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Sustainable Supply Chain Management in the Face of Climate Change

Estimating the Impact of Temperature and Precipitation Changes on Brazilian Soybean Yield

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Abstract

While climate change is known to pose a variety of highly relevant economic risks, there are still many probable implications and economic fields with a lack of available data and research. This thesis explores the potential interrelations of climate change and global supply change management based on the case of Brazilian soybean supply.

The main research question, how a change in temperature and precipitation affects Brazilian soybean yield, is investigated using historical weather and soybean yield data. A panel data crop yield regression model was developed to estimate the impact of changing weather variables on yield productivity. The results suggest that a one-degree Celsius increase in average annual temperature in Brazil leads to a 13.8% decrease in average soybean yield, a 100-millimeter increase in annual precipitation is associated with a 1.5% increase in average soybean yield, and lastly, a one-degree Celsius increase in the average temperature during the driest quarter of the year was found to lead to a 1.6% decrease in average annual soybean yield in Brazil.

By contextualizing these results within the global sustainable soybean supply chain management theory, this thesis further adds valuable insights to the existing new climate economy literature and the relevant discussion of the economic implications of climate change. Lastly, this thesis aims to advocate for how increasing available climate data and analysis can limit potentially harmful consequences and encourage further research in the still-developing field of sustainable supply chain management to provide more information to policymakers and decision-makers.

Keywords: Sustainable supply chain management, Brazilian soybean, climate change, new climate economy literature, crop yield regression, panel data regression

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1. Introduction

Global supply chains are complex networks of interconnected entities, such as manufacturers, suppliers, distributors, and retailers, enabling the production and distribution of goods and services worldwide. These supply chains are essential for international trade and economic growth but are also vulnerable to various challenges (Janvier-James, 2011).

The COVID-19 pandemic, geopolitical conflicts such as the ongoing war in Ukraine, and the Suez Canal blockade are just a few recent examples that show how sensitive global supply chains are and how easily they can be disrupted. Significant delays in global production and transportation of goods can lead to shortages and price increases for many essential and specialty items. As global supply chains continue to evolve and expand, it is essential to develop strategies to mitigate these risks and ensure the stability and resilience of these critical networks (Gurtu & Johny, 2021).

One of the major challenges for global supply chains now and in the future is to account for the various challenges posed by climate change. A significant part of that is to develop strategies to make supply chains more sustainable to account for environmental, social, and economic aspects. To do so, it is crucial to consider how supply chains impact the environment and how a changing environment impacts supply chains (Ghadge et al., 2020).

A prime example is the complex narrative of global soybean trade, specifically with Brazilian soybean production. Soybeans are an essential commodity worldwide with high demand and economic value, and many industries rely on them. Soybean production and trade are therefore essential not only for the Brazilian but the global economy. However, the increased soy demand and trade are also significant reasons for social issues and the increasing deforestation of the Amazonian rainforest, further endangering maintaining a safe climate on earth. The impacts, in turn, of climate change are likely to negatively affect soybean yield in Brazil, potentially putting their economic well-being and the global soybean supply chain at risk. This complex and challenging cause-and-effect circle is multi-faceted and increasingly raises the question of how to source and trade soy sustainably on a global level (De Maria et al., 2020).

To face all these challenges and to consider potential economic implications, a critical first step is to understand how changes in our climate can change the soybean production conditions and potentially shift the global production and trade flows. Understanding this will help evaluate whether an increasing demand for soybeans in the future can be met or if innovative solutions will be required to avoid an economic issue at large.

This thesis develops and contributes a starting point to the required research in this field, aiming to explore the interrelationships between climate change and supply chain design and operations using the example of Brazilian soy supply. Historical data on soybean yield and weather conditions are used to estimate the potential causal relationship between climate and soybean yield. This analysis provides a foundation to explore further relevant questions such as: How can access to improved weather forecasts mitigate the harmful economic impacts of climate change?

The remainder of this thesis is structured as follows.
Firstly, an introduction to the overarching topics of sustainable supply chain management and soybean economics is provided. The concept of sustainable supply chain management is defined, its relevance is explained, and its potential implementation is demonstrated. The importance of soybeans in the global economic context is presented, followed by an overview of global soybean trade dynamics, which provides insights into worldwide supply and demand structures by analyzing production, consumption, export, and import data. Additionally, the potential impact of climate change on soybean production and trade is discussed, with a specific focus on Brazil.
Secondly, a comprehensive literature review summarizes the current state of the new climate economy literature. It provides an overview of previous research in crop yield forecasting based on statistical models.
Thirdly, the datasets used for the purpose of this research, including historical soybean yield and temperature and precipitation in Brazil, are introduced. The research methodology is explained, including the pre-processing of the data and the model selection process for estimating the relationship between weather variables and soybean yield. An overview of the results of the analysis is presented and discussed.
Next, the economic implications of the findings are contextualized within the field.
Lastly, a brief conclusion summarizes and reiterates the main findings of this research while also acknowledging the limitations of this research and providing guidance for using the presented results and suggestions for further research.

2. Conceptual Background

2.1 Sustainable Supply Chain Management

2.1.1 Concept Definition

Supply chains have been an elementary part of business processes for many decades, yet supply chain management can be considered a comparably new and still developing field of research. Therefore, perceptions of the discipline differ among researchers, and several definitions, varying in complexity, exist (Janvier-James, 2011). Initially, when the concept of supply chain management was introduced in the 1980s, definitions focused solely on the flow of materials. Nowadays, many additional aspects, such as risk management, performance evaluation, integration, information flow, internal and external networks of relationships as well as governance of supply networks, are being considered when describing the discipline (Ahi & Searcy, 2013).
For the purpose of this study, the definition provided by the Council of Supply Chain Management Professionals is being adopted, which defines supply chain management as "the planning and management of all activities involved in sourcing and procurement, conversion, and all logistics management activities. Importantly, it also includes coordination and collaboration with channel partners, which can be suppliers, intermediaries, third-party service providers, and customers. In essence, supply chain management integrates supply and demand management within and across companies." (CSCMP, 2023).

In recent years the topic of sustainability has become more prevalent across different areas of business operations, including supply chain management. Although there have been a few prior attempts to define sustainable supply chain management, the term was broadly introduced in 2008 by Seuring and Müller. Their definition, which emphasizes the incorporation of the three dimensions of sustainable development, i.e., economic, environmental, and social aspects, into the management of supply chains, remains one of the most cited ones to date (Seuring & Müller, 2008; Nimsai et al., 2020).
Table 1 provides a comprehensive overview of the concept's development over time through selected definitions.

Definition	***Source***
"The strategic, transparent integration and achievement of an organization's *social, environmental, and economic goals* in the systemic coordination of key inter-organizational business processes for improving the long-term economic performance of the individual company and its supply chains."	Carter & Rogers, 2008, p. 368
"The management of material, information and capital flows as well as cooperation among companies along the supply chain while taking goals from all *three dimensions of sustainable development, i.e., economic, environmental and social*, into account which are derived from customer and stakeholder requirements."	Seuring & Müller, 2008, p. 1700
"The integration of sustainable development and supply chain management [in which] by merging these two concepts, *environmental and social aspects* along the supply chain have to be taken into account, thereby avoiding related problems, but also looking at more sustainable products and processes."	Seuring, 2008, p. 132
"The management of supply chains where *all the three dimensions of sustainability, namely the economic, environmental, and social* ones, are taken into account."	Ciliberti et al., 2008, p. 1580
"Adding sustainability to existing supply chain management processes, to consider *environmental, social and economic impacts* of business activities."	Font et al., 2008, p. 260
"The set of supply chain management policies held, actions taken, and relationships formed in response to concerns *related to the natural environment and social issues* with regard to the design, acquisition, production, distribution, use, reuse, and disposal of the firm's goods and services."	Haake & Seuring, 2009, p. 285
"The degree to which a manufacturer strategically collaborates with its supply chain partners and collaboratively manages intra- and inter-organization processes for sustainability."	Wolf, 2011, p. 223
"Reflection of the firm's ability to plan for, mitigate, detect, respond to, and recover from potential global risks. Risks involving substantial marketing and supply chain considerations include product development, channel selection, market decisions, sourcing, manufacturing complexity, transportation, government and industry regulation, resource availability, talent management, alternative energy platforms, and security."	Closs et al., 2011, p. 102
"An extension to the traditional concept of Supply Chain Management by *adding environmental and social/ethical aspects*."	Wittstruck & Teuteberg, 2011, p. 142
"The creation of coordinated supply chains through the voluntary *integration of economic, environmental, and social considerations* with key inter-organizational business systems designed to efficiently and effectively manage the material, information, and capital flows associated with the procurement, production, and distribution of products or services in order to meet stakeholder requirements and improve the profitability competitiveness, and resilience of the organization over the short- and long-term."	Ahi & Searcy, 2013, p.339

"SSCM is the voluntary *integration of social, economic, and environmental considerations* with the key inter organizational business systems to create a coordinated supply chain to effectively manage the material, information and capital flows associated with the procurement, production and distribution of products or services to fulfill short term and long term profitability, stakeholder requirements, competitiveness and resilience of the organization. "	Dubey et al., 2016, p.1120
"SSCM is concerned with *integrating environmental, social and economic goals* across a focal firm's supply chain processes, has emerged as an approach for firms to improve sustainable (i.e. *environmental, social and economic*) outcomes in their supply chains."	Koberg & Longoni, 2019, p. 1085

***Table 1** Sustainable Supply Chain Management Definitions Across Selected Literature*

Most of these definitions have a common ground as they highlight the (voluntary) integration of the environmental and social dimensions together with economic goals in the management of supply chains in order to create more sustainable processes and products/services. On the one hand, there is a focus on the external driver of growing customer and stakeholder demands, requiring a more holistic approach to supply chain management. Moreover, on the other hand, a company's internal evaluation of its impact on the environment and society throughout the entire process of product development, production, distribution, use, and disposal or service offering is put into focus. Additionally, the concept of transparency seems of importance. Furthermore, Closs et al. (2011) add the dimension of having the "ability to plan for, mitigate, detect, respond to, and recover from potential global risks," whereas Wittstruck & Teuteberg (2011) incorporate the concept of ethics in their definition.

Comparing these 12 definitions alone shows a certain level of ambiguity in defining the term sustainable supply chain management. However, Seuring & Müller (2008) developed a clear and concise definition that includes the most important aspects and can, after comparison with more recent definitions, still be deemed relevant today. Therefore, Seuring & Müller's definition will be adopted for the purpose of this study. Sustainable supply chain management can hence be described as "the management of material, information, and capital flows as well as cooperation among companies along the supply chain while taking goals from all three dimensions of sustainable development, i.e., economic, environmental and social, into account which are derived from customer and stakeholder requirements." (Seuring & Müller, 2008).

2.1.2 Relevance

Considering the sustainability of supply chains as an integral business success factor continuously gains more relevance for several reasons.
First, sustainable supply chain management reduces the environmental impact of business operations by reducing waste, minimizing resource use, and reducing greenhouse gas emissions. This helps mitigate the adverse effects of climate change and protect the environment for future generations.
Secondly, on a social scale, sustainable supply chain management helps to promote fair labor practices and safe working conditions and also supports local communities. This helps companies to fulfill their social responsibility to stakeholders, including employees, customers, and the communities in which they operate.
Thirdly, sustainable supply chain management can lead to economic benefits on two dimensions. On the one side, it can lead to cost savings and ensure long-term business viability by improving operational efficiency, managing risk, enhancing resilience, and overall creating a more sustainable business model that can adapt to changing economic and environmental conditions. On the other side, there is a growing stakeholder and foremost customer demand for more sustainability and transparency. While this trend is likely to gain even more traction in the upcoming years, businesses can significantly benefit through an improved company reputation, increased customer loyalty, and improved brand recognition by staying ahead or at least on time with these developments (Jørgensen & Pedersen, 2018).

Specifically, looking at the topic of climate change and its possible impacts on supply chain management highlights the relevance of sustainability considerations in the field.
Climate change is defined as a long-term shift in global or regional climate patterns caused by human activities, particularly the emission of greenhouse gases, and characterized by changes in temperature, precipitation, and extreme weather events. It poses significant risks to natural ecosystems, human health, and socio-economic systems and requires urgent action to mitigate its impacts and adapt to its effects (IPCC, 2018).

Dasaklis & Pappis (2013) analyzed the potential impacts of climate change on supply chain management regarding strategic and operational planning, as demonstrated in Figure 1. They identified three main areas impacted by climate change: regulatory, physical, and market. The regulatory dimension is concerned with external requirements and factors that directly impact supply chain management decisions, such as laws promoting emission reductions across the supply chain, or indirectly, such as an increase in energy prices. The physical dimension is, for example, concerned with changes in climate and extreme weather patterns, as well as the reduced availability of raw materials due to climate change. Lastly, the market dimension highlights the increasing customer demand for more environmentally sustainable products, service offerings, and overall business operations. All these factors together were found to have relevant implications for supply chain management on both the strategic and the operational level.

On the strategic level, climate change requires supply chain management to rethink entire supply chain network designs. On the operational level, planning and risk mitigation efforts are becoming more complex as supply chain disruptions are expected to increase and become more severe (Dasaklis & Pappis, 2013).

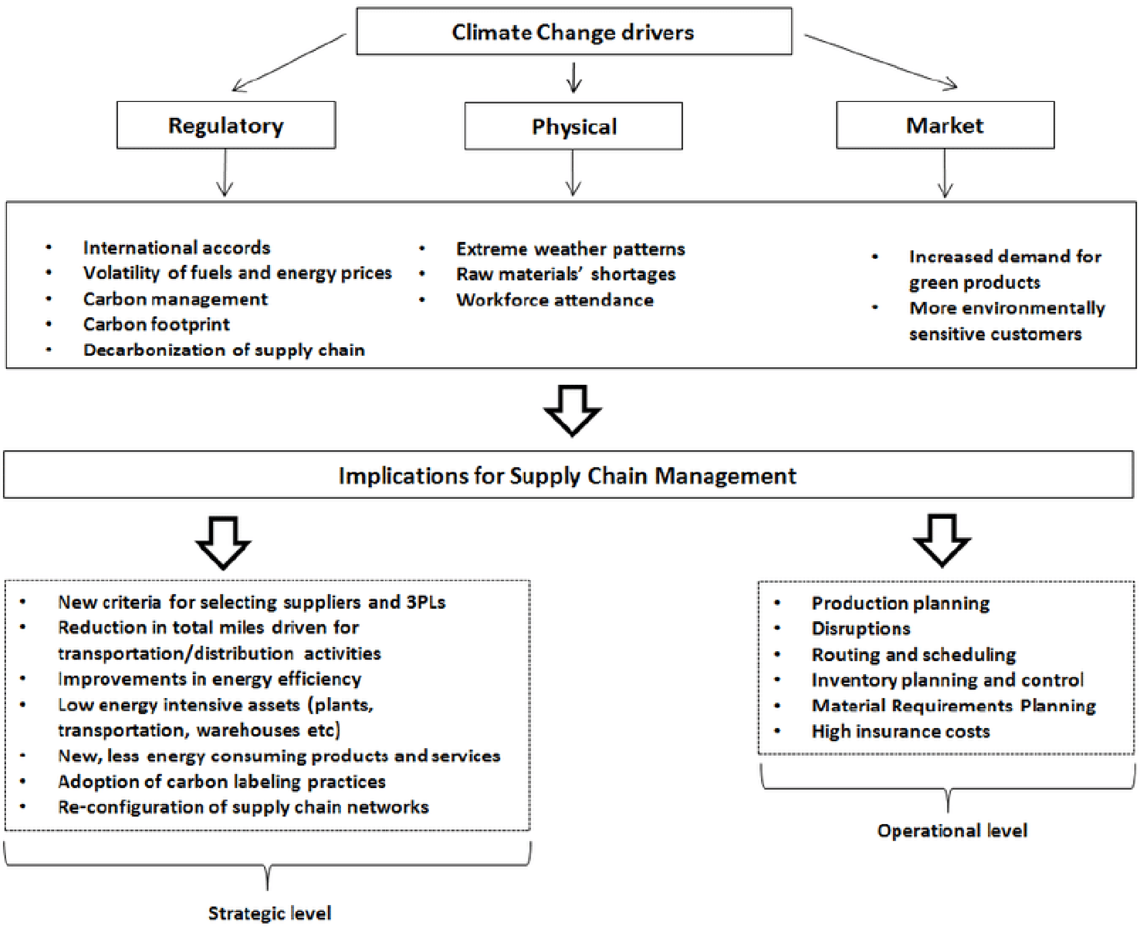

Figure 1 *Implications of Climate Change Drivers for Supply Chain Management (Dasaklis & Pappis, 2013)*

Considering these implications, it becomes clear why the concept of sustainable supply chain management is of growing importance for the long-term success of any business and hence also a topic of high and continuously increasing value within academic research.

