REPORT

# HOW DEFORESTATION-INDUCED LOCAL AND REGIONAL CLIMATE CHANGES AFFECT AGRICULTURAL PRODUCTION IN THE BRAZILIAN AMAZON

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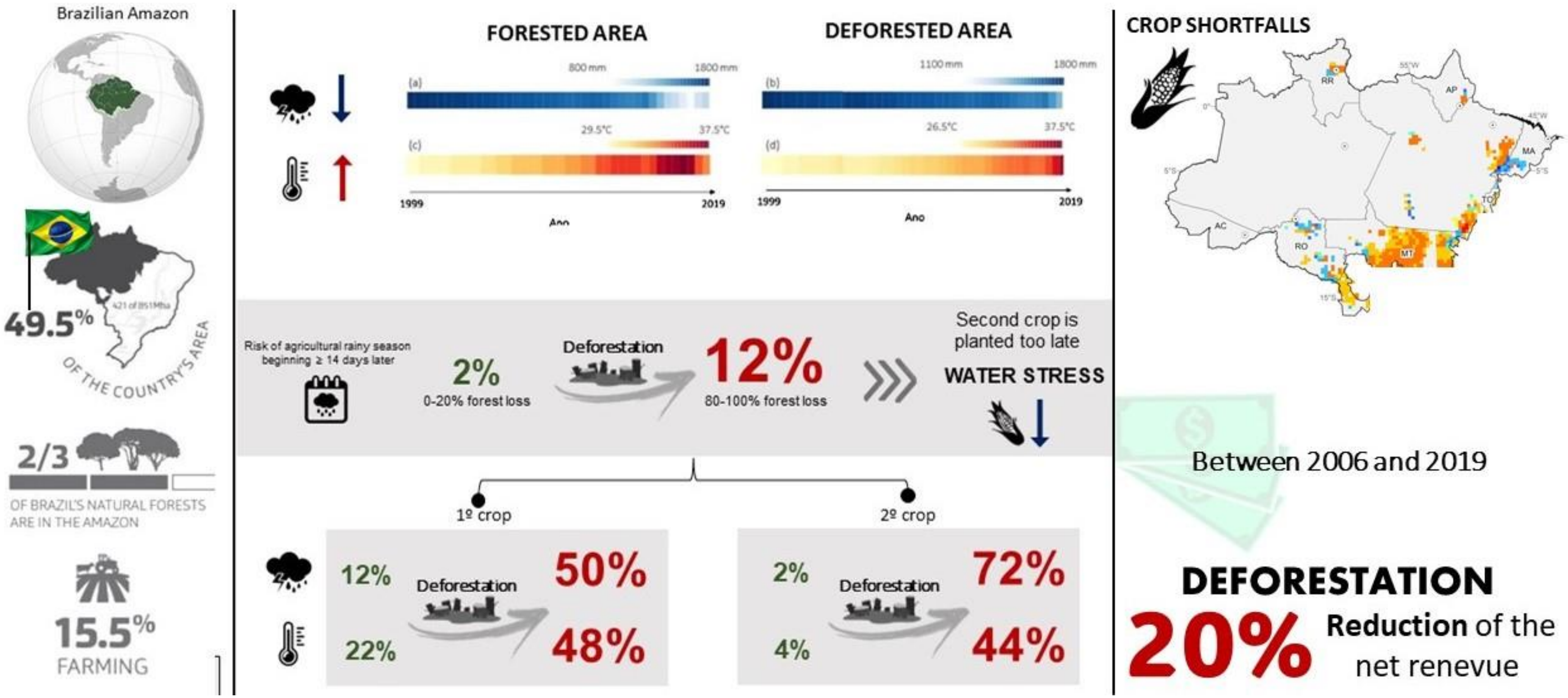
# 1. Deforestation-induced local and regional climate changes and their economic impacts on agricultural production


## Abstract

Forest loss in the Brazilian Amazon has significantly impacted the climate. At both local and regional scales, areas that experienced higher levels of deforestation show a correlation between the extent of forest loss and several climate-related outcomes, such as delayed onset of the agricultural rainy season, reduced rainfall volumes, and increased temperatures. Since 1980, there has been a consistent delay in the onset of the agricultural rainy season, with an average shift of 30 days. Yet this change is not uniformly distributed. In largely deforested areas, the delay in the onset of the agricultural rainy season has resulted in a 76-day shift, representing an augment of 40% from more conserved areas. Between 1999 and 2019, some regions have experienced reductions in rainfall of up to 40% during the first crop season and 23% in the second season. The warming trend is more pronounced during the first crop season, with maximum air temperatures in some areas increasing by up to 15%. Amazon deforestation amplifies the risks of climate change from local to regional scales, with the impact being more pronounced at the regional level. Conserving the Amazon Forest is crucial for ensuring favorable climatic conditions for agricultural production, which depends on the climate, given that over 90% croplands are rainfed. Our results indicate that regional climate change is increasingly impacting crop productivity, with maize showing greater vulnerability. We identified significant potential economic losses associated with these climate impacts. From 2006 to 2019, deforestation alone led to an estimated economic loss of US$ 761.3 million for soybean production and US$ 273.3 million for maize, amounting to a loss of around US$ 1.03 billion. This represents an average annual loss of US$ 73.3 million. These losses are quantified as US$ 20.30 per hectare for soybean and US$ 7.53 per hectare for maize, indicating a significant economic impact on a per-hectare basis. Furthermore, after deducting production costs, these losses represent 10% and 20% of the net revenues for soybeans and maize cropping, respectively. To sustain agricultural productivity in the Amazon, it is crucial to conserve and restore its native vegetation.

**Graphical abstract**



### 1.1. Contextualization

Since the early 1980s, Brazil's grain production has increased more than fivefold (IBGE, 2022), transforming the country to a major global agricultural supplier. Brazil now supplies 50% of the world's soy demand and 10% of maize, and stands out as the largest exporter of beef, contributing to 20% of global beef exports (TRASE, 2021). Over the last two decades, national exports of soybeans and maize have exceeded 1.1 billion tons, representing 12.6% of global exports (ComexStat, 2022). However, this agricultural expansion has incurred significant environmental costs, with croplands expanding on newly deforested areas and pastures encroaching on the Amazon's native vegetation. The conversion of forests to agricultural lands has caused biophysical changes that threaten the region's ecosystem services (Zscheischler et al., 2018; Gatti et al., 2021).

Research highlights the Amazon forest's critical role in influencing rainfall patterns and temperature seasonality (Pires & Costa, 2010; Boers et al., 2017; Strand et al., 2018; Leite-Filho et al., 2019, 2021, 2024). Climate regulation is a vital ecosystem service provided by the forest, essential for sustaining agriculture within and beyond the region (Strand et al., 2018; Costa et al., 2019; Leite-Filho et al., 2021). Significant effects include a one-month extension of the dry season since the 1970s, a decrease in dry season evapotranspiration by 15% to 40%, and a consistent drop in atmospheric humidity over the Amazon in the past two decades.

As a result, rising temperatures are impacting the Amazon, with projections indicating that deforestation alone could raise temperatures to levels akin to the worst global warming scenarios by 2100 (Leite-Filho et al., 2024). Irregular and below-average rainfall, such as the 50% reduction in the 2020/21 season, led to a loss of 7.3 million tons of grains. The impact of the 2021/2022 drought on soy production was estimated at R$72 billion, with a 12% decline in Brazil's Agricultural GDP from the first to the second quarter of 2022 (IBGE, 2022). The 2023/2024 drought further caused a loss of 11.8 million tons of soybeans, with economic impacts exceeding R$ 4.45 billion, and a 10% decrease in maize production resulted in an additional loss of R$ 2.11 billion. These agricultural losses impair food security, hence affecting Brazilian society and global markets, influencing price-setting policies, transport logistics and public stock planning (Assad et al., 2007). It is estimated that a 1% increase in tropical deforestation results in an average 0.5% decrease in yield productivity, and preventing deforestation in the southern Brazilian Amazon could avert agricultural losses of up to USD 1 billion annually (Leite-Filho et al., 2021).

### 1.2. Objectives and research questions

Despite the profound impacts of deforestation on the local and regional climate of the Brazilian Amazon—manifested as drying, warming, and disruptions in weather patterns—there is limited scientific literature as to how these changes have already affected agricultural outputs. To fill this gap, here, we present a comprehensive analysis of the impacts of local and regional climate change due to deforestation on agricultural productivity in the Amazon over the past two decades, focusing on soy, maize, and pasture yields.

Our study answers the following questions: (a) What spatial patterns of climate change have occurred in the Brazilian Amazon from 1999 to 2019? (b) How has deforestation aggravated local and regional climate risks during the same period? (c) How have these climatic changes affected soy, maize, and pasture yields from 1999 to 2019? (d) What spatial factors have influenced yields in the Brazilian Amazon from 1999 to 2019? (e) What are the economic losses associated with diminished yields from deforestation-related factors discussed in question (c)?

The report is organized into two sections to address these five research questions. Firstly, we examine deforestation-induced climate changes at local and regional scales, addressing questions (a) and (b) using maps and time-series analyses to depict changes in precipitation, temperature, and the timing and duration of rainy and dry seasons. Secondly, we explore the economic impacts of these changes on soy and maize, covering questions (c), (d), and (e) through residual analyses, identification of spatial determinants of yield variations, and estimation of economic losses due to deforestation impacts. Each section includes visual support, such as maps and infographics, to communicate the findings and their implications. The overarching goal is to provide insights that can guide conservation strategies and climate mitigation advocacy.

## 1.3. Results

### 1.3.1. Deforestation-induced local and regional climate changes

#### 1.3.1.1. Mean long-term climate trend

We estimated the onset of the agricultural rainy season for each grid-cell of 28 x 28 km using the anomalous accumulation method (Liebmann et al., 2007) on BR-DWGD rainfall data (Xavier et al., 2022) (Methods). Trends in annual rainfall amount and maximum air temperature were assessed for each crop season. Together with the onset of the agricultural rainy season, these variables are the ones for which there are statistically significant shifts over the last four decades, as determined by the Mann-Kendall test ($p < 0.05$) (Fig. 1.1).

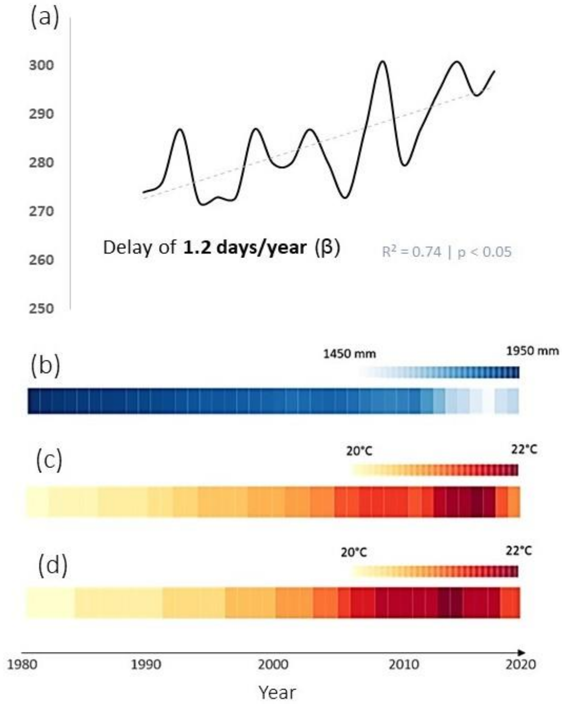



**Figure 1.1.** Climate trends in the Brazilian Amazon from 1999 to 2019. Trends in the mean onset of the agricultural rainy season (a), annual rainfall volume (b), maximum air temperature (c), and minimum air temperature (f). Statistically significant decreasing trends in rainfall volume, warming air temperature, and onset delay are statistically significant based on the Mann–Kendall test ($p < 0.05$).

A consistent trend in the delay of the onset of the agricultural rainy season resulted in a cumulative temporal shift of 30 days since 1980, on average, for the Brazilian Amazon as a whole (Figure. 1.1a). In areas that have experienced the highest levels of deforestation (with accumulated forest loss exceeding 80%), this delay has resulted in a 76-day cumulative shift, representing a 40% difference compared to more conserved areas where accumulated deforestation is less than 20%. In 1980, soybeans were usually sowed in the first week of September and harvested in the first week of January. Yet, as of 2020, soybeans were sowed around the third week of October. This shift has set off a chain reaction, resulting in a delay in maize sowing until early March and final harvesting taking place in the initial week of May. In addition, there has been a statistically significant decrease in rainfall amount (Figure. 1.1b). The average annual rainfall amount that was around 1800 mm in the 1980s dropped to 1400 mm by 2020. In parallel, there has been a significant increase in air temperatures ($p < 0.05$). The average maximum air temperature has reached 40°C, a rise of 2°C compared to that of the 1980s (Figure. 1.1c). The average minimum air temperature has reached 22°C (Figure. 1.1d).

#### 1.3.1.2. Geographic distribution of climate changes over the last two decades

These changes are not equally distributed across regions and planting seasons, so their impact on the double cropping system varies depending on the location within the biome and the specific crop seasons. Based on the onset of the agricultural rainy season and the number of days necessary for cultivating soybean and subsequently maize, we define the first season from the first day of the onset to the 140th day, and the second season from 141st to 260th day. Onset of the agricultural rainy season delayed 5 to 10%, depending on the region over the last decade (2010-2019) in comparison with the previous decade (1999-2009) (Figure. 1.2a). The southern and southeastern Amazon, where double cropping system is widely practiced, have experienced the most significant delays. In addition to changes in the rainy seasonality, some regions have experienced significant reductions in rainfall amounts during both the first and second crop seasons, decreasing by as much as 40% in the first season and 23% in the second season over the recent decade when compared with the previous one (Figures. 1.2e and 1.2f). The warming trend, on the other hand, is more pronounced during the first crop season, with some regions experiencing maximum air temperatures up to 15% higher than that of the previous decade (1999-2019).

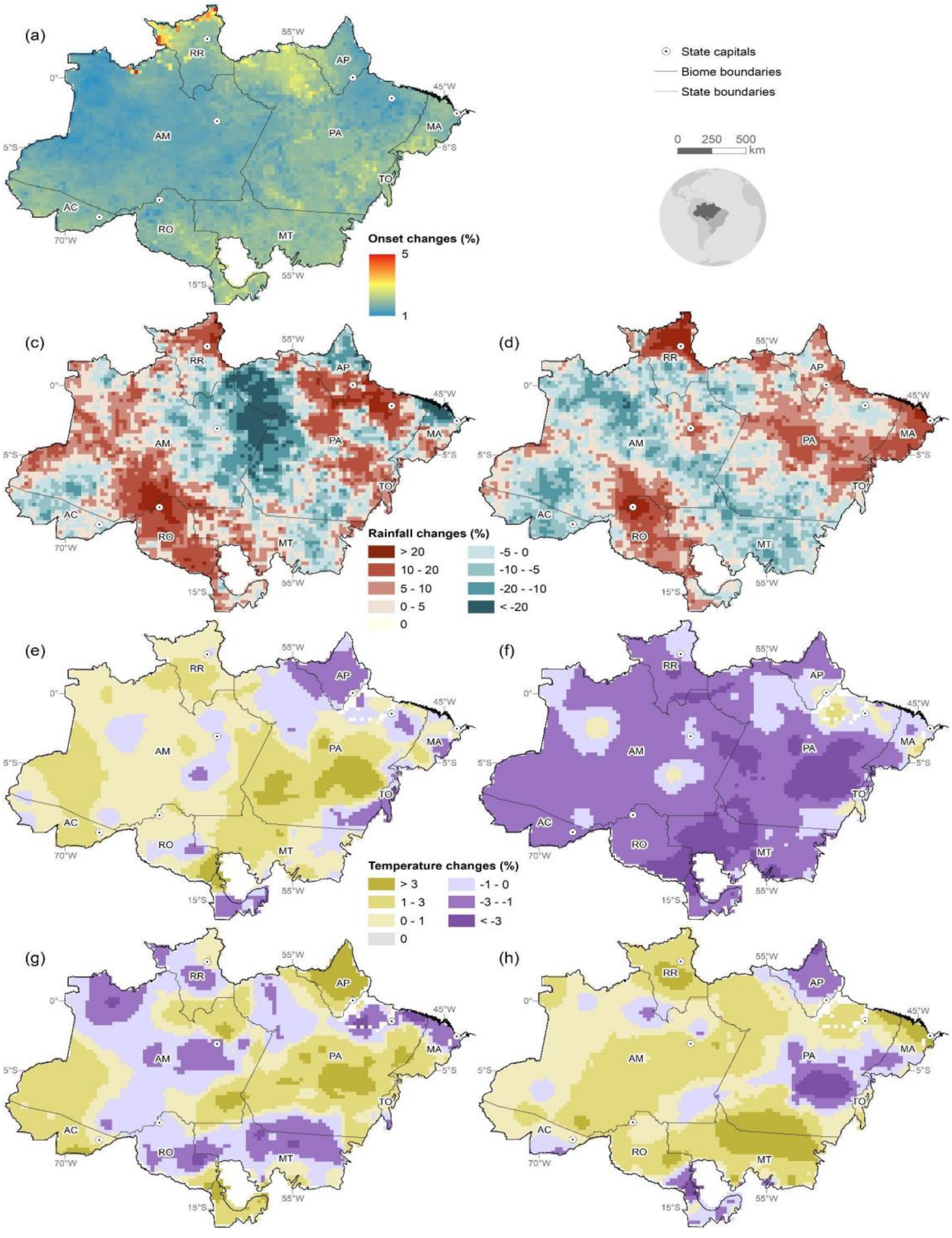



**Figure 1.2.** Spatial changes on regional climate in the Brazilian Amazon over the last decade (2010-2019) compared to the previous decade (1999-2009). Changes in the onset of the agricultural rainy season (a), rainfall volumes during the first (b) and second crop seasons (c), maximum air temperature during the first (d) second crop seasons, minimum air temperature during the first (e) and second crop seasons and native vegetation loss by 2019 (f).

#### 1.3.1.3. Differences between deforested and forest conserved regions

More pronounced climate changes are observed in regions with higher percentages of forest loss. The onset of the rainy season has experienced a delay. For grid-cells with less than 20% of forest loss, the rainy season has accumulated an average delay of 1.2 days per year, resulting in a total delay of approximately 24 days from 1999 to 2019. In contrast, grid-cells with more than 80% of forest loss have experienced an average delay of 1.9 days per year, the equivalent of a total delay of 40 days.

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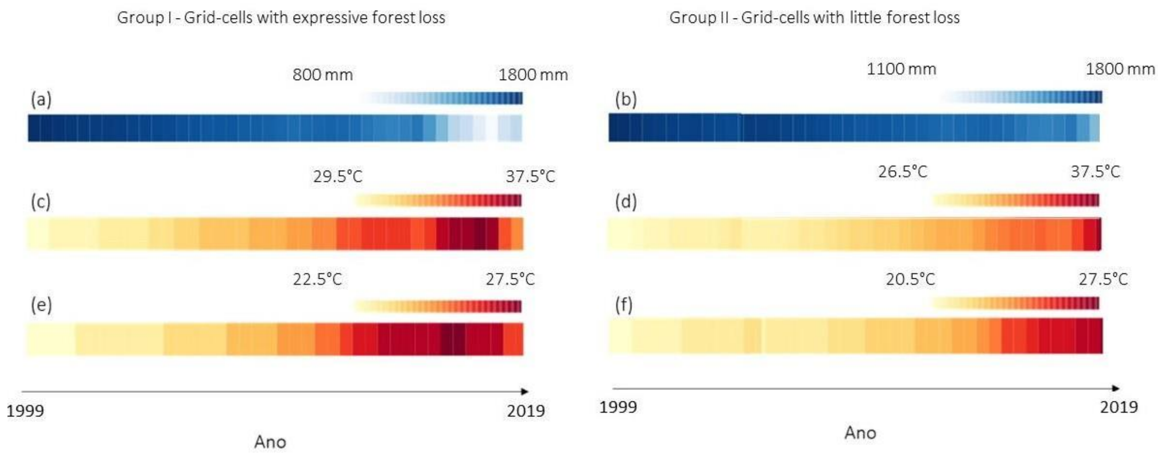



**Figure 1.3.** Climate trends between 1999 and 2019 (20 years). Mean annual rainfall volume (a, b), maximum temperature (c, d) and minimum temperature (e, f) for grid-cells with extensive forest loss (a, c, e) and grid-cells with little forest loss (b, d, f). All decreasing trends in rainfall volume and warming temperature trends are statistically significant based on the Mann-Kendall test ($p<0.05$).

