in the following equation:

$$I_{i,T} = E\left[y_{i,t} | w_{ijsT} = \tilde{w}_{ijsT}, t \in T\right] - E\left[y_i | w_{ijs} = \bar{w}_{ijs}\right] \tag{7.2}$$

The first term on the right-hand side of Equation 7.2 is the average predicted yield in municipality i given climate change during a 10-year period T. T is defined as a set of three 10-year periods, including 2051-2060, 2071-2080, and 2091-2100. $\tilde{w}_{ijsT}$ is the value of the projected weather variable in growth stage s averaged over the 10 years in period T. The second term is the predicted yield given the average weather $\bar{w}_{ijs}$ during the reference period

[3] For the expression parsimony, I consolidate the term X_{js} and W_j into a single vector w_{js}. I also drop the yield deviation variable since the average yield deviation is close to 0 and it won't have much impact on average yield into the future.

(2009 to 2018). Equation 7.2 can be rewritten as:

$$I_{i,T} = \sum_s \sum_j \hat{\beta}_{sj} \tilde{w}_{ijsT} - \sum_s \sum_j \hat{\beta}_{sj} \bar{w}_{ijs}, \tag{7.3}$$

$$\text{where} \quad \tilde{w}_{ijsT} = \frac{1}{10} \sum_{t=1}^{10} w_{ijst} \tag{7.4}$$

7.3 Forecasting Results

Figures 7.1 to 7.6 display the average projected weather metrics annually from 2050 to 2100. Despite annual variability and the internal dynamics of the climate model, these figures illustrate a distinct upward trend in both growing degree days (GDDs) and harmful degree days (HDDs) across all three stages in the coffee-producing municipalities. In contrast, total precipitation exhibits a slight downward trend over the projection period. Trends for other weather variables are not distinctly marked as either increasing or decreasing. Table 7.2 shows the observed weather distribution $w_{sj,(2009,2018)}$ in the 5^{th}, 25^{th}, 50^{th}, 75^{th} and 95^{th} percentile from the reference period 2009 to 2018. Table 7.3, 7.4, and 7.5 present distributions of key weather variable changes Δw_{sj} for three different ten-year intervals toward the end of the 21^{st} century. Each column of the weather change table reflects the difference at each percentile between the reference period and a future period.