2.1.3 Implementation

Shifting towards sustainable supply chain management can be a somewhat complex process, as successfully integrating sustainability into supply chain management requires a holistic approach that involves collaboration between suppliers, partners, and customers to create sustainable solutions that promote economic, social, and environmental sustainability (UN Global Compact, 2015).

The UN Global Compact (2015) has identified the following complementary actions that businesses should take in order to transform their supply chain into a more sustainable one:

"Commit:

- *Develop the business case by understanding the landscape and business drivers.*
- *Establish a vision and objectives for supply chain sustainability.*
- *Establish sustainability expectations for the supply chain.*

Assess:

- *Determine the scope of efforts focusing primarily on areas where there is the greatest actual and potential risk of adverse impact on people, environment and governance.*

Define and implement:

- *Communicate expectations and engage with suppliers to improve performance.*
- *Ensure alignment and follow up internally.*
- *Enter into collaboration and partnerships.*

Measure and communicate:

- *Track performance against goals and be transparent and report on progress."*

A crucial success factor across these steps is the availability of relevant data, especially in order to analyze and understand the current situation and assess future threats and changing conditions. Thorough analysis provides the necessary foundation to gain a deeper comprehension of possible economic implications in the mid- and long-run (UN Global Compact, 2015).
Hence, this research aims to provide this baseline work for the global Brazilian sourced soybean supply chain and therefore, indirectly also many businesses across the globe.

2.2 Soybeans

2.2.1 Relevance and Usage

The soybean is a legume originally domesticated over three thousand years ago in the North-Eastern part of China that has been a food essential traditionally grown and consumed in China and Eastern Asia for thousands of years before becoming a highly demanded global commodity by the 20th century (Hymowitz, 1970).

Today, soybeans are one of the world's most widely traded agricultural commodities, with major producers and consumers located in countries such as the United States, Brazil, China, and Argentina. As such, soybeans play a significant role in global trade and economic growth (Kingsbury et al., 2023). In 2021, Soybeans were estimated to have a total trade value of $78.5B, an increase of 22.4% compared to the previous year (The Observatory of Economic Complexity, 2021). For comparison, the soybean trade value is estimated to be three times the size of rice (De Maria et al., 2020).
World soybean production itself increased from approximately 160 million tons in an area of 70 million ha in 1998 to 350 million tons in 125 million ha in 2018 (Karges et al., 2022). In addition to its economic value, soybeans, being one of the most essential commodities in international trade, plays a vital role in global food security – one of the world's most pressing current and future challenges (Sun et al., 2018).

The reason soybeans are such an essential commodity for the world economy is their versatility and widespread use in various industries. Though the percentage of soybeans used in each industry may vary by country, region, and year based on factors such as local demand, production capabilities, and market conditions, the United States Department of Agriculture (USDA) provides data supporting the following global breakdown:
Around 70% of the world's soybean production is used for livestock feed, particularly in the poultry, swine, and dairy industry, as it is a cost-effective and nutritious source of protein for animal feed and hence plays a major role in supporting the global meat and dairy industries.
Due to its high nutritional value, approximately 17% are used for food products, such as tofu, soy milk, and other plant-based meat substitutes. Soybeans are also used as an ingredient in many processed foods, such as baked goods, cereals, and snacks. A large share of the world's population relies on soy products as the primary source of protein.

The third largest usage sector, with about 6%, is industrial purposes, such as in the production of plastics, textiles, and cosmetics, followed by an estimated 2% used for biofuel production, particularly biodiesel. Biodiesel is a renewable energy source that is becoming increasingly popular due to its lower carbon footprint compared to traditional fossil fuels. The remaining percentage of soybean production is used for seed production, as well as other uses such as pharmaceuticals and chemicals (USDA, 2021; Hart, 2017).

In summary, soybeans are highly relevant for the world economy due to their widespread use in food production, livestock feed, biofuel production, industrial uses, and overall global trade.

2.2.2 Global Soybean Trade

Nowadays, 170 countries are directly involved in global soybean trade flows – either as exporters, importers, or both. Most trade occurs between China, Brazil, and the United States of America (USA), creating a trade flow triangle across the Pacific Ocean, as seen in Figure 2. Historically being the soybean crop production center, China has become the leading importer to meet its growing consumer demand. In contrast, the USA and Brazil together are responsible for around 80% of the world's soybean exports (De Maria et al., 2020).

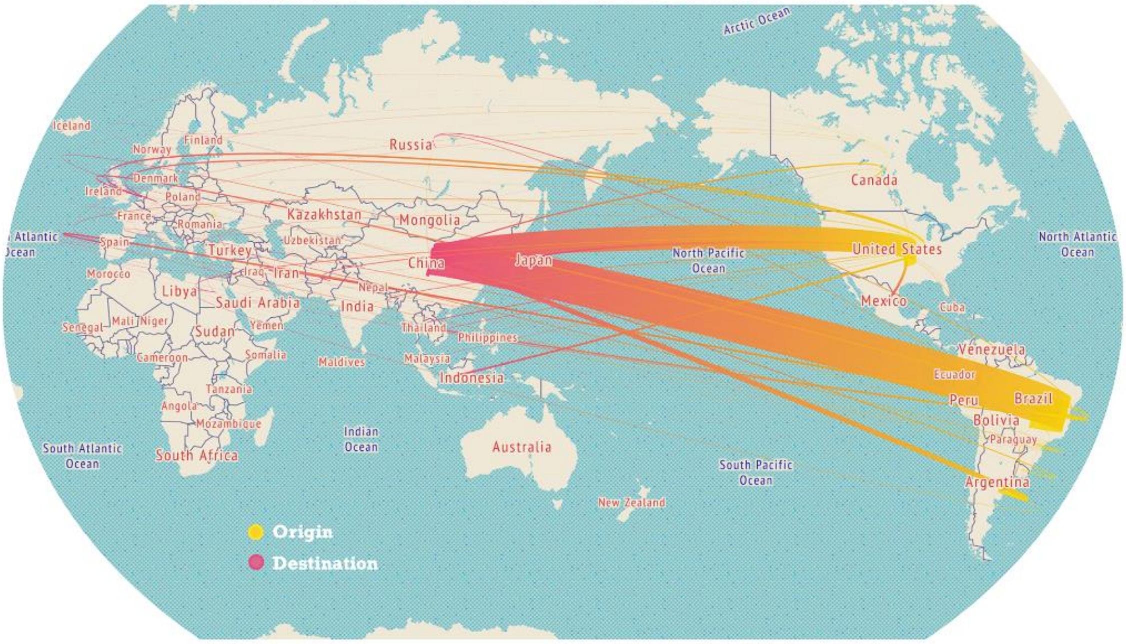

Figure 2 *Global Soybean Trade Flows in 2017 (De Maria et al., 2020)*

Production

In 2018 global soybean production (Figure 3) was estimated to be around 350 million tons, an increase in value of 8.4 times since 1968. This extensive growth in soybean production is supported by both factors: extensification and intensification. The soybean harvesting area grew by 4.3 times within this 50-year time span, mainly driven by Brazil and Argentina, while the average crop yield almost doubled at the same time, driven by Brazil and the USA (De Maria et al., 2020).

In 2018, five countries produced 88.1% of the world's soybean. The number one producer was the USA with 123.7 million tons, which was equal to 35.8% of total world production, followed by Brazil with 118.9 million tons (33.8%), Argentina with 37.8 million tons (10.8%), China with 14.2 million tons (4.1%) and India with 13.8 million tons (4.0%) (De Maria et al., 2020).

As of 2019, Brazil overtook the USA as the top soybean-producing country, with a production volume of around 129.5 million tons in 2021/22 compared to the USA with 121.5 million tons. This trend of Brazil being the number one soybean producer in the world is expected to continue in the following years (US Department of Agriculture, 2023).

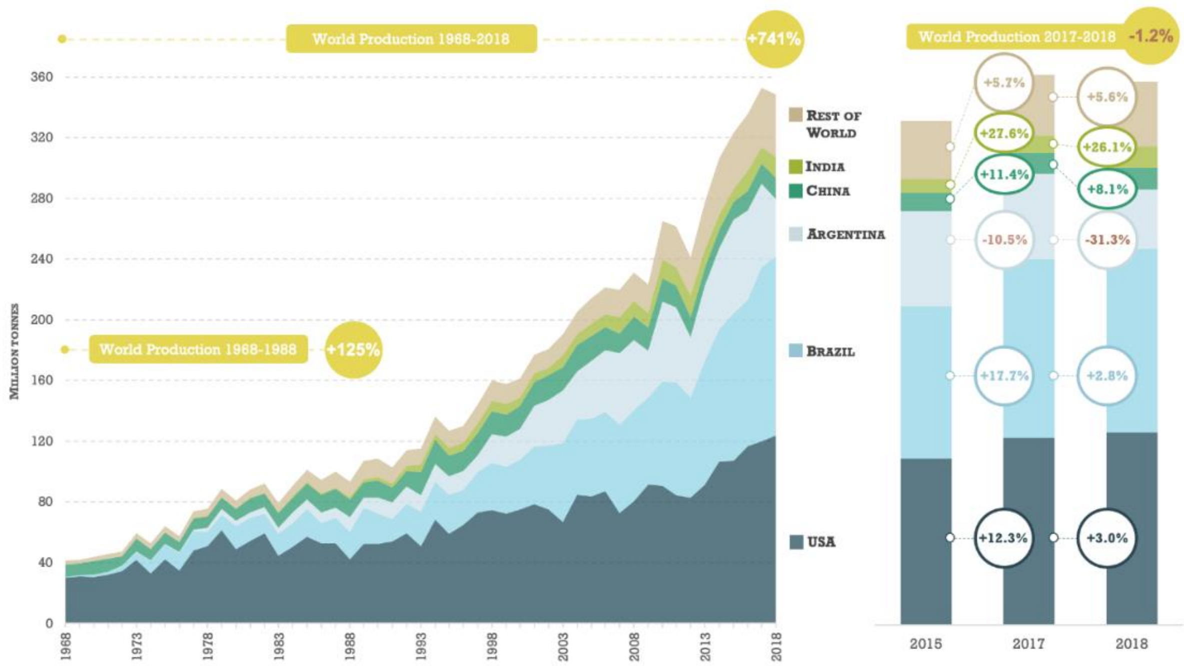

Figure 3 *Global Soybean Production 1968-2018 (De Maria et al., 2020)*

Export

In line with production quantities, the Americas represent the leading soybean exporters, with most soybeans traded globally from the USA, Brazil, and Argentina (Figure 4). While in 1997, approximately 2/3 of soybean exports originated in the USA, Brazil has now become the main soybean exporter in the world, accounting for 44.6% compared to the USA with 37.9% and Argentina with 4.9% in 2017. This development can be explained by less favorable weather conditions in the USA and the international trade frictions that the USA has been facing with China (De Maria et al., 2020).

In 2022/2023, Brazil is forecasted to export 92 million tons of soybeans compared to 54 million tons by the USA (US Department of Agriculture & USDA Foreign Agricultural Service, 2023).

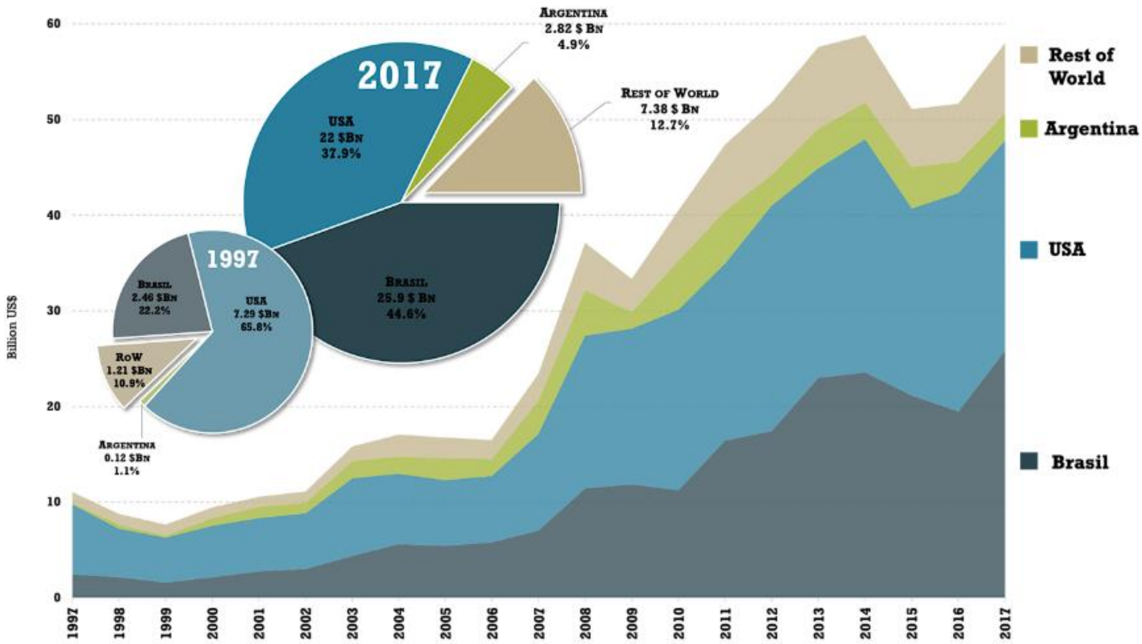

Figure 4 *Global Soybean Export Flows 1997-2017 (De Maria et al., 2020)*

Consumption

Regarding soybean consumption, the five largest consumers – China, the USA, Argentina, Brazil, and the EU – alone consume around 80% of global produce. As shown in Figure 5, total global consumption has more than doubled from approximately 150 million tons in 1999 to around 350 million tons in 2019 (De Maria et al., 2020).

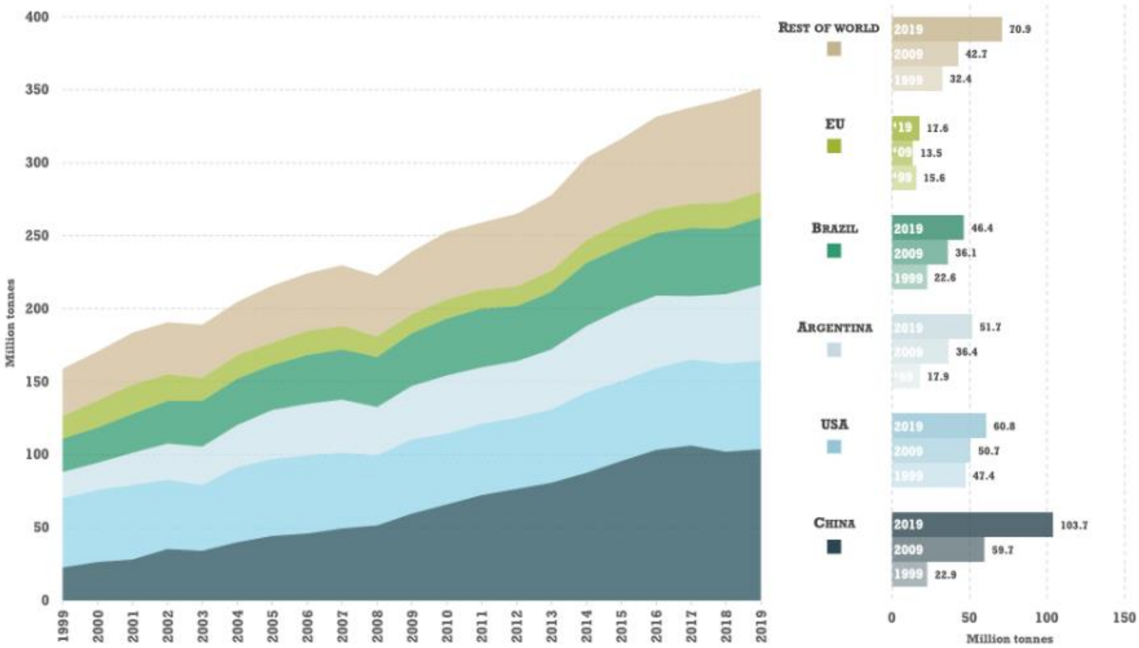

Figure 5 *Global Soybean Consumption 1999-2019 (De Maria et al., 2020)*

While the increase in consumption is a global trend, the main driving consumer groups are China and the "the rest of the world" category. For many years the USA was the main soybean consumer. In 2009 China surpassed the USA and became the consumer of almost 1/3 of the world's soybean within another ten years. This strong increase in soybean consumption in China and many other mainly developing economies accounted for in the "rest of the world" category can be explained by the growing demand for livestock products by an emerging middle class with more spending power for such commodities in these countries (De Maria et al., 2020; Lee et al., 2016).

Import

These trends in consumption are reflected accordingly in global soybean import flows, with China being the leading importer accounting for 63% of all soybean imports in 2017 compared to only 5.5% in 1997 (Figure 6). While soybean production in the country remains relatively stable over this 20-year time span, the increase in consumption demand created a growing need to import foreign soybeans. Beyond China, the Asian continent as a whole was responsible for 80% of all soybean imports in 2017. In comparison, the second and third largest importers globally, Mexico and the Netherlands, together only accounted for 5.8% (De Maria et al., 2020).

