GABRIEL MEDEIROS ABRAHÃO

INTERACTIONS BETWEEN DEFORESTATION AND ATMOSPHERIC COMPOSITION ON THE CLIMATE OF AMAZÔNIA AND CERRADO AND THEIR CONSEQUENCES TO AGRICULTURE

Thesis presented to the Applied Meteorology Graduate program of the Universidade Federal de Viçosa in partial fullfillment of the requirements for the degree of *Doctor Scientiae*.

Adviser: Marcos Heil Costa

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Assent:

Gabriel Medeiros Abrahão
Author

Marcos Heil Costa
Adviser

A chuva e a neve caem do céu e para ele não voltam sem ter regado a terra,
tê-la feito florescer e dar semente ao que semeia e pão ao que tem fome
Livro de Isaías, 55:10

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ABSTRACT

ABRAHÃO, Gabriel Medeiros, D.Sc., Universidade Federal de Viçosa, July 2021, **Interactions between deforestation and atmospheric composition on the climate of Amazônia and Cerrado and their consequences to agriculture**. Advisor: Marcos Heil Costa.

Brazilian crop production has managed to grow expressively in the last 15 years with relatively little conversion of natural vegetation. Deforestation in the major Brazilian biomes however is still far from zero, and rates have been going up with the recent dismantling of public environmental governance (EG). Deforestation leads to changes in regional climate, which along with global climate change affects crop yields, often negatively. EG can benefit production by minimizing these effects. This thesis investigates how interactions between deforestation-induced and global climate change can affect Brazilian double cropping systems. These systems in Brazil play an important role on global grain production. Although modelling studies have suggested that they can be severely affected by global climate change, there's little empirical understanding of their sensitivity to climate. Chapter 1 examines how past climate variability affected municipality-level statistics of soybeans and second crop maize yields and double cropping adoption, and evaluate the impacts of projected global changes in climate. Double cropping in parts of Brazil with strong precipitation seasonality is more likely to occur when the rainy season is larger than 200 days, with no DC in municipality-years below 150 days. CMIP6 models project years with the rainy season shorter than 200 days to be more likely by 2035-2050 under the SSP2-4.5 scenario in key double cropping regions in central Brazil. Soybean yields are projected to decline by ~12%, a result that is not substantially affected by yield model specification. Second crop maize yields are found to be less sensitive to changes in climate than soybeans, with no significant impacts on the country average. However, models that explicitly account for vapor pressure deficit project substantial (>10%) impacts on second crop maize yields in regions with projected rainy season shortening. Chapter 2 uses a fully coupled climate system model and the empirical yield models from Chapter 1 to evaluate how different plausible EG futures can affect the Brazilian production of soybeans and 2nd crop maize. We perform simulations combining two land use scenarios representing different levels of EG and two global climate change scenarios (RCPs 2.6 and 8.5). We find that soybean yields are negatively affected in all scenarios, but differences in EG can impact yields as much as differences in atmospheric composition (RCPs). Stronger environmental governance can prevent soybean production losses equivalent to 442-527 million USD year^{-1} in the Amazon and 670-1347 million USD year^{-1} in the Cerrado by 2050, up to 10% of projected production. Collectively, Brazilian soybean farmers have much to gain with better environmental governance and it would be in their interest to enforce and even extend private zero-deforestation agreements in the Amazon and Cerrado biomes.

Keywords: Double cropping. Statistical crop model. Climate change. Brazil. Deforestation. Biogeophysical climate change. Land use and land cover change. Earth system models

RESUMO

ABRAHÃO, Gabriel Medeiros, D.Sc., Universidade Federal de Viçosa, julho de 2021, **Interações entre desmatamento e composição atmosférica no clima da Amazônia e do Cerrado e suas consequências para a agricultura.** Orientador: Marcos Heil Costa.

A produção de grãos no Brasil cresceu expressivamente nos últimos 15 anos com relativamente pouca conversão de vegetação natural. Porém, taxas de desmatamento nos principais biomas brasileiros ainda estão longe de zero, e vem crescendo com o recente desmantelamento da governança ambiental (GA) pública. O desmatamento leva a mudanças no clima regional, que juntamente com mudanças climáticas globais afetam a produtividade agrícola. Uma boa governança ambiental pode beneficiar a produção agrícola minimizando esses efeitos. Esta tese investiga como interações entre mudanças climáticas globais e induzidas pelo desmatamento podem afetar os sistemas de dupla safra no Brasil. Esses sistemas tem um papel importante na produção mundial de grãos. Apesar de estudos de modelagem sugerirem que eles podem ser severamente afetados por mudanças climáticas globais, ainda há pouca compeensão empírica de sua sensibilidade ao clima. O Capítulo 1 examina como variações no clima passado afetaram a produtividade de soja e milho segunda safra e a adoção de dupla safra por município, e avalia os impactos de projeções de mudanças climáticas globais nesses sistemas. A adoção de sistemas de dupla safra em regiões do Brasil com forte sazonalidade da precipitação ocorre com mais frequência onde a estação chuvosa dura mais de 200 dias, e não foi observada em nenhum município e ano onde ela durou menos de 150 dias. Modelos do CMIP6 indicam que anos com a estação chuvosa menor que 200 dias ocorrerão com mais frequência em 2035-2050 no cenário SSP2-4.5 em regiões chave que praticam dupla safra no Brasil. A produtividade de soja deve diminuir ~12% no mesmo período, um resultado que não é afetado substancialmente pela escolha de especificação dos modelos. A sensibilidade da produtividade de milho segunda safra ao clima parece ser menor do que a de soja, com impactos médios no país não sendo estatisticamente significativos. Porém, modelos que explicitamente consideram o efeito do déficit de pressão de vapor indicam impactos substanciais (>10%) em regiões onde a estação chuvosa deve se encurtar. No Capítulo 2, um modelo acoplado do sistema climático é usado em combinação com os modelos de produtividade estimados no Capítulo 1 para avaliar como diferentes futuros plausíveis da governança ambiental no Brasil podem afetar a produção de soja e milho segunda safra usando cenários de uso do solo representando dois níveis de GA e dois cenários de mudanças climáticas globais (RCPs 2.6 e 8.5). A produtividade de soja é negativamente afetada em todos os cenários, mas diferenças entre cenários de GA podem afetar a produtividade tanto quanto diferenças entre os RCPs. Uma governança ambiental mais forte pode prevenir perdas de produção de soja equivalentes a 442-527 milhões de USD por ano na Amazônia e 670-1347 milhões de dólares por ano no Cerrado, até 10% da produção total projetada para 2050. Coletivamente, produtores de soja brasileiros tem muito a ganhar com uma governança ambiental forte, e seria do interesse deles aplicar ou até expandir acordos de desmatamento zero na Amazônia e no Cerrado.

Palavras-chave: Sistemas de dupla safra. Safrinha. Modelo de produtividade. Mudanças climáticas. Desmatamento. Efeitos biogeofísicos no clima. Mudança de uso e cobertura do solo. Modelos do sistema terrestre

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gained with environmental governance. A positive value of 10% in column (D) means that yearly production value under SEG in 2050 is projected to be 10% higher than under WEG in the same year. Prices assumed for value calculations in column (E) are average producer prices in Brazil in the period 2010-2016, 194 USD ton^{-1} for maize and 406 USD ton^{-1} for soybeans (FAO 2021). 103

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General introduction

Brazil has consolidated its role as one of the main global grain producers in the last decade, recently becoming the world's largest soybean producer and the second-largest maize exporter (FAO 2020). Although agricultural growth in Brazil is historically associated with the expansion of natural vegetation, those positions have been achieved after a period of fast growth in crop productivity and quickly declining Amazon and Cerrado deforestation rates (Dias et al. 2016). But despite this past decoupling of crop production and deforestation, the future of natural vegetation in Brazil remains uncertain.

Amazon deforestation has been steadily rising after 2013. This reversion is generally attributed to two factors (Fearnside 2017, Rochedo et al. 2018). First, to the revision of the Forest Code in 2012, which weakened regulations for the conservation of natural vegetation in private lands and gave amnesty to the majority of illegal deforestation that happened before 2008 (Soares-Filho et al. 2014). Second, to rising commodity prices, which had been on very low levels before then (Nepstad et al. 2004, Fearnside 2017).

Several factors suggest that this new trend of increasing deforestation rates is unlikely to stop anytime soon. Several long-term infrastructure projects such as dams and roads are planned to be built near vulnerable areas (Fearnside 2016, Hilário et al. 2017). Dangerous precedents were set for relaxation of environmental governance as a tool for political bargaining (Rochedo et al. 2018), and the enforcement of environmental regulations has all but stopped under the new executive government (Ferrante and Fearnside 2019). In the neighboring Cerrado biome, all these factors are combined with much more permissive regulations (Soares-Filho et al. 2014) and the absence of specific public (Cisneros et al. 2015) and private (Nepstad et al. 2014, Gibbs et al. 2015) anti-deforestation policies.

The deforestation of these biomes has documented consequences to one of the main determinants of agricultural production: climate. The substitution of natural vegetation with pasturelands or crop agriculture influences climate through two main effects. One of them is biogeochemical, caused by the release of CO_2 in the vegetation and soil which add to other sources such as fossil fuel emissions. Land cover and land use change is the largest source of greenhouse gases (GHG) emissions from Brazil (Azevedo et al. 2018). These GHG emissions disturb global biogeochemical cycles and lead to global changes in climate, which can be of different magnitudes and directions in the climate of each region (Tebaldi et al. 2021).

However, deforestation also causes more immediate effects on the climate of the region where it occurs. Converting vegetation changes the physical and physiological characteristics of the land's surface, which modulate the exchanges of energy, mass, and momentum between it and the atmosphere above (Costa et al. 2007, Bonan et al. 2008, Zhang et al. 2014). In tropical regions, deforested surfaces normally have a higher albedo than natural vegetation, reflecting a larger portion of incoming solar radiation and consequently leaving less energy for surface processes. These deforested surfaces also tend to have lower rugosity, generating less turbulence and consequently less ascending motion which is important for the precipitation process. The shallower roots and other physiological properties of converted vegetation also lead to less evapotranspiration, which changes the partition of available energy between latent and sensible heat fluxes. The reduction in latent heat fluxes leads to higher air temperatures and reduces moisture and instability in the air column above, which are important for the rainy season onset in the Amazon. In general, the literature agrees that tropical deforestation above certain levels leads to a hotter and drier climate with a shorter rainy season in the case of Brazil (D'Almeida et al. 2007, Lawrence and Vandecar 2014, Mahmood et al. 2014, Wright et al. 2017, Gentine et al. 2019).

However, these direct effects of deforestation on climate depend on interactions with the background state of the atmosphere and the ocean, which can change substantially with global climate change in this century. Because these interactions can be highly nonlinear, the effects of the same deforestation patterns can be significantly different under different GHG concentrations (Brovkin et al. 2013). Li et al. (2016) attempt to quantify these interactions in a simple earth system model and suggest that the increases in temperature with deforestation are higher under wetter conditions, where latent heat fluxes play a larger role in the surface's energy balance. Swann et al. (2015), which find little reductions in precipitation with Amazon deforestation in a regional atmospheric model, suggest that these reductions would likely be larger under the drier boundary conditions expected for the future (Joetzjer et al. 2013). Wright et al. (2017) show that large-scale circulation patterns on the rainy onset in the Amazon are regulated by forest evapotranspiration and photosynthesis, both of which change substantially with the radiative and physiological effects of higher atmospheric CO_2 concentrations (Costa and Foley 2000). The physiological effect of doubled CO_2 concentrations in the Amazon, which leads to stomatal closure, alone can have influences on atmospheric and oceanic circulation stretching far into the tropical Atlantic and Pacific oceans (Sampaio et al. 2020).

These interactions were explored at a global level in the LUCID (Land Use and Climate, Identification of Robust Impacts) series of experiments of the Climate Model Intercomparison Project (CMIP). These experiments are performed at a global level, and they only explore a few global land use scenarios that do not represent well the spatial patterns of deforestation in Brazil and which project deforestation totals below even the most optimistic regionally-based projections (see Chapter 2 and Figure 2.1). Different spatial patterns of deforestation can lead to very different circulation patterns even when total rates are the same (Saad et al. 2010, Lawrence and Vandecar et al. 2014, Khanna et al. 2017).

In general, climate change induced by both increases in GHG concentrations (Rosenzweig et al. 2014) and by deforestation's biogeophysical effects are likely to affect crop agriculture in the region negatively. These negative impacts of deforestation-induced changes on the Brazilian climate may be an important incentive for the agricultural sector to conserve natural vegetation (Costa et al. 2019, 2020). Under the also generally negative effects of global warming, the importance of conserving natural vegetation as a climate regulator may be even larger (Oliveira et al. 2013, Pires et al. 2016, Flach et al. 2021).

However, the few works that attempt to combine the effects of these two climate forcings on agriculture under plausible scenarios do not consider interactions between them. All previous studies use one method to estimate the effects of deforestation on one or more climate variables and then linearly add these effects to the results of climate model simulations of future atmospheric composition scenarios (Oliveira et al. 2013, Pires et al. 2016, Flach et al. 2021). Although useful for gauging the relative magnitudes of these effects, this approach ignores the interactions between the forcings. These interactions can make the impacts of deforestation-induced climate change on agriculture higher or lower under global climate change and change its spatial patterns.

The highly productive double cropping systems adopted in the region, which depend on a large rainy to plant two crops in the same year, are especially sensitive to changes in climate (Oliveira et al. 2013, Pires et al. 2016, Abrahão and Costa 2018, Spera et al. 2020). In these systems, a second crop (commonly maize) is planted right after soybeans in the same year. Planting two crops dramatically increases profitability and diversifies the farmer’s income. Double cropping has seen widespread adoption in Brazil in the last decades, contributing to the intensification of crop agriculture (Abrahão and Costa 2018, Xu et al. 2021). In 2018 68% of all Brazilian maize was planted as a second crop (IBGE 2021). However, planting two crops in the same year demands a very long rainy season to accommodate both cycles, and shorter rainy seasons are expected with both deforestation-induced and global climate change (Arvor et al. 2014, Spracklen et al. 2016, Pires et al. 2016, Abrahão and Costa 2018, Teixeira-Filho et al. 2019b)

This work explores how interactions between deforestation-induced and global climate change can affect Brazilian double cropping agriculture. Chapter 1 investigates how the yields of soybeans, 2^{nd} crop maize, and the adoption of double cropping systems have responded to climate variations in the past. Using climate model projections from CMIP6, I then estimate how these systems may respond to future global climate change. Chapter 2 uses a fully coupled climate system model to analyze how different land use scenarios representing plausible futures of environmental governance in Brazil can influence climate under two different atmospheric composition scenarios. Using the relationships obtained in Chapter 1, I estimate how these changes in climate affect double cropping agriculture in Brazil until mid-century. By comparing impacts between scenarios, I further estimate the value of stronger environmental governance for Brazilian agriculture.

Chapter 1: Sensitivity of soybean and maize yields to climate in double cropping systems in Brazil

Abstract

Double cropping agricultural systems in Brazil play an important role on global grain production. Although modelling studies have suggested they can be severely affected by global climate change, there's little empirical understanding of their sensitivity to climate. Here we examine how the past climate affected municipality-level statistics of soybeans and second crop maize yields and double cropping adoption, and evaluate the impacts of projected changes in climate. Double cropping in parts of Brazil with strong precipitation seasonality is more likely to occur when the rainy season is larger than 200 days, with no DC in municipality-years below 150 days. CMIP6 models project years with the rainy season shorter than 200 days to be more likely by 2035-2050 under the SSP2-4.5 scenario in key double cropping regions in central Brazil. Soybean yields are projected to decline by ~12%, a result that is not substantially affected by yield model specification. Second crop maize yields are found to be less sensitive to changes in climate than soybeans, with no significant impacts on the country average. However, models that explicitly account for vapor pressure deficit project substantial (>10%) impacts on second crop maize yields in the regions with projected rainy season shortening.

1.1) Introduction

Brazil has almost tripled its soy and maize production since the turn of the century, recently becoming the world's largest soybean producer and third largest maize producer (USDA 2020, FAO 2020). Although part of this growth has been linked to the displacement of the country's natural vegetation, most of it was due to agricultural intensification (Macedo et al. 2012, Spera et al. 2014). In the country's largest agricultural state, Mato Grosso, cropland has increased ~50% from 2003 to 2011 while soybean production doubled and maize production tripled (Spera et al. 2014, IBGE 2019). This intensification is the product of not only substantial technological gains in yields (Santos et al. 2016) but also increases in cropping frequency.

In several parts of the country, farmers adopt double cropping systems, in which two crops are planted in the same season (Abrahão and Costa 2018, Xu et al. 2021). The most common system involves planting maize after soybeans. In 2018, 68% of all Brazilian maize was produced as a second crop in a double cropping system, called *safrinha* maize. The growing season in most of the country is limited mainly by the rainy season, which can last more than eight months in some regions (Waha et al. 2012, Abrahão and Costa 2018). These systems are possible because, by using shorter cycle varieties of both crops, farmers can accommodate two cycles in a single rainy season.

These systems are sensitive to climate on several fronts (Cohn et al. 2016, Costa et al. 2019). First, the feasibility of double cropping depends on the duration of the rainy season, which varies substantially across regions and between years (Spangler et al. 2018, Abrahão and Costa 2018). In some regions, the rainy season is not sufficiently long every year, and since the end of it is not easily predictable, farmers have to decide whether to risk double cropping mostly based on how early rains start (Costa et al. 2019). Accommodating two crop cycles in one season also means planting both crops in non-optimal periods. The middle of the rainy season is normally at the peak of summer. Planting soybeans early to make time for a second crop later is not optimal, potentially making the plants more exposed to high temperatures and lower solar radiation in the reproductive stage, which can negatively affect yields. Excessive rainfall in the transition between crops can also be challenging for the soybean harvest and subsequent maize planting operations. Finally, maize is more likely to experience drier conditions in the reproductive period, which may often fall in the wet-dry season transition (Pires et al. 2016).

Although the effects of climate on those systems in Brazil have often been studied using deterministic crop models (e.g. Pires et al 2016, Noia Junior et al. 2019, Andrea et al. 2020), there is little statistical understanding of the observed responses of crop yields to climate in Brazil (Hsiang et al. 2013, Cohn et al. 2016). A significant body of literature on other countries suggest that the exposure to very high temperatures reduces grain yields not only through direct effects of temperature on crop physiology but also by the association with high evaporative demand and water stress (Schlenker and Roberts 2009, Lobell et al. 2013, Schauberger et al. 2017, Rigden et al. 2020). Furthermore, empirical evidence from the Mato Grosso state, the largest producer in the country, indicates that cropping frequency (i.e. single cropping versus double cropping) is more sensitive to climate variability than crop yields (Cohn et al. 2016). Since the multiple drivers of soy yields, maize yields and cropping frequency might co-vary differently in the future, it is important to understand their effects separately (Rigden et al. 2020).

In this work we examine the sensitivity of the yields of Brazilian soybeans and the associated double cropping systems to climate. We analyze the effects of extreme temperatures, vapor pressure deficit and precipitation on soybean and second crop maize yields using different statistical model specifications. Since these variables may co-vary differently in the future, we examine how the different specifications influence projections of yield impacts under the SSP2-4.5 climate change scenario as simulated by five CMIP6 models. We also investigate under which conditions double cropping is historically practiced in Brazil and how those may change under the same climate change scenario.

1.2) Data and methods

1.2.1) Agricultural statistics

We used yearly soybean and second crop maize harvested area and yields from the *Pesquisa Agrícola Municipal* (PAM), collected per municipality. Soybeans data includes both soybeans planted as single cropping and as part of a double cropping system, while second crop maize includes only maize harvested after another crop in the same season. Although the soybeans data is available for 1973-2018 and second crop maize for 2002-2018, the period of study for soybean yields is constrained to 2004-2014 due to the cropping calendar dataset (see below).

One potential confounding factor in the data is that maize can also be planted after a main cash crop without the main purpose of producing grains – as a cover crop to prevent wind erosion, or to produce animal feed), with little investment on its management (Alvarenga et al. 2002). With the development of maize varieties and cropping techniques specifically for grain production in a double cropping system, the former practice has been increasingly less common. In modern soy-maize double cropping systems, the second crop maize can be just as economically important as the first crop. However, the former are also counted as second maize in the PAM data, and very low yields (<2 ton ha^{-1}) are common, especially in the earlier years of the dataset. For this reason, we limit our analyses of double cropping occurrence to the 2009-2014 period.

Irrigation can substantially change the dependence of agriculture on climate, especially on rainfall seasonality. Since yearly irrigated areas are not reported in the PAM, we also use the total irrigated area per municipality in 2015 reported in ANA (2017) divided by the harvested soy area in that year as an indicator of irrigation adoption in each municipality.

1.2.2) Cropping calendars

Information on planting and harvest dates is necessary to accurately represent the actual climate that crops were exposed to (Jägermeyr and Frieler 2018). This is especially true for Brazilian soybeans and maize planted in double cropping systems, since the strong seasonality of precipitation makes the sensitivity of yields particularly dependent on planting dates (Pires et al. 2016, Zanon et al. 2016, Nóia Júnior and Sentelhas 2019). We use the growing season from an extended version of the dataset described in Zhang et al. (2021). These authors estimate soybean and second crop maize planting dates for the Brazilian state of Mato Grosso at the field scale (500 m) using remote sensing. We use a version of their dataset that applies the same methods to all of Brazil for the period 2004-2014.

Their planting and harvest estimates are obtained by analyzing the time series of vegetation indexes in each 500 m pixel they classify as soybeans or double cropping in a given year. Planting and harvest dates vary among the pixels within each municipality. Since we only have yield data at the municipality level, we use as planting dates for a given municipality and year the 5% percentile of pixel-level planting dates within that municipality and year. Likewise, we use the 95% percentile of harvest date within the municipality-year as the harvest date for the municipality (Figure 1.1). We also investigate the sensitivity of our results to alternative growing season definitions using narrower percentile pairs of planting and harvest dates (25%-75% and 50%-50%).

For extracting historical climate from the Xavier et al. dataset (see below), we use the growing season definitions for each year in the period 2004-2014. For extracting climate anomalies from climate models, we use the average planting and harvest dates of each municipality.

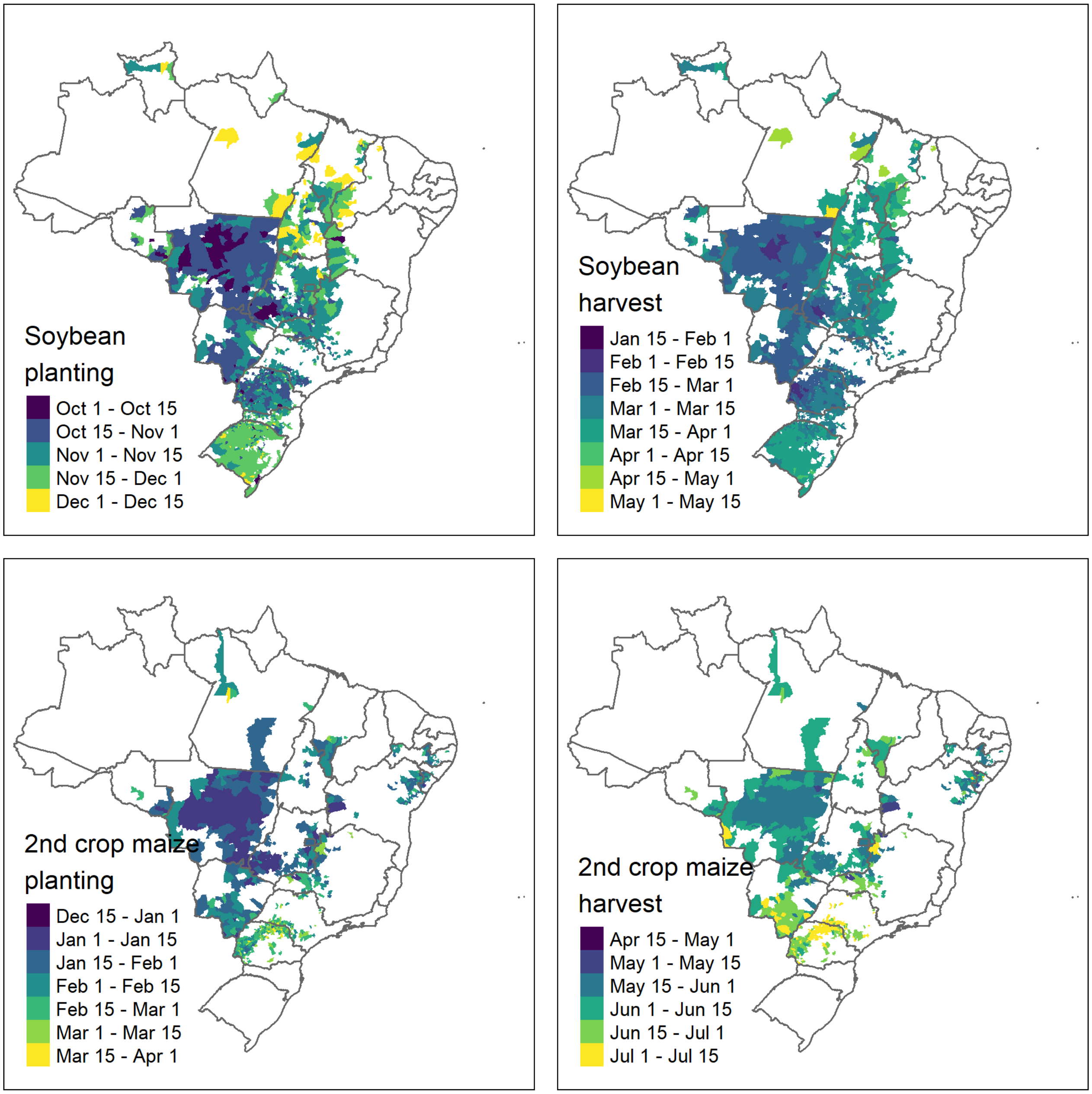


Figure 1.1 Average growing seasons for the period 2004-2014.

1.2.3) Climate indicators

To account for the nonlinear effects of different temperature ranges, we used a growing degree days (GDD) approach to temperature effects. GDDs are a measure of accumulation of time of exposure to a certain range of temperatures and is widely used for estimating the development rates of different crop varieties. In the last decade, several studies have shown that GDDs in different temperature ranges are good predictors of crop yields (e.g. Roberts et al. 2013, Butler and Huybers 2015). The rationale is that exposure to temperatures up to a certain threshold (generally around 30°C for temperate crops) is beneficial to crops, and exposure to temperatures above that threshold has an abruptly negative effect on yields (Schlenker and Roberts, 2009). The cumulative degree days in this warmer, damaging range, are often called Extreme Degree Days (EDD). When GDD is used combined with EDD, GDD use is restricted to describe cumulative degree days in the beneficial range from a lower temperature threshold up to the lower threshold for EDD.

The negative effect of EDDs on yields occurs through several pathways. Very high temperatures can directly affect yields by leading to oxidative stress, damage to enzymes and tissues and, during the reproductive stages, flower abortion (see e.g. works cited in Barnabas et al. 2008, Butler and Huybers 2015, Schauberger et al. 2017). Higher temperatures also speed up crop development, which leads to less time for biomass accumulation in the cycle (Soltani and Sinclair 2012). However, a large portion of the effects of high temperatures on yields is actually related to water stress (Lobell et al. 2013, Schauberger et al. 2017). Higher temperatures lead to higher vapor pressure deficit (VPD), which induces higher evapotranspiration (ET) demand. Higher ET also leads to more depletion of soil moisture. High temperatures are also partially caused by soil moisture stress, since water availability regulates the partition between sensible and latent heat fluxes into the atmosphere (Pitman 2003).

Climate data was derived from the dataset of Xavier et al. (2016), which is based on daily weather station data interpolated to a 0.25°x0.25° grid. The dataset includes daily precipitation, average relative humidity, minimum, maximum, and average temperatures. All derived variables were calculated for the growing season periods defined in the previous section for each 0.25° pixel, and averaged inside the area of each municipality. Vapor Pressure Deficit (VPD) was calculated for each day using relative humidity and daily maximum and minimum temperatures with the method described in Allen et al. (2006) and averaged across all days of the growing season.

To calculate GDD and EDDs, we used a sine wave method to approximate the diurnal variation between daily maximum and minimum temperatures (Schlenker and Roberts 2009). For both crops, we use a lower threshold of 10°C to calculate GDDs. Unless otherwise noted, we use 30°C as the threshold that separates GDD and EDD, which is close to those used elsewhere for soybeans and maize (Schenker and Roberts 2009, Butler and Huybers 2015). Using alternative thresholds in the 27-33°C range does not meaningfully change the coefficient estimates presented here (see Results and Discussion).

1.2.4) Double cropping adoption

The practice of double cropping in Brazil is highly dependent on a large rainy season that can accommodate two crop cycles (Pires et al. 2016, Abrahão and Costa 2018, Costa et al. 2019). Here we attempt to identify thresholds for double cropping adoption. We estimate measures of the rainy season (RS) onset, end, and length using a modified version of the Anomalous Accumulation method (Liebmann et al. 2007, Arvor et al. 2014, Abrahão and Costa 2018). This method defines the rainy season as a period of precipitation consistently above a value, here defined as 2.5 mm day $^{-1}$, representative of a soybean seedling's needs (Abrahão and Costa 2018).

To indicate the feasibility of double cropping in a given municipality-year, we define a quantity called double cropping (DC) fraction. In a given municipality and year, DC fraction is the second crop maize harvested area divided by soybeans harvested area. As soy-maize is by far the most common rotation, values closer to 1 indicate that a large portion of the soybeans in the municipality was followed by second crop maize in a DC system, while values closer to zero indicate that the double cropped area is small relative to total soy area.

We remove several municipality-years from the double cropping adoption analysis to minimize three major confounding factors. First, precipitation in some regions in the southern part of Brazil does not have a strong seasonal pattern. In these regions, the adoption of double cropping is more tied to intraseasonal rainfall events. For this reason, we remove the states of Paraná, São Paulo and Mato Grosso do Sul from the rainy season analysis. Second, irrigation is commonly used to plant two or even three crops in the same year even in regions with very short rainy season such as in Bahia state. Although to our knowledge there is no countrywide data specific on soy irrigation, we attempt to minimize this effect in our sample by excluding municipalities with more than 10% irrigated area relative to total soy area in 2015 (ANA 2017). Finally, the dataset might record in a municipality-year will register harvested second crop maize even when the second crop essentially failed or was planted primarily as a cover crop, with a different type of management that does not have maize production as a goal (Alvarenga et al. 2002). Therefore, when not directly evaluating yields, we also remove from the sample all municipality-years with second crop maize yields lower than 2 ton ha^{-1}, which is much lower than the ~4 ton ha^{-1} yields necessary to pay for the production costs around 2010 (CEPEA 2010).

1.2.5) Estimating the influence of climate on yields

Many widely employed estimates of the effects of climate on economic activity involve statistical approaches using historical data (e.g. Deschênes and Greenstone 2007, Schlenker and Roberts 2009, Hsiang 2016). A major issue when estimating yield responses to climate is separating the climate response from the many non-climate factors that can also influence yields and potentially confound the analysis due to omitted variable bias. Factors such as soil type and quality, choice of varieties, crop, soil and pest management practices influence yields as much or more than climate factors (Sentelhas et al. 2015) and are difficult to measure, especially at larger scales. Since these factors are often correlated with climate, their omission can severely bias the estimation of climate effects.

