Compound Hot and Dry Extreme Climate Events in Brazil's Breadbasket Region for Soybeans

- Recent Trends and Future Predictions

Lena M. Rester

University College Fryslân, University of Groningen

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Dr. Sarah C. Feron

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Abstract

Progress in achieving global food security is slow and climate change contributes as a risk factor, making farming more difficult and increasing yield losses. Brazil, the largest producer of soybeans, has increasingly felt the negative effects of heat and drought. By analyzing climate trends and identifying areas prone to climate extremes, agricultural planning and production can potentially be improved, increasing food security. Therefore, this paper analyzes the change in the frequency of occurrence of compound hot and dry events (CHDE) in Brazil between the two periods 1981-2010 and 2035-2064. Additionally, this study investigates the individual contributions of heatwaves and droughts to the occurrence of CHDE and assesses whether the CHDE will potentially impact soybean production. The CHDE are modeled using 3 Global Climate Models from the Coupled Model Intercomparison Project Phase 6 under the Shared Socio-Economic Pathway scenario 245. The model predictions imply that there will be an increase in CHDE which is mainly caused by an increasing number of heatwaves, rather than a change in intensity and duration of droughts. Additionally, the study found that the CHDE will occur in areas of soybean plantations at a magnitude that could potentially cause crop losses. The findings of this study motivate further research to quantify the CHDE's effects on Brazil's soybean production and highlight the importance of research for adaptive soybean production in Brazil creating resilience to CHDE.

Keywords: compound events, heat, drought, soybeans, Brazil

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In 2015, the United Nations set out a path to 'end poverty, protect the planet and ensure that by 2030 all people enjoy peace and prosperity' (United Nations Development Programme, 2022) by outlining the 17 Sustainable Development Goals (SDGs). The second goal, SDG 2: 'Zero Hunger', aims to 'end hunger, achieve food security and improved nutrition and promote sustainable agriculture' (United Nations Genral Assembly, 2015). However, as of 2020, around 768 million people were undernourished, accounting for approximately 10% of the global population and approximately one in three people did not have access to adequate food (*The State of Food Security and Nutrition in the World 2021*, 2021). This situation has become worse since 2014: while the number of undernourished people has decreased by around 200 million people between 2005 and 2014, from 2014 to 2019 this trend has turned around and the number of undernourished people increased by 60 million (FAO, IFAD, UNICEF, WFP, & WHO, 2020, p.4). This trend is predicted to continue, hence, the current outlooks to achieve the SDG 2030 goals concerning food security are grim. As stated by the FAO: 'The world is not on track to achieve targets for any of the nutrition indicators by 2030' (*The State of Food Security and Nutrition in the World 2021*, 2021, p.38).

Climate change is considered one of the most important factors to contribute to this food insecurity, next to other factors such as political instabilities and wars, economic and social inequalities, unsustainable farming practices or the global COVID-19 pandemic (*The State of Food Security and Nutrition in the World 2021*, 2021). Changing climatic conditions make food production more difficult. For example, more rainfall or higher temperature can cause outbreaks of pests and diseases, it can change the locations with suitable climate for crop production and an increasing number of climate extremes such as floodings can destroy crops (*The State of Food Security and Nutrition in the World 2021*, 2021). Those decreases in agricultural productivity become especially noticeable when they occur in so-called breadbaskets (*The State of Food Security and Nutrition in the World 2021*, 2021). Breadbaskets are regions where staple crop production, such as rice, soybean, or maize, is concentrated globally. Therefore, interruptions in the supplies or reduction in yields in those regions can further deteriorate food insecurity (Naqvi, Gaupp, & Hochrainer-Stigler, 2020).

Consequently, examining climate change in breadbaskets is crucial to safeguarding a stable global food supply.

One global breadbasket is Brazil, producing the most soybeans globally. Soybeans are considered the world's most important source of vegetal protein and represent more than 32% of the global agricultural revenues (Toloi, Bonilla, Toloi, Silva, & Nääs, 2021). With an increasing population and expected dietary preference shifts (Fehlenberg et al., 2017), soybeans are of global importance and great economic relevance. As of 2020, the largest producer and exporter of soybeans was Brazil (FAOSTAT, 2022). Of the globally produced 353,463,735 tons of soybean, Brazil produced 34,5% and exported 23,5% (FAOSTAT, 2022). Their exports amounted to 28,6 billion USD (Statista Research Department, 2022).

Given the economic importance of soybean production to Brazil and its contribution to the global food supply, a stable production is important. However, soybean production is susceptible to changes in temperature and precipitation (Geirinhas et al., 2021; Getirana, Libonati, & Cataldi, 2021; Gusso, Ducati, Veronez, Sommer, & Silveira Junior, 2014; Hamed, Van Loon, Aerts, & Coumou, 2021; Jin et al., 2017) and particularly to their co-occurrence in the form of Compounding Hot and Dry Events (CHDE) (Hamed et al., 2021). Compound events (CE) are broadly defined as at least two climate or weather events co-occurring on a certain spatial or temporal scale or as 'a combination of multiple drivers and/or hazards that contributes to societal or environmental risk' (Zscheischler et al., 2018).
The first time that attention has been given to CEs, was with the Special Report on Climate Extremes (SREX) publication in 2012 by the Intergovernmental Panel on Climate Change (IPCC, 2012). Until then, climate events and their impacts were mainly analyzed as univariate events, meaning individual drivers/events were singled out to create predictions or models for an impact analysis (Messori et al., 2021). This had been the conventional practice due to its 'simplicity', rather than analyzing the combined effect of two or more drivers/events (Leonard et al., 2014; Messori et al., 2021). The analysis of combined climate events requires researchers to understand the dependencies and correlations between the different climate variables (Zscheischler et al., 2018), making research more complicated (challenges in CE analysis are outlined by Raymond et al. (2020)). However, there are several

advantages to CE research that make it an important field to study and has made the study of CEs a 'highly diverse and thriving research field' (Zscheischler et al., 2020). Firstly, in many cases the combination of climate/weather events can lead to more significant impacts than when occurring individually (Leonard et al., 2014; Raymond et al., 2020; Zscheischler et al., 2018). For example, high temperatures can cause stress to plant growth, however, if combined with little to no precipitation, plant growth is more strongly inhibited than if the heat is accompanied by rain (Zscheischler et al., 2020). This shows that if we were to project individual climate and weather events, their impact might seem less significant and thus lead to insufficient adaptation and risk preparation (Leonard et al., 2014; Zscheischler et al., 2018). Thus, the second benefit of CE analysis is its contribution to better preparedness and responses to impacts of climate and weather events (Leonard et al., 2014; Raymond et al., 2020; Zscheischler et al., 2018). Furthermore, with climate change, the co-occurrence of climate and weather events is predicted to increase (Leonard et al., 2014; Raymond et al., 2020). This is expected to have significant impacts on socio-economic systems such as food production and security, infrastructure, health systems, insurances and water provisions (Challenges in these sectors due to CEs are outlined by Raymond et al. (2020)). Hence, analyzing climate change through the lens of CEs will provide more meaningful information and will help align climate modeling with impact modeling (Zscheischler et al., 2018).

Thus, to inform food stability and security, Brazil's possible developments of future climate and weather extremes in the form of CEs need to be better understood. Based on the predictions of the IPCC (2021), the individual extremes (heat and drought) are expected to increase. Yet, there has been no research conducted on whether they will occur more frequently in combination in Brazil and if so where. Therefore, this research will *investigate the future trends of CHDE during the soybean production season (September to May) in Brazil*. Specifically, this research compares the frequency of occurrence of CHDE during the baseline period 1981-2010 to the predicted frequency of occurrences of CHDE in 2035-2064, using climate models from the Coupled Model Intercomparison Project Phase 6 (CMIP6). Future predictions are made based on the Shared Socio-economic Pathway scenario 245 (SSP245), which predicts limited political and socio-economic development, resulting in slow progress to achieve the SDGs and a 2-3°C global temperature increase by the end of the century (O'Neill et al., 2016; Riahi et al., 2017). Knowledge about trends and location of CHDE occurrences can support Brazil in adapting to those anticipated changes and consequently contribute to global food security. Even without calculating concrete agricultural production yield losses, mapping CHDE is necessary, which is why the second aim of this research is to identify where the CHDE will occur. Lastly, the differences in changes in mean temperature and precipitation and their uncertainties should be given attention, as Bevacqua et al. (2022) point out. Since temperatures will rise worldwide which makes the majority of droughts hot droughts, precipitation trends will determine the future occurrences of CHDE (Bevacqua et al., 2022). Therefore, this research also addresses the question of how temperature and precipitation changes contribute individually to the occurrence of CHDE in Brazil.

The remainder of the paper is structured as follows: the first section outlines the current understanding of compound events, examines the state of research on CHDE in Brazil in soybean production and provides information on the characteristics of soybean production. This is followed by a methodology section in which an in-depth description of the research process will be provided. The research question(s) will be addressed in the result section and contextualized in the discussion section. After presenting the limitations, the paper is finalized with a conclusion to highlight the findings and suggestions for further research.

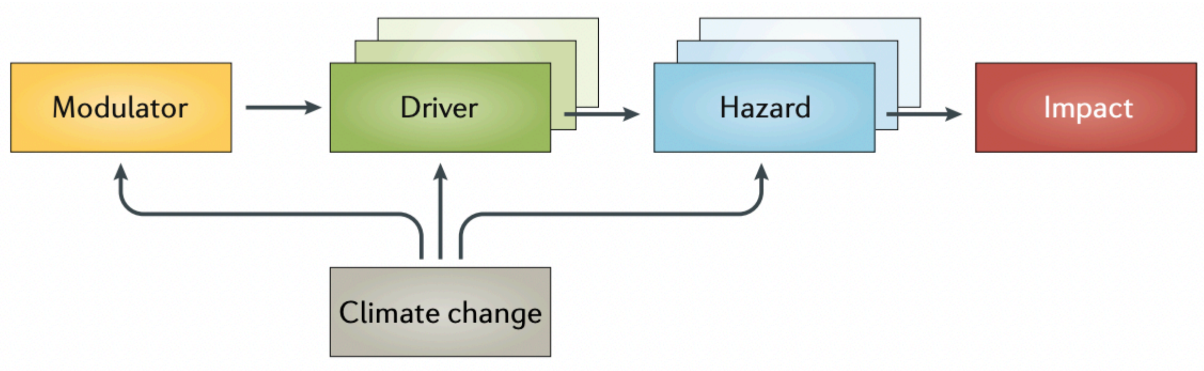
Literature Review

Extreme Events and Compound Events

From a biophysical perspective, an extreme climate or weather event (climate referring to a weather pattern over a longer time period of at least 30 years and weather referring to local and short term events (IPCC, 2021)) is defined as the 'occurrence of a value of a weather or climate variable above (below) a threshold near the upper (lower) tails of the range of observed values' (IPCC, 2012). If, for example, in a region 90% of the observed temperatures for one month are below 25°C, the occurrence of 26°C in that particular month can be considered an extreme event. From an impact analysis perspective, however, climate and weather events are defined as extreme events if their occurrence results in hazardous physical events or *disasters* that have consequences for the society and environment. Consequences could, for example, be loss of life, property damage, infrastructure, health impacts and/or interruption of the economic system (IPCC, 2012; Leonard et al., 2014). Their critique towards the biophysical definition of extreme climate or weather events is that an extreme event definition based on thresholds does not necessarily lead to actual extreme impacts and on the other hand, statistically non-extreme events can cause severe impacts on society (IPCC, 2012; Messori et al., 2021; Zscheischler et al., 2020). Regardless of the perspective, the following characteristics of extreme climate and weather events are similar for both definitions (see Figure 1): the biophysical event or the environmental component of the event, is considered a *hazard* which has a potential impact on society and/or the environment. For instance, in this research, drought is a hazard with the potential to impact agricultural production. A hazard is caused by *drivers* which are weather systems such as storms, cold fronts or stationary high-pressure systems. The frequency, intensity and location of a driver can further be affected by *modulators* which are low-frequency variabilities in climate modes such as an El-Niño-Southern-Oscillation (ENSO) (Leonard et al., 2014; Raymond et al., 2020; Zscheischler et al., 2020).

Figure 1

Elements of a compound weather and climate event



Note. Generalized scheme of an extreme event. It consists of modulators, drivers, hazards, leading to an impact, arrows indicating the causal links between the different factors. In compound events, multiple drivers or hazards might occur simultaneously or consecutively in time and space. Reprinted from 'A typology of compound weather and climate events' by J. Zscheischler, O. Martius, S. Westra, E. Bevacqua, C. Raymond, R. M. Horton, … E. Vignotto, (2020), *Nature Reviews*

Earth & Environment, *1*(7), 333–347. Retrieved from https://doi.org/10.1038/s43017-020-0060-z. Copyright 2020 by Springer Nature Limited.

Looking at those hazards individually is considered a univariate climate or weather event analysis. However, weather events often co-occur with other hazards, leading to so-called compounding climate or weather events. The IPCC provides the most recent and concise definition of compound events: Accordingly, a compound extreme event takes place when '*the combination of two or more - not necessarily extreme - weather or climate events that occur i) at the same time, ii) in close succession, or iii) concurrently in different regions, can lead to extreme impacts that are much larger than the sum of the impacts due to the occurrence of individual extremes alone*' (IPCC, 2021, p.1598)

Breaking down this definition, one can identify the following characteristics of a compound event. Firstly, through the co-occurrence of two or more hazards their individual impacts are amplified. Consequently, events that are not considered extreme in the biophysical sense can also contribute to the occurrence of compound events as long as they lead to a combined extreme. Secondly, what is understood as 'compound' can be interpreted on different spatial and temporal scales. Given the loosely defined scale by the IPCC, Zscheischler et al. (2020) try to define compound events further to allow for better analysis, understanding and comparison of CEs. A four-type categorization of CEs is proposed: Preconditioned Compound Events (PCE), Multivariate Compound Events (MCE), Temporally Compounding Events (TCE) and Spatially Compounding Events (SCE) (see Appendix A).

Analysis Approaches to Compound Events

How extreme events and compound events are defined is further determined by the analysis approach. There are two ways to analyze CEs: the top-down/scenario-led approach versus the bottom-up/system-centric approach (Leonard et al., 2014; Raymond et al., 2020; Zscheischler et al., 2018).

A bottom-up approach uses the impact as a vantage point for the CE analysis. The first step is to apprehend the system that is affected by climate variables and as a second step to identify the climate variables (drivers and hazards) based on the affected system. Thus, the extremeness of events is impact based rather than based on biophysically defined thresholds. While the advantage of this approach is that it is more likely to identify all impact-related variables (Zscheischler et al., 2018), it is rather case-specific. Example studies that have used this approach for CHDE are the Russian hot and dry event in 2010 (Grumm, 2011), the extreme and unexpected wheat yield loss in France in 2016 caused by a PCE (Ben-Ari et al., 2018) or the extreme hot and dry event in Germany in 2018 (Zscheischler & Fischer, 2020). In all cases, significant socio-economic impacts fueled the interest in understanding how such an event could occur and why it has not been predicted. The analyses uncovered unexpected combinations of climate variables which could then be searched for in climate projections to estimate the likelihood of the re-occurrence of such events. Results from those studies show that changes in our climate have led to unprecedented compound events with extreme impacts and that their likelihood of occurrence will increase in the future.

On the other hand, a scenario-led/top-down approach focuses on the analysis and quantification of physical processes first (Zscheischler et al., 2018). Using climate models, the occurrence of different climate variables and hazards can be displayed and predicted. In a second step, those climate models can then inform impact models, which determine crop yields, flood risk or energy production on a more general scale than bottom-up/system-centric approaches (Zscheischler et al., 2018). However, bottom-up approaches can inform scenario-led approaches because they can serve as a source for defining biophysical extreme events that are meaningful to research. Examples of previous research on CHDE and how they inform this research are presented in the next section.

CHDE in Brazil and in Relation to Agricultural Production

To understand the climate processes causing CHDE in Brazil, Geirinhas et al. (2021) conducted an analysis to identify its modulators and drivers. The research focuses on heavily populated regions over the time period 1980-2018. Their analysis shows that compound droughts (defined as a value less than -1 using a 3-monthly Standard Precipitation Index (SPI)) and heatwaves (defined as 3 consecutive days above the 80th, 90th or 95th percentile of a 15-day dynamic mean maximum temperature) have been occurring more frequently and more intensely over the study period. Furthermore, they identified the possible causal climatic processes and the dependencies between droughts and heatwaves which lead to their co-occurrence. As stated by the IPCC (2021), weather systems favorable for extreme heat are unfavorable for rain, leading to a positive feedback loop, giving rise to the compounding of heatwaves and droughts. This is the case for Brazil, where atmospheric circulation patterns cause clear skies, thus bringing precipitation deficits and low humidity while simultaneously letting through high amounts of shortwave radiation (Geirinhas et al., 2021). Due to the high amount of shortwave radiation, temperatures on the ground increase and raise the evaporative demand. This, in turn, decreases the already stressed soil moisture, increasing soil dryness to the point where it is so low that incoming solar radiation is emitted as sensible heat instead of latent heat (evaporation), which exacerbates temperature due to missing evaporative cooling (Geirinhas et al., 2021). Hence, as long as such an atmospheric circulation pattern persists over Brazil, heat and drought feed into each other. This mechanism is also observed in other regions impacted by CHDE (Grumm, 2011; Hamed et al., 2021; Zscheischler & Fischer, 2020).

While the research by Geirinhas et al. (2021) has identified the drivers and modulators of CHDE in Brazil, its impacts on agriculture have not been quantified. Instead, an analysis conducted in the US portrays the effects of high temperatures and low precipitation on soybean yields in the time period 1946-2016 (Hamed et al., 2021). They noted that heat and drought (defined as the 95th and 5th percentiles of temperature and soil moisture respectively) are amongst the most limiting factors for soybean production, explaining around ⅓ of US' soybean yield variability. They highlight that especially the combination of heat and drought will create more severe impacts. To exemplify, the authors found that in the US, CHDE led to four times the impact of individual heat extremes and three times that of individual droughts. Furthermore, the analysis by Hamed et al. (2021) shows that crop yields are particularly sensitive to end-of-growing season CHDE and that a short drought during the reproductive stage can lead to irreversible damages. Additionally, the analysis points towards an increased CHDE frequency for the time period studied.

Future predictions of CHDE occurrences in relation to agricultural production have been researched in China, a global breadbasket for maize and wheat (Lu, Hu, Li, & Tian, 2018). Lu et al. (2018) found that the frequency of compounding hot days (defined as the 90th percentile of a dynamic 21-day daily mean temperature) and droughts (10th percentile of precipitation of all growing-season wet-days) will increase for 2030-2050 compared to 1980-2015. However, they noticed differences in local trends and between crops which is argued to provide useful information for resilience planning and underlines the importance of local understandings of compound events.

Thus, research shows that CHDE significantly impact agricultural productivity, such as soybean production, and that certain locations have observed and/or will observe increases in their frequency of occurrence. However, so far, there are only univariate analyses of future drought and temperature changes conducted for Brazil. For instance, Geirinhas et al. (2021) attribute an increasing dryness in Brazil to the 67% price increase in soybeans between May 2020 and June 2021 and Assad et al. (2019) have analyzed the effect of increasing temperatures in Brazil on agriculture and yield projections. Under the RCP8.5 scenario of the 5th Assessment Report, a global warming scenario of over 3°C by the end of the century (leading to 4-8°C warming in Brazil), the yield loss risk for soybean production in Brazil would increase and losses of 30-34% by 2050 compared to a 1960-1990 baseline are predicted (Assad et al., 2019).

Given this general increase in temperatures, the IPCC (2021) argues that even if the frequency and intensity of droughts remain unaffected by climate change, CHDE are expected to increase because with higher temperatures, the frequency of heatwaves over Brazil will increase. This increases the likelihood of droughts and heatwaves to occur simultaneously. Bevacqua, Zappa, Lehner, & Zscheischler (2022) point out that this is exactly why attention must be brought to changes in precipitation patterns. Changes in mean temperature are much larger than expected changes in mean precipitation, so most droughts will be hot droughts. Thus, the most uncertainty in modeling CHDE comes from the uncertainty in precipitation trends and a good representation of precipitation patterns is crucial for robust estimates of the development of CHDE in the future (Bevacqua et al., 2022).

Soybean Production Regions and Cycle in Brazil

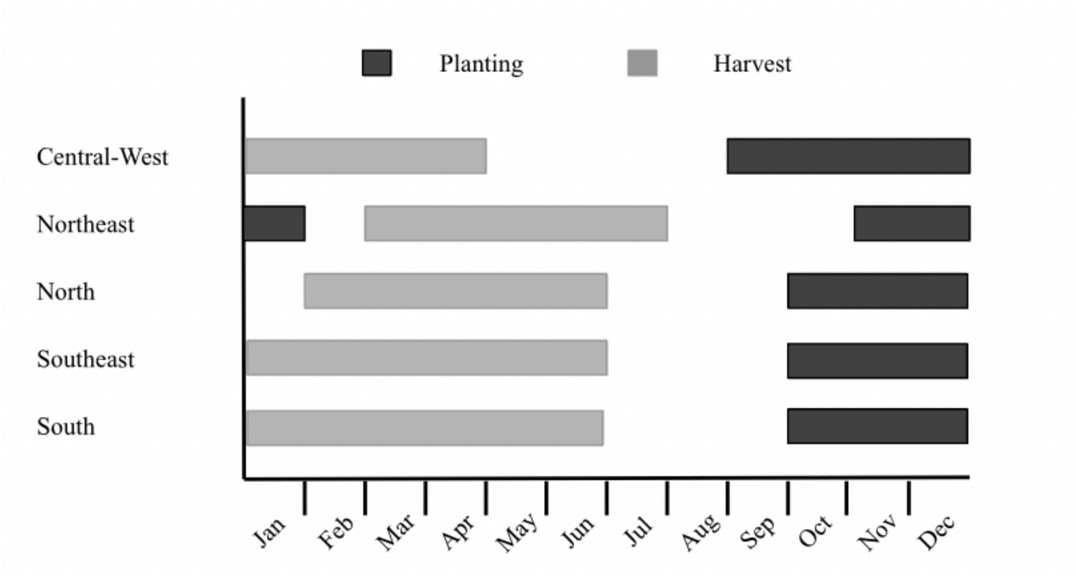
Finally, as this research set out with the aim to assess the relevance of the trends in CHDE for soybean production, characteristics in the Brazilian soybean production are outlined below.

During 2017-2019, the main production areas for soybeans were located in Central-West Brazil, which makes up 43% of the national soybean production. The second-largest contributors are the southern states, with 32% of the total national soybean production. Furthermore, the states Bahia (5%), São Paulo and Minas Gerais produce soybeans (Yadav-Pauletti, 2021) (For an overview of the regions see Appendix B).

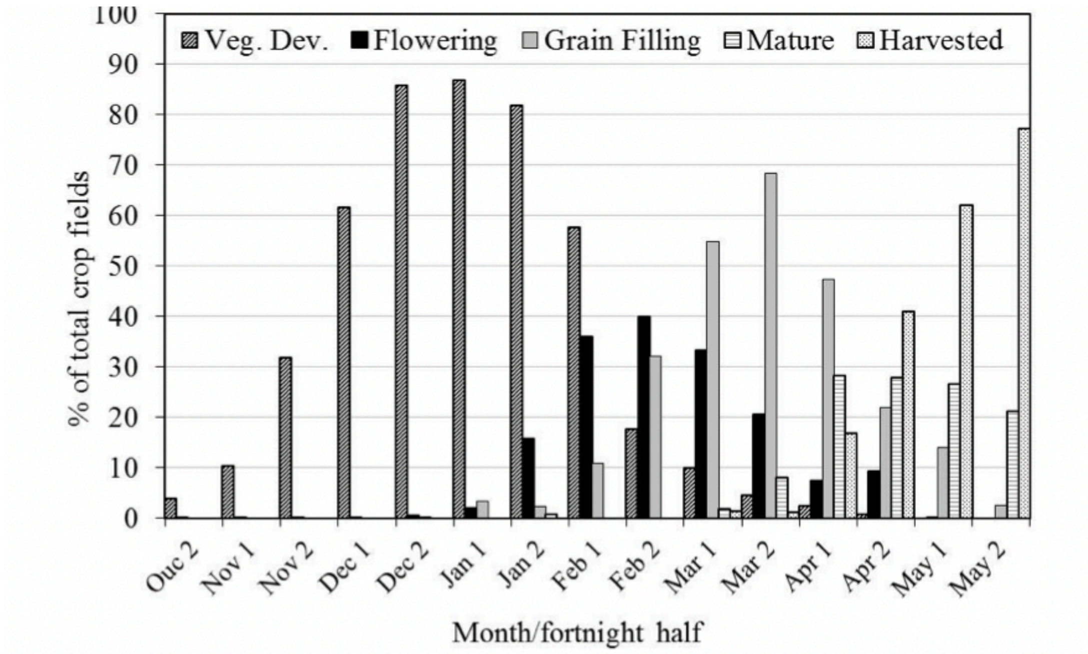
There are minimal variations in the life cycle of the soybean production across Brazil due to the slight differences in seasonality (Yadav-Pauletti, 2021). In the Central-West Brazil region, which includes the main production areas Mato Grosso, Goiás and Mato Grosso do Sul, planting begins in September and lasts until December. Harvest can start in January, but the main harvest period is from March to April. For the other main production regions the planting season starts in October until December and harvest takes place up until June. This information is represented in Figure 2a (Yadav-Pauletti, 2021). An exemplary representation of the growth stages of soybeans in the southernmost state is given in Figure 2b (Gusso et al., 2014). The vegetative stage takes place from October until January. The reproductive stage starts in January and ends with the harvest during April and May. It can be expected that for states further north, those periods start earlier due to the prior planting date.