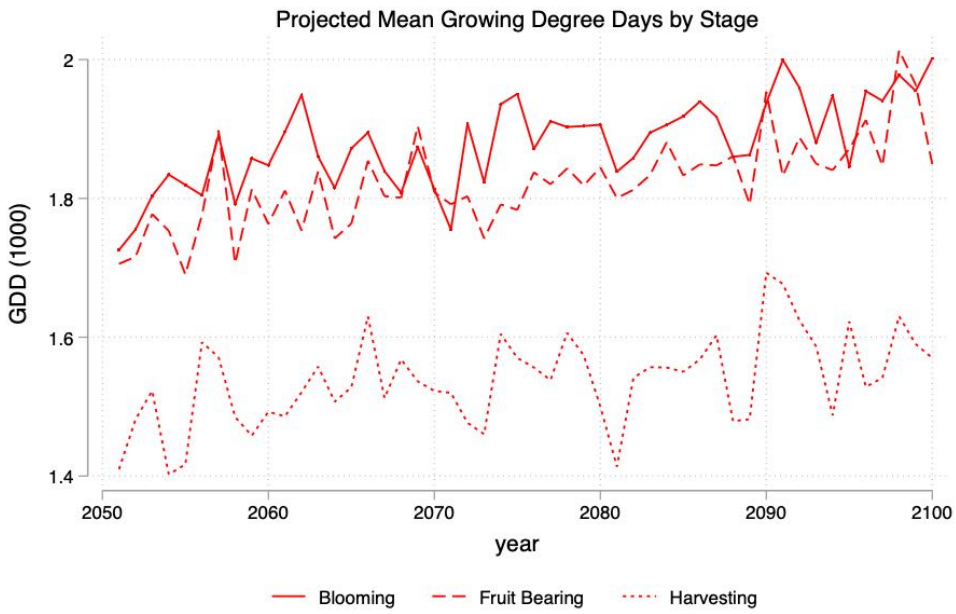


Figure 7.1: Projected Mean Growing Degree Days by Stage

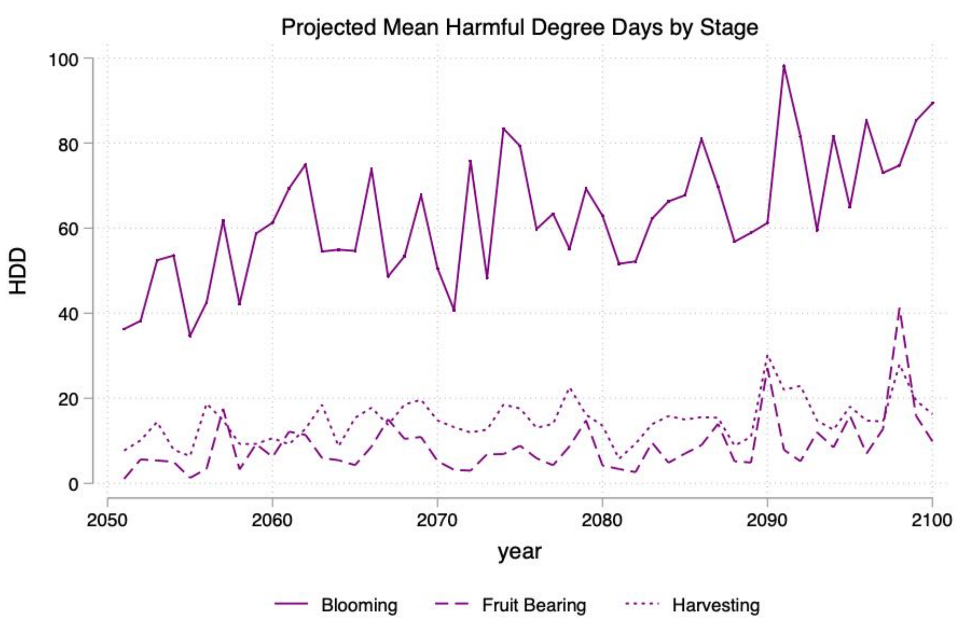


Figure 7.2: Projected Mean Growing Harmful Days by Stage

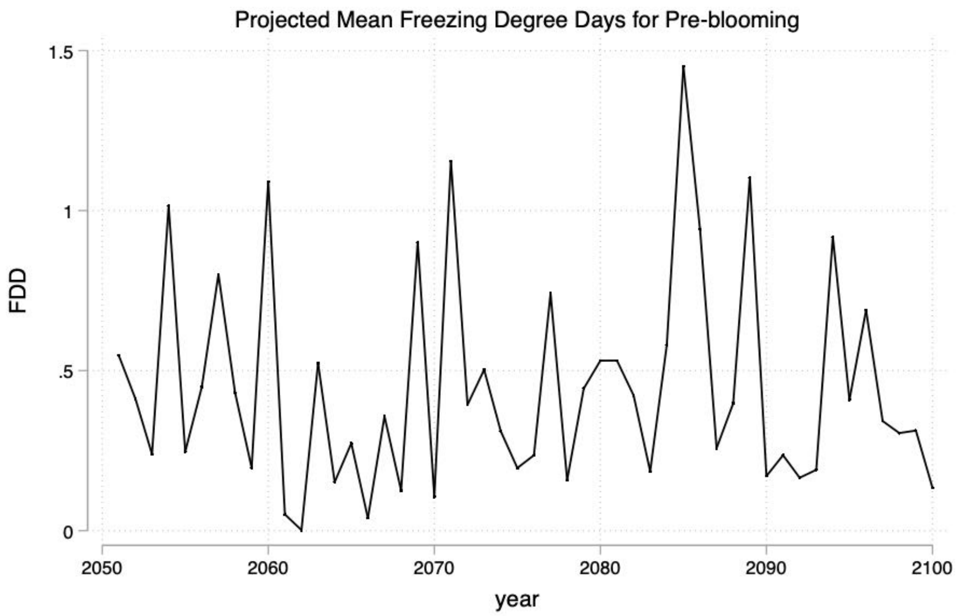


Figure 7.3: Projected Mean Growing Freezing Days by Stage

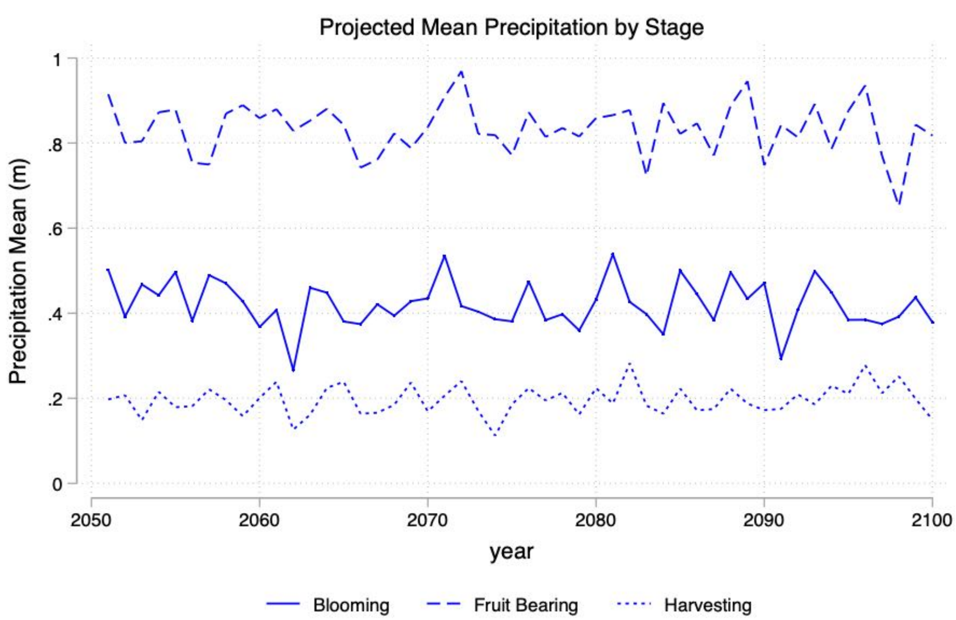


Figure 7.4: Projected Mean Precipitation by Stage

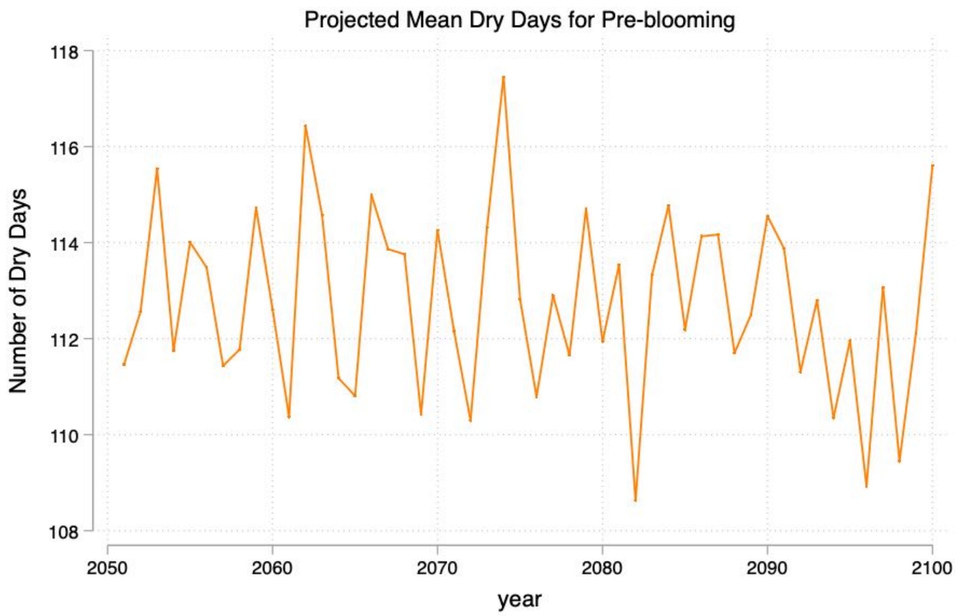


Figure 7.5: Projected Mean Number of Dry Days

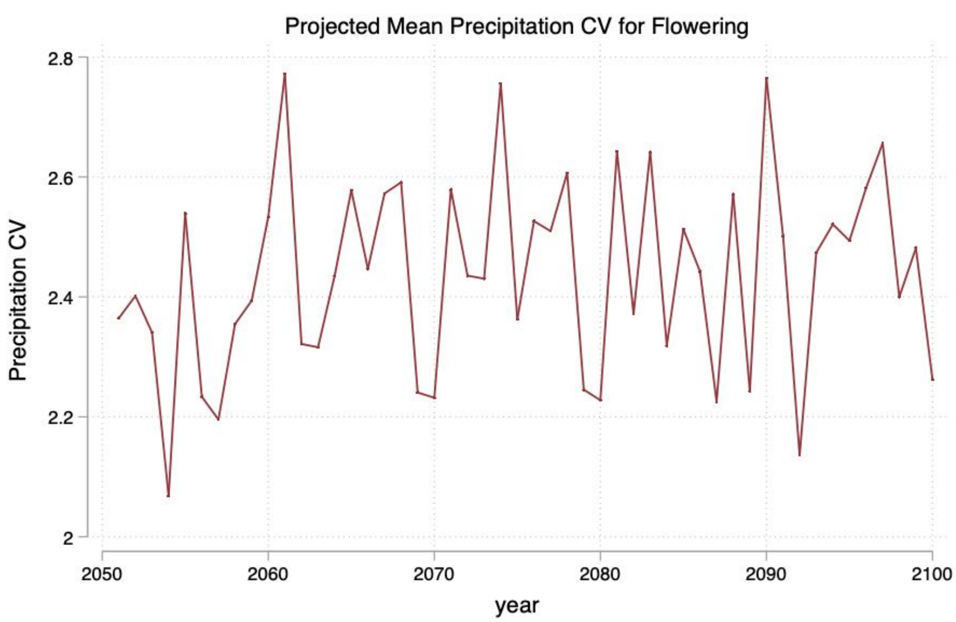


Figure 7.6: Projected Mean Precipitation CV

Under the middle-of-the-road emission scenario (SSP245) from the CNRM-CM6-1 model, major coffee growing regions in Brazil will be warmer, with less rainfall, more dry days during the pre-blooming phases, and more variable precipitation during the blooming stage.

The changes in weather variables across percentiles exhibit different patterns for different variables. For growing degree days (GDDs), rainfall during the blooming and fruit-bearing phases and Precipitation CV during the Pre-blooming phase, impacts tend to follow a normal distribution, such that the biggest change occurs within the 25^{th} and 75^{th} interval. Harmful degree days (HDDs) during all phases show greater increases in the higher percentiles, which means there will be much more extreme hot days. The impact on the number of dry days occurs mostly towards the lower percentiles of the distribution, indicating that there will be greater impacts on regions that observed fewer dry days in the reference period.

Variables	$w_{sj,(2009,2018)}$				
	5p	**25p**	**50p**	**75p**	**95p**
GDD/1000 - Blooming	1.30	1.50	1.64	1.78	1.94
GDD/1000 - Fruit Bearing	1.26	1.42	1.56	1.70	1.83
GDD/1000 - Harvesting	0.84	1.02	1.16	1.34	1.52
HDD - Blooming	0.67	3.64	9.65	26.61	52.43
HDD - Fruit Bearing	0.00	0.03	0.82	4.10	12.58
HDD - Harvesting	0.00	0.04	0.27	1.17	6.07
FDD - Pre-blooming	0.00	0.00	0.00	0.00	0.83
Rainfall - Blooming (m)	0.38	0.76	0.90	1.04	1.24
Rainfall - Fruit Bearing (m)	0.34	0.82	1.03	1.18	1.41
Rainfall - Harvesting (m)	0.06	0.13	0.18	0.25	0.44
Number of Dry Days - Pre-blooming	101.38	109.60	114.22	117.29	121.30
Precipitation CV - Blooming	1.50	1.71	1.87	2.11	2.84

Table 7.2: Weather Distribution 2009-2018

Variables	$\Delta w_{sj,(2051,2060)}$				
	5p	**25p**	**50p**	**75p**	**95p**
GDD/1000 - Blooming	0.13	0.01	0.08	0.12	0.13
GDD/1000 - Fruit Bearing	0.14	0.11	0.12	0.18	0.17
GDD/1000 - Harvesting	0.23	0.12	0.16	0.19	0.20
HDD - Blooming	4.48	6.57	8.01	41.21	59.76
HDD - Fruit Bearing	0.16	0.25	0.82	13.83	23.99
HDD - Harvesting	0.02	0.83	2.11	12.21	32.94
FDD - Pre-blooming	0.00	0.00	0.00	0.00	-0.11
Rainfall - Blooming (m)	-0.11	-0.41	-0.46	-0.46	-0.50
Rainfall - Fruit Bearing (m)	-0.03	-0.42	-0.44	-0.46	-0.43
Rainfall - Harvesting (m)	-0.05	-0.09	-0.12	-0.16	-0.25
Number of Dry Days - Pre-blooming	12.43	8.00	5.98	3.91	1.30
Precipitation CV - Blooming	0.31	0.35	0.38	0.36	0.15

