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Climate Change, Drought, and Agricultural Production in Brazil

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Abstract: Climate change is likely to impact the occurrence of natural disasters such as drought. This paper calculates a standardized precipitation evapotranspiration index (SPEI) and uses it to analyze the frequency, duration and severity of drought in Brazil (1901-2020). Second, the study uses annual panel data to estimate the causal effects of drought on agricultural production (1974-2019), and calculates the distribution of impacts across municipalities. Third, the paper compares annual panel and long difference estimates to shed light on adaptation/intensification over a longer period. Finally, by combining the panel estimates with seven CMIP6 global climate models, the study provides a range of projections for drought impacts (2025-2075). Results indicate that drought severity increased substantially in the second half of the 20th century and again in the 2010s. Estimates show that ten percent of the time droughts reduced municipal production by about 25% or more, with considerable spatial heterogeneity. Long difference estimates indicate intensification in response to more extreme droughts, and (statistically insignificant) adaptation at the median. A substantial risk to agricultural production is identified in the 21st century, especially under more pessimistic global warming scenarios, with annual losses rising to over 35% by 2075. Policy implications are discussed.

Key Words: Climate Change, Drought, Agricultural Production, Brazil
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1. Introduction

Climate change, commonly measured by the increase in average global temperatures, has been empirically demonstrated and is now widely accepted among scholars (Pachauri and Reisinger, 2007; Trenberth et al., 2014). This recognition has encouraged governments worldwide to pursue collective mitigation efforts. Despite progress, significant knowledge gaps remain regarding the evolving trajectories, geographical variation, and relationships among climatic factors such as precipitation, evapotranspiration, and runoff under the influence of global warming. Specifically, little is known about how climate change might alter the frequency, duration, and severity of droughts and, in turn, how these changes could impact agricultural production.

Studying drought in Brazil is of considerable relevance to the international community as the country is among the top five agricultural producers and exporters in the world (FAO, 2021), and is also home to the Amazon rainforest which plays a crucial role in regulating the global climate (Staal et al., 2020; Lapola et al., 2023). Droughts can have large impacts on agricultural production which are important for export earnings as well as domestic and global food security. Understanding the impact of drought in Brazil is also important for developing policies that aim to mitigate the effects of climate change and facilitate the sustainable use of natural resources. Thus, research on drought in Brazil is important not only for the country itself but also for the world.

Despite recent advances in the climatological literature on drought (Marengo et al., 2017; Brito et al., 2018), there remains a scarcity of studies that comprehensively analyze the impact of drought on agriculture. Many studies assess the impact of climate change more broadly on agricultural productivity and land rents, focusing primarily on changes in temperature and rainfall (Assunção and Chein, 2016; Burke and Emerick, 2016). Some studies have assumed that droughts will increase with climate change and have estimated their impact on various outcomes such as migration, human health, and labor markets, among others (Branco and Feres, 2021; Olivieri, 2020; Rocha and Soares, 2015; Mueller and Osgood, 2009). Other studies have found no clear pattern of increased drought occurrence (Delazeri et al., 2018; Brito et al., 2018; Urban et al., 2015), thereby questioning the assumption that droughts will become increasingly problematic. The absence of a consensus is partly because monitoring droughts is not an easy task, given that dryness is the result of a complex combination of geophysical factors (Short Gianotti et al., 2020; Freire-Gonzalez et al., 2017). Additional research is necessary to understand how the timing and characteristics of droughts impact agriculture production (Chambers et al., 2020; Pimenta, 2020).

We seek to contribute to the literature on drought patterns and impacts in a number of ways. First, using a Standardized Precipitation Evapotranspiration Index (SPEI), we analyze various dimensions of drought, including frequency, duration, and severity over more than a century in Brazil. We demonstrate that measures that ignore potential evapotranspiration do not fully capture the increasing severity of droughts that are occurring with climate change. Second, the study examines the causal impact of drought on agricultural production using annual data on 69 crops at the municipal level from 1974 to 2019. Our identification strategy follows the recent economics literature that utilizes panel data to estimate the effects of weather shocks on economic outcomes (Dell et al., 2014; Ortiz-Bobea, 2021). After exploring spatial and temporal heterogeneity of drought impacts, we contrast the annual panel model with long difference estimates (Burke and Emerick, 2016) in order to shed light on the extent to which drought impacts are reduced due to adaptation, or intensified over a longer period of time. Finally, by combining the econometric estimates of drought effects with CMIP6 global climate model projections for the period 2025-2075, the study provides a range of projections of the potential impacts of drought.

Following this introduction, Section 2 of the paper defines our drought measures, presents the climate data, and examines how climate change may have affected drought in Brazil over the past 120 years. Section 3 defines the variables and presents the panel methodologies used to explore how drought has impacted municipal-level agricultural production since the 1970s. Section 4 presents the results. Section 5 provides a range of projections of drought impacts over the next fifty years. Section 6 concludes.

2. Climate Change and Drought in Brazil

This section provides a descriptive analysis of the relationship between climate change and drought in Brazil, using data for the period 1901 to 2020. Key climate indicators— average monthly temperature, precipitation, and potential evapotranspiration—are examined at both national and regional levels, aggregated in 10-year intervals. Results underscore a clear impact of climate change, revealing a consistent rise in average temperatures and potential evapotranspiration, but challenging traditional assumptions about the role of rainfall in drought occurrences.

We then utilize a Standardized Precipitation Evapotranspiration Index (SPEI) to assess the severity, duration, and frequency of drought (Brito et al., 2018). Analyses shed light on the evolution of these dimensions over time, offering insight into diverse regional experiences. A decomposition of drought severity reveals the predominant role of potential evapotranspiration—not changes in precipitation—in driving the escalation of these drought-related dimensions since the 1980s.

2.1 Climate data

The climate data used in this study were obtained from the Climate Research Unit (CRU) at the University of East Anglia, which is widely used in the climatology and economics literature (Auffhammer, 2013). This database provides monthly data at a 0.5 grid level, representing approximately 55 km^2. The gridded climate data were overlaid on a shapefile that delimits Brazil's municipalities, which is the basic unit of analysis in this paper. The raw data represents 3,829 municipalities[1] with monthly information, which in total produces 5,513,760 observations per variable. The variables utilized are average monthly temperature, precipitation, and potential evapotranspiration from 1901 to 2020.

Figure 1 illustrates the evolution of mean temperature, precipitation, and potential evapotranspiration for the whole of Brazil over the past 120 years.[2] The Figure reveals that average temperature displayed no clear trend in the first half of the 20th century, with a particularly notable increase since the 1970s. Specifically, the average temperature in Brazil increased by a full degree Celsius from 24.8 in the 1970s to 25.8 degrees in the 2010s. Average monthly rainfall in Brazil followed a different path. The decadal means were around 145 millimeters in the first half of the period, rose to 149mm for the next 40 years, and then declined to their lowest level (142.1mm) in the 2010s. Notably, the trajectory of average potential evapotranspiration has been similar to that of temperature, with a considerable rise since the 1970s. These results suggest that the heating of

[1] To account for the growth in the number of municipalities over the period, we construct a panel dataset that uses consistently defined geographical units called AMCs. For simplicity, we continue to refer to these as municipalities.
[2] The years shown on the horizontal axis of Figure 1 denote the final year of each 10-year period.

the planet has a stronger correlation with potential evapotranspiration than with precipitation. This has important implications for the measurement of drought.

In data available from the authors, we conduct the same analysis separately for the five macro regions of the country. The first point to note is that there is considerable heterogeneity across regions. The rapid increase in the average temperature since the 1970s has been observed in all regions, including those that are closer to the equator where the average temperature is higher (the North and Northeast). What is different about the South and Southeast regions is that they have experienced a more notable increase in temperature since the beginning of the 20th century. We observe a different story for precipitation. While the level of average precipitation in each region does not appear to have changed much over time, the standard deviation increased in most regions over the entire period. Thus, with regard to drought, it does not appear to be the case that there is a trend of declining rainfall, but the pattern has become more variable over time. When we look at the regional behavior of potential evapotranspiration, we see that the trends of this variable are quite similar to the trends for temperature. We observe an increase in the growth rate from the 1970s onwards in all regions.