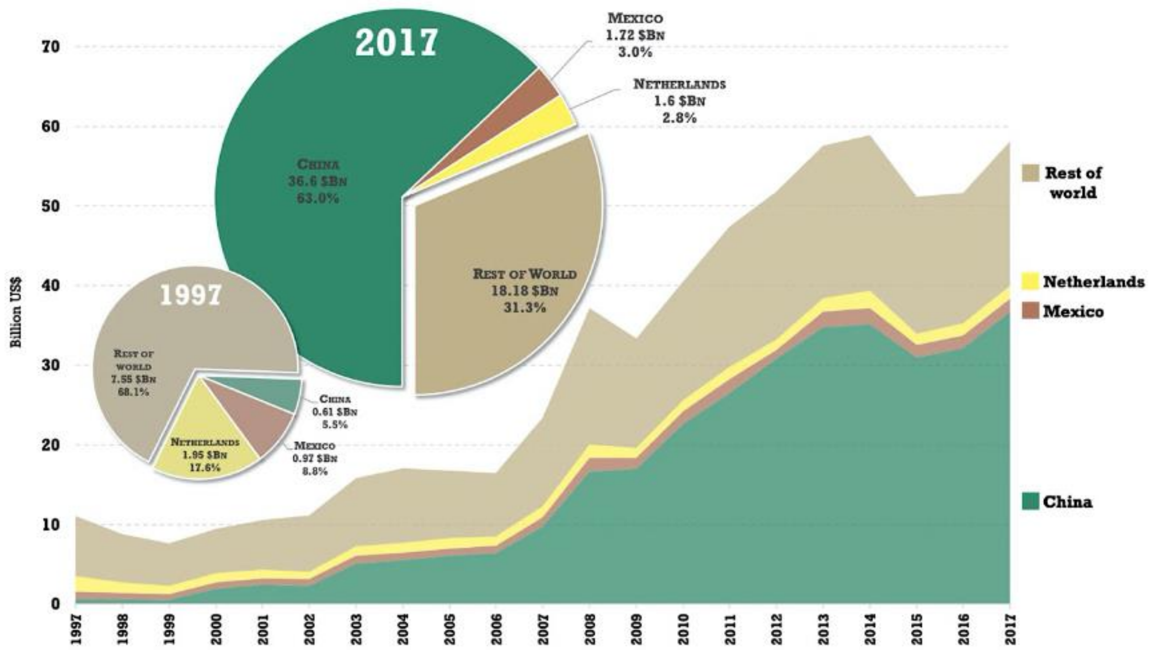

Figure 6 *Global Soybean Import Flows 1997-2017 (De Maria et al., 2020)*

By 2022 China's yearly imports already rose to 96 million tons of soybeans, followed by the EU with 14.4 million tons and Mexico with 6.4 million tons (US Department of Agriculture & USDA Foreign Agricultural Service, 2023).

These trade dynamics not only show the economic relevance of soybeans for the entire world but mainly for China, Brazil, and the USA as major players in international soybean trade.

2.2.3 Climate Change Impact

Like in many other economically relevant areas, climate change is likely expected to have a significant impact on global soybean production and trade. The effects can vary by region, and growing conditions, but developing an understanding of and addressing the potential impacts of climate change on agriculture is a significant challenge that will require ongoing research and innovation (Souza & Almeida, 2019).

There are five main pillars of how soybean production will be influenced: temperature and precipitation, pests and diseases, carbon dioxide concentration, extreme weather events, and changes in growing conditions.
Soybeans are sensitive to changes in temperature and precipitation patterns. Increased temperatures can reduce yield by reducing the number of pods and seeds per plant. Changes in precipitation patterns, such as increased drought or flooding, can also reduce yields.

Secondly, climate change can alter the distribution and prevalence of pests and diseases that can affect soybean plants, potentially increasing the risk of crop damage and yield loss. Thirdly, higher concentrations of carbon dioxide in the atmosphere, which are associated with climate change, can increase soybean yields by promoting the growth and development of the plant. Moreover, extreme weather events, such as hurricanes, floods, and droughts, can cause significant damage to soybean crops, leading to lower yields and economic losses. Lastly, climate change can alter growing conditions for soybeans, such as changes in soil moisture, nutrient availability, and pest pressure, which can affect crop growth and yield.
As changes in temperature and precipitation patterns impose the most immediate and direct impact, these are relevant variables to analyze the impact of changing climatic conditions on soybean yield (Lobell & Gourdji, 2012; Souza & Almeida, 2019; IPCC, 2014).

Generally, soybean planting occurs in the spring, followed by a growth stage in the summer and harvest in the fall. The most weather susceptible is the growing stage, where the flowering and pod development takes place. High temperatures and inadequate rainfall during this time can cause stress on the plants and lead to a reduction in yield (Endres & Kandel, 2021).

Multiple studies were able to identify a negative relationship between mean seasonal air temperature and crop yields through direct heat stress as well as indirect moisture stress as a result of increased vaporization. These effects were found to be amplified through a decreased level of precipitation resulting in drought. Historical data from 1970-2013 suggests that there is a compound heat-drought effect on crops, as soybean yield decreased more during growing seasons in which higher temperatures were complemented by decreased precipitation. Hence, a combination of hot and dry conditions, as expected to become more likely under global warming, creates a potential risk to global agricultural output, including soybean yield (Lesk et al., 2021).

Figure 7 shows the standardized soybean yield sensitivity to mean growing season maximum air temperature estimated as the linear slope coefficient (βT), with units of σ of yield per σ of temperature, suggesting an overall decline by 0.3-0.4 standard deviations (σ) per σ of increasing temperature (Lesk et al., 2021).

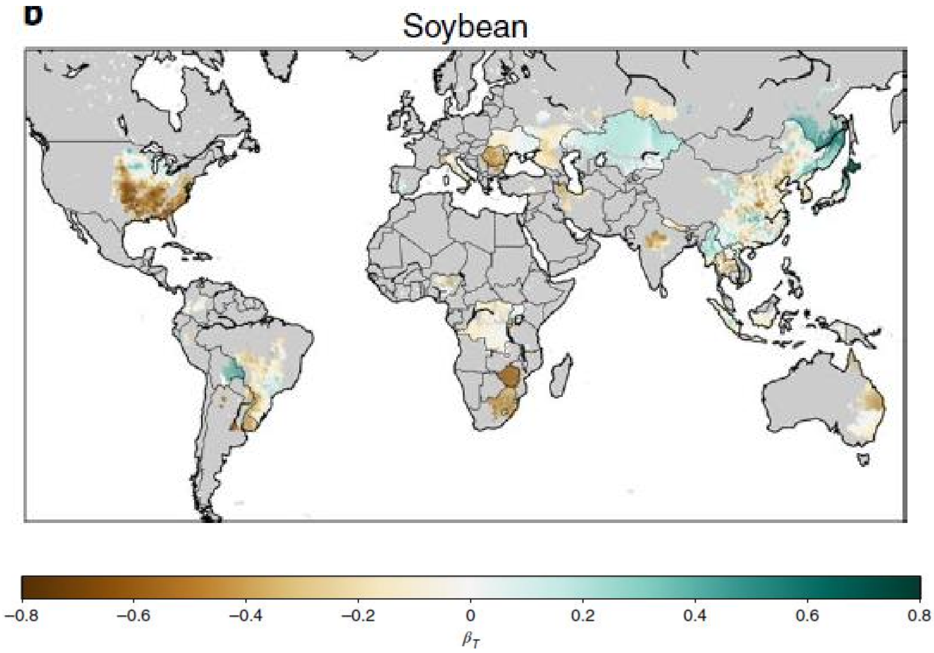

***Figure** 7 Standardized Soybean Yield Temperature Sensitivity (Lesk et al., 2021)*

The potential shift in global soybean yield

Climate change is expected to have complex and region-specific effects on soybean growth and yields. While some regions may experience increased yields due to longer growing seasons and higher carbon dioxide concentrations, others may experience decreased yields due to increased temperatures and changes in precipitation patterns. Additionally, changes in pest and disease pressures and water availability may further complicate the picture (Schauberger et al., 2020).

Lesk et al. (2021) conducted an extensive global analysis of the impact of stronger temperature–moisture couplings on a range of crop yields using historical patterns in agriculture and weather along with several climate model projection scenarios. Their research concluded that global corn and soybean yields can be expected to fall by 5% between 2050 and 2100 due to the combination of a drier and hotter climate. While reductions are mainly expected in the Midwest of the USA and European producers such as Romania, Bulgaria, and Italy, some areas in India, China, and Japan are expected to experience improved growing conditions for soy. As these regions have a monsoon season, an increase in precipitation will likely be able to outweigh an increase in temperature. Changing conditions across the globe will hence impact what countries will be able to export soy profitably.

Another study found that climate change may also lead to increased soybean yields in some regions in northern latitudes, such as Russia and Canada, where temperatures are currently too cold for optimal soybean growth. However, the study also found that most major soybean-producing regions, including Brazil and the United States, will likely experience decreased yields due to climate change. The study highlights that the effects of climate change on soybean production will depend on a range of factors, including the specific growing conditions in each region, as well as the extent and rate of climate change. While some areas may benefit from the changing climate, overall, the impacts of climate change on global soybean production are expected to be negative (Schauberger et al., 2020).

2.2.4 The Brazilian Perspective

While the already observable impact of climate change on agricultural production around the world is often linked with the overarching issue of global food security (Cedric et al., 2022), the economic perspective of producer countries should also not be neglected. As currently the world's largest soybean producer and exporter in the world, the impact of climate change on soybean production in Brazil is highly relevant to the country's economy and the global soybean supply chain.

Soy is extremely important for the Brazilian economy, as it is one of Brazil's main agricultural commodities and a significant source of export revenue. According to data from the Brazilian Ministry of Agriculture, Livestock, and Supply, soybeans represented about 14% of Brazil's total exports in 2021, making it the country's second-largest export product after iron ore and accounting for a value of approximately US$ 48 billion (Brazilian Ministry of Agriculture, Livestock, and Supply, 2021).
Soybeans are a crucial source of income for Brazilian farmers across the country as they are grown in many different regions of Brazil, including the states of Mato Grosso, Paraná, and Rio Grande do Sul. However, the economic impact of soybean on the Brazilian economy extends beyond just its production. It encompasses various industries that produce inputs and machinery and facilitate logistics and transportation. These industries have a significant presence in the country and provide ample employment opportunities (De Maria et al., 2020).

At the same time, Brazilian soybean exports have been found to be directly linked to illegal deforestation, which is a primary environmental concern in Brazil and for the world climate. A recent study found a direct linkage between soybean production in the Mato Grosso region and illegal deforestation. The study estimated that over a quarter of total deforestation in the region between 2012 and 2017, most of it illegal due to the lack of licenses, took place on soybean farms. It is estimated that more than 80% of the soy produced on these farms is exported to global markets, with 46% going to China and 14% to the EU. Deforestation has severe negative impacts on biodiversity and climate, and illegal deforestation exacerbates these impacts (Vasconcelos et al., 2020).

Furthermore, illegal deforestation also has an economic cost, potentially affecting trade. For example, the EU-Mercosur trade deal, expected to increase Brazil's exports and imports by over US$ 250 billion, was put at risk by the record number of fires in the Amazon in 2019, of which many are believed to be linked to illegal activities. At the same time, global companies and investors have also expressed their concerns that they might be forced to boycott Brazilian commodities because of the increased risks of land grabbing and deforestation (Vasconcelos et al., 2020).

Hence, Brazil and the global economy are facing a challenging situation in how to increase production in order to continue meeting the growing global soybean demand without causing further ecosystem loss. To increase sustainable production many measures on different levels, such as the promotion of crop expansion over degraded pasture, increased productivity on livestock systems, and financial incentives for ecosystem protection, are needed (Sparovek et al., 2018).

At the same time, however, there is a crucial need to account for potential changes in soybean yield across the country due to changing climatic conditions. Climate change is expected to have a significant impact on soybean yield in Brazil, as changes in temperature and precipitation patterns can affect crop growth and development.

Research suggests that substantial reductions in some regions of the country are to be expected. For example, a 2012 study analyzing the overall impact of climate change on global crop productivity using statistical models suggests that climate change is likely to lead to a decline in soybean yield in Brazil, with some regions experiencing reductions of up to 30% by the year 2050. The study also highlights that the negative impacts of climate change on soybean yield are expected to be more pronounced in certain regions of Brazil, such as the north-eastern and south-eastern regions, which are projected to experience higher temperatures and reduced precipitation (Lobell & Gourdji, 2012).

Taking all these factors into account creates a complex narrative for a future, sustainable supply of Brazilian soybean.

3. Literature Review

Numerous scholars have explored the causal relationship between weather variation and agricultural output and attempted to forecast crop yield using statistical models under different climatic scenarios. The following section presents an overview of existing literature, including methodologies and the most relevant findings in this field, summarizing relevant studies, presenting different methodological approaches, relevant developments within the new climate economy literature, and lastly, existing studies investigating the impact of climate change on Brazilian soybean yield.

3.1 Crop Yield Prediction Using Regression Models

There are three main categories of state-of-the-art crop yield prediction methods used in contemporary research: linear models, machine learning models, and crop models (Ansarifar et al., 2021). While these three approaches have complementary strengths and limitations, the use of linear statistical models trained on historical yield and weather data, such as growing season average temperature and precipitation, has established itself as a common approach in crop yield prediction (Lobell & Burke, 2010). Regression models are the most widely used method because of their simple and straightforward nature while simultaneously resulting in reliable crop forecast models (Kumar et al., 2014). Numerous scholars have evaluated the predictive power of crop yield estimation models using different regression techniques with satisfactory results (Shastry et al., 2017). A selection of these studies is chronologically presented in this section. The research body suggests that multiple linear regression, specifically, is the statistical model most commonly used for yield prediction (Gopal & Bhargavi, 2019).

Isik & Devadoss (2006) were among the first scholars within this century to develop an econometric crop yield model depending on weather variables. Their research evaluated the impact of climate variables such as temperature and precipitation levels on the mean, variance, and covariance of crop yields in order to examine the potential implications of global climate change on agricultural output. Using historical crop yield and climate data, they developed their econometric model based on the 1978 Just-Pope stochastic production function as follows:

$$y_{it} = f(x_{it}; \beta) + \omega_{it} h(x_{it}; \delta)^{1/2}$$

Equation 1 *Just-Pope Stochastic Production Function*

where y_{it} is representing the crop yield for region i at year t, x the weather variables, with the stochastic term with mean zero and variance σ_{ω}^{2} and β and δ being the production function parameters to be estimated. An estimation of the first part of the equation after the equal sign accounts for the effects of the independent variables on mean crop yields, and an estimation of the second part accounts for the effects of the independent variables on the variance of crop yields. Isik & Devadoss (2006) used the maximum likelihood method to estimate the Just-Pope production method. The results of their analysis showed that, based on their econometric model, the impact of temperature and precipitation on crop yields varies across different crops.

Lobell & Burke (2010) used the perfect model approach with a crop model based on simulated historical variability in order to analyze the capability of three different statistical models – time series, panel, and cross-sectional – to predict the impact of variance in mean temperature and precipitation on crop yield. Under the assumption that a change in temperature or precipitation will have the same percent impact on yields independent of yield levels, they argued to follow the conventional approach of using log units to express yield.
For the time-series model, the simulated data were fitted to the following equation:

$$log(Y_t) = \beta_0 + \beta_1 T_t + \beta_2 P_t + \varepsilon_t$$

Equation 2 *Time-Series Log-Crop-Model*

with Y_t being yield, T_t being growing average temperature, and P_t being growing season total precipitation in year t, respectively. The model parameters to be fit were represented by β0-2, and their values were obtained using least-squares. ε is an error term.
The panel regression model approach combines the data, including site-specific intercepts, in order to account for omitted time-invariant variables. Lobell & Burke (2010) combined the 198 sites under analysis using the following equation:

$$log(Y_{i,t}) = \beta_{i,0} + \beta_1 T_{i,t} + \beta_2 P_{i,t} + \beta_3 T_{i,t}^2 + \beta_4 P_{i,t}^2 + \varepsilon_t$$

Equation 3 *Panel Regression Model with Squared Terms*

with $\beta_{i,0}$ representing an intercept for each site i to, as mentioned, balance the absence of variables accounting for spatially varying factors such as soil quality, for which no

observations are present. Additionally, this model includes squared terms for T and P, which, in time-series models, are usually omitted as there is a limited number of observations and temperature and precipitation have a comparably narrow range, providing the opportunity to reasonably approximate yield through a linear function.
The third method used for comparison in their analysis was the cross-section model, which computed the average yields, temperature, and precipitation at each site for estimation. This formula again includes squared terms for T and P in order to account for nonlinearities in yield:

$$log(Y_{i,avg}) = \beta_0 + \beta_1 T_{i,avg} + \beta_2 P_{i,avg} + \beta_3 T_{i,avg}^2 + \beta_4 P_{i,avg}^2 + \varepsilon_t$$

Equation 4 *Cross-Section Model*

Lobell & Burke's research concluded that generally, statistical models are a valuable tool for predicting yield responses to changing climatic conditions. All three statistical approaches have been able to replicate some of the significant aspects of the simulated responses to changes in temperature and precipitation, exhibiting comparably low bias non-parametrically measured through the median error. For instance, all three methods had a median error of less than 2% for predicting impacts of +2◦C. Based on their findings, the effectiveness of statistical models depends on the particular response being studied. Time-series models were found to be more effective in estimating precipitation responses, while panel and cross-section methods were found to be more reliable in the prediction of temperature responses. Lobell & Burke also highlight that the accuracy of different statistical approaches is influenced by the spatial scale of the training data and the scale at which output projections are required. Generally, statistical models are better suited for broader scales of interest, resulting in more reliable climate projections (Lobell & Burke, 2010).