A common approach to overcome this issue involves leveraging the availability of panel data (repeated measurements in space and time) on both yields and climate in a fixed effects estimation, which we employ here. A fixed effects model in this case essentially indentifies the effects of intertemporal variations of climate on intertemporal variations on yields. The fixed effects are terms that represent a municipality-specific intercept, controlling for any municipality-specific unobserverd factors that influence yields that are invariant in time. They account for example for soil type, slope, usual choices of varieties and management, and indirect factors that influence management intensity such as distance to markets.

Naturally, many management related factors cannot be assumed to be time-invariant. A major case is the development and adoption of new technologies. Based on the rapid advancement and near-instant adoption of soybean technologies in Brazil in the last decades (Abrahão and Costa 2018), we assume that these factors are monotonically and uniformly changing in time, and are accounted for in a linear time trend.

We start with measures of yield (soybeans or 2nd crop maize) $Y_{i,t}$ and a vector of several weather variables $\boldsymbol{W}_{i,t}$ for each municipality i and year t. We estimate several multiple linear regression models where the dependent variable is $log(Y_{i,t})$ and the independent variables are combinations of weather variables $\boldsymbol{W}_{i,t}$, plus a linear time trend γ and a municipality-specific fixed effect α_i. $\boldsymbol{W}$ can contain the growing season GDD, EDD, average VPD or average daily precipitation (Prec). $\boldsymbol{\beta}_w$ are the coefficients representing sensitivities of log yields to one unit of each weather variable in $\boldsymbol{W}$.

$$\log(Y_{i,t}) = \alpha_i + \gamma t + \boldsymbol{\beta}_w \boldsymbol{W}_{i,t} + \varepsilon_{i,t}$$

One potential disadvantage of the fixed effects approach is that it relies on the response to weather fluctuations to identify the yield response to climate, which does not account for long-term adaptation. Farmers may adapt and respond differently to long-term changes in the expected distribution of weather than they do to short-term variations (Kolstad and Moore 2020). However, studies in data-rich settings with long records find little evidence of differences between these responses (Burke and Emerick 2015, Hsiang et al. 2016).

Since the models derived will be used for out-of-sample estimation under climate change scenarios, we employ two main strategies to minimize the influence of potential overfitting on our main conclusions. First, we evaluate the ability of each model specification (combination of climate variables) to reproduce observed variation in yields by calculating the exponential of the Mean Absolute Error (MAE) in a 10-fold cross-validation procedure. This provides a measure in yield units (tonnes per hectare) of the out-of-sample prediction skill of each model.

As mentioned in the previous sections, a common problem in empirical modelling of crop yields arises from the following facts (Hsiang 2016, Rigden et al. 2020): (i) the explanatory climate variables that are measured (temperature, precipitation, EDD) are actually proxies for quantities that actually affect yields, such as soil moisture availability and plant water deficit; (ii) the correlation between the proxies and these quantities may change with i.e. global climate change and (iii) climate variables are very correlated with each other. Therefore, there is a problem with the identification of the effects of a given climate variable on yields, making the estimated effects not necessarily valid in conditions different from those of the sample.

We attempt to address this issue by estimating (and applying) a number of models with different specifications, including variables that are proxies for water availability (precipitation), evaporative demand (VPD, EDD) and nonlinear thermal effects (GDD, EDD). By comparing the coefficient estimates in different specifications, we discuss what effects these coefficients are and are not likely to be capturing. When estimating the effects of changes in climate on yields, we apply four different models with different specifications and compare their results. This has the effect of minimize the identification bias arising from using a single specification. Nevertheless, it should be noted that research suggests that even VPD and precipitation together cannot properly account for the effects of soil moisture dynamics, leading to overestimation of effects of climate change on maize yields in the US (Rigden et al. 2020).

1.2.6) Climate change scenario

To estimate how climate change might impact Brazilian double cropping systems, we use simulation results from five climate models that are part of the Climate Model Intercomparison Project phase 6 (CMIP6). We calculate all climate variables for the 2045-2050 period on the simulations under the SSP2-4.5 scenario, which assumes the radiative forcing reaches 4.5 W m^{-2} by 2100 and a middle of the road socioeconomic pathway (Gidden et al. 2019). The models used are BCC-CSM2-MR, CanESM5, EC-Earth3-Veg, GFDL-CM4, and MRI-ESM2-0.

To minimize model-specific bias, we also calculate the average of each variable for the historical simulations of each model in the period 1995-2013. Since our yield models depend on the anomalies of climate variables with respect to a long-term mean, the anomalies associated with the future scenarios are calculated as the difference between the average in the future period (2035-2050) years and the average of the historical period (1995-2013) of each model. For each model, the anomaly of a climate variable *W* in municipality *i* is:

$$\Delta W_i = \overline{W}_{i,1995-2013} - \overline{W}_{i,2035-2050}$$

Yield model predictions are made by applying the estimated climate coefficients to climate model anomalies. For a given climate model and municipality i, the predicted percentage change in yields ΔY_i is given by multiplying the coefficients βw of each climate variable w to the corresponding anomaly Wi, and exponentiating since the model is logarithmic:

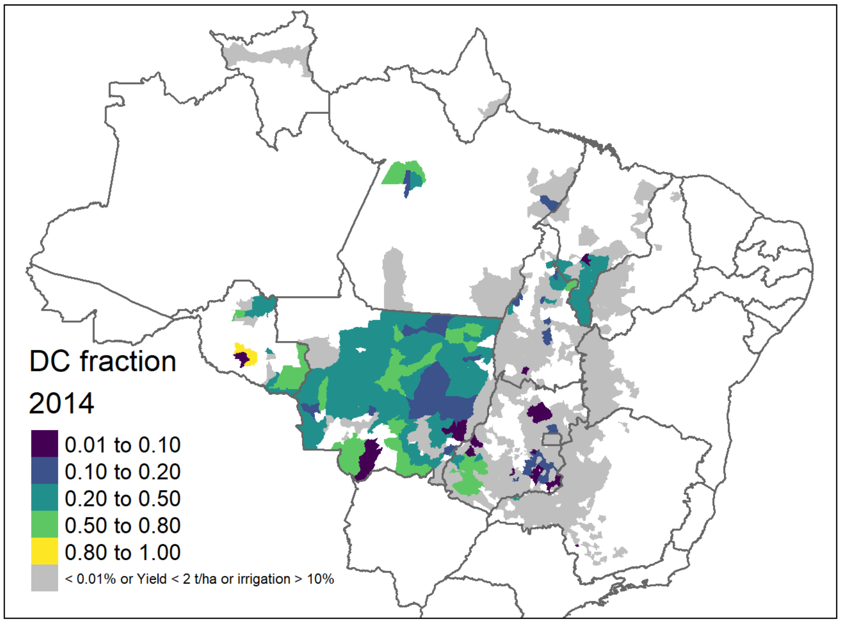
$$\Delta Y_i(\%) = 100 \times \left(e^{\sum \beta_w \Delta W_i} - 1\right)$$

Our double cropping feasibility analysis depends on absolute values of RS length (RSL), not just anomalies. To estimate the rainy season length in each year in the 2045-2050 period corrected by model bias (*RSLcorrected*) we take the anomalies in RS length as described for each model and add them to the average RS length in the reference observed Xavier et al. dataset mean for the period 2004-2014.

$$RSLcorrected_{i,t,model} = \overline{RSL}_{i,2004-2014,model} + \left(RSL_{i,t,model} - \overline{RSL}_{i,1995-2013,model}\right)$$

1.3) Results and discussion

1.3.1) Double cropping and the rainy season



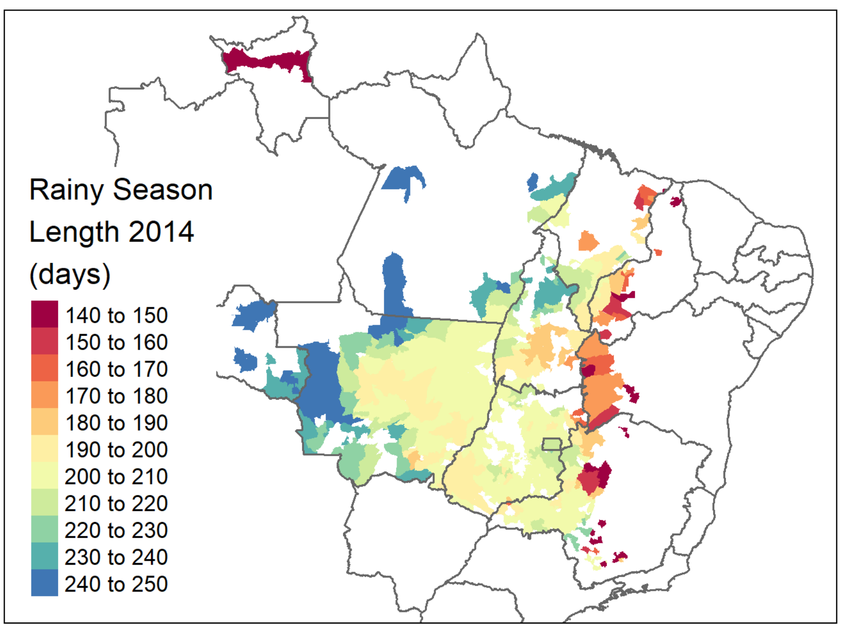


Figure 1.2 Double cropping fraction (top) and rainy season length (below) for the 2014 harvest year We analyzed the likelihood of a municipality-year to have at least 1% double cropping fraction in 10-day intervals of rainy season length.

About half of municipalities had at least 1% DC in years when the rainy season was longer than 200 days (Figure 1.3). The likelihood of double cropping declines fast below this threshold, and double cropping was not present in municipalities when the rainy season was shorter than 150 days. Yields also decline somewhat between 200 and 150 days, albeit slightly. This supports the hypothesis that a rainy season with less than 200 days is not ideal for double cropping in Brazil (Abrahão and Costa 2018), although it is not a clear-cut threshold.

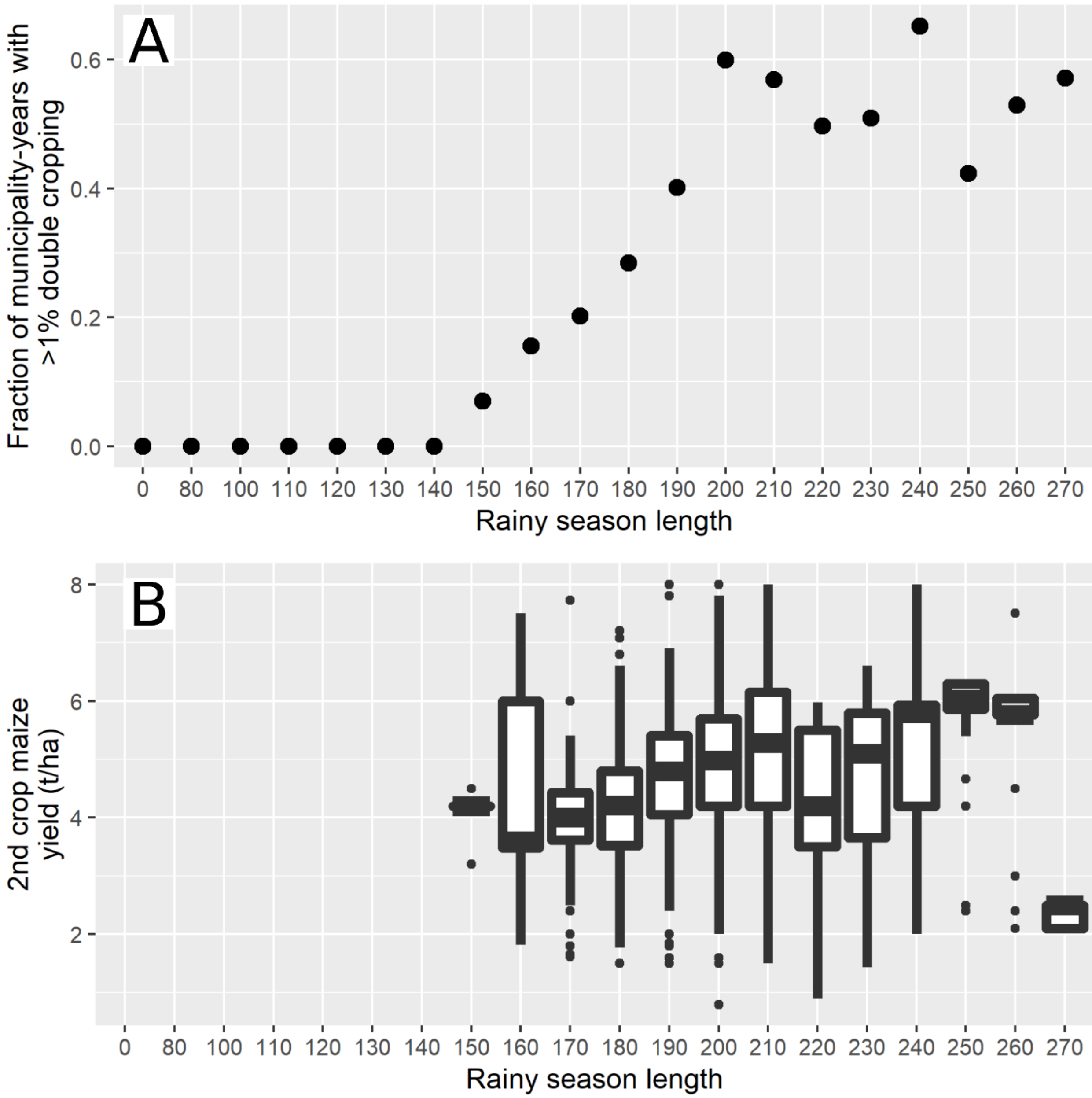


Figure 1.3 Double cropping likelihood and yields for 10-day intervals of rainy season length. Fraction of municipality-years with at least 1% DC fraction (A) and second crop maize yields (B)

Farmers do not have perfect knowledge of the duration of the rainy season at the time they decide whether or not to double crop. This is a risk-based decision, informed by the onset of the rainy season and the experience of past years in the region (Costa et al. 2019). The likelihood of double cropping is smaller on municipalities that experience more frequent years with less than

200 days in the rainy season (Figure 1.4A). There is also a clear geographical pattern of frequency of short rainy seasons, with a sharp northwest-southeast gradient roughly along the transition between the Amazon and Cerrado biomes (Figure 1.4B).

The ensemble of climate models represents this observed gradient reasonably well, with some underestimation of the frequency of short rainy season years (Figure 1.4C). Under SSP2-4.5 (Figure 1.4D), they project shorter rainy seasons along that gradient. Several important second crop maize producing regions such as central Mato Grosso and western Maranhão switched categories, from experiencing short rainy seasons (rainy seasons with less than 200 days) in less than 50% of years in the historical period to more than 70% in 2035-2050. The regions that switched categories produced 7.7 million tonnes of second crop maize in 2014, 14% of the country's production in that year.

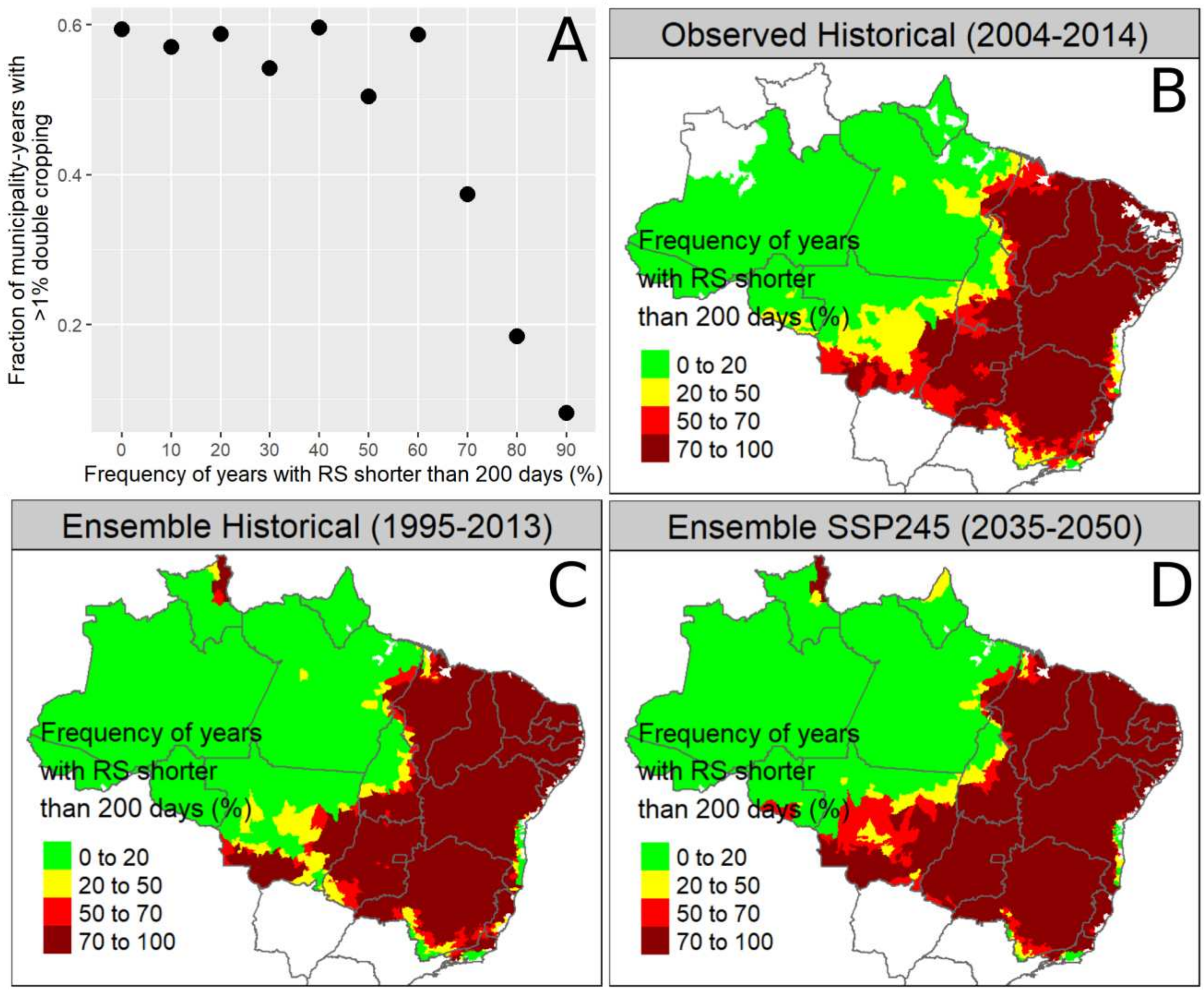


Figure 1.4 Fraction of municipality-years with at least 1% double DC fraction by frequency years with rainy season shorter than 200 days, aggregated in 10% frequency intervals (A). Frequency of years with rainy season shorter than 200 days in (B) the historical period in the Xavier el al. dataset; (C) the historical period in the ensemble of climate models and (D) SSP2-4.5 projections

1.3.2) Yield models

For soybeans, all model specifications show a strong positive trend in yields of about 3 pp year^{-1} (Figure 1.5), which can be attributed to technological developments and explains most of the variation the models along with the municipality fixed effects (R^2 = 0.45). From the individual climate variables, VPD is the variable that leads to the higher reduction in MAE relative to the trend only model, followed by precipitation and the DDs. The effect of GDDs and EDDs in the DD-only model is on the same order of magnitude as those found by others for soybeans and maize in the United States (Schlenker and Roberts 2009, Roberts et al. 2013, Butler and Huybers 2015), being positive for GDDs and more strongly negative for EDDs. This supports the notion that higher temperatures are beneficial for yields up to a threshold and strongly negative above this threshold. Here we show results using 30°C as this threshold, but the conclusions are similar when using somewhat higher and lower thresholds and other definitions of the growing season (Supplementary Figure 1.1, Supplementary Figure 1.2), this configuration being the one with the lowest cross-validation MAE.

	Soybean yield (log, fixed effects)							
	Trend	VPD	Prec	DD	VPD+Prec	VPD+DD	DD+Prec	VPD+DD+Prec
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Year	0.02299***	0.02893***	0.02567***	0.02308***	0.02896***	0.02991***	0.02559***	0.02990***
	(0.02160, 0.02437)	(0.02767, 0.03020)	(0.02434, 0.02700)	(0.02171, 0.02445)	(0.02770, 0.03022)	(0.02864, 0.03118)	(0.02427, 0.02692)	(0.02863, 0.03117)
VPD		-0.09219***			-0.08389***	-0.10347***		-0.09648***
		(-0.09684, -0.08755)			(-0.08975, -0.07803)	(-0.10881, -0.09813)		(-0.10302, -0.08994)
Precipitation			0.04900***		0.01027***		0.04584***	0.00815***
			(0.04526, 0.05275)		(0.00584, 0.01470)		(0.04197, 0.04970)	(0.00373, 0.01256)
GDD				0.00019***		0.00009***	0.00013***	0.00009***
				(0.00014, 0.00025)		(0.00004, 0.00014)	(0.00008, 0.00018)	(0.00004, 0.00013)
EDD				-0.00227***		0.00107***	-0.00121***	0.00103***
				(-0.00263, -0.00191)		(0.00071, 0.00143)	(-0.00156, -0.00085)	(0.00067, 0.00140)
exp(MAE)	1.1274	1.1151	1.1212	1.1255	1.1150	1.1145	1.1202	1.1144
Observations	6,285	6,285	6,285	6,285	6,285	6,285	6,285	6,285
R^2	0.48036	0.59235	0.53576	0.49444	0.59388	0.59939	0.53967	0.60034
Adjusted R^2	0.40683	0.53458	0.46997	0.42269	0.53624	0.54246	0.47425	0.54346
Note:								*p<0.1; **p<0.05; ***p<0.01

Figure 1.5 Soybean log yields regression results. MAE is calculated via 10-fold cross-validation, and shown here exponentiated for ease of interpretation. The EDD threshold used is 30°C.

The model that combines precipitation and VPD shows almost no decrease in MAE compared to the individual models. Although the magnitude of the VPD coefficient is reduced slightly, the precipitation one is reduced more than threefold. This suggests that the effect of precipitation is mostly via VPD, the two variables being strongly correlated (Supplementary Figure 1.1, Supplementary Figure 1.2). In fact, model (2), with only VPD and the trend as independent variables has almost the same MAE as the model that includes all variables. Similarly, considering VPD with GDD and EDD leads to small reductions in MAE and a reduction in the magnitude of both GDD and EDD effects, the latter becoming slightly positive. This is consistent with the bulk of the yield loss from high temperatures being caused by water stress (Lobell et al. 2013, Justino et al. 2013, Carter et al. 2016), although this sensitivity is also heavily modulated by soil water availability, which we did not consider in this study (Rigden et al. 2020).

For second crop maize, the technological trend is even stronger (~5 pp year^{-1}, Figure 1.6). This trend and the fixed effects largely dominate the observed variation in yields, the MAE of the saturated model being only slightly smaller than that of model (1) – the trend-only model. VPD, GDD, and EDD effects behave similarly to those of the soybeans models. However, they indicate a much weaker sensitivity to climate than that of soybeans, with all climate-related coefficients being substantially smaller in magnitude.

	2nd crop maize yield (log, fixed effects)							
	Trend	VPD	Prec	DD	VPD+Prec	VPD+DD	DD+Prec	VPD+DD+Prec
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Year	0.05826^{***}	0.05886^{***}	0.05577^{***}	0.05771^{***}	0.05736^{***}	0.05936^{***}	0.05542^{***}	0.05800^{***}
	(0.05486, 0.06166)	(0.05550, 0.06223)	(0.05216, 0.05939)	(0.05413, 0.06129)	(0.05370, 0.06101)	(0.05579, 0.06294)	(0.05166, 0.05918)	(0.05412, 0.06188)
VPD		-0.04316^{***}			-0.03704^{***}	-0.05217^{***}		-0.04580^{***}
		(-0.05873, -0.02758)			(-0.05366, -0.02042)	(-0.06997, -0.03436)		(-0.06493, -0.02666)
Precipitation			0.02093^{***}		0.01196^{**}		0.02061^{***}	0.01042^{*}
			(0.01015, 0.03172)		(0.00052, 0.02339)		(0.00978, 0.03143)	(-0.00112, 0.02197)
GDD				0.00002		0.00005	0.00001	0.00004
				(-0.00007, 0.00010)		(-0.00004, 0.00013)	(-0.00007, 0.00010)	(-0.00004, 0.00012)
EDD				-0.00036		0.00058	-0.00026	0.00051
				(-0.00103, 0.00032)		(-0.00016, 0.00131)	(-0.00093, 0.00041)	(-0.00023, 0.00125)
exp(MAE)	1.1586	1.1582	1.1580	1.1580	1.1578	1.1578	1.1574	1.1577
Observations	1,443	1,443	1,443	1,443	1,443	1,443	1,443	1,443
R^2	0.61636	0.62558	0.62094	0.61670	0.62689	0.62700	0.62112	0.62797
Adjusted R^2	0.53822	0.54894	0.54335	0.53787	0.55015	0.54990	0.54280	0.55070
Note:								*p<0.1; **p<0.05; ***p<0.01

Figure 1.6 2nd crop maize log yields regression results. MAE is calculated via 10-fold cross-validation, and shown here exponentiated for ease of interpretation. The GDD-EDD threshold used is 30°C.

1.3.3) Estimated effects under climate change

Our results suggest that different model specifications can explain a substantial portion of observed soybean yields in Brazil, and that the effects of some variables may vary significantly depending on the other variables included in the model. This raises the question of how the choice of model can influence on assessments of yield impacts of changes in climate, since the different climate variables may not co-vary in the same way as they historically did under global climate change. Here we neglect the yield trends and focus on four yield models for each crop: i) GDD + EDD only; ii) VPD only; iii) GDD + EDD + VPD and iv) GDD + EDD + VPD + Prec.

We primarily present yield impacts estimated by applying the yield models to the average climate anomalies of the ensemble of five climate models, but there is also substantial variability in climate anomalies across climate models (Supplementary Figure 1.6, Supplementary Figure 1.7, Supplementary Figure 1.8, Supplementary Figure 1.9). All models indicate increases in GDD, EDD and VPD in both the soybean and 2nd crop maize growing seasons in SSP2-4.5. CanESM5 (for soybeans) and both CanESM5 and BCC-CSM2-MR (for maize) show increases in EDD much stronger than the other models for all regions. This difference is not as prominent in GDD for both models, but present. The two climate models do not necessarily follow this pattern in VPD increases though. For example. BCC-CSM2-MR VPD increases in the maize growing season are relatively modest in the MATOPIBA and GO, MG regions. This suggests somewhat different patterns of covariation between warming and increased evaporative demand in the two models. EDD and VPD increases are overall twice higher in the earlier soybean growing season than in the maize one, while GDD changes are of similar magnitude. There is no consensus among the climate models used on the sign of changes in precipitation in any region, with the exception of an increase in the South's soybean growing season.

Overall, the different yield model specifications lead to qualitatively very similar results for both crops. Uncertainty in climate projections stemming from the five different climate models is far larger than that from the choice of yield model specification (Figure 1.7, Supplementary Figure 1.10, Supplementary Figure 1.11). The use of different EDD thresholds does not lead to significantly different country average projections (Supplementary Figure 1.3, Supplementary Figure 1.4, Supplementary Figure 1.5). Narrower definitions of the growing season lead to generally more pessimistic predictions for soybeans and more optimistic ones for second crop maize, although most of these differences are within the 90% uncertainty range.

For soybeans, all yield models indicate significant negative impacts of climate change in all regions. Effects are the strongest in MT (~-20%), followed by MS, SP (~-16%), MATOPIBA and GO, MG (~-14%) and relatively small effects in the South (~-4%). Differences between yield models are often not significant at 90% confidence for the ensemble mean impacts. Impacts from the VPD only model are generally stronger than from the GDD+EDD+VPD and GDD+EDD+VPD+Prec, which include the moderately positive effect of increases in GDD. The GDD+EDD model shows generally comparable or slightly weaker impacts than those of the VPD only model. EDD impacts on soybeans are especially strong in the generally drier region along the north-south borders of the states of Mato Grosso, Goiás, Maranhão, and Pará (Figure 1.8). On the other hand, VPD effects are strongly positive (>20%) in the southernmost municipalities of the country due to the moistening of the atmosphere in the region, an effect not present when accounting for GDD+EDD only.

For second crop maize yields, all models indicate very small impacts in all regions (Figure 1.7). On regional average, all statistically significant effects ($p < 0.10$) are negative, although they do not exceed -4%. These small impacts in comparison to those of soybean yields stem both from smaller climate anomalies and the smaller sensitivities to those anomalies in the estimated models. Accounting for VPD effects also lead to strong positive effects in the southernmost municipalities (Figure 1.9).

Second crop maize models that include VPD also reveal hotspots of strong negative impacts (-10-15%) in the western portion of Maranhão state and a few municipalities in Mato Grosso and Pará. These regions have relatively late harvest in June, and the climate models project an increased frequency of years with short rainy seasons (Figure 1.4). This leads to sharp increases in VPD which are not accompanied by proportionally high EDD increases (Supplementary Figure 1.7). Since average temperatures are lower in the fall, most of the warming happens below the 30°C threshold, which increases GDD but not EDD.

It's important to note that the physiological effect of increased CO_2 concentrations on yields is not explicitly included in the models. These effects are generally positive (yields increase with higher CO_2 concentrations), have decreasing gains with higher CO_2 concentrations, and vary substantially between crop varieties and across environmental conditons (Tubiello et al. 2007, Toreti et al. 2020). Published Free Air CO_2 Enrichment (FACE) experiments indicate that the physiological effect of a 200 ppm increase in CO_2 concentrations (about two times the 97 ppm 2010-2050 increase in the RCP4.5 scenario considered here) can lead to yield increases somwhere between 20% and 40% in maize and from ~20% in soybeans to even yield decreases in some genotypes (Kimball 2016). Therefore, the expected positive effects of the elevated CO_2 concentrations could be of similar magnitude to the negative effects of changes in climate shown here. For this reason, the estimated impacts under RCP4.5 here should be viewed more as an assesment of the sensitivity of yields to changes in climate than as an impact prediction.