This initial glance at the data that will be used to construct measures of drought suggests that global warming is present across the country, with a considerable increase in average temperature and potential evapotranspiration over the past four decades. Notably, while the standard deviation of precipitation has increased, the mean level of precipitation has not exhibited a downward trend (with the exception of the 2010s). These findings suggest that factors beyond average rainfall levels may be more closely linked to the incidence of drought, such as potential evapotranspiration and possibly the variance of precipitation.

2.2 Construction of long-run drought variables

Droughts are complex and multidimensional phenomena. There is no single definition of drought, and there are various types, including meteorological, agricultural, and hydrological (Dai, 2011; Mishra and Singh, 2010). Droughts depend on a variety of factors, but generally involve a period of below-average precipitation. In order to measure droughts comprehensively, it is important to use a metric that reflects the imbalance between the supply and demand of water. One such measure that has been proposed in the literature is the Standardized Precipitation Evapotranspiration Index (SPEI). The SPEI was introduced by Vicente-Serrano et al. (2010), and is based on the balance between precipitation and potential evapotranspiration. The SPEI takes into account not only the amount of precipitation but also the climatic conditions that influence evapotranspiration, such as temperature, wind, and radiation. The incorporation of evapotranspiration is essential in a period of accelerated global warming, and we demonstrate that measures that ignore potential evapotranspiration do not fully capture the increasing severity of droughts in Brazil in recent decades. Thus, the SPEI provides a more accurate representation of drought conditions as they relate to agricultural production.

We create the SPEI by using the monthly climate variables at the municipal level. Specifically, we calculate the SPEI value considering a 12-month window in municipality *m* and month *r*, such that:

$$SPEI_{m,r} = \frac{(P_{m,r}-PE_{m,r})-mean(P_{m,r}-PE_{m,r})}{sd(P_{m,r}-PE_{m,r})} \tag{1}$$

Where $P_{m,r}$ is the sum of precipitation in the previous 12 months *r* in municipality *m*. $PE_{m,r}$ is calculated in a similar way, but is the sum of potential evapotranspiration. The difference between the two gives us a measure of the water balance in each municipality that is available for agricultural production. In order to standardize the index, we subtract the mean and divide by the standard deviation of ($P_{m,r}$ - $PE_{m,r}$). Because recent decades have seen a significant increase in temperature, which can affect potential evapotranspiration, we decided to use the period between 1901 and 1980 to calculate the municipal-level means and standard deviations used in (1).

The next step is to define when a drought starts and ends. We specify that a drought begins in a municipality when two consecutive months of SPEI are equal or below a specific threshold, -1, and that a drought ends in the month in which the SPEI once again becomes positive (SPEI > 0). Then, following the work of Brito et al. (2018), we compute the different dimensions of drought in a time window of 5 years. Specifically, we calculate the following three measures for each municipality and time window: a) drought duration is the average number of consecutive months of drought; b) drought frequency represents the total number of events in the 5-year window; and c) drought severity captures the absolute integral of SPEI below zero during the months of drought. Drought severity constitutes the most comprehensive measure of drought as it considers not only how often and how long droughts occur but also their intensity.

2.3 Evolution of drought dimensions

In this section, we present an analysis of the evolution of drought in Brazil using the SPEI. We first present the data on evolution of drought severity for Brazil and its five macro regions, and then briefly comment on the duration and frequency of droughts.

Drought severity

The top portion of Figure 2 shows the average drought severity for Brazil in each 5-year window, while the bottom portion depicts drought severity for each of the five regions. It can be seen that the severity of droughts in Brazil fluctuated around a mean of about 5.6 in the first half of the 20th century and then increased by about 60% to a mean of 9.0 for the next 60 years, with considerable variation. We then observe a sharp increase in drought severity during the decade ending in 2020. The mean level of severity in this last decade was about four times the level of 1901-1950.

When we examine the severity of drought across regions, we notice some important differences. Many droughts are not national in scale. For example, the increase in drought severity in the 1930s took place in the Southeast and South. The increase in drought severity in the 1960s, in contrast, occurred in the Center-West far more than in any other region. Another interesting point is that the increasing drought severity that is evident in the 21st century occurred most dramatically in the Northeast and North, followed by the Southeast and Center-West. The increase in the South was of much more modest proportions. Relative to the first half of the 20th century, drought severity in the 2010s was about five times higher in the Center-West and Northeast, and about four times higher in the Southeast and North. Only in the South was it largely unchanged.

Drought duration and frequency

In data available from the authors, we also examine the average duration and frequency of droughts in five-year windows for Brazil and its five macro regions. At the level of Brazil, the pattern of drought duration was similar to drought severity, with an increase of about 50% in the second half of the 20th century followed by an additional 100% in the decade ending in 2020. Whereas droughts had an average duration of close to 5 months in the first half of the 20th century, this rose to 14 months in the 2010s. At the regional level, the data show considerable heterogeneity. Mean drought duration in the 2010s was greater than 25 months in the Northeast, around 12 months in the Center-West, North, and Southeast, and only 4 months in the South.

The frequency of drought in 5-year windows follows a different pattern than that of drought severity and duration. For Brazil as a whole, the data show a positive trend in the frequency of droughts from the beginning of the 20th century (with about 0.3 in the first decade) to a peak in the early 1960s, when an average of 1.4 droughts occurred. From 1951 to 2010 there was an average of about one drought every five years, which was about 50% above the frequency in the first half of the 20th century. Drought frequency did not rise in the 2010s. Thus, the increase in severity in this decade was due to both longer and deeper droughts, but not more frequent ones. Again, there is considerable heterogeneity across regions. The South is the only region where drought frequency in the 2010s was roughly similar to the 1901-50 period.

2.4 The importance of potential evapotranspiration: A decomposition

Brazil experienced a four-fold increase in the severity of droughts in the 2010s relative to the first half of the 20th century. To identify whether precipitation or potential evapotranspiration was the primary driver of this rise, we conducted a decomposition exercise to calculate the SPEI under two alternative counterfactuals. In the first, we fixed precipitation in each municipality at the 1901-80 level and calculated the SPEI for every municipality and month, allowing only potential evapotranspiration to vary. Next, we calculated the severity of drought over the entire period. We then repeated the process, fixing potential evapotranspiration and calculating the SPEI with only precipitation variation. By comparing drought severity with these two counterfactuals we were able to determine which component accounted for a larger share of the increase in the 2010s relative to the first half of the 20th century. For Brazil as a whole, the increase in drought severity was 4.4 times larger when only potential evaporation varied. It was at least twice as large in all regions, and in two regions it was almost 8 times greater. Thus, changes in potential evapotranspiration, which reflect changes in temperature, have been a more important determinant of rising drought severity than changes in precipitation.

3. Data and Methodology

This section defines the variables and methods used to estimate the impacts of drought on agricultural production in Brazil in the period 1974-2019. Utilizing the SPEI, in Section 3.1 we create a variety of short run measures of drought to complement the long run measures of severity, duration, and frequency analyzed in Section 2. We also describe the annual production data on the 69 principal crops, and the construction of a municipal level Fisher quantity index which is used as our dependent variable. Section 3.2 presents the methodology for estimating the causal effects of droughts on agricultural production using an annual municipal-level panel. Because droughts are relatively rare events, this section also shows how we calculate the distribution of drought impacts so that we can analyze different percentiles of this distribution. Finally, we show the long run panel specification used to estimate long differences as in Burke and Emerick (2016).