Kumar et al. (2014) used time series weather and yield data for three different crops in their analysis, applying a step-wise multiple regression model. They concluded that within their research area of forecasting paddy, wheat, and sugarcane crops in the southern Gujarat area in India, step wise multiple regression analysis can be regarded as a highly efficient method.

Similarly, Sellam & Poovammal (2016) used linear regression analysis to analyze the predictive power of environmental parameters like Area under Cultivation, Annual Rainfall, and Food Price Index for crop yield over a 10-year time period with satisfactory results.

Their findings also suggest that yield is mainly dependent on annual rainfall compared to the other variables under evaluation.

Shastry et al. (2017) contributed to the research body by comparing the results of different regression models, namely quadratic, pure quadratic, linear, polynomial, generalized linear regression, and stepwise linear regression models, for different crops. Their results suggest that different regression models provide the best fit for different crops and data sets. At the same time, they were generally able to support the utilization of regression techniques for yield prediction through satisfactory results.

Shah et al. (2018) used multivariate polynomial regression, support vector machine regression, and random forest models to predict crop yield based on humidity, temperature, and rainfall data obtained from the United States Department of Agriculture, resulting in the best results for the support vector machine regression approach.

Sharma et al. (2018) applied stepwise regression to forecast crop yield based on maximum and minimum temperature, rainfall, and humidity during crop growing seasons as well as historical crop yield data for soybean and wheat for eight districts within the Malwa agroclimatic zone. The forecast model they developed was a modification of previously studied models using composite weather indices.

Sharma et al. used step-wise regression to select the significant variables and then evaluated model performance with various statistical parameters. Their main finding was that the predictive power of their model varied across the different regions, which they explained through the context that crop management practices apart from the weather, which was not accounted for in the model, varied widely across the regions (Sharma et al., 2018).

Gopal & Bhargavi (2019) presented a novel approach for crop yield prediction combining two of the most commonly used approaches, the statistical model of multiple linear regression and the machine learning algorithm of the artificial neural network, into a new hybrid model resulting in better accuracy than the two individual models, support vector regression, k-nearest neighbor, and random forest models. However, thus far, these findings have not been sufficiently validated by other scholars.

Gbadamosi et al. (2019) studied the impact of potential changes in the climate on the yield of root and tuber crops in Nigeria using the k-means classification algorithm and multiple linear regression. In their case, only rainfall was found to have a strong linear relationship with yield.

For Nigerian root and tuber crops, temperature and CO2 emission were found not to be a good fit under their model to predict yield.

Joshi et al. (2020) conducted a study evaluating the performance of stepwise multiple linear regression, general additive, and support vector machine models to estimate yield for maize and soybean in the US central corn belt using total rainfall, average air temperature, and the difference between maximum and minimum air temperature on different timescales (weekly, biweekly, and monthly). While all models presented acceptable results, the supply vector machine model was able to outperform the other two due to its ability to model nonlinear functions. Joshi et al. also found that adding the temperature difference to the independent variables was able to significantly improve all yield estimation models, advocating for the inclusion of additional weather variables beyond average temperature and precipitation where respective data is available (Joshi et al., 2020).

Ansarifar et al. (2021) developed a new crop yield predictive model, called the interaction regression model, based on a combinatorial optimization algorithm, selecting the most revealing environmental and management variables and detecting their most noticeable interactions, which are then quantified through multiple linear regression. Their interaction regression model aims to describe the relationship between crop yield (y) and a set of environmental and managerial independent variables (X) as follows:

$$\widehat{y_i} = \beta_0 + \sum_{j \in P} X_{i,j}\beta_j + \sum_{m \in M} b_m Z_{i,m} \qquad \forall i \in N$$

Equation 5 *Interaction Regression Model*

where N is the set of sample observations (with one sample per county per year), P is the set of explanatory variables, M is the set of intertheactions, $\widehat{y_i}$ is predicted crop yield of sample i, β_0 is the intercept of crop yield, β_j is the additive effect of variable j, $X_{i,j}$ is the explanatory variable j of sample i, b_m is the effect of interaction m, and $Z_{i,m}$ is the interaction variable m of sample i (Ansarifar et al., 2021).

Even though Ansarifar et al. (2021) conducted a comprehensive case study comparing the performance of their proposed model with eight other machine learning models predicting the yield of two crops in 293 counties in the US between 2015 and 2018 with satisfactory results, this novel model has not been tested in further applications.

Lesk et al. (2021) used a simple linear regression model to estimate historical crop yield sensitivity to heat. They argue for the use of such a simple model to aid the interpretability of spatial patterns while also addressing the main limitation of this approach of reduced specificity through using seasonal mean temperature instead of accounting for sub-seasonal temperatures. However, comparing their results to those of a multi-model study, they found sufficiently consistent results across both, arguing that such a simplified approach can be justified (Lesk et al., 2021).

3.2 New Climate Economy Literature

The risks and costs of inaction regarding the physical and economic impacts of climate change provide a compelling case for the urgent need to shift towards a sustainable, low-carbon economy through bridging the gaps between the academic and scientific climate and economic communities, policymakers, and business leaders (Global Commission on the Economy and Climate, 2014; Global Commission on the Economy and Climate, 2018; International Institute for Sustainable Development, 2018).

In order to do so, a thorough understanding of the impact of changes in climate on economic outcomes is a fundamental pre-requisite. One of the major problems in this field has been differentiating between the effects of climate and other potentially correlated characteristics on such outcomes. These probable cross-sectional correlations have been a significant challenge in identifying causative effects and hence evaluating the past, present, and future impacts of a changing climate. In recent years, there has been a rapid growth in research using panel methodologies to examine how variation in weather variables such as temperature, precipitation, and extreme weather events over time within a given spatial area can influence economic outcomes such as agricultural output, national income, industrial output, labor productivity, political stability, energy use, health, migration and more. In order to isolate the effect of climatic variables from the numerous other correlated factors, longitudinal data is being used in this approach (Dell, Jones & Olken, 2014).
The standard panel regression models within this new climate economy literature usually build upon the form:

$$y_{it} = \beta C_{it} + \gamma Z_{it} + \mu_i + \theta_{rt} + \varepsilon_{it}$$

Equation 6 New Climate Economy *Standard Panel Regression Model* with y being the economic outcome, C the climatic variables and Z other time-varying observables with t indexing time and i spatial areas. The inclusion of other time-varying observables is a methodological choice as it may absorb residual variation, resulting in more precise estimates, yet simultaneously posing the risk of over-controlling, hence negatively affecting cross-sectional estimation, in the case of the variables being endogenous to the weather variation. Therefore, it is rather recommended to only include credibly exogenous regressors as control variables Z_{it}. In addition, these models include fixed effects for the spatial areas, μ_i, to absorb observed and unobserved fixed spatial characteristics, isolating weather shocks from potential sources of omitted variable bias. Moreover, does the inclusion of time-fixed effects, θ_{rt}, account for common trends, separating the relevant relationships from idiosyncratic local shocks. As these time-fixed effects may differ within subsamples of the spatial areas, the subscript denotes r instead of i (Dell et al., 2014).

3.3 Climate Change Impact on Brazilian Soybean Yield

While Vogel et al. (2019) suggest that climate conditions explain 20%–49% of the variance of global aggregated yield anomalies, there are studies reaching back as early as 1994 that specifically attempted to estimate the impact of climate change on Brazilian soybean yield.

De Siqueira et al. (1994) used two different crop growth models (CERES and SOYGRO) under several climate change scenarios generated by GISS, GFDL, and UKMO, which were selected based on previous agroclimatic studies, to simulate the production of wheat, maize, and soybean for 13 specific sites in Brazil. Their research concluded that global warming would result in a reduction of wheat and maize season length and yields, while soybean was less likely to be affected due to the CO2 effect and soybean yield, therefore even expected to increase.

De Siquiera et al. (1994) further found differences in the regions under analysis. Specifically, regions in the Northeast were found to be expected to be more vulnerable to soybean production under changing climatic conditions.

Justino et al. (2013) evaluated the viability of cultivating maize and soybeans within the states of Mato Grosso and Para using future climate scenarios for the time span of 2070 – 2100. They used observational data and regional climate simulations (HadRM3) for crop modeling with the DSSAT software. While they found a substantial reduction to be expected for maize yield, their results for soybean yield were rather ambiguous. Under different scenarios, assuming variability in soil treatment, water stress, and greenhouse warming conditions, productivity could be expected to rise or decrease.

Da Silva et al. (2021) simulated soybean yields for 16 strategically selected agroclimatic zones in Brazil, which were to represent the production area in the country, using 40 different future climate scenarios for the year 2050. Their research found that soybean yield is expected to vary by +1 to +32% across the zones in the average scenario compared to current yields. However, this positive development is only explained by the positive effect of increasing CO2 on crop water productivity, overcoming the adverse effects of temperature and water stress increases.

Silva et al. (2023) estimated the effect of temperature and precipitation on soybean yields (kg/ha) using panel data regression at the municipal level within the Cerrado biome and at the farm level in a subset region known as Matopiba using historic data from 1980 to 2016. Their analysis resulted in an estimated reduction of 6% in soybean yield for each one degree Celsius increase in temperature.

Furthermore, on the methodological side, Schwalbert et al. (2020) explored the use of satellite imaging combined with weather data to develop more accurate models to forecast Brazilian soybean yields. They used Long-Short Term Memory (LSTM), Neural Networks, satellite imagery, and weather data to compare the performance of different algorithms for forecasting soybean yield on different days of the year (DOY) using the normalized difference vegetation index, the enhanced vegetation index, land surface temperature and precipitation as independent variables in the northern region of the Rio Grande do Sul state in southern Brazil. They were able to forecast soybean yield at a municipality scale with a mean absolute error of 0.24 Mg ha^{-1} at DOY 64 with a superior performance found for the LSTM neural networks compared to other algorithms with the exception of DOY 16 where multivariate OLS linear regression was found to provide the best performance.

While there is clearly already a substantial research body on soybean yield prediction under different climatic scenarios in Brazil, what all these presented studies have in common is that their analysis focuses on a pre-selected area within Brazil rather than the entire country.
At the same time, there is a variety of research in this field on a global scale, such as by Lesk et al. (2021) and Vogel et al. (2019), whose approaches were presented above.

To the best of the author's knowledge, however, there is no published research specifically looking at the potential impact of climate change on the entity of the Brazilian country. As national production quantities are expected to increase with global demand, soybean cultivation area is increasing rapidly across the country, creating a need for forecasting models accounting for all regions of the country (Cattelan & Dall'Agnol, 2018), which is why this research aims to contribute to the availability of relevant data taking the Brazilian perspective.

4. Research Question and Hypotheses Development

The aim of this research is to understand and contextualize the potential impact of climate change on the global soybean supply chain by following the main research question:

How does a change in temperature and precipitation affect Brazilian soybean yield?

Based on the presented literature, the following hypotheses were developed.
The research body suggests that soybean yield, among other factors, is highly subjected to temperature and precipitation, especially during the growth stage in the summer months. The optimum temperature during soybean growth is estimated at 18 to 26 degrees Celsius (Novikova et al., 2020). Considering the average Brazilian climate, the risk of exceeding this temperature frame is extensively higher than in the opposite scenario. With temperatures rising above 29 degrees Celsius, soybean plants generally were found to suffer from heat stress, with a decrease in photosynthesis and limited growth and development resulting in a negative effect on yield and quality (Jianing et al., 2022). Therefore, the first hypothesis is as follows:

H1: An increase in annual average temperature leads to a decrease in soybean yield.

Furthermore, the presented research body suggests that sufficient moisture availability is crucial for soybean growth, with yield decreasing due to both insufficient but also excessive precipitation (Sellam & Poovammal, 2016). Due to drought posing a higher risk to soybean growth, the second developed hypothesis is the following:

H2: A decrease in annual precipitation leads to a decrease in soybean yield.

Lastly, the existing literature emphasizes the importance of evaluating the amplified effect of a decreased level of precipitation on moisture stress during times of high temperature, already increasing the level of vaporization (Lesk et al., 2021). A combination of heat and drought is therefore expected to further decrease soybean growth through a more substantial temperature-moisture coupling effect, leading to the third hypothesis:

H3: An increase in average temperature during drier periods leads to a decrease in soybean yield.

5. Data

Two different datasets were used to estimate the impact of temperature and precipitation changes on Brazilian soybean yield: the first one containing historical crop yield data and the second one containing historical temperature and precipitation data.

Dataset 1: Historical crop yield data

The first dataset is retrieved from an aggregate database system called SIDRA provided by the Brazilian Institute of Geography and Statistics (IBGE - Instituto Brasileiro de Geografia e Estatística). The used dataset is the following: “Produção Agrícola Municipal: Tabela 1612 - Área plantada, área colhida, quantidade produzida, rendimento médio e valor da produção das lavouras temporárias” which is a collection of agricultural production data on the municipality level (SIDRA IBGE, 2022). The division of all 5,570 Brazilian municipalities can be seen in Figure 8.

After filtering the dataset, it provides values for the *average yield of soybean production* (in kilograms per hectare) on an *annual basis for the ten-year span 2011 – 2020* for *5,563 municipalities*.

Figure 8 *Brazilian Municipalities (Kasecker et al., 2018)*

Figure 9 provides a first overview of the concentration of the area used for soybean production. However, it is important to mention that this is only capturing a specific moment in time (2015) in the middle of the ten-year time span under analysis. The used dataset clearly shows the level of diversification in soybean production across the country. While in 2011, only 1,831 municipalities presented values for soybean yield, by 2020, this number increased to 2,388. Even though it is not possible to indefinitely verify if all of these municipalities became new soybean production areas or if some of them simply improved their reporting standards, the literature supports a rapid increase in soybean cultivation areas across the country (Cattelan & Dall'Agnol, 2018).