Figure 2

Soybean production and growing cycle in Brazil



a)



b)

Note. a) Crop calendar for different regions in Brazil. Adapted from 'Brazil Soybeans 2020/21: Another Season with a Record Harvest.' By S. Yadav-Pauletti, (2021). Retrieved from https://ipad.fas.usda.gov/highlights/2021/06/Brazil/index.pdf. Copyright by U.S. Department of Agriculture. b) Soybean Growth Cycle in Rio Grande do Sul. From 'Monitoring Heat Waves and Their Impacts on Summer Crop Development in Southern Brazil' by A. Gusso, J.R. Ducati, M.R. Veronez, V. Sommer, & L. G. da Silveira Junior, (2014), *Agricultural Sciences*, *05*(04), 353–364.). Retrieved from https://doi.org/10.4236/as.2014.54037. Copyright 2022 by authors and Scientific Research Publishing Inc.

Vulnerability of Soybeans to Drought, Temperature and CHDE

The most critical periods during which drought has the greatest effect on plant growth and pod development is during the seed germination, seed emergence (part of the vegetative stages) and the flowering to grain filling period (reproductive phases) (Gusso et al., 2014; M., A., C., & P., 2013; Viana, Goncalves, Silva, & Matos, 2013). While the most precipitation is required during the reproductive stage (Viana et al., 2013), Yadav-Pauletti (2021) has observed that due to insufficient rainfall early in the season (during the vegetative stage), Mato Grosso experienced a decrease in biomass production in 2020 in comparison to the previous year. Thus, while water needs are highest during the reproductive stage, these findings suggest that dry conditions during the planting and early stages can also negatively affect crop production. Furthermore, Hamed et al. (2021) found that crops can be irreversibly damaged by the occurrence of short drought periods during the crop's reproductive stage.

Temperatures optimal for soybean development are recorded to be in the range of 20°C to 35°C, with ideal conditions between 25°C and 30°C (de Avila, Boucas Farias, Silveira, & Gustavo, 2013; Gusso et al., 2014; Hamed et al., 2021; Viana et al., 2013). Temperatures above 35°C can cause reduced growth and impact crop quality and yield (de Avila et al., 2013). If high temperatures coincide with drought, impacts and consequent crop yield losses are even higher (Cohen et al., 2021; de Avila et al., 2013; Hamed et al., 2021).

To summarize the current state of research, the modulators and drivers of CHDE in Brazil have been identified and it is known that CHDE have occurred and are occurring more frequently in Brazil. However, future analyses of CHDE in Brazil have not been conducted, nor have they been researched in relation to soybean agricultural production, although it is clear that the changing climatic conditions could potentially increase soybean's susceptibility. Hence, this research aims at closing the gap in the research of future CHDE developments in Brazil with regard to agricultural production, specifically soybean production.

Methodology

Methodological Approach and Research Design

In order to answer the research questions about the trends and locations in the occurrence of Compounding Hot and Dry Events in Brazil are, 3 Global Climate Models (GCM) from the Coupled Model Intercomparison Project Phase 6 (CMIP6) are being analyzed. Two time periods, baseline scenario 1981-2010 vs future predictions for 2035-2064, are being compared by estimating the frequency of CHDE occurrences for each period. Estimating the frequency of CHDEs is important as it is an 'indicator for potential impacts of global warming on agriculture and food security' (Lu et al., 2018).

A CHDE in this research is defined using the typology of Zscheischler et al. (2020). Compound Hot and Dry Events can be considered Multivariate Compound Events, as they are driven by atmospheric circulation patterns, which cause the two hazards heatwave (hazard implying extreme temperatures) and drought (hazard implying the absence of precipitation) (Geirinhas et al., 2021). These two hazards occur spatially and temporally simultaneously, thus opposing them to Temporally Compounding Events where the hazards would take place consecutively and to Spatially Compounding Events where they would occur in different regions.

This trend analysis can be considered a scenario-led approach since it is not centered on a case study. Thus, the extremeness of the individual hazards is defined using a biophysical definition explained further below. Nonetheless, the impact extremeness and relation to soybean production of the CHDE analyzed in this research will be informed by previous research outlined in the Literature Review.

Overall, predictions on the change of CHDE occurrences in Brazil can be made by conducting a climate data analysis to quantify the occurrences of CHDE during two time periods. The results are then discussed, taking into account the knowledge on soybean's climate sensitivity, its production cycle and its production areas in Brazil.

Data Sources

For future predictions, 3 models from the CMIP6 have been selected. The Coupled Model Intercomparison Project (CMIP) is considered 'society's most robust and reliable source for climate information' (Carlson, Eyring, van der Wel, & Langendijk, 2017). It is a platform for climate researchers and institutions worldwide to develop, share, compare and analyze global climate models. By setting standards and protocols, the CMIP ensures consistency and comparability. The models included in the CMIP are thus used in a majority of climate research papers, such as the IPCC assessment reports (Carlson et al., 2017). Models from the most recent Phase 6 have been selected as they provide higher resolution and new processes not included in the previous models, thus, being possibly the most accurate climate models we have today (Kim, Min, Zhang, Sillmann, & Sandstad, 2020; Langendijk & Carlson, 2017). Furthermore, Kim et al., (2020) identified that the advantage of CMIP6 over CMIP5 is that they have a reduced bias in extreme temperature indices over South America and better simulations for extreme precipitation over tropical and subtropical regions, which is particularly relevant for this analysis. Moreover, CMIP6 GCMs include the newest climate scenarios based on the 'Shared Socio-economic Pathways' (SSP) and 'Representative Concentration Pathways' (RCP) (O'Neill et al., 2016).

The RCP are scenarios for possible changes in future greenhouse gas (GHG) emissions and radiative forcing, which have been used for previous assessment reports by the IPCC (O'Neill et al., 2016). The SSPs have been developed to represent five possible future narratives, using demographic, economic, political and technological developments. Each scenario indicates the society's adaptation and mitigation ability to climate change in the presence of different climate policies (O'Neill et al., 2016; Riahi et al., 2017). By combining the SSPs with RCPs, forcing pathway combinations are created which represent possible integrated scenarios for climate and societal change (O'Neill et al., 2016). The possible combinations are depicted in a matrix provided in Appendix C. For a full description of the scenarios and their combinations see O'Neill et al. (2016).

For this analysis, the SSP245 scenario is used, which is a combination of the SSP2 and RCP4.5. The SSP2 is described as the 'Middle of the Road' and envisions a socio-economic development where historical trends and patterns are continued, the progress in achieving the SDGs is slow and thus societal and environmental issues remain, although some improvements are being made (Riahi et al., 2017). Similarly, the RCP 4.5 represents an intermediate scenario, often considered the most probable baseline scenario if no climate policies are implemented, leading to a temperature increase between 2 to 3°C (O'Neill et al., 2016). Hence, the SSP245 scenario provides a likely future prediction if we do not manage to change our current climate change strategy drastically.

The CMIP6 provides a multitude of models from different research institutes using the SSP245 scenario. Criteria to identify models suitable for this analysis are that they provide daily values for precipitation and maximum temperatures as well as historical data. Additionally, by consulting the research by Kim et al. (2020), who compared the performance of GCMs in the CMIP6 to reanalyses such as ERA5 in modeling climate extremes, the best performing models for modelling temperature and precipitation extremes, have been selected. Accordingly, the CNRM-ESM2-1, the IPSL-CM6A-LR and the MRI-ESM2-0 model are used to create an equal-weighted multi-model mean. The advantage of using a multi-model mean over single-model forecasts is that while each model has its uncertainties resulting from parameterization, initial and boundary conditions, the combination of multiple models 'increases the skill, reliability and consistency of model forecasts' (Tebaldi & Knutti, 2007, p.2055).

An additional check for consistency and coherence of the CMIP6 models is added through a comparison to an ERA reanalysis dataset provided by the Copernicus Climate Change Service. The ERA reanalysis datasets provide reliable data for many relevant climate variables. It is a widely used dataset across the climate change literature because it creates complete and accurate descriptions of past and present climates across the globe at any given time by combining historical observations with modeled data (ECMWF, 2020). Thus, for the season September to May in the time period 1981 – 2020, maximum temperature and total precipitation for the area 34°S to 6°N and 74°W to 34°E have been downloaded from the 'ERA5 hourly data on single level from 1979 to present' dataset.

Model Validation

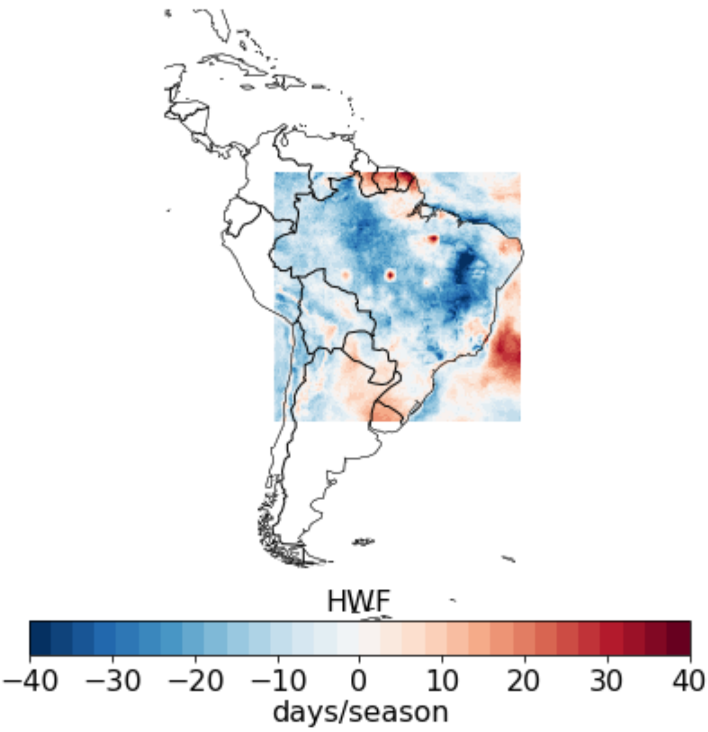
The validation of the Multi Model Mean (MMM) is made by calculating the seasonal values of Heatwave Frequency (HWF, see Table 1) and the SPI for the present time period 2011-2020 based on the baseline period 1981-2010 for both, the ERA model and the MMM of the 3 GCMs. The values from the ERA model are then subtracted from the MMM, creating maps displaying the differences between the GCM's MMM and the reanalysis data (ERA) for HWF and SPI.

Regarding the HWF, as shown in Figure 3, blue values represent areas in which the ERA model predicts more heatwaves than the MMM. Thus, for the time period 2011-2020, the ERA model generally predicts around 20-30 more HW days during the season (September to May) than the MMM, especially in the North-East region. Similarly, the magnitude in SPI values for dry and wet periods is stronger in the ERA model than in the MMM. However, the patterns are similar in both models (see Appendix D1 (D2) for HWF (SPI) values for ERA, MMM and their differences).

Overall, the differences in the heatwave days and the SPI values are not too strong, making the use of the MMM appropriate.

Figure 3

Difference in HWF between ERA5 and GMM for 2011-2020 during the season September-May



Data Analysis Procedure

Timeframe

Since CHDE events will impact soybean production if they occur during the growing season, the timeframe for the analysis is set from September until May (Gusso et al., 2014; Hamed et al., 2021). As a baseline, the timeframe 1981-2010 is used and the future prediction covers the time period 2035-2064. Both are 30-year time periods to account for climatological variability. The baseline period was limited by the data availability of the ERA5 dataset, nonetheless, it represents a relevant time when it comes to soybean production. Current intensive soybean production has only started in the 1970s in Brazil (see Appendix E), thus the time period represents a climate in which soybean production was very effective (de Sowa & Busch, 1998). Mid-century is a relevant future time period, as possible changes in climate will require adaptation and mitigation strategies to be employed now and it is in line with the current policy frameworks where commitments to climate adaptation and mitigation are made for the years 2030 and 2050 (IPCC, 2018). Furthermore, end-of-the-century projections are more uncertain (S. Zhang & Chen, 2021).

Heatwaves

Given the huge impact extremes can create in just a matter of days, this research adopts the definition used by Feron et al. (2019), Ridder et al. (2020) and Russo et al. (2014) who define a heatwave as at least 3 consecutive days during which the maximum daily temperature exceeds the calendar day 90th percentile. This definition is similar to the ETCCDI's (Expert Team on Climate Change Detection and Indices) definition of Warm Spell Duration Index as an 'annual count of days with at least 6 consecutive days when daily maximum temperatures > 90th percentile' (X. Zhang, 2009). Due to this definition, daily data is needed (Perkins, 2015).

Using daily maximum temperatures instead of daily average temperatures is relevant as crops can be damaged by too high temperatures (Luo, 2011; Viana et al., 2013). Furthermore, using a relative-based threshold such as the 90th percentile is preferred over heatwave indicators for different impacts or sectors, such as health, wildfires or power, as it is transferable across regions and time (Perkins, 2015; Russo et al., 2014). This transferability is important as crops can be accustomed to different temperatures and temperature variabilities across the season and regions (Hamed et al., 2021; Luo, 2011; Viana et al., 2013). The 90th percentile has similarly been used by Lu et al. (2018) and by Hamed et al. (2021) when analyzing the impacts of CEHDs on wheat and maize in China and soybean yields in the US, respectively.

In order to identify heatwaves, as a first step, the dynamic climatological average daily maximum temperature (DCATXx) for each calendar day is determined. The DCATXx is calculated by aggregating 15 days centered on each calendar day during the season for the 30 years reference period from 1981-2010. Thus, in total data from 15 days for 30 years for one calendar day are used to calculate the DCATXx. By using a dynamic average value, one can account for the within-season variability of temperature and thermal tolerance of the crop at different growth stages (Lu et al., 2018) and it makes the reference value for further calculations more robust and less susceptible to outliers. Secondly, to identify the heatwaves for the baseline period, each daily maximum temperature recorded for the past

(1981-2010) will be compared with the dynamic climatological average of that respective day. If the temperature is above the 90th percentile, it is classified as an Extreme Heat Day (EH). As a third step, in order to identify a heatwave, the extreme hot days are filtered, with the condition that at least 3 consecutive days need to be above the 90th percentile. From that, the indicators presented in Table 1 can be calculated.

Table 1

Indicators for the characterization of heatwaves

Indicator	Description
Heatwave Number (HWN)	The number of heatwaves within a season (September to May)
Heatwave Duration (HWD)	The length (in days) of the longest HW during the season
Heatwave Amplitude (HWA)	The highest temperature anomaly (in °C) of a HW day, i.e. the difference between the temperature at the 90th percentile and the actual recorded temperature, during the season
Heatwave Frequency (HWF)	Number of HW days per season
Extreme Heat Days (EH)	Number of days with temperatures above the 90^{th} percentile during the season
Heatwave Day above 35°C	Number of HW days per month on which the temperature is ≥ 35°C

Note. Adapted from 'Observations and Projections of Heat Waves in South America' by Feron, S., Cordero, R. R., Damiani, A., Llanillo, P. J., Jorquera, J., Sepulveda, E., … Torres, G. (2019). *Scientific Reports*, *9*(1), 8173, https://doi.org/10.1038/s41598-019-44614-4.

The same procedure is employed for the time period 2035-2064, starting at step 2: The daily maximum temperatures predicted for 2035-2064 are compared to the DACTXx for the time period 1981-2010 and the 6 indicators are calculated. To identify changes between the two periods, values calculated for the past time period are subtracted from the future time period.

Droughts

In order to identify droughts, the Standard Precipitation Index (SPI) is used. It is a good measure for droughts due to its simplicity by only using precipitation data. Despite this simplicity, it has proven to work accurately also compared to more complex indices such as the Standard Precipitation Evapotranspiration Index or the Palmer 'Drought Severity Index (Balbo et al., 2019; Tigkas, Vangelis, & Tsakiris, 2019). However, if there are extreme changes such as a 2°C increase in temperature over 30 years, the SPI is not able to compute the effects of temperature increase to drought severity in terms of intensity and duration (Balbo et al., 2019). But since only the occurrence and frequency are being investigated, it does not impact the results of this research. Furthermore, Tigkas et al. (2019) evaluate the use of SPI in light of agricultural droughts and find that it is a widely used and effective tool for identifying droughts in agriculture.

The SPI is calculated using a long-term precipitation record of at least 30 years (WMO, 2012), hence, in this case for the season during the baseline period 1981-2010. Similar to the heatwave calculation, it uses 'moving averaging windows', called timescales (WMO, 2012). The timescales can vary from 1 month to 72 months. For example, if calculating the SPI for days in November, using a 1-month timescale, only the precipitation data for November is used, whereas on a 6-month timescale, the precipitation data from June to November is used (WMO, 2012). By using different timescales, the impact on different water resources is reflected. Soil moisture, for example, varies on shorter timescales, whereas groundwater storages only show an impact from long-term droughts for which long timescales should be used. The WMO (2012) suggests the use of 1 to 6 month SPI for agricultural droughts. In this research, a 1-month SPI will be used, as it is related to 'short-term soil moisture and crop stress, especially during the growing season.' (WMO, 2012, p.7).

The SPI is then expressed as the standard deviation of the precipitation from the calculated long-term mean of a fitted normal distribution (McKee, Doesken, & Kleist, 1993; WMO, 2012). However, as precipitation is not normally distributed, the SPI requires a transformation from a better fitting distribution to a normal distribution. In this case, the gamma distribution is used, as it is understood as a reliable fit for precipitation distributions (McKee et al., 1993; WMO, 2012). Daily precipitation values are then being compared to the standardized values and their deviation from this mean value gives an indication of how dry or wet the day is. This results in the drought classification shown in Table 2. For this research, a day identified as extremely dry, indicating drought, is defined when the SPI value is <= -2.

Table 2

Interpretation of the SPI values

SPI	Cumulative Probability	Interpretation
≤ -2	0.0228	Extremely dry
-1.5	0.0668	Severely dry
-1.0	0.1587	Moderately dry
-0.5 – 0.5	0.305 – 0.6915	Near normal
1.0	0.8413	Moderately wet
1.5	0.9332	Very wet
≥ 2	0.9772	Extremely wet

Note. Adapted from 'Standardized Precipitation Index (SPI)' by NASA (n.d.), https://gmao.gsfc.nasa.gov/research/subseasonal/atlas/SPI-html/SPI-description.html

Compound Extreme Hot and Dry Events

The definition of a CHDE is what Zscheischler et al. (2020) describe as a multivariate compound event, hence, a day on which hazards, i.e. heatwaves and droughts, occur simultaneously at the same location. In order to identify the CHDE using climate data, the binary mapping strategy as described by Ridder et al. (2020) will be used. First, for each hazard a binary map will be created that appoints to every position (latitude & longitude) at each time step (day) either a 0 (the hazard does not exceed the threshold) or a 1 (the hazard exceeds the threshold). This creates two matrices X and Y (one for heatwaves and one for draughts) of the size time x latitude x longitude containing the values 0 and 1. Each element in the matrix is displayed as a capital letter with the subscript 'i'. As a second step, those two matrices will be compared, creating a third matrix Z of the same size, again containing the binary values 0 and 1. The values will be assigned based on the following criteria:

$$Z_i = \begin{cases} 1, \ (X_i = 1 \wedge Y_i = 1) \\ 0, \ \text{otherwise} \end{cases} \quad (1)$$

Meaning, only if both hazards exceed their respective threshold at the same time and location, Z will indicate a 1, to indicate a compound climate event. Using this matrix, the number of CHDE per season and per month can be calculated. This can be used to compare the difference between the two time periods.

In order to answer the research question(s), the number of CHDE are calculated for each month during the soybean's growing season for the baseline and future time period. To identify trends, their anomaly, i.e. the difference in the number of occurrences between the two periods, is calculated as well. Secondly, mapping the CHDE during the different months brings their occurrences into relation with soybean production. It helps to identify whether they will occur in areas of soybean plantations and whether they occur in very sensitive time periods during the soybean's production cycle. Additionally, given the concerns brought forward by Bevacqua et al. (2022) and the third research aim, the two hazards, heat and drought, are investigated individually.

Results

Trends in CHDE Occurrences in Brazil

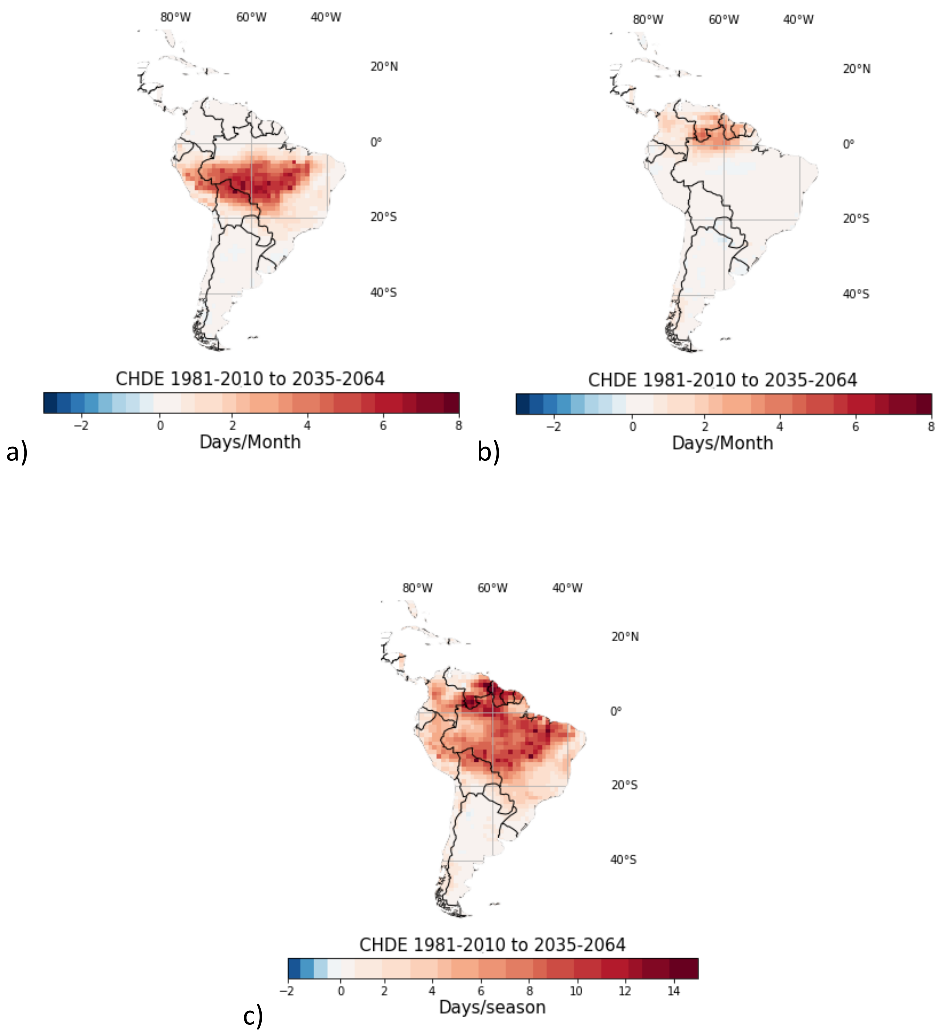
In the baseline period, the average maximum number of CHDE per month was less than 1 occurrence, meaning that in most years, almost no CHDE occurred. The likelihood was the highest during September and May in the Central-West and South of Brazil. In comparison, for the period 2035-2064, the multi-model mean predicts an average maximum of 5 CHDE for all months in the season, with September registering a maximum of 8.5 and December the lowest maximum of 1.13 events. Again, the Central-West area is affected strongly, particularly in September, October and May, while during the austral summer months, the northern states Roraima, Pará, Amapá and Maranhão register the most CHDE (See Figure 4a and b for selected months, for a complete overview see Appendix F). Comparatively, in both periods, the months from December until April are less affected by the occurrence of CHDE than the rest of the season.