Table 7.3: Weather Variable Changes in 2051-2060 Compared to 2009-2018

Variables	$\Delta w_{sj,(2071,2080)}$				
	5p	**25p**	**50p**	**75p**	**95p**
GDD/1000 - Blooming	0.18	0.10	0.16	0.20	0.20
GDD/1000 - Fruit Bearing	0.16	0.12	0.15	0.22	0.20
GDD/1000 - Harvesting	0.29	0.17	0.22	0.28	0.26
HDD - Blooming	6.06	10.86	19.54	56.43	83.48
HDD - Fruit Bearing	0.14	0.33	0.73	11.72	23.64
HDD - Harvesting	0.18	0.69	1.74	17.96	44.72
FDD - Pre-blooming	0.00	0.00	0.00	0.00	-0.83
Rainfall - Blooming (m)	-0.18	-0.41	-0.50	-0.47	-0.51
Rainfall - Fruit Bearing (m)	-0.02	-0.40	-0.39	-0.39	-0.35
Rainfall - Harvesting (m)	-0.05	-0.10	-0.13	-0.14	-0.24
Number of Dry Days - Pre-blooming	10.83	6.70	6.38	4.21	1.50
Precipitation CV - Blooming	0.28	0.48	0.51	0.55	0.67

Table 7.4: Weather Variable Changes in 2071-2080 Compared to 2009-2018

Variables	$\Delta w_{sj,(2091,2100)}$				
	5p	**25p**	**50p**	**75p**	**95p**
GDD/1000 - Blooming	0.25	0.20	0.24	0.30	0.26
GDD/1000 - Fruit Bearing	0.30	0.25	0.24	0.34	0.30
GDD/1000 - Harvesting	0.34	0.25	0.28	0.33	0.31
HDD - Blooming	10.05	19.63	30.55	83.70	120.27
HDD - Fruit Bearing	0.72	2.41	5.53	42.46	65.56
HDD - Harvesting	0.19	1.35	2.66	20.89	51.01
FDD - Pre-blooming	0.00	0.00	0.00	0.00	-0.83
Rainfall - Blooming (m)	-0.18	-0.47	-0.51	-0.59	-0.59
Rainfall - Fruit Bearing (m)	-0.04	-0.42	-0.44	-0.48	-0.45
Rainfall - Harvesting (m)	-0.04	-0.09	-0.11	-0.10	-0.20
Number of Dry Days - Pre-blooming	8.33	5.30	5.38	4.01	1.20
Precipitation CV - Blooming	0.32	0.51	0.53	0.65	0.29

Table 7.5: Weather Variable Changes in 2091-2100 Compared to 2009-2018

The anticipated rise in growing degree days (GDDs) and harmful degree days (HDDs) are direct consequences of higher daily maximum and minimum temperatures. The reduction in freezing degree days (FDDs) on average reflects a warming trend that diminishes the likelihood of frost events that can be detrimental to coffee crops. To better understand the magnitude of climate change effects on relevant temperature variables, it is useful to revisit the definition of the degree day metrics. According to the methodology discussion in chapter 4, the degree day metrics are calculated using the sinusoidal approximation, an example of which is shown in Figure 7.7 (Snyder, 1985). TM and Tm indicate the observed daily maximum and minimum temperatures. TB and Tb represent the upper and lower temperature thresholds. For temperatures surpassing the TB (upper threshold), the area us defined as the HDD. Instead, the excess warmth becomes damaging, contributing to what we term as harmful degree days. On the contrary, any temperature plunging below $0°C$ and its persistence over a given duration is labeled as FDD. The area between the two thresholds is the GDD.

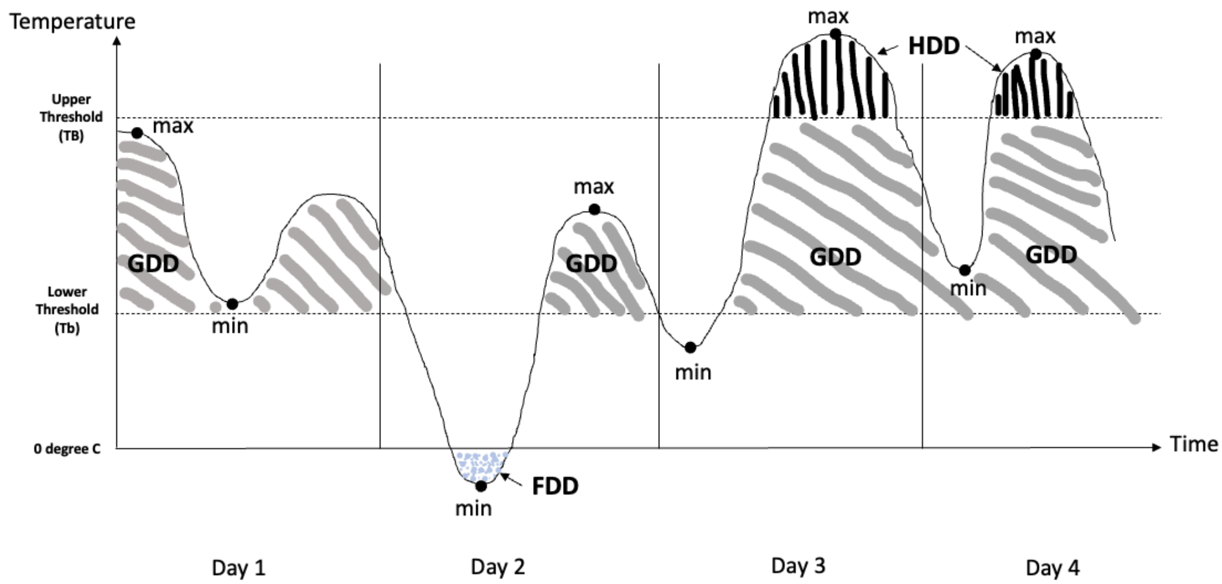


Figure 7.7: Degree Days Definition

Table 7.6 provides a direct comparison of the relationship between daily minimum and maximum temperature, and the GDD and HDD. When the upper bound and lower bound is 32 and 10 degree Celsius, it is noticeable that in one day, with 1 degree Celsius increase in minimum temperature and 1 degree Celsius increase in maximum temperature, the percentage change in HDD is much greater than that of the GDD. We can also visualize this relationship using Figure 7.8. For example, if the maximum temperature and minimum temperature both increase by 2 degree Celsius, from $32°C$ to $34°C$ and $12°C$ to $14°C$ accordingly, the percentage gain in HDD (purple area divided by red area) is much greater than the percentage gain in the GDD (brown area divided by yellow area).

Tmin	Tmax	GDD	HDD	% Change GDD	% Change HDD
12	34	12.742	0.258	-	-
13	35	13.523	0.477	6.13	84.61
14	36	14.262	0.738	11.93	185.64
15	37	14.963	1.037	17.44	301.25
16	38	15.630	1.370	22.67	430.25