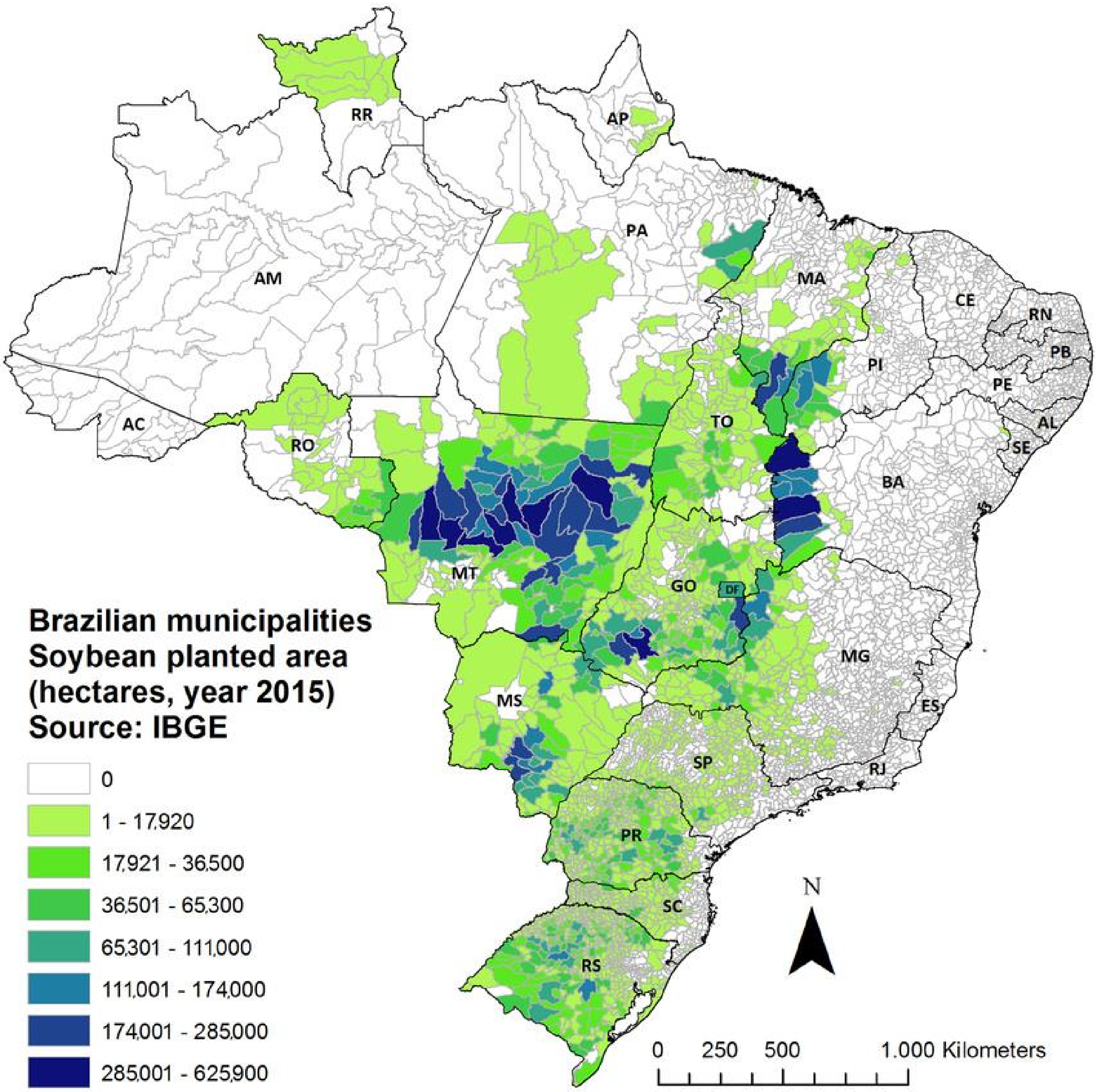

Figure 9 *Brazilian Soybean Cultivation Area (Martinelli et al., 2017)*

Dataset 2: Historical temperature and precipitation data

The second dataset is the "Statistically enriched geospatial datasets of Brazilian municipalities for data-driven modelling," published in 2022 by Abdalla et al. This dataset contains a variety of *temperature and precipitation variables* for each of the *5,570 Brazilian municipalities* on an *annual level ranging from 1981 to 2020*. The raw data was sourced by the scholars as described in the following:

> The observed precipitation came from the Climate Hazards Group Infrared Precipitation with Stations data (CHIRPS), with a daily temporal resolution and a spatial resolution of approximately 5 km (0.05°). The observed temperature drawn from the NCEP Climate Forecast System Reanalysis (NCEP/CFSR) at a 6-hour temporal resolution and a spatial resolution of approximately 50 km (0.5°). The NCEP/CFSR gridded dataset was spatially downscaled to a higher spatial resolution of 5 km (0.05°) using bilinear interpolation in order to have the same spatial resolution as CHIRPS (Abdalla et al., 2022, p. 2).

Considering these spatial resolutions, the quantity of values used to calculate the available averages for the temperature and precipitation variables, as presented in Table 2, varies between 1 – 5,213 for temperature and 1 – 5,235 for precipitation, respectively, depending on the size of the municipality.

Temperature (values provided in Kelvin)	CHG-bio1	Annual average temperature
	CHG-bio2	Average Daytime Temperature Variation (Monthly average(Tmax-Tmin))
	CHG-bio3	Isothermality ((bio2/bio7) (* 100))
	CHG-bio4	Temperature Seasonality (standard deviation * 100)
	CHG-bio5	Maximum temperature of the hottest month
	CHG-bio6	Minimum temperature of the coldest month
	CHG-bio7	Annual thermal amplitude (bio5-bio6)
	CHG-bio8	Average temperature of the wettest quarter
	CHG-bio9	Average temperature of the driest quarter
	CHG-bio10	Average temperature of the hottest quarter
	CHG-bio11	Average temperature of the coldest quarter
Precipitation (values provided in millimeters)	CHG-bio12	Annual Precipitation
	CHG-bio13	Precipitation of the wettest month
	CHG-bio14	Precipitation of the driest month
	CHG-bio15	Precipitation seasonality (coefficient of variation)
	CHG-bio16	Precipitation in the wettest quarter
	CHG-bio17	Precipitation of the driest quarter
	CHG-bio18	Precipitation in the warmest quarter
	CHG-bio19	Precipitation of the coldest quarter

Table 2 *Temperature and Precipitation Variables (Abdalla et al., 2022)*

6. Methodology

6.1 Pre-processing of Data and Variable Selection

To align with the available crop yield data, the historical temperature and precipitation data set was reduced to the values of the relevant years for analysis and the 5,563 municipalities for which soybean yield data is available in the IBGE dataset. Furthermore, all additional variables, such as statistical computations provided by the data set, that were of no relevance for the purpose of this analysis were removed. For further potential geospatial analysis, a column with the respective states was added to the data set.
In the next step, all 3,041 municipalities that did not produce soybeans in any of the ten years were removed. The remaining data set contained 1,680 municipalities with values for all ten years and 842 municipalities with partial data.

Additionally, boxplots for data in both sets were created to check for outliers. For the weather variable data set, all outlier data points were cross-checked with external sources, such as for example, the 1290mm of precipitation in the wettest month for the municipality of Japaratinga (AL) in 2013 compared to an overall mean value of 291mm for this variable which was verifiably explained by heavy rains leading to floods in eastern parts of Brazil in December 2013. In the yield data set, five extreme outliers that are likely to either be an error in reporting or the result of another weather unrelated factor, e.g., new crop, were removed. Boxplots for the main variables can be found in Appendix D.

Lastly, a combination of multicollinearity analysis and variable prioritization based on estimated relevance for crop yield grounded on previously presented literature was used in the weather variable selection process. The correlation matrix (Appendix A) revealed a high correlation (> |0.7|) among a variety of predictor variables, which was an argument to limit the number of variables included in the model to a minimum to avoid a high level of multicollinearity compromising the regression results. As represented in the existing body of literature, including variables to account for temperature and precipitation levels are required for the minimum baseline model. Hence, annual average temperature and annual precipitation were the base variables chosen to be included in the model. Based on the research presented by Lesk et al. (2021), it was also deemed relevant to include an additional variable to account for the heat-moisture coupling effect to add additional value to the model. Therefore, the average temperature of the driest quarter was also chosen to be included in the analysis.

6.2 Descriptive Analysis of Data

To get a better first understanding of the available data, some basic descriptive computations were performed. For a bigger picture view, the municipality-level data was aggregated at the national level. Figures 10 and 11 show the 2010 – 2020 development of the mean values across all municipalities for the annual average temperature in Kelvin and the annual precipitation in millimeters, respectively.

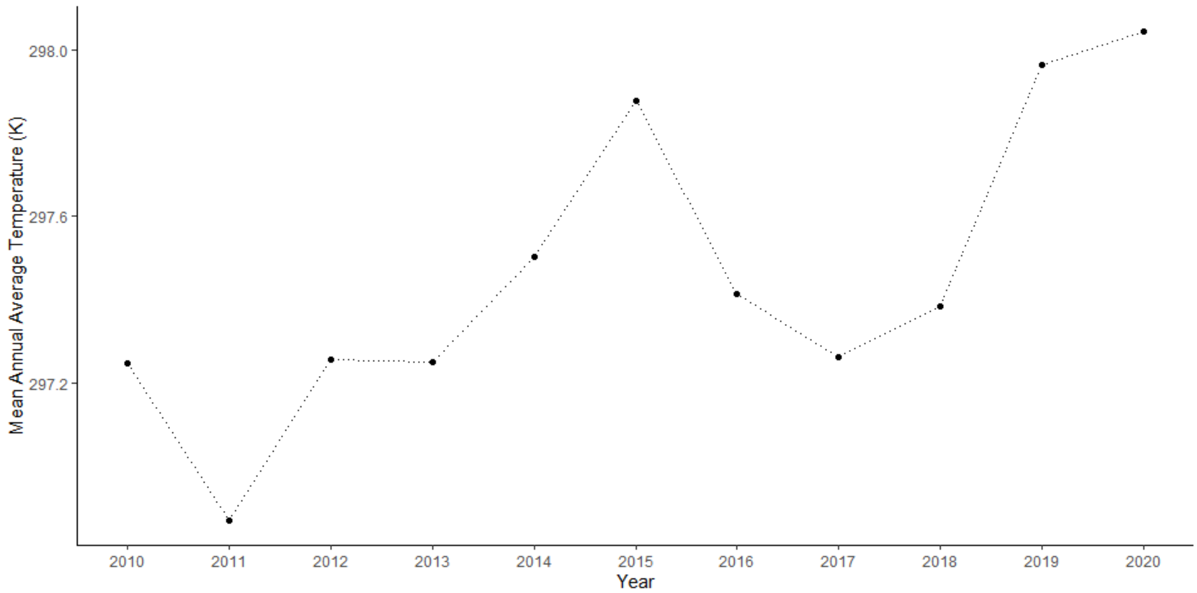

Figure 10 *Temperature Development*

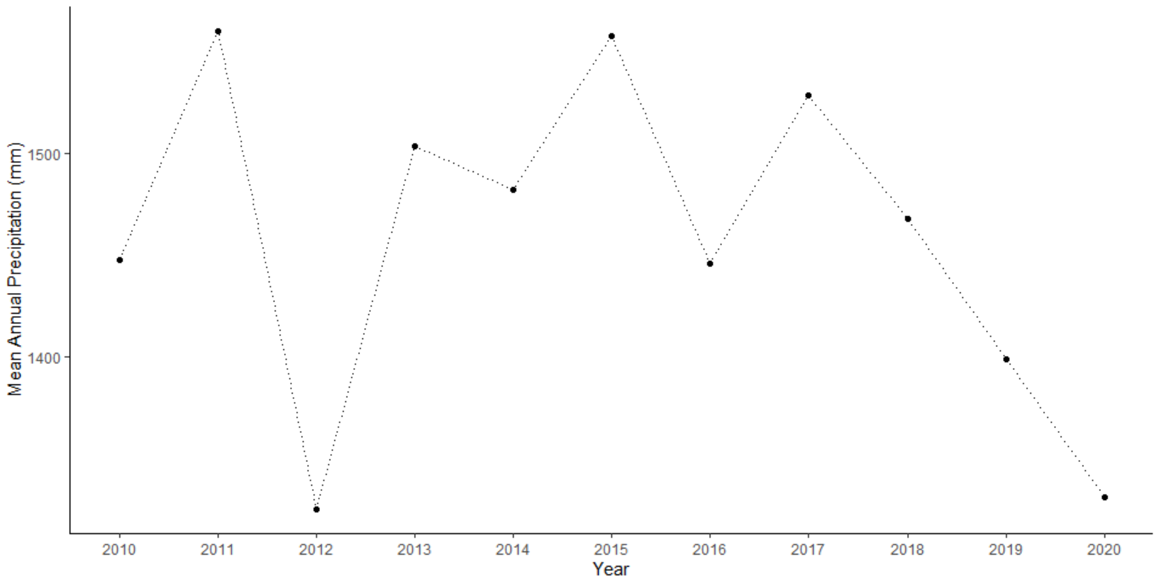

Figure 11 *Precipitation Development*

The data, showing variation throughout the years, suggest a slight upward trend for temperature over time and a complementary slight downward trend for precipitation, especially in the last four years of the data set. While 2012 and 2020 were the driest years within this time span, 2020 was also the warmest year on average.

Figure 12 shows the 2011 – 2020 development of the mean values across all municipalities for the annual average soybean yield in kilograms per hectare.

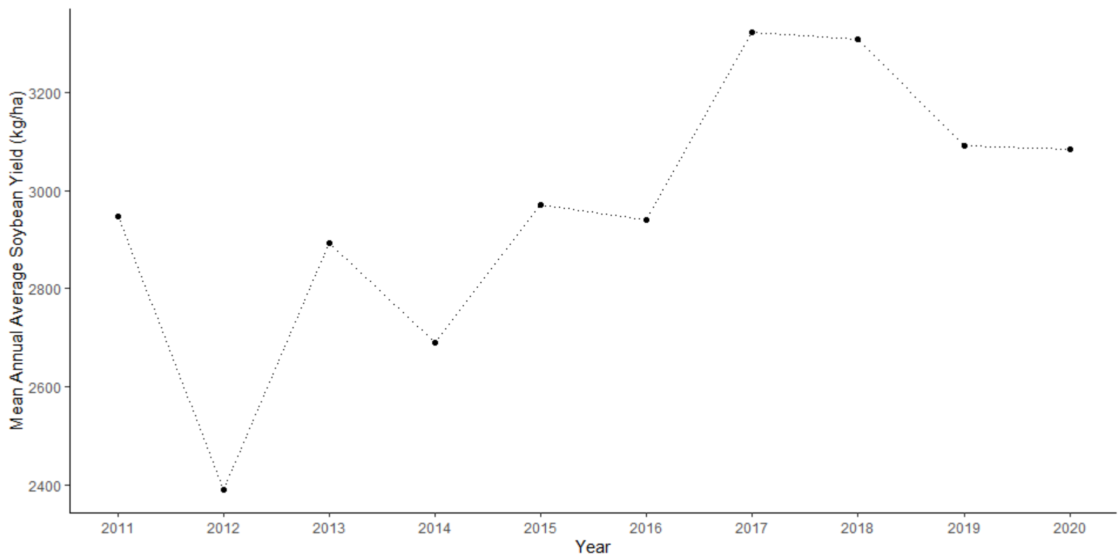

Figure 12 *Yield Development*

As excepted, the data shows an overall trend of increased productivity likely driven by other technological and managerial factor adaptation to meet the increasing demand. While this shows the importance of analyzing the data on a yearly and regional level to be able to compare the effects of weather parameters on yield, there are still some possible inferences to be made from these graphs.

For instance, it can be seen that in this recent period of higher temperature and lower precipitation years, the yield has also gone down, whereas in 2017, the temperature was lower and precipitation higher, potentially leading to an increase in yield.

Additionally, Table 3 provides an overview of the most relevant statistics for the dependent variable average annual soybean yield in kilograms per hectare, and the three selected independent variables annual average temperature in Kelvin, annual precipitation in mm, and average temperature of the driest quarter in Kelvin. For ease of interpretation, the variables presented in Kelvin were also converted into Celsius.

Histograms and scatterplots, visually presenting the distribution of all included variables, can be found in Appendix B and Appendix C, respectively.

Total Descriptive Statistics

	N	Mean	Median	St. Dev.	Min	Max
Average annual yield (kg/ha)	21,284	2,664	3,000	640.5	108	12,000
Annual average temperature (K)	61,083	298.1	298.3	2.4	289.3	303.0
in Celsius		*24.9*	*25.2*	*2.4*	*16.2*	*29.9*
Annual precipitation (mm)	61,028	1,361.5	1,364.3	544.9	132.3	3,995.7
Average temperature driest quarter (K)	61,083	297.1	297.3	3.3	285.1	304.3
in Celsius		*24.0*	*24.2*	*3.3*	*12.0*	*31.2*

Table 3 *Descriptive Statistics*

6.3 Model Selection

The introduced data contains agricultural production and weather variables on a municipality and year level and can hence be classified as panel data, which is a combination of cross-sectional and time series data (Rajarathinam & Suba, 2022).

As previously noted, when working with a panel data set with output based on a geographical entity and unit of time as a function of a vector of explanatory variables and an error term, a panel data regression model has proven itself as useful as it allows accounting for time-invariant variation. Especially within agricultural production estimation, panel models acknowledge the fact that spatial locations vary not only in climate but also in numerous other factors (e.g., soil quality) that may be correlated with climate. By incorporating a fixed effect for each geographical entity, these models account for all non-changing differences over time, ensuring that the resulting deviations in weather from the average are no longer linked to inherent disparities in space that could lead to a false correlation, thus solely relying on weather deviations from the average that are random and independent (Blanc & Schlenker, 2017).

Hence, the model chosen for this analysis is a standard panel regression model of the form:

$$ln(Y_{i,t}) = \beta_1 T_{i,t} + \beta_2 P_{i,t} + \beta_3 C_{i,t} + \mu_i + \theta_t + \varepsilon_{i,t}$$

***Equation** 7 Brazilian Soybean Yield Regression Model*

where the dependent variable $Y_{i,t}$ represents the annual average soybean yield for any municipality i in year t. Even though there is only a slight tendency toward a negatively skewed distribution of annual soybean production (skewness: -0.45; as can be seen in Appendix B), the dependent variables have been transformed with the natural logarithm (ln), to allow for better interpretability of the results. As presented in section 6.1, the independent variables included in the model are annual average temperature ($T_{i,t}$), annual precipitation ($P_{i,t}$) and average temperature of the driest quarter ($C_{i,t}$) representing the heat-moisture coupling effect. While the annual precipitation and the average temperature of the driest quarter are distributed fairly symmetrically, annual average temperature was found to be slightly negatively skewed (skewness: T: -0.55, P: 0.48, C: -0.29; as can be seen in Appendix B). To ensure that this is not impacting the model, a log-log model was estimated to compare the results to the model presented in Equation 2. As the results were found to be the same, it was decided not to transform annual average temperature with the natural logarithm as that would decrease the ease of interpretation of the results.