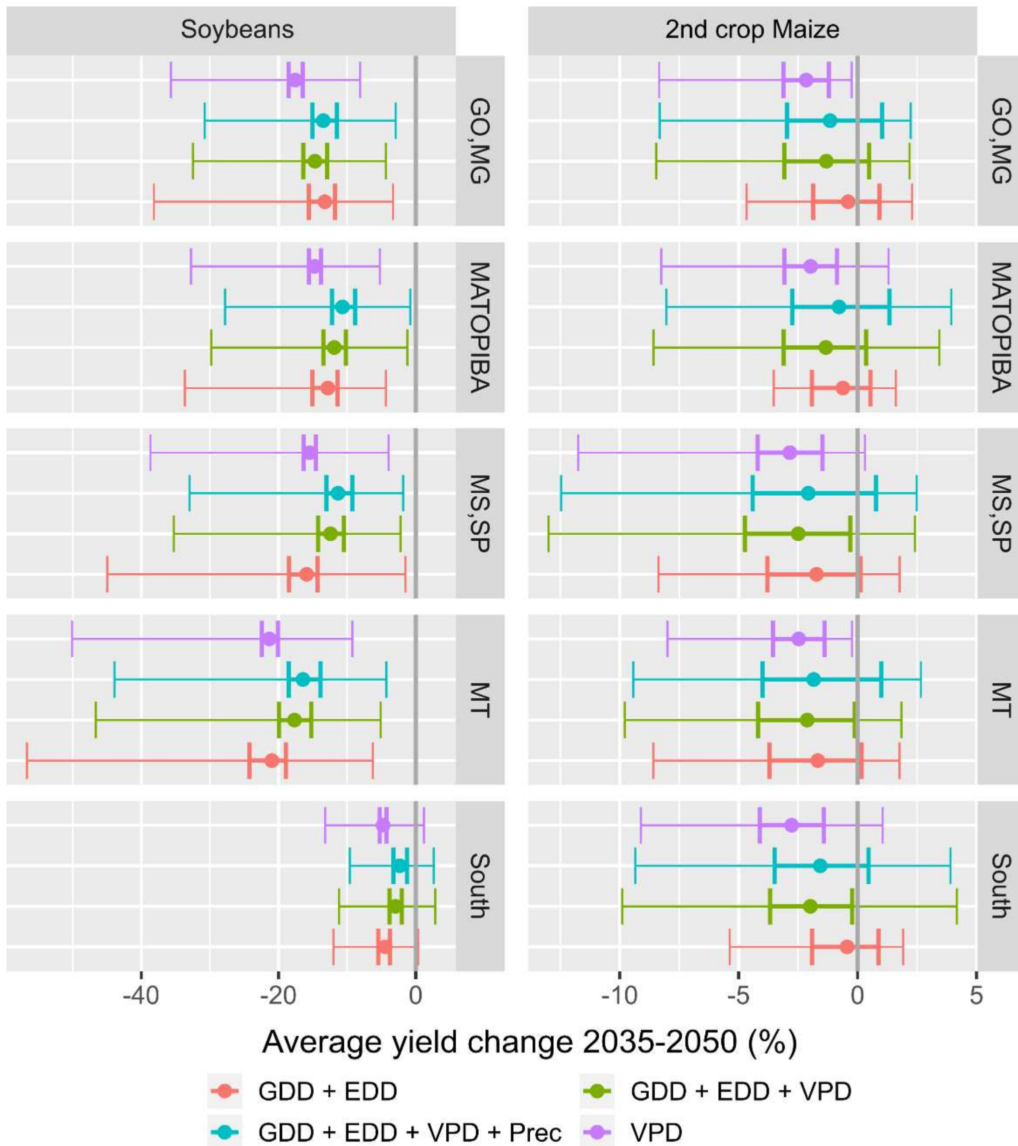


Figure 1.7 Ensemble and regional mean impacts on yields under climate change (SSP2-4.5, 2035-2050). Inner, thicker whiskers represent 90% confidence limits based on 100 bootstrapped resampled estimates of each model applied to the climate anomalies of the ensemble average of climate models, thus representing yield model uncertainties. Outer, thinner whiskers represent the confidence limits when applying each yield model to all individual climate models, representing uncertainty in both yield and climate models.

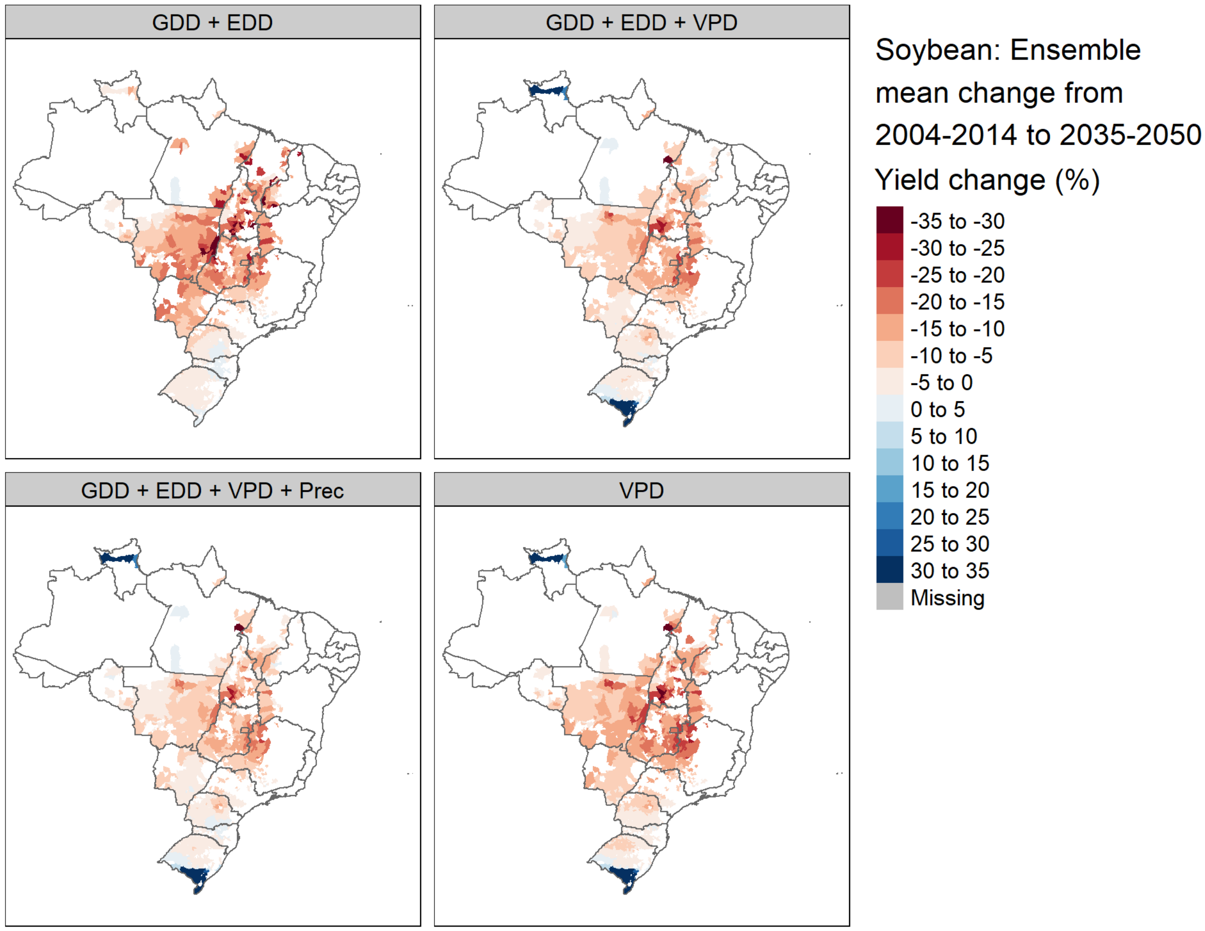


Figure 1.8 Effects of ensemble mean climate anomalies on soybean yields

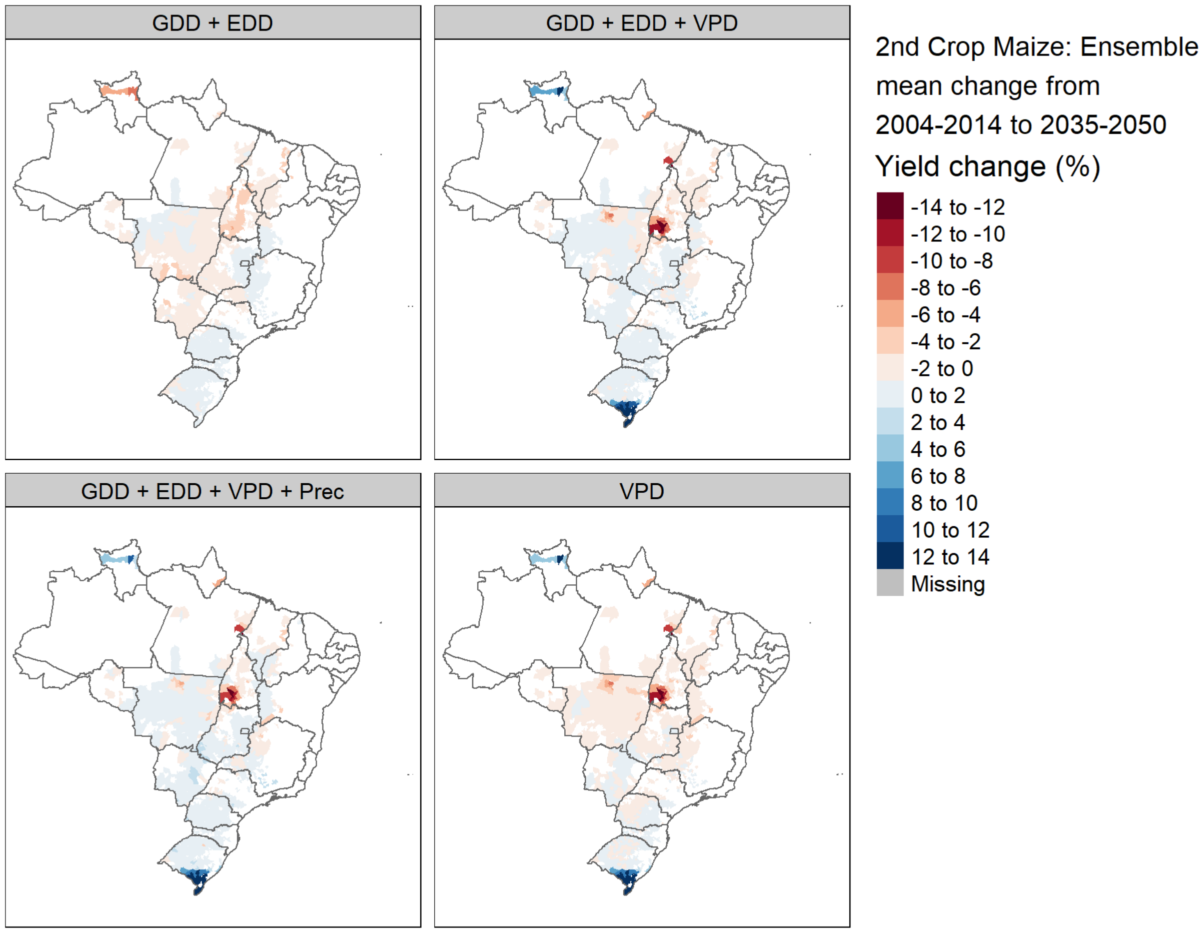


Figure 1.9 Effects of ensemble mean climate anomalies on 2nd crop maize yields

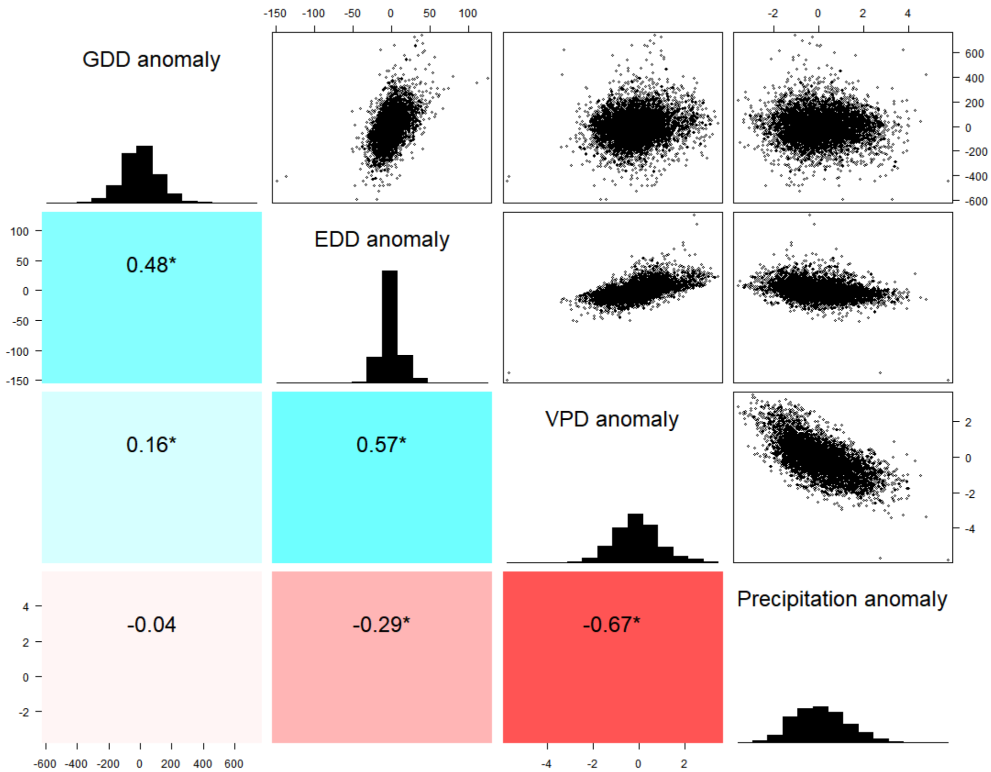
1.4) Conclusions

Double cropping in parts of Brazil with strong precipitation seasonality is more likely to occur when the rainy season is larger than 200 days, with no DC in municipality-years below 150 days. Second crop maize yields appear to be reduced by shorter rainy seasons, likely due to increased water stress conditions in the late stages of plant development. Climate models project increased frequency of rainy seasons below 200 days in key double cropping regions in the Mato Grosso and Maranhão states.

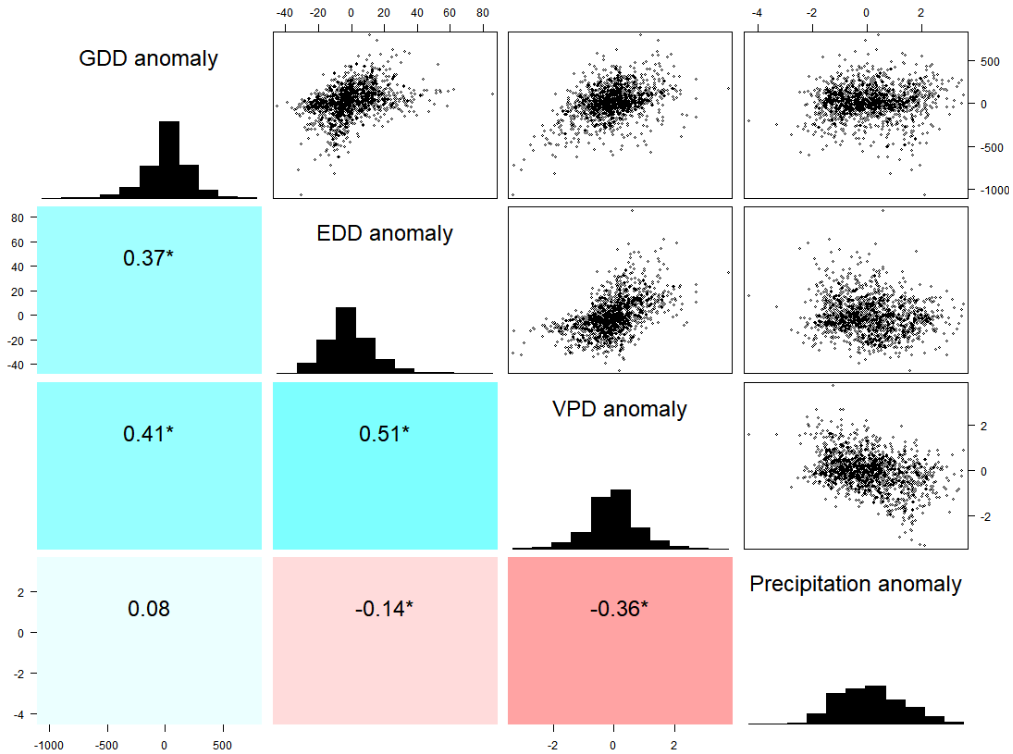
Vapor pressure deficit is more important in describing soy and maize change yields than extreme heat. Statistical models that include as climate variables just VPD, just GDD and EDD, and combinations of those with precipitation predict very similar yield impact changes when forced with 2035-2050 SSP2-4.5 climate anomalies. For soybeans, these changes are negative throughout the country, being the strongest in the MT state (~-20%), followed by central and northeastern Brazil (MATOPIBA, MS, SP, MG and GO, ~-14%) and weaker but statistically significant in the South (~-4%). Differences between climate models are much stronger than yield model fit uncertainty, but all combinations of yield and climate models still predict negative soybean yield changes in all regions except the South.

Second crop maize sensitivity to climate was found to be smaller than that of soybeans. Combined with generally weaker warming and drying in the second crop maize season for 2035-2050, projected impacts are much weaker. All statistically-significant impacts are negative, with the strongest regional average losses predicted by VPD in MT of -4%. However, models that include VPD predict much stronger (up to -14%) negative impacts inside the MATOPIBA and MT regions in places where climate models predict an increased frequency of short rainy seasons. These impacts are caused by drying with warming only below the 30ºC threshold, therefore not being present in predictions with the GDD and EDD only model. Although the choice of variables in the statistical yield models does not change significantly aggregated impacts, explicitly accounting for VPD is important in regions affected by changes in rainfall seasonality.

1.5) Supplementary Material

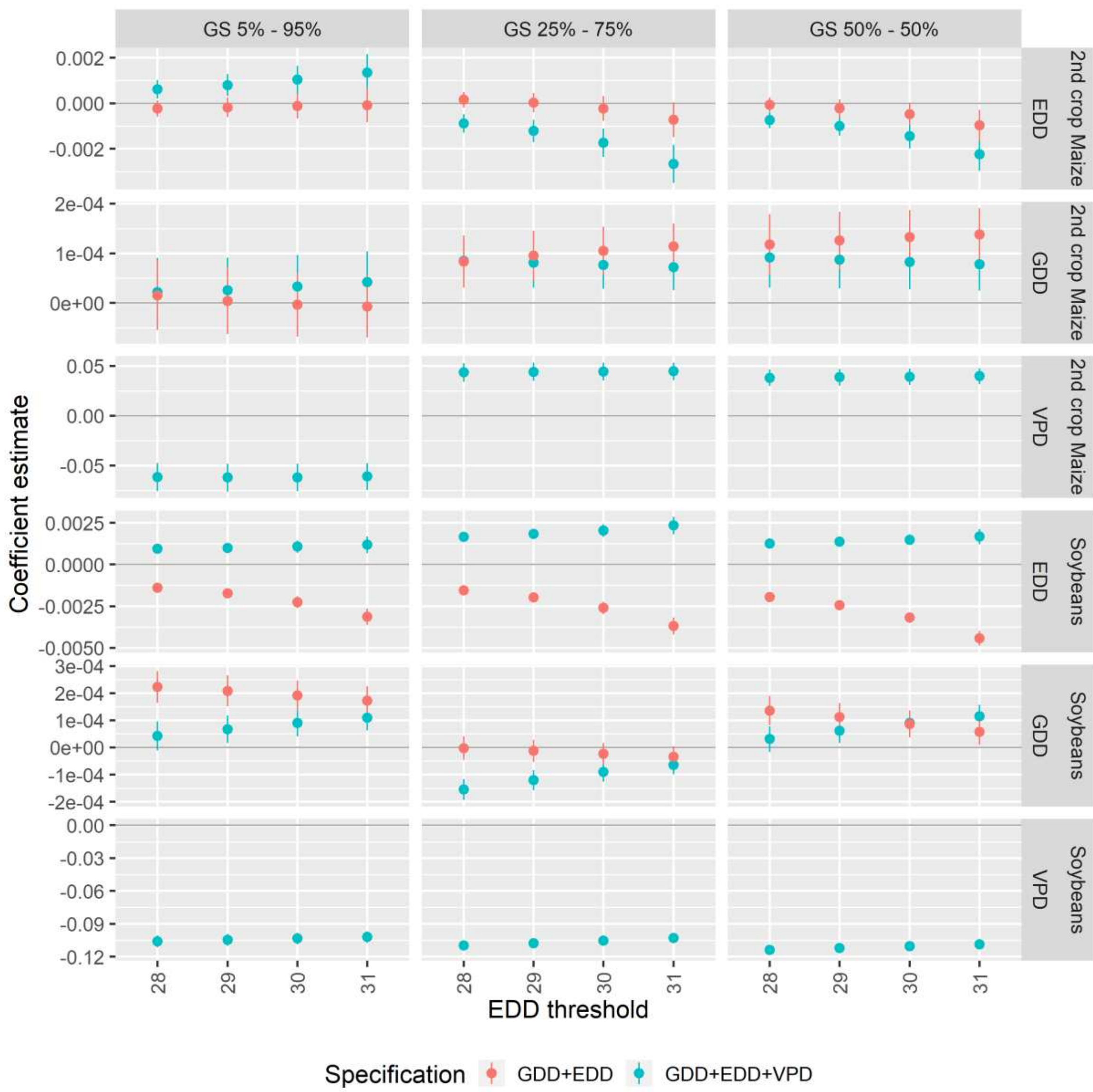


Supplementary Figure 1.1 Soybeans: correlation between independent variables

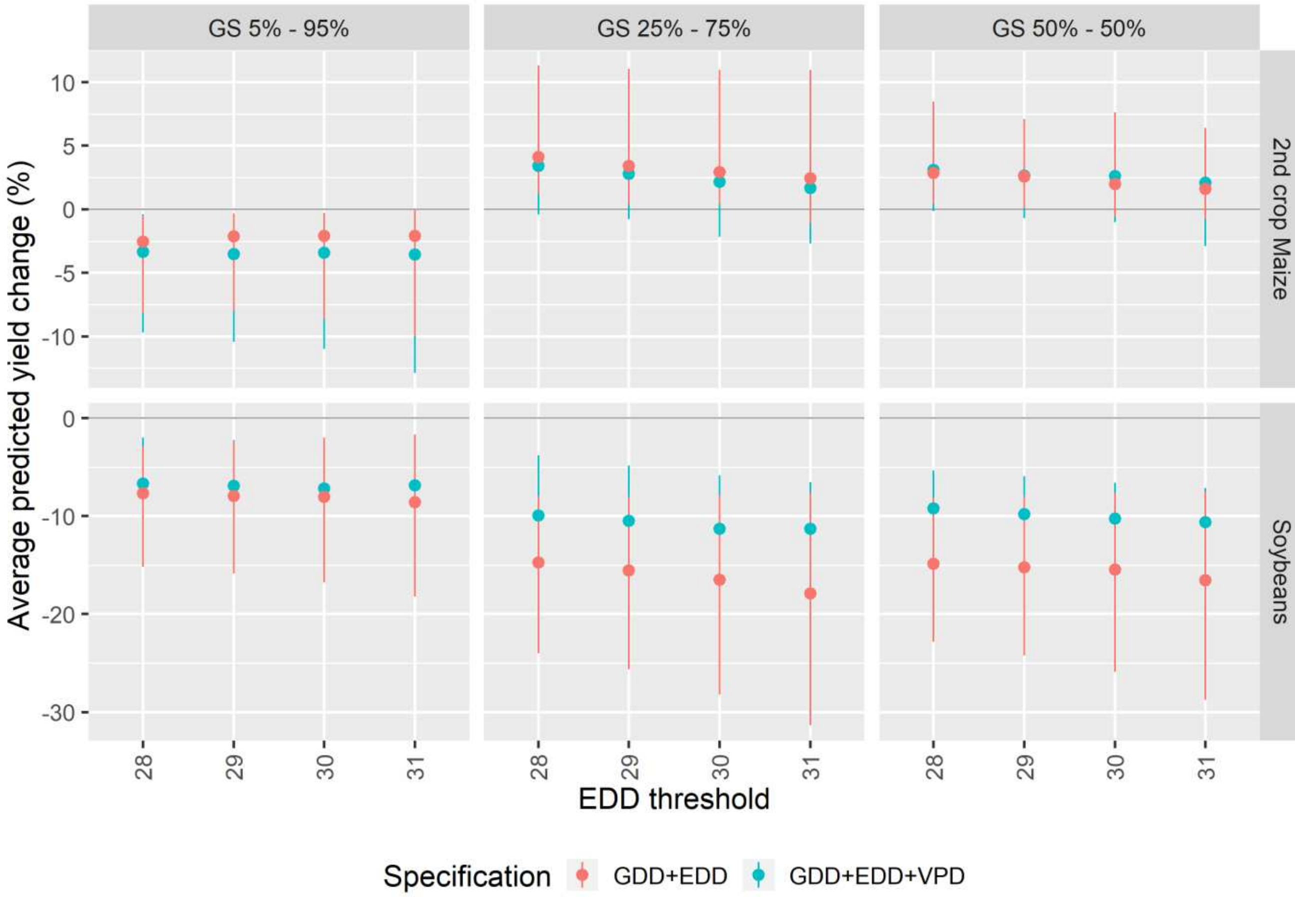


Supplementary Figure 1.2 2nd crop maize: correlation between independent variables

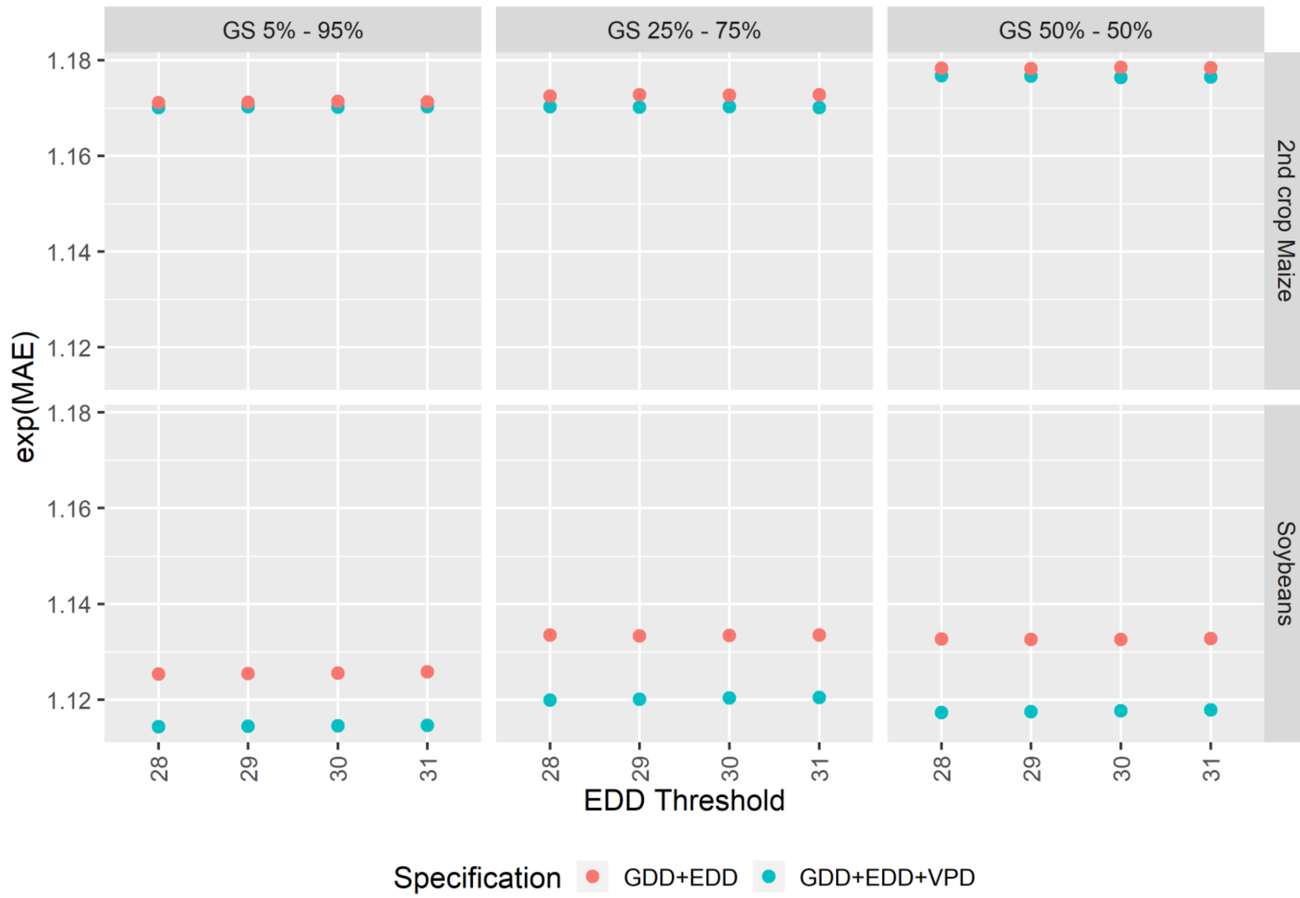
1.5.1) Model coefficients and fits for other thresholds and calendars



Supplementary Figure 1.3 Coefficient estimates of GDD + EDD and GDD + EDD + VPD models for other EDD thresholds and growing season definitions. GS 5% - 95% is the definition used in the main text, which assumes the growing season goes from the observed 5% percentile of planting

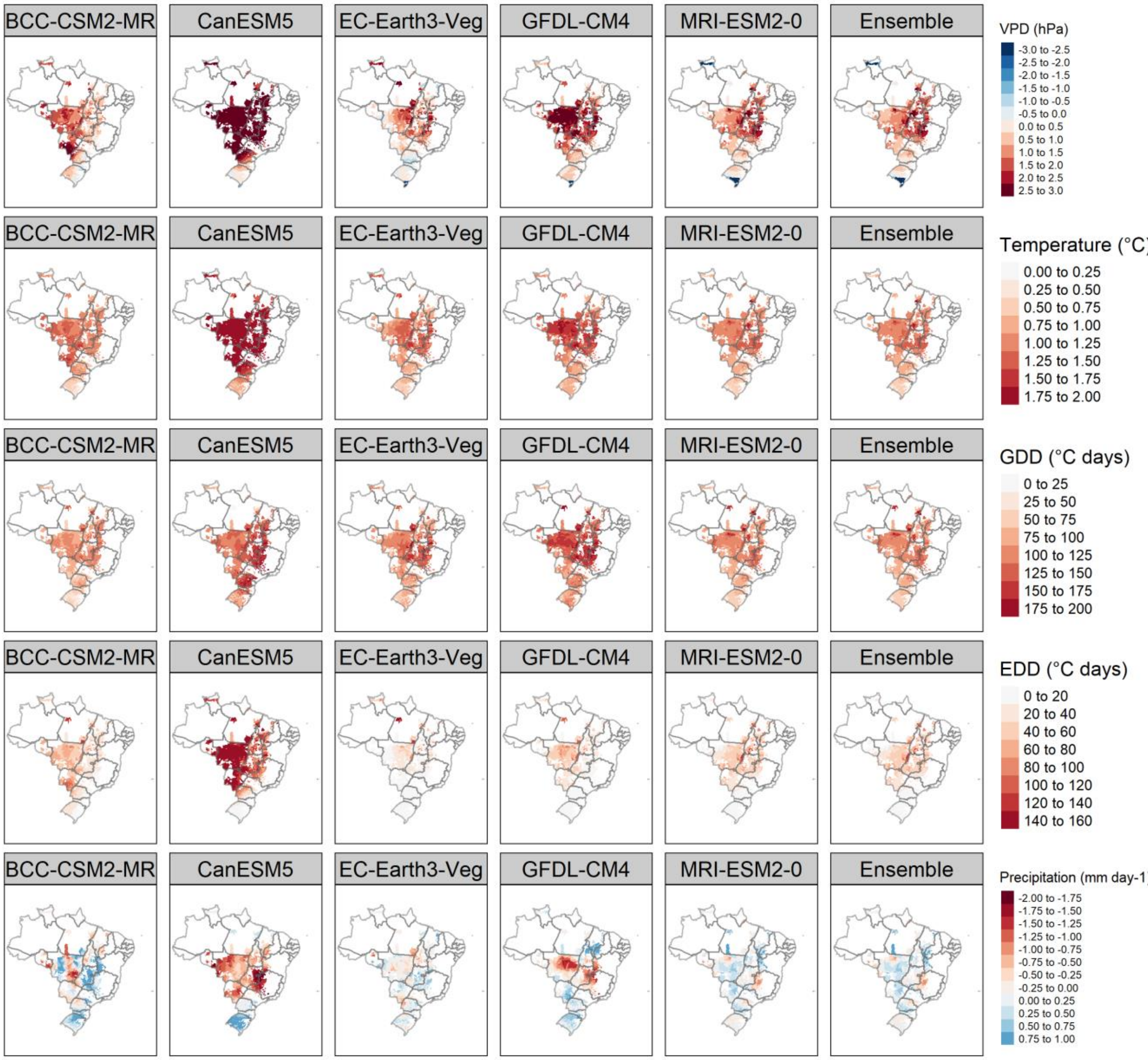


Supplementary Figure 1.4 Country-wide mean impacts on yields under climate change (SSP2-4.5, 2035-2050) of GDD + EDD and GDD + EDD + VPD models for other EDD thresholds and growing season definitions. GS 5% - 95% is the definition used in the main text, which assumes the growing season goes from the observed 5% percentile of planting dates and the 95% percentile of harvest dates, and the other two definitions follow the same convention. Whiskers represent 90% confidence limits based on 100 bootstrapped resampled estimates of each model applied to the climate anomalies of the ensemble average of climate models.