Table 7.6: The Relationship between Temperatures and the Degree Days

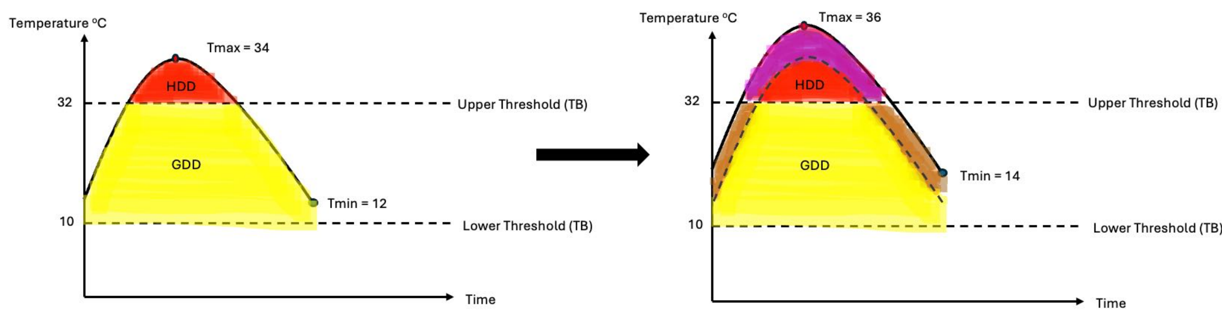
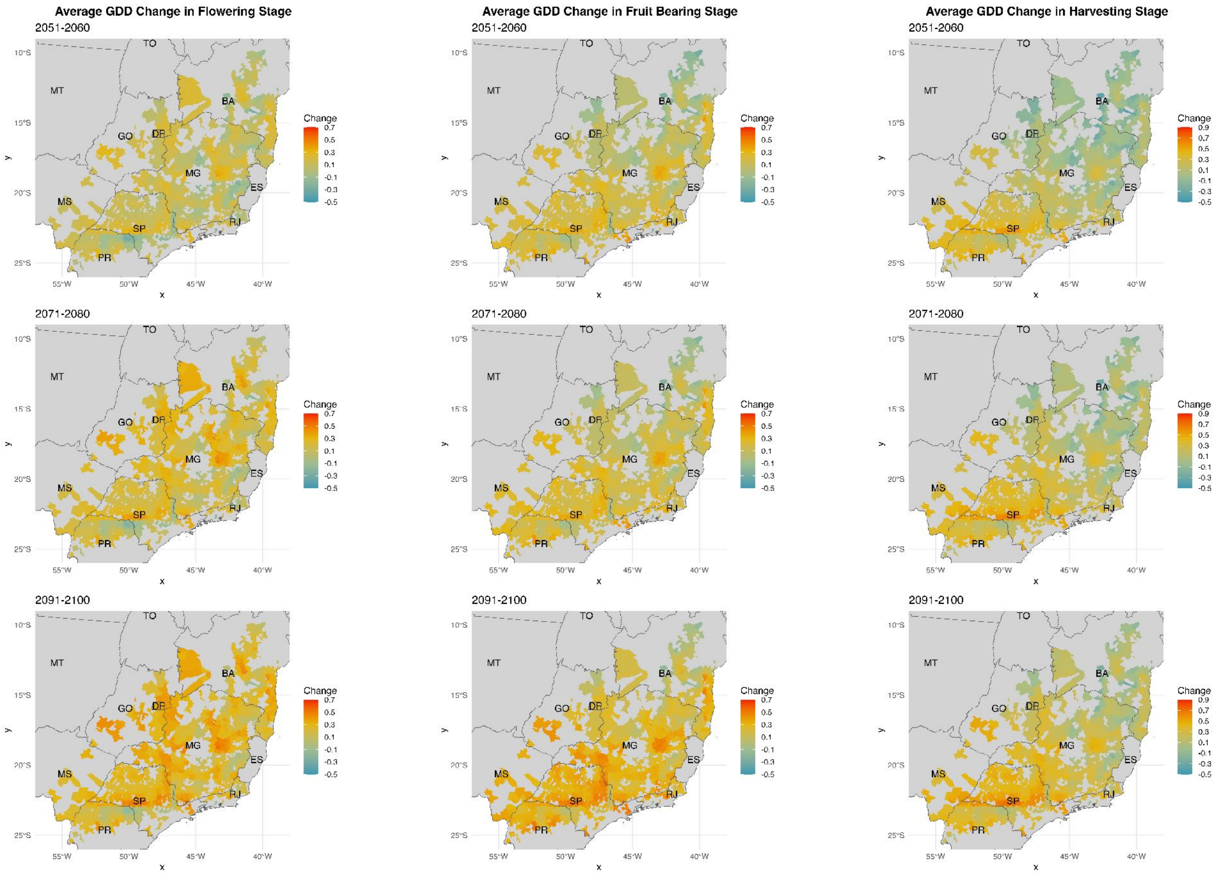


Figure 7.8: Degree Days and Temperature

Total rainfall is projected to follow a downward trajectory across all three growth stages for coffee plants. In the meantime, precipitation CV during the blooming phase is projected to increase for most producing regions, indicating more intense periods of rainfall following longer dry spells.

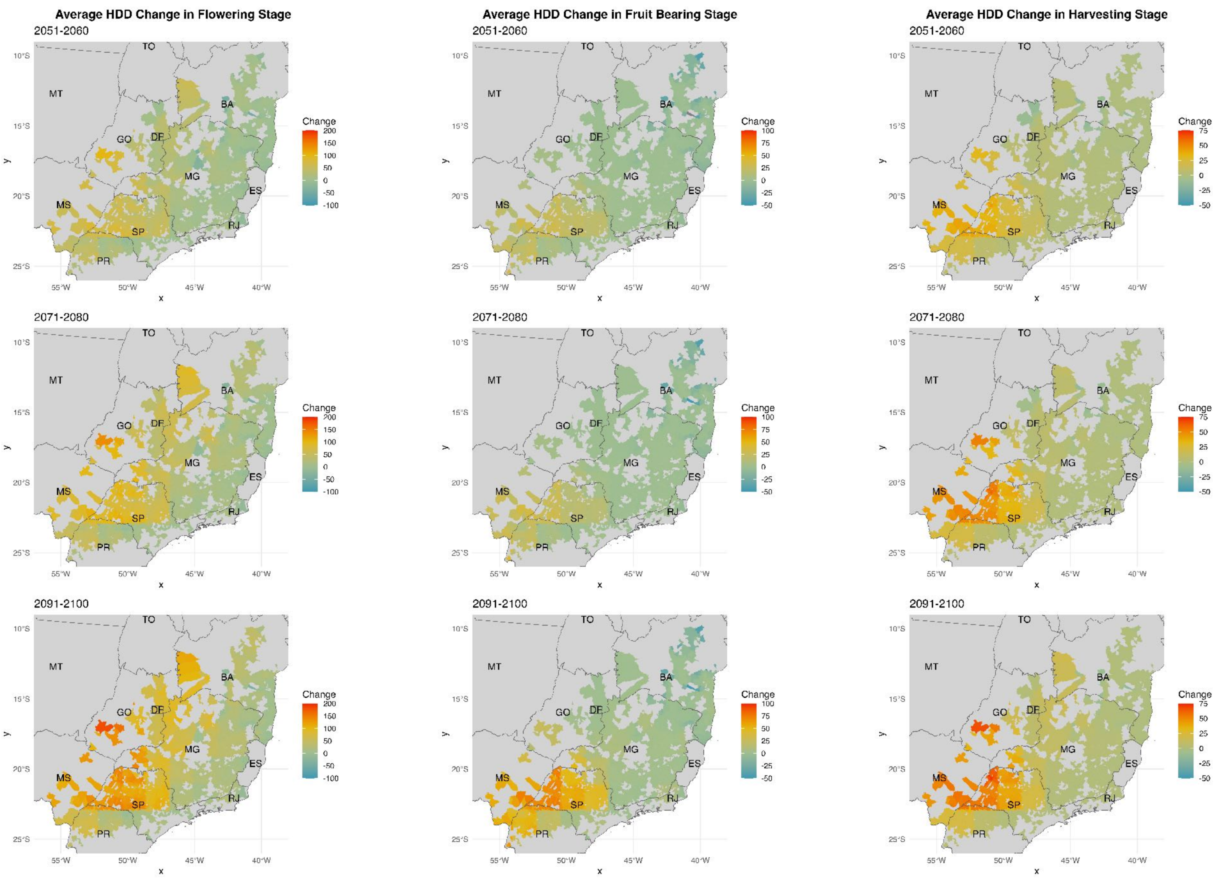
The impact of climate change on local weather patterns also demonstrates spatial heterogeneity. Figure 7.9 visualizes the change in growing degree days across major coffee-producing municipalities, with columns representing growing stages and rows representing time periods. Generally, an upward trend in GDD is observable in the regions shown, particularly during the flowering and fruit-bearing stages. During the harvesting period, areas in Bahia and northern Minas Gerais (MS) exhibit a relatively smaller increase in GDD when compared to the municipalities in São Paulo (SP), Paraná (PR), and Mato Grosso do Sul (MG).



(a) (b) (c)

Figure 7.9: GDD Projection across Different Regions

The change in harmful degree days (HDDs) exhibits greater spatial heterogeneity across coffee-producing municipalities, as depicted in Figure 7.10. Overall, there is a significant increase in HDDs in the southern regions, particularly in São Paulo and Mato Grosso do Sul, across all three stages. Meanwhile, Goiás (GO) is expected to experience increased exposure to temperatures above $32°C$ primarily during the flowering and harvesting phases. This trend intensifies as we approach the end of the century. It is important to note that, although the color scheme remains consistent across all three columns, the actual values represented are different. The most pronounced increase in HDDs is forecasted during the flowering stage. Conversely, the remaining regions in the country are not expected to undergo substantial changes in HDDs.



(a) (b) (c)

Figure 7.10: HDD Projection across Different Regions

Freezing degree days (FDDs) during the pre-flowering stage exhibit a relatively consistent trend across both spatial and temporal dimensions in Figure 7.10. FDDs are infrequently observed in many municipalities within the sample. From 1980 to 2018, the average FDDs are 0.26. Consequently, in most locations, changes in FDDs are minor, with small negative values nearing zero FDD.