In addition, there are statistically significant reductions in rainfall volume and statistically significant warming ($p < 0.05$). Grid-cells with less than 20% of forest loss have experienced a decrease in annual rainfall volume by approximately 100 mm per decade. In contrast, grid-cells with more than 80% of forest loss experienced an average decrease of approximately 180 mm per decade (Figures. 1.3 a and b). Grid-cells with less than 20% of forest loss, maximum temperatures have risen by 1.5°C since 1999. Yet in grid-cells with more than 80% of forest loss the maximum temperatures have increased by approximately 2.5°C over the same period (from 30°C to 32.5°C) (Figures. 1.3 c and d).

#### 1.3.1.4. Spatial association of regional climate changes with forest loss

Climate patterns in the study region has a strong interannual and interdecadal variability, largely influenced by Surface Sea Temperature gradients of the North and South Atlantic (Marengo et al., 2001), and a strong influence of dry season evapotranspiration (Fu & Li, 2004), in response to a seasonal increase of solar radiation (Myneni et al., 2007), complicating the attribution of climate changes to forest loss. Therefore, to calculate climate anomalies due to the forest loss, we had firstly to remove the influence of geographic location, elevation and interannual variability (which reflect the effects of large-scale climate mechanisms). Our methodology comprises four primary steps, as follows: First, we employed machine learning techniques to model the spatial variability of climate. This involved generating maps that accurately capture the climate variations across the Brazilian Amazon. Subsequently, in the second step, we rigorously assessed the accuracy of these models to ensure their reliability and representativeness of the spatial climate patterns. In the third step, we applied a detrending procedure to the climate data, aimed at eliminating any long-term trends or patterns that could potentially influence the analysis (See method section).

For the onset of the agricultural rainy season, both Cramer's V (0.69) and Spearman's ρ (0.63) exhibit associations with forest loss. In the first crop season, significant relationships are observed between forest loss and anomalies in rainfall volume (Cramer's V = 0.58, Spearman's ρ = 0.49) and maximum temperature (Cramer's V = 0.47, Spearman's ρ = 0.45). Similarly, in the second crop season, anomalies in rainfall volume (Cramer's V = 0.51, Spearman's ρ = 0.45) and maximum temperature (Cramer's V = 0.58, Spearman's ρ = 0.55) also exhibit significant associations with forest loss percentages (Fig. 1.4).

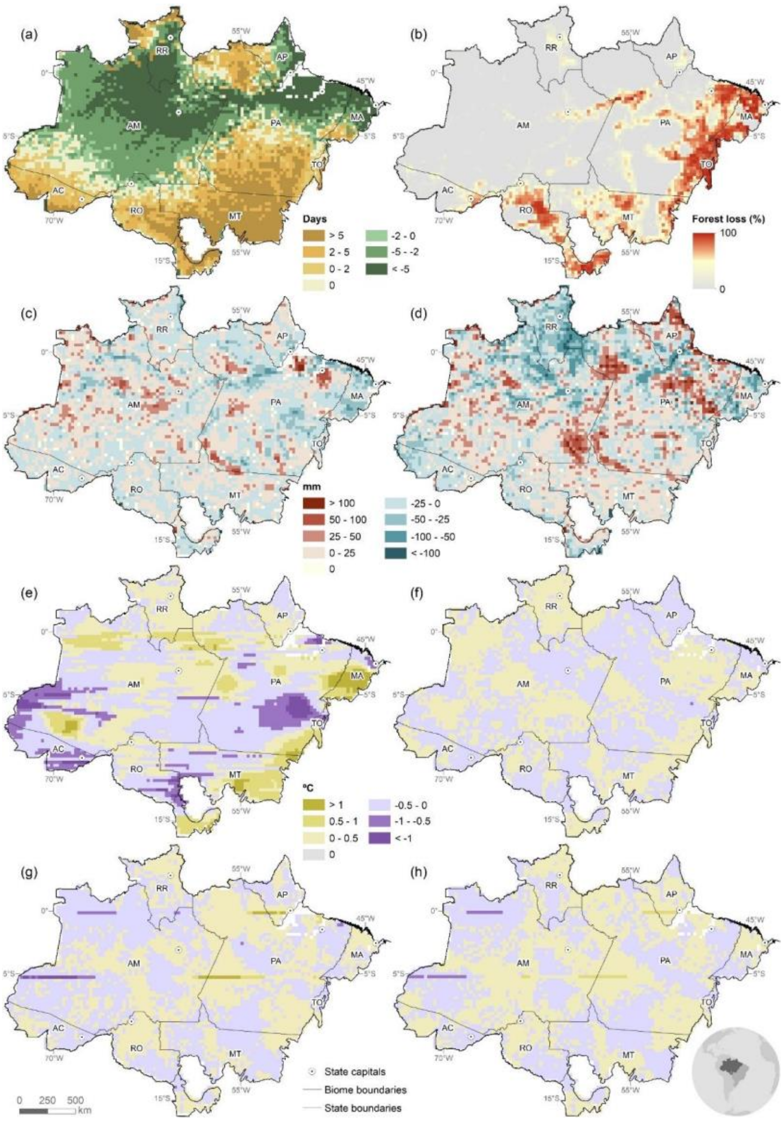



**Figure 1.4.** Spatial association between accumulated forest loss and estimated climate anomalies in the Brazilian Amazon. (a) Onset of the agricultural rainy season; (b) Rainfall volume during the first crop season; (c) Maximum air temperature during the first crop season; (d) Minimum air temperature during the first crop season; (e) Rainfall volume during the second crop season; (f) Maximum air temperature during the second crop season; (g) Minimum air temperature during the second crop season; (h) Accumulated Forest loss.

#### 1.3.1.5. Climate risks to soy-maize double-cropping due to deforestation

Grid-cells with large forest loss present a higher risk of experiencing delays in the onset of the agricultural rainy season compared to areas with lower levels of forest loss (Figure. 1.5a). For the onset of the agricultural rainy season, a delay ≥ 14 days (two weeks) may occur once every ten years in regions with ≥ 80% of native vegetation (Probability of occurrence Po ≈ 0.1), whereas Po for regions with ≤ 20% of native vegetation loss is negligible (Po ≈ 0.02). During the first crop season, areas with ≥ 80% of native vegetation loss may face a reduction in rainfall ≥ 100 mm in a return period of every five years, conversely areas with ≤ 20% of native vegetation loss may face a reduction in rainfall ≥ 100 mm once every ten years. Nevertheless, the time of return for the same level of forest loss at regional geographical scale doubles, indicating reduced risks due to forest conservation at regional scale. In the second crop season, areas with native vegetation loss ≥ 80% may experience a reduction in rainfall ≥ 100 mm once every seven years. In contrast, regions with native vegetation loss ≤ 20% may experience this reduction in a return period of twelve years and half, which also doubles when considering the regional geographical scale. (Figure. 1.5).

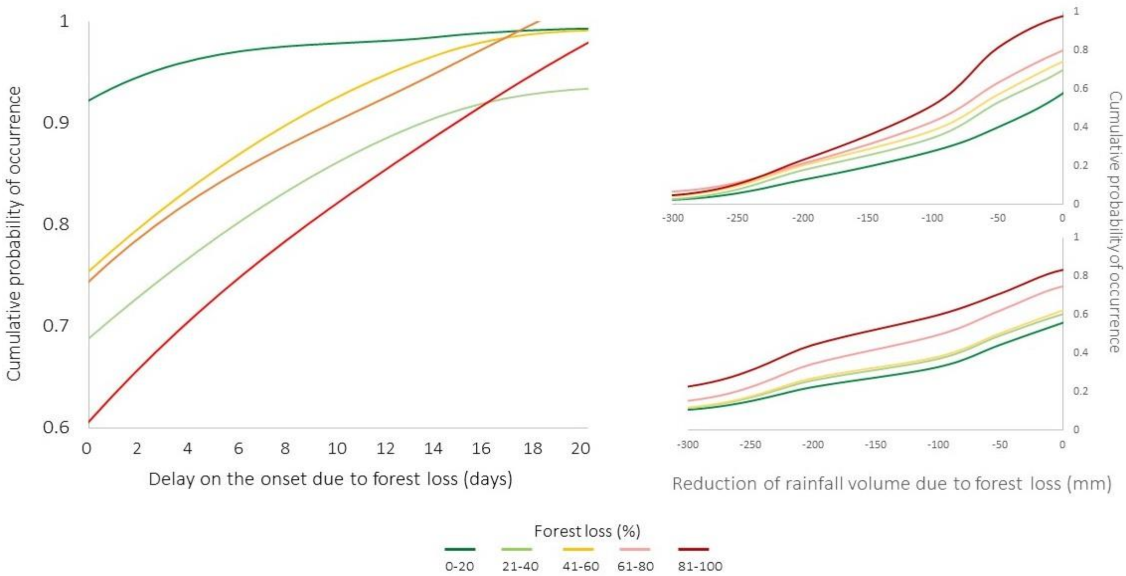



**Figure 1.5.** Cumulative probability density functions (CPDF) functions for the onset of the agricultural rainy season and rainfall anomalies in different intervals of native vegetation loss in the Brazilian Amazon. (a) onset of the agricultural rainy season, considering a maximum delay of 14 days; (b) rainfall anomalies during the first and second crop seasons, highlighting a critical reduction threshold of 100 mm in both seasons. CPDFs are calculated by using a Monte Carlo Simulation with 10 k iterations.

In conjunction with reductions in rainfall patterns, higher air warming occurs in areas with large forest loss over both cropping seasons (Figure. 1.6). Particularly, the risks of maximum air temperature warming attributable to forest loss are more pronounced in the first crop season compared to the second season. Increase of at least 0.5°C in maximum air temperature during the first crop season, above the mean maximum air temperature of the recent period, may happen once every eight years in areas with native vegetation loss ≥ 80%, as opposed to negligible chances in areas with ≤ 20% of native vegetation loss (Figure. 1.6a). During the second crop season, an increase of at least 0.5°C in maximum air temperature, above the climate normal, may occur once every four years in areas with native vegetation loss ≥ 80% and once every 20 years in areas with ≤ 20% of native vegetation loss. Both effects are also augmented or reduced, respectively for large or small percentages of forest loss, when considering a regional scale.

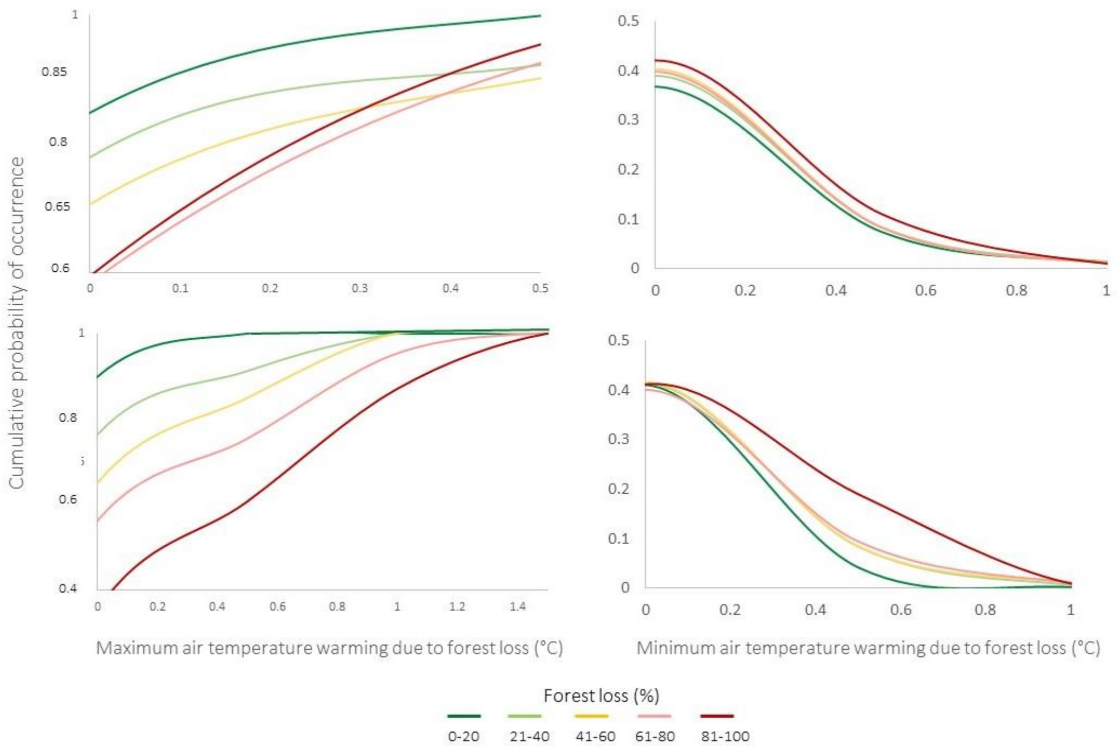



**Figure 1.6.** CPDF functions for temperature anomalies in different intervals of native vegetation loss in the Brazilian Amazon. (a) Maximum air temperature during the first crop season; (b) Maximum air temperature during the second crop season; (c) Minimum air temperature during the first crop season; (d) Minimum air temperature during the second crop season. CPDFs are calculated by using a Monte Carlo Simulation with 10 k iterations.

### 1.3.1.6. Risks of reduced rainfall due to forest loss from local to regional scale

Modeling studies (Akkermans et al., 2014; Zemp et al., 2017; Sampaio et al., 2007) and empirical research (Lawrence & Vandecar, 2014; Leite-Filho et al., 2021) indicates that the impact of forest loss on rainfall varies depending on the geographical scale, i.e. the size of the grid-cell of analysis and the extent of forest loss. By examining CPDFs at local (28 x 28 km) and regional (112 x 112 km) geographic scales (Figure. 1.7), this becomes apparent. Grid-cells with higher levels of forest loss (80-100%) are more susceptible to substantial decreases in rainfall and delays in the onset of the agricultural rainy season, irrespective of the geographic scale. Yet this effect is particularly more pronounced at the regional than at the local scale.

At a local geographical scale (28x28 km grid-cells), areas with significant forest loss present a higher risk of experiencing delays in the onset of the agricultural rainy season compared to areas with lower levels of forest loss (Figure. 1.7). For the onset of the agricultural rainy season, a delay of ≥ 14 days (two weeks) may occur once every ten years in areas with ≥ 80% of native vegetation. Meanwhile, in areas with ≤ 20% of native vegetation, the chances of such a delay are negligible. However, when considering a regional geographical scale (112x112 km grid-cells), a delay ≥ one week in the onset of the rainy season may happen approximately every 20 years. Specifically, when analyzing areas with forest loss exceeding 80%, the likelihood of such a delay on a regional scale diverges significantly. Calculating the return period for these probabilities over a span of 20 years highlights that shifts in seasonality and forest cover critically influence regional agricultural planning and risk assessment.

In regions where forest loss exceeds 80%, a reduction in rainfall volume ≥ 150mm during the first crop season at the local scale may happen every 10 years (Figure 1.7). This risk increases at a regional scale to once every 8 years during the same crop season. However, when considering a regional scale, these risks decrease for regions with less than 20% forest loss (indicating reduced risks due to forest conservation at a regional scale) and increase to once every 2 years for regions with 80% forest loss (indicating increased risks due to forest loss at a regional scale). In the second crop season, at the local scale, there is a Po ≈ 0.42 of a reduction of ≥ 200mm in an area with forest loss > 80%. This risk further increases to Po ≈ 0.57 when considering a regional size with the same accumulated forest loss.

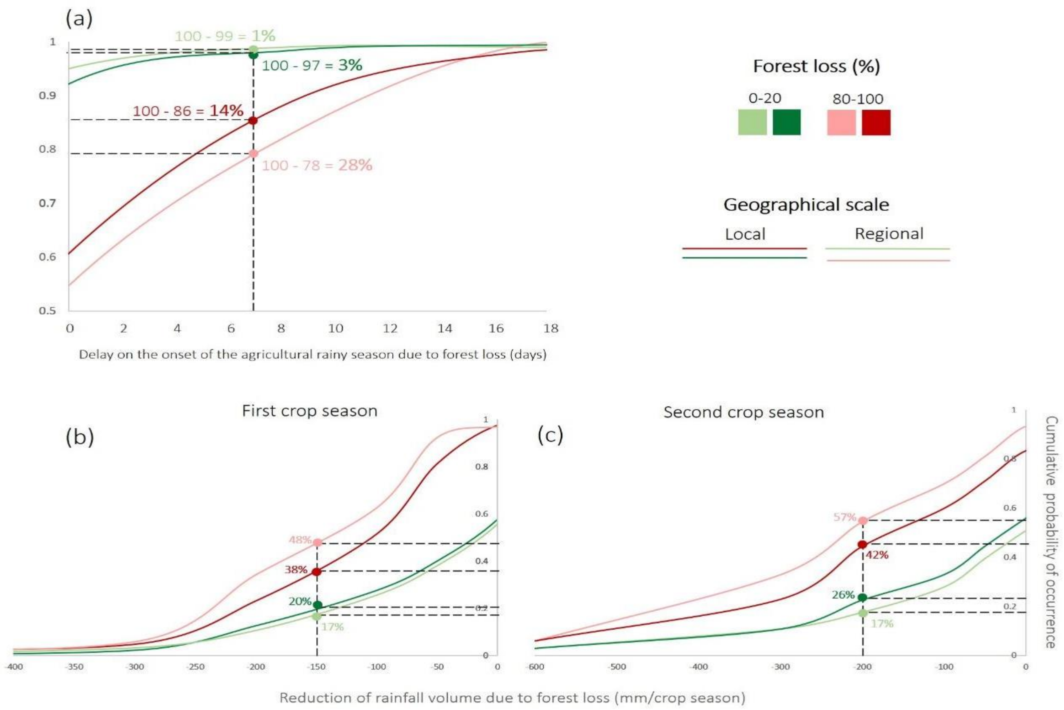



**Figure 1.7.** CPDFs for (a) anomalies of onset of the agricultural rainy season for two contrasting forest loss intervals and different geographical scales (28×28 km and 224 x 224 km grid-cell sizes) and CPDFs for anomalies of rainfall volume for two contrasting forest loss intervals and different geographical scales (28×28 km and 224 x 224 km grid-cell sizes) for the (b) first and (c) second crop seasons.

## 1.4. Economic effects of deforestation-induced local and regional climate

### 1.4.1. Effects of deforestation induced climate change on yields

To evaluate the influence of deforestation induced climate change on soybean and maize crop yields, it is essential to remove trends associated with factors beyond climate, like technological advancements improving productivity. To this end, we employed a generalized additive model on historical yield data (Hastie & Tibshirani, 1987). As a result, we calculate residues, which represent the deviation between the estimated (expected) yields and the observed yields (Method section). Despite an overall increase in soybean and maize yields between 2006 and 2019, when the effects of technological investment are removed, negative yield residues have become more prevalent and pronounced, affecting a larger portion of cropland in recent years (Mann-Kendall test, statistically significant at a 95% confidence interval, $p<10^{-5}$; Figure. 1.8).