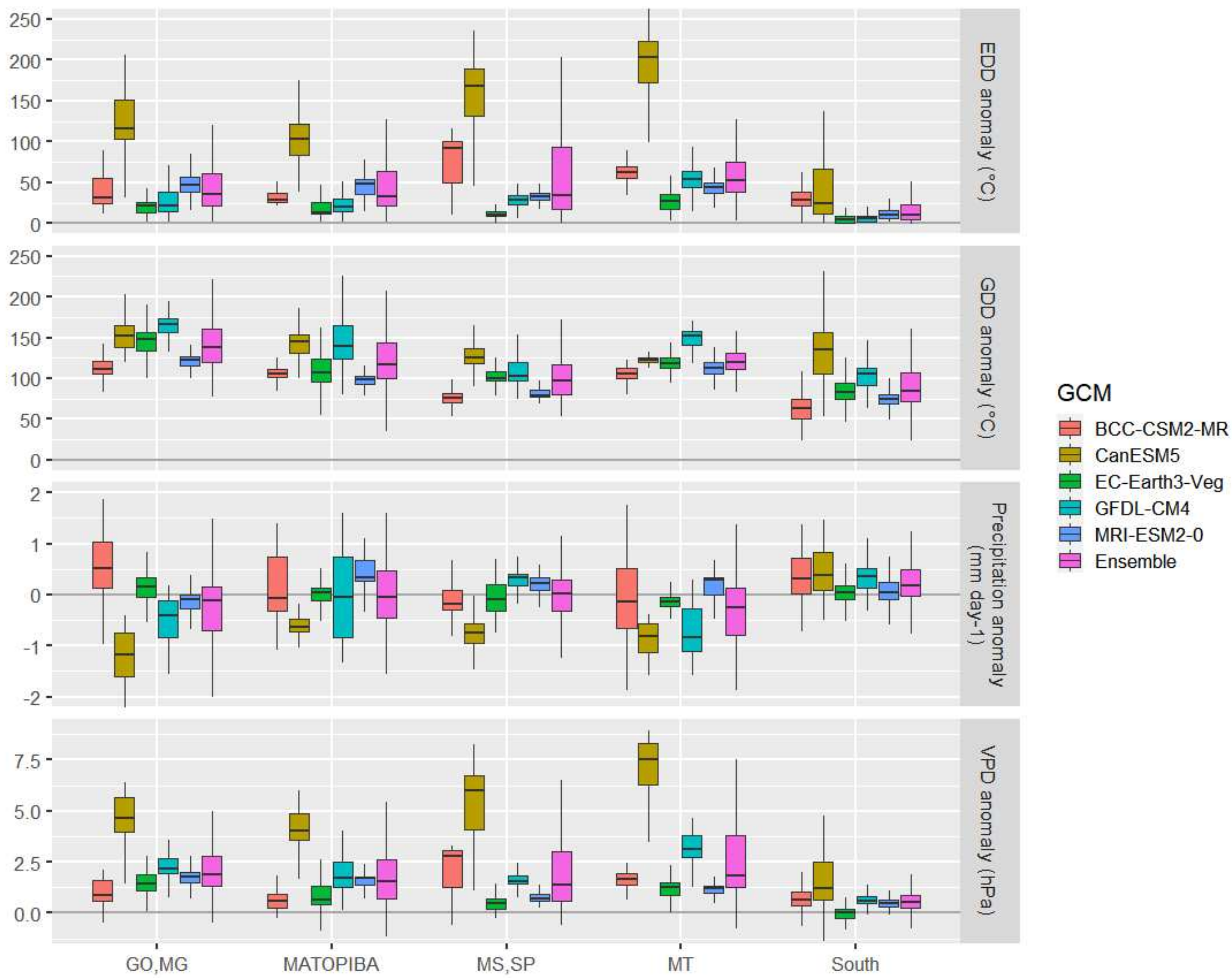
Supplementary Figure 1.5 10-fold cross-validation MAE of GDD + EDD and GDD + EDD + VPD models for other EDD thresholds and growing season definitions. GS 5% - 95% is the definition used in the main text, which assumes the growing season goes from the observed 5% percentile of planting dates and the 95% percentile of harvest dates, and the other two definitions follow the same convention.

1.5.2) Projected changes in climate variables during the growing seasons

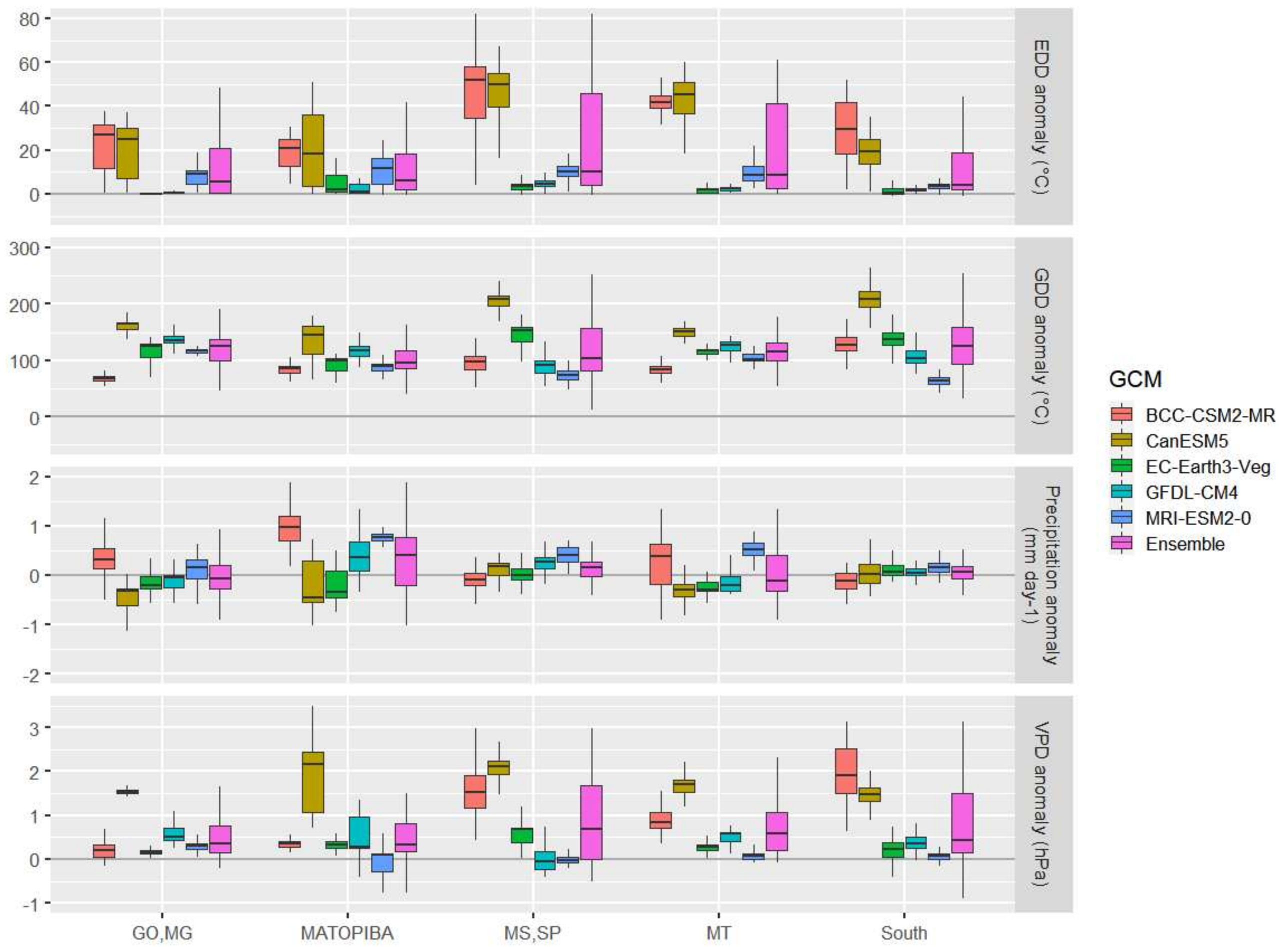


Supplementary Figure 1.6 Average changes in climate variables during the soybean growing season on the scenario (2035-2050)

Supplementary Figure 1.7 Average changes in climate variables during the 2nd crop maize growing season on the scenario (2035-2050)

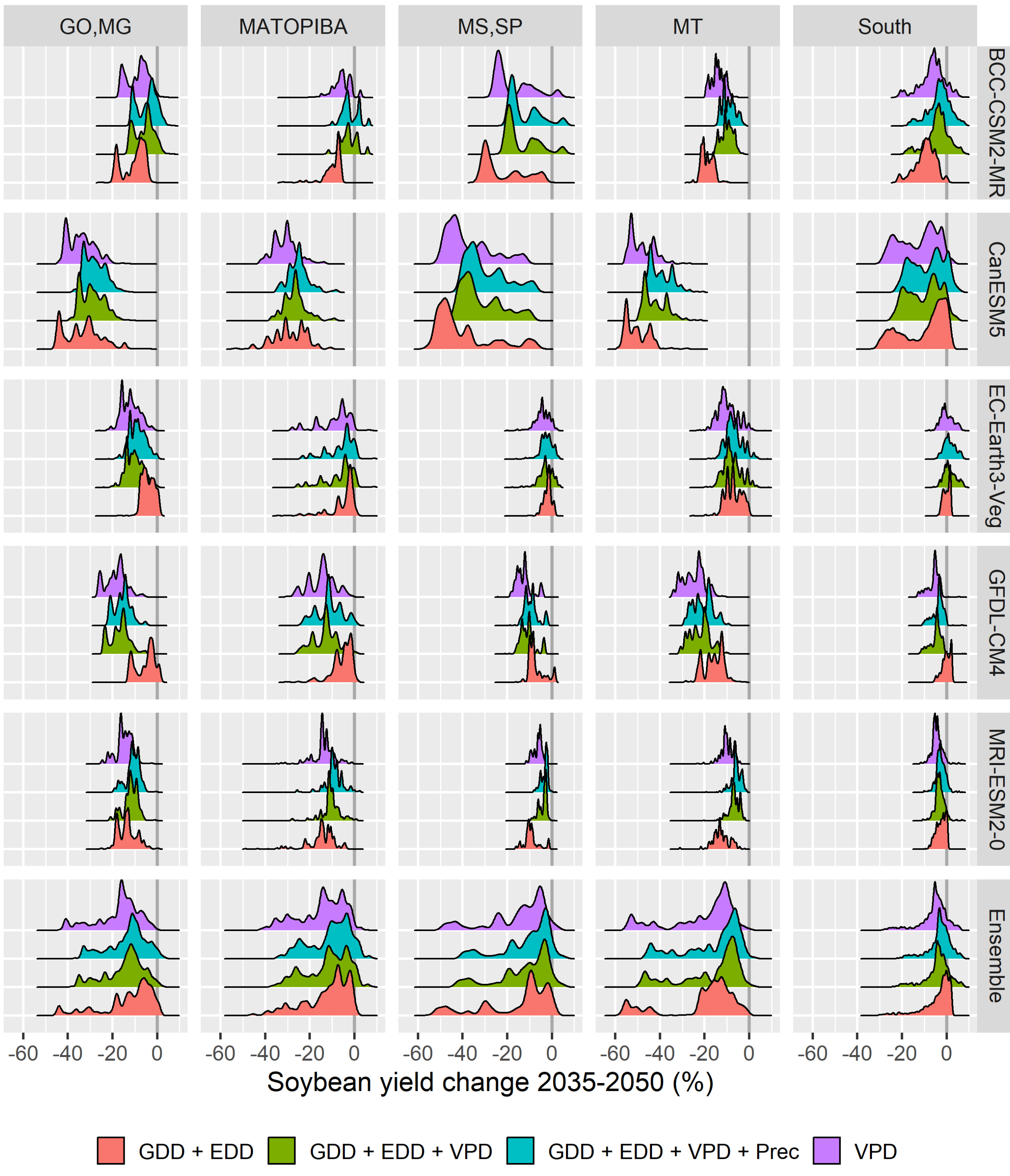


Supplementary Figure 1.8 Average changes in climate variables during the soybean growing season on the SSP2-4.5 scenario (2035-2050). Boxplots represent the spatial variability inside each region.

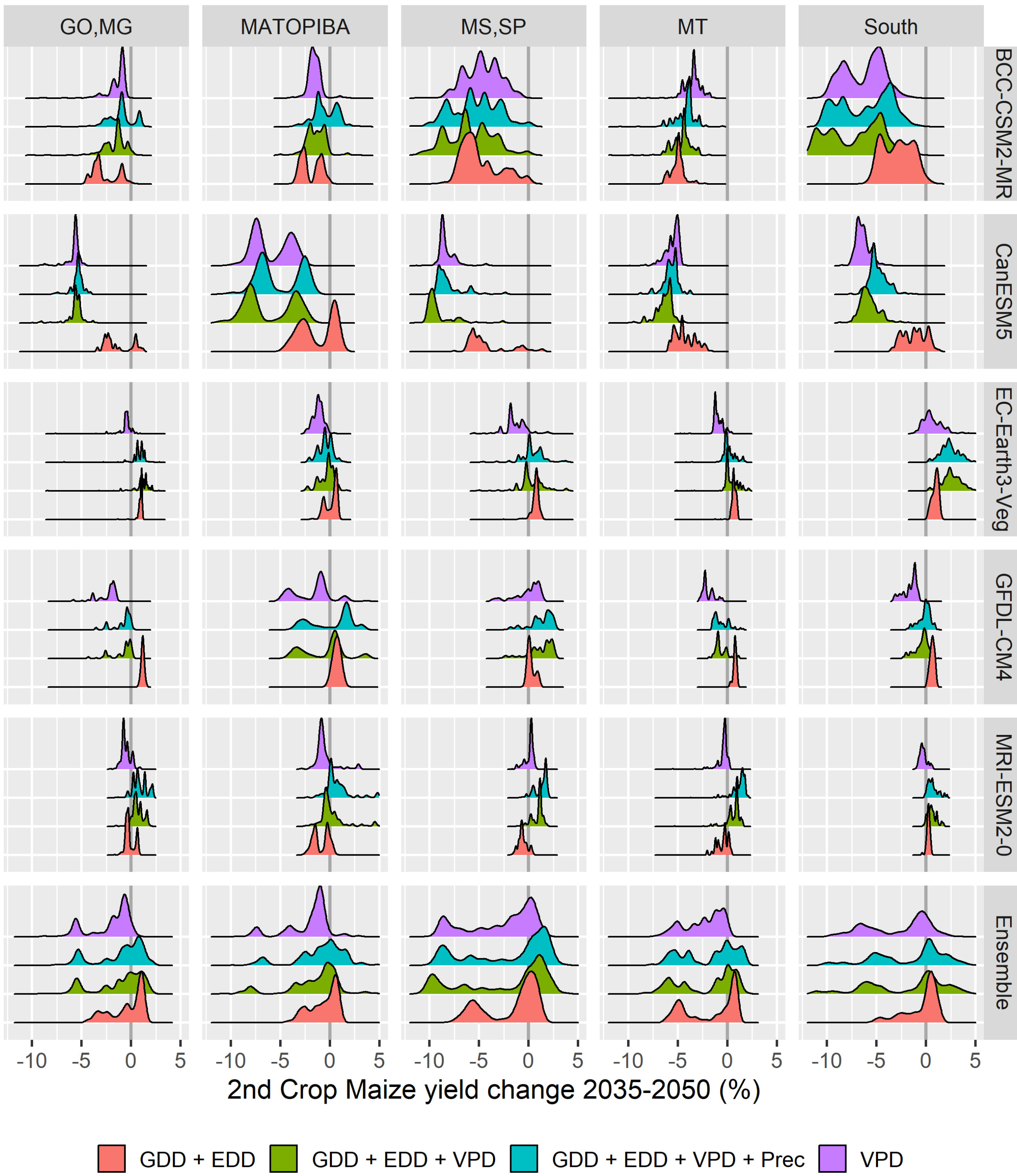


Supplementary Figure 1.9 Average changes in climate variables during the 2nd crop maize growing season on the SSP2-4.5 scenario (2035-2050). Boxplots represent the spatial variability inside each region.

1.5.3) Decomposing uncertainties in climate change impact estimates



Supplementary Figure 1.10 Density plots of average soybean yield impacts for 2035-2050



Supplementary Figure 1.11 Density plots of average 2nd crop maize yield impacts for 2035-2050

Chapter 2: Soybean production in Brazil benefits from environmental governance under climate change

Abstract

Brazilian crop production has managed to grow expressively in the last 15 years with relatively little conversion of natural vegetation. Deforestation in the major Brazilian biomes however is still far from zero, and rates have been going up with the recent dismantling of public environmental governance (EG). Deforestation leads to changes in regional climate, which along with global climate change affects crop yields. EG can benefit production by minimizing these effects. Here we use a fully coupled climate system model and empirical yield models to evaluate how different plausible EG futures can affect the Brazilian production of soybeans and 2nd crop maize using land use scenarios representing two levels of EG and two global climate change scenarios (RCPs 2.6 and 8.5). We find that soybean yields are negatively affected in all scenarios, but differences in EG can impact yields as much as different RCPs. Stronger environmental governance can prevent soybean production losses equivalent to 442-527 million USD year^{-1} in the Amazon and 670-1347 million USD year^{-1} in the Cerrado by 2050, up to 10% of projected production in some regions. Collectively, Brazilian soybean farmers have much to gain with better environmental governance and it would be in their interest to enforce and even extend private zero-deforestation agreements in the Amazon and Cerrado biomes.

2.1) Introduction

Currently Brazil is the world's largest soybean producer and the second largest maize exporter, having produced 34% of the world`s soybeans in 2019 (FAO 2021). This status was achieved recently after decades or fast growth. Soybean and maize production have increased more than four-fold between 1980 and 2019 (IBGE 2021). A large part of the early growth can be attributed to cropland expansion, with the planted area of both crops more than doubling (Zalles et al. 2019). Before the turn of the century this expansion happened primarily over natural vegetation, being responsible for a good share of the deforestation of the Amazon and Cerrado biomes (Morton et al. 2006, Gibbs et al. 2010).

However, after significant changes in public and private environmental governance in the early-2000s direct conversion of natural vegetation to croplands reduced considerably (Macedo et al. 2012, Zalles et al. 2019, Song et al. 2021). These policies included systematic satellite-based monitoring and several governmental command-and-control measures such as fines and restricted access to credit, but also major private agreements such as the Soy Moratorium (Nepstad et al. 2014, Gibbs et al. 2015, Soares-Filho and Rajão 2018). Although falling commodity prices at the time also likely played a role in the initial reduction, soybean profitability has long risen back to pre-2006 levels (Macedo et al. 2012).

After the moratorium, crop production continued increasing in part through area expansion over pasturelands (Zalles et al. 2019), but most importantly through crop intensification. In the same period, soybean and maize yields almost doubled and tripled, respectively. The trend towards intensification was even more prominent on the rise of double cropping systems. These systems benefit from the long and consistent rainy season in parts of the country, allowing farmers to plant both soybeans and a second crop (most often maize) in succession in the same year (Abrahão and Costa 2018, Xu et al. 2021). Today, more than 60% of all Brazilian maize is planted as a second crop after soybeans (IBGE 2021).

Although total deforestation rates declined sharply in that period, they are still far from zero. On the contrary, they have been steadily increasing since 2012 after changes in the political environment marked by the amnesty of a large portion of past deforestation with the new Forest Code (Rochedo et al. 2018, Soares-Filho and Rajão 2018, INPE 2021). Soybean farmers still play a small role, benefiting from lower land prices and some deforesting parts of their properties for cattle ranching (Skidmore et al. 2021). A recent study estimates that up to 20% of soybean exports to the EU could still be contaminated by some degree of illegal deforestation (Rajão et al. 2020). However, the large majority of deforestation happens in a very small number of properties, mainly for low productivity cattle ranching (Rajão et al. 2020, Skidmore et al. 2021).

With this resurgence of deforestation, soybean farmers may be losing a crucial ecosystem service provided by natural vegetation: climate regulation. Substituting natural vegetation with crops or pastures in both Cerrado and Amazonia leads to important changes in biophysical properties of the land surface such as albedo, rooting depth and surface roughness. These changes can substantially affect local and regional climate (Bonan et al. 2008, Lawrence and Vandecar 2014, Lawrence et al. 2016). There is empirical evidence that natural vegetation loss has already substantially increased average and maximum temperatures (Alkama and Cescatti 2016, Cohn et al. 2019), reduced rainfall (Teixeira-Filho et al. 2021), delayed the onset of the rainy season (Butt et al. 2012, Teixeira-Filho et al. 2019a) especially in drier years (Teixeira-Filho et al. 2019b), and increased the frequency of dry spells in the beginning of the rainy season (Teixeira-Filho et al. 2019a) in some regions of those two biomes. These changes in climate are harmful to agriculture in the region (Oliveira et al. 2013), especially to the double cropping systems which are dependent on a longer rainy season (Pires et al. 2016, Costa et al. 2019, Brumatti et al. 2020, Spera et al. 2020). The value of this climate regulation service for soybeans alone can approach and sometimes exceed the opportunity costs of conservation in frontier regions with both high deforestation and high soybean density (Strand et al. 2018, Flach et al. 2021).

Previous works on the impacts of deforestation-induced climate change in Brazil however ignore many of its interactions with global climate change. These works either focused on the effects of past deforestationor simply combined independent estimates of deforestation-induced changes in climate with climate model projections of greenhouse gas (GHG) induced global climate change (Oliveira et al. 2013, Pires et al. 2016, Spera et al. 2020). However, it is known that these two forcings do not add up linearly (Costa et al. 2000). The effect of land use conversion in climate depends largely on background climate conditions and levels of water stress (Gentine et al, 2019). Changes in atmospheric circulation can substantially alter the water balance and the surface flux responses to forest loss (Sampaio et al. 2020). Changes in rainfall are especially nonlinear, being very sensitive to background atmospheric circulation and CO_2 concentrations due to both its physiological and radiative effects (Costa and Foley 2000, Spracklen and Garcia-Carreras 2015, Sampaio et al. 2020, Boysen et al. 2020). Interactions with ocean circulation tend to make changes in temperature and precipitation more drastic than when they are not accounted for (Nobre et al. 2009, Davin and Noblet-Ducoudre 2010). Feedbacks between climate and forest dieback may also lead to tipping points after which forest loss is self-amplifying (Cox et al. 2000, Hirota et al. 2001, Pires and Costa 2013, Zemp et al. 2017).

The magnitude and spatial patterns of natural vegetation loss also have a large nonlinear influence in its regional impacts. Very high levels of tropical deforestation tend to make the climate of most of the region warmer, drier and with a delayed rainy season (Lawrence and Vandecar 2014, Spracklen and Garcia-Carreras 2015). More realistic patterns of land use change in the other hand are known to create mesoscale circulation patterns. Those often lead to dipoles of temperature and precipitation anomalies tens of kilometers in length, which can make deforestation in one region affect other, relatively remote ones (Saad et al. 2010, Badger and Dirmeyer 2016, Khanna et al. 2017).

Here we evaluate how different plausible environmental governance futures can affect the Brazilian production of soybeans (1st crop) and 2nd crop maize under global climate change. We compare simulations of a fully coupled global climate model using two land use scenarios that represent continuing pathways of two distinct classes of environmental governance in Brazil (weak and strong), under the atmospheric composition of lower and upper bound Representative Concentration Pathways (RCPs 2.6 and 8.5). By applying an ensemble of econometric models of the impacts of climate in Brazilian double cropping systems to the climate scenarios, we compare projected changes in cropping area, yields and total production from 2012 to 2050 between environmental governance scenarios and RCPs. We also compare estimated yield changes with those simulated by the land use scenarios used in the CMIP5.

2.2) Data and methods

2.2.1) Climate model simulations

To evaluate the impact of environmental governance on climate, we performed several fully coupled simulations with the Community Earth System Model version 1.0.6 (CESM – Hurrell et al. 2013) using land use scenarios that represent two very different levels of environmental governance (EG) in Brazil for 2012-2050 under the atmospheric composition of RCPs 2.6 and 8.5. This setup allows us to distinguish the impacts from biogeophysical (from the land-use scenarios) and biogeochemical (from the RCP atmospheric composition) climate change and interactions between them. Then, we estimated the effects of those changes in agricultural yields in Brazil using recently published econometric models from Chapter 1 (Abrahão et al. 2021). We also compare the results of these runs with those made using original CESM RCP simulations used in the Climate Model Intercomparison Program phase 5 (CMIP5), which used global land-use scenarios consistent with each RCPs narrative.

The climate simulations with CESM were set up to reproduce the original CMIP5 CCSM4 RCP 2.6 and 8.5 simulations in all aspects except for the land-use scenarios (Table 2.1, Figure 2.1). The CCSM4 setup fully couples the atmosphere, ocean, sea ice, and land surface components of the model (see Supplementary Table 2.1 for information on individual components). It uses the prescribed atmospheric composition pathways of the RCPs instead of the more modern Earth System Model approach of prescribing emissions and representing the carbon cycle endogenously. This setup ensures that differences in climate output between different land-use scenarios are due only to the biogeophysical effect of the land-use scenarios. Although the land use change emissions in the EG scenarios are not quite compatible with the atmospheric concentration pathways of the RCPs, the difference in cumulative land use CO_2 emissions by 2030 between the EG scenarios is 13.5 Gt CO_2, only ~1% of the total cumulative emissions budget for RCP2.6 between 2005 and 2030 (Rochedo et al. 2018, Schwalm et al. 2020).

The land surface component of the model is the Community Land Model version 4 (CLM – Oleson et al. 2010, Lawrence et al. 2012), which includes transient land cover change between fractions of 15 Plant Functional Types (PFTs), each one with its specific biophysical parameters. To account for the internal variability of the climate system, we perform an ensemble of four simulations for each scenario. Each simulation uses as initial conditions a different realization of the historical CCSM4 20th-century all-forcings scenario ending in 2005. These are exactly the same initial conditions used on four of the ensemble members in the original CMIP5 RCP simulations.

Table 2.1 Scenarios used in the CESM simulations

Scenario name	**Atmospheric composition pathway**	**Land use pathway (Brazil)**	**Land use pathway (rest of the world)**
RCP8.5-WEG	RCP8.5	WEG	Same as RCP scenario
RCP8.5-SEG	RCP8.5	SEG	
RCP8.5-CMIP5	RCP8.5	CMIP5 (RCP8.5)	
RCP2.6-WEG	RCP2.6	WEG	
RCP2.6-SEG	RCP2.6	SEG	
RCP2.6-CMIP5	RCP2.6	CMIP5 (RCP2.6)	

2.2.1.1) Land use scenarios

We compare the outcomes of two regionally-informed scenarios for Brazil (SEG and WEG) with the original land use scenario components of the RCPs 2.6 and 8.5 used in the CMIP5 for 2005-2012 (Table 2.1, Figure 2.1, Figure 2.2). The original RCP 2.6 and 8.5 scenarios were used only in conjunction with their respective atmospheric composition scenarios, and the derived combination scenarios are labeled CMIP5 in this study. Both original CMIP5 scenarios were originally developed by applying their respective scenario storylines to integrated assessment modeling frameworks, with the IAMs IMAGE for RCP2.6 (van Vuuren et al. 2007) and MESSAGE for RCP8.5 (Riahi et al. 2011) at their cores. The allocation of land use to grid cells in RCPs is made using relatively simple allocation schemes that use global parameters and allocation rules, and simple land use dynamics. This allocation process makes the spatial patterns of land use change relatively homogeneous and land use classes more or less constrained to their historical extent.