3.1 Drought and agricultural production variables

Additional drought variables

We construct measures in different time horizons—quarterly, annual, and quinquennial—so that our characterization of drought is comprehensive and flexible. The idea is to estimate the effect and timing of all types of shortages classified in Dai (2011). For quarterly droughts, we calculate the SPEI in a three-month window (SPEI-03) and generate dummy variables that assume one if the SPEI-03 is below -1 in any month, and zero otherwise. We compute each dummy variable for March, June, September, and December in every municipality and year. For annual droughts, we use SPEI in a twelve-month window (SPEI-12) in December so that every monthly observation of precipitation and potential evapotranspiration is within the same calendar year. We then generate three dummy variables to characterize moderate, severe, and extreme annual droughts in each municipality and year, defined as SPEI-12 between 0 and -1 (moderate), SPEI-12 between -1 and -2 (severe), and SPEI-12 below -2 (extreme). For the quinquennial time window, we use the measures of drought severity and frequency that were analyzed in Section 2. To facilitate interpretation of the regression coefficients, we standardize the quinquennial measures by dividing by their standard deviations. We don't subtract their means because these variables should never be positive (severity) or negative (frequency). We exclude drought duration because of collinearity with drought severity (correlation > 0.9). In sum, we utilize nine drought variables in our models (4 quarterly, 3 annual, and 2 quinquennial). All correlations are below 0.43 in absolute value, and three quarters are below 0.15.

Data and variables on agricultural production

The main annual data source on crop production in Brazil is the Municipal Agricultural Production (PAM) survey conducted by the Brazilian Institute of Geography and Statistics (www.ibge.gov.br). The survey provides municipal level data on the quantity and value of production for 69 principal crops (33 annual and 36 perennial) from 1974 to 2019, allowing for a comprehensive analysis of the impact of droughts on agricultural production over time. With PAM data, we also calculate state level prices. Animal production is not included in PAM, and is excluded from our study. As described above, we use over 3,800 consistently defined geographical units. For simplicity, we continue to refer to these as "municipalities."

Our dependent variable for agricultural production is based on a Fisher quantity index, calculated as follows: 1) for every municipality m and year t, we first calculate the change in aggregate production between years t-1 and t with a Laspeyres quantity index. This index uses state level prices for all crops from year t-1 to aggregate production: $Q^L_{t,t-1} = \frac{\sum_{i=1}^{N} p_{i,t-1} q_{i,t}}{\sum_{i=1}^{N} p_{i,t-1} q_{i,t-1}}$. 2) For every municipality m and year t, we also calculate a Paasche quantity index which only differs from the Laspeyres by using prices from period t: $Q^P_{t,t-1} = \frac{\sum_{i=1}^{N} p_{i,t} q_{i,t}}{\sum_{i=1}^{N} p_{i,t} q_{i,t-1}}$. 3) The Fisher index is the geometric average of the Laspeyres and the Paasche: $Q^F_{t,t-1} = (Q^L_{t,t-1} Q^P_{t,t-1})^{1/2}$. 4) We use observed values of municipal output in 2019, and multiply them by this index to recover all other years. Thus, our dependent variable in each municipality and year ($Y_{m,t}$) is expressed in constant 2019 Brazilian reais (R$). The Fisher index is a superlative index, and because it does not use logs it can easily handle zero values of municipal production of some crops in some years.

3.2 Methodology

Our identification strategy follows the recent economics literature that utilizes panel data to estimate the effects of weather shocks on economic outcomes (Dell et al., 2014; Ortiz-Bobea, 2021). We rely on annual variation in droughts within municipalities over time, and assume that these are as good as random once we control for time invariant municipal unobservables and time varying state-level unobservables. This assumption allows us to obtain causal estimates of the effect of droughts on agricultural production, controlling for other factors that may influence this relationship.

Our main estimating equation is as follows:

$$\log(Y_{m,t}) = \alpha_m + \beta D_{m,t} + \gamma(\alpha_s * t) + \delta(\alpha_s * t^2) + u_{m,t} \qquad (2)$$

Where $\log(Y_{m,t})$ is the logarithm of agricultural production based on the Fisher index in municipality m and year t, α_m is the municipal fixed effect, the time trend t is modeled with a quadratic function that differs by state s, α_s are state dummies, and $u_{m,t}$ is a random error.[3] $D_{m,t}$ is the vector of nine (quarterly, annual and quinquennial) drought measures that vary by municipality and year. β are the coefficients of interest that capture the effects of droughts on agricultural production. In the estimation, errors are clustered at the municipal level. We also explore heterogeneity by estimating separate versions of equation (2) by biome or sub-period.

In the results section below we describe the coefficients β as the "effects" of drought. In most cases, however, we are not interested in the separate effects of quarterly, annual, and quinquennial droughts. In order to summarize the joint effect of all the different types of drought in each municipality and year, we define the "impacts" of drought as follows:

$$Impact_{m,t} = \beta D_{m,t} \qquad (3)$$

Thus, drought impacts are defined as the percentage difference between observed output and predicted output based on the systematic component of (2). We calculate the drought impacts by using the estimated effects (β) and multiplying them by every municipality's observed vector of drought variables in each year. Because droughts are relatively rare events, we then calculate the distribution of drought impacts so that we can present information on different percentiles of this distribution. This allows us to contrast drought impacts at the median with impacts at other percentiles. Again, we sometimes use heterogenous versions of (2) to calculate the impacts for a specific biome or subperiod. The majority of our analysis below, and Section (4) that constructs projections for the period 2025-2100, focuses on drought impacts rather than drought effects.

Long differences

We examine potential adaptation to droughts over time using the long differences approach proposed by Burke and Emerick (2016). They estimate a single first-difference—or a two-period panel—over a long period of time, such as 20 years. While the panel data model in equation (2) estimates drought effects on an annual basis, long difference models extend the interval between observations to a much longer period of time, allowing for the possibility that agents could adapt and reduce the short run impacts of drought, or that drought impacts could intensify over time. The difference between the annual and long difference estimates sheds light on the degree of adaptation/intensification over time.

We adapt the Burke and Emerick (2016) approach in three ways to fit our setting. First, because we have a relatively long panel, we estimate the model in equation (2) with three observations at 20-year intervals, thus spanning 40 years. Second, rather than average each observation over 5, 10, or more years, as they do, we estimate the model for six different starting years (1974, …, 1979), calculate the distribution of impacts for each one, and then average the impacts at each percentile. We obtained more stable results with this approach, while at the same time reducing the influence of any single atypical year. Finally, they have a single coefficient of interest that measures how

[3] Model specification tests indicated that the model with state level quadratic trends performed better than models with a) no time effects, b) year fixed effects, and c) biome level quadratic trends. All models included municipal fixed effects.

crop yields are affected by exposure to extreme heat. This permits them to compare this coefficient from the annual and long difference models, providing evidence on *average* adaptation/intensification. In our case, we have a vector of drought variables. Thus, as above, we calculate the distribution of impacts so that we can analyze adaptation/intensification not solely at the mean or median, but at other percentiles as well.[4]

4. Drought Impacts on Agricultural Production

Section 4.1 presents the main results. Section 4.2 contrasts the annual panel with long difference estimates in order to shed light on the extent to which drought impacts are reduced due to adaptation, or intensified, over a longer period of time.

4.1 Main results

Drought effects (estimated coefficients)

We began by estimating three separate models with only the quarterly, annual, or quinquennial drought variables, and then estimated a final model with all variables combined. In the final model the signs are all the same as in the restricted models. The final model was estimated with over 174 thousand observations and has an adjusted R^2 of 0.85. All coefficients are statistically significant at the one percent level.

Figure 3 presents the estimated coefficients graphically for ease of interpretation. In terms of the timing of droughts across quarters, the critical periods are January-March and April-June, when a drought occurrence decreases agricultural production on average by 5.6 and 11.7 percent, respectively. These two quarters coincide with the growing and harvesting season of the principal annual crops in Brazil (soybeans, corn, cotton, etc.).[5] The third quarter also has a small negative effect, while a drought in the fourth quarter appears to have a positive effect.[6] Turning to the annual drought dummies, we observe a non-linear relationship: moderate droughts decrease agricultural production by 4.8 percent, while these effects rise to 11.4 and 6.9 percent, respectively, for severe and extreme droughts. From a long-run perspective, a one standard deviation increase in the frequency and severity of droughts in the past five years reduces agricultural production by 1 and 3 percent, respectively. While small, this suggests that above and beyond the effect of contemporaneous droughts in a specific year, the history of droughts in a given location has a persistent effect.