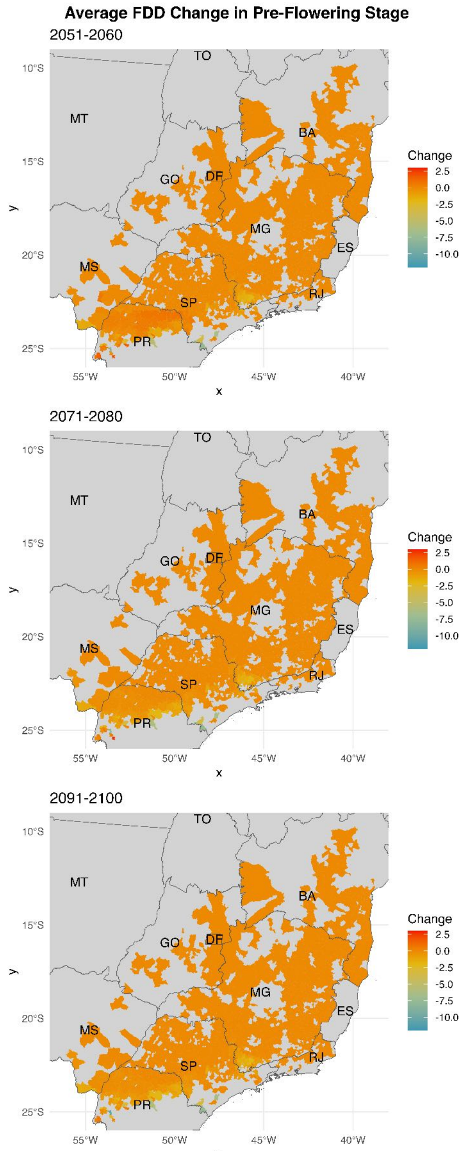


Figure 7.11: Pre-Flowering FDD Projection across Different Regions

Contrasting with the trends observed in growing degree days and harmful degree days, changes in precipitation do not exhibit a strong intensification over time relative to the reference period. As illustrated in Figure 7.12, the average change in precipitation remains relatively consistent across the decades 2051-2060, 2071-2080, and 2091-2100 for each growth stage of coffee plants. Notably, during the fruit-bearing stage, the majority of coffee-producing municipalities in Bahia (BA) are projected to experience an increase in rainfall. In contrast, other coffee-producing regions are anticipated to experience a decrease in total rainfall. Precipitation patterns during the flowering and harvesting stages display less spatial heterogeneity than in the fruit-bearing stage.

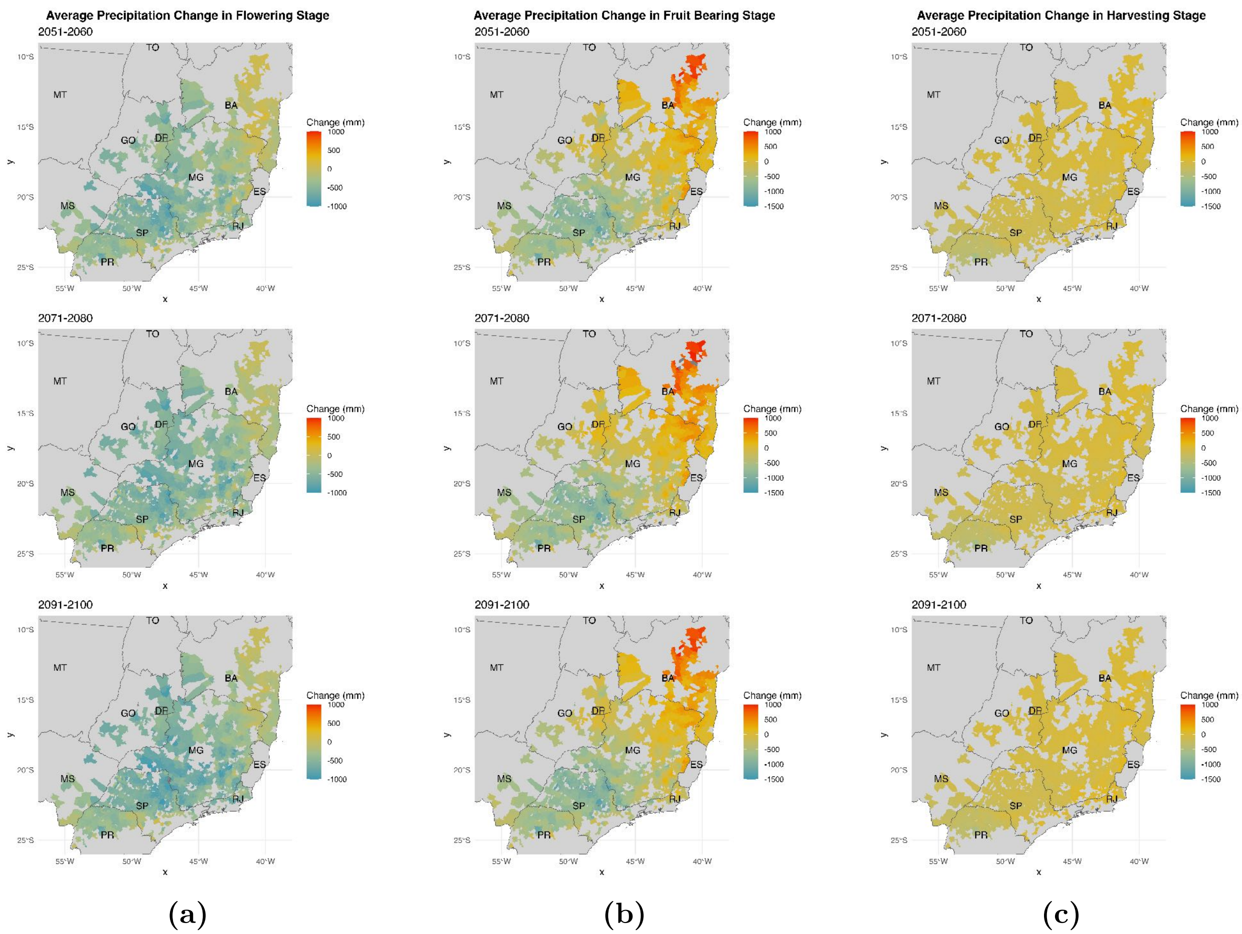


Figure 7.12: Precipitation Projection across Different Regions

Another key metric of interest is the number of dry days during the pre-flowering period, which coincides with the harvesting phase of the previous production season. The number of dry days is defined as the total days with no more than 5 mm of precipitation. The spatial distribution of changes in this metric is depicted in Figure 7.13. Municipalities in Paraná

(PR), Mato Grosso do Sul (MS), São Paulo (SP), and several coastal areas in Bahia (BA) are projected to experience drier conditions during the floral dormancy phase. Conversely, the impact on the number of dry days in the other municipalities is expected to be negligible.

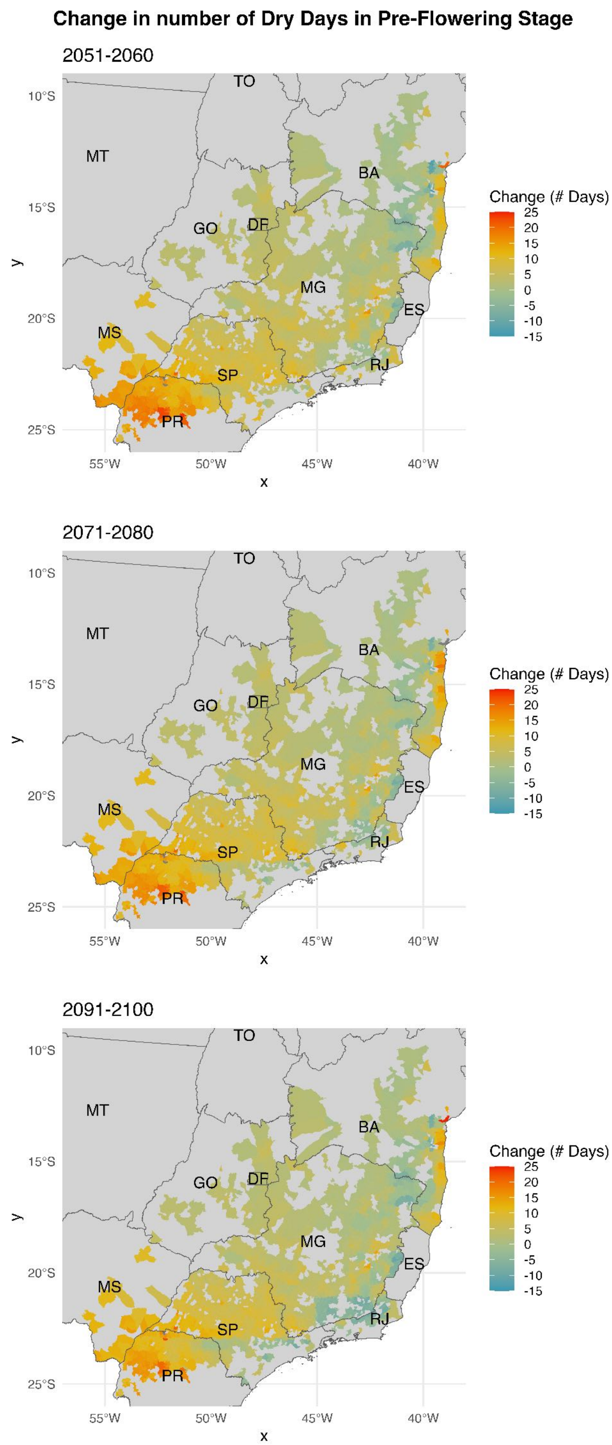


Figure 7.13: Pre-Flowering Number of Dry Days Projection across Different Regions

In Figure 7.14, the precipitation coefficient of variation (CV) during the blooming phase is projected to increase for most producing regions, except in several municipalities in the state of Bahia (BA). This change indicates that the majority of coffee-producing municipalities will experience more scattered rainfall during the blooming phase. Given the decreasing average volume of rainfall in most regions during this period, this new pattern could entail more intense periods of rainfall following longer dry spells.