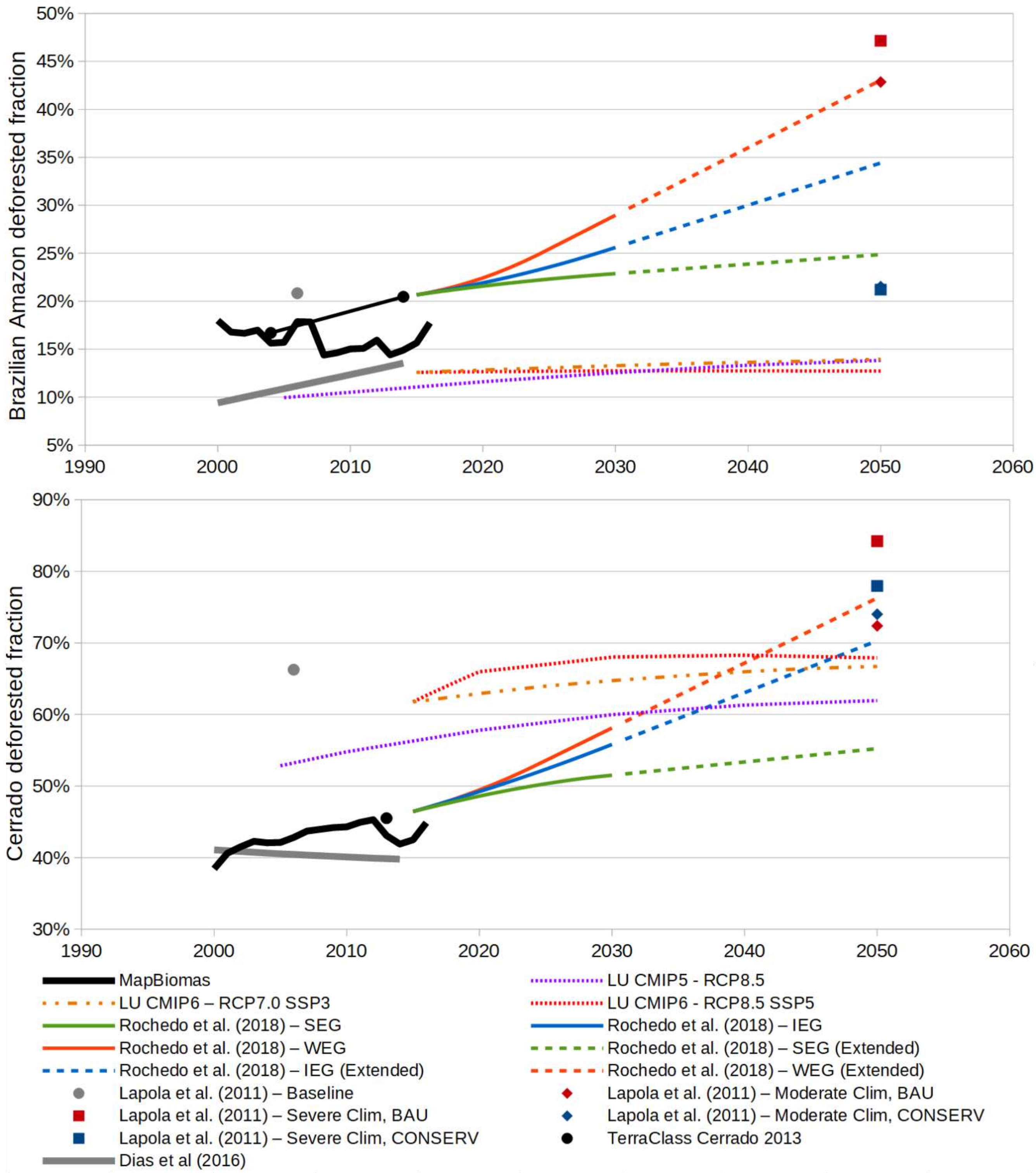


Figure 2.1 Comparison between several historical datasets and published land use scenarios for the Brazilian biomes Amazon (top) and Cerrado (bottom).

The RCP8.5 narrative leads to very inefficient land use management globally, with the largest loss in the forest area of all CMIP5 RCPs and medium growth in crops and pastures (Lawrence et al. 2012). Although RCP2.6 leads to the lowest greenhouse gas concentrations of the RCPs, that is achieved with relatively little use of land management for carbon mitigation and large-scale expansion of biofuel crops. This combination leads to global primary vegetation loss in RCP2.6 to be actually higher than the intermediary RCPs 4.5 and 6.0, being smaller only than in RCP8.5.

The regionally informed land use scenarios were taken from Rochedo et al. (2018, Figure 2.1, Figure 2.2). These scenarios were originally developed to investigate the possible outcomes of recent (post-2011) political shifts towards reversing and relaxing several environmental policies that were instrumental to reducing deforestation rates earlier in the century in Brazil. They represent different levels of environmental governance in the Brazilian biomes Amazon and Cerrado, based on past records of land use changes in different eras of environmental policy.

The Weak Environmental Governance (WEG) scenario assumes the abandonment of pre-2011 deforestation control policies and strong political support for predatory agricultural policies. WEG is a worst-case scenario, representing a total deconstruction of environmental governance in Brazil. In this scenario, deforestation rates return to pre-2005 levels, a period before major changes in environmental policy. These policies reduced deforestation rates by about 50% in the Cerrado and about 80% in Amazonia by 2012. The Strong Environmental Governance (SEG) scenario, on the other hand, assumes the expansion of pre-2011 deforestation command-and-control policies and strong political support for the environmental agenda, including economic incentives for forest conservation. Under SEG, deforestation rates decrease by more than half by 2030, according to the National Policy for Climate Change (MMA 2008). We refer to these two scenarios collectively as EG (Environmental Governance) scenarios.

Based on these assumptions, the land use scenarios were generated by Rochedo et al. (2018) using the OTIMIZAGRO model in simulations from 2012 to 2050. OTIMIZAGRO is a spatially explicit model that simulates land use, land use change, forestry, deforestation, regrowth, and carbon emissions, based on assumptions about agricultural land demand and environmental policies. It has been developed and calibrated specifically for Brazilian biomes, and previous versions of it have been used in several assessments of conservation strategies in Brazil (e.g., Soares-Filho et al. 2006, 2012, Rochedo et al. 2018). OTIMIZAGRO's framework allows for specific assumptions and parameters in four spatial levels: biome, micro-region, municipality, and a 25-ha raster grid.

This setup allows the simulation of very realistic spatial clustering patterns and representation of phenomena such as the advancement and dislocation of agricultural frontiers. Consequently, natural vegetation loss in the EG scenarios coincide more with 2016 cropping areas (Supplementary Figure 2.7) than in the RCP scenarios (Figure 2.2). Therefore, the biogeophysical climate impacts of LU change are expected to be more concentrated in areas with more agricultural land in the EG scenarios.

An important feature of the EG scenarios is that the expansion of soybeans is very similar between them. In both there is little expansion of soybeans over natural vegetation and the primary destination of new agricultural lands is pasture, consistent with recent trends (Macedo et al 2012, Lapola et al. 2013, Spera et al. 2016, Strassburg et al. 2017). Since future agricultural demand trajectories are the same, in both EG scenarios the national soy area increases by very similar amounts (~57%), expanding mostly over established pastureland. Pasture dynamics in the other hand are very different, pasture area increasing 10% in SEG and 70% in WEG, with SEG favoring intensification over extensification.

The model's output, a categorical 25-ha yearly grid of 31 different land use types, was aggregated to the 0.9°x1.25° CLM grid as fractions of the larger cell for each land use type. The OTIMIZAGRO land use type fractions were then aggregated to fractions of the 15 CLM Plant Functional Types (PFTs), as described in Supplementary Table 2.2. Since OTIMIZAGRO only simulates Brazil's land use patterns, our final PFT fraction maps use the land use scenario of the corresponding RCP outside of Brazil. To facilitate the comparison between scenarios, we define the "natural vegetation loss" metric as the change between 2012 and 2050 in the percentage of Crops and C4 Grasses PFTs of each cell.

It is important to note that the baseline land use maps for the CMIP5 and the Rochedo et al. scenarios are very different, leading to substantially different aggregated levels of natural vegetation fraction (Figure 2.1). While the CMIP5 2005 base map is ultimately based on the FAO reported land use fractions, which matches census data totals, the Rochedo et al. is ultimately based on Brazil-focused satellite surveys of land cover. To get the climate model to smoothly transition to the 2012 level in the SEG and WEG scenarios, we linearly interpolate PFT fractions from the 2005 CMIP5 initial conditions until they reached the Rochedo et al. baseline in 2012.

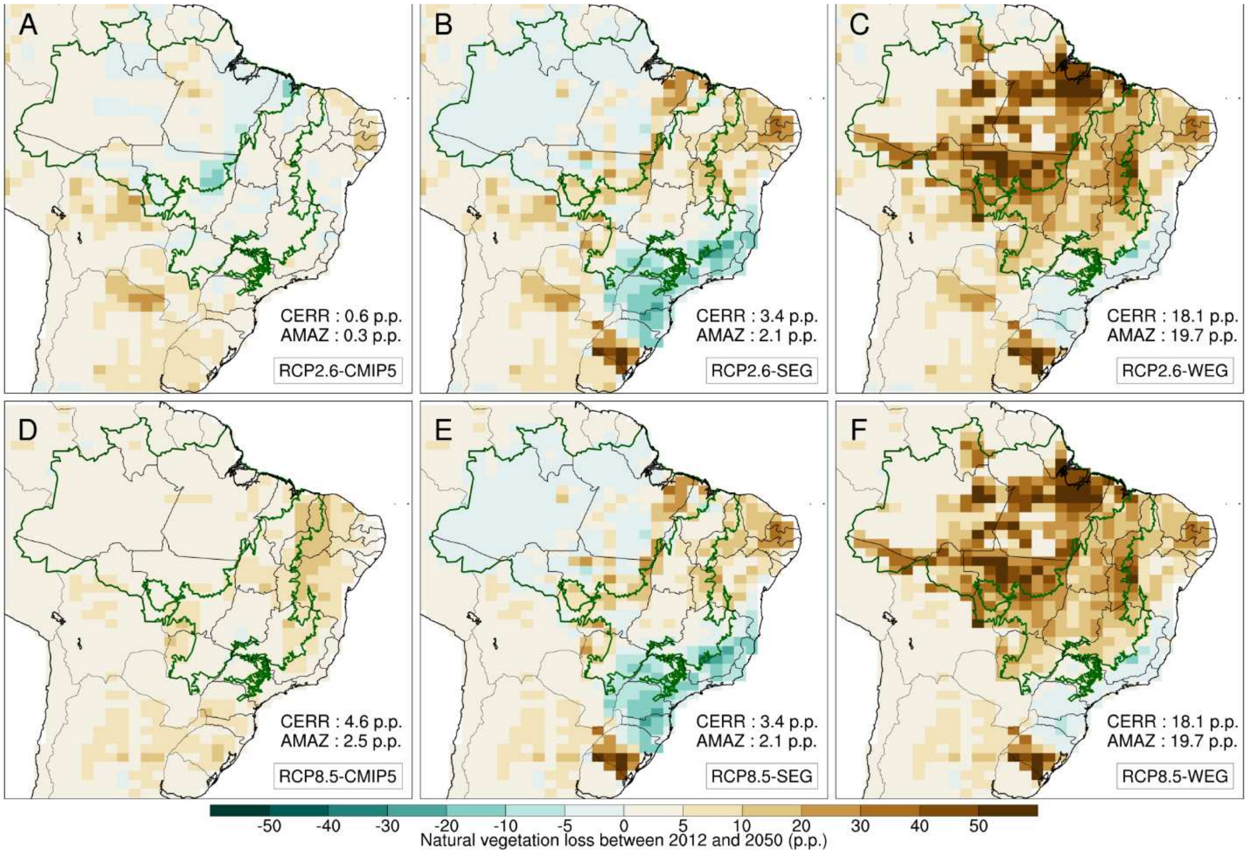


Figure 2.2 Natural vegetation loss between 2012 and 2050 for all scenarios used in the study. Numbers in the inset indicate the average vegetation loss in the Amazon (AMAZ) and Cerrado (CERR) biomes, in percentage points (p.p.) of the biome's area. Amazonia and Cerrado boundaries are drawn in thick green lines, Amazonia being in the northwest and the Cerrado being in the center of Brazil. Land use scenarios outside Brazil does not differ among the same RCP scenarios.

2.2.2) Evaluation of effects on climate

The large difference in baseline land use levels does not allow a direct comparison of climate outcomes between scenarios or against a common historical scenario. Instead, we use the difference in the end-points of a linear regression over the period 2012-2050, referred to as trends. This difference is an estimate of the total change – in the same units as the original variable – over the period when the land use scenarios are consistent. The regressions are calculated using the ordinary least squares (OLS) method. To assess uncertainty in the trend estimation, we estimate the distribution of the trend parameter by performing a 500-sample bootstrap in each of the ensemble members and pooling them for a total of 2000 estimates. Therefore, this distribution accounts for uncertainty due to both trend estimation and internal climate variability between ensemble members.

There is evidence that land use change in the region impacts climate the most in the transition from the dry to the rainy season (RS), potentially causing changes in the onset and duration of the rainy season (Butt et al. 2011, Wright et al. 2017, Gentini et al. 2019, Teixeira-Filho et al. 2019a,b). To investigate these changes we additionally calculate onset and end dates of the rainy season using a modified version of the Anomalous Accumulation (AA) method (Liebmann et al. 2007). This method identifies a period where accumulated rainfall is consistently above a daily value, which we set to 2.5 mm day^{-1} following Abrahão and Costa (2018). Rainy season onset calculated with AA has been shown to correlate well with double cropping adoption (Arvor et al. 2014, Abrahão et al. 2021) and early soybean planting dates (Zhang et al. 2021b).

2.2.3) Agricultural yield models

To evaluate the effects of the climate outcomes under different land use scenarios to regional agriculture, we apply the set of models of the sensitivity of Brazilian soybeans to climate variations estimated by Abrahão et al. (2021) described in Chapter 1. These are simple log-linear models that estimate changes in yields given changes in a set of climate variables aggregated over the crop's growing season. For consistency between regions, we used a growing season from October 15 to March 1. This period encompasses most of the soybean planting dates observed in

Zhang et al. (2021) and avoids the first half of October, in which the rainy season in some years hasn't started yet in a few major soybean planting regions (Abrahão and Costa 2018).

The set of climate variables are: i) Cumulative Growing Degree Days (GDD); ii) Cumulative Extreme Degree Days (EDD); iii) average Vapor Pressure Deficit (VPD) and iv) average daily precipitation (Prec). GDD and EDD indicate the exposure to temperatures below and above 30ºC, and are commonly used to express the nonlinear response of crop yields to temperature. (e.g. Schlenker and Roberts 2009, Butler and Huybers 2015). Under the common climate conditions of our study area, EDD tends to increase nonlinearly with average temperatures and have strong negative impacts on crop yields, and GDD tends to increase moderately or even decrease with average temperatures and have mild positive impacts on yields. Model coefficients are shown in Supplementary Table 2.3.

The yield models used calculate only changes in yields. The reference for the calculation of changes is the ensemble means of 1990-2005 from the original CCSM4 historical runs. The procedure is the following: i) multiply the log-linear coefficients to each yearly climate variable; ii) exponentiate to obtain yields in t ha^{-1}; iii) evaluate the yearly effects in 2012-2050 on each scenario and ensemble member with the trend method described in the previous section; iv) average yield estimates for the historical reference period; and iv) calculate percent differences between iii) and iv). The result is the average change in yields from 2012 to 2050 due to changes in climate expressed as a percentage of the yields obtained under 1990-2005 climate.

2.2.4) Effects of environmental governance

The land use and atmospheric composition scenarios used broadly represent two dimensions of environmental governance. The RCP pathways represent global environmental governance in terms of curbing greenhouse gas emissions. The SEG and WEG scenarios represent the outcomes of two very different pathways of regional environmental governance in terms of deforestation control policy. Here we focus on the latter, regional environmental governance. We estimate the climate and agricultural impact of these distinct governance choices by calculating the difference between outcomes of the WEG and SEG scenarios. We also estimate the effects of each additional p.p. of natural vegetation loss by performing linear regressions between the difference in natural vegetation loss and the difference in outcomes between WEG and SEG.

2.3) Results

2.3.1) Changes in climate

All six scenarios present considerable warming during the soybean growing season in most of the country in the period 2012-2050 (Figure 2.1). Most of the warming signal is due to differences in atmospheric concentration, the RCP2.6 scenarios showing an average warming of 0.43ºC in the Amazon (0.39°C in the Cerrado), while the RCP8.5 ones show average warmings of 1.33°C and 1.42ºC for the Amazon and Cerrado, respectively. However, differences in warming due to the different LU scenarios are evident, with clear patterns of higher temperatures in regions with more natural vegetation loss (Figure 2.2, Supplementary Figure 2.2).

This relationship is clear when comparing differences in warming and natural vegetation loss between WEG and SEG (Supplementary Figure 2.1, Supplementary Figure 2.2). For each

10 p.p. of natural vegetation loss, a pixel warms on average ~0.1 °C more during the soybeans growing season in the Amazon and in Cerrado under RCP8.5. In the Cerrado under RCP2.6 this relationship is still positive but less clear, likely due to strong warming in the southwestern borders of the biome. These regions lose relatively little natural vegetation under the EG scenarios, but is likely still influenced by very high natural vegetation losses in the neighboring countries present in the LU scenario (CMIP5) of RCP2.6 but absent in RCP8.5's.

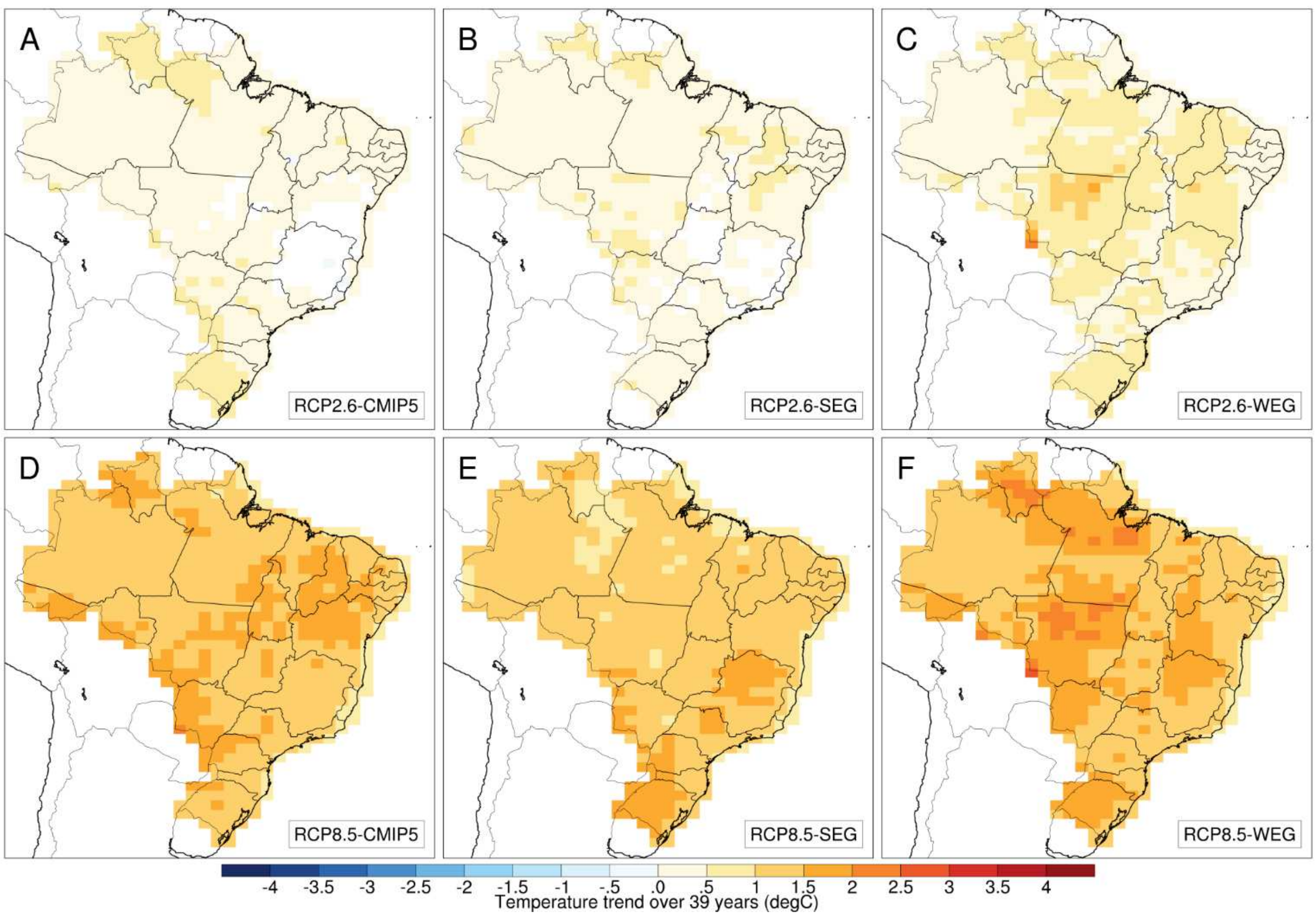


Figure 2.3 Change in average soybeans growing season temperatures in the period 2012-2050, calculated as the difference of the endpoints of the regression against time, (ºC 39 years^{-1}) for each scenario (A-F). Only changes significant at the 5% level are shown.

For scenarios with the same atmospheric concentration pathway, WEG is generally warmer than SEG in most regions during the soybeans growing season. The RCP2.6-CMIP5 scenario shows less warming than its SEG counterpart (RCP2.6-SEG) while RCP8.5-CMIP5 is between RCP8.5-SEG and RCP8.5-WEG, the same order than that of total natural vegetation loss for each scenario (Figure 2.2). Although the RCP2.6-SEG scenario has more natural vegetation loss concentrated in some key soybean producing regions in the Cerrado relative to RCP2.6-CMIP5 (Figure 2.2, Supplementary Figure 2.7), this pattern is not always reflected in temperature changes, suggesting a substantial role of non-local effects from biome-scale LU changes somewhat overcoming local, pixel-scale patterns in this specific case.

The spatial pattern of soybean growing season EDD, GDD and VPD broadly follows that of temperatures, with VPD displaying slight decreases only in small regions in central-southeastern Brazil (Supplementary Figure 2.8, Supplementary Figure 2.9, Supplementary Figure 2.10). Precipitation patterns are more complex, with both increased natural vegetation loss and GHG atmospheric concentration leading generally to somewhat increased precipitation in the southwestern parts of the Brazilian Amazon and reduced precipitation in the northern amazon and parts of Cerrado (Supplementary Figure 2.11, Supplementary Figure 2.12). These patterns in the Amazon resemble southwest-northeast dipoles, suggesting the formation of large-scale thermal cells in the prevailing wind direction due to land use change (Saad et al. 2010, Khanna et al. 2017) and the advection of more moisture to the western parts of the Amazon with CO_2-induced stomatal closure (Langenbrunner et al. 2019).

During the 2nd crop maize growing season (January 15 to June 15) warming also occurs in nearly all regions, being generally far less intense than the warming during the soybean growing season in all scenarios (Supplementary Figure 2.4). The differences between WEG and SEG scenarios also generally follow natural vegetation loss patterns in the Amazon (Supplementary Figure 2.5). In the Cerrado and in other regions in the southern portion however, WEG shows slightly less warming than SEG even though it has overwhelmingly more natural vegetation loss. This pattern of less warming in WEG is concentrated on the fall months (not shown), and could be related to increases in precipitation in the same regions that tends to happen in regions with less natural vegetation loss than the surrounding regions (Supplementary Figure 2.6). Still, warming is well correlated with natural vegetation loss difference in the Amazon and in the Cerrado under RCP2.6 in these months, with 0.05-0.07 ºC of warming difference for each 10 p.p. of natural vegetation loss (Supplementary Figure 2.3).

2.3.2) Yield impacts

The warming patterns are largely reflected on estimated yield negative changes (Figure 2.4, Figure 2.6) due to the high sensitivity of yields to EDD and VPD in the models(Supplementary Table 2.3), both of which increase with warming. Soybean yield impacts are negative and significant in most of the Amazon and Cerrado biomes in all scenarios, being so in the entire country in the RCP8.5 scenarios. As with temperature, the effects of natural vegetation loss are clear in the patterns of yield loss, with higher losses in pixels and scenarios with more natural vegetation loss (Supplementary Figure 2.13, Supplementary Figure 2.14). For each 10 p.p. of natural vegetation loss, a pixel shows 1.7 p.p. more yield change by 2050 under RCP2.6 in the Amazon (Figure 2.5). In Cerrado this relationship is not statistically significant. However, under the atmospheric concentration of RCP8.5 natural vegetation is more important for yield loss, which increases to 2.3 and 1.6 p.p. for each 10 p.p. of natural vegetation loss respectively in the Amazon and Cerrado.

This implies an interaction between GHG-induced warming and LUC warming, with the negative climate impacts of natural vegetation loss on soybean yields being stronger under the higher background warming of RCP8.5. However, this general trend masks important regional differences caused by different atmospheric circulation patterns between RCPs in the Cerrado. Notably, most of the GO and MS states in south-southeastern Cerrado show substantially more warming and thus stronger negative yield impacts of natural vegetation loss in RCP2.6 than in RCP8.5 (Supplementary Figure 2.13). In general, most of the Cerrado shows somewhat stronger negative impacts of natural vegetation loss under RCP2.6, but in the biome transition region in southern MT where natural vegetation loss differences are higher impacts are much stronger under RCP8.5. This makes the overall relationship tend towards a higher sensitivity to natural vegetation loss in the region under RCP8.5 (Figure 2.5). In all of the Amazon negative impacts of natural vegetation loss are higher under RCP8.5.

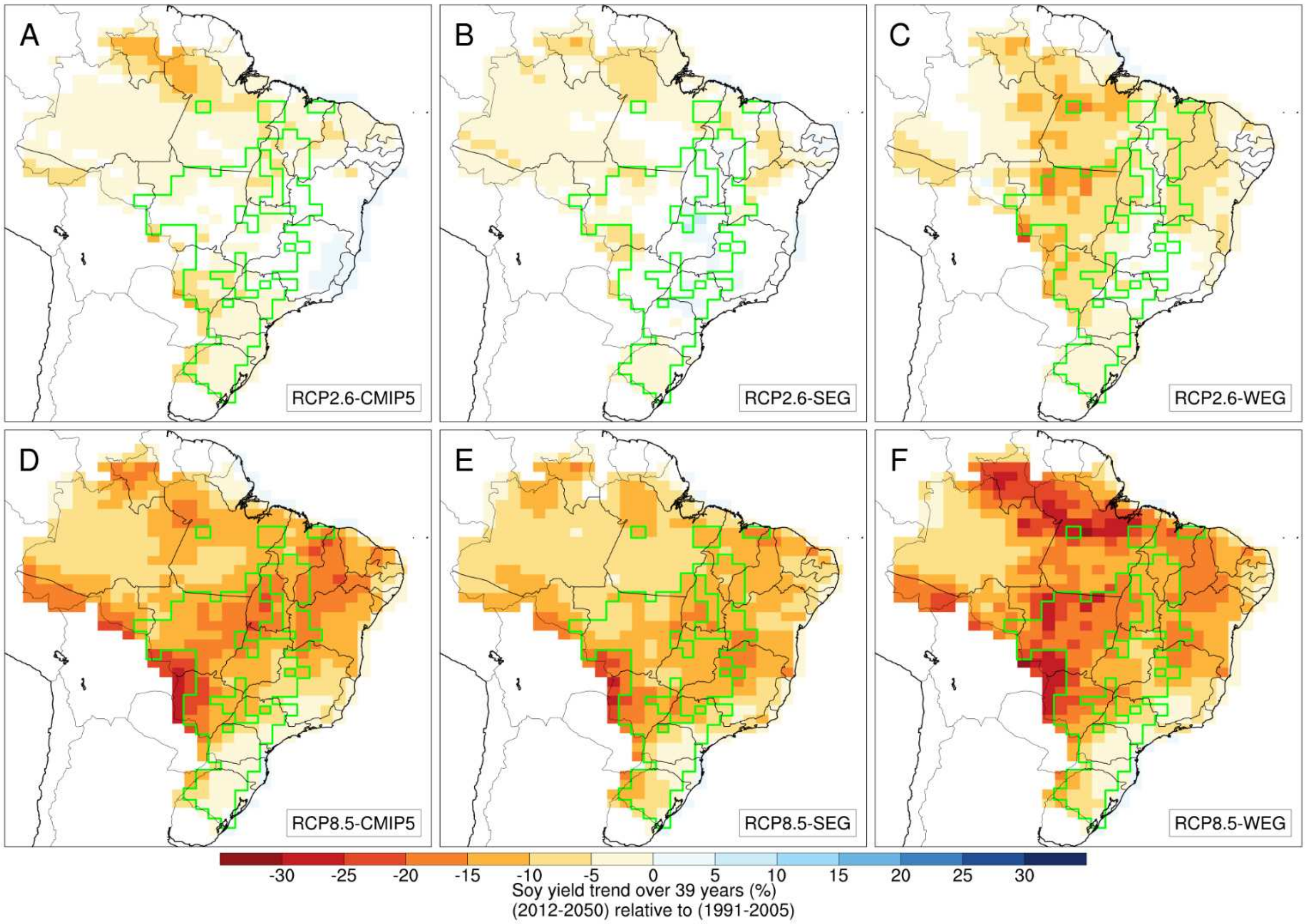


Figure 2.4 Soybean yield change due to changes in climate in the period 2012-2050 for each scenario, average of the ensemble of 4 yield models. Values are presented as percent changes in relation to average estimated historical yields (1991-2005). The extent of pixels with at least 1% soybean area in 2012 is marked in green.

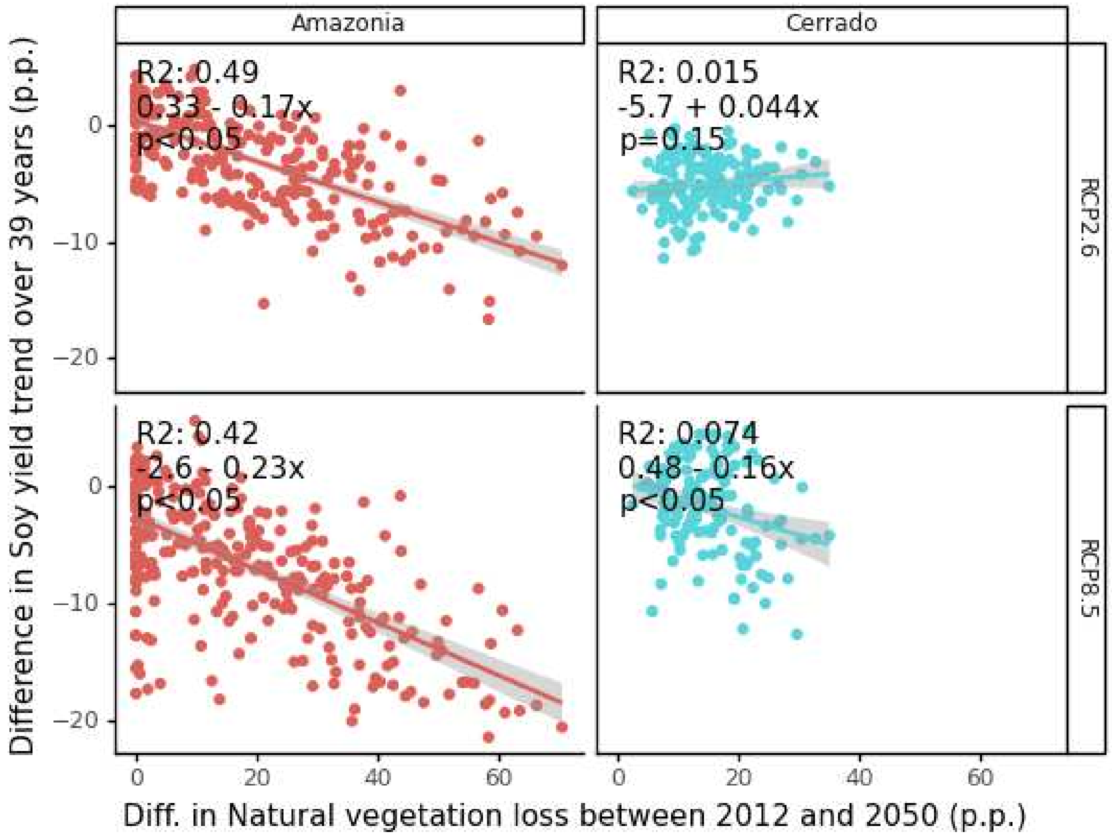


Figure 2.5 Relationship between natural vegetation loss and estimated soybean yield change over 2012-2050. Each point represents the difference in natural vegetation loss and in estimated yield change (average of the ensemble of yield models) between the WEG and SEG scenarios. Gray zones represent the 95% confidence interval of the regression.