Additionally, the model includes municipality fixed effects μ_i and year fixed effects θ_t. The municipality fixed effects are included to absorb observed and unobserved fixed spatial characteristics, isolating weather-shocks from potential sources of omitted variables bias, and the year fixed effects aim to account for common trends, separating the relevant relationships from idiosyncratic local shocks. $\varepsilon_{i,t}$ is the error term (Dell et al., 2014).

In the process of developing this baseline crop yield panel regression model, a variety of alternative models were developed and tested. These include different fixed effects models based on a two-predictor variable version of the model presented above, including only the temperature and precipitation variables. Starting with a simple regression model without any fixed effects, first only municipality fixed effects were added, then municipality and year fixed effects. In another step, a region-specific time trend in the form of a state-year trend was added, replacing the year fixed effects. Similarly, the municipality fixed effects were replaced by state fixed effects based on the 26 Brazilian states. Lastly, the average temperature of the driest quarter variable was added to the model to represent the heat-moisture coupling effect.

To assess the stability and reliability of the estimated regression results and hence ensure the validity of the developed model, a series of additional robustness checks were run. Analyzing how the regression results hold up under different specifications or conditions helps to evaluate whether the findings are robust and not overly sensitive to specific modeling choices or assumptions (Lu & White, 2014). The robustness analysis includes using clustered standard errors, adding weights to the model, substituting the predictor variables with alternative variables, including outliers in the analysis, and using a balanced panel through the removal of missing values.

7. Results and Discussion

7.1 Regression Model

This section presents the results of the regression model analysis described above. Table 4 provides an overview of the results of all models and their respective results, followed by an analysis of the introduced hypotheses.

Table 4: Yield Regression Analysis

	Dependent variable:					
	ln(Yield)					
	(1)	(2)	(3)	(4)	(5)	(6)
Annual average temperature	0.015***	-0.031***	-0.160***	-0.017***	-0.158***	-0.138***
	(0.001)	(0.003)	(0.005)	(0.002)	(0.004)	(0.005)
Annual precipitation	0.0001***	0.0001***	0.0001***	0.0002***	0.0002***	0.0001***
	(0.00000)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Average temperature driest quarter						-0.016***
						(0.001)
Municipality FE	No	Yes	Yes	No	Yes	Yes
State FE	No	No	No	Yes	No	No
Year FE	No	No	Yes	Yes	No	Yes
State-year trend	No	No	No	No	Yes	No
Observations	21,234	21,234	21,234	21,234	21,234	21,234
R^2	0.027	0.309	0.466	0.210	0.446	0.472
Adjusted R^2	0.027	0.216	0.394	0.208	0.370	0.401
Residual Std. Error	0.265 (df = 21231)	0.238 (df = 18715)	0.209 (df = 18706)	0.239 (df = 21201)	0.213 (df = 18694)	0.208 (df = 18705)
Note:						* p<0.1; **p<0.05; ***p<0.01

H1: An increase in annual average temperature leads to a decrease in soybean yield.

The first hypothesis is concerned with exploring if a significant, negative relationship between the annual average temperature and the level of soybean yield exists.

First of all, all six models indicate that there is a significant relationship between the annual average temperature and the level of soybean yield at a 1% significance level.

The simple OLS regression (model 1) suggests that a one Kelvin increase in the annual average temperature is associated with a 1.5% increase in the level of the average annual yield. However, only at a R^2 of 2.7%. Adding the municipality fixed effects (model 2) already significantly improves the model and reveals a negative relationship between temperature and yield. Further, adding the year fixed effect improves the model, suggesting that an increase of one Kelvin in the annual average temperature leads to a 16% decrease in the average yield (model 3). When replacing the municipality fixed effects with state fixed effects (model 4), this value drops to 1.7%. However, the state fixed effects model is also performing considerably worse than the municipality level fixed effects model. Replacing the year fixed effects with a state-year trend (model 5), on the other hand, only slightly changes the model outcome, indicating a 15.8% decline in yield. Lastly, the three-predictor variable model, including the heat-moisture coupling variable (model 6), suggests a negative relationship at the level of 13.8%, while overall also being the best performing model out of these six, reaching a R^2 of up to 47.2% (adjusted R^2 40.1%).

H2: A decrease in annual precipitation leads to a decrease in soybean yield.

The second hypothesis is concerned with exploring if a significant, positive relationship between the annual precipitation and the level of soybean yield exists.

Again, all six models indicate that there is a significant relationship between the annual precipitation and the level of soybean yield at a 1% significance level.
In this case, the coefficients remain more constant across the different variations of the model, ranging from a 1% to a 2% increase in yield with a 100-millimeter increase in annual precipitation. The municipality and year fixed effects models (3 and 6) support the 1% relation.

H3: An increase in average temperature during drier periods leads to a decrease in soybean yield.

The third hypothesis is concerned with exploring whether a significant, negative relationship between the average temperature of the driest quarter and the level of soybean yield exists.

Model 6 shows that, at a 1% significance level, a one Kelvin increase during the driest quarter is associated with a 1.6% decrease in soybean yield.

Overall, the results show that none of the three presented hypotheses can be rejected based on the available data used for analysis.

7.2 Robustness Analysis

Clustered Standard Errors

The first robustness analysis conducted is the inclusion of clustered standard errors, as this addresses potential correlation or heteroscedasticity within clusters of observations. Observations within the same municipality may exhibit correlated errors due to unobserved heterogeneity or common shocks. If this is the case and these correlations are ignored, the assumption of independence of errors is ignored, resulting in biased and inefficient standard errors. Clustered standard errors are, therefore, more reliable and robust if within-cluster dependencies exist. Furthermore, heteroscedasticity may occur when the variance of the error term varies systematically across the different municipalities. As this would violate the assumption of homoscedasticity, standard errors estimated under this assumption may be biased and inefficient. Clustered standard errors allow for the variance to differ across the municipality, increasing the accuracy and robustness of the standard error estimates (Wooldridge, 2019).

Using clustered standard errors for the analysis produced the same results for the annual average temperature variables, reduced the significance level of annual precipitation from the 1% to the 5% level, and led to the average temperature of the driest quarter to become insignificant. The Average Temperature of the Driest Quarter becoming statistically insignificant can be explained by it being highly correlated with the Annual Average Temperature (correlation coefficient: 0.85, see Appendix A). Even though this variable is not statistically significant with clustered standard errors, this does not necessarily imply that it is not a meaningful addition to the model, especially when considering the specific context of it adding the coupling effect to the model (Lesk et al., 2021). As can be seen in Table 4, adding this coupling variable to the model only slightly changed the model output, which can be used as an argument for keeping all three predictor variables in the model despite the result of the clustered standard error robustness check.

Weights

As the panel data consists of observations over time and across different regions, which may have different levels of variability in their yield and weather data, using weights can help to account for the differences in variability across regions and ensure that the estimates are not biased towards regions with higher variability. Ideally, weights based on soybean harvesting area or production value would be used to assign more weight to the municipalities with higher agricultural area/production value and less weight to municipalities with lower agricultural area/production value. However, due to limited available data, weights based on average municipality yield are used as a proxy (You et al., 2009; Ortiz-Bobea et al., 2021).

Adding weights to the regression model only slightly changes the variable coefficients while maintaining all significance levels. The weighted model suggests that a one Kelvin increase in the annual average temperature is associated with a 13.7% decrease in yield compared to 13.8% of the baseline model. Similarly, a 100-millimeter increase in the annual precipitation leads to a 2% increase in yield versus a 1% increase in the model without weights. Lastly, in the weighted model, a one Kelvin increase in the average temperature of the driest quarter suggests a 1.7% decrease in soybean yield compared to 1.6%.

Alternative Variables

Another well-implemented approach to assessing model robustness is the substitution of the predictor variables with suitable alternatives that capture similar constructs (Peterman et al., 2021; Deschênes et al., 2007). To do so, the annual average temperature is being replaced by the average temperature during the hottest quarter, the annual precipitation by the precipitation during the driest quarter and the average temperature of the driest quarter by the precipitation of the warmest quarter.

All three substitute variables were found to be significant at a 1% level. The effect of the average temperature of the hottest quarter on yield seems smaller than that of the average annual temperature, with a 6.7% decrease per Kelvin, compared to the 13.8%. However, the direction and general trend align with that of the baseline model, and as this substitute variable only represents one-quarter of the annual temperature, a deviation to some extent was to be expected. Similar results can be observed regarding the precipitation of the driest quarter as a substitute for annual precipitation, suggesting a 10% increase in yield with a 100-millimeter increase in precipitation. Again, the direction of the relation is supported by this result, and the higher value of the coefficient can be explained by the increased risk of drought stress during the driest quarter. The replacement variable accounting for the heat-moisture coupling effect, precipitation during the warmest quarter, suggests that a 100-millimeter increase in precipitation leads to a 2% increase in yield productivity. As this variable measures the coupling effect from the opposite perspective (measuring precipitation instead of temperature), it supports the results of the baseline model.

Including outliers

As outliers were previously removed from the data set and hence the model, another robustness check is the inclusion of outliers in the model. Outliers can have a significant impact on regression results, affecting coefficient estimates, standard errors, and model fit. By including outliers in the analysis, it can be examined whether the estimated coefficients remain robust and whether the model performance is stable in the presence of extreme observations. This helps to evaluate the sensitivity of the results to influential data points. If the coefficients change substantially or become insignificant in the presence of outliers, it indicates potential instability or fragility in the estimated relationships (Finger, 2010; Newlands et al., 2014).

The inclusion of previously dropped outliers resulted in no changes in the regression coefficients or the significance levels. This seems like a reasonable result considering that the number of extreme outliers dropped from the model was very small, with only five observations.

Balanced panel

Lastly, as the panel used for the regression analysis is unbalanced, robustness analysis is conducted by removing missing values from the data set to obtain a balanced panel for comparison of results. This serves the purpose of evaluating the sensitivity of the estimated coefficients and overall model performance to variations in the panel's composition by assessing whether the results hold when only considering a subset of observations that have complete data over the entire panel period (Reimers & Klasen, 2013).

Similarly, to adding weights to the regression model, using the balanced instead of the unbalanced panel only slightly changes the coefficients. For annual average temperature, that change is from -13.8% to -13.1%, for annual precipitation from 1% to 2%, and for the average temperature of the driest quarter from -1.6% to -1.8%.

Overall, it can be observed that the robustness tests support the model results of the baseline model, suggesting that the findings are robust and not overly sensitive to specific modeling choices or assumptions.

A summary of all results of the robustness analysis can be found in Table 5.

Table 5: Yield Regression Robustness Analysis

	Dependent variable:					
	ln(Yield)					
	Baseline Model	Clustered SE	Weights	Alternative variables	Including outliers	Balanced panel
Annual average temperature	-0.138***	-0.138***	-0.137***		-0.138***	-0.131***
	(0.005)	(0.023)	(0.005)		(0.005)	(0.007)
Annual precipitation	0.0001***	0.0001**	0.0002***		0.0001***	0.0001***
	(0.00001)	(0.0001)	(0.00001)		(0.00001)	(0.00001)
Average temperature driest quarter	-0.016***	-0.016	-0.017***		-0.016***	-0.018***
	(0.001)	(0.013)	(0.001)		(0.001)	(0.001)
Average temp hottest quarter				-0.067***		
				(0.003)		
Precipitation driest quarter				0.001***		
				(0.00003)		
Precipitation warmest quarter				0.0002***		
				(0.00001)		
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21,234	21,234	21,234	21,118	21,284	14,354
R^2	0.472	0.472	0.501	0.461	0.470	0.488
Adjusted R^2	0.401	0.401	0.433	0.388	0.399	0.423
Residual Std. Error	0.208 (df = 18705)	0.208 (df = 18705)	0.004 (df = 18705)	0.210 (df = 18591)	0.209 (df = 18750)	0.210 (df = 12717)
Note:						* p<0.1; ** p<0.05; *** p<0.01

7.3 Interpretation of Results

When it comes to interpreting the regression model results, two fundamental prerequisites are important to consider. First, the coefficients associated with the independent variables in a logged model represent the estimated percentage change in the dependent variable for a one-unit increase in the corresponding independent variable, holding all other independent variables constant. And secondly, while the Kelvin and Celsius scale differ in zero points of the thermometer, they are related unit for unit, meaning that a one-unit increase in the Kelvin scale is equal to a one-degree increase in Celsius which was confirmed by running the model after transforming all values to Celsius resulting in the same beta coefficients (Libretexts, 2020).

Accordingly, the results of the regression analysis can be interpreted as follows. A one-degree Celsius increase in annual average temperature led to a 13.8% decrease in average annual soybean yield in Brazil. Additionally, the results suggest that a 100-millimeter increase in annual precipitation is associated with a 1.5% increase in average annual soybean yield in Brazil. Lastly, a one-degree Celsius increase in the average temperature during the driest quarter of the year was found to lead to a 1.6% decrease in average annual soybean yield in Brazil.
It can be argued that these results can, in fact, be interpreted as causal due to the use of random variation in weather over time to identify the relationship between yield and temperature, and precipitation (Dell et al., 2014).
The robustness testing showed that temperature is the most significant variable out of the three included in the model, as shown in the analysis with clustered standard errors. As it is further the predictor variable with the highest coefficient, it can be concluded that temperature is the most relevant in estimating yield productivity within this model.

Comparing these findings with those of other scholars shows a trend that supports the results of the presented regression analysis. For example, Silva et al. (2023), who conducted a similar study limited to the Cerrado biome, an area that covers around 20% of Brazil’s territory, concluded that a one-degree Celsius increase in temperature reduces productivity by 6% within all municipalities in the Cerrado biome, but up to 32% in the Matopiba region, a subarea of the biome. This increased sensitivity in the Matopiba region was explained by the already higher average temperature within the area by the authors. Furthermore, a 100-millimeter increase in precipitation was associated with a reduction of 0.2% to 1% in soybean yield. These results are based on observations made between 1980 through 2016 and, similarly to the model presented in this research, include fixed effects and detrending variables to account for technological advances, irrigation growth, etc..

According to various climate change models, the trend of increasing temperatures and more frequent droughts can be categorized as long-term changes in the climate, which are expected to continue throughout the following decades (IPCC, 2020). Depending on different scenarios, Brazil is expected to experience an increase in annual average temperature between one to five degrees Celsius and an average decrease in precipitation between 5% and 20% within this century, with high variation across the country's regions (PBMC, 2013).
Appendix E and F contain visual representations of the climate projection data for temperature and precipitation modeled from the global climate model compilations of the Coupled Model Inter-comparison Projects overseen by the World Climate Research Program, which are the basis for the Intergovernmental Panel on Climate Change (IPCC) reports. Appendix G further highlights the differences in regional climate projections based on the National Assessment Report (RAN1) of the Brazilian Panel on Climate Change (PBMC).

These projections on a country, and even more so on a regional level, demonstrate the relevance of the presented regression results. While weather fluctuations are already impacting yield productivity, thus far, technological developments have shown limited historical adaptation potential to extreme heat. The main strategies currently observed in Brazil are the expansion of farmland and an increase in irrigated land area. Further strategies to adapt to a changing climate include extensive changes in the overall farming systems, requiring significant investments or even land abandonment. Current research concludes that technological inventions will be needed to reduce water dependency under changing climatic conditions, as the current system is deemed unsustainable in the long run (Silva et al., 2023).

8. Economic Implications for Global Supply Chains

Connecting these results back to the global soybean supply chain, it becomes clear that a changing climate, which has been shown to likely have an adverse effect on Brazilian soybean production, will also have direct implications for global soybean trade and hence a relevant spill over effect on many other economies. As supply chains are highly linked, and with soy being a commodity used across many industries, a potential shift in supply will affect many companies, industries, and even countries as a whole.

First and foremost, a relevant question for the future will be if technological advances will be able to allow for profitable soybean production within Brazil under challenging climatic conditions while there is a continuously growing global demand for soy. Additionally, or alternatively, it will be interesting to understand if the improving conditions for soybean growth in other areas of the world will be able to compensate for the potential yield losses in the leading exporter country Brazil, which currently many countries and industries have built a strong dependency on. While the overall changing climatic conditions around the world will impact what countries will be able to export soy profitably, Brazil is facing a problematic predicament as soy is currently one of the primary agricultural commodities and a significant source of export revenue, and hence to this day extremely important for the Brazilian economy.

Linking these findings to the decomposition of climate change drivers impacting supply chain management by Dasaklis & Pappis (2013) presented in section 2.1.2 shows the relevance of implementing a sustainable supply chain approach to (Brazilian) soybean.

In the regulatory area, Brazilian soy production is already facing challenges with the Soy Moratorium and other international agreements driving the demand for “zero deforestation soy”. As mentioned before, one strategy to overcome challenging climatic conditions thus far has been the expansion of cropland, which the results of this research support is likely to be further needed in the future; however, simultaneously conflicts regulatory interventions for global supply chain carbon management.