Drought impacts

We now discuss the joint impact of all of the different types of drought. To do this, we utilize equation (3) to calculate the distribution of impacts, recalling that each observation described by the distribution is the percentage impact on production in each municipality and year. Figure 4 shows the distribution of drought impacts for four different models. In the top left we used the homogenous model (eq. 2), while in the other three we used heterogeneous versions of (2) that allowed coefficients to vary by biome (top right), sub-periods of roughly 15 years each (bottom

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[4] We note that when we compare the long difference and annual panel models, for consistency both are estimated with six different initial years and the same span of 40 years.

[5] In fact, when we estimate separate models for annual and perennial crops, these two quarterly effects rise to about -10 and -15 percent for annual crops, respectively.

[6] The coefficient on the 4th quarter is the sole case where the qualitative result is different in the restricted model. When we estimate a model that only includes quarter dummies, the coefficient on the 4th quarter is still positive, but it is very small (0.001) and statistically insignificant.

left), and both biome and subperiod (bottom right). Using the homogenous model, the impact of drought at the median municipality-year is about -9%. However, about ten percent of the time (p10 in the figure) there are droughts that cause reductions in output of 24% or more, and at the first percentile output falls by 35%. Allowing for heterogeneous coefficients by biome or subperiod reduces the impacts at the median. It also leads to a much more pronounced effect on the more extreme events, and this is especially true in the model that varies by biome. In the spatially heterogenous (biome) model, we now observe negative impacts of 45% at the 10th percentile, with total losses occurring one percent of the time. This is roughly equivalent to about 200 municipalities having a total loss once every five years. Given the relevance of the heterogenous models, we explore these results further in the next two figures.

Figure 5 shows the distribution of impacts for three prominent biomes in Brazil based on the spatially heterogenous model. The Cerrado, which is where soybeans, corn and other annual crops have boomed in recent decades, has a distribution that is most similar to Brazil as a whole which was shown in the homogenous model in Figure 4. The semi-arid Caatinga, which includes a large portion of the Northeast of Brazil and is one of the poorest areas of the country, has impacts that are far larger than the other biomes. Whereas droughts cause losses of around 40% at the median in the Caatinga, this only happens around one percent of the time in the Cerrado. In the Caatinga, ten percent of the time droughts caused reductions in agricultural output that are around 90%. Droughts have much more modest impacts in the Mata Atlântica, which includes many important agricultural areas in the Southeast and South of the country. Drought induced losses are only about 8% at the 10th percentile of the distribution. This is similar to the median impact in the Cerrado.

Figure 6 shows the distribution of impacts for three subperiods estimated with the temporally heterogenous model that allows coefficients to vary by subperiod. This permits us to examine how the impacts of drought have been increasing over time. The figure shows that the bottom half of the distribution has been shifting down with each subperiod, indicating that droughts have been causing increasingly larger negative impacts. Whereas the worst ten percent of droughts caused production losses of 21% or more in the 1970s and 1980s, this rose to 23% in the 1990s and early 2000s and to over 45% in the most recent 15 years. This is consistent with the data on the increasing severity of long run droughts that was presented in Figure 2.

Figures 7 and 8 show maps of Brazil, estimated with the heterogenous model by biome, that permit us to visualize where the most severe drought impacts have occurred. The black lines within the maps delineate the biomes. Figure 7 shows the 10th percentile of impacts for each municipality as we have defined impacts thus far—the percentage decline in agricultural output. Because we only have 46 years, this is roughly equivalent to the fifth worst drought in each location over the entire period. It is clear that the most severe droughts in percentage terms occur in the semi-arid portion of the Northeast of Brazil (the Caatinga biome). Figure 8, in contrast, displays the impacts in monetary terms, corresponding to the fifth worst loss in 2019 R$ in each municipality throughout the period. Here we see that, in addition to the Caatinga, many large losses take place in the Cerrado biome (center, upper half of the country) where the soybean boom has been taken place in recent decades. The Mata Atlântica and Pampa biomes also show large loses as these are important regions for agricultural production.

4.2 Annual panel versus long difference results

To compare estimates between the annual panel and long difference models, we first calculated the predicted impacts of drought using equation (3) for the annual panel and an analogous version for the long difference model. Figure 9 presents the distribution of impacts for the two models along with 95% confidence intervals. We also calculated the ratio of impacts at each percentile of the distributions in order to assess the share of short run drought impacts that was eliminated due to adaptation or magnified due to intensification in the long run. At the median of the distributions, the long difference model predicts smaller impacts than the annual panel, suggesting that producers may have been able to adapt to the less severe droughts that happen more frequently. The median impact with the long difference model is not statistically different from zero, while the median impact from the annual panel is. Using 95% confidence intervals, however, the difference between the median impacts of the two models is not statistically significant. At the 25th percentile, the predicted impacts from the two models are roughly equal, suggesting no adaptation. And at the 5th percentiles, the impacts are about 60% larger in the long run, suggesting intensification. At the 5th percentile, the difference between models is statistically significant.[7] We conclude that there may have been some adaptation at the median of impacts, but it is not statistically significant. At the lower percentiles that reflect more severe droughts, however, there is clear evidence of intensification of impacts. Importantly, unlike in the approach of Burke and Emerick (2016), we reveal heterogeneity in the degree of adaptation/intensification, and this could have important implications for developing adaptation strategies.

5. Projections of drought impacts from 2025 to 2075

Methodology

In this section, we provide projections of drought impacts for the 21st century. Our strategy relies on combining the coefficients estimated with the homogenous annual panel and projected droughts derived from climate models.[8] We rely on climate model projections from the Coupled Model Intercomparison Project Phase 6 (CMIP6).[9] A number of the models provide information on both precipitation and potential evapotranspiration which permits us to construct SPEI-3 and SPEI-12 measurements to calculate our diverse drought variables. We then calculate impacts as in equation (3). We describe the methodology in more detail below.

Step one involved the selection of climate models from the more than thirty available within CMIP6. The selection criteria required that all included models have a) monthly data on precipitation and potential evapotranspiration up to 2075, and b) data on the 20th century for comparison with the CRU data, enabling an analysis of the similarity in data generating processes. Seven models successfully met these criteria: CM6, CM6HR, HadGEM3, IPSL, ESM2, Earth3, and UKESM1. Based on these seven models, we also constructed an "ensemble" model as the mean of the underlying models.

Second, following the climatology literature (Ortega et al. 2021; Dantas et al., 2022), we utilized a Taylor diagram (Taylor, 2001) to determine if any of the climate models dominated the others in their similarity to CRU precipitation and potential evapotranspiration. The Taylor diagram is a graphical tool that compares the standard deviation, correlation coefficient, and centered root mean

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[7] At the 10th percentile of impacts, the difference between the two models is significant with 90% confidence intervals.

[8] Our approach assumes that future climate adaptation is mirrored in past climate sensitivities. The long difference results suggest that this may not be accurate. If intensification occurs, our projections should be interpreted as a lower bound.

[9] See https://www.wcrp-climate.org/ and https://www.wcrp-climate.org/images/modelling/WGCM/CMIP/CMIP6FinalDesign_GMD_180329.pdf .

square difference of model outputs against CRU observations (1901-1980). The resulting diagrams revealed that there was no single model that outperformed the others for both climate variables. For precipitation, the ensemble model demonstrated the best performance in terms of correlation and standard deviation. However, for potential evapotranspiration, the Ukesm1 model outperformed the others in terms of correlation, while the Earth3 model was preferred in terms of standard deviation. Since there was no clear winner among the models, we chose to compute the projections for each CMIP6 model and then to estimate the average impact across them.[10] Following the guidance of Burke et al. (2015), we report results for all models in order to provide a sense of the uncertainty surrounding the impacts that results from variability in the climate models. As in previous sections, we also calculate the distribution of impacts so that the analysis is not limited to the mean or median.