Second crop maize yield impacts also broadly follow the warming patterns on its growing season (Figure 2.6). However, since both i) warming is generally less intense between January and June than it is in the soybeans growing season between October and February and ii) the sensitivity of 2nd crop maize yields to warming in the models used is lower than that of soybean yields; projected yield impacts are much smaller than in soybeans. Estimated 2012-2050 yield decreases only surpass 10% in scenarios under RCP8.5 and in regions where soy-maize double cropping is not commonly practiced such as in the Pantanal biome in southwestern Brazil. The weaker Cerrado warming in WEG relative to SEG scenarios is also reflected on yield losses, with yield impacts being slightly lower in WEG than in SEG in large parts of Cerrado under both RCPs

(Supplementary Figure 2.14). Still, regions with more natural vegetation loss tend to show higher 2nd crop maize yield impacts, 0.4-0.6 p.p. per each 10 p.p. of natural vegetation loss in both biomes, with impacts also being slightly more sensitive to natural vegetation loss under RCP8.5 (Supplementary Figure 2.15).

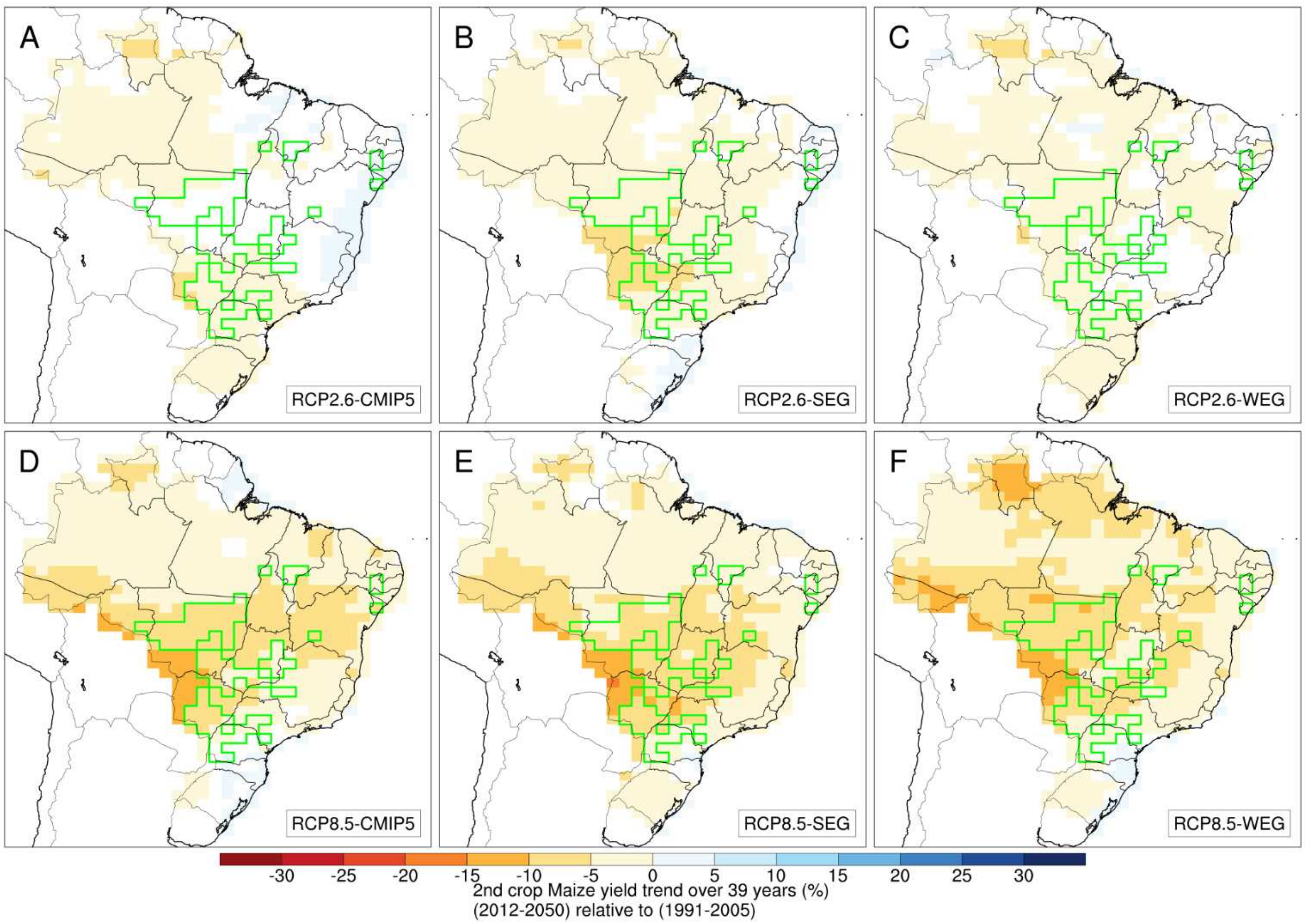


Figure 2.6 2nd crop maize yield change due to changes in climate in the period 2012-2050 for each scenario, average of the ensemble of 4 yield models. Values are presented as percent changes in relation to average estimated historical yields (1991-2005). The extent of pixels with at least 1% 2nd crop maize area is marked in green.

On biome average the choice of LU scenario can be about as impactful to soybean yields as the choice of atmospheric concentration scenario (RCP). Under RCP2.6, all yield models indicate average (weighted by 2016 harvested area) losses between 0 and 5% for the CMIP5 and SEG scenarios in both biomes, less than 3% in the yield model ensemble mean. RCP2.6-WEG shows much larger impacts, 9.5% (6%) in the Amazon (Cerrado). Under RCP8.5, ensemble mean losses are 15, 10 and 19% for the CMIP5, SEG and WEG scenarios respectively in the Amazon and 14, 11 and 15% in Cerrado. In the Amazon, models that include VPD indicate higher losses on the worst LU scenario under RCP2.6 (RCP2.6-WEG) than in the best scenario under RCP8.5 (RCP8.5-SEG).

Biome average impacts on second crop maize follow similar patterns. However, even though all significant yield impacts are also negative, they are much weaker as previously discussed. An important difference is that impacts under SEG than under WEG are stronger in the Cerrado under both RCPs. Most of the impacts are apparently changes in moisture, since the yield model that does not include changes in VPD indicates substantially weaker impacts.

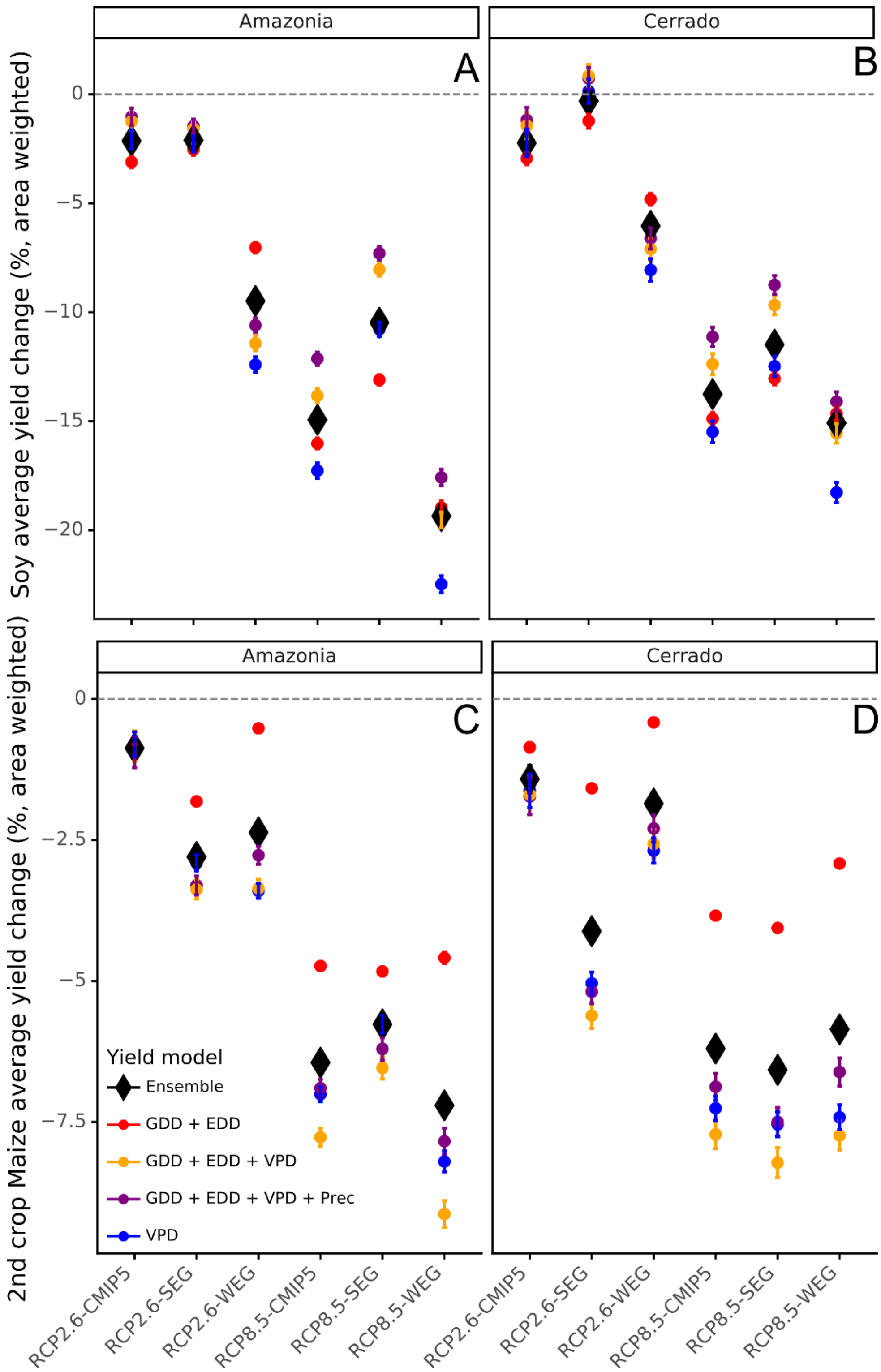

Amazonia
Cerrado
A
B
C
D
Soy average yield change (%, area weighted)
2nd crop Maize average yield change (%, area weighted)
0
−5
−10
−15
−20
−2.5
−5
−7.5
Yield model
Ensemble
GDD + EDD
GDD + EDD + VPD
GDD + EDD + VPD + Prec
VPD
RCP2.6-CMIP5
RCP2.6-SEG
RCP2.6-WEG
RCP8.5-CMIP5
RCP8.5-SEG
RCP8.5-WEG

Figure 2.7 Average soybean (A, B) and 2nd crop maize (C, D) yield change due to changes in climate in the period 2012-2050, weighted by 2016 soybean harvested area for each yield model. Values are presented as percent change in relation to average estimated historical yields (1990-2005). Error bars represent the 95% confidence interval from 2000 bootstrapped trend estimates, 500 for each CESM ensemble member.

2.3.3) Production gains with environmental governance

Negative yield impacts of climate change in nearly the whole country mean that, given current yield levels, the increases in crop production in the future are expected to be less than proportional to increases in crop area (Table 2.2). The SEG and WEG scenarios project roughly the same increases in cropping area between 2012 and 2050, ~170% more soybean area in the Amazon and ~74% in the Cerrado; and ~85% more 2nd crop maize area in the Amazon and ~68% in the Cerrado. Given current (2012) yield levels, this expansion would potentially lead to a ~163% increase in soybean production in the Amazon and ~71% in the Cerrado; and a ~73% increase in 2nd crop maize production in the Amazon and ~63% in the Cerrado. These increases in production are somewhat lower than the increases in area because the expansion tends to happen toward regions with historically smaller yields than the current production hotspots. As crop production increases in these areas, yields are expected to converge towards those of neighboring high yielding regions due to technology spillover and network effects (Magalhães and Diao 2009), but this effect is unlikely to substantially affect our comparisons between scenarios.

The negative impacts of climate on yields can substantially reduce this potential for increased production. Under RCP8.5-WEG for example, climate effects would make soybean production increase only 112% for a 163% increase in area. These losses in potential production between scenarios follow the pattern of yield impacts (Figure 2.7), being more intense under RCP8.5 and with the exception of 2nd crop maize in Cerrrado more intense under WEG than in SEG.

Since SEG and WEG project very similar increases in crop areas, the differences in total production between SEG and WEG allow us to estimate the value gained with stronger environmental governance. Gains are proportionally the highest for soybeans in Amazonia under RCP8.5, with total soybean production in the biome being 9.7% higher in SEG than in WEG, equivalent to 527 million USD year^{-1} assuming 2010-2016 crop prices (FAO 2021). However, since current production is higher there, the highest soybean value gains are in the Cerrado under RCP2.6, surpassing 1.3 billion USD year^{-1} by 2050 or 6,4% of the biome`s projected production under WEG. These gains are smaller in Amazonia under RCP2.6 and in Cerrado under RCP8.5, reflecting the heterogeneous differences between WEG and SEG yield impacts in the Cerrado under each RCP (Supplementary Figure 2.13). Environmental governance leads to smaller gains on second crop maize production in Amazonia and even to slight losses in Cerrado due to less warming in the fall under WEG than under SEG.

These values also imply an average value of the climate regulation service to crops provided by each hectare of natural vegetation (Table 2.2, column F). These values were calculated by dividing the difference in total crop production value between SEG and WEG on each biome by the difference in natural vegetation loss between SEG and WEG on the same biome. An hectare of natural vegetation is estimated to bring 6-7 USD year^{-1} to soybean production in the Amazon and in the Cerrado 22 USD year^{-1} under RCP8.5 and double that amount (44 USD year^{-1}) under RCP2.6. These average values however ignore the influences natural vegetation loss in one region can have on the climate of another region. Although there is some level of spatial coherence between natural vegetation loss and yield impacts (Figure 2.5), the patterns of change in precipitation imply that both EG and RCP scenarios lead to very different atmospheric circulation patterns that impact remote regions (Supplementary Figure 2.12).

Table 2.2 Projected changes in cropping area and production between 2012 and 2050 under different environmental governance (EG) scenarios. Production change values in column (B) consider only the change in cropping area and its distribution. Production change values in column (C) also consider the modeled climate impact on yields. Columns (D) and (E) show the difference in total yearly production value (assuming average historical prices) between the SEG and WEG scenarios, which can be interpreted as the value gained with environmental governance. A positive value of 10% in column (D) means that yearly production value under SEG in 2050 is projected to be 10% higher than under WEG in the same year. Column (F) in column (E) divided by the difference in natural vegetation loss in each region, showing the implied climate regulation value per ha of natural vegetation. Prices assumed for value calculations in column (E) and (F) are average producer prices in Brazil in the period 2010-2016, 194 USD ton^{-1} for maize and 406 USD ton^{-1} for soybeans (FAO 2021).

			(A)	(B)	(C)	(D)	(E)	(F)
	RCP	EG	Area increase	Production increase (potential)	Production increase (w/ climate effects)	EG value (SEG-WEG)		
			(%)	(%)	(%)	(% of WEG)	(million USD year^{-1})	(USD ha^{-1} year^{-1})
			Soybeans					
Amazonia	RCP2.6	SEG	168	161	156			
		WEG	170	163	139	7.3	442.3	6.0
	RCP8.5	SEG	168	161	133			
		WEG	170	163	112	9.7	527.2	7.1
Cerrado	RCP2.6	SEG	74	71	71			
		WEG	73	70	61	6.4	1347.4	44.9
	RCP8.5	SEG	74	71	50			
		WEG	73	70	45	3.5	669.9	22.3
			2nd crop maize					
Amazonia	RCP2.6	SEG	85	75	69			
		WEG	84	73	69	0.2	1.2	0.0
	RCP8.5	SEG	85	75	64			
		WEG	84	73	60	2.4	13.9	0.2
Cerrado	RCP2.6	SEG	68	63	56			
		WEG	68	63	60	-3.0	-109.7	-3.7
	RCP8.5	SEG	68	63	52			
		WEG	68	63	54	-1.4	-48.7	-1.6

2.4) Discussion and conclusions

The results have shown clear relationships between points and scenarios with more natural vegetation loss and more warming. The obtained range of temperature sensitivity to natural vegetation loss in the soybeans growing season obtained with our climate modeling experiment (0.05-0.12ºC $10p.p.^{-1}$) is within the range of empirical analyses of observed and satellite derived mean annual air temperatures (Zhang et al. 2014, Alkama and Cescatti 2016, Cohn et al. 2019), although this local metric does not account for non-local effects that may be significant (Cohn et al. 2019, Winckler et al. 2019, Boysen et al. 2020). The extrapolated range of 0.5-1.2ºC with 100% natural vegetation loss is also within the range of previous modeling experiments of scenarios assuming complete deforestation in the region, although on the lower end of this range since nonlocal effects are likely weaker in our partial deforestation scenarios (D'Almeida et al. 2007, Davin and de Noblet-Ducoudre 2010).

We find that the warming effect of natural vegetation loss tends to be stronger in the Amazon under RCP8.5 and stronger in the Cerrado under RCP2.6. One possible explanation is that a good portion of the warming in RCP8.5 relative to RCP2.6 is due to the physiological effect of increased atmospheric CO_2 concentration on stomatal conductance (Kooperman et al. 2018, Sampaio et al. 2020). Under the higher concentrations of RCP8.5 plant stomata tend to close, reducing evapotranspiration rates and therefore increasing the amount of sensible heating. This effect is much weaker in C4 pastures, and also weaker in Cerrado than in Amazon vegetation (Costa and Foley 2000). Therefore, higher CO_2 concentrations tend to make differences in sensible heat flux between natural vegetation and grasslands weaker overall, but stronger in the Amazon than in the Cerrado. The physiological effect also tends to be weaker in the Cerrado since water limitations play a larger role in stomatal conductance there than in the water abundant Amazon (Gentine 2019).

The spatial patterns of temperature sensitivity to land use change depend on regional atmospheric circulation patterns. These can be very model-dependent due to differences in vegetatation physiology parametrization and atmospheric circulation patterns in response to atmospheric GHG concentrations (Boysen et al. 2014, 2020). Although, as stated, the general behavior of warming with natural vegetation loss is consistent with both modeling and empirical evidence, the finer spatial patterns of response to remote deforestation and its interactions with atmospheric composition will likely differ in other modeling settings. Therefore, they should be treated mostly as evidence of the importance of such interactions. Nevertheless, this version of the CCSM4/CESM model is among the CMIP5 models that best represent circulation and climate patterns (Yin et al. 2012, Pires et al. 2016, Costa et al. 2019) and key vegetation processes (Baker et al. 2021) over South America.

Climate change negatively influences yields of both soybeans and 2nd crop maize in all scenarios analyzed. Yield impacts are substantially stronger on soybeans than on 2nd crop maize due to the small sensitivity of 2nd crop maize yields to climate in the Abrahão et al. (2021) empirically-derived models. This behavior is the opposite of the results found using deterministic crop models elsewhere (Pires et al. 2016, Brumatti et al. 2020, Spera et al. 2020). This smaller sensitivity of 2nd crop maize is likely because the very decision to plant a second crop after soybeans is determined by climate conditions during the soybean cycle, especially by how late the rainy season starts (Pires et al. 2016, Cohn et al. 2016, Abrahão and Costa 2018, Costa et al. 2019, Brumatti et al. 2020, Abrahão et al. 2021). Therefore, the sensitivities used here may be valid only for years when the climate was expected to be favorable for double cropping, and the decision to plant a second crop was made.

Accounting for changes in double cropping feasibility due to the delaying of the rainy season onset found here (Supplementary Figure 2.16) would likely increase the negative impacts of climate change on 2nd crop maize production substantially, but due to the current lack of a formal empirical model of feasibility is left for future work. Nevertheless, the magnitudes of 2nd crop maize yield reductions due to differences in land use are similar to those found by Spera et al. (2020), although the scenarios considered are not directly comparable.

It is important to note that the yield models used here do not account for potential increases in yields due to the physiological effect of increased CO_2 concentrations on yields. This effect is expected to partially offset yield losses in both RCPs and be more prominent in the higher CO_2 RCP (RCP8.5), with some crop modelling studies suggesting net yield increases under that scenario (Pires et al. 2016, Figueiredo Moura da Silva et al. 2021). However, its magnitude is still highly uncertain and known to be dependent on complex interactions between crop varieties and regional climate (Ainsworth et al. 2002, Long et al. 2006, McGrath and Lobell 2013, Sakurai et al. 2014, Thomey et al. 2019). The non-representation of the physiological effect of CO_2 does not affect our final EG value results because we calculate the difference in yields between environmental governance scenarios under the same RCPs in the same periods, therefore comparing effects under the same CO_2 concentrations.

Despite differences in magnitude, yield impacts on both crops indicate that differences between land use governance scenarios can be as impactful as those between opposing atmospheric concentration scenarios. This impact of land use is particularly prominent for soybeans in the Amazon, where the average yield impacts from all yield models under RCP2.6-WEG are nearly the same as those under RCP8.5-SEG. The CMIP land use scenarios, consistent with each RCP's narrative, lead to low-end yield impacts under RCP2.6, comparable with SEG, and somewhere between SEG and WEG impacts under RCP8.5. Although these positions about regionally informed EG scenarios are compatible with the implied RCP narratives (which were later made explicit in the CMIP6 framework), differences between land use scenarios can be substantial. The 5-10 p.p. difference between SEG and WEG soybean yield impacts in Brazil found in both regions and RCPs are, for example, of similar magnitude to the interquartile range of all different climate and crop models used by Nelson et al. (2014) to evaluate the effects of climate yield shocks on the global agricultural economy. Therefore, the choice of regional land use scenario for evaluating climate impacts on yields in Brazil may be as impactful as the choices of the climate model, crop model, or atmospheric concentration pathway.

Projected changes in area and production (Table 2.2) imply that, given current trends of soybean expansion, the Brazilian soybean production has much to lose with weak environmental governance and much to gain with strong environmental governance in the future. Despite large differences in policy assumptions and total natural vegetation loss by 2050, both EG scenarios project a similar expansion in soy cropping area that happens mostly on former pasturelands. This similarity is because both EG scenarios were designed to have the same food demand trajectory. The land use transition simulations reflect the decoupling of cropland expansion and deforestation in the late 2000's decade, after which the vast majority of soybean expansion happened over land that was previously cleared (Macedo et al. 2012, Gollnow and Lakes 2014, Maciel et al. 2020, Song et al. 2021). Most of the additional natural vegetation loss in WEG makes way to pastureland expansion, reflecting observed behavior in the last decades. In SEG, growths in demand for cattle beef are fulfilled by increased productivity instead.

The current decoupling of cropland expansion and deforestation suggests that any benefits to soybean farmers from deforestation are already outweighed by the benefits of avoiding deforestation and its negative effects. Some of those are related to public policies put in place after 2005 that would likely be at least less enforced in a weak environmental governance future, such as fines, hurdles for obtaining land clearing permits, and restricted access to public credit programs (Nepstad et al. 2014, Cisneros et al. 2015, Santiago et al. 2018). However, this decoupling is also largely associated with international market pressure for environmentally friendly soybeans, which led to private no-deforestation agreements. These include the Soy Moratorium in the Amazon and many private environmental certification schemes (Cohn and Rourke 2011, Garret et al. 2013, Nepstad et al. 2014, Gibbs et al. 2015, Silva and Lima 2018). Although these private agreements are far from fully preventing deforestation for soybeans (Rajão et al. 2020, Skidmore et al. 2021), they are part of a growing trend towards global private environmental governance that has been particularly effective in the case of soybeans (DeFries et al. 2013, Schouten et al. 2018). Since the Brazilian soybean production is mostly export-driven, most soy producers will likely still be responsive to international market pressures to not deforest even under weak public governance.

However, deforestation by other actors can greatly hurt the production of soybeans via climate impacts on yields. The majority of deforestation in the Amazon and Cerrado happens in a very small number of properties (Rajão et al. 2020) which tend to be relatively large but raise cattle with very little efficiency (Godar et al. 2014, Skidmore et al. 2021). In our EG scenarios, this deforestation does not substantially increase cattle production either –moderate productivity gains are enough to compensate for the smaller expansion of pasturelands in SEG. On the other hand, the climate effects of natural vegetation loss decrease total soybean production in all subregions analyzed. Since these effects occur in combination with global climate change, conserving natural vegetation can alleviate future losses. In the state of Mato Grosso alone, which produced ~10% of the world’s soybeans in 2019 (FAO 2020, IBGE 2021), strong environmental governance can lead to an additional revenue of 1 billion USD per year in soybean production by 2050 under RCP8.5, or 10% of all its production under WEG (Supplementary Table 2.4).

Brazilian soybean producers have much to gain with better environmental governance, from the climate regulation services to more immediate benefits such as better access to markets. Although adaptation measures such as irrigation could prevent some of the losses from deforestation-induced climate change, these measures can be costly, and their adoption is constrained by water and infrastructure availability (Costa et al. 2019). Furthermore, direct conversion from forests to soybeans has been trending downward even as total conversion rates increase (Goldman et al. 2020). Although deforestation does not seem to be attractive to soybean production as a whole, it can bring individual benefits to some farmers.

Weak environmental governance benefits only a few “free-riders” that add very little to the country’s or even their region’s economy in the long run (Instituto Escolhas 2021). Still, the rural caucus of the Brazilian Congress (which represents large landholders) has been strongly advocating for the further dismantling of environmental governance on many fronts. Soaring commodity prices, the weakening of environmental legislation, and lack of enforcement (Sauer 2018, Rochedo et al. 2018, Ferrante and Fearnside 2019) are leading to a sharp acceleration of deforestation rates (INPE 2021).

Suppose soybean farmers, the respective supply chain, and their representatives become aware of the benefits of strong environmental governance for their business. In that case, there is much they could do to curb natural vegetation loss. The results presented here show that it would be in their interest to extend the soy moratorium to the much less protected Cerrado biome (Strassburg et al. 2017, Soterroni et al. 2019), where impacts on production are expected to be larger and soybeans play a larger role on forest conversion (Song et al. 2021). They would also benefit from better enforcement of existing cattle agreements (Lambin et al. 2018).

However, such measures combined with soybean expansion could create problems for cattle production, which would likely be pressured with higher land prices and the need for the intensification of systems that traditionally use very little technology. Policies that simultaneously accommodate conservation, soybean expansion, and cattle intensification do exist. A prominent solution is to provide incentives to the adoption of integrated crop-livestock systems (ICLS), which leverage the intensive management practices of soybeans to improve low-yielding pastures. Although the adoption of these systems is still low due to high upfront costs and cultural and knowledge barriers, they demonstrably boost profitability and stocking rates and can be applied to a large portion of the Cerrado biome (Gil et al. 2015, Nepstad et al. 2019).

Expanding agricultural production in a way that is economically and environmentally sustainable to both crop and cattle agriculture under the added threat of a changing climate will demand much cooperation between farmers, traders, and the government. Fortunately, Brazilian soybean farmers are well accustomed to working collectively and to successfully advocating for their interests. Applying these skills towards fostering environmental governance and cattle intensification is a win-win strategy, one which can simultaneously conserve forests and increase soybean and cattle production.

2.5) Supplementary material

Supplementary Table 2.1 CESM components configuration

Component	Name	Grid	Reference
Atmosphere	CAM4 - Community Atmosphere Model 4	0.9°x1.25°, 27 levels with top at 2.194 hPa	Neale et al. (2013)
Ocean	POP2 – Parallel Ocean Program 2	1.125° longitude, 0.27°-0.64° latitude, 60 levels	Danabasoglu et al. (2012)
Surface	CLM4 – Community Land Model 4	0.9°x1.25°	Lawrence et al. (2012)
Land hydrology	RTM – River Transport Model	0.5°x0.5°	Oleson et al. (2010)
Sea ice	CICE4 – Los Alamos Sea Ice Model	Same as ocean	Holland et al. (2012)

Supplementary Table 2.2 Mapping from land use classes in Rochedo et al. (2018) to CESM Plant Functional Types (PFT). For Primary Vegetation classes, we applied a combination of PFTs with the same fraction as those in the primary vegetation maps by Ramankutty and Foley (1999, RF99). For a description on the mapping of RF99 classes to CESM PFTs, refer to Oleson et al. (2010).

Rochedo et al. (2018) land use class	**CESM PFT**
Water	Ignored
Urban	Ignored
Pasture	C4 grasses (PFT 14)
Pasture in protected area	C4 grasses (PFT 14)
Savanna	Primary vegetation (RF99)
Savanna in protected area	Primary vegetation (RF99)
Forest	Primary vegetation (RF99)
Forest in protected area	Primary vegetation (RF99)
Soy	Crops (PFT 15)
Sugarcane	Crops (PFT 15)
Maize	Crops (PFT 15)
Cotton	Crops (PFT 15)
Rice	Crops (PFT 15)
Wheat	Crops (PFT 15)
Dry beans	Crops (PFT 15)
Coffe (Arabica)	Crops (PFT 15)
Coffe (Robusta)	Crops (PFT 15)
Oranges	Crops (PFT 15)

Cassava	Crops (PFT 15)
Bananas	Crops (PFT 15)
Cocoa	Crops (PFT 15)
Tobacco	Crops (PFT 15)
Maize (2nd season)	Crops (PFT 15)
Dry beans (2nd season)	Crops (PFT 15)
Planted forest	Broadleaf evergreen trees (PFT 5)
Soy-Maize	Crops (PFT 15)
Soy-Wheat	Crops (PFT 15)
Maize-Wheat	Crops (PFT 15)
Soy-Dry beans	Crops (PFT 15)
Maize-Dry beans	Crops (PFT 15)
Dry beans-Dry beans	Crops (PFT 15)

Supplementary Table 2.3 Soybean yield model coefficients from Abrahão et al. (2021). These can be interpreted as the sensitivity of log-yields to one unit change in each variable.

	Variable coefficient			
	GDD	**EDD**	**VPD**	**Prec**
Units	log(t ha^{-1})/(ºC day)	log(t ha^{-1})/(ºC day)	log(t ha^{-1})/(hPa)	log(t ha^{-1})/ (mm day^{-1})
Model				
GDD+EDD	0.0002129	-0.003728	-	-
GDD+EDD+VPD	0.0001028	0.0007704	-0.09755	-
GDD+EDD+VPD+Prec	0.0001003	0.0006135	-0.08478	0.01398
VPD	-0.08999	-	-	-

Supplementary Table 2.4 Projected changes in soybeans cropping area and production between 2012 and 2050 under different environmental governance (EG) scenarios on key states. Production change values in column (B) consider only the change in cropping area and its distribution. Production change values in column (C) also consider the modeled climate impact on yields. Columns (D) and (E) show the difference in total yearly production value (assuming average historical prices) between the SEG and WEG scenarios, which can be interpreted as the value gained with environmental governance. A positive value of 10% in column (D) means that yearly production value under SEG in 2050 is projected to be 10% higher than under WEG in the same year. Prices assumed for value calculations in column (E) are average producer prices in Brazil in the period 2010-2016, 194 USD ton^{-1} for maize and 406 USD ton^{-1} for soybeans (FAO 2021).