Looking at the difference between the two periods, Figure 4c illustrates the difference of CHDE occurrences for the whole season. In no region CHDE seem to decrease. Instead, there is an increase of ca. 8-12 CHDE, especially in Central-West, North and North-East Brazil. Given that there were almost no CHDE during the baseline period, it is not surprising that those changes are driven by changes during the months September, October and May in the regions outlined above, as those months and regions are predicted to have the most CHDE.

As the CHDE are driven by heatwaves and droughts, a further analysis of the two drivers provides a clearer picture of the complex CHDE and its characteristics. Thus, in the following, trends in the heatwave characteristics (for an overview of all maps see Appendix G) and SPI (for an overview of all maps see Appendix H) are outlined.

Figure 4

Difference in CHDE between time periods 1981-2010 and 2035-2064 for a) September, b) March and c) the whole season (Sep-May)



Heatwave characteristics

Heatwave Frequency and Extreme Heat Days

The number of Extreme Heat days (EH) denotes the number of days that record a temperature above the 90th percentile. Thus, during the baseline period 27.5 days (10% of the 275 days of the season) are considered EH days. The heatwave frequency describes how many of those days are taking place in a sequence of at least 3 days. During the baseline period a minimum of 6 up to 22 days, with a mean of 15 days, are identified as HW days. Thus, around half of the days that are considered an extreme heat day, are a heatwave day.

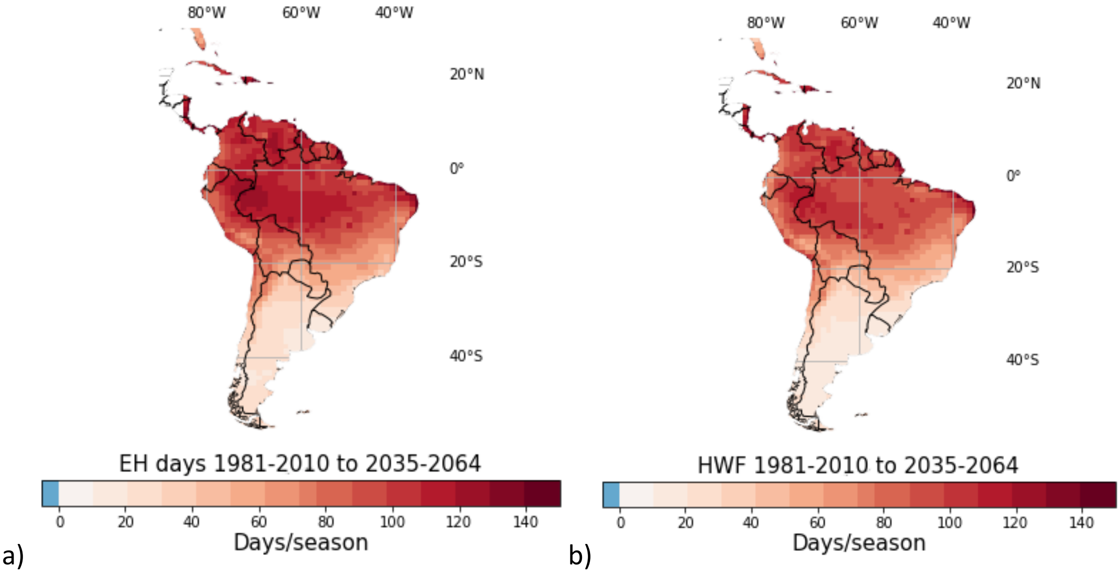
Comparing the baseline period to the predictions for 2036-2064, the number of EH days is anticipated to increase to a minimum of 14 days up to a maximum of 233 days. On average, 103 days are predicted to exceed the 90th percentile of the baseline period, pointing towards an increase in extreme temperature during the investigated season (see Figure 5a). Out of those EH days, an average of 98 days fall under the category of HW days. This means that the number of HW days is more than 6 times of that of the baseline period and that more than ⅓ of the season reach temperatures that are considered a HW, based on the temperature values of the baseline period (See Figure 5b). Furthermore, extremes of about 240 HW days can be reached in some areas.

As depicted in Figure 5, the increase in EH and HW days is taking place almost everywhere in Brazil, more strongly however in Central-West, North and North-East regions. The South and South-East of Brazil are less affected.

Summed up, for the future time period under the SSP245 scenario, more days are predicted to exceed the climatological 90th percentile. Out of those days, the majority of days can be considered heatwave days.

Figure 5

Increase in a) EH days and b) HWF



Heatwave Number and Duration

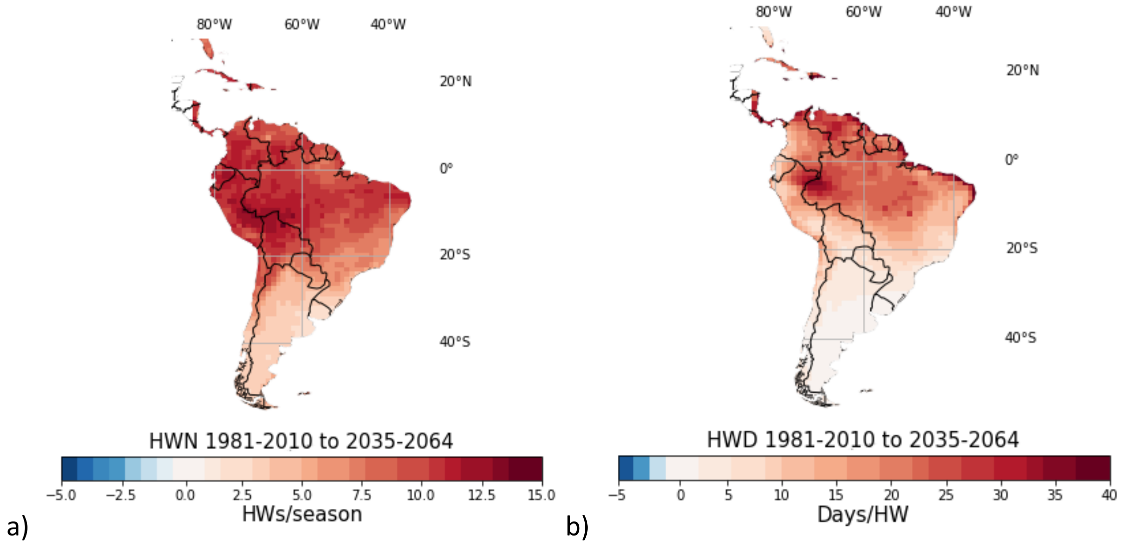
An increase in heatwave frequency could either lead to an increase in the number of HWs or an increase in the duration of HWs. To distinguish between these two, the indicators HWN, describing the number of HWs occurring during a season, and HWD, which calculates the average duration of a HW in a region per season, will be used.

Figure 6a depicts the increase in HWN from 1981-2010 to 2035-2064. On average, in one season (September – May) there will be around 10 to 12 more HWs for most regions. Considering that during the baseline period, 3 HWs occurred on average, there is a three- to four-fold increase over the observed time span.

Next to the number of HWs, their duration also increases, particularly in Central-West, North-East and North Brazilian states (particularly in Mato Grosso, Tocantins and Goiás, along the northern coast and the western border of Amazonas). While HWs were around 5 to 10 days long in the baseline period, they will increase on average by 30 to 40 days in Central-West, North-East and North Brazil and by around 10-20 in most other regions, as shown in Figure 6b. Thus, heatwaves will become more frequent and longer, with some heatwaves lasting for more than a month.

Figure 6

Increase in a) HWN and b) HWD



Heatwave Amplitude and Absolute Temperatures

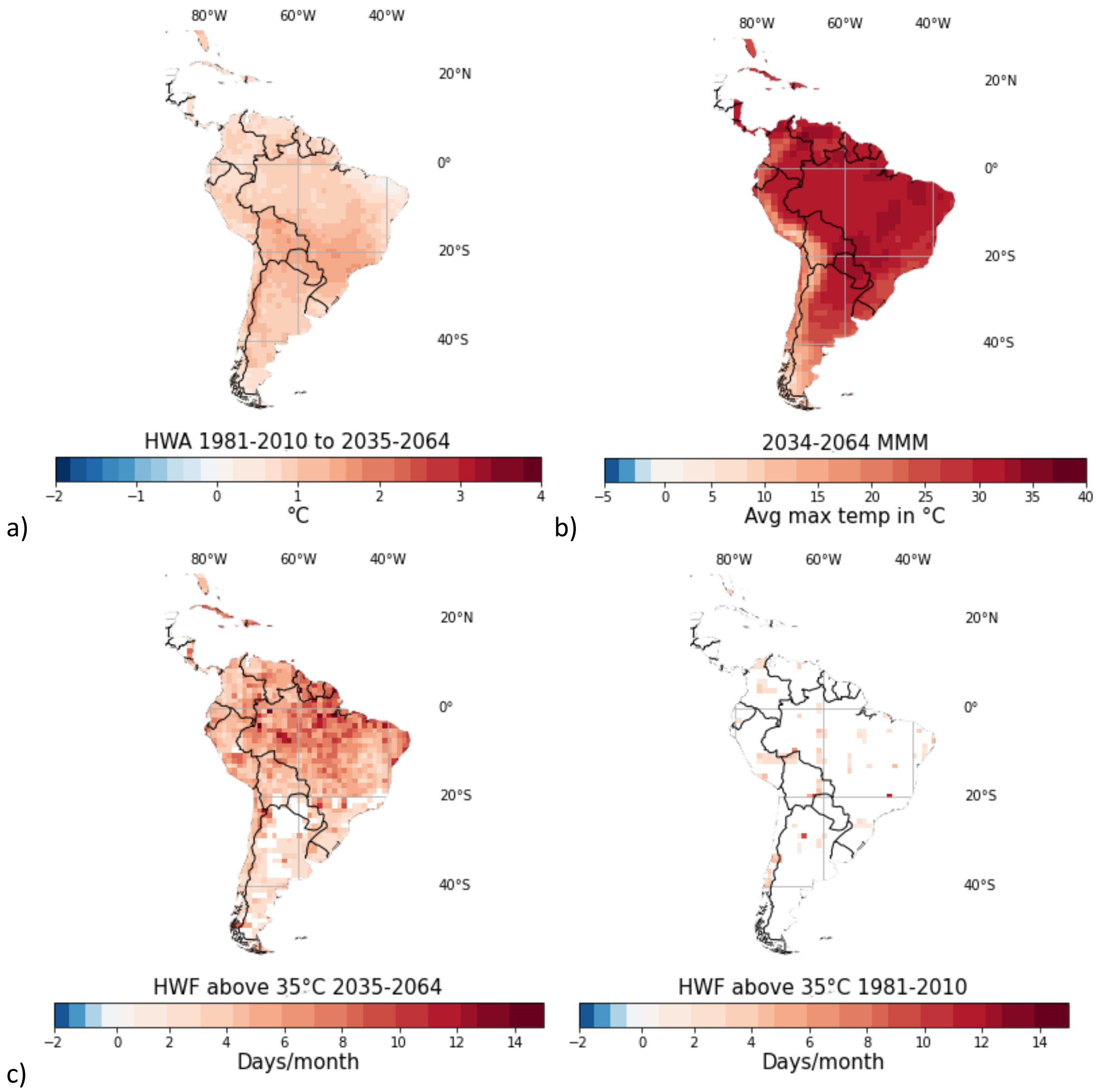
The last indicators discussed in this paper to describe heatwaves is the heatwave amplitude (HWA) and absolute temperatures. The HWA shows the difference between the temperature on the hottest day of a HW during a season minus the climatological 90th percentile temperature of that day. An increase in HWA would indicate that not only the number of hot days increases (by an increase in the temperature on the days below the 90th percentile) but also that the hot days become hotter.

There is a slight increasing trend in the HWA which ranges from 0°C - 5°C for the baseline period and from 1°C to 6°C for the future time period. In Figure 7a one can see that, particularly in the south of Brazil, there is an increase in the HWA of 1-2°C.

Since the amplitude does not give an indication on absolute temperatures, which are relevant for crop production, a map of the average maximum temperature for the future time period and the average number of HW days with temperatures above 35°C for September during the baseline and future time period are displayed in Figure 7b and c (for an overview of all months see Appendix G4). It clearly shows that Brazil's maximum temperatures will be at around 30°C-35°C and that ca. 4-10 HW days per month (depending on the month and region) will exceed the 35°C threshold compared to almost no HW days with temperatures higher than 35°C during the baseline period. Considering that there are around 10-20 HW days per month (see Appendix G3), around half of the HW days reach temperatures higher than 35°C.

Figure 7

a) HWA difference between 19810-2010 and 2035-2065, b) absolute maximum temperature averaged over the season for 2035-2064, and c) number of HW days above 35°C for September 1981-2010 and 2035-2064



Standardized Precipitation Index

Next to increasing temperatures and more heatwave days, the question is what the role of changes in precipitation is. Are CHDE occurring more frequently due to an increasing HWF which results in a more likely co-occurrence of a HW day with a dry day? Or are dry days increasing simultaneously?

Generally, the season investigated can be divided into 3 categories based on the SPI: September, October and May are dry months, November, March and April are transitional months and December to February are predominantly wet months (see Figure 8).

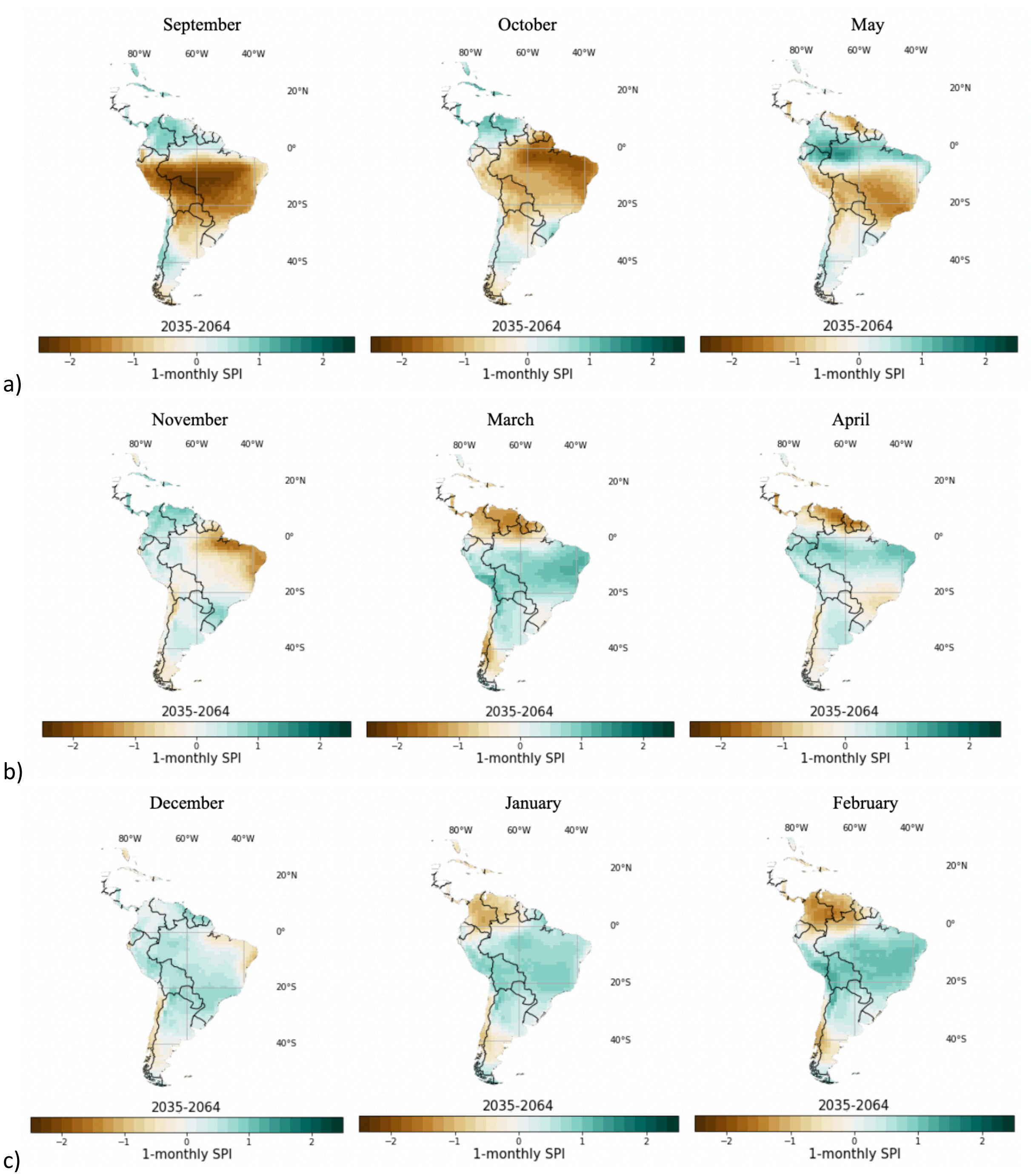
During the dry months for the period 2035-2064, almost all of Brazil can be considered extremely dry with SPI values lower than -1,5. Only the areas in the South and North of Brazil make an exception as they are least affected by droughts during these 3 months. For example, in October and May, regions in Santa Catarina and Rio Grande do Sul are even characterized as near normal to moderately wet.

During the transitional month November, Central-West, South and most areas in North and South-East Brazil are considered near normal to moderately wet, however, the North-Eastern coastal area still experiences droughts. In the transitional months of March and April, the pattern is reversed, with South, South-East and Central-West Brazil being characterized by dryness, whereas North Brazil and the North-Eastern coast experience precipitation. From December until February, Brazil is dominated by rainfall, making it normal to moderately wet.

In comparison to the baseline years, the patterns of drought and wetness stay the same, however, there are slight intensifications for each precipitation characteristic. Meaning, areas affected by drought become drier and areas affected by (heavy) rainfall, receive more rainfall (see Appendix H1). This, for example, turns areas during February, March and November that are considered moderately dry (-1) in the baseline period into severely dry areas (-1.5) in the future time period. Likewise, severely dry areas during September, October and May are turning into extremely dry areas (-2) or are getting close to the threshold. Overall, there is, however, not a large increase in areas considered extremely dry (-2) which is the threshold to be considered relevant for CHDE in this research.

Figure 8

SPI values for future time period 2035-2064 for a) dry months, b) transitional months, and c) wet months



Discussion

Trends in CHDE Occurrence in Brazil

The initial objective of this research was to identify the trend in the frequency of occurrence of CHDE in Brazil during the production season of soybeans. To reach this aim, a comparison of the modeled CHDE during the baseline and future time periods has been performed, which indicates that there are strong increases in CHDE during the months September, October and May. In contrast, the austral summer months are less affected, with CHDE mainly occurring in northern regions. During September, October and May, the likelihood for a CHDE to occur has increased five-fold and they specifically occur in Central-West and South of Brazil. Considering that there were almost no CHDE occurrences during the baseline period, this increase shows that Brazil will have to deal with unprecedented climate extremes.

Next to occurring more frequently, we can also assume that the CHDE will last for an extended period of time due to the increase in HWD. An implication of this is the possibility that the crops are exposed for a longer time to such extreme conditions, increasing the likelihood of crop damage and reduced capacity to recover (Hamed et al., 2021).

Individual Contributions of Heat and Drought to CHDE

By looking at the individual trends for heatwaves and droughts, one can identify the drivers for this increase in occurrence. As outlined in the Results section, there are no changes in the pattern of droughts and only few areas with a decreasing SPI to below -2 (i.e. an increase in drought). Hence, it seems less likely that the increase in CHDE is driven by changing intensity and patterns of drought but rather by a change in HWF. As mentioned in the Results, HWF increases substantially during the whole season and there are certain months during which HWF increases the most, such as September and May. Those are the same months during which the most CHDE occur because the increase in HWF overlaps with the dry periods. Thus, the increase in CHDE is driven by an increase in HWF.

Overall, this observation goes hand in hand with the statements by the IPCC (2021), predicting that already an increase in temperature will increase CHDE as it increases the likelihood of co-occurrence. As a result, where the CHDE will take place is determined by where droughts will occur because temperatures (and consequently heatwaves) will increase in almost every region. In this case, this is shaped by the seasonal patterns in Brazil, where during austral spring, drought is more prevalent in northern and central regions, whereas during austral spring and fall, it is dominant in southern and central Brazil. This is in line with the argument by Bevacqua et al. (2022) that due to an overall increase in temperatures and thus heatwaves, the occurrence of CHDE is determined by the precipitation patterns, hence the areas droughts occur. Furthermore, regarding spatial trends in Brazil, changes in precipitation patterns do not seem to be extremely different to the past, although they will become stronger (in both directions, wetter and drier). Consequently, the areas that will be affected by CHDE are the areas that are currently already affected by droughts.

Relating CHDE to Soybean Production in Brazil

In Central-West Brazil, CHDE primarily occur during the planting season, in September. While the reproductive stages during which water demand is highest are not affected by CHDE, the planting season is still a sensitive period to CHDE occurrences. In cases of drought during the planting season, planting might be delayed (Yadav-Pauletti, 2021). This can affect plant growth negatively, as for example Mato Grosso indicated a decrease in biomass compared to the previous season in 2020 due to insufficient rainfall early in the season (Yadav-Pauletti, 2021). Furthermore, if planting is delayed, other weather conditions might change. For example, flowering during the right photoperiod is critical for soybeans (de Avila et al., 2013). Thus a delay in planting could potentially misalign the photoperiod with the flowering stage of soybeans.

In southern and southeastern states, CHDE coincide mainly during the harvest season. While there has been little research on how drought, heat or CHDE affect soybean yield during the end of its production cycle in Brazil, Hamed et al. (2021) indicate that the greatest reductions in soybean yield in the US are caused by CHDE occurrences at the end of the season. Although it has not been quantified how strongly soybean production will be affected by CHDE in Brazil, based on the research by Hamed et al. (2021), one can say that a risk of decreased yield production is likely. More research to quantify this risk is needed in Brazil.

Lastly, an unexpected finding of this research is regarding northern and northeastern states. Viana et al. (2013) state that there is a plan to expand production in Maranhão, Piauí, Tocantins and Bahia due to favorable weather conditions such as optimal temperatures. However, this decision is based on investigations conducted during the early 2000s without considering future climate developments. Yet, this research shows that the most northern regions in those states are where CHDE will frequently occur during October, November and January until April. Hence, it is the region where CHDE will occur during the most vulnerable states of the soybean production cycle.

Taken together, these results show an overlap between critical growing stages of soybeans and the occurrence of CHDE. Considering the absolute temperatures, around half of the HW days record temperatures above 35°C. Therefore, it is very likely for a CHDE to exceed the viable temperature range of soybeans, of 20-35°C, with the ideal temperatures being at around 25°C-30°C. At temperatures above 35°C, soybean crop quality and yield have been recorded to be highly impacted. Since this is combined with drought, soybean production can be expected to decrease in the near future.

Albeit the most critical stages of the soybean production cycle are not as strongly affected by the occurrence of CHDE, their occurrences at the beginning and end can still negatively affect crop production. It might delay planting and thus misalign other crucial climate factors (i.e. appropriate photoperiod), consequently leading to decreased production.

Furthermore, the results suggest that cropland expansions should be planned by taking into account future climate developments. For example, according to the findings of this research, cropland expansion plans proposed by Viana et al. (2013) based on research from the 2000s, would not be seen as beneficial.

Limitations

This research has shown an upward trend in CHDE occurences that can potentially impact soybean production. Yet, its magnitude might have been underestimated due to the choice of the models. As seen in the validation with the ERA5 model, the MMM displays a lower HWF and weaker droughts. This could mean that the trends might be even stronger than displayed here. Thus, to ensure higher reliability of the MMM, more models would need to be used. Using three models is sufficient for a general idea of the trends, however, adding more models can yield more robust results.

The suggestion to use further models to receive more robust results is supported by the analysis of the model spread. By calculating the standard deviation (SD) of the models' spread around the MMM, one can identify how close the models are to the MMM or if there are large deviations. The SD and MMM for each month can be found in Appendix I, showing that the SD is smaller than the MMM and that the variations are in an acceptable range. However, during May and November, the SD is almost as large as the MMM, suggesting that in these cases the models show different severity in their trends. Nevertheless, the general direction of the trend is clear, i.e. there is an increase in the number of CHDE, but the accuracy could be improved by including more models.