Finally, we chose two Shared Socioeconomic Pathway (SSP) scenarios that are commonly used and were present in all seven models:

- SSP126: A sustainable development scenario with low challenges to mitigation and adaptation. Global mean surface temperature (GMST) is projected to increase by 1.6°C by 2099.
- SSP585: A high greenhouse gas emissions scenario with very high challenges to mitigation and adaptation. GMST is projected to increase by 4.4°C by 2099.

Results

Figure 10 illustrates the impact of droughts in 5-year intervals based on averaging the impacts of the seven models. To provide context, we include a comparison with the mean impact observed in Brazil between 1975 and 2019 based on the annual panel model using CRU data. Several points are worthy of note. First, the magnitude of the drought impacts experienced in the period 2015-19 was unprecedented. Second, setting this quinquennial aside, the two SSP scenarios track quite well the trend in mean impacts from the 20 years up to 2015. Third, the two scenarios generate mean impacts that are pretty similar from 2025 to 2050. It is only after mid-century that they begin to diverge significantly. Finally, if the world were to follow the more pessimistic scenario (SSP585), the potential adverse impacts of drought on agricultural production in Brazil would be severe. By 2075, droughts would cause production losses of over 35% each year on average.

Figure 11 provides a sense of the uncertainty surrounding the mean estimated impacts for each SSP. The figure shows the mean impact for each of the seven models, the mean of the models, and the ensemble, for two subperiods and for the entire 50-year period. We note the following. First, it is curious that the ensemble—which averages the climate data from the seven models prior to calculating droughts and then impacts—produces impacts that are considerably more negative than the mean of the models for both SSPs. We focus on the individual models and their mean impacts in what follows. Second, when considering the entire 50 years, the mean of the models is -18% under the more optimistic scenario (SSP126) and -24% for the more pessimistic scenario (SSP585). This is also reflected in the range of average estimated impacts across models. They vary from -5% to -35% for SSP126 and -5% to -49% for SSP585. Third, where the scenarios differ most is in the final 25 years of the period when SSP126 shows a mean impact of -20% and SSP585 a mean impact of -32%. Finally, in all periods the EARTH3 model produces the smallest impacts

[10] Whereas the ensemble model averages the climate data from the seven models prior to calculating the drought variables and projecting the impacts, the mean impacts of the models calculates the impacts from each model separately and then takes the average in each municipality and year. The ensemble is not included in this mean.

and the CM6HR produces the largest. In the final 25 years under SSP585, for example, EARTH3 data lead us to project an average decline in agricultural production due to drought of only 5%, whereas the CM6HR model suggests that the impact could be as large as -65%. Clearly, there is considerable uncertainty in these projections.

We end this section by moving away from mean impacts and commenting briefly on the distribution of impacts under the two SSP scenarios. In Figure 12, we use the mean of the seven models to calculate the distribution of impacts in the final 25 years for both SSPs. These distributions are quite different. SSP126 has much more density between 0 and -30%, while under SSP585 droughts with losses between -30% and -60% would occur much more frequently. Which pathway the world follows is of crucial importance for agricultural production in Brazil and elsewhere.

6. Conclusions

In this paper, we first documented changing climate conditions in the past 120 years and showed how they have contributed to the increasing severity of drought in Brazil. Using a standardized precipitation evapotranspiration index (SPEI), drought severity rose by 60% in the second half of the 20th century relative to the first half, and then more than doubled in the 2010s. Demonstrating the importance of using the SPEI, a decomposition analysis showed that rising evapotranspiration—correlated with rising temperature—explained more of the increase in drought severity in this period than changes in precipitation, although in the 2010s both factors were important. Considerable regional heterogeneity exists, with drought severity increasing the least in the South of Brazil.

We then studied the impacts of drought on agricultural production between 1974 and 2019, with particular attention to heterogeneity across space, over time, and at different percentiles of the distribution of impacts. The results indicate that drought impacts were relatively small at the median of all municipalities and years. But in a model that allows for heterogeneity by biome, ten percent of the time we estimate drought impacts that reduce production by 45% or more. Results also indicate that drought impacts have risen throughout the period. We also estimated a long differences model with twenty-year intervals spanning a forty-year period. A virtue of our approach is that we can uncover heterogeneity in adaptation/intensification. A comparison with the annual panel results suggests that there may have been some adaptation at the median, reducing the impacts of drought, but that this was not statistically significant. At the lower percentiles that reflect more severe droughts, however, there is clear evidence of intensification of impacts. These differences are statistically significant.

Finally, we combined our historical estimates of effects with seven different CMIP6 climate models to project a range of possibilities for drought impacts between 2025 and 2075. A substantial risk to agricultural production is identified, especially in the case of the more pessimistic SSP585 scenario, with average annual losses rising to over 35% of production by the end of the period based on the mean of the models. This has profound implications for Brazilian and global food security, as well as for export earnings and development in Brazil.

Our study suggests several main areas of concern where policy could play an important role and where more research is needed. First, the long difference results suggesting intensification of impacts of the most severe droughts over the longer run are alarming. Policy should seek to assist farmers to adapt to the increasing severity of droughts in Brazil in order to reduce their impacts. This could take a variety of forms, including expanding access to irrigation, adoption of drought resistant seeds, and shifting production to less vulnerable locations. Additional research is needed on the viability and cost effectiveness of these alternatives. Second, the projection of drought impacts throughout the 21st century provides an urgent call to action to mitigate climate change. This is a global challenge, but a failure to make significant progress suggests large negative impacts on Brazilian agricultural production as well as threats to global food security. Finally, in terms of our ongoing research, this study utilized data on municipal production that did not include inputs. Our plan is to extend this research by using the decadal Agricultural Censuses from 1985 to 2017 so that we can study drought impacts on total factor productivity and on poverty among agricultural producers.

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Figure 1: Climate Variables for Brazil