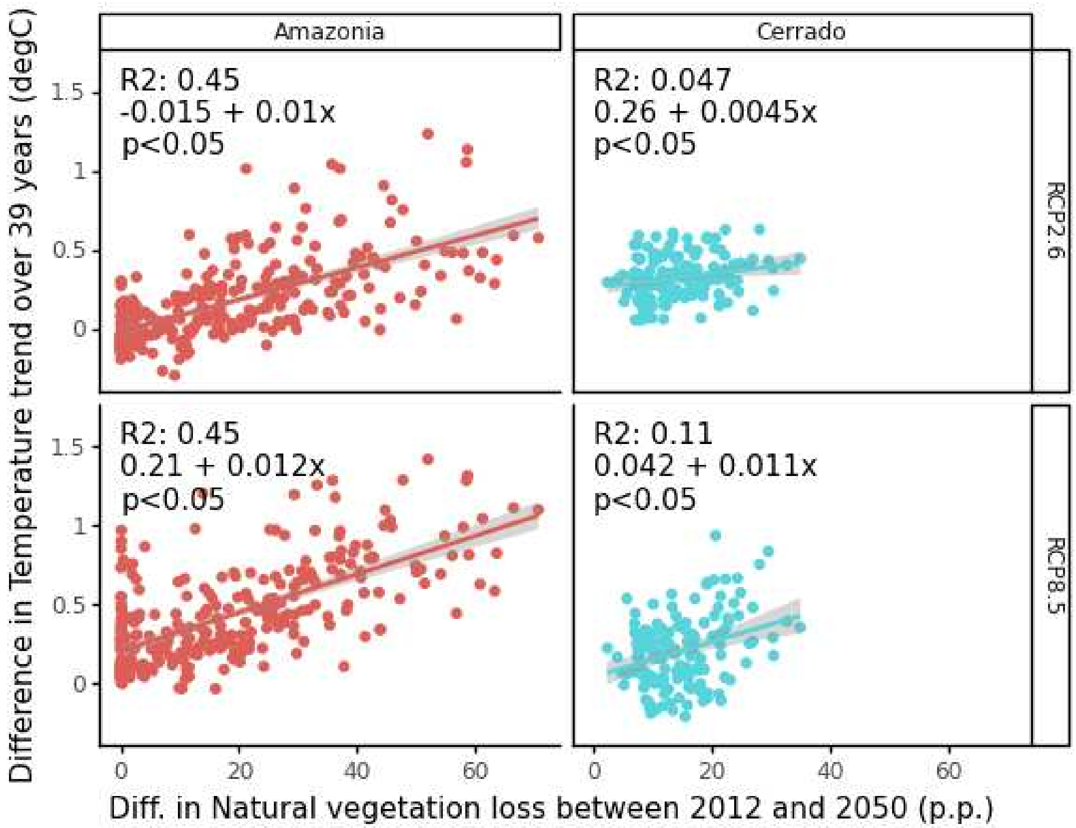
			(A)	(B)	(C)	(D)	(E)
	RCP	EG	Area increase	Production increase (potential)	Production increase (w/ climate effects)	EG value (SEG-WEG)	
			(%)	(%)	(%)	(% of WEG)	(million USD $year^{-1}$)
			Soybeans				
AM	RCP2.6	SEG	1141	1141	1086		
		WEG	929	929	861	23.4	1.6
	RCP8.5	SEG	1141	1141	1000		

			(A)	(B)	(C)	(D)	(E)
	RCP	EG	Area increase	Production increase (potential)	Production increase (w/ climate effects)	EG value (SEG-WEG)	
			(%)	(%)	(%)	(% of WEG)	(million USD year^{-1})
		WEG	929	929	719	34.3	2.0
GO	RCP2.6	SEG	90	83	87		
		WEG	90	82	76	6.1	404.7
	RCP8.5	SEG	90	83	62		
		WEG	90	82	61	0.3	17.5
MA	RCP2.6	SEG	83	123	120		
		WEG	86	127	118	1.2	10.3
	RCP8.5	SEG	83	123	97		
		WEG	86	127	97	0.2	1.8
MT	RCP2.6	SEG	64	61	58		
		WEG	64	61	46	7.8	883.8
	RCP8.5	SEG	64	61	44		
		WEG	64	61	30	10.1	1029.4
PA	RCP2.6	SEG	553	547	529		
		WEG	560	547	490	6.8	49.7
	RCP8.5	SEG	553	547	479		
		WEG	560	547	413	13.0	83.1

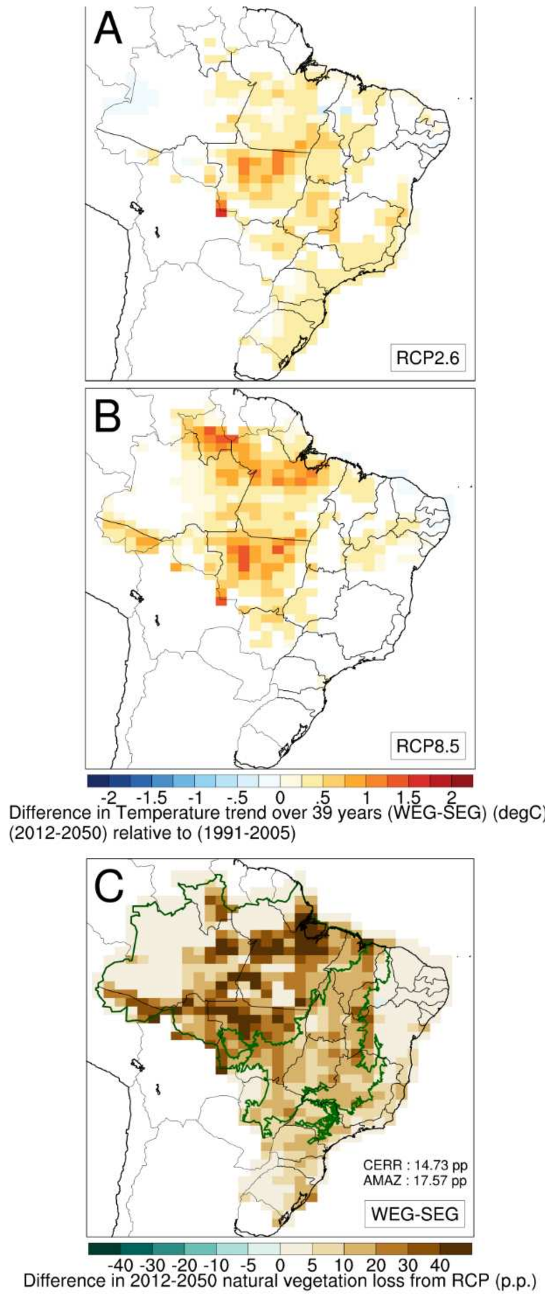
Supplementary Table 2.5 Projected changes in 2nd crop maize cropping area and production between 2012 and 2050 under different environmental governance (EG) scenarios on key states. Production change values in column (B) consider only the change in cropping area and its distribution. Production change values in column (C) also consider the modeled climate impact on yields. Columns (D) and (E) show the difference in total yearly production value (assuming average historical prices) between the SEG and WEG scenarios, which can be interpreted as the value gained with environmental governance. A positive value of 10% in column (D) means that yearly production value under SEG in 2050 is projected to be 10% higher than under WEG in the same year. Prices assumed for value calculations in column (E) are average producer prices in Brazil in the period 2010-2016, 194 USD ton^{-1} for maize and 406 USD ton^{-1} for soybeans (FAO 2021).

			(A)	(B)	(C)	(D)	(E)
	RCP	EG	Area increase	Production increase (potential)	Production increase (w/ climate effects)	EG value (SEG-WEG)	
			(%)	(%)	(%)	(% of WEG)	(million USD $year^{-1}$)
			2nd crop maize				
GO	RCP2.6	SEG	84	74	67		
		WEG	83	74	71	-21.6	-2.6
	RCP8.5	SEG	84	74	63		
		WEG	83	74	66	-18.3	-2.2
MA	RCP2.6	SEG	58	65	64		
		WEG	64	75	76	-0.8	-6.9
	RCP8.5	SEG	58	65	61		
		WEG	64	75	69	-0.5	-4.9
MT	RCP2.6	SEG	65	58	51		
		WEG	65	58	54	-46.2	-2.0
	RCP8.5	SEG	65	58	48		
		WEG	65	58	47	9.9	0.4
PA	RCP2.6	SEG	2	4	3		
		WEG	18	24	21	-1.4	-14.9
	RCP8.5	SEG	2	4	0		

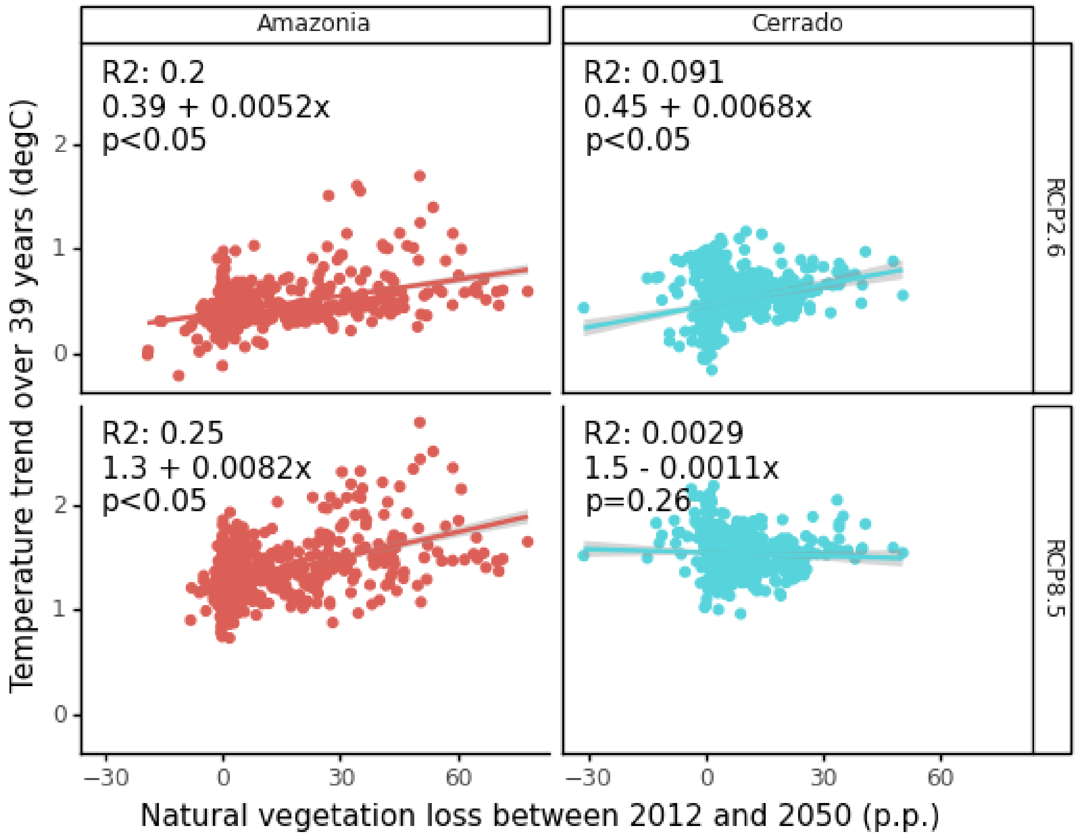
RCP	EG	(A)	(B)	(C)	(D)	(E)
RCP	EG	Area increase	Production increase (potential)	Production increase (w/ climate effects)	EG value (SEG-WEG)	
		(%)	(%)	(%)	(% of WEG)	(million USD year^{-1})
	WEG	18	24	15	-1.2	-13.2



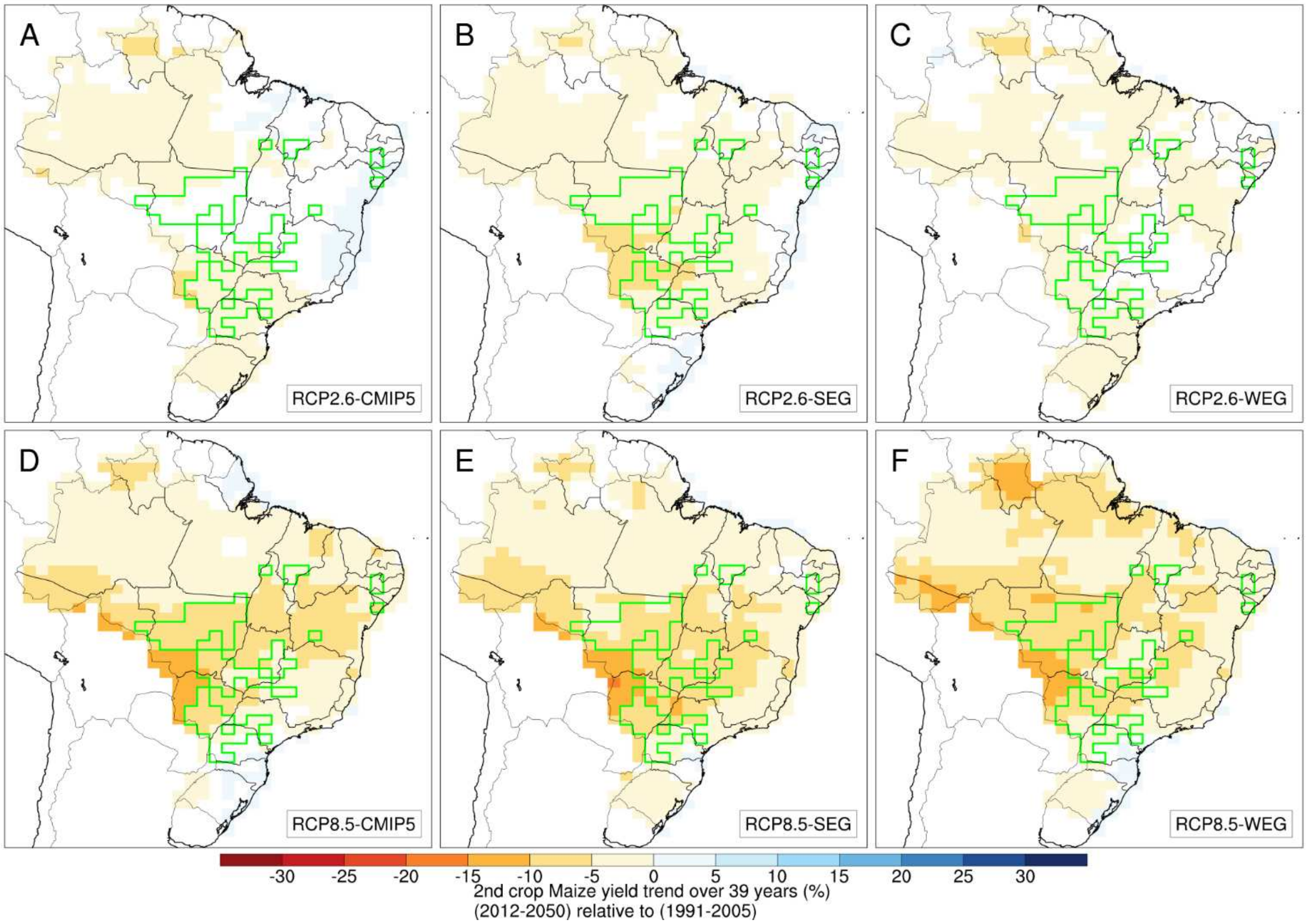
Supplementary Figure 2.1 Relationship between natural vegetation loss and temperature change over 2012-2050 in the soybean growing season. Each point represents the difference in natural vegetation loss and in temperature change between the WEG and SEG scenarios. Gray zones represent the 95% confidence interval.



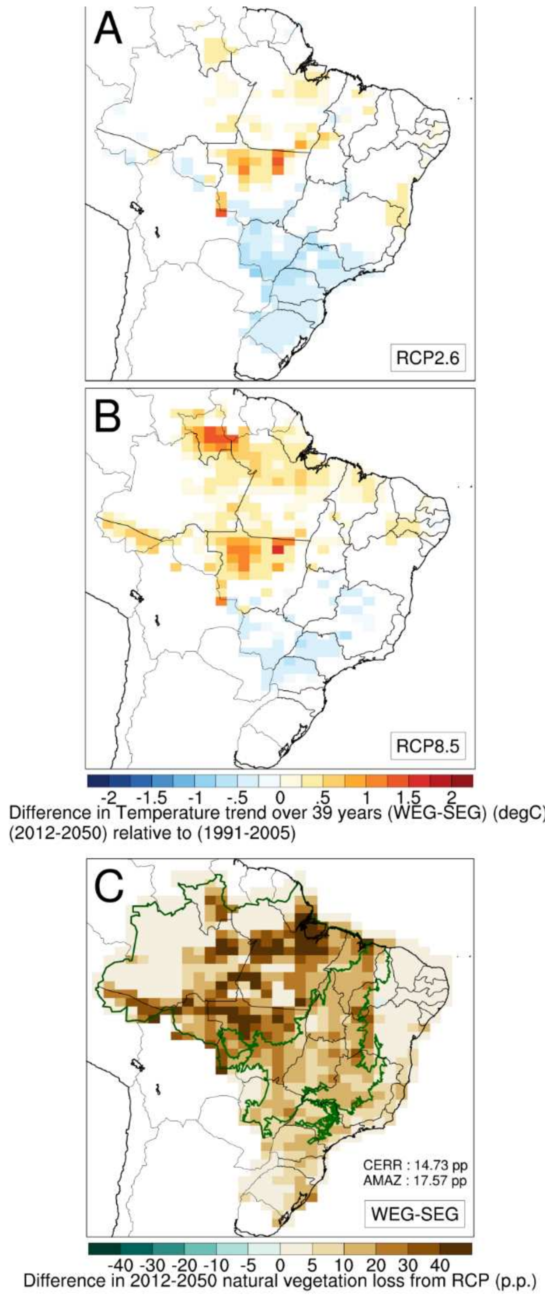
Supplementary Figure 2.2 Difference in warming between WEG and SEG in the soybeans growing season under RCP2.6 (A) and RCP8.5 (B) and difference in natural vegetation loss between the two scenarios (C).



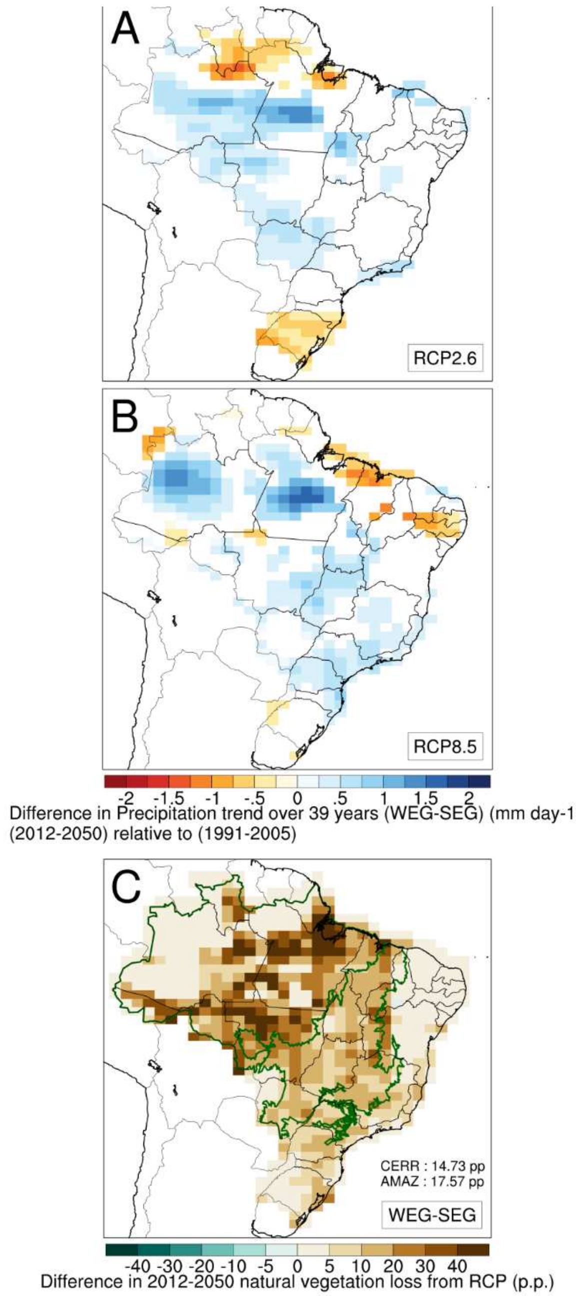
Supplementary Figure 2.3 Relationship between natural vegetation loss and temperature change over 2012-2050 in the 2nd crop maize growing season. Each point represents the difference in natural vegetation loss and in temperature change between the WEG and SEG scenarios. Gray zones represent the 95% confidence interval.



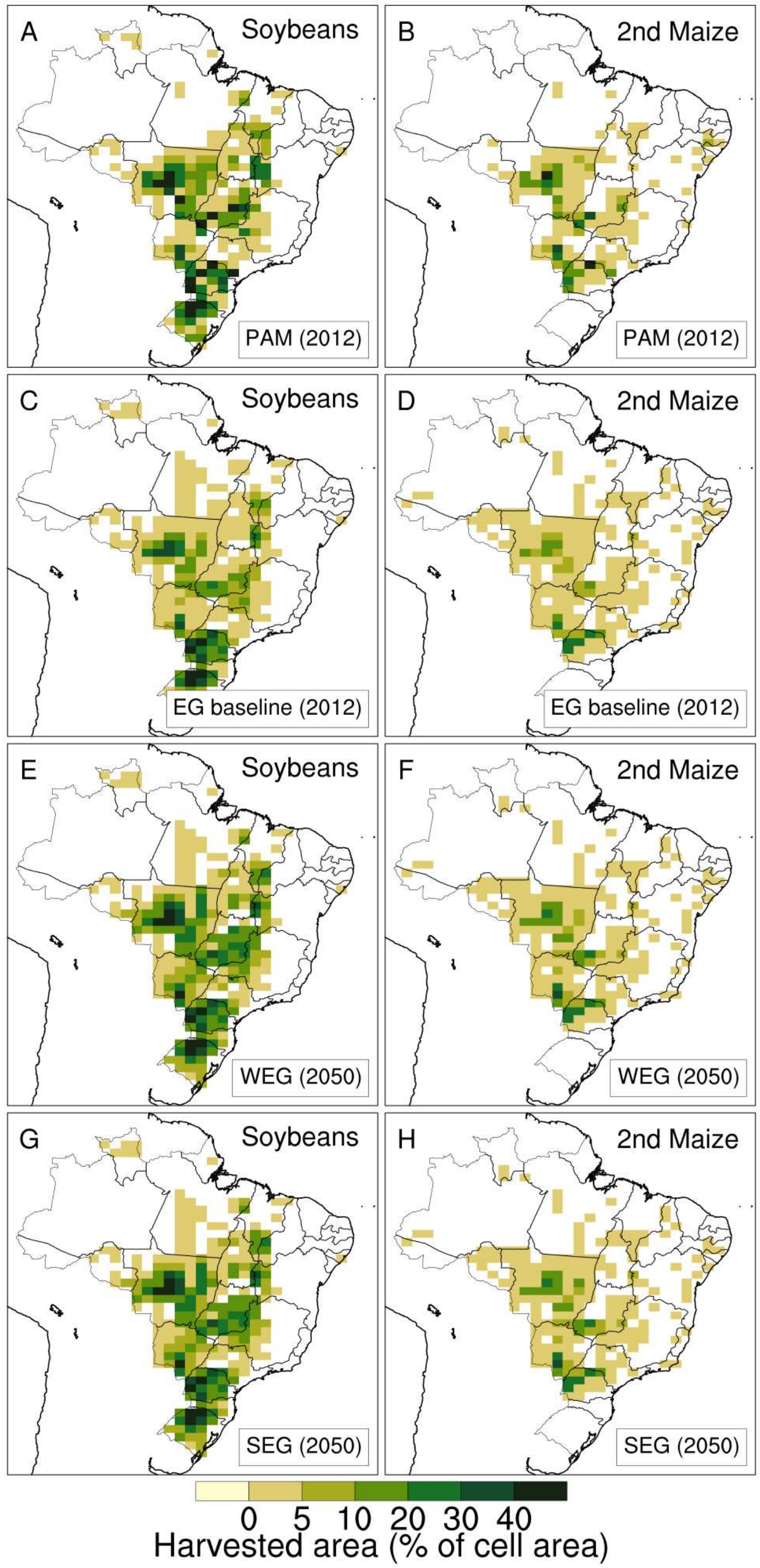
Supplementary Figure 2.4 Change in average 2nd crop maize growing season temperatures in the period 2012-2050 (ºC 39 years-1) for each scenario (A-F). Only changes significant at the 5% level are shown.



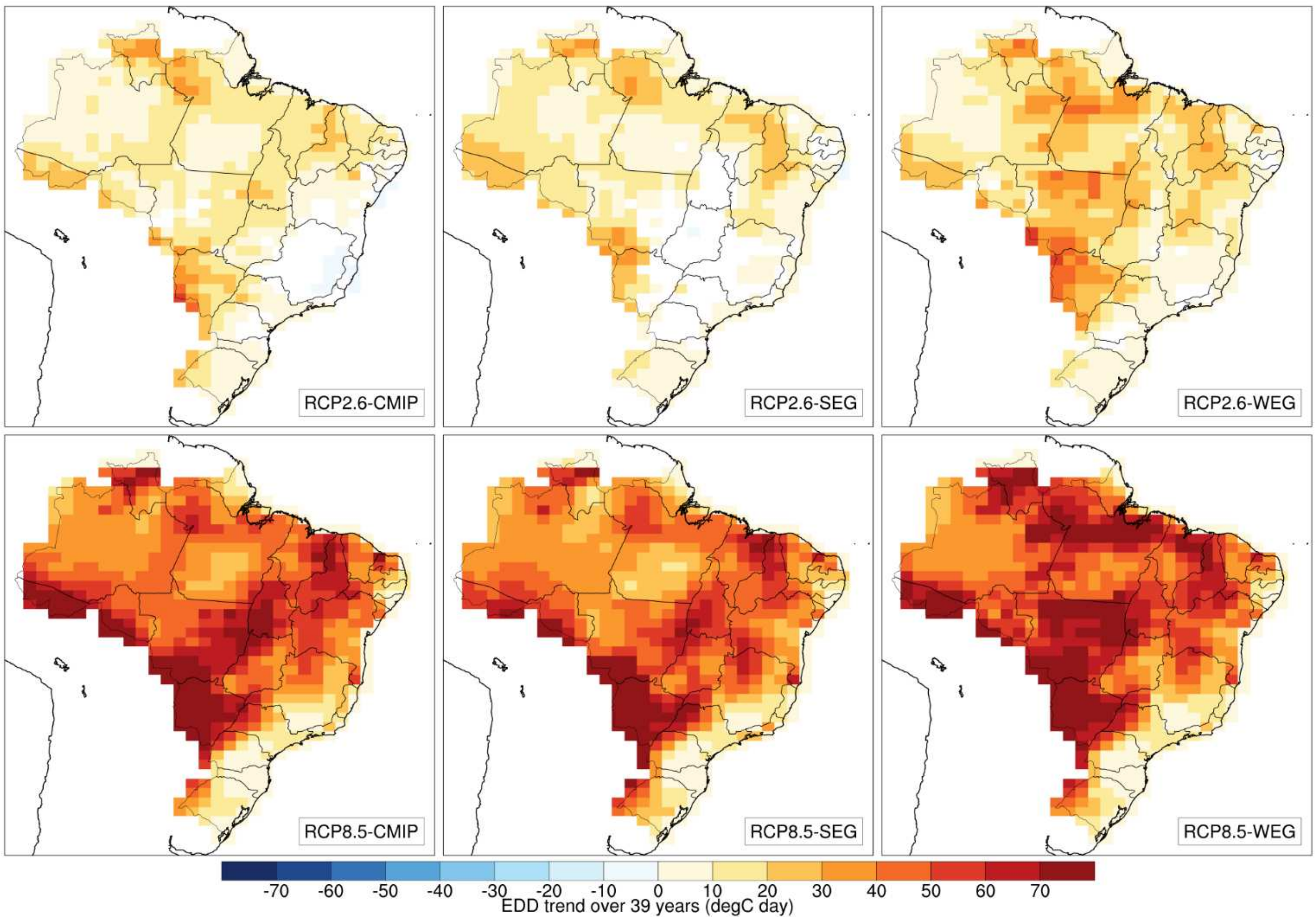
Supplementary Figure 2.5 Difference in temperature changes between WEG and SEG in the 2nd crop maize growing season under RCP2.6 (A) and RCP8.5 (B) and difference in natural vegetation loss between the two scenarios (C).



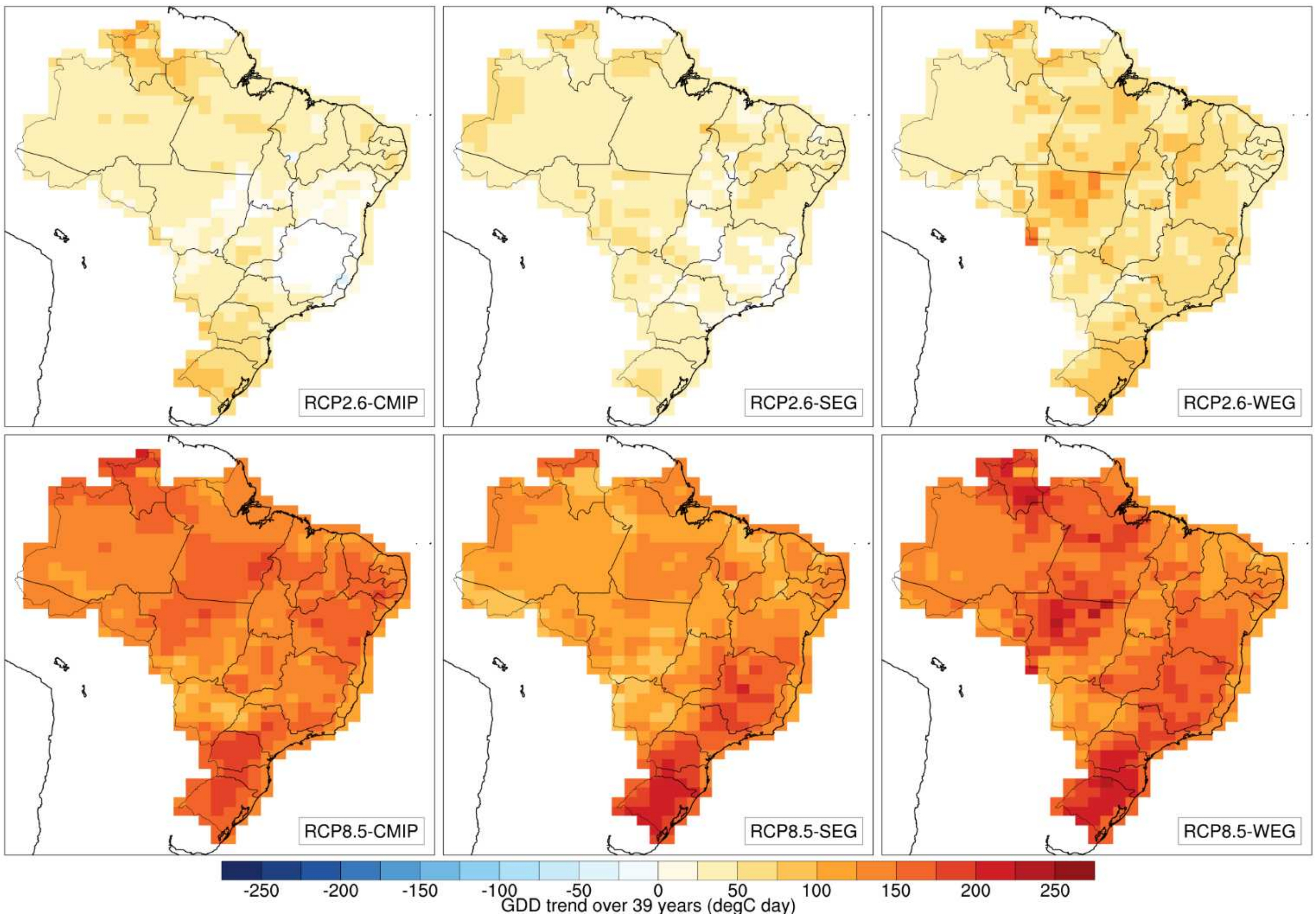
Supplementary Figure 2.6 Difference in precipitation change between WEG and SEG in the 2nd crop maize growing season under RCP2.6 (A) and RCP8.5 (B) and difference in natural vegetation loss between the two scenarios (C).