Another factor influencing the interpretation of the results is the use of thresholds, such as the 90^{th} percentile for heatwaves and a SPI value of -2. Although informed by literature, this method creates relative instead of absolute values, limiting the applicability to soybean production. Meaning CHDE could occur that are extreme for the season while still being in the soybean's tolerance range. On the other hand, the threshold for droughts has been set relatively high, which might have led to underestimations of CHDE. Looking at the precipitation patterns, there are only slight increases in areas reaching the threshold of -2. However, there are notable increases in drought, leading to areas becoming severely dry (-1.5) in the future. While those occurrences are not biophysically considered extreme in this research, they might still lead to relevant impacts, especially when combined with other climate events. The combination of heat and drought alone might be extreme enough at a -1.5 SPI level to impact soybean production, which is why further relevant events might not be captured with the approach of this research.

Even so, this does not negate the general findings, as it has been checked whether the CHDE pose a relevance for soybean production, i.e. by looking at the number of days above 35°C. Furthermore, the aim of this research was not to create an impact analysis but rather to locate potential threats, which now recommends further research to be conducted, such as modelling the quantitative impacts of CHDE on soybean production.

Lastly, one finding was that there could be delays in planting and the growing period due to droughts in September. To investigate this case further and identify whether the effects of drought might even drag into the growing season, a 3-monthly SPI has been calculated. The advantage of a 3-monthly SPI is that it is more sensitive to longer droughts. In this case, the months October, November and to a certain extent December are experiencing more drought than predicted with the 1-monthly SPI whereas in May it decreased **(**Appendix H2). Hence, further research into whether the 1- or 3-monthly SPI is more predictive for soybean crop losses would be beneficial.

Implications and Conclusion

The main goal of the current study was to identify the trends of CHDE in Brazil due to its local and global importance. Brazil is the biggest global producer and exporter of soybean, hence, impacts on its production, through, for example, climate events, can impact food security and can have economic consequences locally and globally. A focus on compound events has been chosen due to previous research indicating that it helps aligning climate modelling (as done in this research) with impact modeling (e.g. quantifying their effects on agriculture) and the finding that the combined effect of heat and drought is more detrimental to soybean production than their univariate counterparts.

This research has shown that there will be an increase in CHDE, which is mainly caused by an increasing number of heatwaves due to an increase in temperature rather than a change in intensity and duration of droughts. Furthermore, the study revealed that the CHDE will occur in areas of soybean plantations at a magnitude that could potentially cause crop losses. However, no quantification of crop losses has been made, which would be a fruitful task for further work.

Moreover, future research should consider investigating the austral winter period, i.e. from Mai to September, which has not been looked at in this research. As it is the drier period of the year, more CHDE might occur during those months. This dry period could potentially become part of a preconditioned compound event by impacting the planting of the soybeans. If the months prior to sowing are extremely dry, the soil might not be suitable for soybeans to germinate. For this reason, comparing results with SPI on different timescales and identifying the best timescale and thresholds to predict crop losses is suggested to be done in future research. Another area to look into would be wet and hot events. The SPI analysis has shown that austral summer months become wetter, which could cause plant diseases (Romero et al., 2022; Velásquez, Castroverde, & He, 2018), thereby impacting soybean production as well.

Moreover, research of this kind can and should be considered in agricultural planning as it can improve food security and production stability, thus, supporting the achievement of SDG 2. As mentioned in the discussion section, there are existing mismatches between future plans for the expansion of soybean production and climate developments in Brazil. The information provided by this research suggests that agricultural planning takes into account the environmental implications of climate change and that research into farming practices resilient to CHDE is undertaken. If soybean production is expected to produce similar or higher quantities in the future, it needs to adapt to the climate changes pointed out in this research.

Additionally, the finding that soybean plantations will be subject to more CHDE in the future underlines the importance of reconsidering the current food system. Soybeans are mainly produced as feed for livestock. While this is already seen as an unsustainable food production method (in terms of land, water and energy used to produce the same amount of calories), insecurities in soybean production caused by climatic factors, could make it even less feasible and sustainable to produce sufficient soybeans for livestock. Alternatives, such as a more plant-based diet, could relieve the pressure on agricultural areas and would not require as much yield (Ritchie & Roser, 2020).

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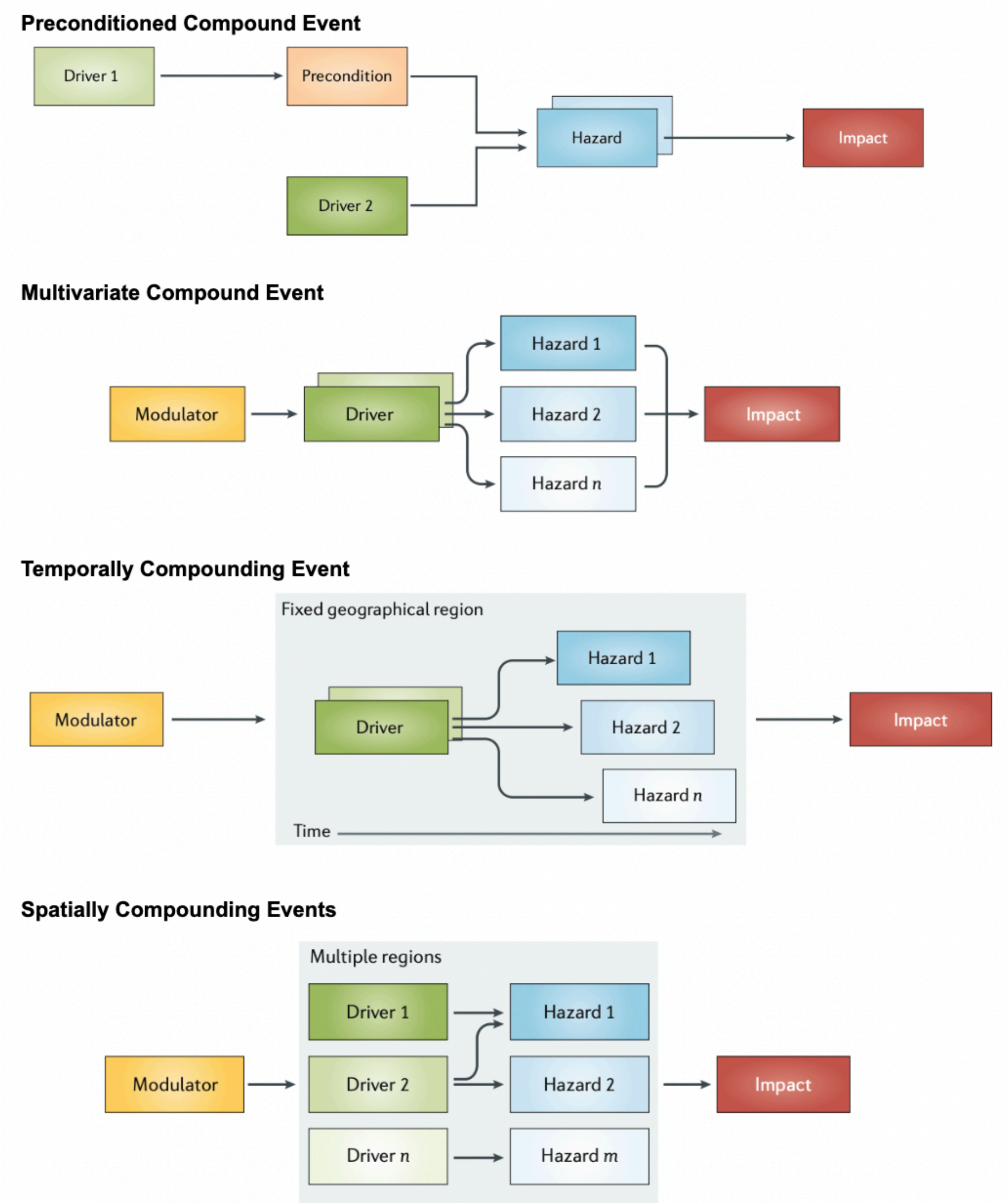
Codes Availability

The Python code (version 3.6.13), using matplot lib (version 3.3.4), used in this study is available upon request by the author.

Appendix A

Figure A1

Typology of Compound Events

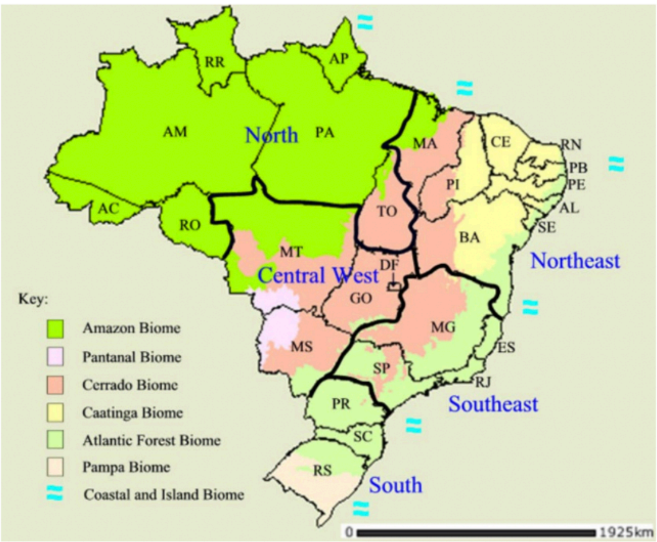


Note. From 'A typology of compound weather and climate events' by J. Zscheischler, O. Martius, S. Westra, E. Bevacqua, C. Raymond, R. M. Horton, … E. Vignotto, (2020), *Nature Reviews Earth & Environment*, *1*(7), 333–347 (https://doi.org/10.1038/s43017-020-0060-z). Copyright 2020 by Springer Nature Limited.

Appendix B

Figure B1

Overview of the regions in Brazil

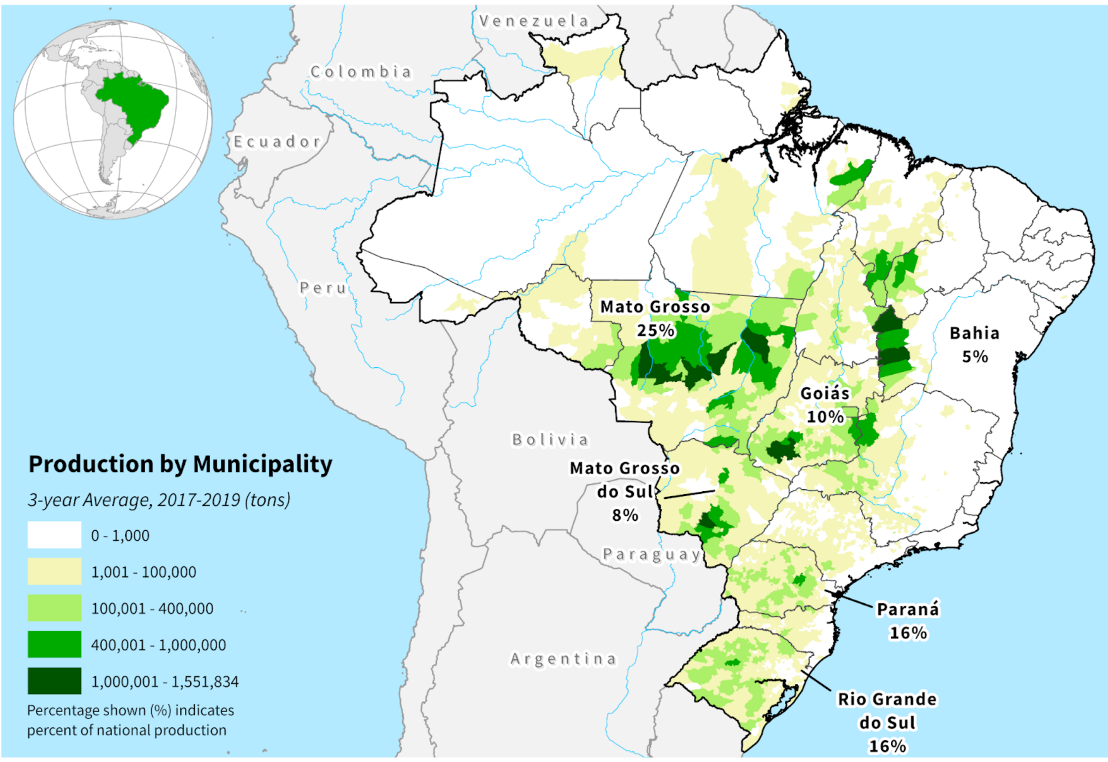


North: Amazonas, Pará, Rondônia, Acre, Roraima, Amapá, Tocantins
Northeast: Maranhão, Piauí, Ceará, Rio Grande do Norte, Paraíba, Pernambuco, Alagoas, Sergipe, Bahia
Central West: Mato Grosso, Goias, Federal District, Mato Grosso do Sul
Southeast: Minas Gerais, Espírito Santo, Rio de janeiro, São Paulo
South: Paraná, Santa Catarina, Rio Grande do Sul

Note. Adapted from 'Brazil Soybeans 2020/21: Another Season with a Record Harvest.' By S. Yadav-Pauletti, (2021). Retrieved from https://ipad.fas.usda.gov/highlights/2021/06/Brazil/index.pdf. Copyright by U.S.Department of Agriculture.

Figure B2

Overview of the main Soybean Production Areas in Brazil

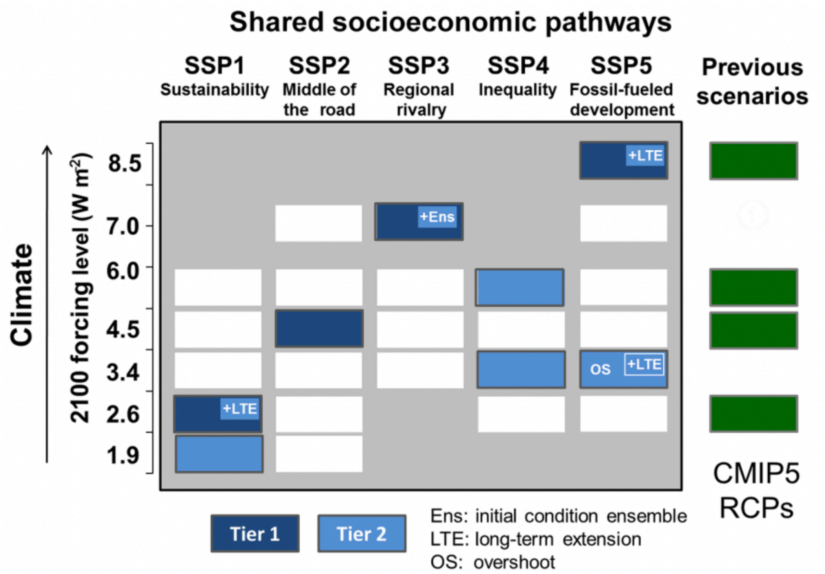


Note. From 'Brazil Soybeans 2020/21: Another Season with a Record Harvest.' By S. Yadav-Pauletti, (2021). Retrieved from https://ipad.fas.usda.gov/highlights/2021/06/Brazil/index.pdf. Copyright by U.S.Department of Agriculture.

Appendix C

Figure C1

Combinations of RCPs and SSPs

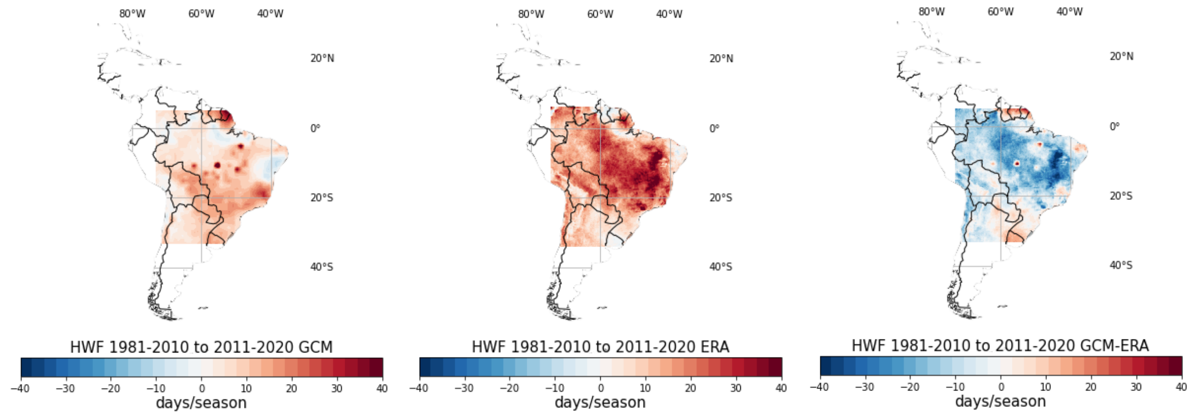


Note. Description provided by the paper: 'SSP-RCP scenario matrix illustrating ScenarioMIP simulations. Each cell in the matrix indicates a combination of socioeconomic development pathway (i.e., an SSP) and climate outcome based on a particular forcing pathway that current IAM runs have shown to be feasible (Riahi et al., 2016). Dark blue cells indicate scenarios that will serve as the basis for climate model projections in Tier 1 of ScenarioMIP; light blue cells indicate scenarios in Tier 2. An overshoot version of the 3.4 W m−2 pathway is also part of Tier 2, as are long-term extensions of SSP5-8.5, SSP1-2.6 and the overshoot scenario, and initial condition ensemble members of SSP3-7.0. White cells indicate scenarios for which climate information is intended to come from the SSP scenario to be simulated for that row. CMIP5 RCPs, which were developed from previous socioeconomic scenarios rather than SSPs, are shown for comparison. Note the SSP1-1.9 scenario indicated here is preliminary (see text)' (O'Neill et al., 2016). From 'The Scenario Model Intercomparison Project (ScenarioMIP) for CMIP6. ' by B.C. O'Neill, C. Tebaldi, D.P. van Vuuren, V. Eyring, P. Friedlingstein, G. Hurtt, … B.M. Sanderson, (2016). *Geoscientific Model Development*, *9*(9), 3461–3482. https://doi.org/10.5194/gmd-9-3461-2016. Copyright by O'Neill et al. 2016

Appendix D

Figure D1

Heatwave Frequency in Days per season (Sep to May) for the difference between the time periods 1981-2010 and 2011-2020 for MMM, ERA, MMM-ERA

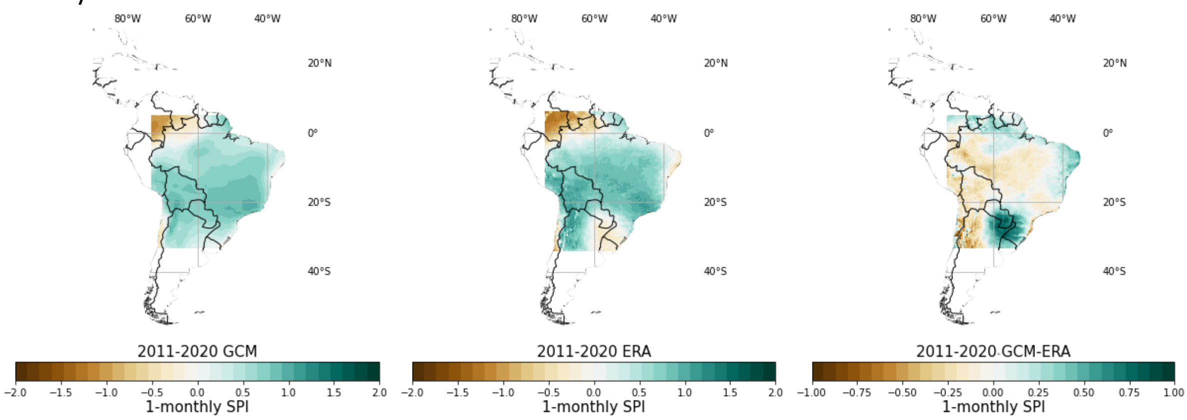


Note. Created by the Author.

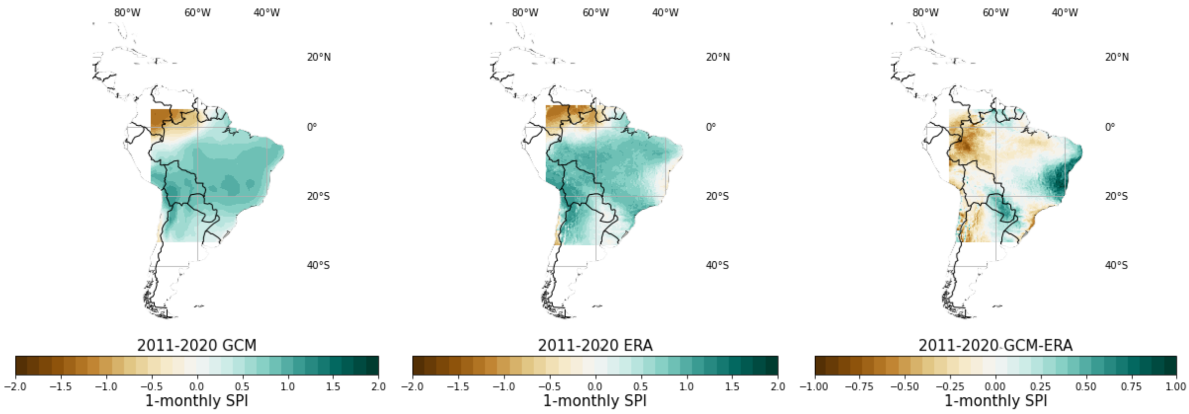
Figure D2

Monthly Standard Precipitation Index for 2011-2020 for MMM, ERA and MMM minus ERA