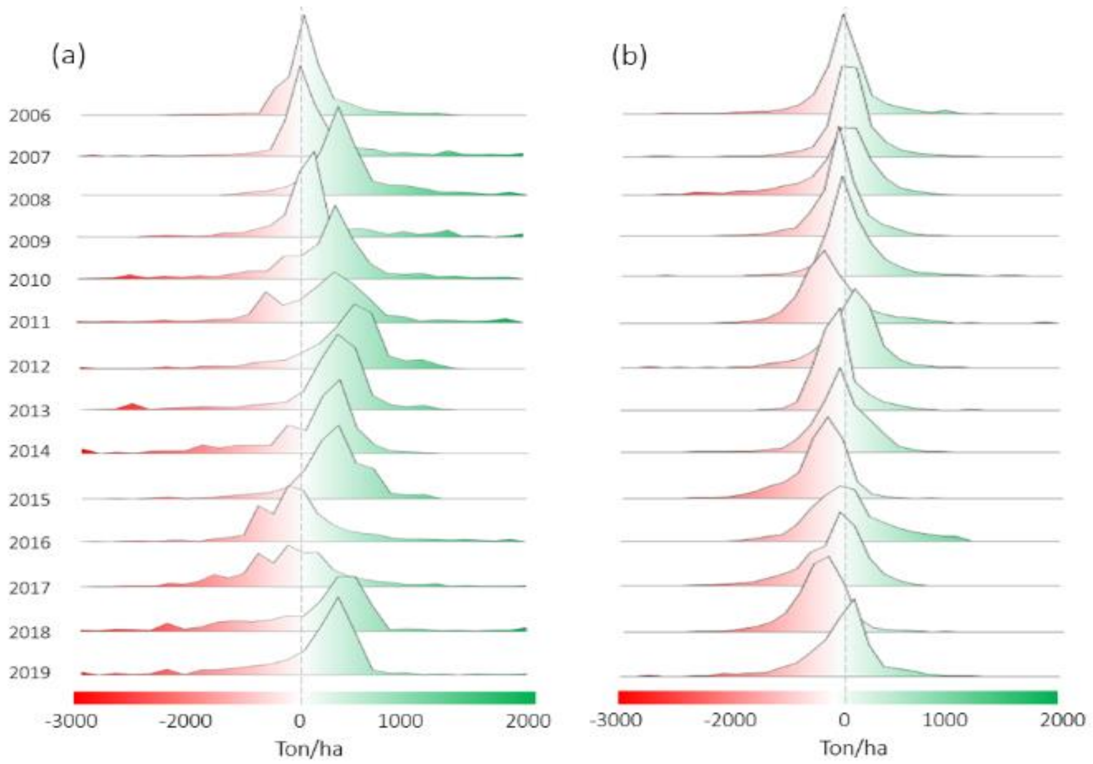



**Figure 1.8.** Soy and maize yield residuals from 2006-2019. (a) Soybean yield fluctuation; (b) Maize yield fluctuation for the Amazon. Both trends are statistically significant at a 95% confidence interval (Mann-Kendall test, p<0.05). The graph does not cover the entire historical climate series because the systematic survey of agricultural production by the Brazilian Institute of Geography and Statistics (IBGE, 2022) started distinguishing maize of double cropping after 2006.

Climate changes are not geographically uniform, and their impact on crop seasons varies across the biome (Figure 1.9). Soybean yield residuals in the Brazilian Amazon range from -1,260 kg/ha to +2,290 kg/ha, while maize yields residuals range from -2,180 kg/ha to +1,490 kg/ha. Notably, maize losses surpass those of soybeans, with maize often referred to as a "suicide crop" due to its higher vulnerability. In this agricultural system, soybeans are typically planted at the onset of the rainy season, followed by maize cultivation in the same area after soybean harvest. The later the second crop is sown, the lower its yield tends to be due to increased water stress at the end of the growing season (Garcia et al., 2018; Heinemann et al., 2008). The second crop, maize, is grown during a period of reduced rainfall, lower mean temperatures, and shorter photoperiods in most crop-producing regions (Borém et al., 2015). These environmental conditions significantly impact yields, particularly depending on a later time of planting.

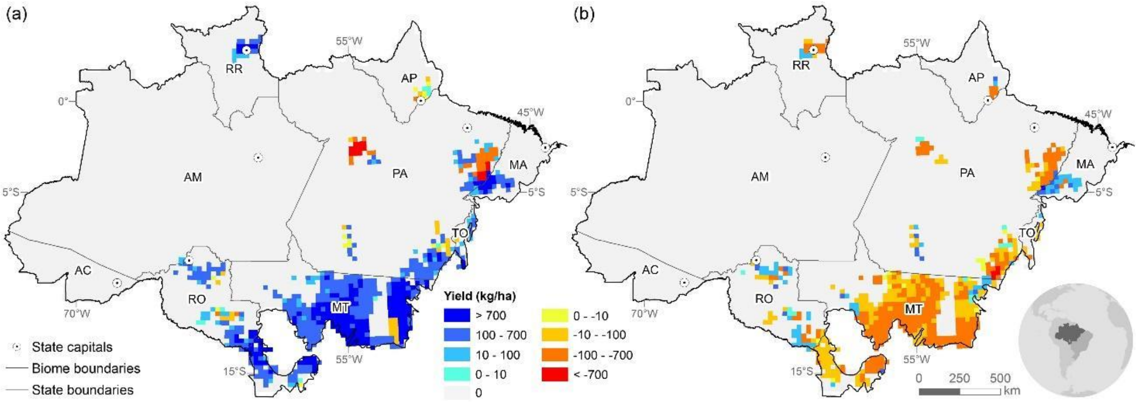



**Figure 1.9.** Spatial distribution of soybean and maize yield residues from 2006 to 2019 in the Brazilian Amazon. The maps display (a) Soybean yield residues (First crop) and (b) Maize yield residuals (Second crop).

### 1.4.2. Spatial determinants of the soybean and maize yields residuals

Five main spatial determinants can explain the soybean and maize yields variations demonstrated above: (1) The investment made by the farmer in their crop depends on their economic yield from the previous year and, consequently, their financial availability; (2) genotype and cultivar (Kurosaki & Yumoto, 2003; Hao et al., 2012), (3) seeding date (Macmillan & Guiden, 2020), (4) air temperature (Kurosaki & Yumoto, 2003), and (5) rainfall amount. These climatic conditions (Determinants 2, 4 and 5), in turn, are particularly influenced by Global Climate change linked to Greenhouse Gases emissions (Lawrence, 2022), the interannual climate variability (In Brazil, significant crop losses are generally associated with adverse climatic effects of El Niño and La Niña phenomena) and (3) Regional climate changes due to land use and cover (Leite-Filho, et al., 2021).

To analyze the influence of these factors in determining the fluctuations of soybean and maize yields in the Amazon, we used soybean and maize yield values in each grid-cell as the dependent variable of a Spatial Autoregressive Model (SAR) applied to panel data (Drukker, et al., 2013), while the explanatory variables were divided into four groups: (1) Normal climatology; (2) Interannual climate variability; (3) Impacts of native vegetation loss on climate and previous crop profitability. For the SAR, we used a weighted 8-cell neighborhood matrix (Tiefelsdorf, et al., 1999) and employed the Akaike information criterion (AIC) to assess the quality of each model relative to others, thereby providing a method for selecting the most appropriate model.

The previous crop profitability, rainfall variability during El Niño years, the impact of native vegetation loss on maximum temperature, and the interannual variability of rainfall, collectively explained 69% ($r^2$) of the variability in soybean yield residuals between 2006 and 2019 ($p < 0.05$; AIC = 1199.5). Maximum temperature anomalies due to native vegetation loss emerged as the most statistically significant spatial determinant contributing to the reduction in soybean yields. For the second crop, rainfall and temperature variations during El Niño, maximum temperature anomalies due to native vegetation loss and the interannual variability in minimum temperatures explained 83% of the maize fluctuations ($p < 0.05$; AIC = 9458,2). The increase in minimum temperatures (both in the interannual variability and variation during El Niño) are the most statistically significant factors (Figure 1.9).

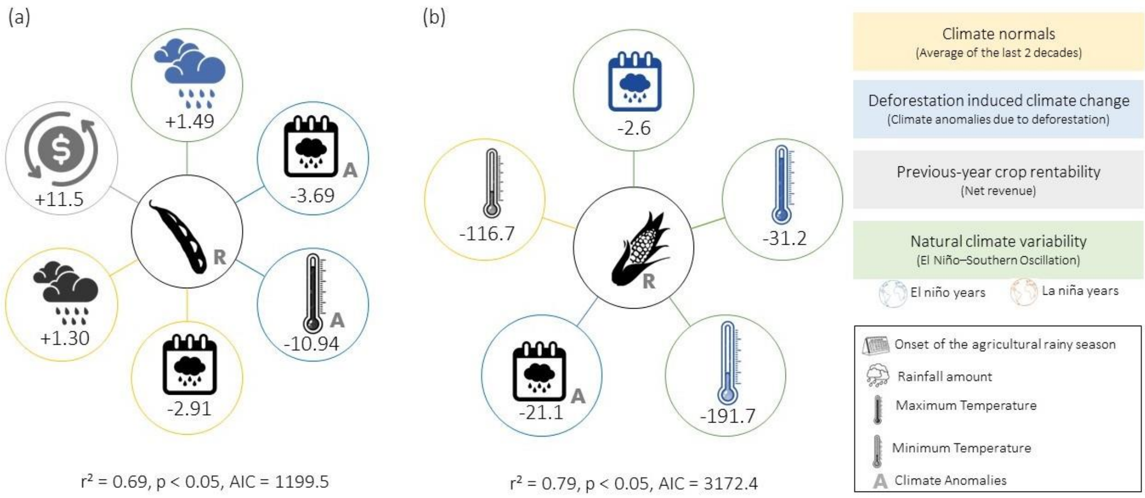



**Figure 1.9.** Spatial determinants of yields for soybean and maize between 2006 and 2019 in the Brazilian Amazon. The estimates are derived from Spatial Autoregressive Models and are presented for (a) Soybean (First crop) and (b) Maize (Second crop).

### 1.4.3. Economic losses linked to deforestation induced climate changes

To quantify potential economic losses associated with regional climate change due to native vegetation loss, we used a spatially explicit five-step procedure outlined in the method section. The economic impacts are estimated using SAR variables of statistically significant climate anomalies for each crop season, the CPDFs, the planted area from PAM spatialized using the OtimizAgro model (Rochedo, et al. 2018), and spatialized prices of soybean and maize from IBGE. All monetary values are adjusted for inflation, using U.S. inflation for values in dollars (USD) and Brazilian inflation for values in reais (BRL). Deforestation in the Amazon has led to missed opportunities to produce 1.9 million tons of soybeans and 182.5 million tons of maize between 2006 and 2019. This accounts for a total potential loss of 184.4 million tons of grains, which could have been mitigated through forest conservation efforts (Figure. 1.10).

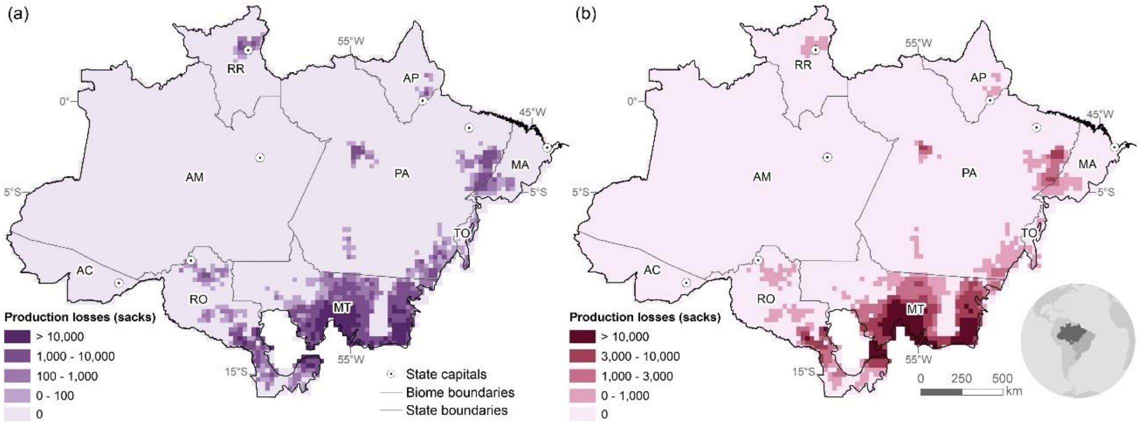



**Figure 1.10.** Production losses (in sacks) associated with the effects of native vegetation loss on regional climate in the Brazilian Amazon between 2006 and 2019 for (a) Soybean (First crop) and (b) Maize (Second crop).

Those missed opportunities imply a potential loss of US$ 761.3 million between 2006 and 2019 for soybean production (Figure 1.11a) and US$ 273.3 million for maize production (Figure 1.11b). Thus, Amazon deforestation entails potential economic losses of US$ 1.03 billion, an annual average loss of US$ 73.3 million. These potential economic losses are tantamount an average of 4% of the gross production value of the soybean and maize during this period in the biome.

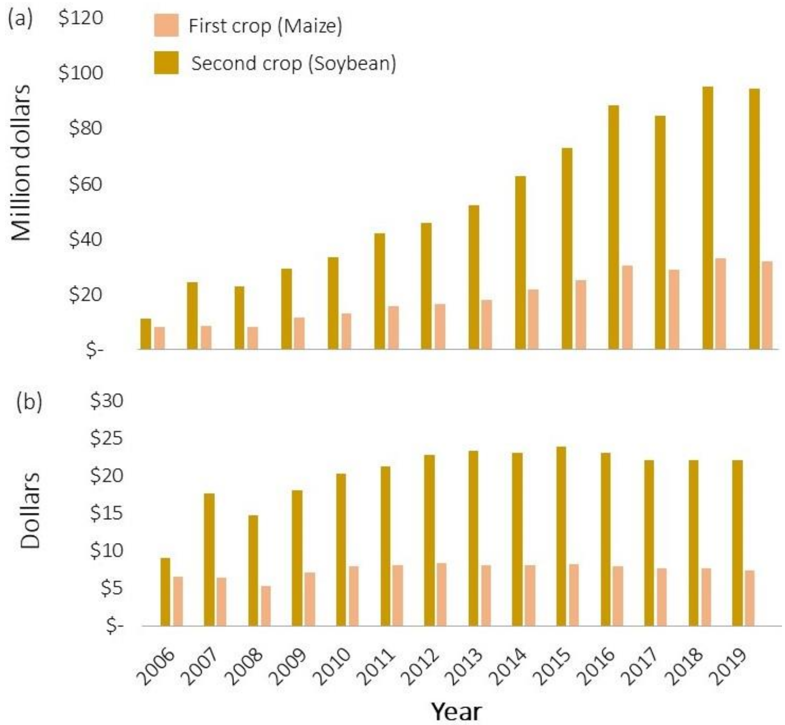



**Figure 1.11.** Annual economic losses (USD) associated with native vegetation loss in the Brazilian Amazon between 2006 and 2019 (a) for soybean and maize, as well as economic losses per hectare due to deforestation during the same period for both crops (b).

Yet, economic losses associated with native vegetation loss are not geographically uniform (Figure 1.12). This uneven distribution of economic losses underscores the need for targeted and region-specific strategies that take into account the ecological and socio-economic dynamics of each area to effectively address and mitigate the adverse effects of native vegetation loss.

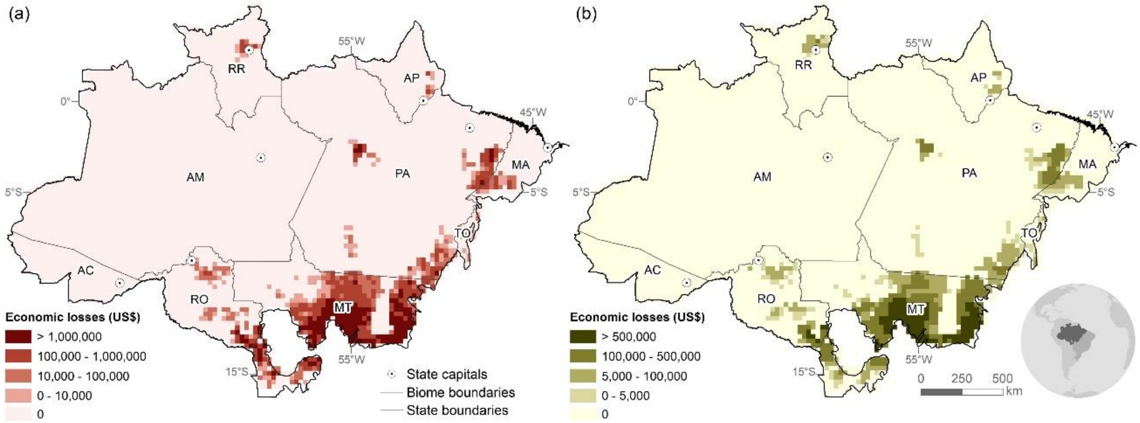



**Figure 1.12.** Total economic losses (USD) associated with native vegetation loss in the Brazilian Amazon between 2006 and 2019. The figure presents the average economic losses and gains resulting from the climate effects of native vegetation loss for (a) soybean (First crop) and (b) maize (Second crop).

By dividing the economic losses by the area planted with the double cropping system, it was possible to quantify the losses due to climate changes caused by deforestation for each hectare (Figure 1.13). This information is extremely useful for farmers, allowing them to make more informed decisions to mitigating climate risks, and to better assess the economic viability of their crops in the face of climate changes. Potential loss per hectare is USD 20.30 between 2006 and 2019 in the first crop and USD 7.53 per hectare in the second crop.

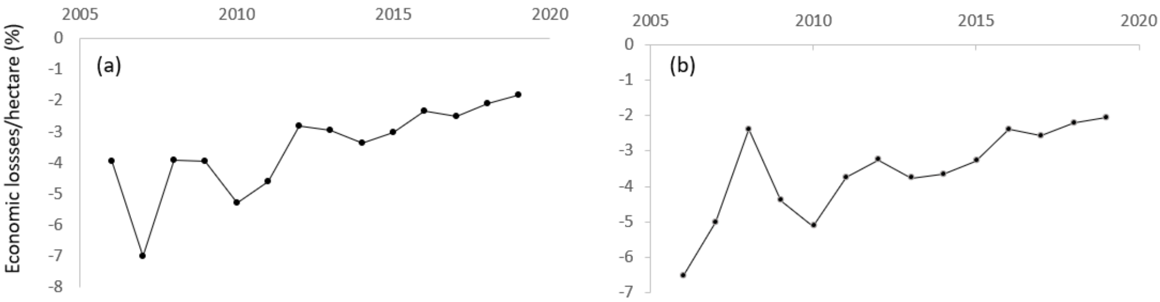



**Figure 1.13.** Total economic losses (USD) per hectare associated with native vegetation loss in the Brazilian Amazon between 2006 and 2019. Average economic losses per hectare (USD/ha) resulting from the climate effects of native vegetation loss for (a) soybean (First crop) and (b) maize (Second crop).

After deducting production costs, the potential economic losses linked to native vegetation loss in the Brazilian Amazon represent, on average, 10% and 20% of the net revenues for soybean and maize over the same period, respectively. It is important to consider the proportion by which deforestation reduces the net revenues, which is the actual profit after deducting production costs. Analyzing the gross production value instead can lead to an underestimation of the economic impacts of deforestation, as the agricultural gross value does not account for the necessary costs to produce the crops. The net production value provides a more accurate assessment of the economic impact on the farmers' profitability margin.