A
Soybeans
PAM (2012)
B
2nd Maize
PAM (2012)
C
Soybeans
EG baseline (2012)
D
2nd Maize
EG baseline (2012)
E
Soybeans
WEG (2050)
F
2nd Maize
WEG (2050)
G
Soybeans
SEG (2050)
H
2nd Maize
SEG (2050)
0 5 10 20 30 40
Harvested area (% of cell area)

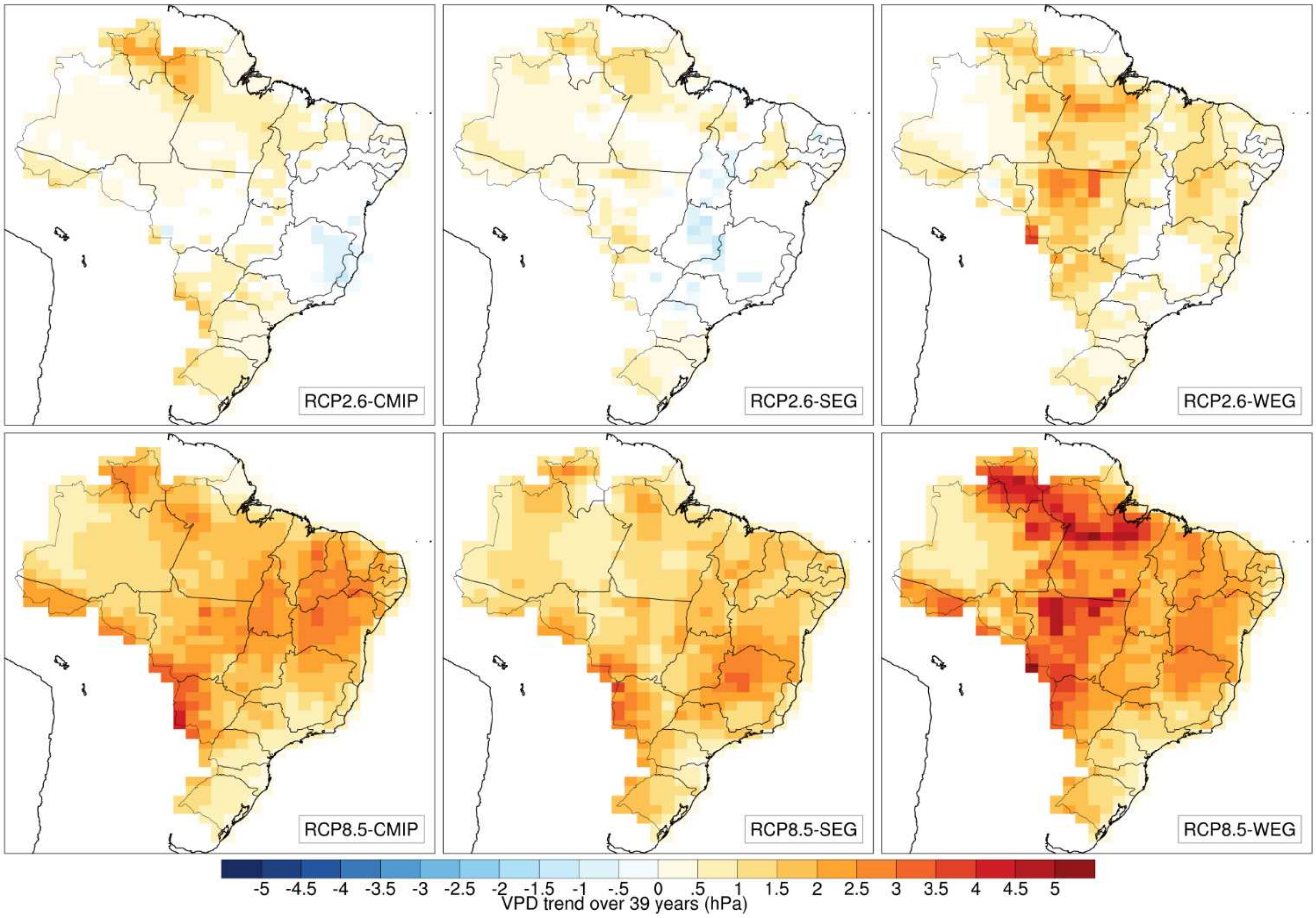
Supplementary Figure 2.7 Harvested area of soybeans (left column) and 2nd crop maize (right column) in 2012 according to PAM in 2012 (A, B); in the common 2012 baseline of the SEG and WEG scenarios (C, D); and in 2050 on the WEG (E, F) and SEG (G, H) scenarios; in percentage of each cell's area.



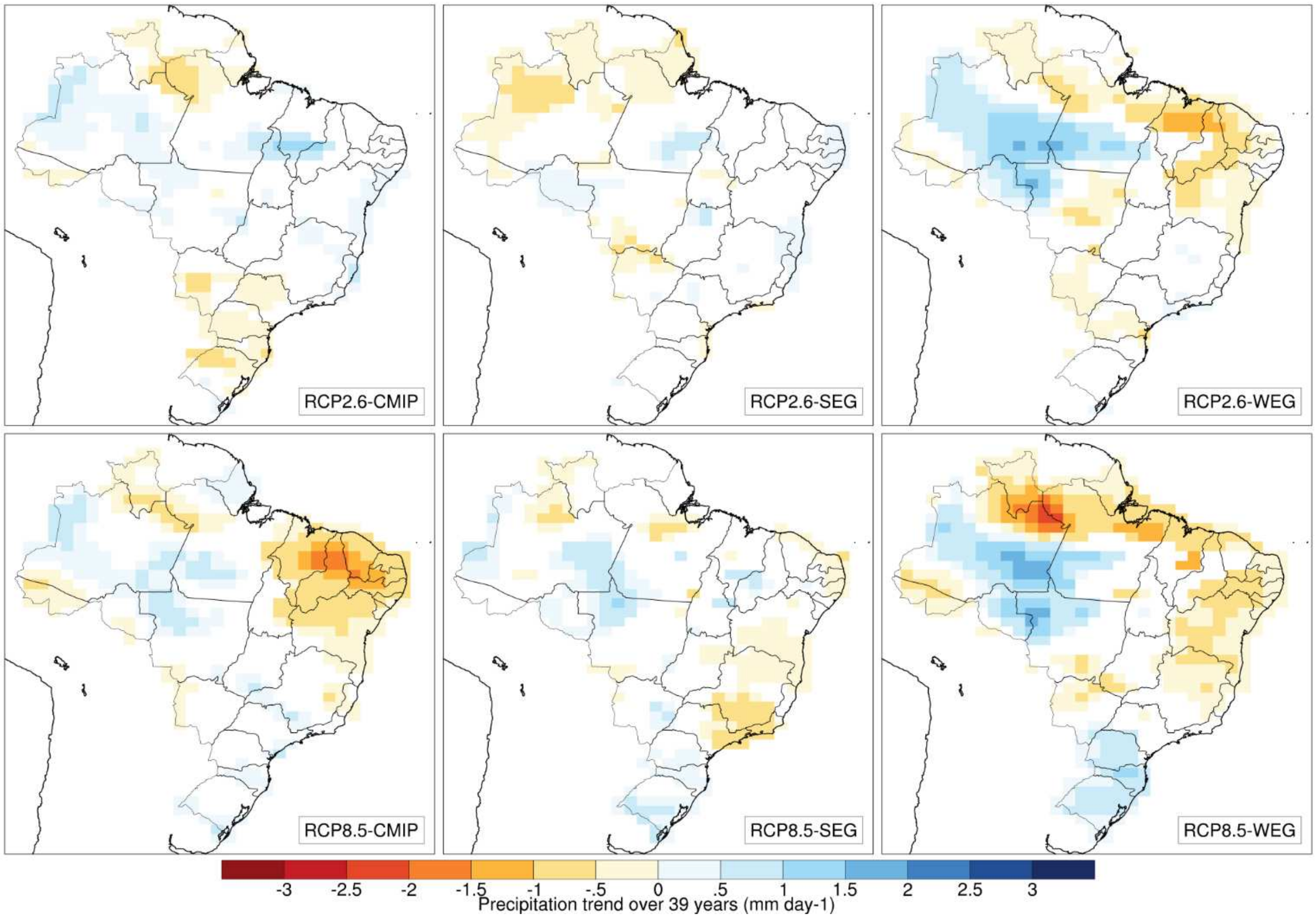
Supplementary Figure 2.8 Change in the soybeans growing season EDD in the period 2012-2050 for all scenarios



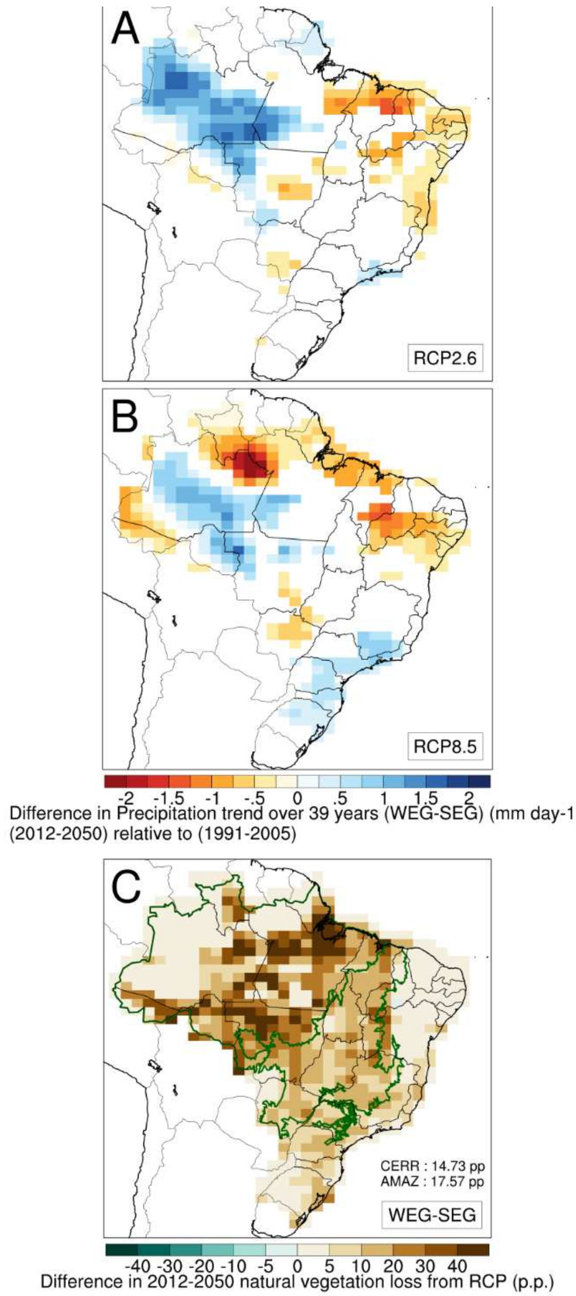
Supplementary Figure 2.9 Change in the soybeans growing season GDD in the period 2012-2050 for all scenarios



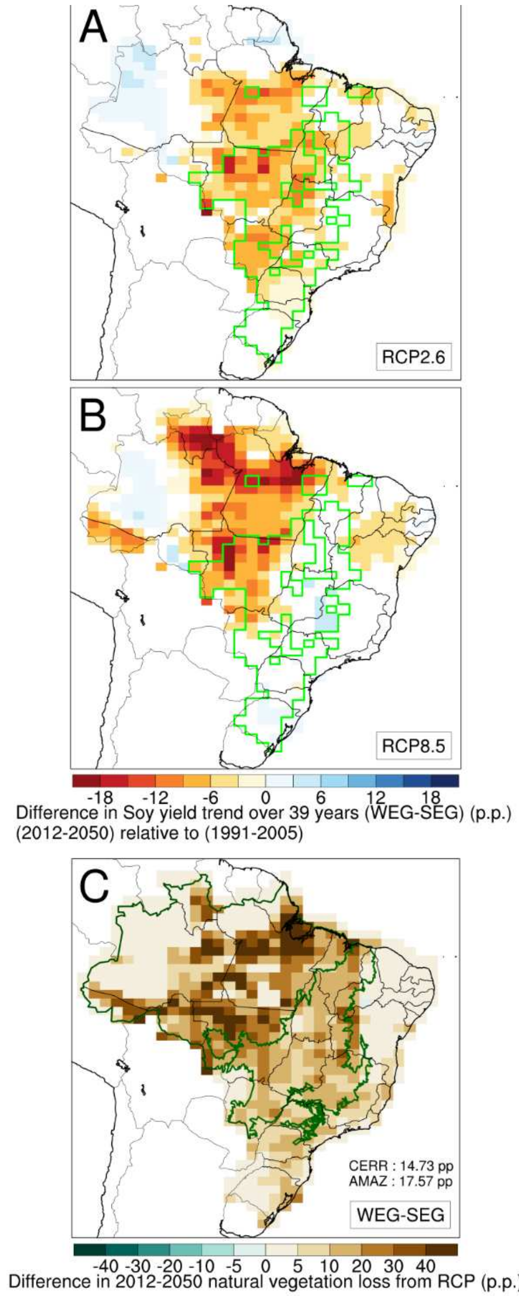
Supplementary Figure 2.10 Change in the soybeans growing season average VPD in the period 2012-2050 for all scenarios



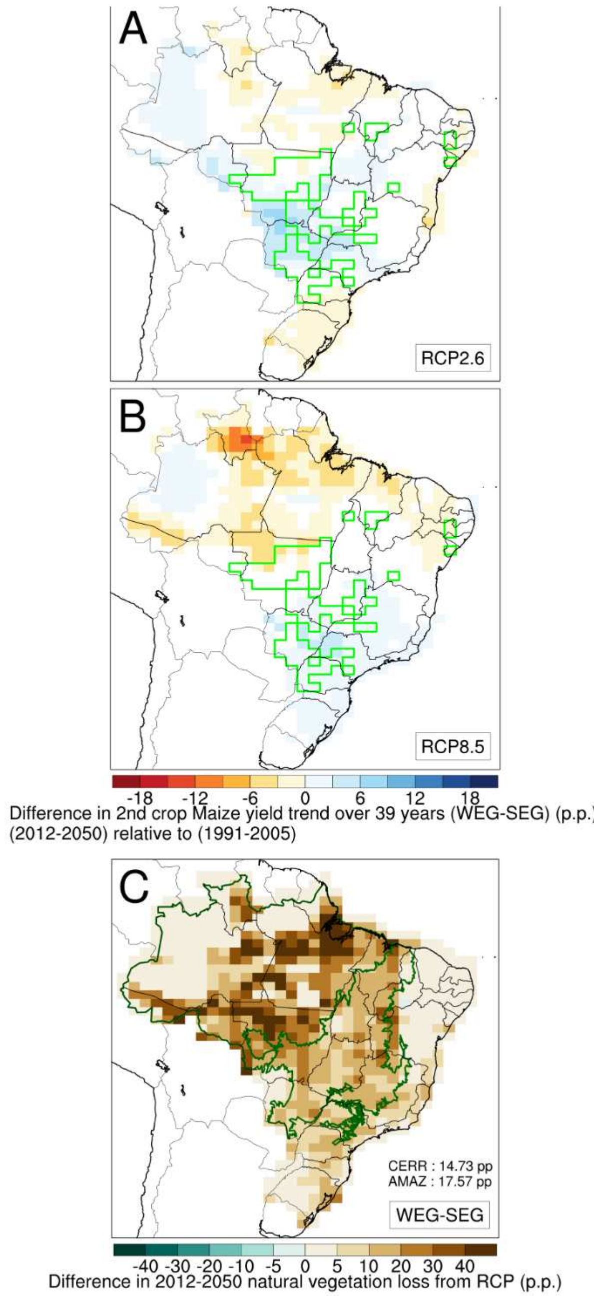
Supplementary Figure 2.11 Change in the soybeans growing season average precipitation in the period 2012-2050 for all scenarios



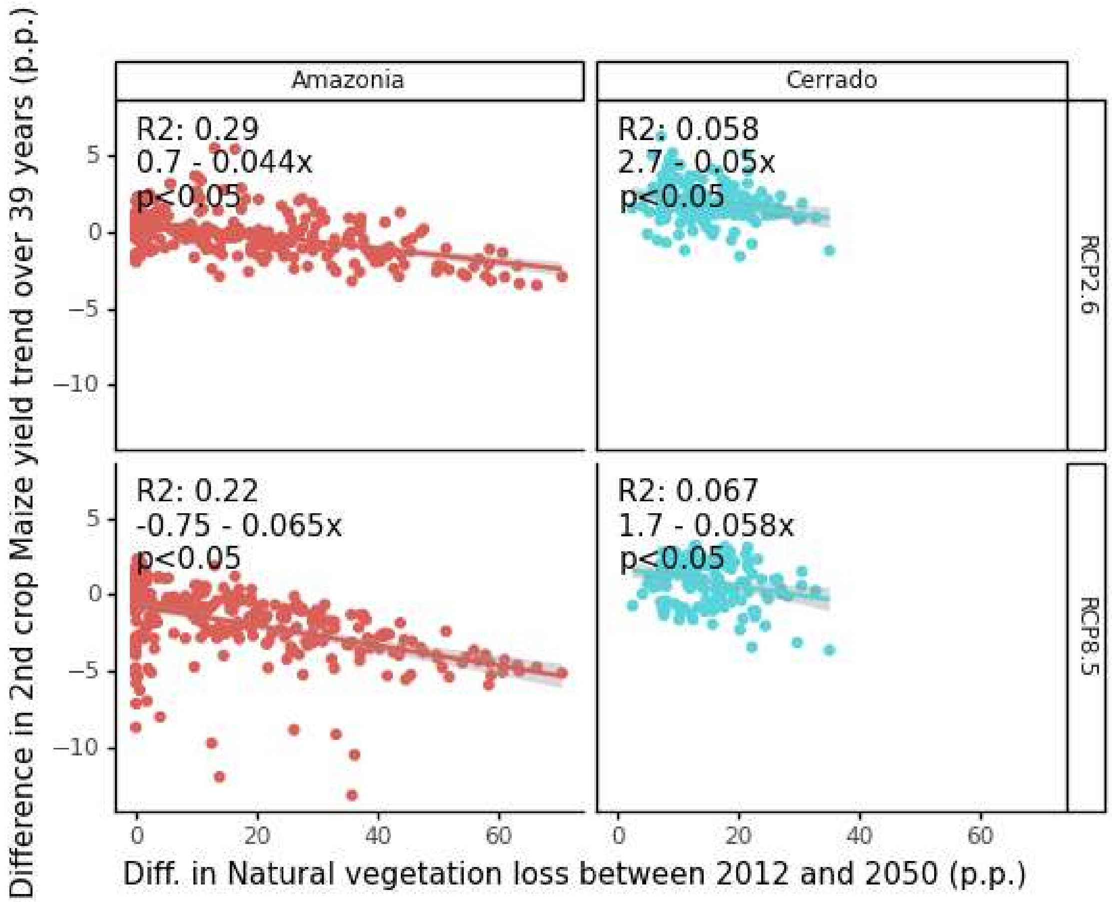
Supplementary Figure 2.12 Difference in average precipitation change during the soybeans growing season between WEG and SEG under RCP2.6 (A) and RCP8.5 (B) and difference in natural vegetation loss between the two scenarios (C).



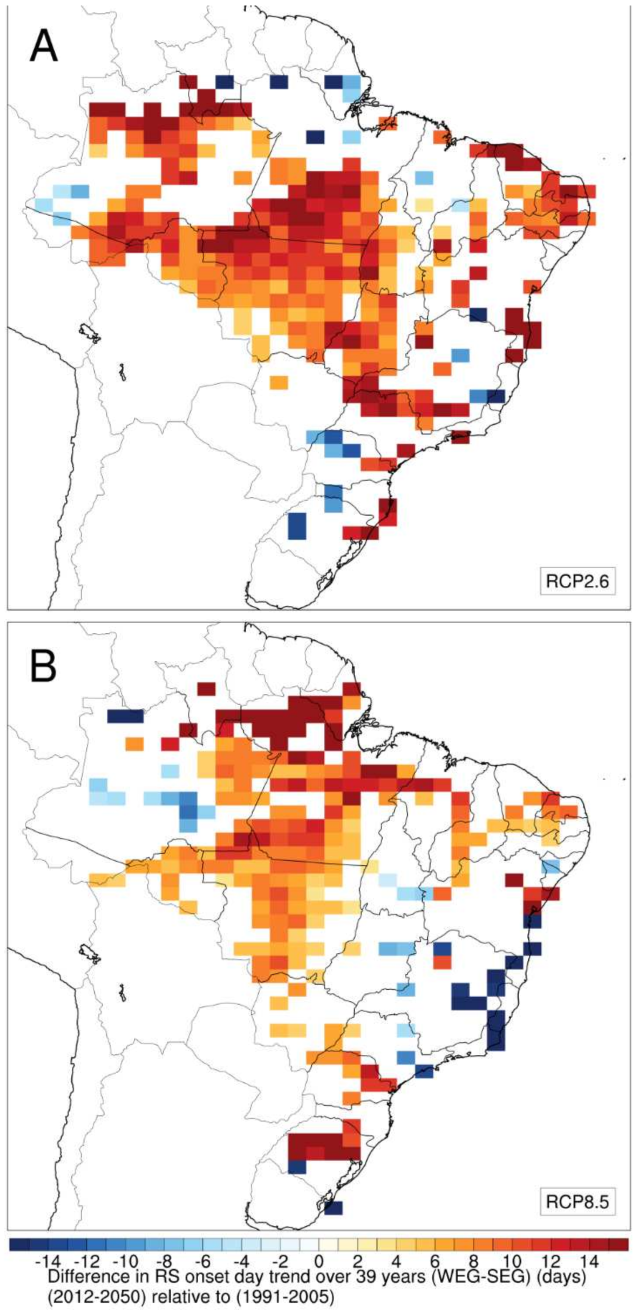
Supplementary Figure 2.13 Difference in ensemble mean soybean yield change between WEG and SEG under RCP2.6 (A) and RCP8.5 (B) and difference in natural vegetation loss between the two scenarios (C).



Supplementary Figure 2.14 Difference in ensemble mean 2nd crop maize yield change between WEG and SEG under RCP2.6 (A) and RCP8.5 (B) and difference in natural vegetation loss between the two scenarios (C).



Supplementary Figure 2.15 Relationship between natural vegetation loss and estimated 2nd crop maize yield change over 2012-2050. Each point represents the difference in natural vegetation loss and in estimated yield change (average of the ensemble of yield models) between the WEG and SEG scenarios. Gray zones represent the 95% confidence interval.



Supplementary Figure 2.16 Difference in rainy season (RS) onset day trend WEG and SEG under RCP2.6 (A) and RCP8.5 (B). Positive values mean that the rainy season tends to start later in WEG than in SEG.

Chapter 3: General conclusions

3.1) Overview and conclusions

Brazilian crop agriculture has experienced tremendous growth in the last decades while making progress toward abandoning predatory extensification over natural vegetation in favor of more intensive practices (Dias et al. 2016). Although this decoupling of crop production and deforestation is still an ongoing process, it happened as public and private policies created incentives for soybean producers to forego deforestation. Current deforested land and agricultural technology are more than enough to fulfill the global demand for soy until mid-century. As international pressure on soybean farmers to avoid deforestation is unlikely to go away anytime soon, soybean production in Brazil appears to be on track for sustainable growth. However, a small number of "free riders", mainly from other industries but also from the soy industry, have been pushing deforestation rates up under a weakening environmental governance.

Preventing the growth of deforestation can be in the interest of soybean production, especially under global climate change. Continuing deforestation leads to regional changes in climate that can be detrimental to agriculture. At the same time, global climate change caused mainly by changes in atmospheric composition also threatens hotspots of agriculture in Brazil. This thesis investigated how these two different forcings can interact and affect Brazilian soybeans and the maize planted after them in double cropping systems.

Chapter 1 describes how double cropping systems adoption and yields have responded to variations in climate in the recent past and what these relationships could mean for agriculture under mid-century global climate change projections. Regarding the adoption of double cropping systems, results indicate that the rainy season duration influences it nonlinearly. Adoption is more likely to occur in municipalities and years where the rainy season is longer than 200 days, becomes increasingly less likely for durations under 200 days and is not found in municipalities and years with a rainy season shorter than 150 days. CMIP6 models project years with the rainy season shorter than 200 days to be more frequent by 2035-2050 under the SSP2-4.5 scenario in key double cropping regions in central Brazil. The econometric yield models indicate that exposure to extreme heat and strong vapor pressure deficit significantly harms soybean and 2nd crop maize yields. The relationships found are relatively weak for 2nd crop maize, although some factors may have confounded the analysis. Climate changes are estimated to reduce soybean yields by ~12% by mid-century, a result robust to choices of yield model specifications.

Chapter 2 investigates how deforestation under a strong (SEG) and a weak (WEG) environmental governance scenario influences regional climate under changing atmospheric compositions using a fully coupled climate system model. By applying the yield models estimated in Chapter 1, I find that soybean yields are negatively affected in all scenarios by 2050. However, differences in land use between environmental governance scenarios can be as important to determine yield impacts as differences in atmospheric concentration between the two most extreme atmospheric concentration scenarios considered in the CMIP5. Weaker climate impacts under stronger environmental governance can prevent soybean production losses equivalent to 442-527 million USD year^{-1} in the Amazon and 670-1347 million USD year^{-1} in the Cerrado by 2050, up to 10% of projected production. This value of environmental governance is found to interact with atmospheric composition differently in each region, being higher in the Amazon under RCP8.5 and higher in the Cerrado under RCP2.6.

In conclusion, Brazilian soybean farmers have much to gain with stronger environmental governance. Deforestation causes changes in regional climate that can strongly affect agricultural production, especially under global climate change by 2050. Environmental governance can prevent these damages, besides providing other benefits to soybean farmers such as better access to markets. If managed well, both crop and cattle production can grow to accommodate growing demands until the middle of the century. And doing so while preserving natural vegetation can be a win-win situation, with benefits ranging from increased agricultural production to preventing biodiversity loss.

3.2) Caveats and recommendations for future research

Although Chapter 1 demonstrated a clear relationship between double cropping adoption and rainy season length, developing a formal econometric model of this relationship would be useful to investigate how projected changes in climate could affect adoption. This could be challenging because the decision to plant a second crop is made before the rainy season ends and is also based in the expected length based on past experiences in that location. This can complicate identification from interannual variability on a fixed effects panel like those used for yields. Some alternatives would be including both a climatology and an annual deviation term, and using the rainy season onset instead of length.

The fact that the choice of planting a second crop is influenced by climate can also be biasing the estimates of the sensitivity of 2nd crop maize to climate. Yields were observed only in years were people chose to plant the second crop, which likely had more favourable weather. The presence of this selection bias can be biasing the coefficient estimates toward zero. This would explain the estimated very low sensitivity of 2nd crop maize yields to climate compared to that of process based crop model assessments. Future research could employ more sophisticated econometric methods to estimate both adoption and yields at the same time and thus correcting for the censoring of unobserved yields. Such methods are commonly employed in other fields such as labour economics.

The interactions between land-use induced and GHG induced climate change presented here were projected using only one coupled climate system model. Several effects involved such as the physiological effects of CO_2 on surface fluxes, the radiative effects of increased GHG concentrations on large scale circulation patterns and the regional circulation patterns arising from spatially heterogeneous deforestation are know to be very model-dependent, specially on smaller scales. Repeating the experiments presented here with an ensemble of coupled climate system models could help identify more robust responses to deforestation and changes in atmospheric concentration, specially in terms of induced regional circulation patterns.

The patterns of precipitation response to deforestation presented in Chapter 2 suggest the formation of anomalous circulation patterns caused by heterogeneous deforestation. Such effects were theorized and observed in the past, but on scales of tens of kilometers. The dipoles of precipitation found here were on the scale of hundreds of kilometers. More careful analysis of changes in circulation patterns could help understand the processes behind their formation, how they differ from smaller scale thermal cells and pehaps most importantly what are their relationships to larger scale changes in atmospheric background circulations caused by changes in atmospheric composition.

There is a growing recognition of the important role of phosphorus limitation on photosynthesis in the Amazon. This limitation, which is not modelled by CESM or by most ESMs to date, leads to differences in projected vegetation distribution (Dionízio et al. 2018) and more importantly weakens the effect of CO_2 fertilization (Fleischer et al. 2019). Phosphorus-deficient leaves tend to have lower photosynthetic rates but also lower stomatal conductance (Jacob and Lawlor 1991). Since the physiological effect of CO_2 on stomatal conductance is a key driver of changes in surface fluxes and rainfall under higher atmospheric CO_2 concentrations in the Amazon

(Sampaio et al. 2020), the phosphorus limitation could lead to weaker effects of GHG concentration on regional climate than shown here.

Here I calculate value of environmental governance using yield impacts and harvested areas projected on the last year of our analysis (2050). Estimates of the value of ecosystem services more commonly evaluate impacts over an entire period, applying an intertemporal discount rate to assume that profits now are worth more than the same profits in the far future to calculate a Net Present Value (NPV). The approach used here was chosen because i) it avoids the assumption of an intertemporal discount rate, to which results can be very sensitive ii) since soybean farmers are not expected to benefit from deforestation in this period in our scenarios, there would be no need to compare the value of decisions in the meantime and iii) both climate forcings increase monotonically and are difficult to reverse (reforestation, carbon capture), therefore using the last year of the series highlight the impacts that will persist for some time after the period of analysis. However, applications that compare the value of different ecosystem services and opportunity costs could require more careful more careful consideration of intertemporal effects.

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