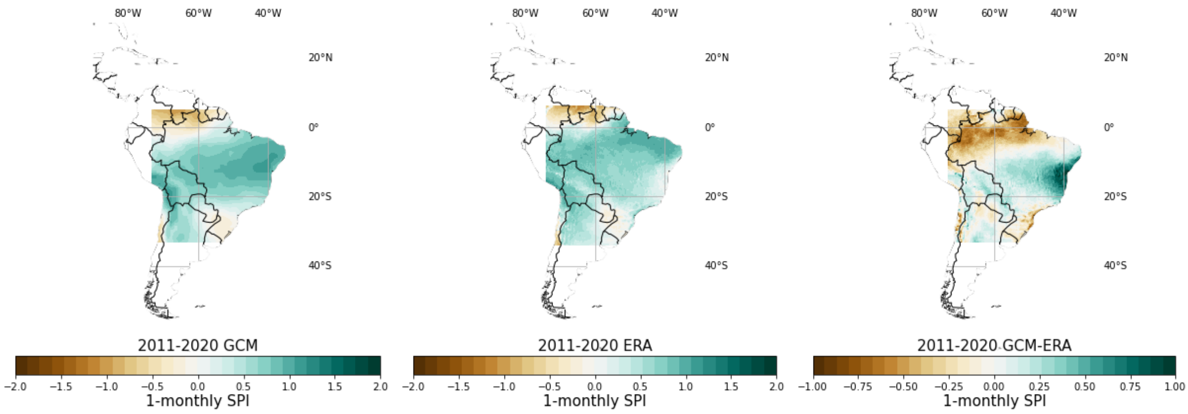
January



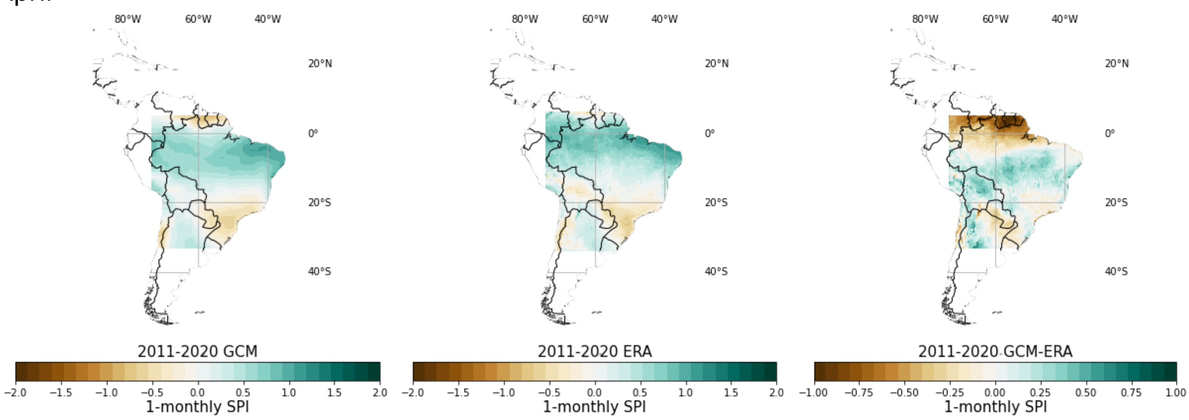
February



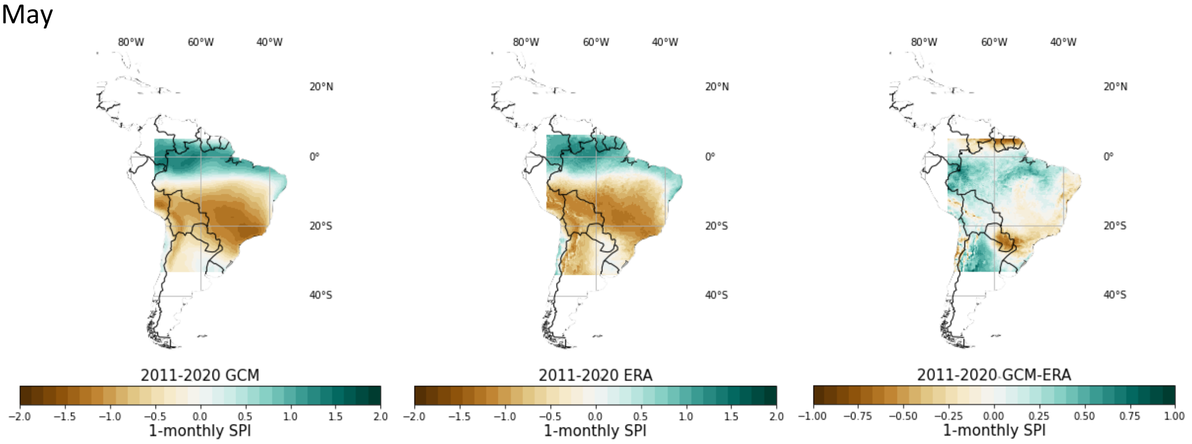
March



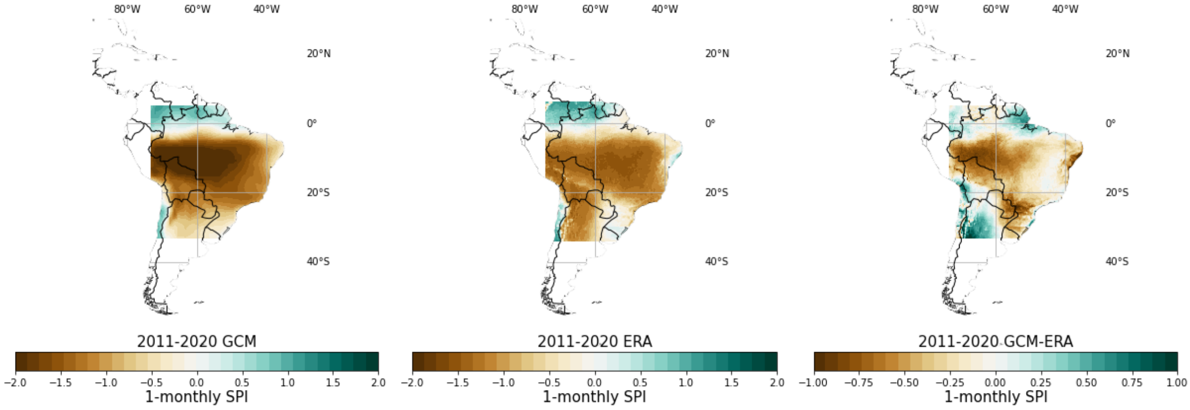
April



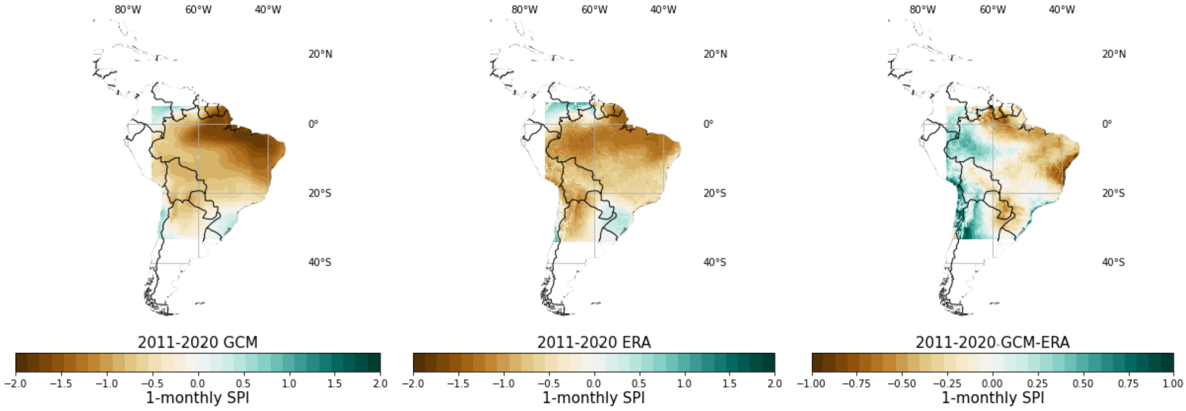
May



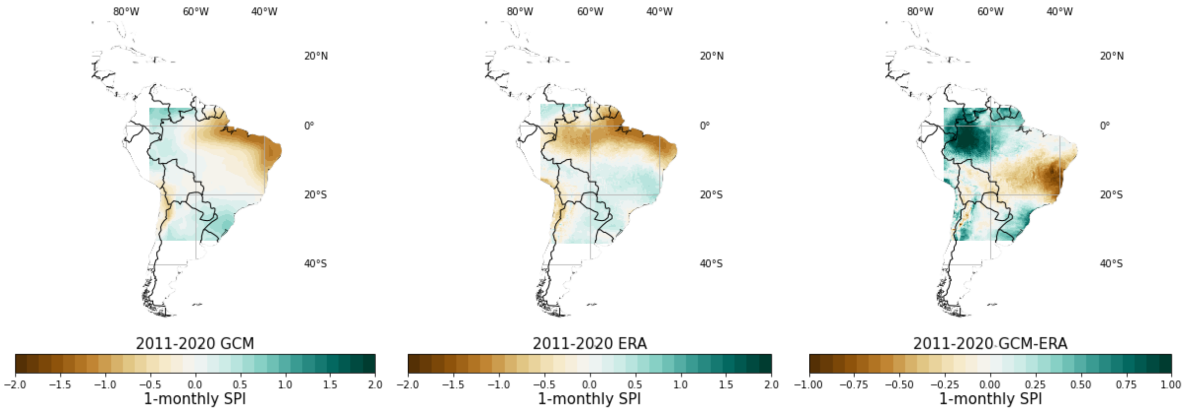
September



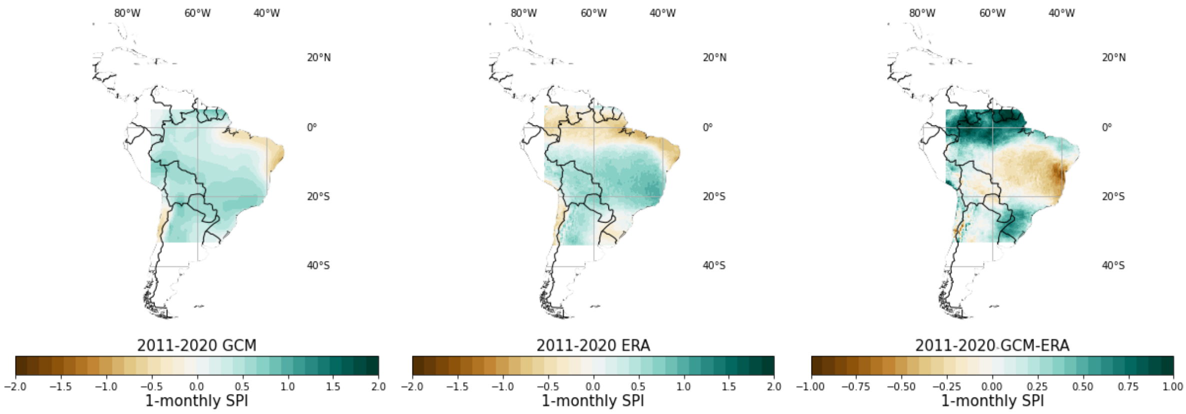
October



November



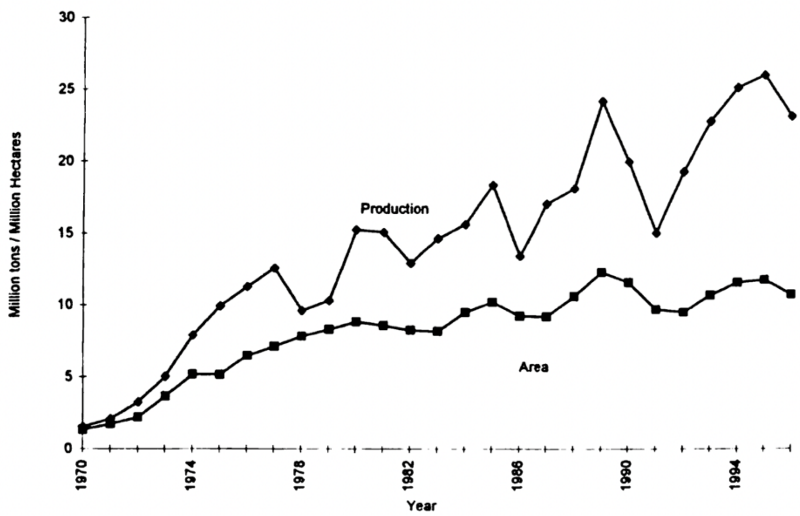
December



Appendix E

Figure E1

Trend in Soybean Production in the 20th Century



Note. Evolution of soybean planted area and production in Brazil, 1970-1996, From 'Networks and Agricultural Development: The Case of Soybean Production and Consumption in Brazil ' by I.S.F. de Sowa, & L. Busch, (1998). *Rural Sociology*, *63*(3), 349–371. https://doi.org/10.1111/ruso.1998.63.3.349, Copyright 1998 by the Rural Sociological Society

Appendix F

Figure F1

CHDE over Brazil for the time periods 1981-2010, 2035-2064 and the difference between the two periods, summarized per season (Sep to May)

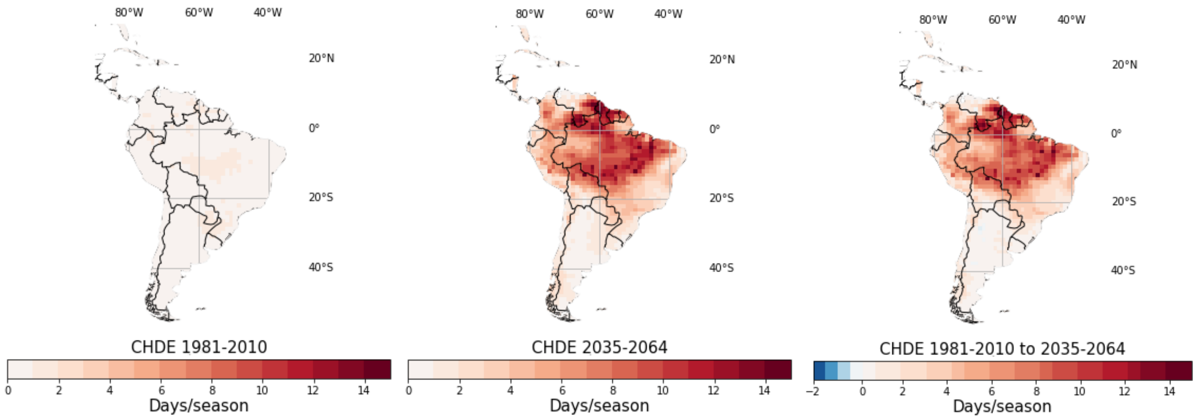
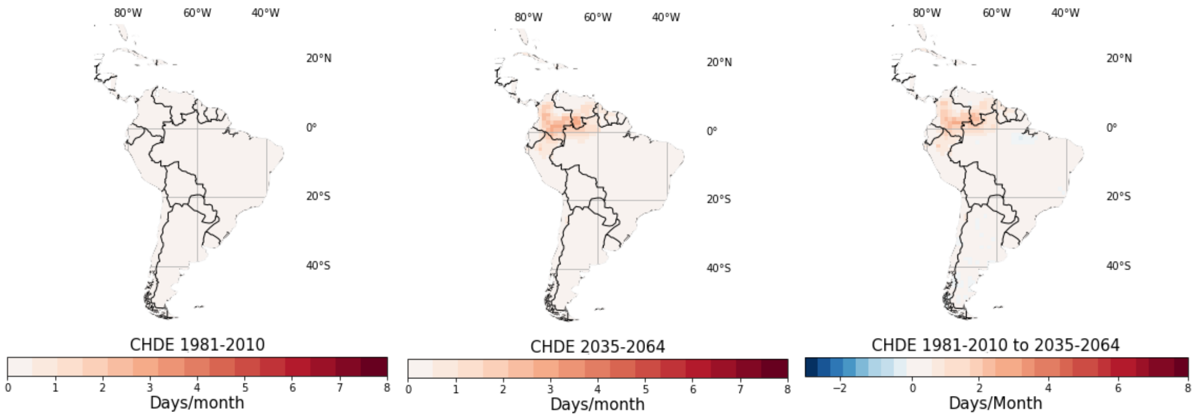


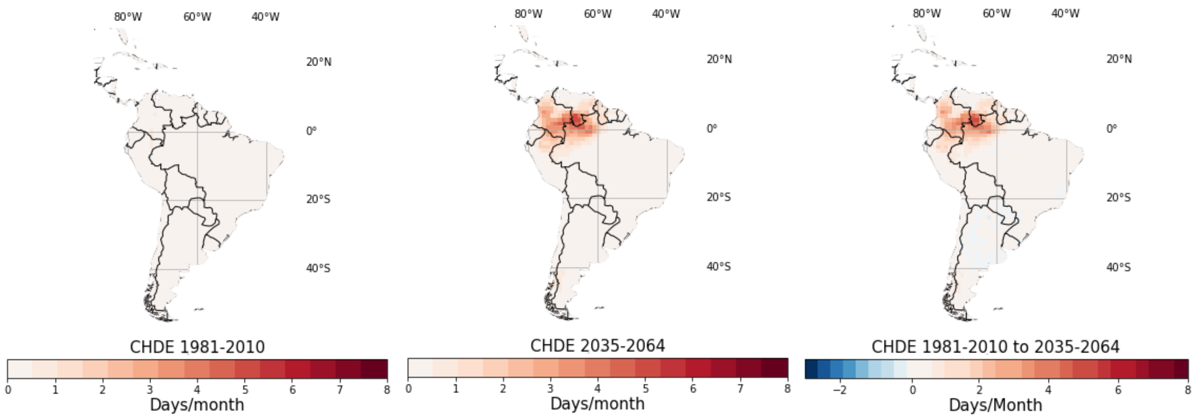
Figure F2

CHDE over Brazil for the time periods 1981-2010, 2035-2064 and the difference between the two periods, summarized per month

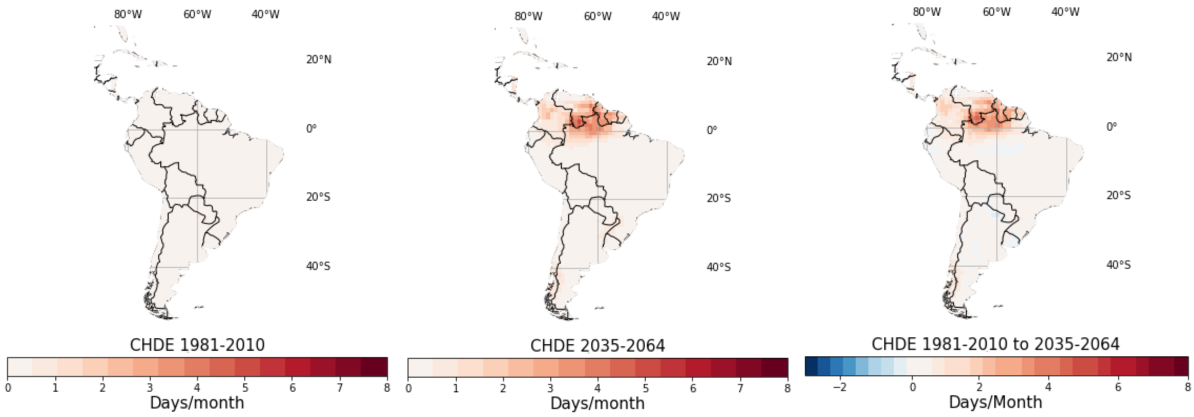
January



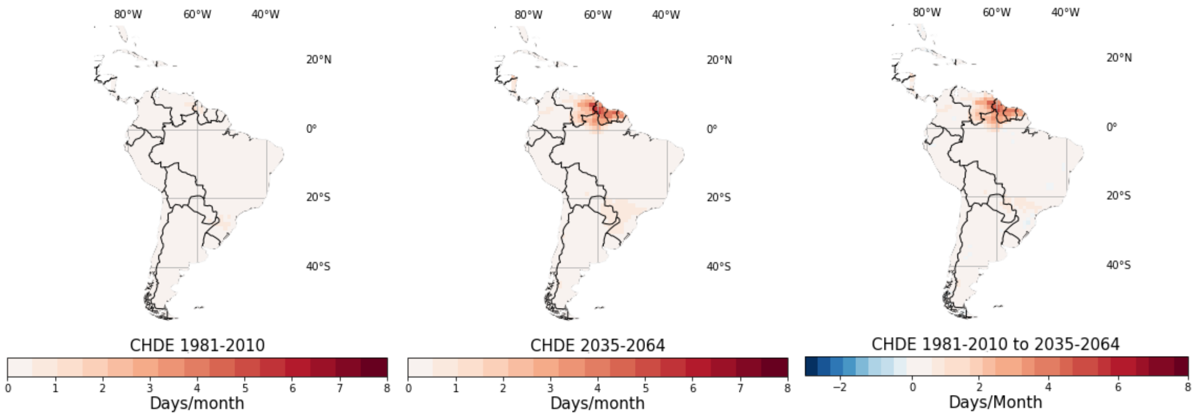
February



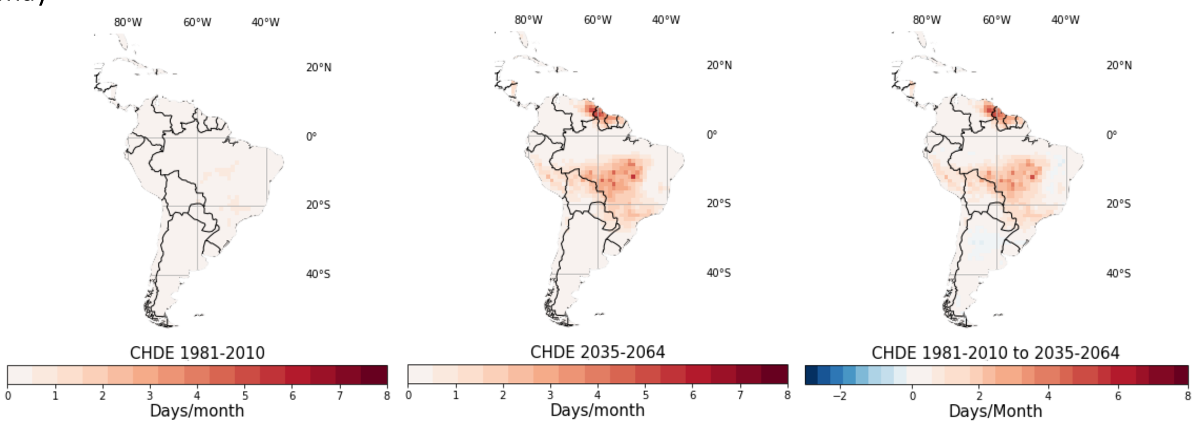
March



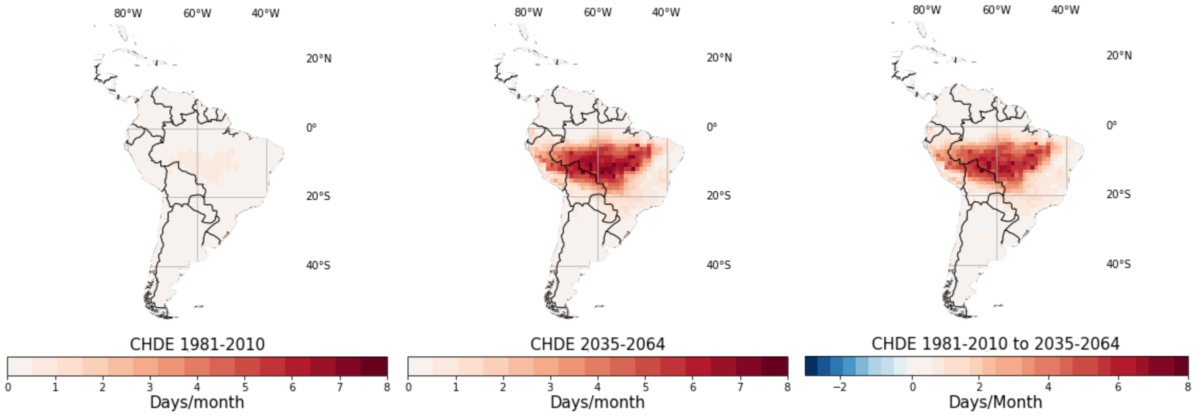
April



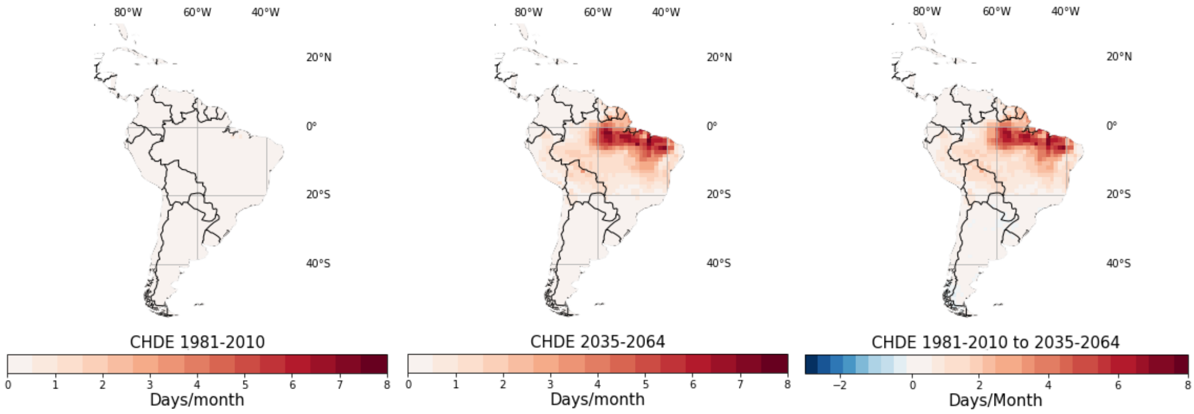
May



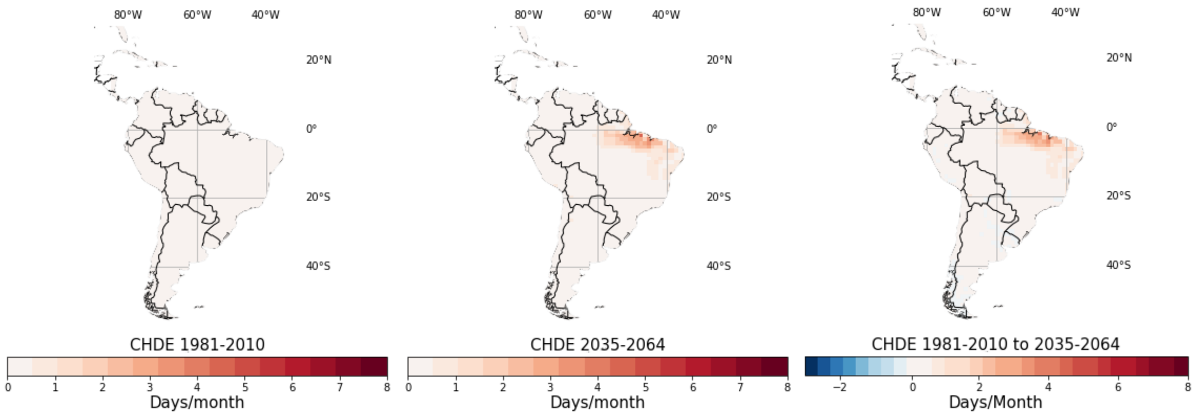
September



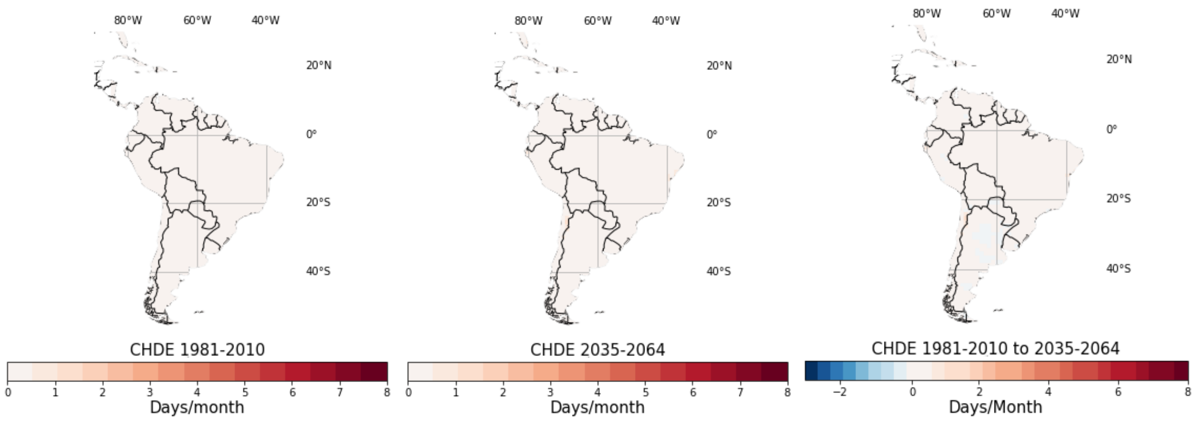
October



November



December


80°W
60°W
40°W
20°N
0°
20°S
40°S
CHDE 1981-2010
0 1 2 3 4 5 6 7 8
Days/month
CHDE 2035-2064
0 1 2 3 4 5 6 7 8
Days/month
CHDE 1981-2010 to 2035-2064
−2 0 2 4 6 8
Days/Month