### 1.5. Final remarks

Notwithstanding uncertainties, our detrending procedure has proven to be a sound methodology to assess the impact of deforestation on the regional climate (Liebmann, et al., 2007; Rochedo, et al., 2018) and consequently on double cropping yields, thus providing a roadmap that policymakers can use to implement region-specific agricultural policies and programs. Successful agriculture in the region is contingent upon a stable climate. The prevalence of hotter and drier conditions therefore presents a challenge for grain production, resulting in more double cropping areas surpassing climatic boundaries for optimal crop growth. This trend coincides with a notable increase in soybean and maize crop shortfalls, especially in regions largely deforested, indicating that deforestation not only impacts large areas of current croplands, but also hinders the expansion of agriculture across the biome. Mitigating climate risks requires investment in adaptation solutions such as irrigation and the development of drought-tolerant cultivars. Still, each strategy presents its own unique challenges. While irrigation can mitigate yield losses under severe water stress and temperature increases of up to 2°C, its effectiveness is greater in drier regions, where water availability is limited and declining (IPCC, 2022), and irrigation systems require access to water, electricity, and significant investments in technology and management (Lathuilliere, et al., 2018). Moreover, Brazil's success in genetic improvement may face challenges due to climate change, including the spread of pathogens, shifts in growing seasons, and more frequent extreme events, such as floods, droughts, and wildfires (Oliveira, et al., 2022). Our research also holds potential significance for insurance companies in assessing crop failure or shortfall risks aimed at fixing insurance premiums. Companies could charge lower premiums to farmers in regions with larger forest cover, because they have less frequent and lower variations in rainfall and air temperature. In turn, this strategy could also incentivize forest restoration in largely deforested regions.

Given that deforestation is a pivotal factor amplifying the climate change impacts on double cropping, conserving the biome’s native vegetation emerges as a vital measure to mitigate those impacts. Approximately 109.7 Mha of Amazon territory (74.3%) are on private properties. Brazil's soy farmers feel justified in opening new areas whenever they have the economic means and motivation. Because these decisions are influenced by shifts in credit and policies (Aragão, et al., 2022), conservation initiatives should include prioritizing sustainable agriculture, excluding deforesters from agricultural supply chains as well as from bank loans via public and transparent traceability platforms (Nunes, et al., 2024), Thus, property-level land-use monitoring is a key for improving the government’s capacity to monitor, prevent and control conversion, degradation by helping strengthening the performance of federal institutions to ensure accountability for environmental crimes and administrative infractions linked to land conversion including deforestation, forest fires and forest degradation. In addition, there is a need to reduce wildfires through the implementation of integrated fire management and fostering coordination with the Amazon states to implementing the Forest Code.

Alongside enforcement and compliance mechanisms, it is essential to implement incentives that discourage conversion, such as payment for ecosystem services including economic subsidies to landowners that converse or restore native vegetation beyond the forest code requirements (Soares-Filho, et al., 2014), and the promotion of a value-based bioeconomy (Carvalho-Ribeiro, et al., 2024). Promoting the rich socio-biodiversity of the Amazon can foster novel pharmaceuticals, energy, and food sectors. Furthermore, ecotourism offers a balanced economic solution by promoting nature conservation and providing environmental education while supporting biodiversity. In the Amazon, there are approximately 300,000 individuals living in settlements established by their ancestors who escaped slavery (*quilombolas*) and indigenous communities representing 180 distinct ethnic groups. These communities are spread across about 400 indigenous territories and 2,500 protected *quilombola* territories, in addition to other territories in the Amazon region. The protection of these peoples' territorial rights is crucial to the conservation efforts of local biodiversity, which is closely linked to the preservation of their cultures and ways of life.

All of this can be translated into a new agricultural development model for the Amazon. This model should reconcile agricultural growth with environmental conservation, emphasizing the restoration of degraded soils and vegetation (Klink, et al., 2020). To this end, it is essential to leverage existing public policies and national plans, such as the Brazilian Forest Code (BRASIL, 2012) and the Plans of Action for Prevention and Control of Conversion and Fires in the Amazon (PPCDAm. Additionally, key agricultural development plans like Safra and ABC/RenovAgro Pan can play a crucial role in this endeavor. Initiatives like the Innovative Finance for the Amazon, Cerrado, and Chaco (IFACC), which involves collaboration between the UN Environment Program,me (UNEP).

Furthermore, it is essential to emphasize the significance of international collaboration. Approximately 60% and 25% of Brazil's soybean and maize production, respectively, were destined to the international markets during our study period. This surge in commodity exports is largely attributed to the rapid development of Asia, notably China, whose share of Brazilian exports increased from 2% in 2000 to 27% in 2022. Consequently, protecting the Amazon becomes a global imperative, as many nations rely on these biomes for food, fuel, feed, and ecosystem services. Collaborative efforts from governments and international partners are necessary to address these challenges comprehensively to leverage existing mechanisms for sustainable agriculture. This includes implementing transparent traceability platforms (e.g. SeloVerde Pará, www.semas.pa.gov.br/seloverde/) to exclude deforesters from agricultural supply chains and bank loans.

In addition to commercial and legal cooperations, Brazil currently can lead on this front, hosting the G20 this year and COP30 in 2025. These events provide a strategic moment for Brazil to champion global change, emphasizing the protection and enhancement of both the Amazon. Furthermore, it presents an opportunity to attract investments aimed at developing an innovative model for an economy centered on production, protection, and green industrialization. It is time for Brazil to demonstrate that preserving the Amazon is essential for safeguarding a more stable climate to sustain Brazilian economy and global grain supply.

In sum, deforestation is a counterproductive agricultural strategy, therefore the conservation of the Amazon Forest is potentially the most effective policy to contribute to global food and biofuel production. The current trajectory of land use in the Brazilian Amazon jeopardizes the sustainability of the country's largely rainfed agricultural systems, as Brazil's agribusiness and global partners push the limits of nature by expanding croplands at the expense of native vegetation. To reverse this course, we need to act now. Quantifying the impacts of deforestation on the region’s ecosystem services, specifically in relation to climate regulation for agriculture, is one important way to convince policymakers and stakeholders to act before it is too late.

# 2. Assessing Amazon reforestation potential for climate regulation


## Abstract

Forest restoration in the Amazon is key for reducing temperatures, increasing precipitation, and ensuring a favorable onset of the rainy season for double cropping systems. Efforts to reverse the impacts of deforestation is thus essential to mitigate adverse climate effects on Brazil`s agribusiness. Yet addressing challenges, like seed availability and land-use competition, is needed for successful reforestation, particularly in areas highly degraded by agriculture. Here, we present a case study conducted in Pará, Brazil, where we developed large-scale simulations of native vegetation restoration to assess the effects of the full compliance of the Forest Code, Brazil's main environmental legislation, on improving ecosystem services, specifically rainfall regulation. The full compliance of the Forest Code across over 200 thousand CAR (the environmental online registry) land-use records would entail a restoration of deficits of Legal Reserve and Areas of Permanent Protection tantamount to 4.5 million and 1 million of hectares, respectively. The strategic implementation of Legal Reserves and Permanent Preservation Areas as required by the Forest Code may translate into a profound positive shift in the rainfall regime, marked by an appreciable increase in precipitation volumes and an earlier onset of the rainy season. Roughly 80% of the existing double cropping areas in Pará would significantly benefit from this earlier onset. Furthermore, the simulations project that 70% of these areas could experience substantial increases in rainfall volumes. In addition to rainfall regulation, forest restoration of highly degraded landscapes is essential for improving ecosystem services, such as carbon sequestration, water regulation, and soil and biodiversity conservation. While this effort would bring benefits to region's agriculture, it could also potently shift the region's development towards innovative high-value products and services of a socio-biodiversity economy based upon the conservation of the Amazon Forest.

### 2.1. Contextualization

Reforestation in the Amazon provides significant opportunities for ecological restoration, climate mitigation, and biodiversity enhancement. Research indicates that areas where forests have regrown experience reductions in mean seasonal temperatures by approximately 1.2 °C and an increase in precipitation by 5 mm/day, demonstrating the capacity of forest regrowth to mitigate adverse climate change effects (Haghtalab, et al., 2022). When consistently applied, restoration enhances the functionality and resilience of landscapes (Strand, et al. 2018). Hence restoration of highly degraded landscapes is essential for watershed management and improving ecosystem services, such as carbon sequestration, water regulation, and soil and biodiversity conservation.

To this end, challenges, such as ensuring seed availability and controlling for fire, must be addressed for successful implementation. In areas degraded by activities like mining or cattle ranching, reforestation requires the careful selection of species and efficient soil management strategies. Evidence suggests that native species can attain survival rates over 90% when optimal conditions are provided, highlighting the importance of tailored approaches to land rehabilitation (Gama, et al., 2013). Nonetheless, the complexities of reforestation in the Amazon, including socio-economic implications and land-use conflicts, present significant hurdles that must be navigated or overcome to achieve sustainable outcomes, both environmentally and economically. Indeed, there is a need to achieve a balance between economic costs and ecological outcomes. Economic incentives can be fostered through payments to landowners engaged in restoration programs. In addition, to be comprehensive and effective, restoration programs must embrace a sound conceptual and methodological framework, including the application of quantitative approaches to assess various environmental contexts and drivers that favor or hinder the increase of natural vegetation cover. Additionally, long-term assessments are indispensable to ensure the persistence of restoration efforts.

Here, we present a case study conducted in Pará, Brazil, where we developed large-scale simulations of native vegetation restoration to assess the impacts of the full compliance of the Forest Code on improving ecosystem services, specifically rainfall regulation. Quantifying these positive benefits is a way to demonstrate the importance of restoring the Amazon Forest for benefiting local and regional economies.

### 2.2. Objectives, research questions and study case

We aimed to develop simulations for large-scale native vegetation restoration to analyze the potential benefits in terms of ecosystem services, with a particular focus on rainfall regulation. The research questions are as follows:

a. What are the potential benefits from implementing large-scale reforestation in the Brazilian Amazon for local and regional rainfall patterns?

b. What are the potential benefits for the agriculture of the region?

Our case study focuses on the state of Pará for three main reasons: (i) As of 2023, the state of Pará boasts an impressive 104 million hectares of natural forest, covering approximately 84% of its total land area; conversely, it is the state with the largest Forest Code (FC) deficits– land-use below compliance that must be restored by landowners' initiatives. (ii) The state has become a major player in deforestation. In 2023, Around 60% of the deforestation occurring in the Brazilian Amazon was concentrated in Pará, alongside its counterpart, Mato Grosso. (iii) Our fieldwork was conducted in Paragominas, a municipality in Pará. Initially, Paragominas' economy heavily relies on industries such as timber, soy, and cattle ranching. At one time, it was notorious for being a significant deforester in the Amazon. Nevertheless, today, it serves as a compelling case study in environmental restauration, illustrating that it is indeed possible to restore heavily degraded areas.

## 2.3. Results

### 2.3.1. Modeling the recuperation of the Forest Code Deficit

We developed a spatially explicit model at a spatial resolution of 10 m to allocate the Legal Reserves (LR) and Riparian Areas of Permanent Protection (APPs) within each one of all land-use registries that are uncompliant with the FC (e.g. only for LR a total of 75 thousand). The model seeks to optimize the individual allocation of LR in terms of lower within property land-use opportunity costs (e.g. prioritizing restoration on pastures thus avoiding soybean plantations), as well as improved landscape connectivity. Figure 2.1 illustrates land-use and coverage in the state of Pará under two distinct scenarios: (a) current (land use as of 2023) and the scenario of full compliance of the FC without further deforestation. The full compliance of the Forest Code across over 200 thousand CAR (the environmental online registry) records would entail a restoration of deficits of Legal Reserve and Areas of Permanent Protection tantamount to 4.5 million and 1 million of hectares, respectively (Table 2.1).

**Table 2.1** Land use and cover in the state of Pará under two scenarios: (a) Current scenario (land use as of 2023) and (b) Potential restoration of LR and APPs and Category colors match those in Figure 2.1.

| Area In Hectares | | | |
|---|---|---|---|
| **Category** | **Current Land Use Scenario** | **Allocation of Potential LR and APPs** | **Difference** |
| Water | 4,810,042 | 4,810,042 | 0 |
| Deforestation prior to 2002 (anthropic) | 17,904,537 | 14,470,245 | -3,434,290 |
| Deforestation after 2008 | 3,630,583 | 1,687,494 | -1,943,089 |
| Native forest vegetation | 91,938,783 | 91,938,783 | 0 |
| Non-forest native vegetation | 5,675,891 | 5,637,285 | 0 |
| Soybean | 585,023 | 504,237 | -80,787 |
| **Restoration** | | 5,568,974 | |
| **Total Area** | 124,544,858 | 124,544,858 | |

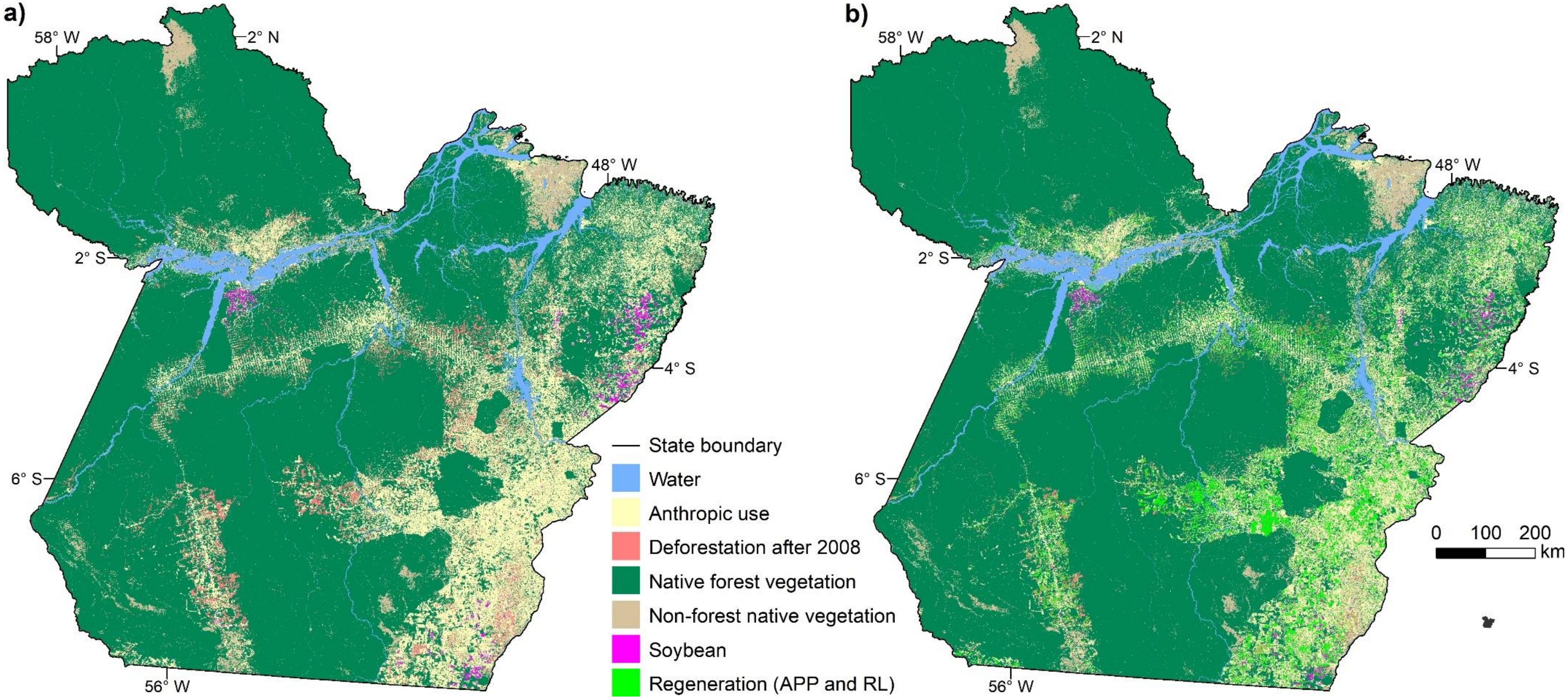



**Figure 2.1.** Land use and coverage in the state of Pará under two scenarios: (a) Current scenario (land use as of 2023) and (b) Scenario of potential regeneration areas through the allocation of RL and APP according to the property level balance of the FC.

In summary, our simulation suggest that the restoration mandated by the FC would entail a reduction 5.5 Mha of deforested areas in Pará, the equivalent of 25% of those areas, emphasizing thus the importance of the implementation of the FC.

### 2.3.2. Climate benefits from large-scale forest restoration

Our study demonstrates a significant correlation between deforestation rates and the average onset of the rainy season anomalies ($O_{i,j,t}$)The positive trend indicates that as deforestation ($D_{i,j,t}$) increases, there is a corresponding rise in the rainfall anomalies, thus suggesting that larger deforested areas experience more severe environmental disruptions, because the removal of forest leads to alterations in regional energy and humidity balance, impacting rainfall and temperature.

The relationship between deforestation and anomalies can be better understood through the estimated regression equation: ($O_{i,j,t} = -0.0007\, D_{i,j,t}^2 + 0.10\, D_{i,j,t} + 2.03$). This model reveals the dynamics of the relationship, showing that while the general trend is positive, it is not linear. The presence of a quadratic term indicates that the effect of deforestation on anomalies may increase at a decreasing rate or might even change direction at higher levels. The regression explains a substantial portion of the variance, with an $R^2$ value of 0.76, indicating that 76% of the variability in environmental anomalies relates to percentage of accumulated deforestation (Fig. 2.2). Yet it is important to note that while the overall trend is consistent, specific data points exhibit fluctuations and deviations. These anomalies could be due to localized factors or temporary influences that dislocate the simple relationship between deforestation and environmental anomalies. Such deviations underscore the need for contextual analysis to thoroughly understand these unique variations. Overall, the results underscore the importance of considering both statistical trends and regional factors when evaluating the impacts of deforestation on climate anomalies.

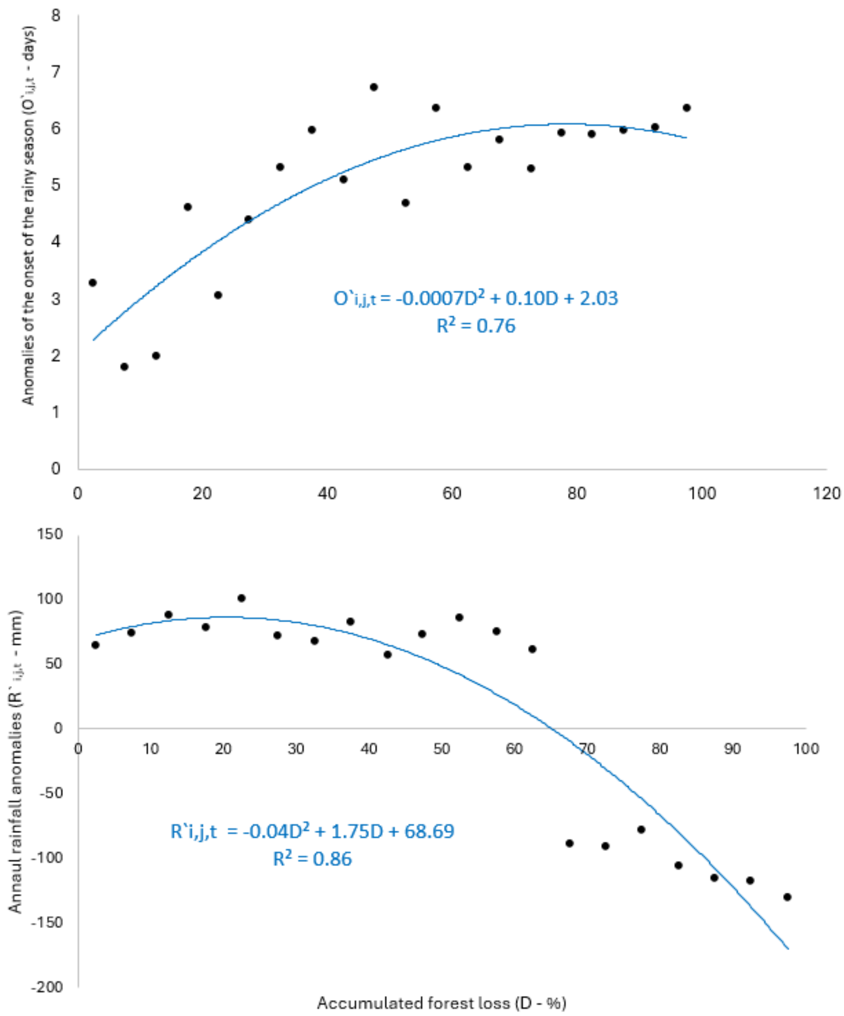



**Figure 2.2.** Mean annual rainfall and onset of the rainy season anomalies per forest loss percentage within 28x28 km grid cells. Best fit polynomial model (blue line). $P'_{i,j,t}$ are the residual annual rainfall anomalies (in mm/year), where the subscripts i and j represent space dimensions and the subscript *t* represent time dimension. D represents the forest loss fraction (in percentage).