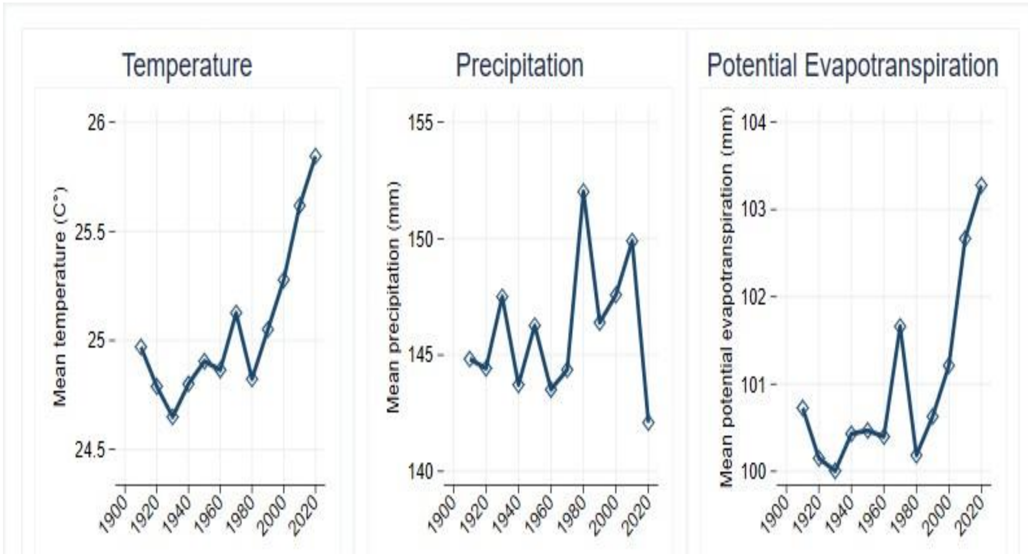

Figure 2: Drought Severity in Brazil and by Region

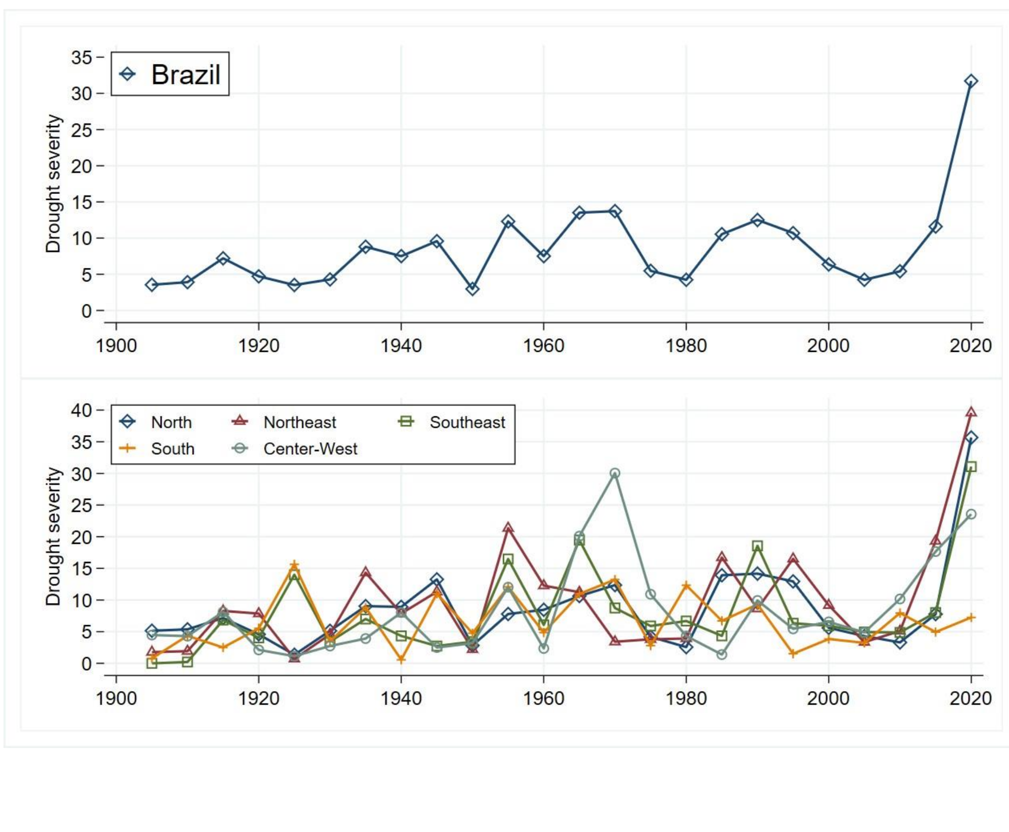

Figure 3: Effect of Drought on Agricultural Production

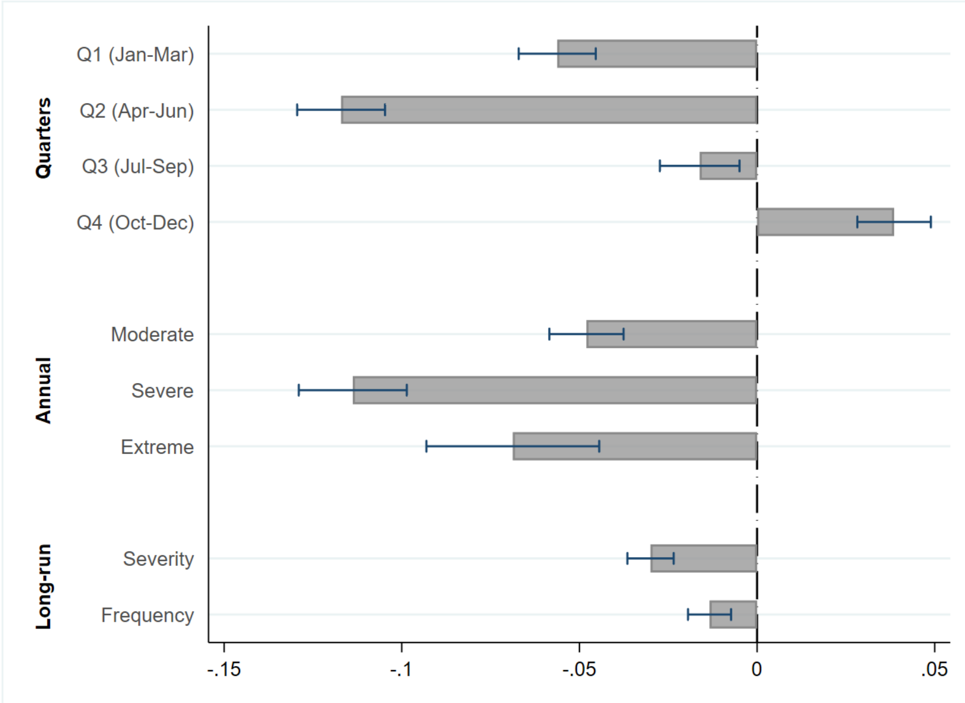

Figure 4: Impacts of Drought on Agricultural Production (Homogeneous and Heterogeneous Models)