I now turn to the projected yield changes associated with climate change. Two factors determine the impact of climate change on coffee yields. One is the projected changes in the weather variables (which we have just summarized). The other is the magnitude of the elasticities of coffee yields with respect to these weather variables; these elasticities, in turn, are derived from the parameter estimates from the yield-response model.

To recap some key results from my econometric modeling in Chapter 5, a 10% increases in GDD during the flowering phase will increase yield by 2.7%. A 10% increases in HDD during the same phase will reduce yield by 5.5%. A 10% increases in FDD during the pre-blooming phase is associated with a yield reduction of 0.045%. If precipitation is increased by 10% in the blooming stage or the fruit-bearing stage, the increase in yield is 0.52% and 0.59% accordingly.

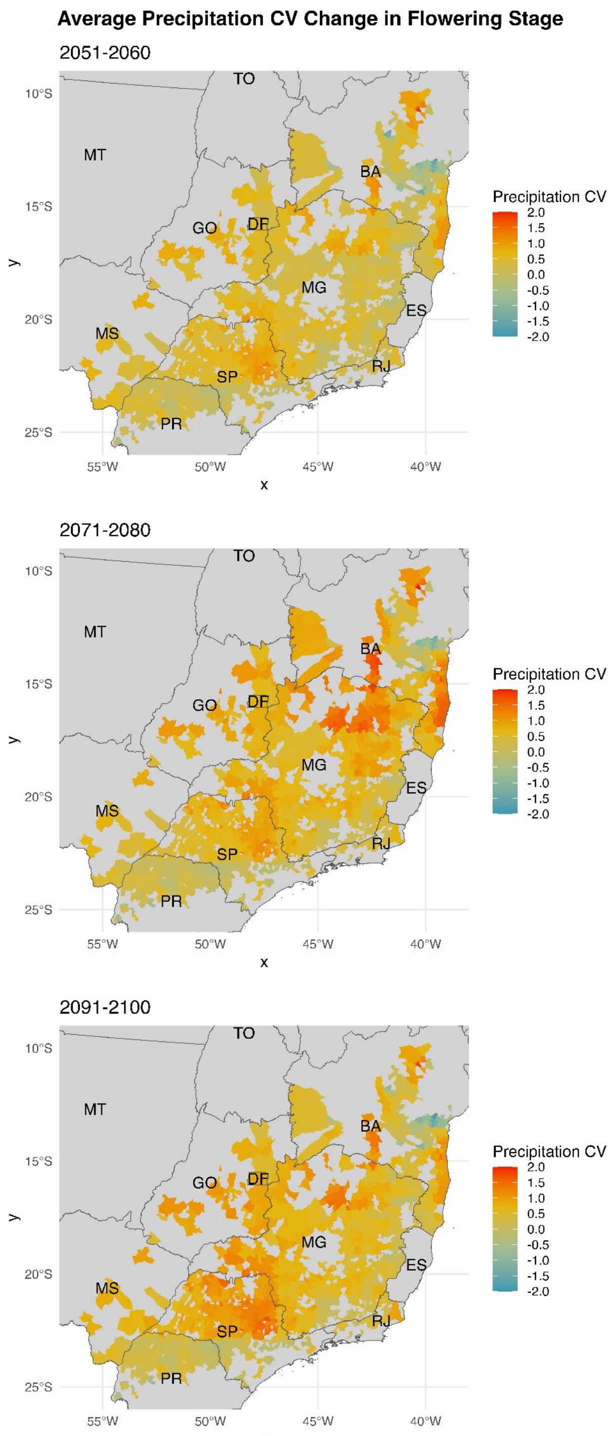


Figure 7.14: Blooming Rainfall Dispersion (CV) Projection across different regions

Using Equation 7.2, I calculate the change in yield given projected weather for each municipality and future time periods. Table 7.7 presents yield impacts in 2051-2060, 2071-2080, and 2091-2100, respectively.

State	Number of Municipalities	Yield | $\bar{W}_{2009,2018}$	Yield Change (mt/ha)			% Change		
			2051-2060	2071-2080	2091-2100	2051-2060	2071-2080	2091-2100
Bahia	145	1.029	0.016	-0.015	-0.033	2%	-1%	-3%
Federal District	1	1.144	-0.044	-0.067	-0.087	-4%	-6%	-8%
Goias	46	1.164	-0.074	-0.08	-0.075	-6%	-7%	-6%
Minas Gerais	525	1.22	-0.111	-0.128	-0.154	-9%	-10%	-13%
Mato Grosso do Sul	17	1.134	0.114	0.224	0.213	10%	20%	19%
Parana	206	1.173	-0.073	-0.053	-0.072	-6%	-5%	-6%
Rio de Janeiro	20	1.2498	-0.113	-0.125	-0.141	-9%	-10%	-11%
Sao Paulo	337	1.1878	-0.072	0.035	0.012	-6%	3%	1%

Table 7.7: Climate Change's Median Impacts on Brazilian Coffee Yields

Almost all states are projected to experience a drop in median yield by the end of the century, with Mato Grosso do Sul (MS) and São Paulo (SP) representing the exceptions. Among the states facing adverse climate impacts, Minas Gerais (MG) is forecast to see a 13% drop in yield. In contrast, Mato Grosso do Sul (MS) will benefit from the climate change, with a projected 19% yield increase by the last decade of the twenty-first century. This finding is consistent with Koh et al.(2020), who found that Mato Grosso do Sul (MS) has one of the lowest climate risk, while Minas Gerais (MG) and Rio de Janeiro (RJ) have the highest overall climate risks.

Figure 7.15 shows the distribution of projected yield changes across municipalities in each state. Bahia (BA) exhibits moderate yield change projections (around 0 mt/ha), with a slight tendency towards a reduction of -0.033 mt/ha by the century's end. Goiás (GO) shows a distinctive pattern, with most yield changes centered around -0.075 mt/ha but with the potential for gains up to 0.4 mt/ha, suggesting a long-tail effect in the distribution. Minas Gerais (MG) shows increasing variability, which may lead to pronounced effects of climate variability on yields over time. In contrast, Mato Grosso do Sul (MS) shifts towards higher yields, with a median gain of 0.213 mt/ha projected for 2091-2100. Paraná (PR) also exhibits growing variability, with the majority of municipalities expecting lower yields, although some may benefit from climatic changes. Rio de Janeiro (RJ) displays moderate, consistent changes with a slight downward trend. Finally, São Paulo (SP) presents a trimodal distribution in yield changes, with a central peak near -0.1 mt/ha and additional peaks suggesting potential yield gains, reflecting a complex interplay of factors influencing yield outcomes.

(a)

(b)

(c)

Figure 7.15: Projected Yield Impacts by State

Table 7.8 displays the average contributions of various weather variables on coffee yield changes across different states for three future periods. Overall, harmful degree days (HDDs) during the blooming periods consistently contribute to yield reductions across all states. Conversely, growing degree days (GDDs) during the blooming periods and HDDs during the harvesting periods are likely to have a beneficial impact on yields in the future.