Appendix G

Figure G1

Extreme Heat Days per season (Sep-May) for 1981-2010, 2035-2064, and the difference between the two time periods

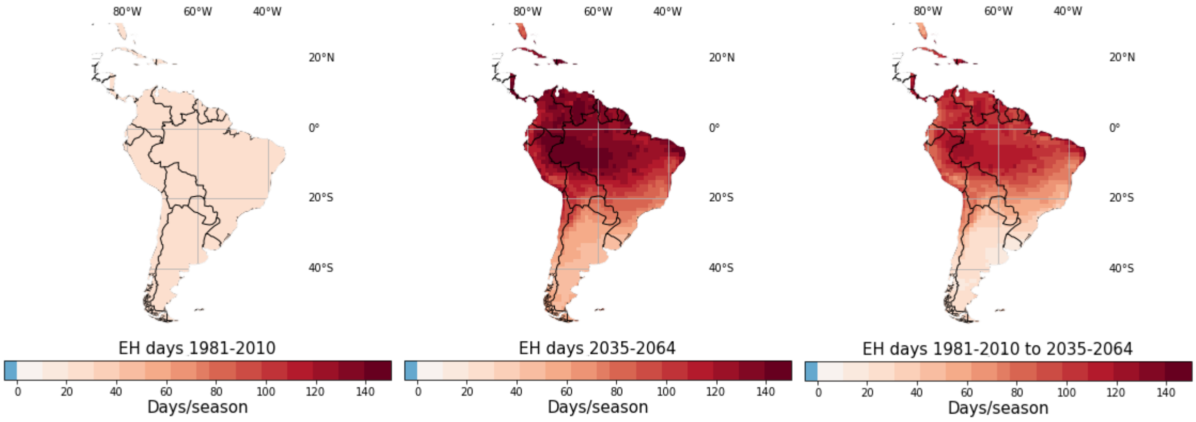


Figure G2

Heatwave Frequency per season (Sep-May) for 1981-2010, 2035-2064, and the difference between the two time periods

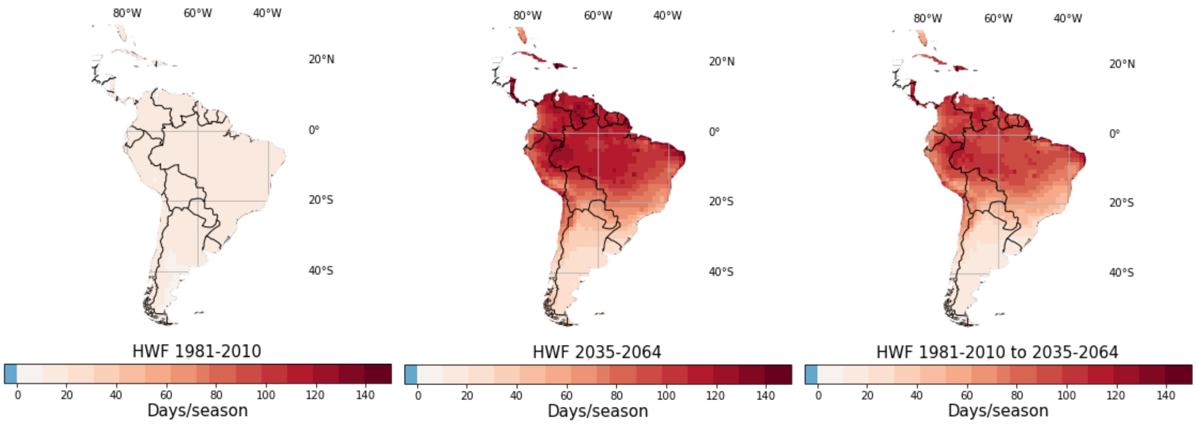
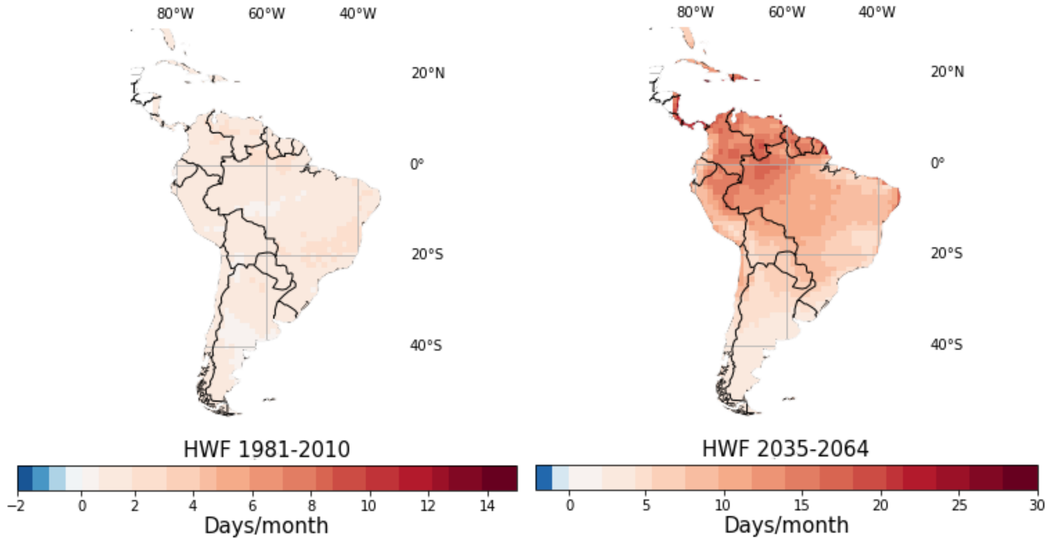


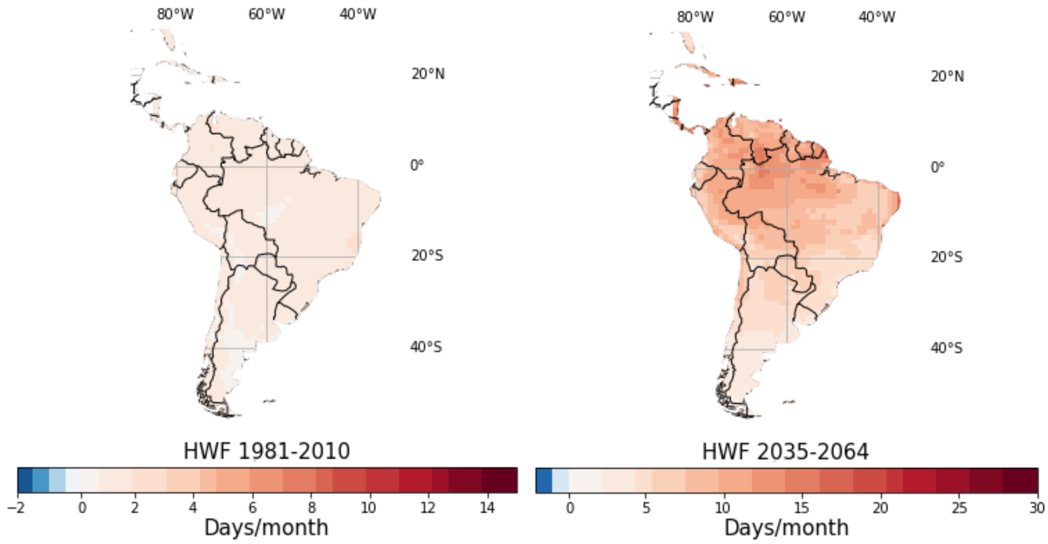
Figure G3

Heatwave Frequency monthly for 1981-2010 and 2035-2064

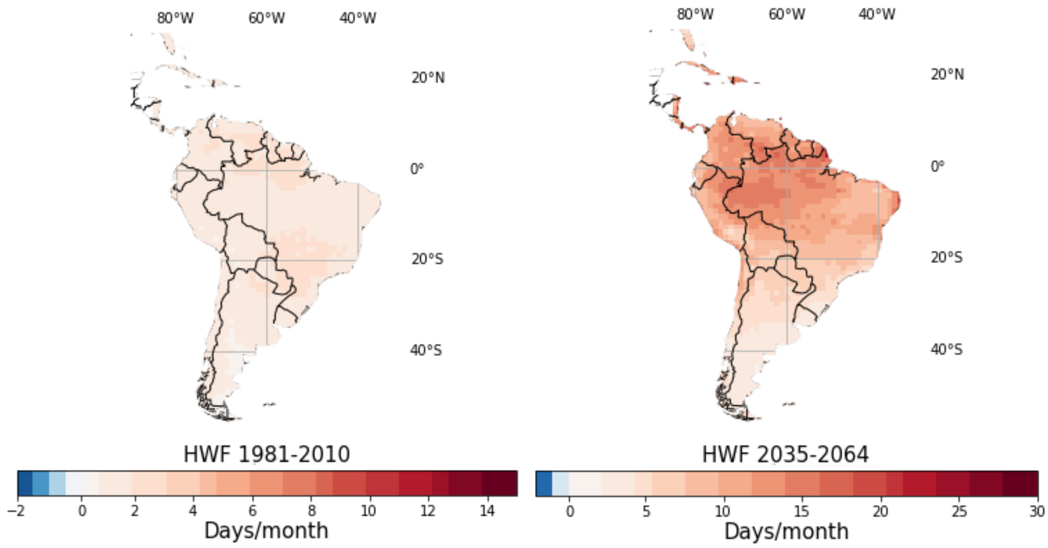
January



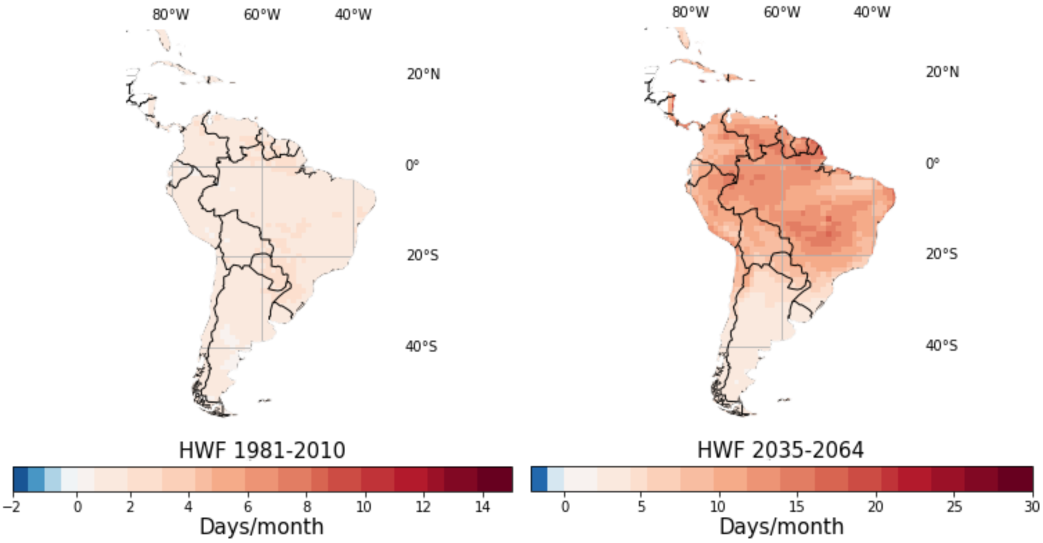
February



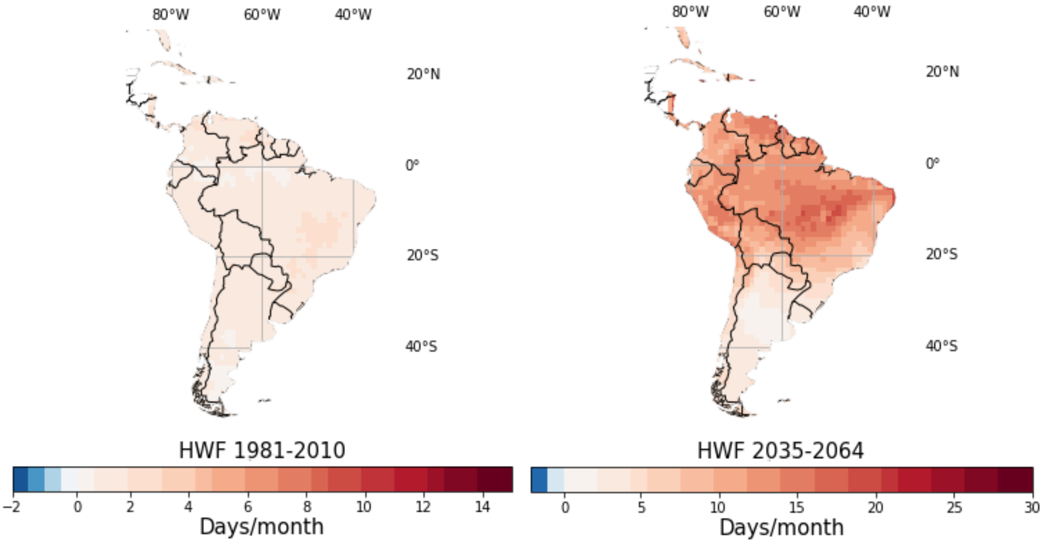
March



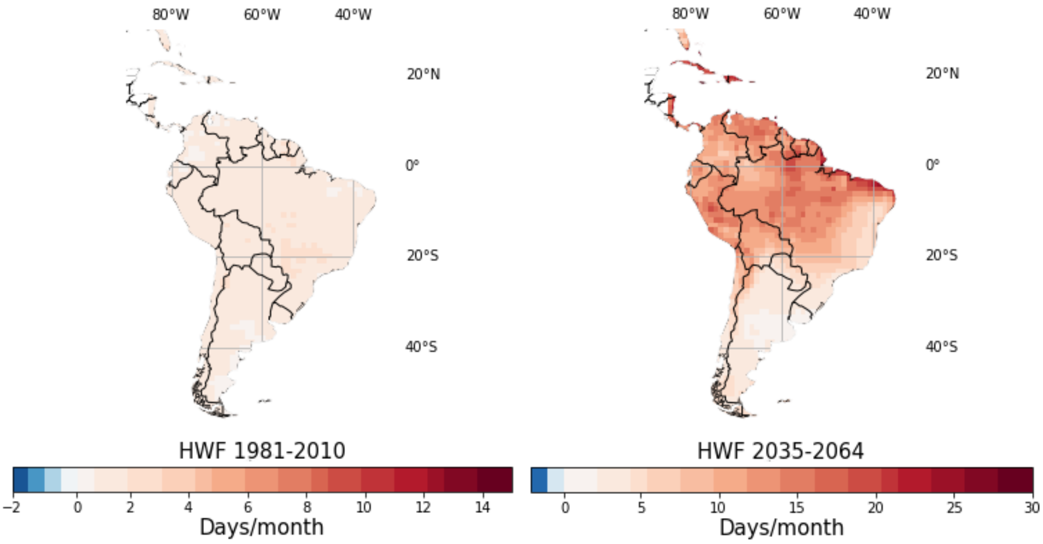
April



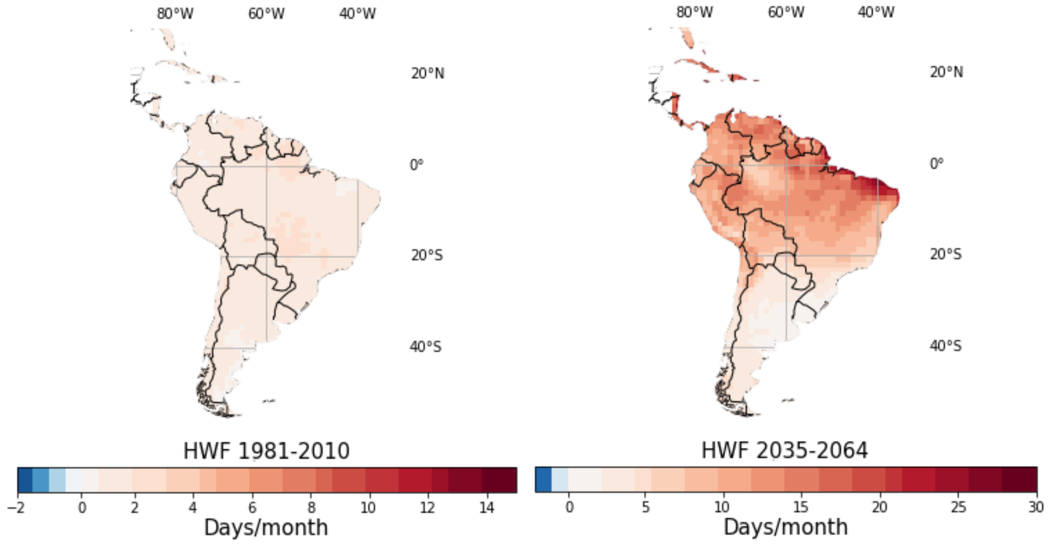
May



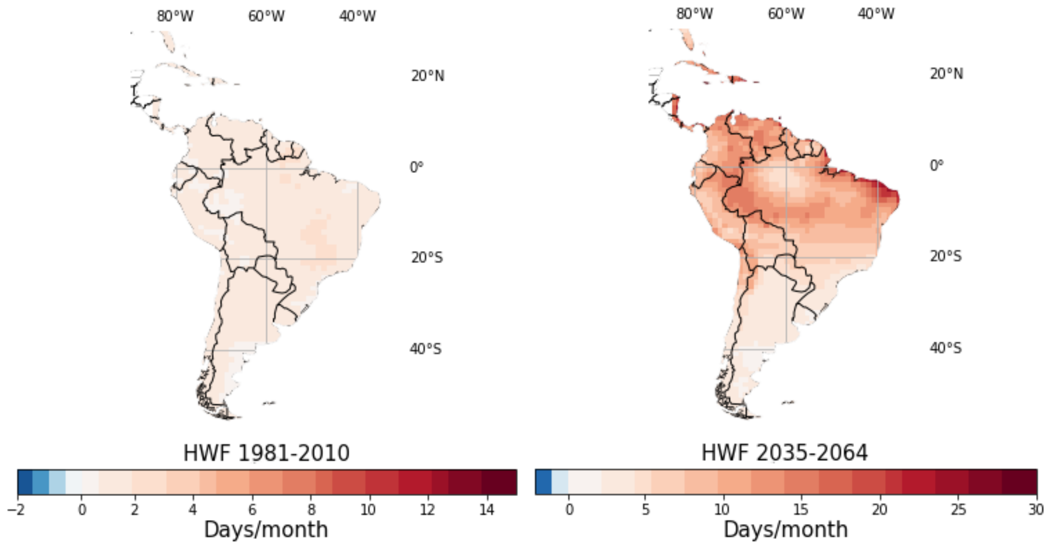
September



October



November



December

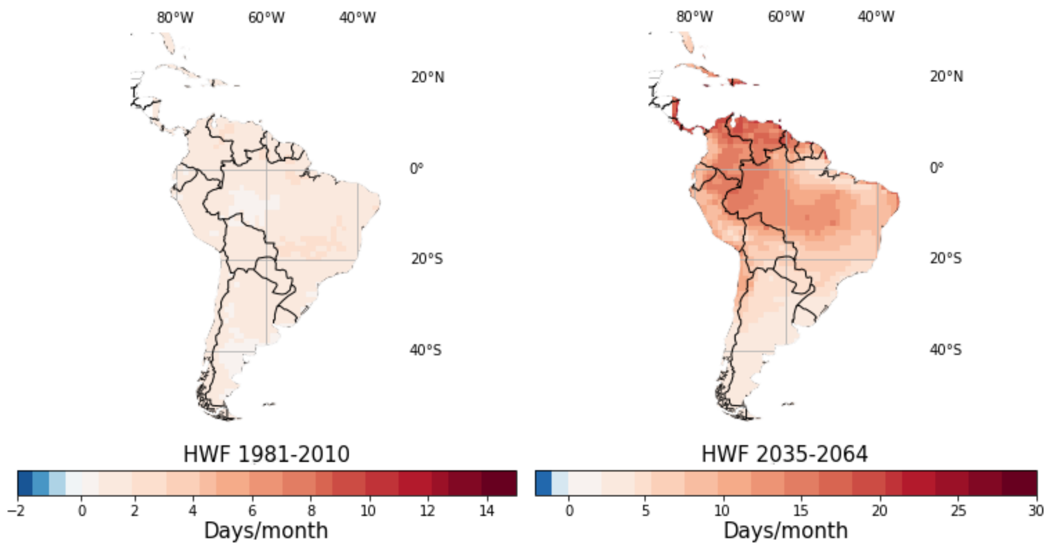
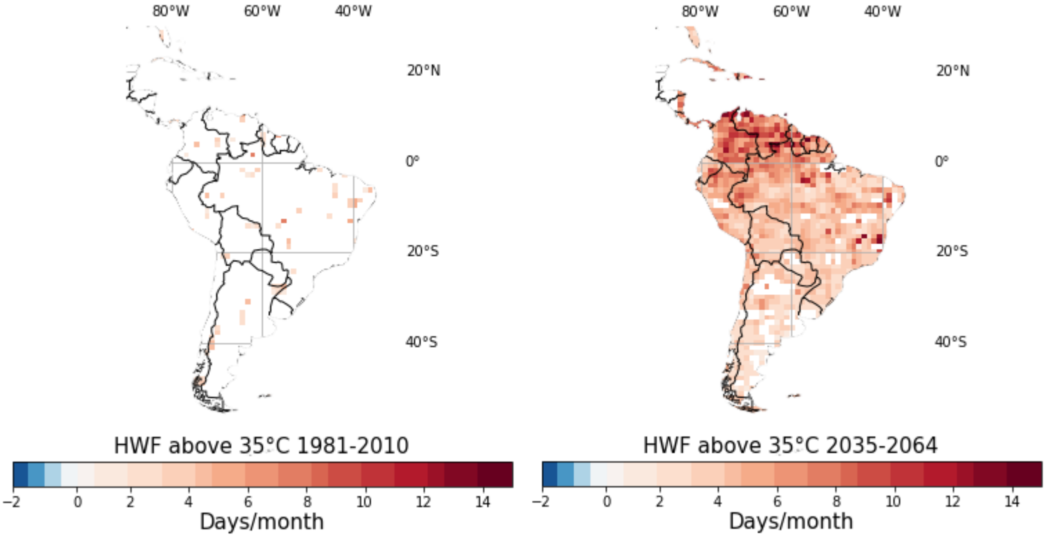