Our analysis reveals a noteworthy correlation between percentage of deforested land and annual rainfall anomalies (*Ri,j,t*). The observed trend shows that as deforestation (*D*) increases, there is a corresponding effect on rainfall anomalies. This relationship is of critical importance because it suggests that forest loss is associated with significant variations in rainfall patterns, which can have substantial impacts on regional climates and ecosystems. The regression model ($R_{i,j,t} = -0.04\, D_{i,j,t}^{2} + 1.75\, D_{i,j,t} + 68.69$) characterizes this relationship, indicating a complex interaction. Initially, as forest loss amounts to 20%, there appears to be an increase in rainfall anomalies, suggesting that moderate levels of deforestation might lead to elevated precipitation levels. However, beyond this point, the equation indicates a drastic reduction in rainfall, with this decrease becoming more pronounced as forest loss exceeds 65%. This implies potentially severe alterations in rainfall patterns beyond these thresholds, reflecting significant ecological and climatic disruptions. The regression model captures a significant portion of the variability in annual rainfall anomalies — 86% of the variation ($R^2 = 0.86$) can be attributed to forest loss.

Building upon the equations and property-level regeneration simulations previously discussed, we rigorously quantified the impact of simulated forest regeneration on the Amazon's rainfall patterns, with a specific focus on both volume and seasonality (Figure 2.3). The strategic implementation of Legal Reserves and Permanent Preservation Areas as required by the FC demonstrates a significant reduction in accumulated forest loss in Pará. This reduction translates into a profound positive shift in the rainfall regime, marked by an appreciable increase in precipitation volume and an earlier begin of the rainy season. Roughly 80% of the existing double cropping areas in Pará would significantly benefit from this earlier onset. Furthermore, the simulations robustly project that 70% of these areas could experience substantial increases in rainfall volumes. Such an increase not only fulfills the critical water requirements of crops, but also has the potential to substantially enhance soil moisture levels. The greatest reductions in accumulated deforestation after regeneration modeling occur in the southeastern and northeastern parts of Pará, the most deforested regions.

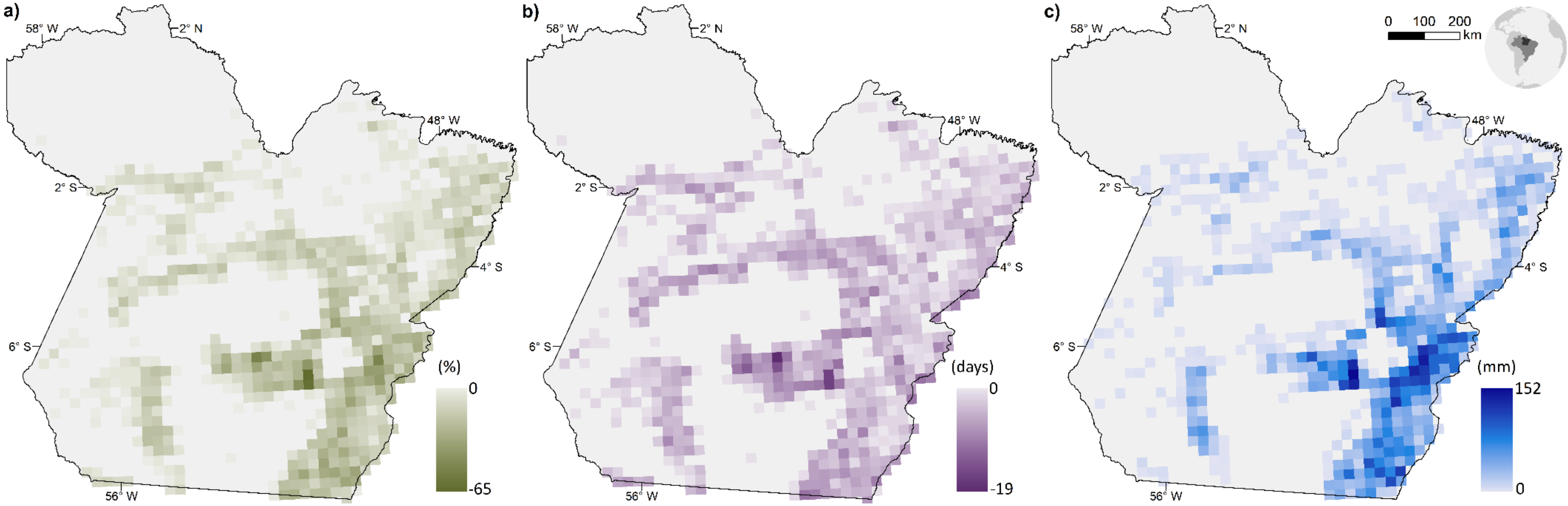



**Figure 2.3.** Increase of forest cover (a) and its effects on the onset of the raining season and rainfall volumes.

Large-scale forest restoration is Pará may result in an average recede of 5 days in the onset of the rainy season for each 28x28 km cells (or 78,400 ha) located in the state of Pará. In some regions, the earlier onset could reach up to 19 days (Figure 2.3b). Additionally, there was an observed average increase of 10 mm in rainfall per 28x28 km pixel (or 78,400 ha) compared to the current land-use. Still, in some regions, this increase could amount to 152 mm (Figure 2.3c).

This earlier onset of the rainy season and increased rainfall volumes suggest a potential return to the hydrological dynamics that were more typical before the occurrence of large-scale deforestation. Specifically, the spatial gradient of the onset of the agricultural rainy season depicts the southward advance of the ITCZ (Intertropical Convergence Zone), corresponding to a gradual implementation of the South American monsoon (from NW to SE) (Liebmann & Mechoso, 2011). This monsoon period is usually after the maximum seasonal temperature during the dry winter season. During this temperature peak, rain formation at the onset of the rainy season is very dependent on forests, which provide water vapor and latent heat to the atmosphere (Wright et al., 2017). The higher rates of evapotranspiration of the rain forest cause an increase of shallow convection that moistens and destabilizes the atmosphere during the initial stages of the transition from the dry season to the rainy season. This mechanism – Shallow convection moisture pump (SCMP, Wright, et al., 2017) – preconditions the atmosphere at the regional scale for a rapid increase in rain-bearing deep convection, which in turn drives moisture convergence and rainy season onset before the complete southward shift of the ITCZ over the region.

Pastureland and soybean croplands are the main types of land conversion for agricultural use in the region. Rainforest evapotranspiration around 3.8 mm.day$^{-1}$ (Costa, et al., 2010) provides sufficient moisture for localized, mesoscale convective events. The injection of water vapor in pastureland regions (1 mm.day$^{-1}$) is a much weaker source of moisture, while in cropland areas, evapotranspiration can be assumed to be zero in the weeks before crop sowing and germination. Moreover, tropical forests around 10°S in the Amazon have higher evapotranspiration rates during the end of the dry season than during the rainy season, because of higher solar radiation and higher vapor pressure deficit (Costa, et al., 2010) and rainforest phenology (Wu, et al., 2016). On the other hand, pastures and croplands have a strong evapotranspiration seasonal cycle, so that larger differences between wet and dry season evapotranspiration are expected in deforested areas. In addition, in pastureland areas, net radiation at the surface is 6.2% less than in the rainforest, while in soybean croplands, the decrease in net radiation is 7.0% (Sampaio, et al., 2007). In short, large-scale restoration would increase the resilience of pasture and crops lands in face of a changing climate

### 2.4. Conclusions and recommendations

Our study highlights the transformative potential of restoring the Amazon Forest, particularly in Pará, the historical largest deforester. Our findings underscore that strategic restoration can offer significant climate benefits, such as the earlier onset of the rainy season and increased precipitation, which are critical for mitigating climate change impacts. These improvements can enhance crop yields and reduce dependency on irrigation systems, promoting a more sustainable agricultural environment. Implementing the FC is thus the main drivers of ecosystem service restauration, resulting in a benefit to the regional agriculture, especially in areas heavily impacted by historical deforestation. And there are many co-benefits, such, biodiversity enhancement and socio-biodiversity economy, hence the promotion of a sustainable bioeconomy in the Amazon.

To maximize the benefits of forest restoration, challenges such as seed availability, competition with agricultural expansion, and socio-economic influences must be addressed. Rehabilitating lands degraded by cattle ranching requires careful species selection and soil management to optimize ecological outcomes. The Paragominas regions illustrates the potential for ecological restauration, demonstrating that transitioning from exploitative land use to ecological restoration can improve the resilience of agriculture.

Our results also encourage farmers in highly deforested areas to promote forest restoration, as these regions could benefit from an extended rainy season. Although individual ranches in the Amazon can be very large, these climate benefits will likely be realized through community efforts. The sustainable management of the forest and potential for a low-risk intensive double cropping system expand the benefits of high forest conservation levels mandated by the Forest Code. Furthermore, preserving the Amazon's vast biological assets can shift the region’s economic towards innovative high-value products and services, leveraging advances in biotechnologies of the Fourth Industrial Revolution (Nobre, et al., 2016). To fully harness the benefits of Amazon restoration, balancing economic costs and ecological outcomes is essential. Economic incentives, such as payments to landowners engaged in restoration programs, can encourage participation. Restoration initiatives should be guided by comprehensive frameworks that include long-term ecological assessments. This holistic approach will ensure successful reforestation efforts, contributing positively to the conservation and regeneration of one of the planet's most vital ecosystems.

# 3. Deforestation-induced local and regional climate changes and associated impacts on pasture quality


## Abstract

The livestock sector is one of the cornerstones of Brazil's economy, with cattle ranching significantly contributing to agribusiness and global trade. This study examines the impact of regional climate change, largely driven by extensive deforestation, on pasture quality in the Brazilian Amazon between 1999 and 2019. We analyzed spatial patterns of rainfall changes during the dry season as well as the lengthening of it over these two decades. In largely deforested areas, we observe reductions in rainfall volume up to 165 mm and the lengthening of dry season up to 89 days, with deforestation alone accounting for 39 days (i.e. 40%). These changes have led to a shift towards lower-quality pastures, hence economic losses from these declines due to reduced forage and increased management costs. Spatial variations in pasture quality highlight the need for targeted interventions to mitigate climate risks. Our findings emphasize the close connection between deforestation, climate change, and livestock productivity, underscoring the urgent need for halting deforestation to ensure the long-term sustainability of the beef industry in the region.

### 3.1. Contextualization

The livestock sector is a cornerstone of Brazil's economy, significantly contributing to agribusiness and international trade. This sector not only supports employment but also places Brazil as the world's largest beef exporter. Brazil is poised to remain a leading global producer of beef, with optimistic export forecasts indicating a strong competitive edge in international markets (Silva, et al., 2008). However, deforestation induced by ranching expansion over Amazon Forest causes regional climate change that significantly impacts pasture quality through rise in temperature, diminished precipitation, and increase in the length of the dry season. Increased temperatures can enhance pasture productivity but may reduce nutrient concentrations, particularly in protein and phosphorus (Martins-Noguerol et al., 2023). Additionally, reduced rainfall over the dry season also affects nutrient concentrations with varying impacts on pasture productivity based on historical grazing intensity and management practices.

### 3.2. Objectives and research questions

Despite the profound impacts of deforestation on the local and regional climate of the Brazilian Amazon, manifested as drying, warming, and disruptions in weather patterns, there is limited scientific literature as to how these changes have already affected cattle ranching. To fill this gap, here we present an analysis of the impacts of regional climate changes due to deforestation on pasture quality in the Amazon over the past two decades. Our study addresses the following questions:

(a) To what extent rainfall changes during the dry season have occurred in the Brazilian Amazon from 1999 to 2019?

(b) To what extent has extensive deforestation aggravated local and regional climate risks to cattle ranching?

(c) How have these changes affected pasture quality in the Brazilian Amazon?

### 3.3. Results

#### 3.3.1. Changes in rainfall volume during the dry season

The Brazilian Amazon has experienced significant spatial variations in the rainfall regime, underscoring the need for geographically targeted interventions. Over the past two decades, there has been a striking lengthening of the dry season up to 89 days, with the most pronounced extension occurring in the southern and eastern Amazon (Figure 3.1a). The prolongation of the dry season directly impacts beef production by hindering the growth of grasses, affecting, as a result, animal health and productivity. Additionally, there has been a notable decrease in precipitation except over the Intertropical Convergence Zone (ITCZ) in the Amazon, which plays a crucial role in shaping the region's rainfall patterns. The reduction in rainfall reaches -165 mm with the most significant decreases occurring in the southern and central parts of the Amazon (Figure 3.1a). This spatial variation indicates that some areas are experiencing dryer conditions than others, highlighting the need for differentiated responses to address these specific challenges. For rain-fed pasturelands, reduced rainfall in the dry season can lead to pasture degradation, water scarcity, and increased vulnerability to drought-related animal health issues.

These changes pose significant challenges for the ranching sector. The prolonged dry period intensifies the duration of elevated climatic risk for the livestock, primarily through reduced forage availability. Soil moisture levels drop under reduced rainfall, negatively affecting grassland health and, consequently, the nutritional quality of forage available for the cattle (Milazzo, 2022). This phenomenon is particularly evident in regions like Queensland, where dry periods averaging eight years correlate with substantial pasture degradation and declines in stock density (McKeon, et al., 2021). Extended dry spells lead to diminished pasture resources, directly affecting the livestock health and productivity (Ogenga & Mugalavai, 2019). The frequency of dry spells exacerbates the likelihood of drought, further straining livestock systems and increasing food insecurity. While providing fodder can temporarily alleviate feeding needs, it entails higher production costs and may lead to long-term pasture degradation if not managed sustainably (Müller, et al., 2015). Drought conditions also lead to decreased hay productivity and hence increased hay prices, forcing ranchers to adapt their feeding strategies (Rodziewicz, et al., 2022).

(a) Lengthening of the dry season

(b) Rainfall variation over the dry season

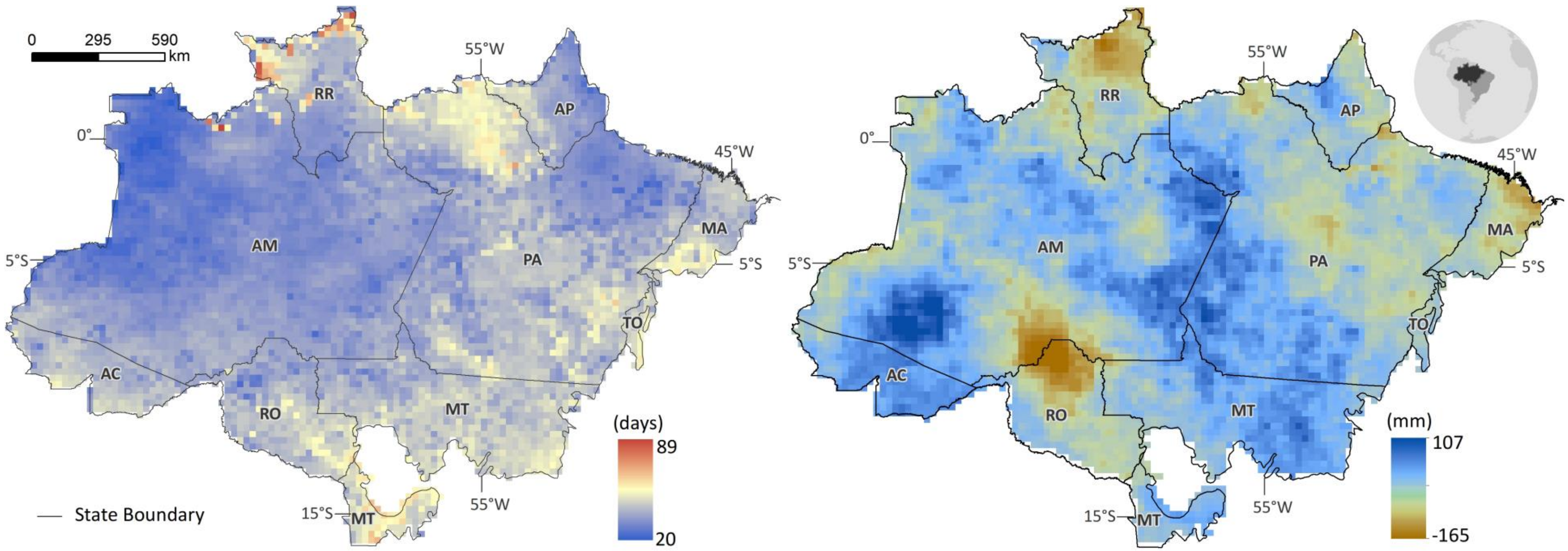



**Figure 3.1.** Spatial changes on rainfall patterns in the Brazilian Amazon over the last decade (2010-2019) compared to the previous decade (1999-2009). (a) Lengthening of the dry season and (b) rainfall volume variation over the dry season.

### 3.3.2. Spatial Variations in Pasture Quality

Figure 3.2a illustrates the historical transition rates between different pasture quality categories, offering a picture of change. The high transition rates between medium and high quality, and vice-versa, suggest a dynamic but not necessarily steady-state equilibrium. The low transition rate from high to low quality might seem encouraging, but this can be misleading, because it does not necessarily reflect a stable situation, but rather a slower deterioration from the top-quality level.

Sankey diagram (Figure 3.2b) provides a visual representation of the overall trend in pasture quality. The diagram clearly shows a movement towards lower-quality pastures, with a shift from high-quality pastures to medium and low-quality pastures. This visual representation starkly indicates a broader problem beyond mere fluctuations. The spatial distribution of these transitions across the Amazon varies as a function of several factors, including management practices, e.g. pasture maintenance, renovation, and rotation, the regional climate, and age of pasture installation, i.e. conversion from forest. Regarding the latter, we can observe, except for Acre, Mato Grosso, and Rondônia, with these two states investing heavily in the expansion of feedlots operations and some cattle intensification, that the overall stock density of the Amazon herd has become virtually the same, and even declined, due to mostly pasture expansion following deforestation (Figure 3.3). As a result, the decline in pasture quality in the region strongly affects the profitability of the beef industry.

(a)

| 2001-2009 | 2010-2019 | Rate |
|---|---|---|
| Low | Medium | 0.33 |
| Medium | High | 0.30 |
| High | Medium | 0.21 |
| Medium | Low | 0.11 |
| Low | High | 0.10 |
| High | Low | 0.03 |

(b)

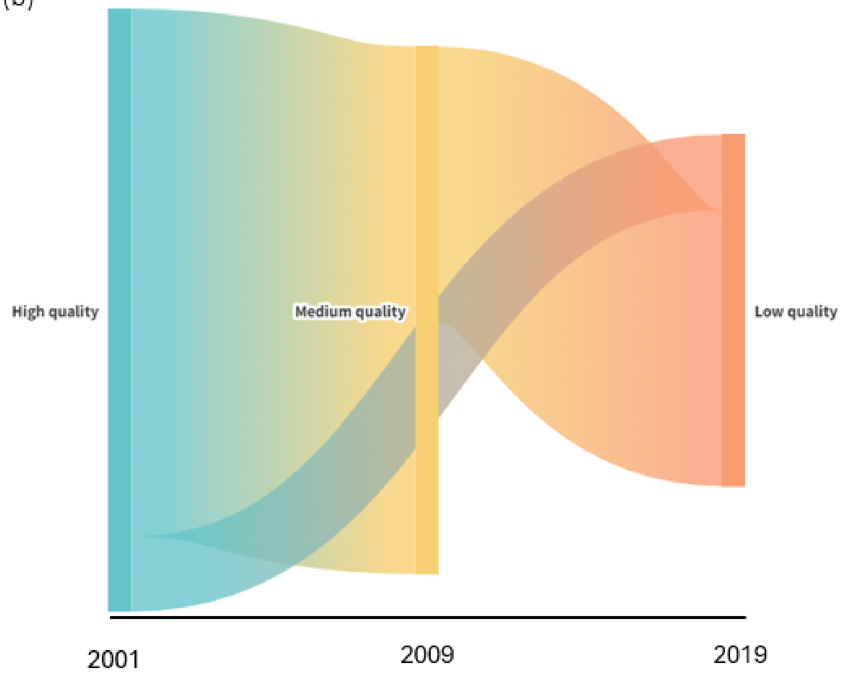



**Figure 3.2.** (a) Transition rates of pasture quality categories from the 1999-2009 to 2010-2019. (b) Sankey diagram of pasture quality decrease. Source Mapbiomas (2024).