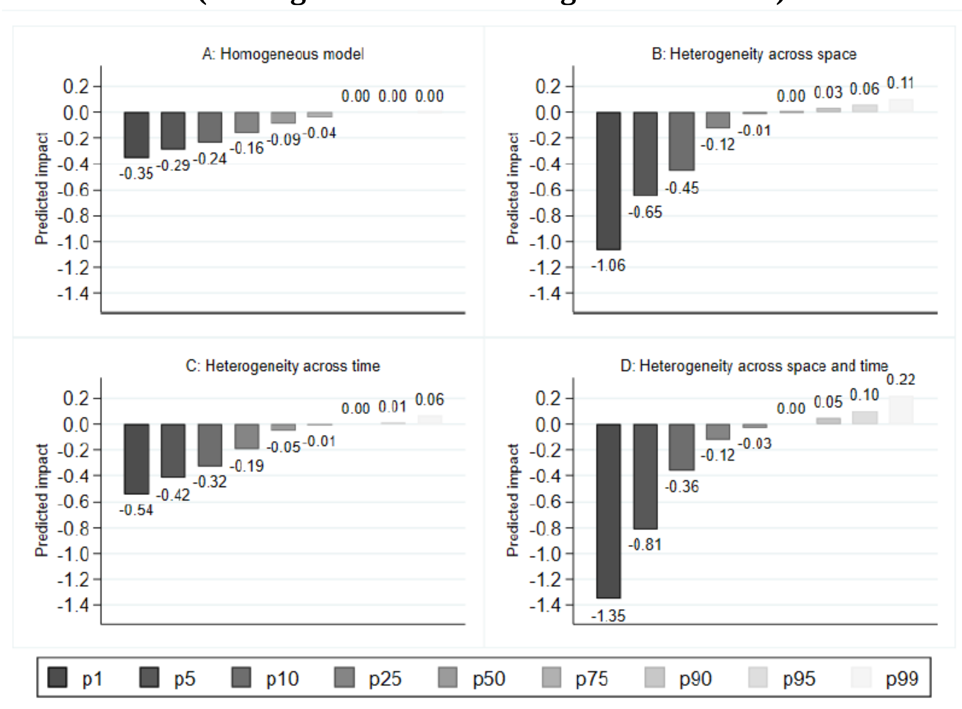

Figure 5: Distribution of Impacts of Drought by Biome

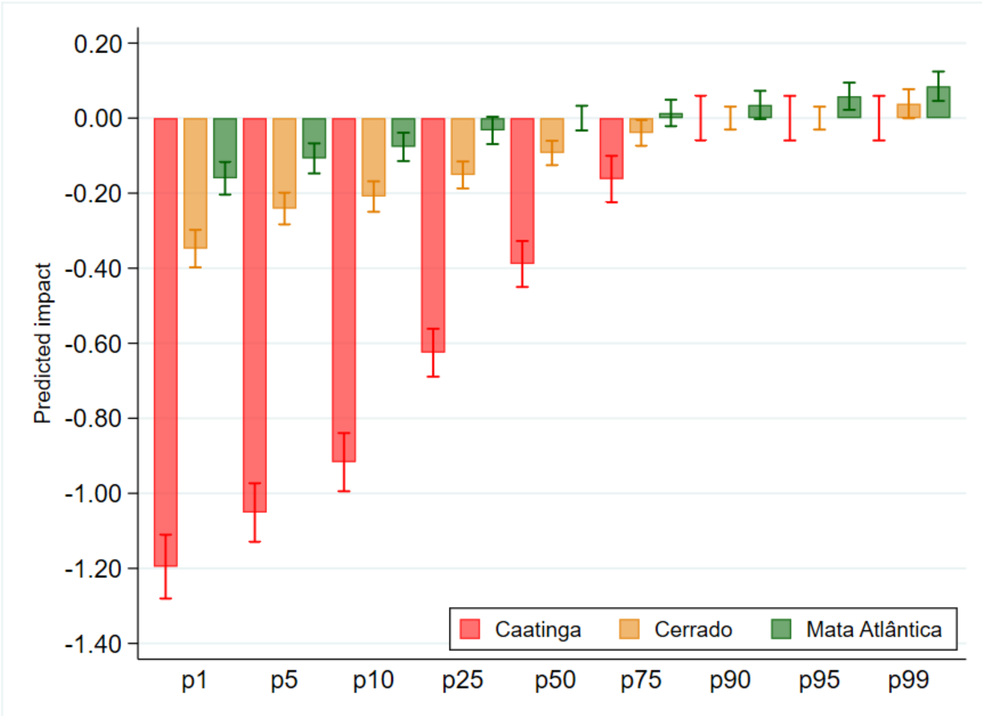

Figure 6: Distribution of Impacts of Drought by Sub-Period

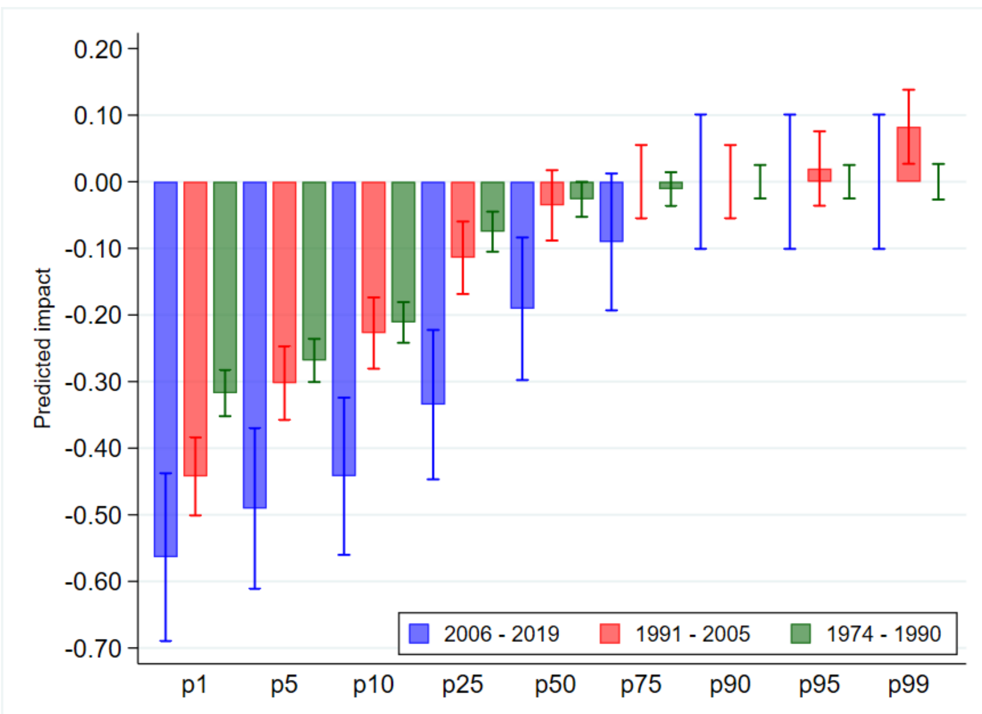

Figure 7: Spatial Distribution of Drought Impacts (10th percentile, %)

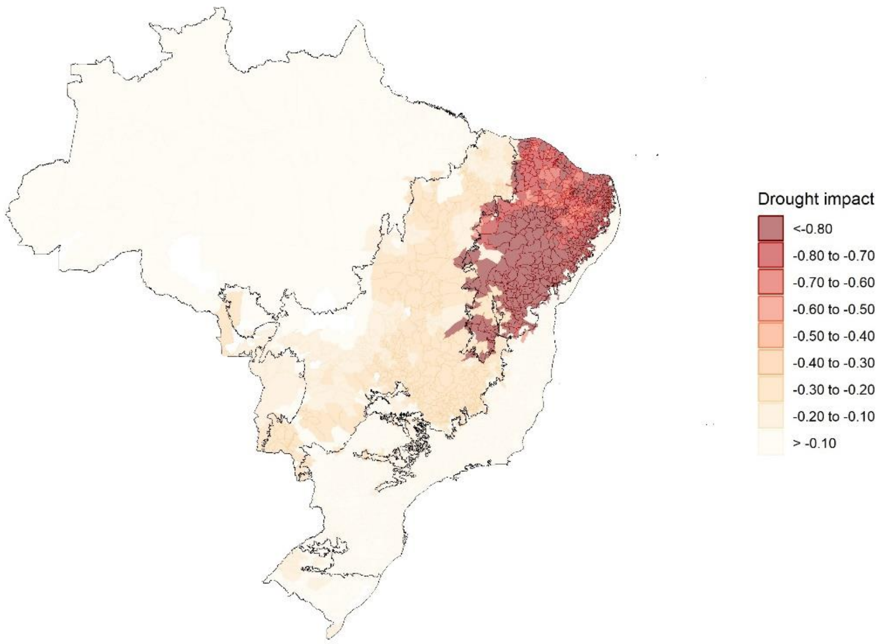

Figure 8: Spatial Distribution of Drought Impacts (10th percentile, R$ of 2019)

