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Compound effects of drought and COVID-19 on soybean production in Brazil: Challenges and policy responses

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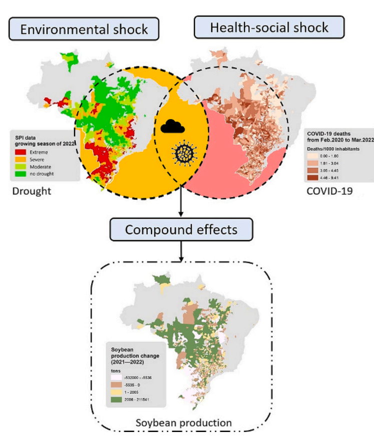
HIGHLIGHTS

- Assessed the impacts of 30 years of droughts on Brazilian soybean production.
- Consecutive years of droughts have higher negative impacts on production than single years.
- Two consecutive years of drought interacted with the COVID-19 pandemic to exacerbate production losses.
- Multiple shocks (droughts, pandemics) interact and exacerbate their impacts on food production systems.

GRAPHICAL ABSTRACT



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ABSTRACT

This study investigates the cumulative and interactive impacts of drought and COVID-19 on soybean production in Brazil, focusing on cascading economic and operational disruptions. The country has faced numerous drought events in recent years (1989 to 2022), culminating with one in 2022 that, together with the occurrence of COVID-19, led to the highest decline in soybean production since 1990 (10.5 % of the total national production). Our analyses based on spatial lagged regression models revealed that the cumulative impacts of consecutive drought events significantly affect soybean production. Furthermore, the study uncovered a significant interactive association between COVID-19 and drought by using spatial lag models, emphasizing the compounded challenges posed by simultaneous shocks of climate change and rising agricultural production costs due to

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pandemic-induced supply chain disruptions. In addition, descriptive statistics on agricultural economics showed that COVID-19 triggered historical peaks in agricultural input prices, forcing producers to enter the 2021–2022 crop season under critical conditions. Specifically, previous losses in soybean production due to droughts during the 2020—2021 season left producers facing financial constraints while contending with historically high production costs for the next season. These results show how the impacts of a global pandemic cascade into soybean production costs (input prices), while highlight the vulnerability of Brazil's soybean production system to multiple shocks. Hence, we envision responses encompassing short-term changes in management practices and land-use decisions at the farm level; mid-term public policies providing risk assessments and emergency credit to address abnormal spikes in production costs caused by socio-health stressors, which would enable producers to secure more suitable input packages, helping to mitigate potential losses associated with co-occurring climate extreme events; and long-term further investments in developing more self-sufficient food production systems, reducing the heavy reliance on imported agricultural inputs—as seen in the Brazilian case—, and development of highly soybean tolerant-drought varieties.

1. Introduction

The global COVID-19 pandemic has put pressure on many socio-economic systems worldwide, including the food production sector. Simultaneously, some regions faced multiple droughts, leading crop production to overwhelming pressure. These compounded effects (Yaddanapudi and Mishra, 2022) have affected the world's leading soybean exporter. For instance, many agricultural production systems depend on fertilizers imported from distant places to make crop production viable, highlighting their global interconnectedness, which makes countries and regions more interdependent (Miller et al., 2024). This is the case of Brazil's imports of potash from Canada and Russia, and phosphorus from Morocco and Egypt—80 % of the national demand for fertilizers is supplied by imports (Almeida and Volotão, 2020), to grow soybeans and other crops (Liu et al., 2018). In addition, many countries rely on food and feed imports to supply their internal demand (Chung and Liu, 2022). For example, in 2019, the global food import dependency ratio was 14.3 % (FAO, 2019), while in 2021, foodstuffs reached the 10th most traded commodity in the world, equivalent to 707 billion dollars (OEC, 2022). These global flows have been pivotal for increasing food security worldwide (FAO, 2022), but at the same time, they make countries and regions more vulnerable to shocks (Cariappa et al., 2021). This vulnerability is attributed to various factors, including the importer's economic capacity to participate in global trade (FAO, 2023), governance systems (e.g., domestic food policies to ensure supply), and international commercial agreements (Brander et al., 2023). But vulnerability is also related to the capacity of food/feed producers to avoid or reduce the impacts of supply disruptions imposed by extreme weather events (e.g., droughts), pandemics (e.g., COVID-19), and wars (e.g., Russian invasion of Ukraine), among others. Such disruptions, therefore, play a significant role in the resilience of production systems around the world (Liverpool-Tasie et al., 2023), while also cause global food prices to increase. These effects cascade to many countries, triggering food insecurity, especially in vulnerable and poor regions (Resnick, 2022).