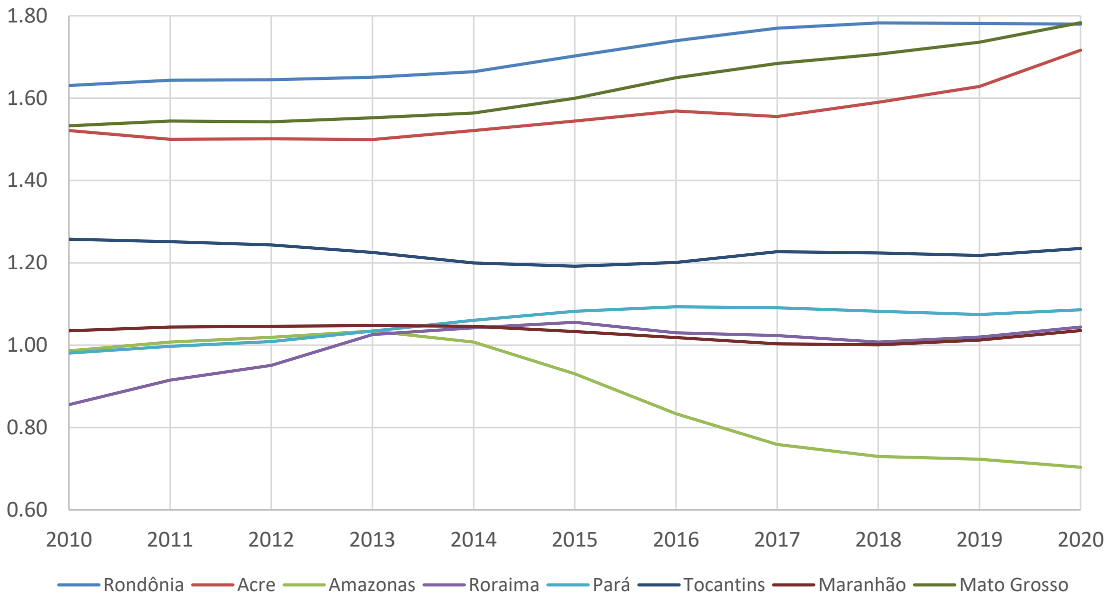



**Figure 3.3** Variation in stock density (heads/ha) in the Amazon states

### 3.3.3. Environmental Determinants of pasture quality

Figure 3.4 shows the intricate interplay of factors shaping the Amazon's environment. Red arrows highlight the key drivers of pasture quality decline, underscoring the significant negative influence of human activities and climate change. Deforestation, leading to habitat fragmentation and altered hydrological cycles, plays a major role. Previous year rentability, an indicator of more intensive ranching practices, can also signify unsustainable land-management practices that deplete soil nutrients and degrade pasture quality. Natural climate variability, with increasing occurrences of extreme weather events like droughts and floods, further exacerbates the pressure on the ecosystem. The spatial distribution of these factors indicates areas of greater vulnerability to degradation, necessitating targeted interventions to mitigate their impact. These factors have a significant impact on rain-fed livestock systems, as they directly affect pasture quality, water availability, and the overall health and productivity of livestock.

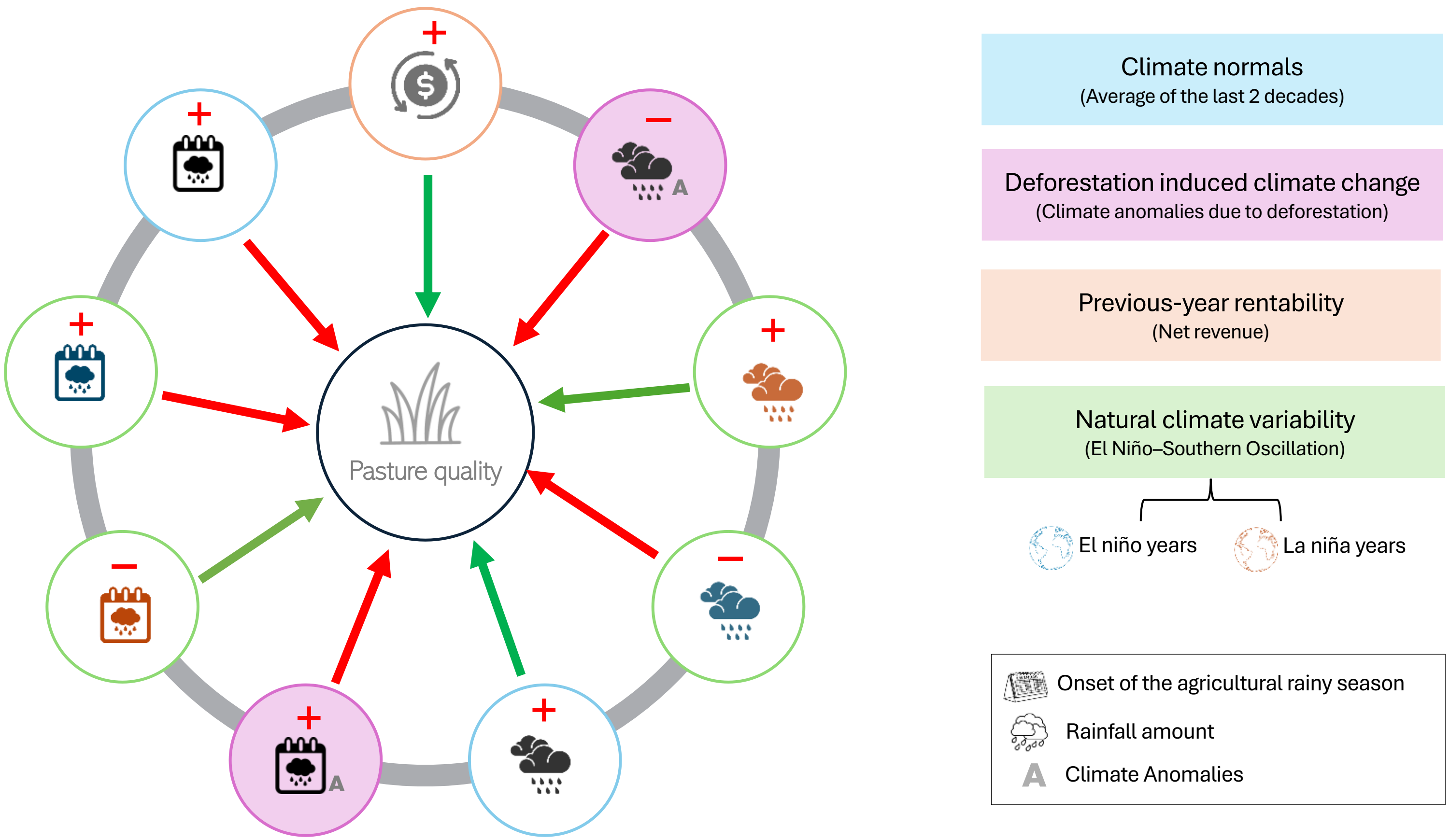


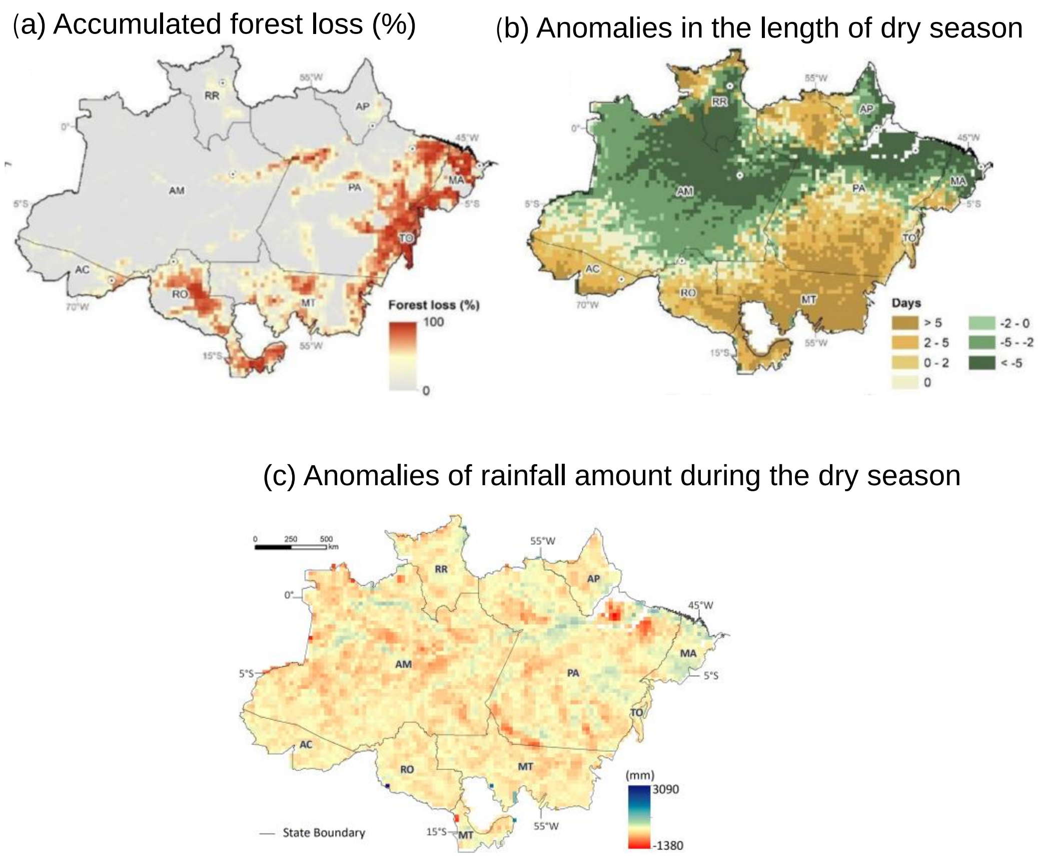

**Figure 3.4.** Weights of evidence of spatial determinants of pasture quality reduction in the Brazilian Amazon from 2001 to 2019. Red arrows indicate the spatial determinants that, when increased (+) or decreased (-), contribute to the reduction of pasture quality, whereas green arrows indicate factors that have the opposite effect.

Figure 3.4 illustrates the complex balance between climate variables in the Amazon. Green arrows represent factors that can potentially contribute to improve pasture quality, whereas red arrows link the factors that influence pasture degradation. Dominant negative impacts of deforestation and climate change often nullify the positive influence of other climate variables. Regardless of the dominant factors, the restoration of pasture quality in the Amazon requires a shift towards sustainable land-management practices that minimize the negative impacts of human activities while maximizing the positive influences of natural processes. The spatial variation in the effectiveness of these practices emphasizes the need for geographically targeted interventions to ensure the most effective forest restoration along pasture renovation strategies.

### 3.3.4. Interconnection between forest loss and pasture quality

Figure 3.5 unveils the interconnectedness between forest loss in the Amazon and pasture quality. Figure 3.5a illustrates the largely deforested areas across the region. The loss of forest cover, especially in the southern and eastern parts of the Amazon, has a cascading effect on the entire ecosystem, disrupting the delicate balance of water cycles, microclimates, and biodiversity.

Figures 3.5 (a) to 3.5 (c) demonstrate the consequences of deforestation on rainfall patterns. The extension of the dry season plus reductions in rainfall during the same period further exacerbates drought conditions, creating a feedback loop that intensifies the pressure on the livestock activities.




| NULL HYPOTHESIS | F-STATISTIC | PROBABILITY | INTERPRETATION |
|---|---|---|---|
| Deforestation does not cause onset anomalies | 0.04 | 0.84 | Causality relationship between deforestation and onset anomalies |
| Deforestation does not cause Rainfall anomalies | 1.42 | 0.24 | Causality relationship between deforestation and rainfall anomalies |
| Dry season extension anomalies does not cause decline in pasture quality | 0.11 | 0.02 | Causality relationship between onset anomalies and reduction of pasture quality |
| Rainfall reduction anomalies does not cause decline in pasture quality | 0.11 | 0.04 | Causality relationship between rainfall anomalies and decline in pasture quality |

**Figure 3.5.** (a) Accumulated Forest loss (%), (b) anomalies in the length of the dry season, (c) Anomalies in rainfall volume during the dry season, Granger causality test with Lag =1, $p < 0.05$.

### 3.4. Final remarks

While reduced rainfall poses significant challenges, some ranchers may adapt through improved management practices and diversification of forage species to mitigate these effects. Ranchers may face herd liquidation as drought intensifies, leading to temporary revenue increases, but long-term income declines due to reduced herd sizes (Rodziewicz, et al., 2022). Effective grazing management becomes crucial, as overgrazing exacerbates land degradation under changing rainfall patterns (Souza, et al., 2020).

Farmers are encouraged to adopt strategies that enhance feed reserves, like fodder, and manage livestock sales to mitigate risks associated with climatic variability (Gray, et al., 2007). Conversely, some argue that traditional practices may not sufficiently address the complexities of climate change, necessitating a shift towards more adaptive and sustainable livestock management strategies to ensure resilience in the face of prolonged dry periods (Salem, et al., 2011). As climate change increasingly poses challenges to pasture quality, thus the profitability of cattle ranching, adaptive management strategies, such as maintaining tree cover in silvopastoral systems, together with moderate and rotated grazing, could, on the other hand, buffer adverse climate effects, upholding soil fertility and pasture quality (Martins-Noguerol, et al., 2023) (Hidalgo-Galvez, et al., 2023). Yet the complexity of these interactions necessitates further research so as to design localized adaptation strategies.

# 4. Stakeholder engagement

**Abstract**

The goal of the stakeholder engagement process is to describe and characterize how farmers have changed their attitudes (opinions and beliefs) and behavior (e.g., farming practices) over the past 20 years in the context of extreme events and changes in temperature and rainfall; outline Amazon farmers' and ranchers' reactions to these extreme climate events; identify factors driving or hindering landowners' responses, including potential maladaptation; and understand farmers' awareness concerning the forest's role in climate regulation and the impact of deforestation on their agricultural activities and land-use decisions. Here, we describe the stakeholder engagement protocol implemented over a 10-month period, comprising five stages: 1) scoping, 2) semi-structured questionnaires, 3) interviews, 4) case study selection, and 5) research dissemination. We contacted over 20 farming organizations and conducted 13 semi-structured interviews and visited four farmers during fieldwork and shared our findings with them. Farmers emphasized the importance of timely planting and using adapted crop varieties along with changing management practices. Ten out of the 13 farmers reported losses ranging from 10% to 40% in years affected by El Niño or La Niña. However, in interviews, farmers dispute claims that their losses are a consequence of climate change, let alone deforestation. This perception highlights the challenges of foresting a dialogue on global climate change along with deforestation impacts on the regional climate with the Brazilian agribusiness.

### 4.1. Contextualization

Stakeholder engagement refers to the active involvement and participation of those directly affected, or "people at stake," in various aspects of a research project. Different levels of stakeholder engagement can be identified, depending on the ultimate aims of the project's engagement activities (Carvalho-Ribeiro et al., 2010). The project team developed a stakeholder engagement protocol, implemented over a 10-month period, comprising five stages: 1) scoping, 2) semi-structured questionnaires, 3) interviews, 4) case study selection, and 5) research dissemination. These steps enabled us to describe and characterize how farmers have changed their attitudes (opinions and beliefs) and behavior (e.g., farming practices) over the past 20 years in the context of extreme events and changes in temperature and rainfall; outline Amazon farmers' and ranchers' reactions to these extreme climate events; identify factors driving or hindering landowners' responses, including potential maladaptation; and understand farmers' awareness concerning the forest's role in climate regulation and the impact of deforestation on their agricultural activities and land-use decisions.

We carried out a dialogue between our researchers at the Universidade Federal de Minas Gerais (UFMG) and farmers in the Brazilian Amazon, particularly in agricultural frontier areas where soy, maize, and cattle are prominent, and deforestation is occurring. Our goal was to inform farmers about our research and to explore their attitudes (opinions and beliefs) and behaviors (how they have been changing their farming activities) over the last 20 years.

### 4.2. Objectives and research questions

We aimed at engaging farmers and cattle ranchers to understand: (a) How agricultural producers of grains, such as soy and maize, and cattle ranchers in the Brazilian Amazon perceive changing climate conditions, particularly those leading to agricultural stress like the 2023 drought; (b) The primary strategies employed by agricultural producers exporting these commodities to respond to extreme climate events; (c) The factors contributing to unintended negative consequences, such as maladaptation, specifically through the expansion of agriculture at the expenses of forests in the Brazilian Amazon; (d) How Amazon farmers perceive the role of the Amazon Forest in climate regulation and whether this perception influences their land-use decisions.

Our study answers the following questions:

I. How do agricultural producers of grains such soy, maize and cattle ranchers perceive changing climate conditions?

II. What are the primary strategies employed by agricultural producers that export these commodities to respond to extreme climate events?

III. What factors contribute to unintended negative consequences, such as maladaptation, specifically through the expansion of agriculture at the expenses of forests in the Brazilian Amazon?

IV. How do Amazon farmers perceive the role of the Amazon Forest in climate regulation and if this perception influences their land-use decisions?

## 4.3. Results

### 4.3.1. How do agricultural producers of grains such as soy, maize, and cattle ranchers perceive changing climate conditions?

In the study, we contacted over 20 farming organizations and conducted 13 semi-structured interviews (Table 4.1). We also visited four farmers during fieldwork and shared our findings with them.

The ages of our interviewees ranged from 37 to 78 years old, with 12 men and one woman. Ten out of the 13 had a degree in either agriculture or economics, and 10 respondents were originally from other regions of Brazil, having migrated to the Amazon between the 1960s and 1980s. Farm sizes ranged from 1,500 to 8,000 hectares, with major crops including soy, maize, sorghum, and sesame. Four out of the 13 farmers have invested in irrigation. Cattle ranching areas ranged from 600 to 3,500 hectares. Our results reveal that producers of soy, maize, and cattle have documented changes in rainfall and temperature over the last 20 years. They report variations across the years, attributing these patterns to climate events, such as El Niño and La Niña.