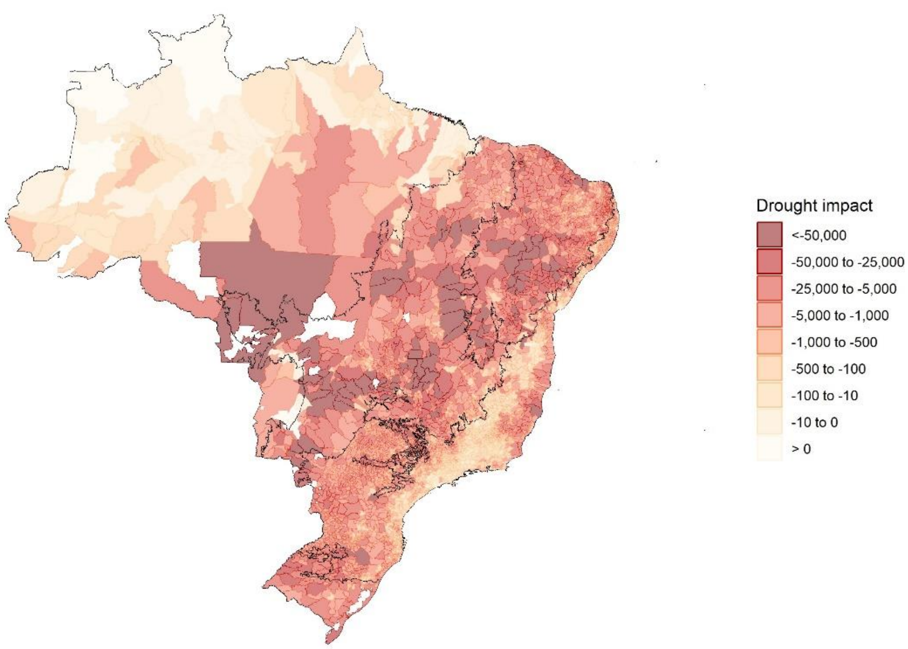

Figure 9: Comparison of Drought Impacts: Annual Panel vs. Long Differences

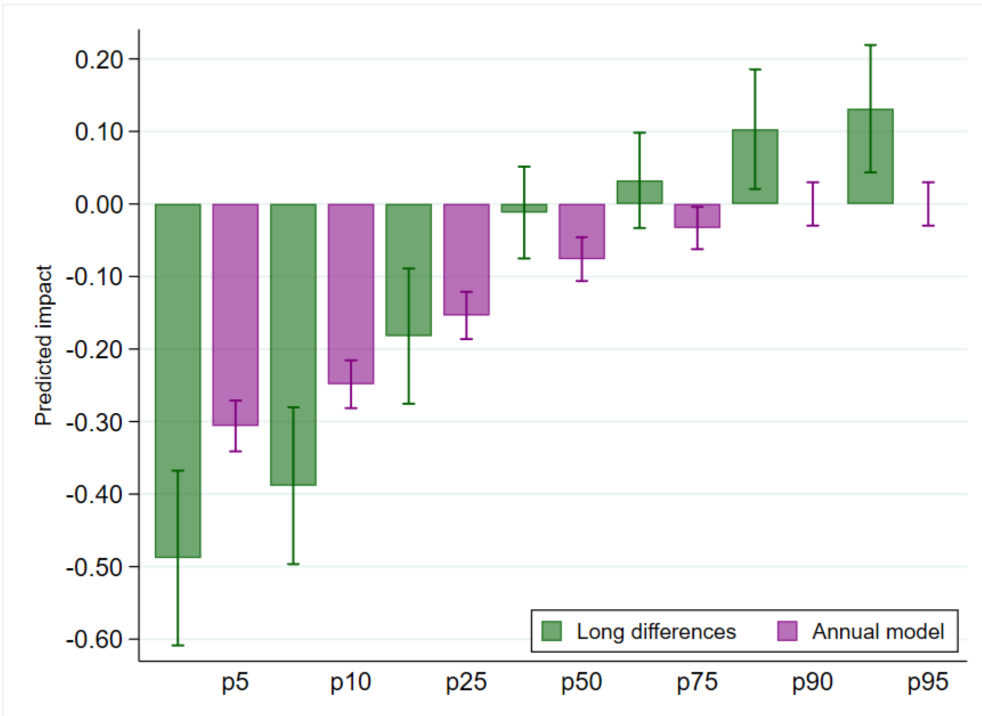

Figure 10: Projected Impacts of Drought with SSP Scenarios (Mean of Models)

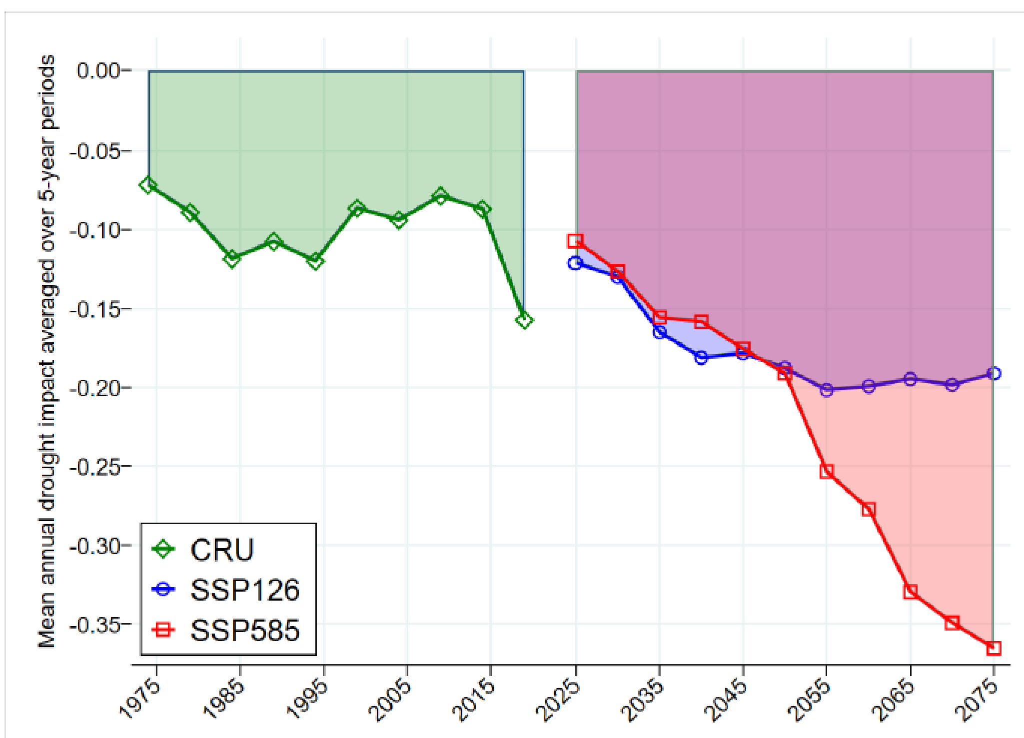

Figure 11: Projected 21st Century Impacts of Drought with SSP126 and SSP585 (All Models)

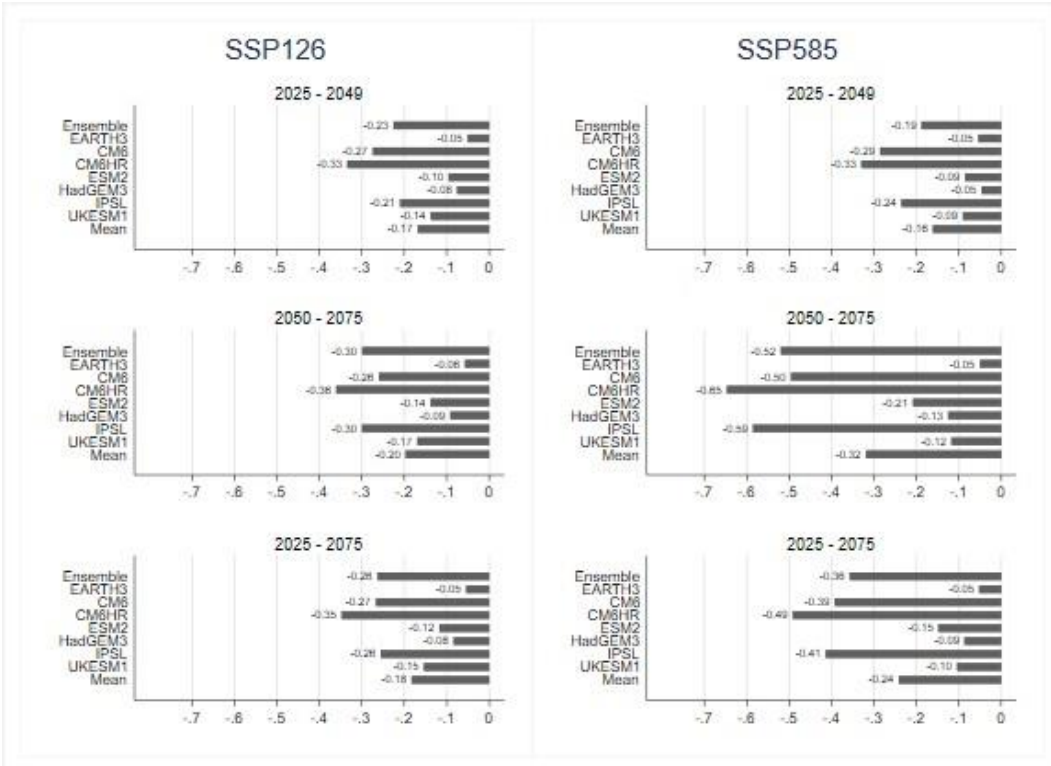

Figure 12: Distribution of Impacts for SSP scenarios: Mean of Models (2050-2075)