The United Nations Environment Programme (UNEP) considers that humanity is already living under a climate emergency, highlighted by the observed increase in global temperature above the pre-industrial period. Attributed to human activities (IPCC, 2023), such changes in climate are responsible for the increase in the number and intensity of extreme weather events (e.g., droughts) around the world over the last few decades—the UN Office for Disaster Risk Reduction estimates an 83 % increase in such events since 1980 (UNDRR, 2021). As rain-fed agriculture is particularly vulnerable to droughts (Madadgar et al., 2017), such vulnerability is exacerbated by climate change (IPCC, 2023). In Brazil, a major food and feed producer and exporter, deforestation has additionally contributed to changes in the regional climate over the last few decades, altering rainfall regimes (Hofmann et al., 2023), and with negative impacts on food production systems, particularly in the Amazon and Cerrado biomes (Leite-Filho et al., 2021). Significant decreases in precipitation (about 11 %) since 1980s have also compromised agricultural production in the Brazilian Atlantic Forest biome, pushing many rural producers out of agriculture (Silva et al., 2023). Such disruptions cascade into global supply chains (Silva et al., 2021), causing significant impacts in many regions and food sectors around the world. This is the case of China's animal protein sector, which relies on soybean imports from Brazil and account for over 40 % of its demand (Silva et al., 2017).

Besides the climate crisis, the Earth is also facing what is considered the sixth mass extinction event (Pievani, 2014; McCallum, 2015) with important consequences to human life-support systems and well-being (Ceballos et al., 2015). Such impacts on biodiversity may also favor the emergence of new diseases threatening human life (O'Key, 2023). At the beginning of 2020, the world experienced the worst pandemic (COVID-19) in a century, leading to multiple disruptions in human systems, such as labor, travel, trade, health, and food security, among others. The pandemic impacted human mobility by placing many people under lockdowns or similar restrictions, affecting local and regional economies (FAO, 2021; Rasul, 2021). The U.S. and Brazil, the largest global soybean producers and exporters, were significantly affected by COVID-19, which caused a large number of deaths [over 1.1 million and 700 thousand, respectively (Hopkins, 2023)]. Although the pandemic started to spread in 2020, it became globally widespread during 2021 (Passarelli-Araujo et al., 2022), and had many impacts on agri-food systems, threatening food security (Mishra et al., 2021; Okolie and Ogundeji, 2022; Yaddanapudi and Mishra, 2022; Hussain et al., 2023). However, the extent to which pandemic-induced disruptions affect agricultural systems largely depends on the intensity and composition of agricultural inputs (e.g., fertilizers, seeds, machinery, labor) (FAO, 2020; Rasul, 2021). In particular, Brazil's soybean sector is highly dependent on these inputs, accounting for 44 % of the national fertilizer demand (GlobalFert, 2021), while over 70 % of major fertilizers, such as potash, come from international suppliers (Liu et al., 2018). Furthermore, in Brazil, the first two years of the COVID-19 pandemic coincided with the occurrence of the cold phase of El Niño Southern Oscillation (ENSO) cycle, termed La Niña (NOAA, 2023). La Niña is associated with drought intensification in Central-Western and Southern Brazil (Cirino et al., 2015), which are major agricultural production areas, particularly of soybean.

Since both climate extremes and pandemics may occur simultaneously, as previous studies are suggesting (Rasul, 2021; Mishra et al., 2021; Yaddanapudi and Mishra, 2022), we argue that the impacts of climate extremes, such as droughts, on agricultural production systems may be exacerbated by the occurrence of pandemics, such as COVID-19, due to disruptions in the flows of people (e.g., laborers) and commodities (e.g., fertilizers), among others. Such interaction was previously evaluated using a global systems model (Haqiqi et al., 2023) and addressed theoretically (Rasul, 2021; Mishra et al., 2021), but only empirically addressed by a single study focusing in the U.S. (Yaddanapudi and Mishra, 2022). This study fills such knowledge gap through an empirical analysis applied to a global agricultural commodity. Using the observed dynamics of soybean production in Brazil between 1990 and 2022 at the municipality basis, this study investigates the cumulative and interactive impacts of drought and COVID-19 on soybean production, focusing on cascading economic and operational disruptions.

2. Methods

2.1. Datasets used in the study

Brazil is divided into 5570 municipalities, among which 2524 constituted soybean production municipalities in 2022, according to the 'Municipal Agricultural Survey' of the Brazilian Institute of Geography and Statistics (PAM/IBGE) [Table 1612 (https://sidra.ibge.gov.br/tabela/1612)]. However, following a previous study on the socioeconomic impacts of soybean production in Brazil (Martinelli et al., 2017), we used 300 ha of soybean planted as the minimum area to consider a municipality as soybean producer. This number constitutes a more systematic, albeit conservative, way to define a municipality as a soybean producer.