When asked about their farming strategies during extreme climate events, farmers emphasized the importance of timely planting (beginning as soon as rainfall reaches 100 mm) and using adapted crop varieties along with changing management practices. Ten out of the 13 farmers reported losses ranging from 10% to 40% in years affected by El Niño or La Niña. The questionnaire survey was conducted with 13 farmers in Paragominas region.

| Table 4.1 Brief Summary of interviews |
|---|
| From Pará, 52 years old. Graduated in Agronomy. Started in 1985 and underwent pasture reforms in 2010. Reported 15% losses in El Niño years. |
| From Pará, 41 years old. Family from Espírito Santo migrated to Pará in the 1970s. Cattle rancher with incomplete high school education. Runs a farm, which is a reference in genetic improvement and ILPF (Integrated Crop-Livestock-Forest systems). |
| From Espírito Santo, arrived in Pará in 1967 and began agriculture and cattle production. Established an alcohol distillery and slaughterhouse. Reported yield drops and stocking rate decreases during El Niño. Implements irrigation, organic matter increase, and no-till farming. |
| From southern Brazil, arrived in Pará in the 80s. Agronomist. Believes production must be carried out in accordance with the Forest Code. Involved in creating Coopercarbon, seeking carbon credits certification for 8,500 hectares of forest. |
| From São Paulo, 78 years old. Arrived in Pará in 1974. Holds considerable pristine forest areas. Faces difficulties maintaining them and expressed interest in selling the forested land. Graduated in Business Administration from FGV. |
| From Mato Grosso do Sul, 49 years old. Initially involved in grain production, then leased a farm and shifted to cattle ranching. |
| In Pará for 33 years. Produces fast-cycle agriculture: açaí, cassava, vegetables, etc., and distributes them. Has a degree in administration and works in the commerce sector. |
| Born in Paragominas, 37 years old. Family from Espírito Santo, arrived in 1981. Started with timber and later focused on agribusiness management. Works in soybean production, largest agricultural hub in the state. Cattle ranching includes breeding, raising, and fattening. Agriculture includes soybeans, corn silage, and ILP. Reported impacts of El Niño on agriculture and cattle. |
| From Paraná, has a technical degree in agriculture, and has always lived in the countryside. In Pará for 20 years. Initially worked as a consultant, then started planting 6,500 hectares of crops with irrigation and cattle ranching. Prefers La Niña as it starts rain earlier. Reported changes in rainfall patterns and area use over the years. |
| From São Paulo, has a technical degree in agriculture. Specializes in soy and cattle production enhanced by technology. Complains about the Forest Code. |

| Table 4.1 Brief Summary of interviews |
|---|
| From southern Brazil, moved to Mato Grosso. Holds a technical degree in agriculture. Mentioned technical development boosts agribusiness competitiveness but finds environmental agendas challenging and calls for more incentives. |
| From São Paulo, has a technical degree in agriculture. Focuses on soy, maize, and cattle production enhanced by technology. Complains about the Forest Code and environmental legislation. |

### 4.3.2. What are the primary strategies employed by agricultural producers that export these commodities to respond to extreme climate events?

Contrary to initial attitudes of denial regarding changes in rainfall and temperature, farmers' behaviors indicate substantial changes in their production systems. Nine out of 13 farmers have been diversifying crops, and all of them have changed their cattle management systems. The four major strategies referred to by the interviewees are: I) Integrated farming and cattle systems, II) Use of genetic resources, III) Infrastructure, production technologies, and equipment, IV) No tillage.

I) **Integrated farming and cattle systems:** Integrated farming and cattle systems, such as Integrated Crop-Livestock-Forestry (ICLF), are considered promising due to both greater efficiency in production along with simultaneous accumulation of carbon in the soil and plant biomass. ICLF systems includes planting Eucalyptus trees in rows in an area under pasture. The soil was dystrophic Red-Yellow Latosol, clayey. The area, cultivated since 1998, was converted to the ICLF system in 2009. In the areas under ICLF, sampling was carried out beneath the trees' influence, in the pasture, and in the transition zone; considering points in the tree lines and points away from them as a reference of distance. In the reference areas (pasture and forest), samples were collected in a cross-section at points approximately 50 m away from each other. Farmers stated that is common to see a significant accumulation only after 5 years under a certain type of management. They found a strong indication that the trees played an important role in the accumulation or preservation of the subsoil.

II) **Use of genetic resources:** Identifying new genotypes adapted to climate change is a key strategy. Farmers state that they are encouraging innovation by strengthening public science and technology institutions and fostering collaboration with private entities; Farmers also support germplasm collection, introduction, and conservation by public institutions; One farmer stated that it has been identifying and domesticating species with potential to reduce climate vulnerability; Other strategy has been the preventive genetic improvement by developing large-scale phenotyping methods and establishing research networks for cultivar development using traditional and molecular techniques. Above all farmers highlighted the importance for facilitating technology transfers and establishing public-private partnerships for seed multiplication and commercialization.

III) **Infrastructure, production technologies, and equipment:** Enhancements in these areas promote resilience and adaptation to climate impacts. Investment in new technologies and partnerships for knowledge transfer is crucial. Farmers are all well-equipped in terms of machinery. In terms of infrastructure, they pointed out the need for further investment in “storage points” silos. Most of the farmers interviewed got funding from the federal government and banks (e.g., BNDS) to implement irrigation and other heavy and soft infrastructure.

IV) **No tillage:** All the farmers highlighted the importance of no tillage and direct plantations. In 2011, Embrapa began developing no-till techniques for renovating degraded pastures in the Amazon. Working alongside rural producers, they developed three no-till planting methods for pastures: aerial seeding, row seeding, and no-till planting of stolons. Dissemination of these practices began in 2014 through technical publications, lectures, field days, and courses. Adoption is increasing, according to reports from trained technicians and ranchers. Farmers acknowledge that productive and well-managed pastures not only ensure the profitability of livestock activities, but also protect the soil against erosion and compaction, maintain biological activity, and increase levels of organic matter and carbon. Farmers understand pasture degradation is a persistent issue and will only be resolved when the rate of recovery and reform surpasses the degradation rate. Traditionally, degraded pastures are improved by planting forage in soil prepared with plows and harrows, but this increases soil vulnerability to erosion, especially in fragile or sloping terrains. In the Amazon's rainy climate, this risk is even more significant, impairing future pasture productivity. No-till farming offers a solution to this problem. Despite significant advancements in this technology since the 1990s for crops, its application in pasture improvement has not been extensively researched in Brazil.

In no-till systems, excess straw can make sowing difficult and hinder the establishment of forages, which have smaller seeds and more fragile seedlings compared to agricultural crops. This issue was addressed by managing vegetation and adjusting desiccation techniques to reduce straw volume. Increasing the seeding rate compensates for lower seedling emergence efficiency. Aerial seeding is recommended when line seeders cannot be used, such as in sloping areas or rocky soil, and requires a higher seeding rate to ensure success. Directly planting seedlings offers time and cost savings in soil preparation operations and requires fewer seedlings while providing better traffic conditions on rainy days. This method reduces tractor operations by 36% compared to traditional methods, where seedlings are spread over ploughed ground and subsequently buried with a leveling harrow and roller-compactor. Direct seeding further decreases mechanized operations by 58% in no-till row seeding and 74% in no-till aerial seeding (EMBRAPA, 2014).

### 4.3.3. What factors contribute to unintended negative consequences, such as maladaptation, specifically through the expansion of agriculture at the expense of forests in the Brazilian Amazon?

All the farmers interviewed have been expanding their production areas over the last 20 years either by buying new land or renting neighboring farms. Five farmers even doubled their initial cropland areas. With the argument of increasing production per ha, farmers have been investing in irrigation pivots (3 out 10 farmers got public funding). Maladaptation literature highlights three broad categories of maladaptation: infrastructural (irrigation pivots), institutional (funding), and behavioral. Adapting to climate change involves changes in attitudes and behavior, which is so important as physical or institutional changes. Farmers highlighted the role of sustainable intensification.

#### 4.3.4. How do Amazon farmers perceive the role of the Amazon Forest in climate regulation and if this perception influences their land-use decisions?

Farmers perceive that forest contribute to water flow regulation, carbon uptake, biodiversity conservation and other essential ecosystem services. Some farmers use the forest soil debris for inoculating in their irrigated soy plantations, reporting higher moisture levels and higher productivity. Above all, most of the farmers were very critical concerning the lack of instruments and programs for receiving payment for ecosystem services from the native forest they conserve in their lands, as mandated by the Forest code.

#### 4.3.5. Final remarks

Farmers emphasized the importance of timely planting and using adapted crop varieties along with changing management practices. Ten out of the 13 farmers reported losses ranging from 10% to 40% in years affected by El Niño or La Niña. However, in interviews, farmers dispute claims that their losses are a consequence of climate change, let alone deforestation. This perception highlights the challenges of foresting a dialogue on global climate change along with deforestation impacts on the regional climate with the Brazilian agribusiness.

# 5. Methodology

## 5.1. Deforestation-induced local and regional climate changes and their economic impacts on agricultural production

### 5.1.1. Methodological summary

#### 5.1.1.1. Data

Daily rainfall amount estimates ($R_{i,j,t}$ in mm.day$^{-1}$) and daily maximum air temperatures ($T_{max_{i,j,t}}$ in °C), were obtained from the Brazilian Daily Weather Gridded Database (BR-DWGD) at the original resolution of ≈1×1 km, which have a high correlation ($r^2 \approx 0.8$-0.9) with in-situ data. The BR-DWGD data replicate well the climate patterns in the Cerrado compared with those of the climate databases AgCFSR/AgMERRA (Ruane, et al. 2015) and NASA/POWER (Bender & Sentelhas, 2018). The BR-DWGD data were aggregated into time-series maps of 28×28 km grid-cell.

Based on the available data from the Municipal Agricultural Production Survey by the Brazilian Institute of Geography and Statistics (IBGE, 2022), we obtained the average yield of soy-maize double cropping system (ton/ha) at the municipal level between 2006 and 2019. The tabular data were also converted into time-series maps of 28×28 km grid-cells by using the Inverse Distance Weighting interpolation.

We calculated the extent of native vegetation loss between 1999 and 2019 using the land-use and land-cover maps from the MapBiomas project, collection 7 (mapbiomas.org). To make the land-use and land-cover change data coincide with the climate data, we transformed the maps into time-series maps of the accumulated percentage of forest loss per 28×28 km grid-cell.

Economic profitability (net revenue) is calculated by summing all the values of the resources (inputs and services) utilized in the production process of soybeans and maize. This involved dividing the data pertaining to production value by the total output. The tabular data was then spatially disaggregated into 28 x 28 km pixels, employing ordinary kriging as the interpolation method (Grego; de Oliveira & Vieira, 2014). To determine profitability, we divided the economic gains from that activity for the respective year by the production cost. The resulting figure can be expressed the profitability of soybean and maize production for the designated year, offering valuable insight into the economic viability of these crops.

#### 5.1.1.2. Areas of *soy-maize double cropping system*

We performed the spatial allocation of *soy-maize double cropping* using the Otimizagro model (Leite-Filho, et al. 2021, Rochedo et al, 2018). Otimizagro is a spatially explicit model that simulates land-use and land-use changes, including agriculture, forestry, native vegetation loss, and regeneration, under various scenarios of agricultural land demand and Brazilian environmental policies. The model spatially allocates nine annual crops (including single and double crops), five perennial crops, and forest plantation using a spatial resolution of 6.25 ha. Otimizagro spatially allocates annual municipal estimates for soy-maize double cropping areas from the Brazilian Institute of Geography and Statistics (IBGE, 2022) over maps of annual soy areas from MapBiomas project, collection 7, using for the favorability map, agricultural suitability for double cropping from Rochedo et al, 2018.

#### 5.1.1.3. The onset of the agricultural rainy season

Based on $R_{i,j,t}$ estimates from the BR-DWGD database, we identified the onset of the agricultural rainy season ($O_{i,j,t}$ ) for each grid-cell. We used the anomalous accumulation method (Liebmann, et al. 2007) (Equation 1). This method has been successfully applied for this purpose in the state of Mato Grosso (Arvor, et al, 2014) and in the Southern Brazilian Amazon (Leite-Filho, et al, 2019). We defined September as the start of the hydrological year since the rainy season in the Cerrado occurs between October and March (Marengo, 1995). The AA method is directly applicable to agriculture, since the water demand of a soybean or maize plant is used as the reference value ($R_{ref}$; mm.day$^{-1}$), so that:

$$AA^{(day)} = \sum_{n=1}^{day}(R_{i,j,t} - R_{ref}) \qquad \text{(Equation 1)}$$

where ($R_{i,j,t}$ in mm.day$^{-1}$). We fixed the $R_{ref}$ *as* 2.5 mm day$^{-1}$, which corresponds to the needs of a soybean seedling (Abrahão & Costa, 2018). Onset of the agricultural rainy season for each grid-cell ($O_{i,j,t}$), where *i*, *j* and *t* refer to space and time dimensions, is defined as the day from which AA remains positive during the longest period recorded (Liebmann, et al. 2007)

#### 5.1.1.4. Definition of the first and second crop seasons

The soy-maize double cropping system involves planting soybeans at the onset of the agricultural rainy season and maize after the soybean has been harvested. The second crop season faces yield challenges due to reduced rainfall amount and photoperiod, with late planting usually undergoing water stress. As our study analyzes each crop season independently, we utilized the $O_{i,j,t}$ values to estimate the crop seasons. We grouped $R_{i,j,t}$ data (mm.day$^{-1}$) and the daily maximum air temperature (°C) from the BR-DWGD database from the day of the onset of the agricultural rainy season (day 1) up to the 140$^{th}$ day. We assume this time interval for the cultivation of the first crop. The second crop season takes place from day 141 to day 260, which typically corresponds to January to April.

#### 5.1.1.5. Climate anomalies due to forest loss for each crop season

Climate patterns in the study region has a strong interannual and interdecadal variability, largely influenced by SST gradients of the North and South Atlantic (Marengo, et al. 2001) and the dry season evapotranspiration, in response to a seasonal increase of solar radiation (Myneni, et al. 2007), complicating the attribution of changes in the climate to native vegetation loss. Therefore, to identify the forest loss signal on the onset of the agricultural rainy season ($O'_{i,j,t}$), rainfall amount ($R'_{i,j,t}$) and maximum air temperature (${T_{max}}'_{i,j,t}$), we had to remove the influence of geographic location, elevation and interannual variability;

the latter reflects the effects of large-scale climate mechanisms as well as anthropogenic climate change.

To determine the anomalies and evaluate the efficacy of our detrending method, we adopted a multi-step procedure adapted from Leite-Filho et al. (2021). Our methodology consisted of three steps, as follows: First, we employed machine learning algorithms to model the spatial variability of climate. This involved the generation of maps that accurately capture the climate variations across the Cerrado. Subsequently, we rigorously assessed the accuracy of these models to ensure their reliability and representativeness of the spatial climate patterns. In the second step, we applied a detrending procedure to the climate data to remove the effects due to geographic location and elevation and in the third step we eliminated any long-term trend or pattern that could potentially influence the analysis. This procedure was crucial for preparing the data for subsequent analyses. Lastly, we validated the detrending procedure to confirm its effectiveness and verify that it did not introduce any biases into the analysis. Each step of our methodology is detailed as follows.

*Modeling the spatial variability of climate*

In the first step, we tested four machine learning algorithms for replicating the spatial patterns of the regional climate over the first and second cropping seasons and the onset of the agricultural rainy season as a function of latitude ($\varphi$), longitude ($\lambda$), and mean elevation ($\zeta$) of each grid-cell. We tested the Random Forest, Support Vector Machine, Generalized Linear Model, and Generalized Additive Algorithms.

*Verification of the spatial modeling of climate variability*

We conducted an evaluation of the four machine learning algorithms to determine their effectiveness in replicating the spatial patterns of the regional climate. The assessment was based on the absolute difference between the observed values and the values estimated from the algorithms. The Random Forest algorithm (RF) with 1000 trees yielded the best accuracy for capturing the climate patterns (Figs. S6 and S7).

*Detrending procedure*

Step 2 aimed at removing the climatological trends due to geographical location and elevation. As the climate spatial patterns replicated from the RF are static over time, the results from Equations S2-4 represent the signal due the interannual variability.

$$O^{*}_{i,j,t} = \left(O_{i,j,t} - \hat{O}_{i,j,t}\right) \text{ (Equation 2)}$$

$$R^{*}_{i,j,t} = \left(R_{i,j,t} - \hat{R}_{i,j,t}\right) \text{ (Equation 3)}$$

$$T_{max}{}^{*}_{i,j,t} = \left(T_{max}{}_{i,j,t} - \hat{T}_{max}{}_{i,j,t}\right) \text{ (Equation 4)}$$

where $i$ and $j$ are the two-dimensions in space and $t$ the time; $O_{i,j,t}$ , $R_{i,j,t}$ , ${T_{max}}_{i,j,t}$ $and$ ${T_{min}}_{i,j,t}$ are the observed mean values of the onset of the agricultural rainy season, rainfall amount and maximum air temperatures over the first and second crops; $\hat{R}_{i,j,t}$ and $\hat{T}_{max\,i,j,t}$ are the estimated values for rainfall amount and maximum air temperatures in the first and second crops and $\hat{O}_{i,j,t}$ are the estimated values of the onset of the agricultural rainy season.

In step 3, for each grid-cell, we then subtracted from the latter results the biome's means for the same climate variables to eliminate the influence of large-scale factors, such as ENSO and anthropogenic GHG climate change. The resulting residue was considered an "anomaly," unexplained by geographic location, elevation, or large-scale time-varying factors. (Equations 5-7).

$$O'_{i,j,t} = \left(O^*{}_{i,j,t} - \bar{O}_t\right) \text{ (Equation 5)}$$

$$R'_{i,j,t} = \left(R^*{}_{i,j,t} - \bar{R}_t\right) \text{ (Equation 6)}$$

$${T_{max}}'_{i,j,t} = \left({T_{max}}^*{}_{i,j,t} - \overline{T_{max}}_t\right) \text{ (Equation 7)}$$

where ${T_{max}}^*{}_{i,j,t}$ , $R^*{}_{i,j,t}$ , $O^*{}_{i,j,t}$ are the differences between the values found and the simulated values from RF for the maximum air temperatures, rainfall amount (in the first and second crops) and the onset of the agricultural rainy season, respectively; $\bar{R}_t$ $\overline{T_{max}}_t$ are the mean maximum air temperatures and rainfall amount for the first and second crops and $\bar{O}_t$ is the onset of the agricultural rainy season calculated for the whole study region; and $O'_{i,j,t}$ , $R'_{i,j,t}$ and ${T_{max}}'_{i,j,t}$ are the climate anomalies that are not explained by the geographic location, elevation and the interannual variability. These anomalies are attributed to the climate signal resulting from forest loss.

#### 5.1.1.6. Verification of the detrending procedure

To verify the effectiveness of the detrending procedure in isolating the climate signal from forest loss, we conducted several assessments. First, we calculated the annual means of each climate variable for the entire study region after applying the detrending procedure. As a result, the detrended annual means converged to zero, indicating that the procedure successfully removed long-term trends associated with geography, interannual variability and anthropogenic GHG climate change.

In addition, we examined the spatial variability of the mean climate anomalies to check whether they exhibit any spatial gradients. This analysis was performed using the Cramer's V (Cramér, 1946) and the Spearman Rank Order Correlation coefficients (Spearman, 1904). The results indicate that after the detrending procedure, the climate anomalies exhibited spatial variability that was solely correlated with accumulated percentage of forest loss per grid- cell. For the onset of the agricultural rainy season, both Cramer's V (0.59) and Spearman's ρ (0.58) exhibit strong associations with forest loss. In the first crop season, significant relationships are observed between forest loss and anomalies in rainfall amount (Cramer's V = 0.56, Spearman's ρ = 0.52) and maximum air temperature

(Cramer's V = 0.47, Spearman's ρ = 0.46). Similarly, in the second crop season, anomalies in rainfall amount (Cramer's V = 0.55, Spearman's ρ = 0.52) and maximum air temperature (Cramer's V = 0.56, Spearman's ρ = 0.54) also exhibit notable relations with forest loss percentages.

#### 5.1.1.7. Soybean and maize residues

The generalized additive model, introduced by Hastie and Tibshirani in 2017, is a flexible statistical modeling approach that extends the concept of linear regression to incorporate nonlinear relationships between predictors and the response variable. The aim is to analyze the relationship between agricultural productivity and time, represented in years. The dependent variable in our study is agricultural productivity, measured in tons per hectare (t/ha). The independent variable is time, represented by the year. When our model contains nonlinear effects, GAM provides a regularized and interpretable solution – while other methods generally lack at least one of these three features.