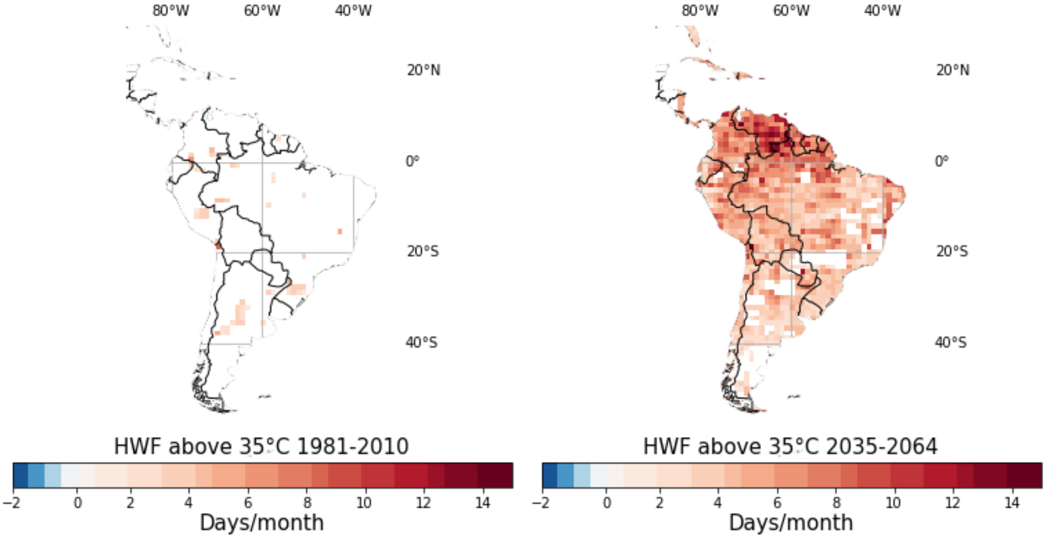
Figure G4

Heatwave Frequency for days above 35°C monthly for 1981-2010 and 2035-2064

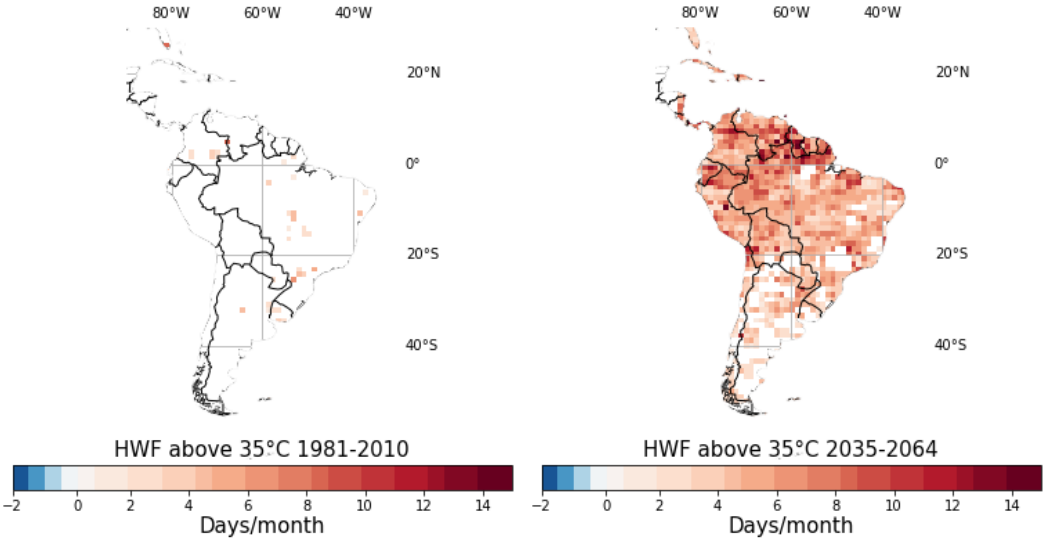
January



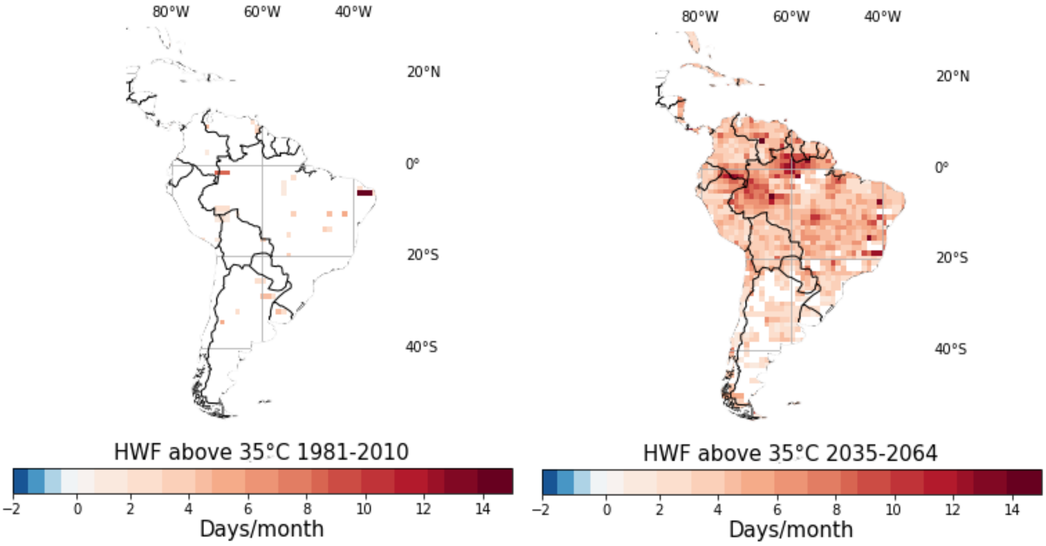
February



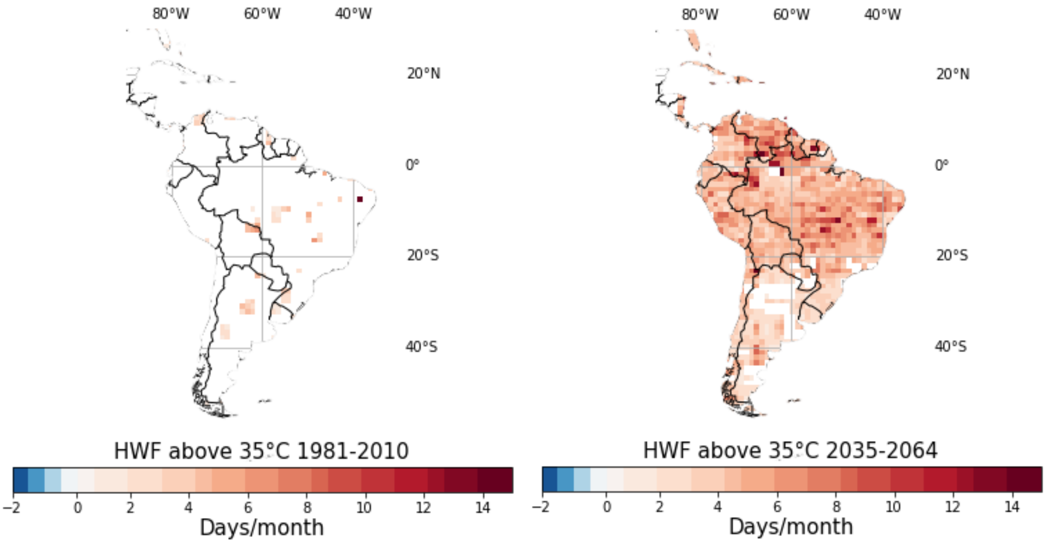
March



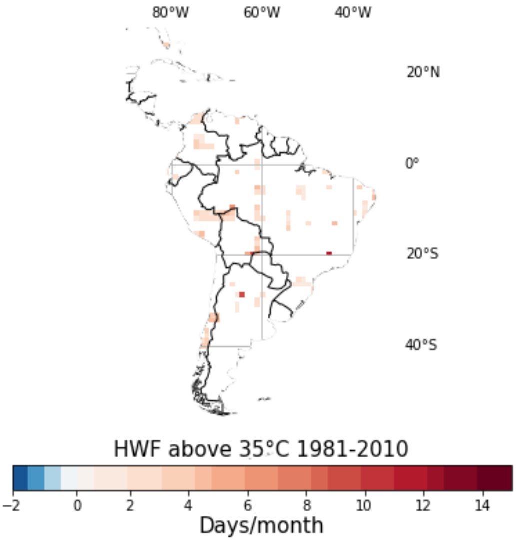
April

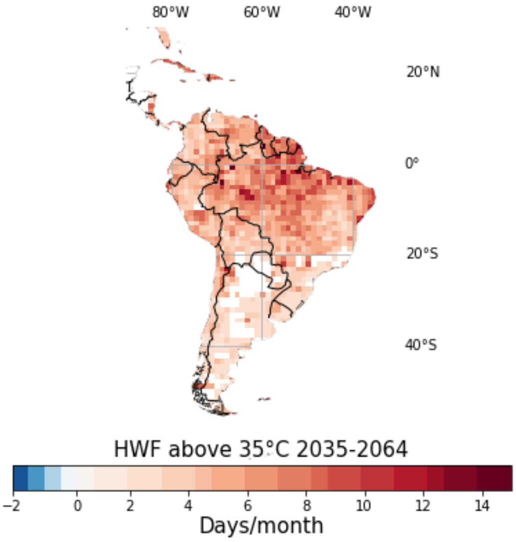


May

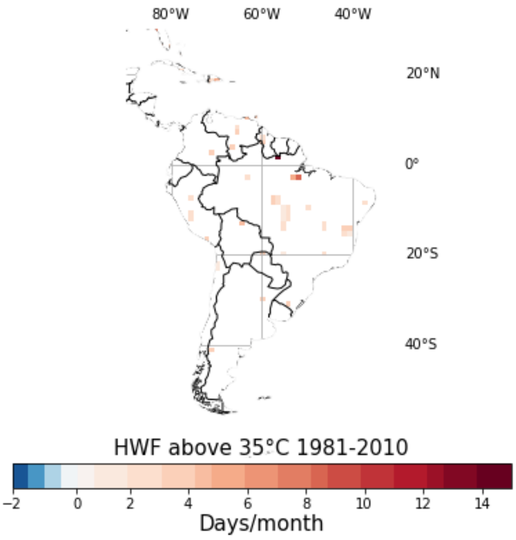


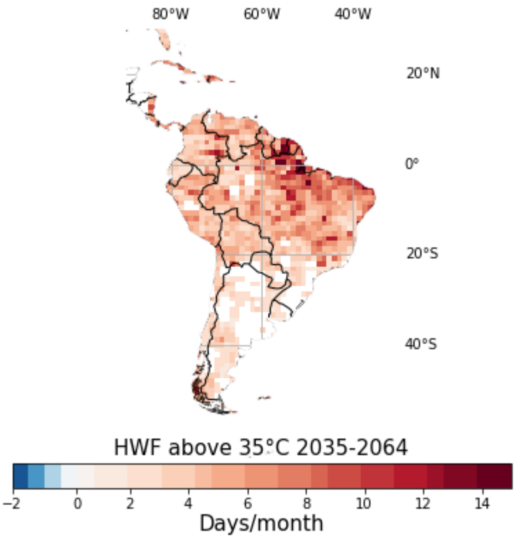
September



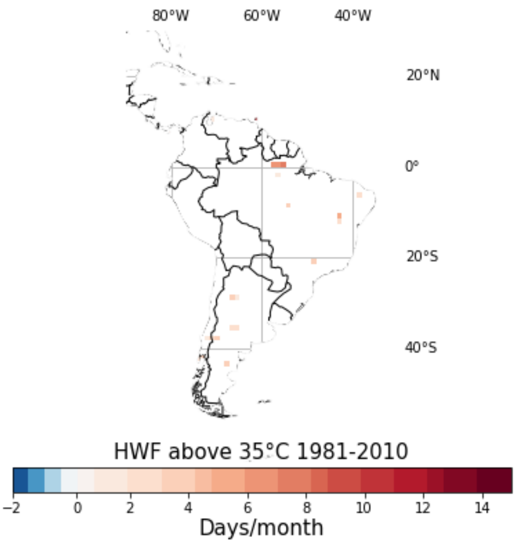


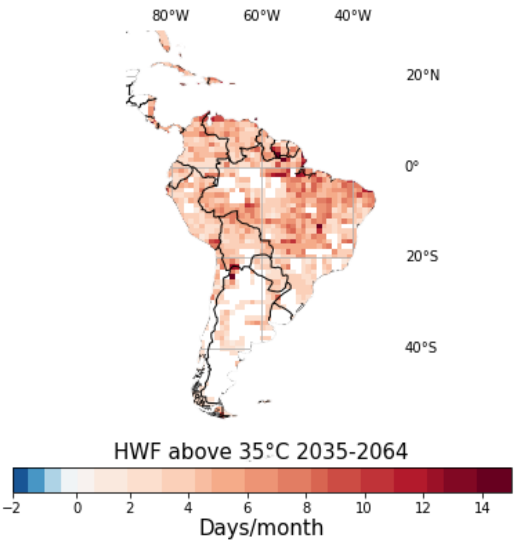
October





November





December

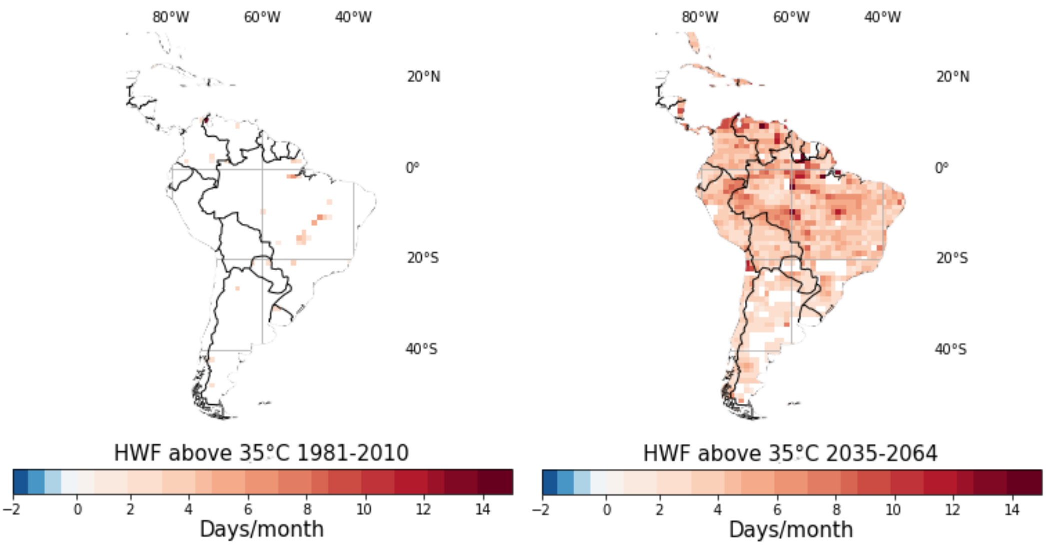


Figure G5

Heatwave Duration per season (Sep-May) for 1981-2010, 2035-2064, and the difference between the two time periods

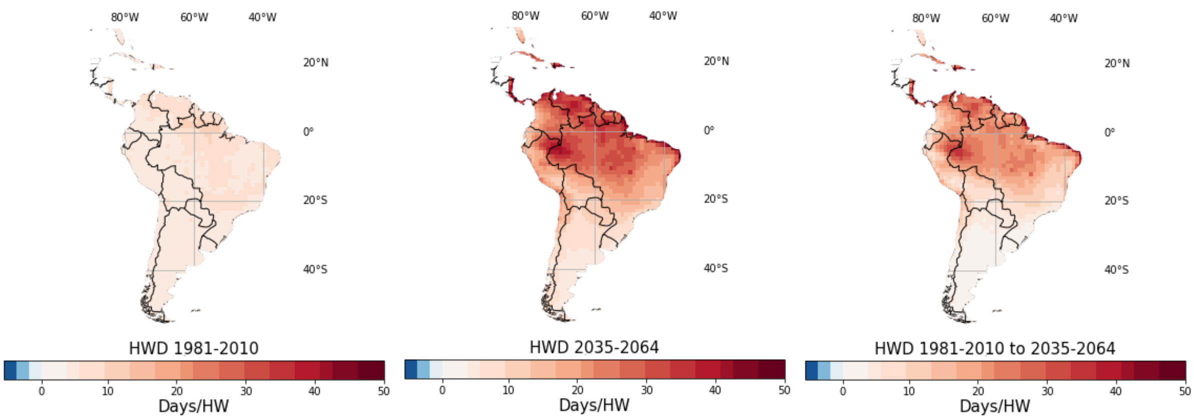


Figure G6

Heatwave Number per season (Sep-May) for 1981-2010, 2035-2064, and the difference between the two time periods

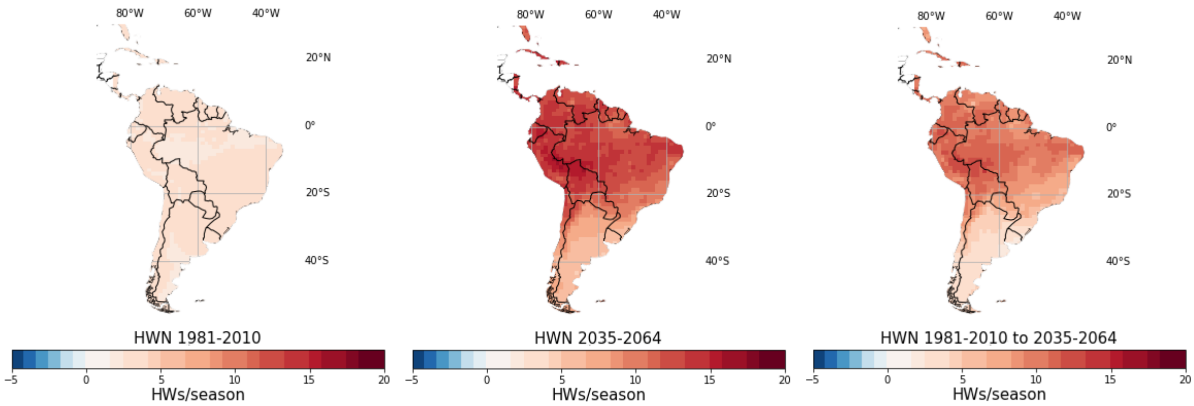
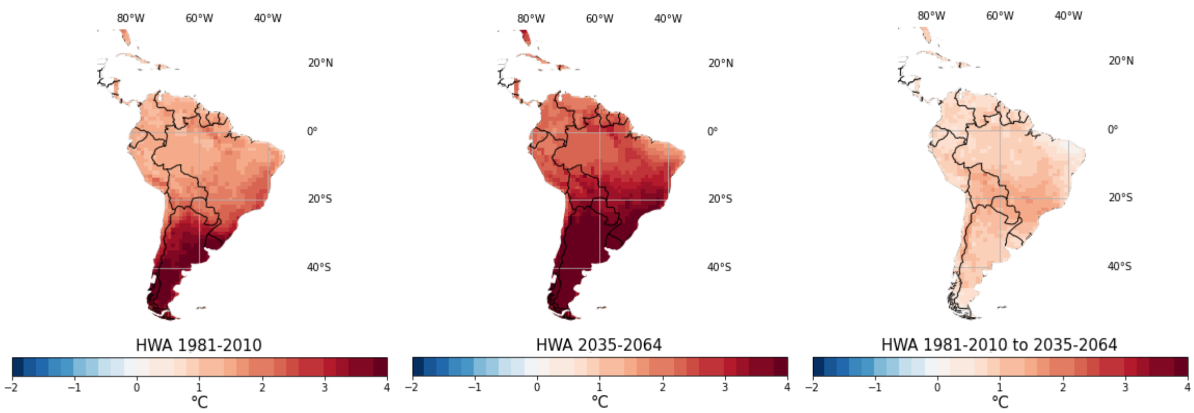


Figure G7

Heatwave Amplitude per season (Sep-May) for 1981-2010, 2035-2064, and the difference between the two time periods

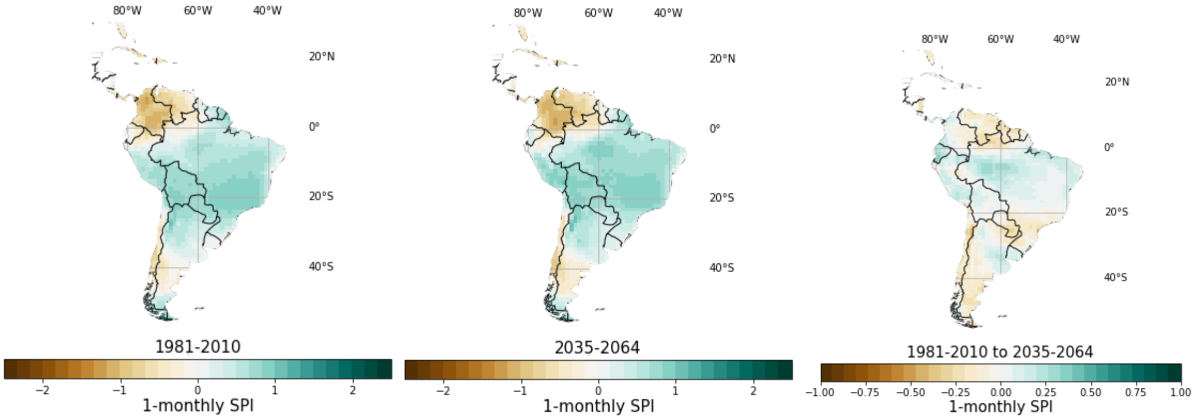


Appendix H

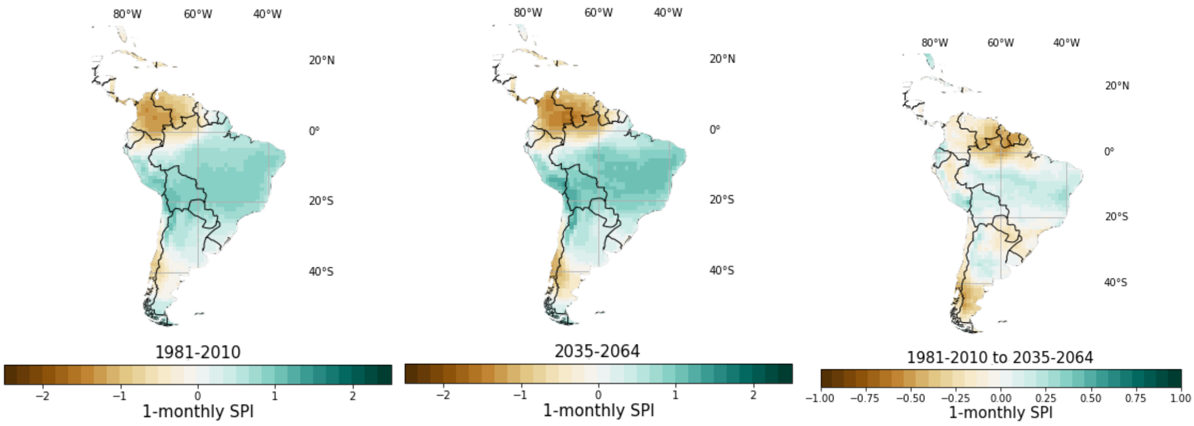
Figure H1

1-monthly SPI for 1981-2010, 2035-2064 and the difference between the two time periods per month