	GDD - Blooming	GDD - Fruit Bearing	GDD- Harvesting	HDD - Blooming	HDD - Fruit Bearing	HDD - Harvesting	FDD - Pre-blooming
2051-2060 Avg. Contribution (mt/ha)							
BA	0.019	-0.011	0.003	-0.004	0.004	**-0.012**	0
DF	**0.025**	-0.009	0.006	**-0.037**	0	0.023	0
GO	0.025	-0.015	-0.005	**-0.051**	0	**0.051**	0
MG	0.016	-0.027	-0.023	-0.014	0	**0.017**	0.002
MS	0.025	-0.041	-0.081	**-0.086**	-0.012	**0.415**	0.006
PR	0.006	-0.027	-0.06	-0.044	-0.007	**0.196**	-0.003
RJ	0.019	-0.041	**-0.042**	-0.009	0	**0.028**	0
SP	0.018	-0.034	-0.06	-0.071	-0.009	**0.248**	0.001
2071-2080 Avg. Contribution (mt/ha)							
BA	**0.035**	-0.02	-0.012	**-0.024**	0.003	-0.006	0
DF	**0.044**	-0.015	-0.02	**-0.066**	0	0.039	0
GO	0.043	-0.023	-0.032	**-0.09**	0	**0.123**	0
MG	**0.03**	-0.031	**-0.041**	-0.028	0	0.022	0.002
MS	0.035	-0.049	-0.084	**-0.112**	-0.014	**0.489**	0.008
PR	0.014	-0.031	**-0.061**	-0.055	-0.007	**0.217**	0.007
RJ	**0.028**	-0.042	**-0.052**	-0.014	0	0.014	0
SP	0.03	-0.038	-0.076	**-0.103**	-0.007	**0.356**	0.002
2091-2100 Avg. Contribution (mt/ha)							
BA	**0.044**	-0.032	-0.024	**-0.032**	0.002	0.002	0
DF	0.058	-0.038	-0.04	**-0.11**	-0.001	**0.096**	0
GO	0.056	-0.045	-0.049	**-0.143**	-0.002	**0.215**	0
MG	**0.043**	-0.053	**-0.054**	-0.048	-0.002	0.037	0.002
MS	0.045	-0.064	-0.091	**-0.152**	-0.03	**0.525**	0.008
PR	0.026	-0.051	-0.067	**-0.078**	-0.018	**0.228**	0.007
RJ	**0.042**	**-0.062**	-0.061	-0.027	-0.003	0.02	0
SP	0.045	-0.062	-0.088	**-0.154**	-0.023	**0.416**	0.002

	Rainfall - Blooming (m)	Rainfall - Fruit Bearing (m)	Rainfall - Harvesting (m)	Precipitation CV - Blooming	Number of Dry Days - Pre-blooming	Yield Change
2051-2060 Avg. Contribution (mt/ha)						
BA	-0.006	**0.021**	-0.001	0.004	0.002	0.019
DF	-0.03	-0.004	0.005	0.012	-0.037	-0.046
GO	-0.039	-0.013	0.007	0.015	-0.047	-0.072
MG	-0.031	-0.018	0.008	0.009	**-0.039**	-0.1
MS	-0.027	-0.034	0.03	0.012	-0.085	0.122
PR	-0.031	-0.045	0.035	0.003	**-0.068**	-0.045
RJ	-0.031	-0.013	0.005	0.005	-0.023	-0.102
SP	-0.043	-0.054	0.016	0.012	**-0.076**	-0.052
2071-2080 Avg. Contribution (mt/ha)						
BA	-0.014	0.027	0.003	0.015	-0.013	-0.006
DF	-0.041	0.004	0.006	0.018	-0.035	-0.066
GO	-0.049	-0.009	0.008	0.02	-0.051	-0.06
MG	-0.037	-0.016	0.008	0.015	-0.039	-0.115
MS	-0.024	-0.034	0.029	0.011	-0.074	0.181
PR	-0.027	-0.045	0.033	0.002	-0.053	-0.006
RJ	-0.032	-0.016	0.002	0.008	-0.008	-0.112
SP	-0.041	-0.053	0.017	0.014	-0.078	0.023
2091-2100 Avg. Contribution (mt/ha)						
BA	-0.014	0.024	0.002	0.009	-0.009	-0.028
DF	-0.042	-0.006	0.004	0.021	-0.029	-0.087
GO	-0.051	-0.017	0.007	0.021	-0.043	-0.051
MG	-0.043	-0.021	0.005	0.014	-0.023	-0.143
MS	-0.026	-0.034	0.027	0.015	-0.066	0.157
PR	-0.03	-0.044	0.029	0.004	-0.038	-0.032
RJ	-0.04	-0.016	-0.005	0.009	0.014	-0.129
SP	-0.048	-0.055	0.015	0.02	-0.071	-0.003

Table 7.8: Average Weather Contribution to Overall Yield Impact

7.4 Implications for Overall Brazilian Production

In light of the evolving impacts of climate change, it's critical to assess the adaptive strategies available to key coffee-producing regions in Brazil. The adaptation assumptions made in this analysis are based on the idea that in the long-term, coffee production will move to regions better suited to handle the changing climate (Bunn et al., 2015).

For municipalities projected to experience a large yield loss, such as Minas Gerais and Rio de Janeiro, it is expected that the area of coffee plantation is likely to decline in the future. This adjustment accounts for the anticipated lower profitability, as changes in temperature, precipitation, and other climate-related factors adversely affect coffee production. Conversely, for regions that are projected to benefit from climate change, such as Mato Grosso do Sul, or states that are projected to have minimal reduction from their reference level, there could possibly be an increase in their coffee harvest area.

Table 7.9 shows the impacts of climate change on total production by state assuming no adaptation takes place. Under the no adaptation scenario, total production across the main coffee growing states with climate change is projected at 1.176 million metric tonnes, which is about 8% lower than the average reference yield assuming no climate change. If there is adaptation, the gap between projected yields and reference yields could be smaller.

The adaptation strategies outlined here highlight a proactive approach to addressing the potential impacts of climate change on coffee production. By adjusting the harvest areas in response to changing yields, municipalities can optimize their coffee production, either by scaling back in unfavorable conditions or expanding in more advantageous settings. This

	Yield (mt/Ha)		Area Harvested (Ha)	Production (million MT)	
State	Yield | $W_{2009,2018}$	Avg Change$_{2051,2100}$	Reference$_{2009,2018}$	No Adaptation$_{2051,2100}$	Reference$_{2009,2018}$
Bahia	1.03	-0.01	116,214	0.118	0.120
Federal District	1.14	-0.06	625	0.001	0.001
Goias	1.16	-0.07	7,352	0.008	0.009
Minas Gerais	1.22	-0.11	699,363	0.762	0.853
Mato Grosso do Sul	1.13	0.16	1,013	0.001	0.001
Parana	1.17	-0.06	58,782	0.065	0.069
Rio de Janeiro	1.25	-0.10	12,903	0.014	0.016
Sao Paulo	1.19	-0.01	175,302	0.207	0.208
			Total Production (million MT)	1.176	1.277

Table 7.9: Impact of Climate Change on Total Production by State: Case of No Adaptation

approach not only helps mitigate the negative impacts but also capitalizes on potential benefits, thereby supporting the sustainability of coffee production in Brazil over the long term.

However, it's important to recognize the limitations of this strong assumption. Shifting coffee production from one region facing greater climate threats to another region harmed less by climate change is influenced by multiple factors, including economic conditions, alternative crop options, and policy interventions, which are not accounted for in this analysis. Moreover, climate change impacts can be highly localized, and generalizing the yield changes across states may overlook significant microclimatic variations at the farm level or even municipality level.

Chapter 8

Limitations and Future Research

This research has provided comprehensive insights into the impacts of climate change on coffee production. However, several limitations exist that future studies should address to enhance the reliability and applicability of the findings.

The analysis lacks specific data on actual coffee growth stages each year. Assumptions had to be made about the timing of flowering, fruit-ripening, and harvesting periods for each municipality. This is particularly challenging in Colombia, where harvest times vary significantly across departments such as Norte de Santander, Huila, Cundinamarca, Tolima, and Valle del Cauca. These variations can lead to measurement errors and biases in yield response models, as the timing of crucial growth stages might differ yearly based on climatic conditions.

Second, The yield data were defined as production divided by the area harvested. This conventional approach does not account for unharvested areas due to plant die-off or selective harvest practices, potentially underestimating the adverse effects of high temperatures. Rising (2016) found a significant negative relationship between extremely hot days and harvested acres. This finding supports the idea that farmers choose not to harvest the coffee tree when it is damaged to some extent. Therefore, the reported area harvested is less than the actual harvestable area. As a result, the reported yield is higher than the actual yield on all harvestable plantings, and the damaging effects of high temperatures are likely to be undermined.

Third, several estimation results from the Growth Stage Alternate Bearing Model are difficult to interpret given established plant science knowledge. For example, in the Brazil analysis, the cumulative warm temperatures during both the fruit-bearing stage (January to April) and the harvesting stage (May to August) negatively influence the yield. Specifically, a 10% increase in GDDs during the fruit-bearing phase correlates with a yield reduction of 1.9%. Similarly, the same increase in GDDs during the harvest season is associated with a yield decline of 2.7%. One way to estimate the true beneficial effects of temperature with coffee yields is to use different thresholds in the degree day calculation for each developmental stage. Additionally, instead of using predetermined degree day thresholds, an alternative approach is to use a more flexible specification, such as a polynomial function that was suggested in a research examining the impacts of climate change on cereal yields (Gammans et al., 2017).

While this study provides valuable insights into the impacts of climate change on coffee production in Brazil and Colombia, its geographic scope is limited. Expanding the research to include other major coffee-producing countries could offer a more comprehensive understanding of the global implications of climate change on the coffee industry. Ideally, this can be done if future researchers have access to a complete panel of detailed production records from producing countries across the world, either at the regional or municipality level. To my knowledge, the only coffee production dataset of coffee producing regions at a high resolution is developed by a group of researchers from the Earth Institute of Columbia University (Sachs et al., 2015). A summary of the database is presented in Figure 8.1 and 8.2. They have combined the information, including municipality data, state level data and spatial data from multiple sources. However, this database is no longer publicly available. Making such a dataset accessible would facilitate broader analyses of regional differences and enable the development of targeted adaptation strategies.