The adopted model is expressed as follows:

$$Y=\beta 0+f(\mathrm{x})+\epsilon \quad \text{(Equation 8)}$$

Where, $Y$ is agricultural productivity (dependent variable), $X$ is time (year), the independent variable, $\beta 0$ is the intercept of the model, $f(X)$ is the smooth function of time, capturing the nonlinear relationship between productivity and year and $\epsilon$ represents the error term.

- Estimation of Smooth Function: The smooth function $f(X)$ is estimated non-parametrically from the data using kernel smoothing. This function captures the non-linear trend in productivity over the years.

- Model Fitting: Model fitting is performed using maximum likelihood estimation, aiming to find the model parameters that best fit the data.

- Model Evaluation: The fitted model is evaluated through diagnostic plots, cross-validation, and model fit measures using AIC.

- Interpretation of Results: Results are interpreted based on the statistical significance of the time variable (year) and the shape of the estimated smooth function, describing how agricultural productivity varies over the years.

#### 5.1.1.8. Evidence for native vegetation loss intensifying regional climate change

To assess the probability of crossing a specific climate threshold, we employed cumulative probability distribution functions (CPDF) (Anderson & Darling, 1954, Johnson & Balakrishnan, 1995). First, we categorized the percentage of native vegetation loss within each 28×28 km grid-cell into five intervals. The intervals encompass ≤ 20% of forest loss (interval 1) to ≥ 80% of forest loss (interval 5). To derive continuous CDFs for each climate variable (maximum air temperatures, rainfall amounts, and the onset of the agricultural rainy season), we performed a Monte Carlo simulation (Metropolis, 1987) with 10,000 iterations.

#### 5.1.1.9. Critical climate thresholds leading to potential crop shortfalls

a) **The onset of the agricultural rainy season:** Soy-maize double cropping in the Cerrado is predominantly rainfed and the rainy season typically spans 6 to 7 months (Abrahão & Costa, 2018). Soybeans are usually planted at the onset of the agricultural rainy season, followed by maize cultivation in the same area after the soybean harvest. Maize is cultivated during a period when there is a reduction in rainfall, mean air temperatures, and shorter photoperiod in most crop-producing regions (Borém, et al., 2015). Consequently, the later the second crop is planted, the lower its yield tends to be, primarily due to water stress towards the end of the growing season (Garcia, et al., 2018). It is worth noting that delaying the soybean planting operation more than 10 days may impair double cropping yields, especially considering the average cycle length of current cultivars such as S100 and M120 (Brumatti, et al. 2020).

b) **Rainfall amount***:* For soybean, on average, a minimum of 450 mm of water is required during its development cycle, with the reproductive stage being particularly sensitive to water deficits, with a daily evapotranspiration rate that can reach up to 8 mm/day (Berlato, Matzenauer & Bergamaschi, 2001; Pas-Campo, 2005). For maize, medium-cycle plants must consume at least 400 mm of water throughout the development cycle.

c) **Air temperature***:* For soybean cultivation, the ideal temperature for development is around 30°C; germination and plant emergence are compromised when the soil temperature falls below 20°C (Setiyono, 2007). Temperatures exceeding 40°C can have adverse effects on soybean growth, including damage to flowering and reduced pod retention (Avila, et al., 2013). In the case of maize, the optimal temperature range for growth, from emergence to flowering, is between 24°C and 30°C. Temperatures above 30°C can negatively impact maize grain yield (Andrade, et al., 2006).

#### 5.1.1.10. Spatial determinants of fluctuations of soybean and maize yields

Five main spatial determinants can explain the fluctuations in soybean and maize yields: the investment made by farmers in their crops, which depends on their previous year's economic yield and financial availability; genotype and cultivar, as discussed by Kurosaki & Yumoto (2003) and Hao et al. (2012); the seeding date, according to MacMillan & Guiden (2020); air temperature, referenced by Kurosaki & Yumoto (2003); and rainfall amount. These climatic conditions, specifically genotype and cultivar, air temperature, and rainfall amount, are influenced by global climate change linked to greenhouse gas emissions, interannual climate variability—which in Brazil often results in significant crop losses due to the adverse climatic effects of El Niño and La Niña phenomena—and regional climate changes caused by land use and cover. To analyze the influence of these factors on fluctuations in soybean and maize yields in the Amazon and Cerrado, we used yield fluctuations in each grid cell as the dependent variable in a Spatial Autoregressive Model (SAR) applied to panel data (Drukker, et al., 2013). The explanatory variables were divided into four groups: normal climatology, which includes average rainfall amount, the onset of the agricultural rainy season, and maximum/minimum temperatures in each pixel from 2006 to 2019 using the TRMM and BR-DWGD databases; interannual climate variability, considering the same climatic metrics during years when the Equatorial Pacific Ocean was warmer (El Niño) or colder (La Niña); impacts of native vegetation loss on climate, analyzing anomalies in the onset of the rainy season, rainfall, and temperatures due to native vegetation loss, calculated using a three-step procedure according to Leite-Filho et al. (2021 and 2024); and previous crop profitability, which involves converting the production cost from the previous crop into profitability. Crop losses impact profitability and affect producer revenue, potentially reducing future investment and contributing to further production losses. The methodology for estimating previous crop profitability is detailed in Supplementary Section SX. The SAR model incorporates the effect of geographic neighborhoods to mitigate spatial dependence between observations, a common issue in geographic data. For this, we used a weighted 8-cell neighborhood matrix (Tiefelsdorf, et al., 1999). We employed the Akaike Information Criterion (AIC) to assess the quality of each model relative to others, providing a method for selecting the most appropriate model.

## 5.2. Assessing Amazon reforestation potential for climate regulation

### 5.2.1. Methodological summary

#### 5.2.1.1. Data

**Climate:** We utilized daily rainfall volume estimates ($\mathrm{R}_{\mathrm{i,j,t}}$ in mm.day$^{-1}$) and daily maximum temperatures ($\mathrm{T}_{\mathrm{max}_{\mathrm{i,j,t}}}$ in °C), from the Brazilian Daily Weather Gridded Database (BR-DWGD) at an original resolution of ≈1×1 km, which has a high correlation ($r^2 \approx 0.8$-$0.9$) with in-situ data. The BR-DWGD data were aggregated into time-series maps at 28×28 km grid-cell resolution. The methods for calculating climate residues due to deforestation follows the previous section’s methodology

#### 5.2.1.2. Property-level modeling for targeted regeneration

To support state environmental agencies in implementing the Forest Code and assist landowners in regularizing their Legal Reserve (RL) deficit, we developed a spatially explicit model to identify areas suitable for native vegetation restoration. This mapping, conducted at the level of rural properties, considers various physical variables to delineate areas most favorable for accommodating the legal reserve deficit. At the discretion of the environmental body, the model can be integrated with CAR 2.0, a system that automatically analyzes rural properties registered in the Environmental Rural Registry (CAR) and systematically verifies their compliance to the legislation. The model runs on the freeware software Dinamica EGO (dinamicaego.com), a sophisticated environmental modeling platform that enables integration with databases such as PostgreSQL/PostGIS. This freeware with a user-friendly graphical interface utilizes intrusive parallel processing; its execution system uses a variable number of execution threads, called workers, driven by task-stealing algorithms to provide load balancing and flexibility for executing simultaneous tasks. In theory, all model components can run in parallel, including operators, loops, and independent map tiles. This architecture drastically reduces the execution time of complex models that can run locally or in the cloud.

The model was executed only for rural properties with Legal Reserves (LR) deficit previously identified by CAR 2.0 and SeloVerde-PA technologies (https://www.semas.pa.gov.br/seloverde), which also provide estimates of the Forest Code conformity of all rural properties registered in CAR in the state of Pará. The computational infrastructure also daily integrates public data from state and federal agencies to combat illegal deforestation, promote environmental and land regularization, and transparently provide traceability of agricultural production.

The LR deficit allocation model has several inputs, including data per rural property: unique identification code, perimeter geometry, and LR deficit area. Statewide coverage data includes land use, permanent conservation areas, and RL deficit allocation probability. The unique identification codes (CAR) and the geometries of rural properties were provided by the Secretariat of State for Environment and Sustainability of the Government of Pará (SEMAS/PA) via a shared database. The LR deficit areas were provided by the SeloVerde-PA platform database. The permanent preservation areas (APP) for conservation were generated using the Forest Code balance model hosted in the SeloVerde-PA and CAR 2.0 platforms. The land use map is the result of combining high-resolution mapping of the state of Pará (see https://csr.ufmg.br/mappia/), the hydrographic base of SEMAS/PA, deforestation observed after 2008 by the PRODES project of the National Institute for Space Research (INPE), and the soybean area from the MapBiomas project - collection 8.0.

The land use classification was performed using a set of images from the Sentinel and Planet satellites, including texture-derived images. A machine learning algorithm with successive rounds of training, totaling more than 1 million sampled pixels, was used for supervised classification. The classified map was smoothed by removing isolated patches with classifications divergent from their neighborhood. The probability map for LR deficit allocation is created from the intersection of five physical landscape variables encompassing the entire state's extent (distance to roads, distance to water sources, distance to large fragments of native vegetation, altitude, and slope) to identify areas most favorable for restoring vegetation to meet or complete the minimum LR required by the Forest Code. Each variable was normalized on a common scale (0 to 255). The intersection of the normalized variables was modeled a Multi-Criteria Analysis (MCA) method, also known as Hierarchical Weighted Analysis. The resulting product is then normalized again.

From the structured input database, the LR deficit allocation model is executed for the unique identification codes of each rural property in the database table. The assumptions for delineating areas most suitable areas for LR restoration consider allocation over the "post-2008 deforestation" class; continuity and contiguity of patches; proximity to property border; proximity to fragments of native vegetation; and avoiding allocation over the soybean cultivation class (allowed only if no other anthropogenic land-use area is available), as well as avoiding allocation in APPs. Dinamica EGO communicates with PostGIS through Python-developed submodels, such as "ExecutePostgisQuery," which executes queries and obtains tabular data, and "GetShapefileFromPostgis," which exports spatial data in vector format (shapefile). The LR allocation is performed for each rural property individually after removing overlaps. This analysis is computationally demanding; however, after all optimizations, it was possible to reduce the processing time to just 30 seconds per rural property. Considering a total of about 73,000 properties with LR deficits in the state of Pará, the complete analysis could be executed in approximately 24 hours, thanks to the software's capability to perform parallel analyses. This feature allows the simultaneous analysis of multiple properties, limited only by the available memory and number processors in the system. The model executes several steps for the unique key codes of each rural property, including geometry acquisition, rasterization, LR deficit area allocation, polygonization, and result unification.

#### 5.2.1.3. Quantifying climate benefits of regeneration across geographic scales

**Percentage of Native vegetation:** Regression analysis is applied to correlate climate anomalies with accumulated native vegetation in each grid cell. We classified the native vegetation fraction into 19 classes: Class 1 has <5% of its area deforested; Class 2 has between 5 and 10% deforested; and so on, until Class 19, with between 90 and 95% deforested. Climate anomalies were normally distributed (Shapiro–Wilk test, $p < 10-5$), allowing us to apply a linear or second-degree polynomial regression between climate anomalies and the predictive variable of native vegetation loss, specifically tailored for this analysis. The statistical significance of all regression coefficients was tested by dividing each estimated coefficient by the standard deviation of the estimate. We also utilized the coefficients of sample correlation between pairs of explanatory variables to identify any collinear relationships between variables included in the empirical models. The best-fit regressions (linear or second-degree polynomial regression) modeled the climate anomalies as a function of percentage native vegetation. All regressions achieved high statistical significance ($p < 10^{-5}$).

**Quantify changes in agricultural climate variables due to native vegetation changes:** We employed the previously mentioned empirical regression models to quantify changes in agricultural climate variables due to changes in native vegetation on a pixel-by-pixel basis. Specifically, we estimated alterations in the onset of the agricultural rainy season, as well as anomalies in maximum and minimum temperature and rainfall attributed to changes in native vegetation. Incorporating insights from our regeneration simulations, we estimate potential benefits of these climate shifts on agricultural practices. Particularly, the earlier onset of the rainy season predicted currently under double cropping systems in the Amazon. In areas where increased rainfall volumes are projected due to regeneration, the additional water availability is expected to enhance crop productivity, reduce dependency on irrigation, and improve soil moisture conditions.

## 5.3. Deforestation-induced local and regional climate changes and associated impacts on pasture quality

### 5.3.1. Methodological summary

#### 5.3.1.1. Data

Daily rainfall amount estimates ($R_{i,j,t}$ in mm.day$^{-1}$) and daily maximum air temperatures ($T_{max_{i,j,t}}$ in °C), were obtained from the Brazilian Daily Weather Gridded Database (BR-DWGD) at the original resolution of ≈1×1 km, which have a high correlation ($r^2$ ≈ 0.8-0.9) with in-situ data. The BR-DWGD data replicate well the climate patterns in the Cerrado compared with those of the climate databases AgCFSR/AgMERRA [6] and NASA/POWER [7]. The BR-DWGD data were aggregated into time-series maps of 28×28 km grid-cell. The methods for calculating climate residues due to deforestation follows the methodology of section 5.1.

The Pasture Vigor Condition module, covering the period from 2000 to 2023, was developed based on the MapBiomas Collection 9 pasture map. This mapping evaluates pasture vigor conditions using the vegetative vigor trend as an indicator to classify pastures into three categories: (a) low vigor, (b) medium vigor, and (c) high vigor. The vigor condition of a pasture area is generally related to management practices, the type of forage plant used, and the degradation stage of the area, with the latter being more closely associated with biological degradation (exposed soil), largely influenced by the climate. We calculated the extent of native vegetation loss between 1999 and 2019 using the land-use and land-cover maps from the MapBiomas project, collection 7 (mapbiomas.org). To make the land-use and land-cover change data coincide with the climate data, we transformed the maps into time-series maps of the accumulated percentage of forest loss per 28×28 km grid-cell.

#### 5.3.1.2. Spatial determinants of pasture quality

Five main spatial determinants can explain pasture quality: investments; genotype and grass species, as discussed by Kurosaki & Yumoto (2003) and Hao et al. (2012) and MacMillan & Guiden (2020); air temperature, referenced by Kurosaki & Yumoto (2003); and rainfall amount. Aiir temperature, and rainfall amount, are influenced by global climate change linked to greenhouse gas emissions, interannual climate variability—El Niño and La Niña phenomena—and regional climate changes caused by land use and cover. To analyze the influence of these factors on pasture quality in the Amazon, we used pasture quality as dependent variable in Weights of evidence model (Drukker, et al., 2013).

The explanatory variables were divided into four groups: normal climatology, which includes average rainfall amount, the onset of the agricultural rainy season, and maximum/minimum temperatures in each grid-cell using the BR-DWGD databases; interannual climate variability, considering the same climatic metrics during years when the Equatorial Pacific Ocean was warmer (El Niño) or colder (La Niña); impacts of native vegetation loss on climate, analyzing anomalies in the onset of the rainy season, rainfall, and temperatures due to native vegetation loss, calculated using a three-step procedure according to Leite-Filho et al. (2021 and 2024); and investments.

## 5.4. Stakeholder engagement

### 5.4.1. Methodology

The protocol comprised five stages: 1) scoping, 2) developing a semi-structured questionnaire, 3) interviews, 4) fieldwork visits and case study selection, and 5) research dissemination (Figure 1). The stakeholder engagement protocol followed the Biodiversa Handbook (https://www.biodiversa.eu/wp-content/uploads/2022/12/stakeholder-engagement-handbook.pdf).

#### 5.4.1.1. Scoping

The first step was defining the desired outcomes, scope, and context of the stakeholder engagement process. The engagement strategy was implemented by considering the reasons for engagement and the goals of the process. This scope was defined by the research team at UFMG and Rainforest Norway, in collaboration with other organizations and cross-sectoral stakeholders. We identified and selected agribusiness stakeholders from governmental and non-governmental organizations focused on grain and cattle ranching, targeting large producers who export soy, maize, or cattle.

To identify stakeholders, a project flyer was disseminated widely, detailing the research objectives and goals. An email with the flyer attached was sent to over 50 governmental organizations involved in soy, maize, and cattle sectors (Annex 2). For organizations that did not respond, telephone follow-ups were conducted. Meetings were arranged with various organizations to present the project and gather suggestions for farmer contacts in different Amazon regions. These scoping meetings were crucial for understanding how to engage farmers and facilitate dialogue effectively. The meetings highlighted the challenges of establishing dialogue on climate change and deforestation topics, as agribusiness farmers often dispute claims linking their activities to climate changes. Our objective was not to challenge their beliefs but to understand how their practices have evolved due to changes in rainfall and temperature patterns. To maintain open communication, we avoided terms like "climate change," instead focusing on "changes in rainfall" and "temperature." This approach aligned with farmers' willingness to engage in this project.

The scoping phase, from January to March 2024, included meetings with governmental and non-governmental organizations in Pará and Mato Grosso states. We discussed the questionnaire structure and sought contacts for prominent farmers who export grains or cattle. These organizations helped test and refine the questionnaire, enhancing communication between researchers and farmers. Participation in the stakeholder identification process helped define and refine the issues considered and provided comprehensive information on stakeholders involved. The engagement's purpose was primarily normative, emphasizing the process’s benefits (e.g., increased learning, trust, and reduced conflict). Our stakeholder involvement followed the Biodiversa handbook's

"Inform" level, aiming to update interested parties with balanced information to help them understand the problem, identify alternatives, and find solutions.

#### 5.4.1.2. Semi-Structured Questionnaire

The questionnaire was structured into four sections associated with the project's major research questions. In the introduction, we explained that interviewees were selected for their prominence in the area. We emphasized the study’s significance in understanding changes in rainfall and temperature on agricultural productivity, assured confidentiality, and encouraged honest responses. The initial questions focused on farm characterization, including total farm size, annual crop area variation, and cattle management systems, aiming to understand changes in agriculture and no-till practices. We collected interviewees' personal stories to contextualize climatic and socio-economic timelines.

We addressed recent climate variations (2020-2022, La Niña, and 2023, El Niño), inquiring about farmers' perceptions of agricultural impacts and quantification of losses. An infographic was used to facilitate discussions. We explored farmers' memories of climate patterns since the 1990s, considering significant shifts and extreme events, and prompted responses regarding documented changes in rainfall and temperature. Further questions addressed changes in farming practices, crop varieties, and potential financial losses. Farmers listed cultivated crops and grasses, highlighting changes over time in cropping systems and motivations for these changes.

#### 5.4.1.3. Project Research Questions

| Scope | Questionnaire |
|---|---|
| a) Perception of changing climate conditions and its impact on agriculture | How was your farm in the 90s? How is it in 2024? Changes in rainfall and temperature? Why change crop varieties and management systems? |
| b) Strategies in response to extreme climate events | List of crops and management systems |
| c) Factors contributing to unintended consequences like maladaptation | Expansion of crop area and irrigation projects |
| d) Farmers' perception of the Amazon Forest's role in climate regulation | Awareness of forest benefits: water, carbon uptake |

#### 5.4.1.4. Stakeholder Interview

Research interviews with farmers were unique, given their different experiences, behaviors, and motivations compared to academic researchers. We sought permission to record and transcribe interviews, clarify ethical protocols (Process number), and assured participants' confidentiality. Our approach emphasized open-ended, non-directive questions and thorough understanding of responses. We clarified that the project included a fieldwork trip and asked if farmers were willing to participate. Interviews were transcribed using COLAB.

### 5.4.1.5. Fieldwork in Selected Case Studies

During the interviews conducted from April to June, six farmers expressed willingness to receive the research team on their farms during the fieldwork scheduled for August. Following the interviews, we re-contacted these farmers to confirm our visit plans and informed them that journalists would also accompany the research team. Four farmers agreed to host the team and journalists in Paragominas in August, 2024. Arrangements were made with these farmers to organize the fieldwork, with one farm visited per day.

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