In line with that, the market-driven trend of increased demand for green products from environmentally sensitive customers is also likely to lead to companies aiming to source soy from regions where it can be produced as sustainably as possible. The main issue for Brazil here, under consideration of the presented findings, is that higher irrigation levels will be needed in the future to balance the effects of higher temperatures and less precipitation on crop productivity. Combined with the issue of deforestation and the likely expected improved growing conditions in other countries, this might further incentivize many organizations to shift towards alternative sources of soybean.

Lastly, as sufficiently discussed, climate change is also expected to have relevant physical impacts on soybean supply through changing conditions and extreme weather patterns. These physical attributes will pose significant strategic and profitability challenges for the Brazilian soybean supply.

Overall, the combination of all these factors raises many relevant questions regarding potential future sustainable supply chain management decisions on the strategic as well as operational levels. The global soybean supply chain network is likely to change as climate change is imposing a variety of new criteria for the selection of suppliers and accounting for challenges in production planning and potential disruptions.

Considering the, in the definitions identified, three dimensions of sustainable supply chain management: economic, environmental, and social, the findings of this research emphasize that there will likely be significant challenges in achieving and maintaining a sustainable global soybean supply chain, with Brazil being the leading producer and exporter. Climate change can be expected to have relevant impacts in all three dimensions a decreasing productivity will have economic implications for the Brazilian economy, environmental implications for the Brazilian biosphere, especially the Amazonian rainforest, and social implications, mainly but not exclusively, for farmers and other workers across the soybean supply chain.

To fully understand the complexity of the global soybean supply chain, and climate change's impact on it and to then develop strategies further for shifting towards a more sustainable soybean supply chain management, much more information and consideration is needed than the scope of this research can cover. Nonetheless, as the aim of this thesis was to provide relevant data and analysis as a starting point to better understand the current situation as well as to assess future threats through changing conditions, the findings of this research can be used to open the conversation and encourage collaboration in this field.

9. Conclusion, Limitations, and Future Research

This thesis aims to contribute to understanding the potential impact of climate change on the global soybean supply chain by investigating the interrelationship between soybean crop productivity and relevant weather variables such as annual precipitation and average temperature. To do so, panel regression model analysis was conducted using historic soybean yield and weather data from 2011 – 2020 on a municipality level. The results were tested and validated through several robustness checks.

The findings support all three developed hypotheses: A decrease in soybean yield was found to be associated with an increase in the annual average temperature, a decrease in the annual precipitation, and an increase in the average temperature during the driest quarter. Annual average temperature was found to have the highest impact on soybean yield, with a one-degree Celsius increase leading to a 13.8% decrease in yield. A 100-millimeter increase in annual precipitation was found to be associated with a 1.5% increase in average annual soybean yield, and a one-degree Celsius increase in the average temperature during the driest quarter of the year was found to lead to a 1.6% decrease in crop productivity. These findings contribute to the limited literature and growing discussion of climate variation's impact on agricultural output.

However, several limitations to this research also need to be highlighted. The main limitations are related to the used data sets, which are based on a lack of availability and accessibility of the required data.
First and foremost, it is essential to mention that the use of annual weather data limits the value of the research output as it does not allow accounting for weather variation throughout the year. Having daily weather data to, for example, account for days of heat through temperature bins as well as uneven intra-annual precipitation distribution has been found to be relevant in improving regression results. Therefore, the analysis would have benefitted from the availability and inclusion of additional weather variables that consider the frequency of the different weather realizations, revealing nonlinear effects (Fishman, 2016).
Similarly, the analysis could further be enhanced through a higher spatial resolution, e.g., using gridded geospatial data instead of municipality level data.
Another main limitation regarding the underlying data is the few years of observations. The ten-year time period is a fairly short period resulting in a limited sample size.

Moreover, it is important to mention that the presented model does not account for other climate-related variables, such as the concentration of CO_2 in the atmosphere and its fertilization effects on soybean yield that could be relevant but are challenging to account for (Silva et al., 2023).
Lastly, further research could benefit from including and testing additional weights, applying the geographically weighted regression technique, and further exploring the clustering of standard errors on different levels.

By contextualizing the results of this research within the global sustainable soybean supply chain management theory, this thesis further adds to the relevant discussion of the economic implications of climate change and advocates for how an increase in available climate data and analysis can limit potentially harmful consequences. Finally, this thesis aims to encourage further research in the field to provide more information to policy- and decision-makers within the still-developing field of sustainable supply chain management.

Beyond the scope of this research, an exciting topic for future research will be the actual application of climate projection data to forecast soybean yield using estimates from historic weather fluctuations to investigate the long-term impacts of climate change on soybean yield productivity in Brazil. The major challenge in this field lies in assessing and accounting for how much adaptation is likely to occur (Dell et al., 2014). Nonetheless, the availability of any research and data in this field is highly relevant and valuable. Hence, further research in this area, building on the findings and limitations of this study, is highly encouraged.

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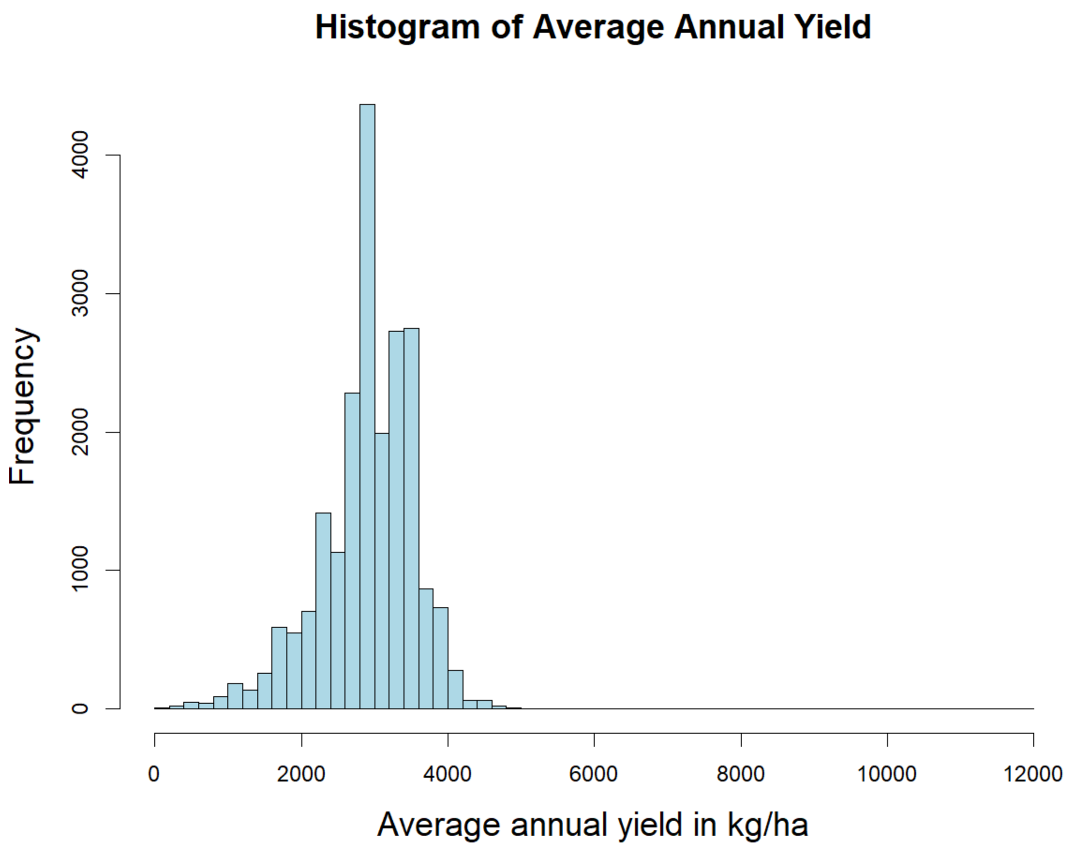
11. Appendices

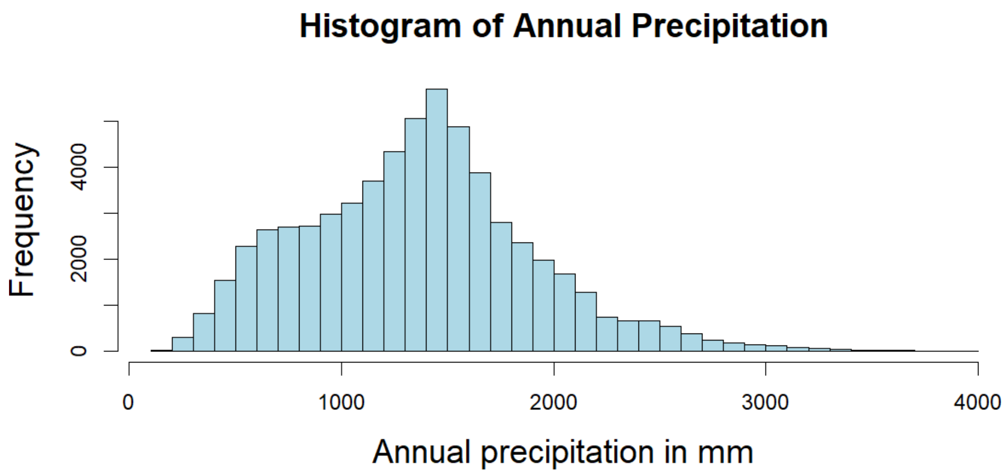
11.1 Appendix A: Correlation Matrix

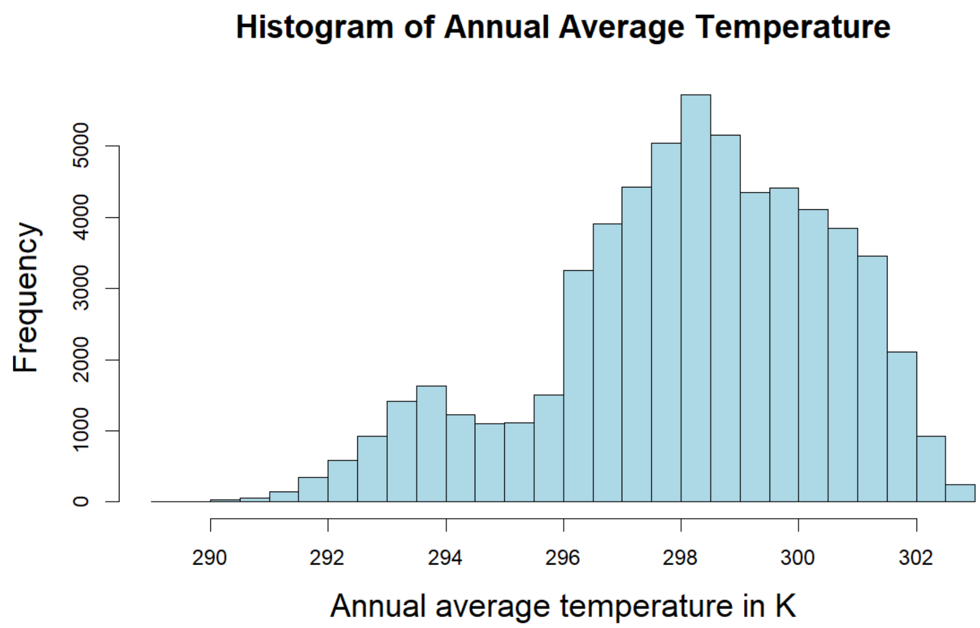
	Temperature											Precipitation							
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	1.00	-0.60	0.29	-0.74	0.43	0.79	-0.59	0.75	0.85	0.92	0.96	-0.25	0.04	-0.61	0.59	0.10	-0.68	-0.52	0.05
2		1.00	-0.28	0.86	0.26	-0.87	0.93	-0.38	-0.67	-0.38	-0.74	0.12	-0.14	0.36	-0.44	-0.20	0.47	0.46	-0.21
3			1.00	-0.50	-0.22	0.55	-0.61	0.13	0.37	0.14	0.40	-0.15	0.01	-0.17	0.30	0.02	-0.25	-0.29	0.19
4				1.00	0.10	-0.89	0.89	-0.50	-0.76	-0.47	-0.88	0.22	-0.08	0.48	-0.56	-0.13	0.60	0.49	-0.10
5					1.00	0.07	0.32	0.31	0.27	0.63	0.27	-0.07	-0.07	-0.20	0.12	-0.05	-0.20	-0.26	-0.02
6						1.00	-0.92	0.49	0.83	0.62	0.89	-0.21	0.09	-0.46	0.55	0.15	-0.58	-0.60	0.23
7							1.00	-0.35	-0.68	-0.34	-0.74	0.17	-0.11	0.36	-0.47	-0.16	0.48	0.47	-0.23
8								1.00	0.45	0.67	0.69	-0.29	-0.02	-0.60	0.52	-0.01	-0.63	-0.12	-0.28
9									1.00	0.76	0.88	-0.16	0.08	-0.43	0.47	0.16	-0.53	-0.64	0.30
10										1.00	0.82	-0.15	0.07	-0.53	0.49	0.13	-0.57	-0.46	0.09
11											1.00	-0.22	0.08	-0.59	0.61	0.15	-0.69	-0.55	0.11
12												1.00	0.76	0.54	-0.38	0.84	0.60	0.40	0.66
13													1.00	0.14	0.22	0.90	0.15	0.24	0.51
14														1.00	-0.69	0.16	0.89	0.32	0.35
15															1.00	0.08	-0.77	-0.31	-0.23
16																1.00	0.16	0.19	0.65
17																	1.00	0.40	0.36
18																		1.00	-0.23
19																			1.00

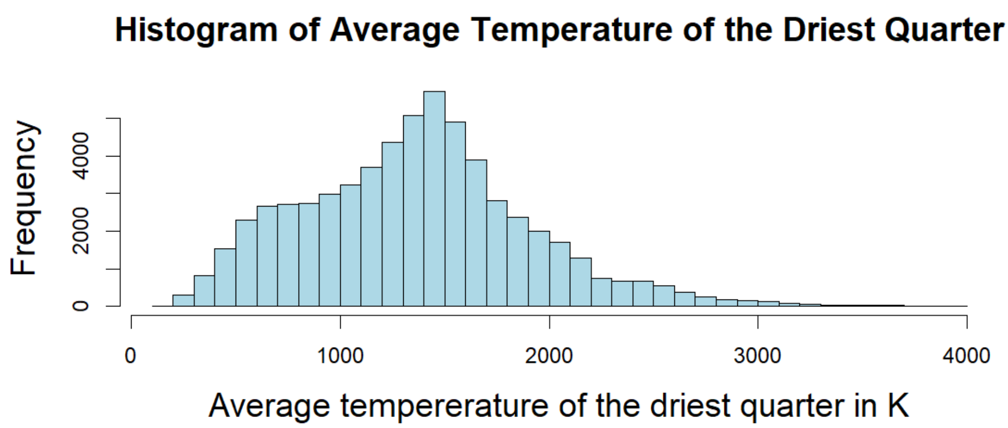
**The table with variable names and numbers (1-19) can be found in section 5*

11.2 Appendix B: Descriptive Analysis Histograms

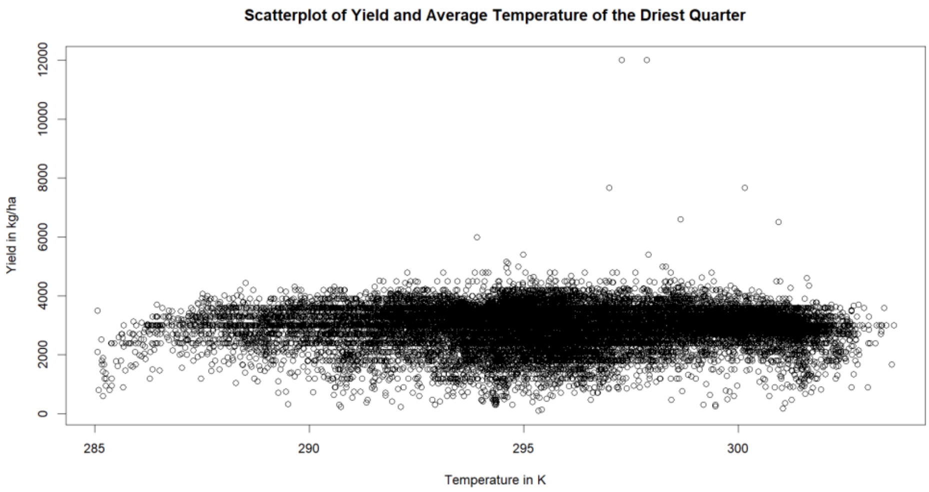


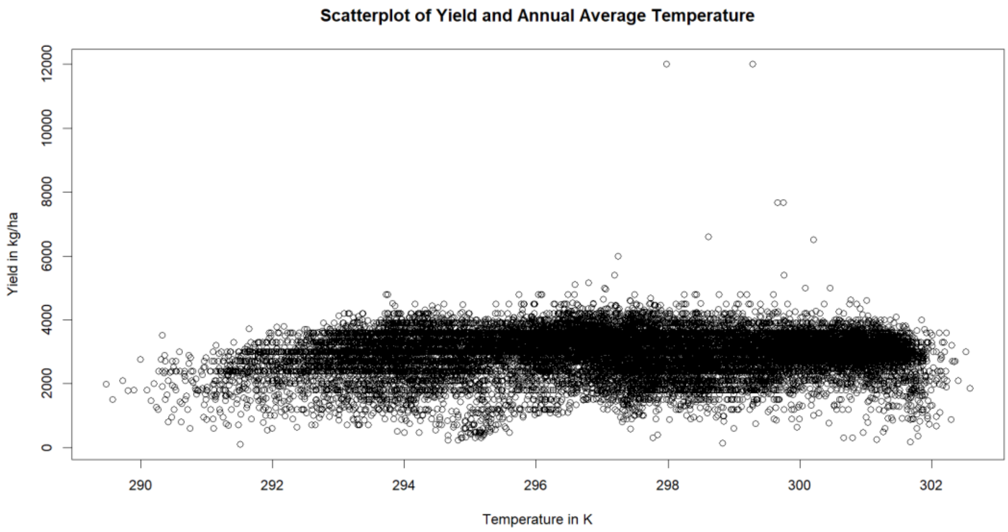

Histogram of Annual Precipitation
Frequency
0
2000
4000
0
1000
2000
3000
4000
Annual precipitation in mm