Country	Production	Coverage	Resolution	Source
Brazil	2,720 kt	country-wide	municipality (5503)	IBGE
Vietnam	1,650 kt	country-wide	raster image	Cafecontrol
Colombia	696 kt	country-wide	raster image	Oficina de E. y P. Básicos Cafeteros
Indonesia	411 kt	6 regions	raster image	Schroth (2014)
Ethiopia	390 kt	country-wide	raster image	GAIN (2013)
India	300 kt	country-wide	state (13)	Coffee Board (India Gov.)
Mexico	270 kt	country-wide	raster image	Gonzalez (2010)
Guatemala	240 kt	country-wide	vector layers	MFEWS
El Salvador	82 kt	country-wide	raster image	Poyecto Programa Ambiental
Nicaragua	78 kt	country-wide	raster image	MFEWS
Tanzania	50 kt	country-wide	raster image	Caparo et al. (2015)
Haiti	21 kt	country-wide	vector image	Coffee Supply Chain Risk Ass. Miss.
Rwanda	21 kt	country-wide	points	Nzeyimana (2014)
Yemen	14 kt	country-wide	raster image	Maxey (2015)
Total	7,766 kt	global	country	ICO, FAO, USDA FAS
		global	inferred raster	Monfreda et al. (2008)
		global	points	Bunn et al. (2015), CIAT

Figure 8.1: Sources of spatial coffee production in the Earth Institute Coffee Production Database (Sachs et al., 2015)

Country	Variables	Time	Space	Organization
India	Planted, Produced, Yield	32 years (1951 - 2013)	15 growing regions	Knoema
Brazil	Harvested, Produced	yearly (1990 - 2012)	5624 municipalities	IBGE
Indonesia	Area, Produced, Yield	2011	20 districts (Kecamatan)	Dinas Pertanian
Rwanda	Area, Agroforested, Yield	2005	10 growing regions	NAEB
Vietnam	Area	2012, 2013	11 provinces + other	GAIN
Brazil	Fertilizer use	2002	5 regions	FAO
global	Harvested, Produced, Yield	1961 - 2012	86 countries	FAO
global	Produced (by variety), Stocks, Export, Consumption	1960 - 2013	79 countries	USDA FAS
global	Fertilizer use	1995 - 2002	24 countries	FertiStats

Figure 8.2: Sources of global and sub-country data on coffee yields in the Earth Institute Coffee Production Database (Sachs et al., 2015)

Besides improving upon the above limitations, it is also critical to think about global coffee demand moving forward. Just like any other commodity, the main determinants of coffee prices are market supply and demand. This dissertation examines how climate change could affect the production side of the international coffee market, it is also vital to evaluate the future of coffee consumption.

Coffee remains one of the world's most popular beverages, with a vast market that spans across the globe. Recent trends in the global coffee market have shown a notable rise in consumption, particularly in emerging markets. Countries like China and India, traditionally tea-drinking nations, have exhibited significant growth in coffee consumption due to increasing urbanization and changes in consumer preferences (Daily Coffee News, 2023). Meanwhile, traditional markets such as the United States and European countries continue to show steady demand (U.S. Department of Agriculture, Foreign Agricultural Service, 2023).

Two key drivers that influence global coffee demand are the population growth, and incomes growth. As discussed by Torga et al. (2020), the rising global population and increasing per capita income are positively correlated with coffee consumption. The Joint Research Centre (JRC) of the European Commission produces projections on global population trends for the second half of the twenty-first century. Under the most optimistic pathway, the world population peaks at around 8.7 billion between 2050 and 2060, then drops to 7.3 billion by the end of the century. In the most pessimistic scenario, the world population is projected to reach 13.6 billion (Ueffing et al., 2022). There will likely be a significantly larger population to feed in 2100, with a greater share of the population in places like Sub-Saharan Africa and India, and a lesser share in high-income countries. Therefore, it can be expected that coffee consumption in the low-income regions will expand faster than that of the developed countries.

Furthermore, income growth often leads to urbanization, another driver of coffee consumption. Urban areas typically have better access to a variety of coffee products, including specialty coffee shops and international brands, which contribute to increased consumption. The expansion of the coffee culture in urban centers around the world highlights the link between income growth and coffee demand. In low-income regions, where income growth is expected to be faster, the potential for increased coffee consumption is substantial. As these regions develop economically, their populations will likely increase their coffee intake, following patterns observed in more developed markets.

Additionally, an aging global population may also further boost coffee demand (Silva et al., 2000). As the global population ages, particularly in developed countries, the demand for coffee may rise. Older consumers often have established coffee-drinking habits and may prefer higher-quality or specialty coffee products, contributing to an overall increase in coffee demand. Additionally, with improved healthcare and longer life expectancy, the senior demographic will remain active consumers for a more extended period, sustaining coffee consumption levels.

As demand increases, the pressure on coffee supply exacerbated by climate impacts could lead to a sustained upward trend in prices. Without significant expansion in coffee-growing land or drastic improvements in agricultural technology and practices, it is plausible that coffee prices will experience upward pressure as demand growth outpaces the projected increases in worldwide yields. Therefore, it is important to understand and mitigate the effects of climate change on global coffee market, as well as to explore alternative agricultural practices and diversification strategies to maintain supply stability.

Chapter 9

Conclusion

This dissertation has studied the impacts of climate change on global coffee production through a two-step process. First, the response of coffee yields to temperature and precipitation variables during key growth stages in Brazil and Colombia was analyzed. Then the estimated weather-yield relationship is used to forecast potential impacts of climate change on Brazilian coffee production through the end of the century.

The results from the first stage analysis reveal some interesting findings. First, Brazil displays pronounced biennial fluctuations in coffee yields. Growing degree days (GDDs) are found to positively impact yields during the blooming stage, while harmful degree days (HDDs), measured by temperature exposure over $32°C$ during the same period contribute to yield reductions. The relationship between total precipitation during each growth stage and yields displays varied dynamics. Precipitation dynamics also play a critical role; increased rainfall benefits yields during the flowering and fruit-bearing stages but harms them during the harvesting phase. An extended dry period initially boosts yields but becomes detrimental if it surpasses a critical duration of 104 days.

The study in Colombia highlights the positive effects of GDDs during the flowering and harvesting periods and the negative impacts of excessive rainfall during the fruit-bearing stage, illustrating the diverse effects of weather fluctuation on coffee yields between Colombia and Brazil.

The analysis also explores the role of elevation in coffee production, uncovering distinct regional responses in Brazil and Colombia. In Brazil, higher altitudes intensify the negative impacts of extreme temperatures and precipitation on yield variations due to the cultivation of different coffee varieties that vary in their environmental tolerance. In contrast, in Colombia, elevation does not significantly alter the influence of climatic factors on coffee yield.

Under the middle-of-the-road SSP245 emission scenario from the CNRM-CM6-1 model, Brazil's major coffee-growing regions are projected to experience warmer temperatures, decreased rainfall, and more pronounced dry periods during the pre-blooming phases, with fluctuating precipitation during the blooming phase. Most states are expected to witness yield declines by the century's end, with exceptions in Mato Grosso do Sul and São Paulo. Future projections indicate a significant 13% reduction in coffee yields for municipalities in Minas Gerais by the end of the century. Conversely, municipalities in Mato Grosso do Sul are anticipated to benefit from climate changes, potentially seeing a 19% increase in yields by 2100. The main drivers of changing yields are HDDs during the blooming periods, GDDs during the blooming periods and HDDs during the harvesting periods. HDDs during the blooming periods consistently contribute to yield reductions across all states. GDDs during the blooming periods and HDDs during the harvesting periods are projected to have a beneficial impact on yields in the future.

In conclusion, the findings of this dissertation underscore the profound and varied impacts that climate change is likely to have on coffee production in Brazil and Colombia, two of the world's leading coffee producers. These results highlight the need for adaptive strategies tailored to specific regional and varietal characteristics to mitigate the adverse effects of changing climatic conditions. Specifically, it is important to understand which producing regions will benefit from climate change and which will become less suitable for coffee production. As coffee is a major crop grown in many developing countries and consumed worldwide, the adverse impact of climate change on yields pose significant risks not only to local economies and livelihoods but also to global coffee supply chains. Addressing these challenges requires coordinated efforts from policymakers, researchers, and industry stakeholders to develop sustainable solutions that can ensure the resilience of coffee production in the face of climate change. The future of coffee, a critical economic resource and a staple in the daily lives of millions, depends on our ability to adapt to these impending climatic shifts. I hope the findings in this dissertation can play a small role in this process.

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