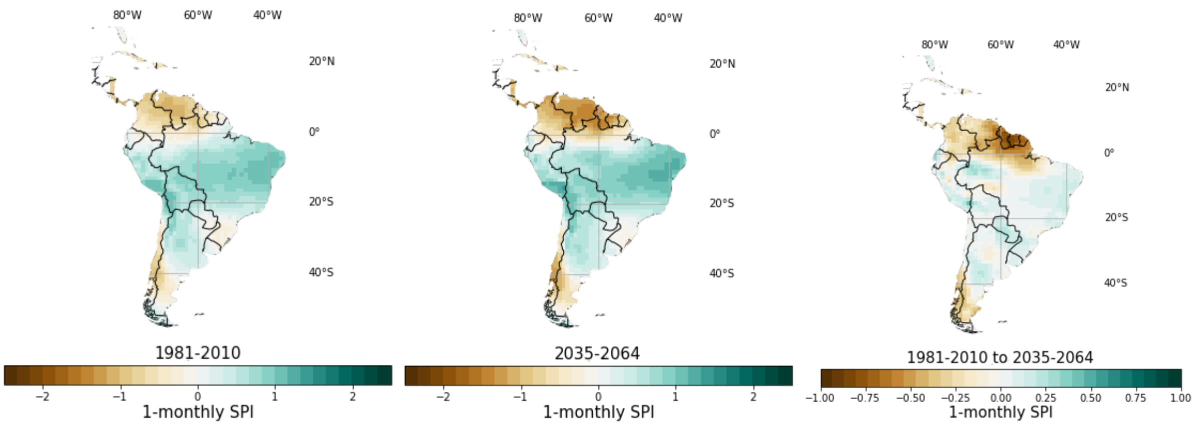
January



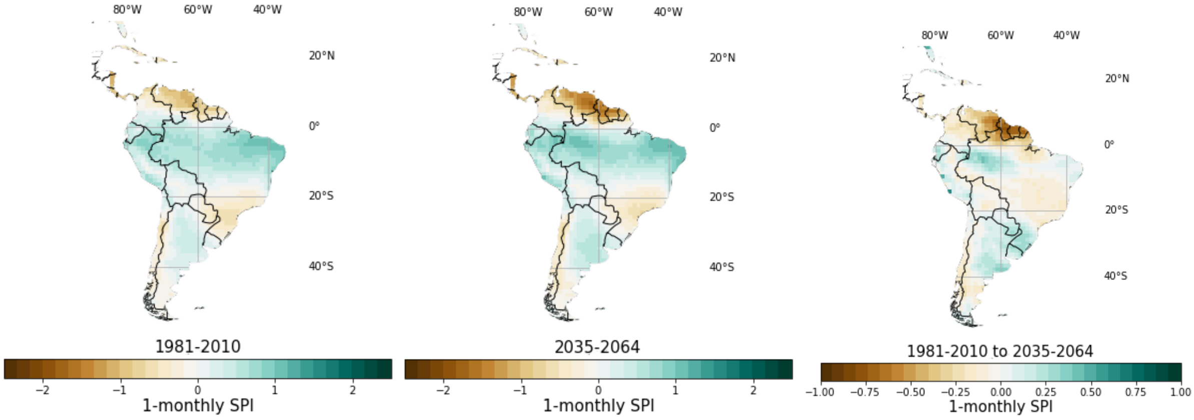
February



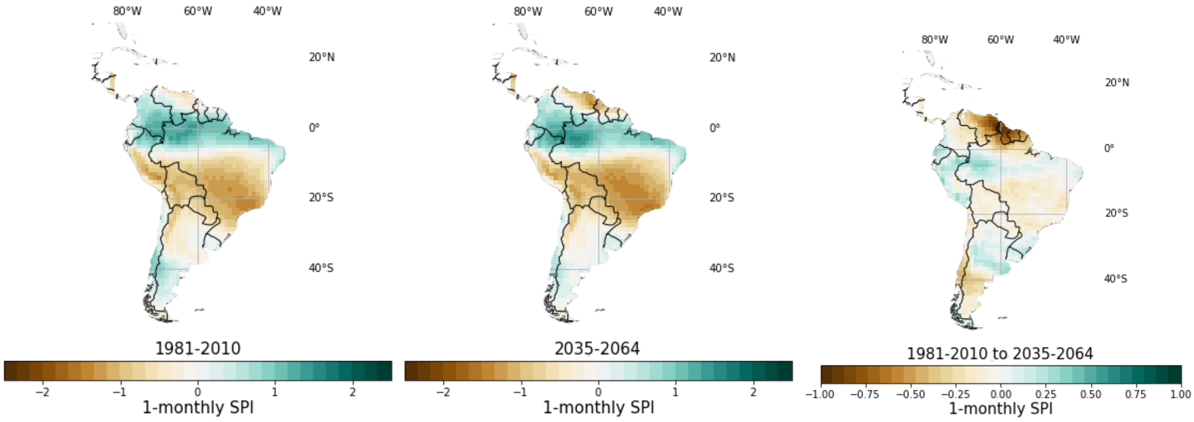
March



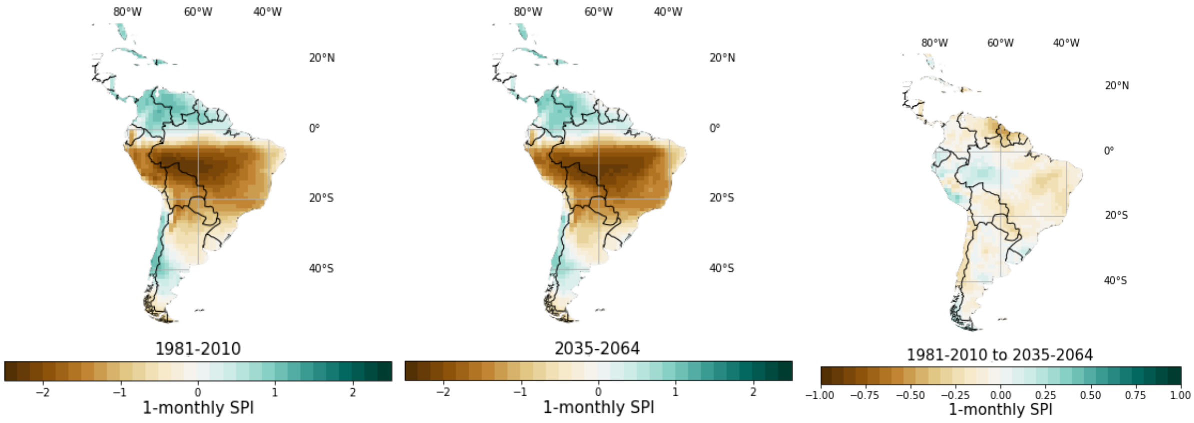
April



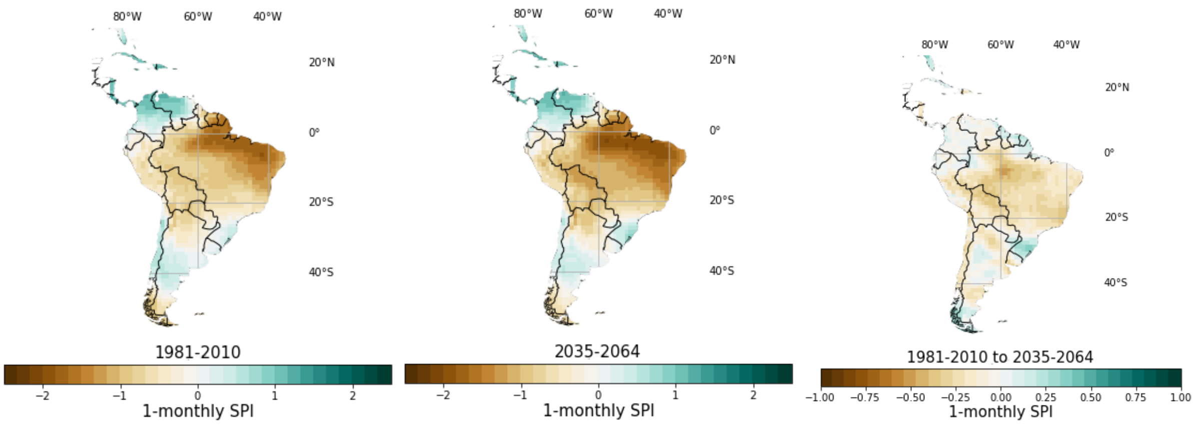
May



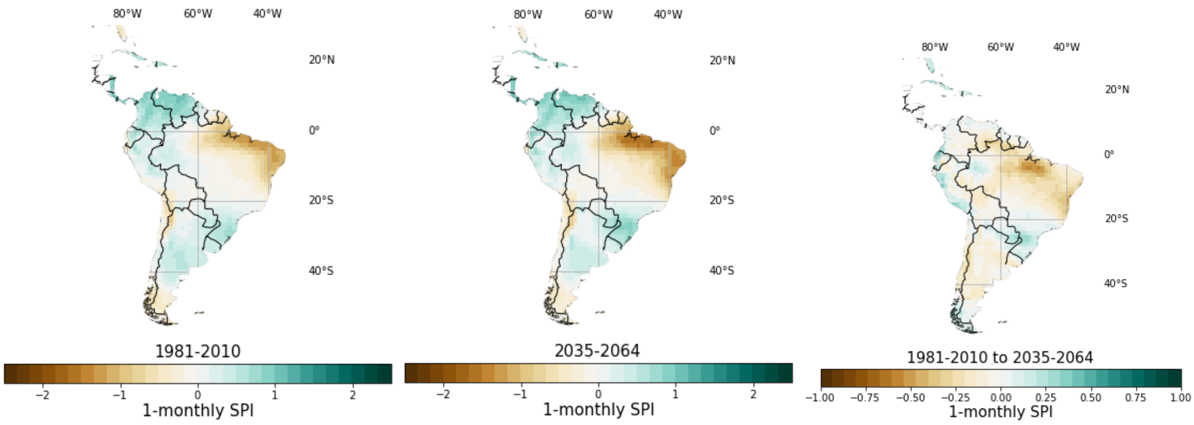
September



October



November



December

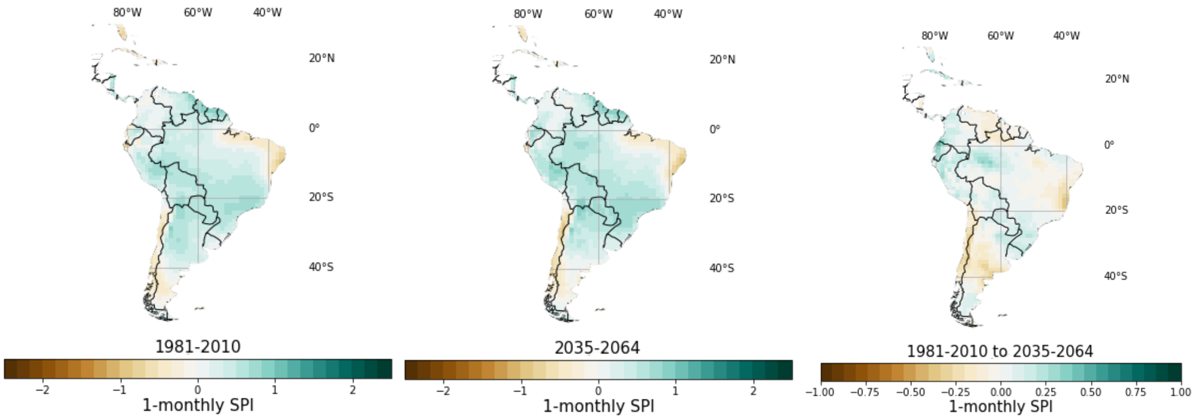
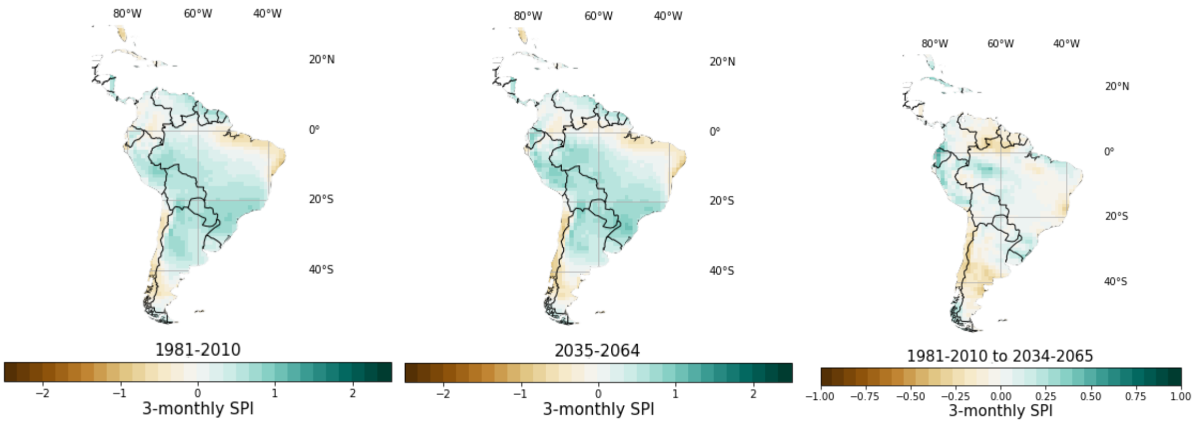


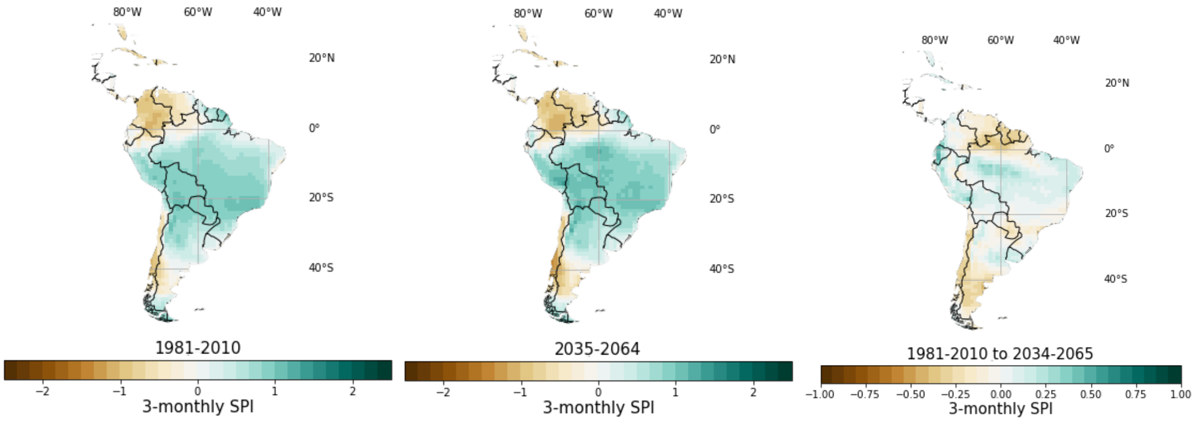
Figure H2

3-monthly SPI for 1981-2010, 2035-2064 and the difference between the two time periods per month

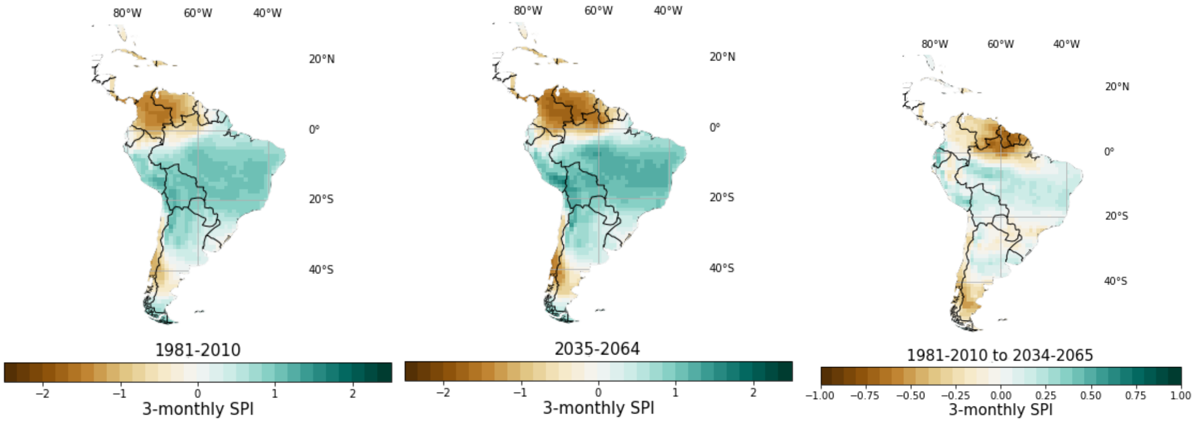
January



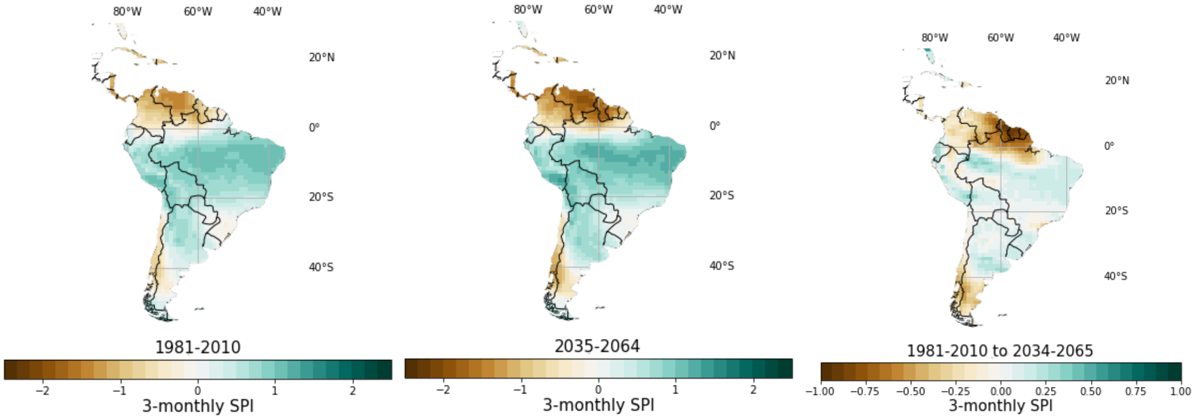
February



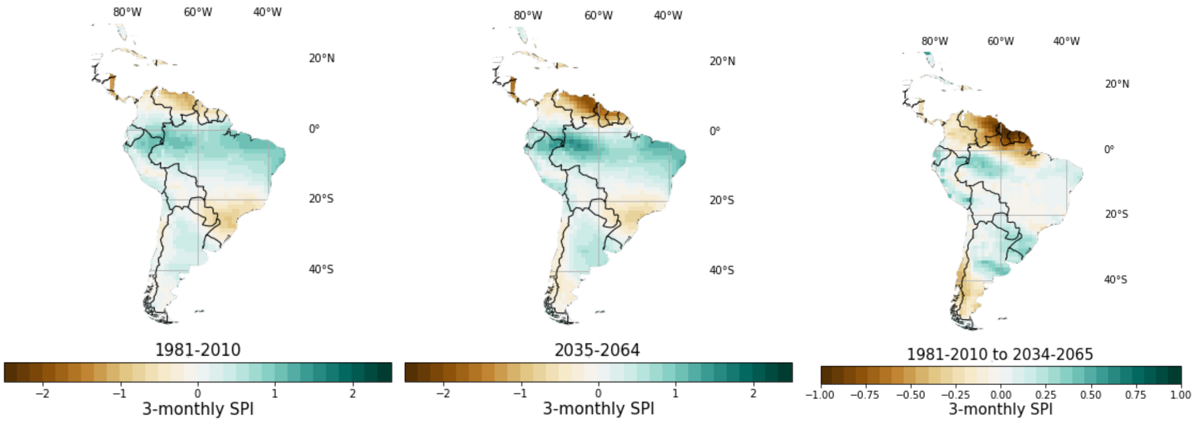
March



April



May



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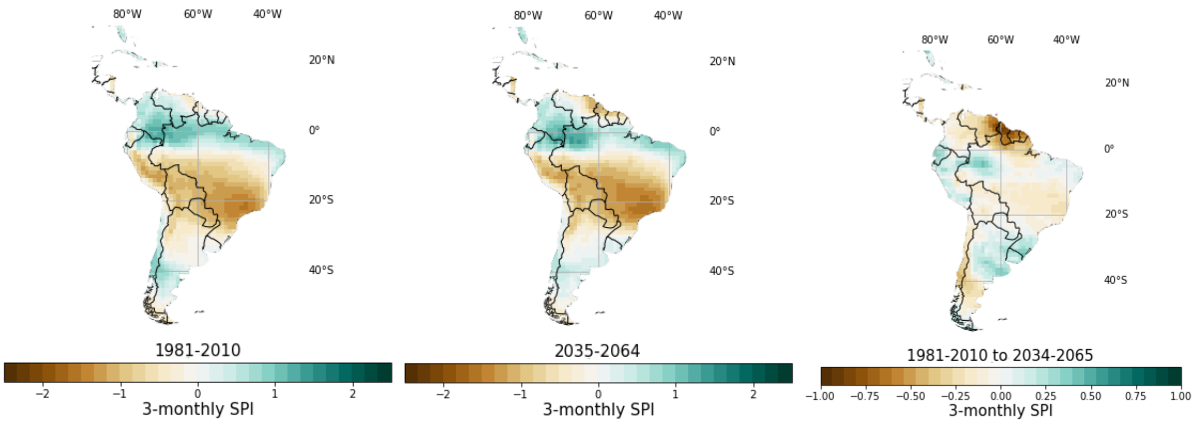
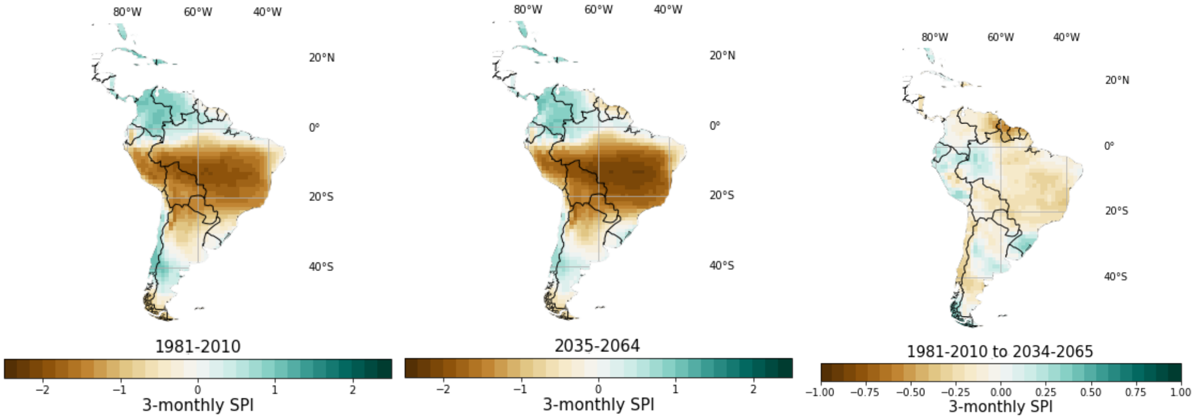
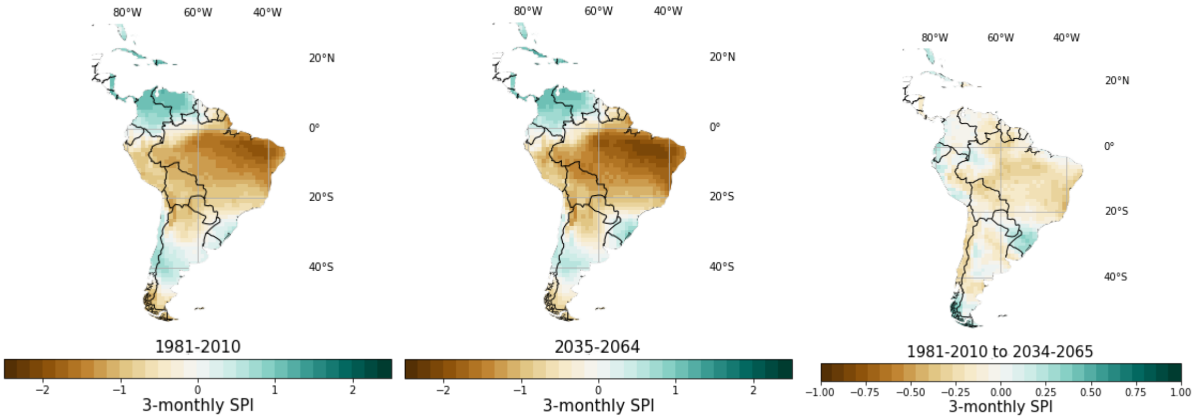


October



November



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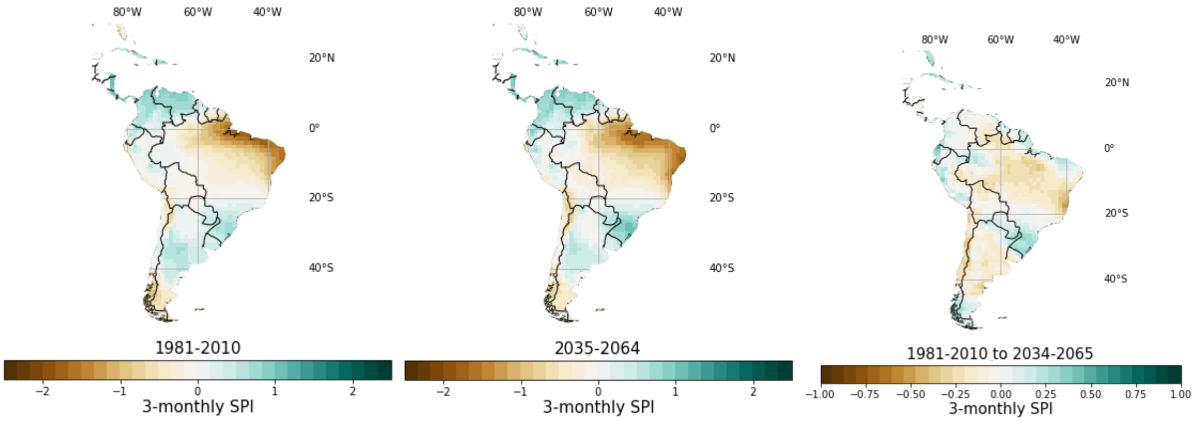

Appendix I

Figure I1

Standard deviation of the Multi Model Mean for the difference between the number of CHDE in 1981-2010 vs in 2035-2064