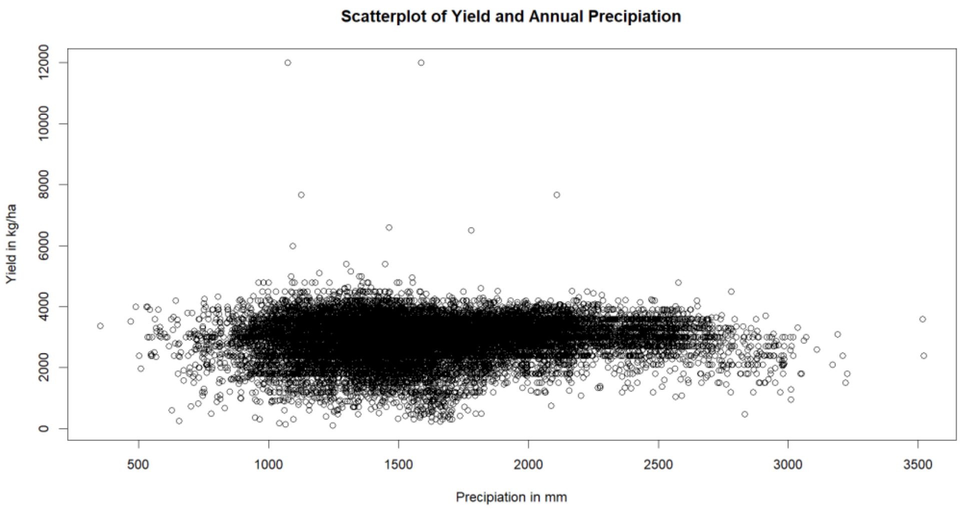

Histogram of Annual Average Temperature
Frequency
0
1000
2000
3000
4000
5000
290
292
294
296
298
300
302
Annual average temperature in K


Histogram of Average Temperature of the Driest Quarter
Frequency
0
2000
4000
0
1000
2000
3000
4000
Average tempereerature of the driest quarter in K

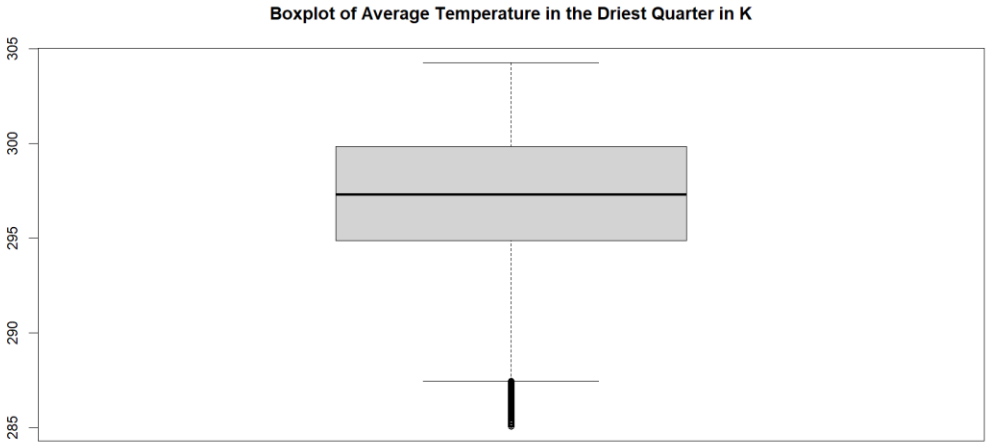
11.3 Appendix C: Descriptive Analysis Scatterplots

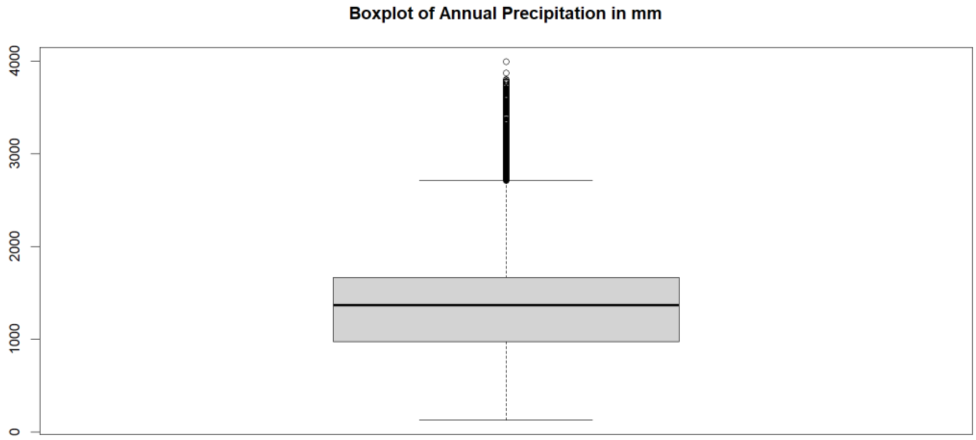


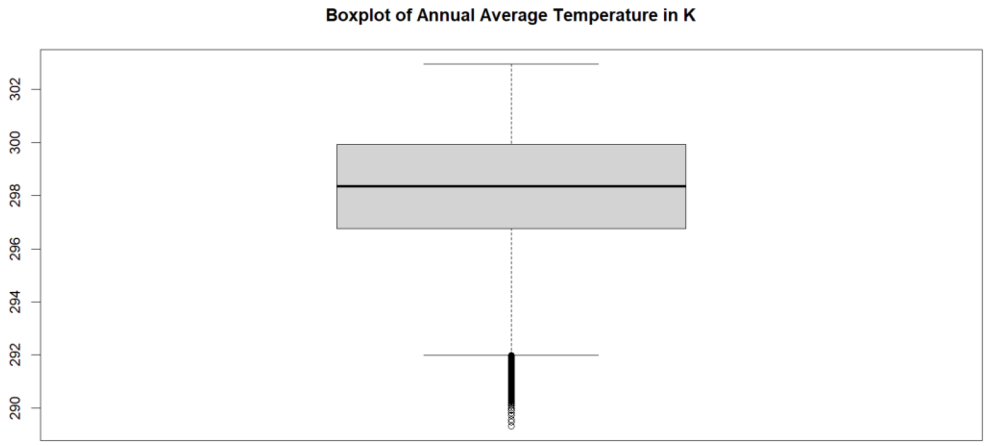


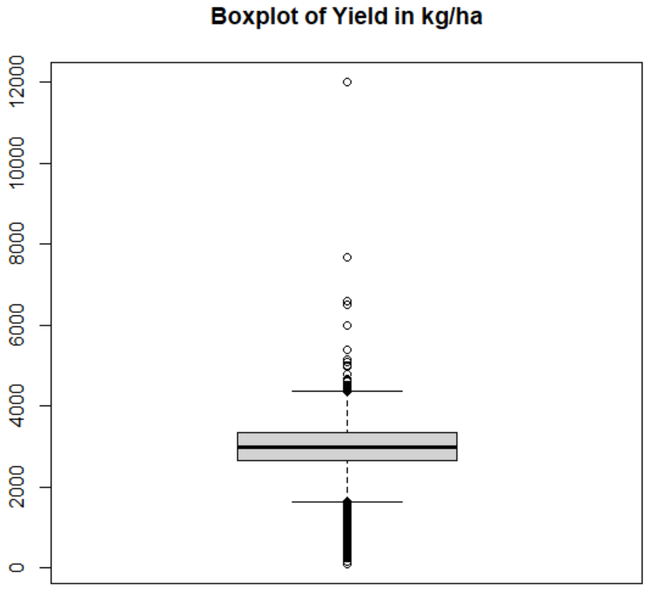


11.4 Appendix D: Descriptive Analysis Boxplots

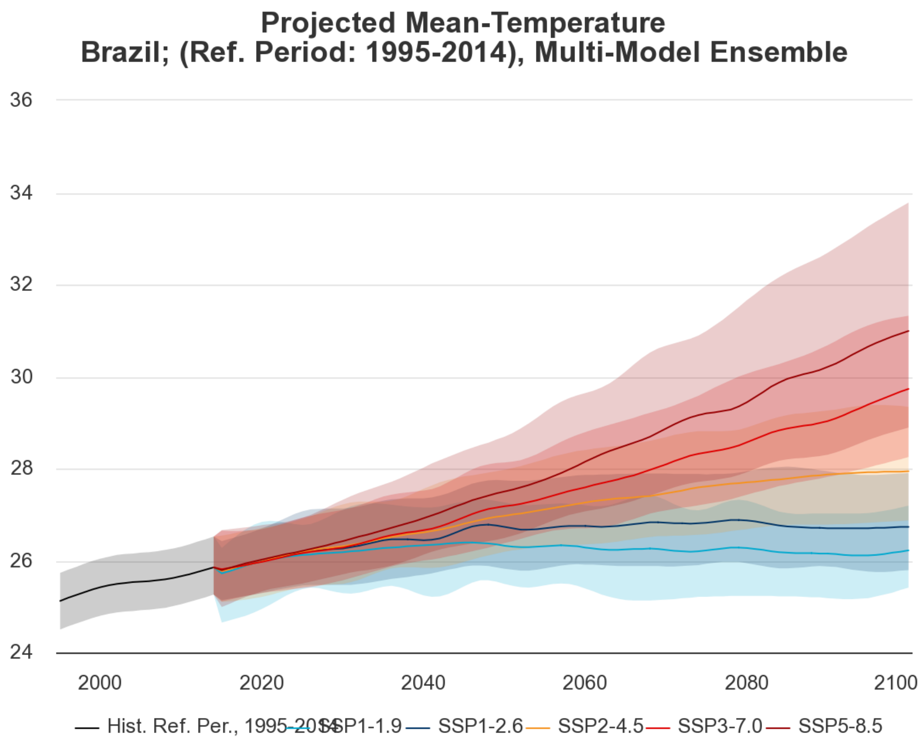






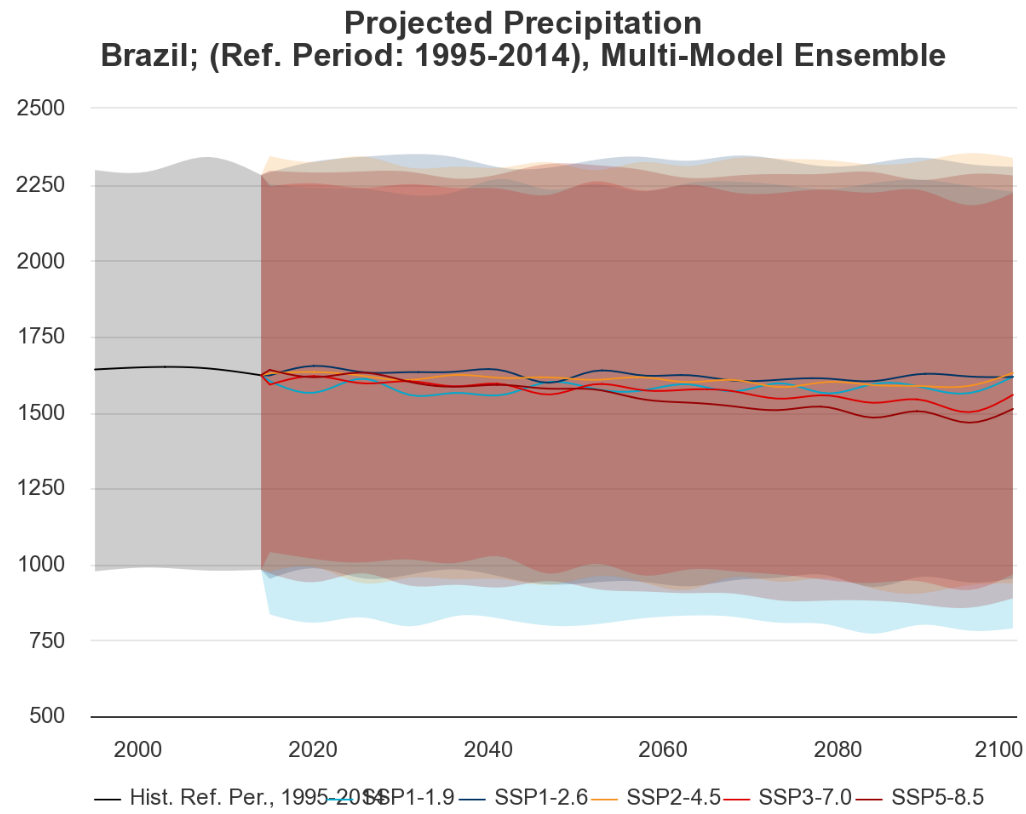


11.5 Appendix E: Climate Projections Temperature



Source: *The World Bank Group (2021)*

11.6 Appendix F: Climate Projections Precipitation



Source: *The World Bank Group (2021)*

11.7 Appendix G: Regional Climate Projections

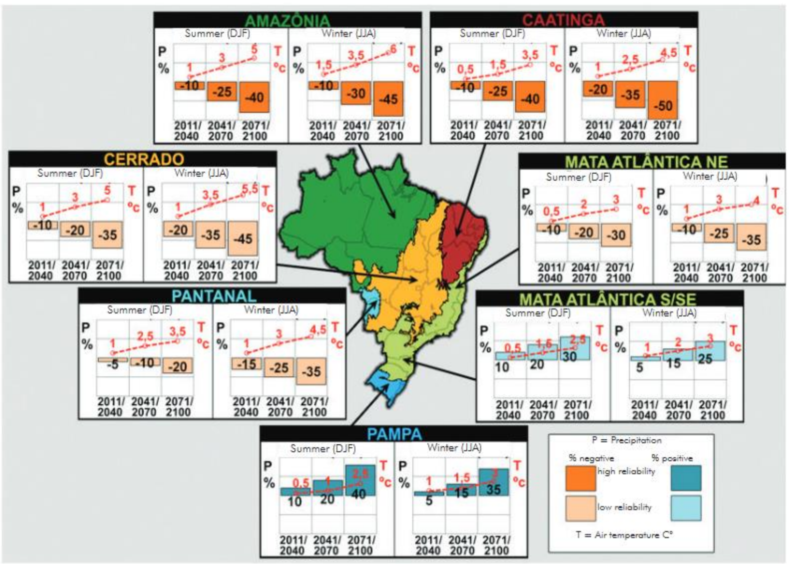


Figure SEF. 6. Regional climate projections in the Brazilian Amazônia, Cerrado, Caatinga, Pantanal, Mata Atlântica (northeast and south/southeast sections) and Pampa biomes, for the beginning (2011 to 2040), middle (2041 to 2070) and end (2071 - 2100) of the 21st century, based on the scientific results of global and regional climate modeling. The regions with different colors on the map indicate the geographic domain of the biomes. The keys are found at the bottom right corner. [GT1 9]

Source: *PBMC (2013)*

11.8 Appendix H: Table State Code

States

State Name	# Code
Acre	1
Alagoas	2
Amapa	3
Amazonas	4
Bahia	5
Ceara	6
Distrito Federal	7
Espirito Santo	8
Goias	9
Maranhao	10
Mato Grosso	11
Mato Grosso do Sul	12
Minas Gerais	13
Para	14
Paraiba	15
Parana	16
Pernambuco	17
Piaui	18
Rio de Janeiro	19
Rio Grande do Norte	20
Rio Grande do Sul	21
Rondonia	22
Roraima	23
Santa Catarina	24
Sao Paulo	25
Sergipe	26
Tocantins	27