To assess droughts, we calculated the Standardized Precipitation Index (SPI) using a temporal resolution of one month (i.e., SPI scale 1) in every municipality, from 1989 to 2022. This calculation used time series climate data obtained from the Climate Hazards Group InfraRed Precipitation with Station data [CHIRPS (https://www.chc.ucsb.edu/data/chirps)]. The SPI has been used in previous studies to determine drought effects in crop production in Brazil (Pereira et al., 2018; Pacheco and Andrade, 2024) and is considered a robust yet simple estimate based only on precipitation data (Yuan et al., 2018). Thus, it represents a suitable model to evaluate the spatio-temporal occurrence and extent of droughts.

To assess the onset, spread and magnitude of COVID-19, we used the number of deaths directly associated with COVID-19 reported between February 2020 and December 2022 on a per municipality basis, obtained from the Brazilian national statistics on health ['Painel Coronavírus' (https://covid.saude.gov.br/)]. We used only death records as they constitute a more reliable measure of COVID-19 infection in Brazil (Marinho et al., 2021). Death cases were normalized per one thousand inhabitants using population data obtained from the Brazilian Institute of Geography and Statistics (IBGE) 'Population Estimates' of 2020 [Table 6579 (https://sidra.ibge.gov.br/Tabela/6579)].

In addition, we also used data on rural labor obtained from the most recent 'Brazilian Agricultural Census' (of 2017) [Table 6884 (https://sidra.ibge.gov.br/tabela/6884)], together with data on global prices of agricultural commodities and agricultural inputs derived from the trade statistics 'Primary Commodity Prices' of the International Monetary Fund [IMF (https://www.imf.org/en/Research/commodity-prices)]. Finally, soybean production costs were obtained from the National Supply Company [Conab (https://www.conab.gov.br/info-agro/custos-de-producao)].

2.2. Standardized Precipitation Index (SPI)

The Standardized Precipitation Index (SPI) was proposed by McKee et al. (1993) to evaluate drought events. It uses long-term time series of climate data to calculate the probabilities of each precipitation event while standardizing the results (i.e., mean of 0 and standard deviation of 1) (Vicente-Serrano et al., 2012). This index has been widely used to evaluate drought events at different time scales. For instance, it has been applied to understand how extreme climate events, such as droughts, affect agricultural production outputs (Teixeira et al., 2013; Leng and Hall, 2019; Abdelmalek and Nouiri, 2020). The SPI can be calculated over different time spans [periods ranging from one month (scale 1) to 6 months (scale 6), or even 12 months]. Scale 1 has been used for understanding droughts (e.g., short-term droughts known as "*veranicos*" in Brazil, ranging from one week to a month) and impacts on agriculture. However, longer time spans such as Scale 6 are important to understand groundwater storage and other associated phenomena of the water cycle (Ndehedehe et al., 2023). Originally, McKee et al. (1993) used a gamma distribution to convert the precipitation time series to standardized scores. However, some authors pointed out the enhanced adaptability of the Pearson III model (Guttman, 1999; Vicente-Serrano, 2006; Quiring, 2009). In this study we used the SPI method described by Vicente-Serrano et al. (2012). First, based on monthly precipitation data from CHIRPS, obtained from 1989 to 2022, at 5 km spatial resolution, the mean monthly precipitation for each Brazilian municipality was extracted considering the municipal boundaries at 1:250.000 scale (IBGE, 2021). Then, the SPI-scale 1 was calculated on a per municipality basis (Vicente-Serrano et al., 2012).

The soybean growing season in Brazil is from October to March (Silva et al., 2017), with the most crucial months of the growing season with respect to droughts being November to March, when droughts exert the most negative impacts on crop's performance (Teixeira et al., 2013). For instance, Teixeira et al. (2013) found that the period from December to March explains 80 % of total soybean yields. To evaluate drought impacts on crop production outcomes, we created an SPI metric representing drought information along the soybean growing season for every municipality within each agricultural year [i.e., beginning in September of the previous year and ending in August of the next year (Conab, 2019)]. This constitutes an important step since soybean is cultivated in different biomes throughout Brazil (Silva et al., 2020a), thus drought events may not necessarily exert the same impacts across space, even if they occur over the same month and with the same intensity across different municipalities over the same growing season. This spatio-temporal phenomenon was previously demonstrated by Vicente-Serrano (2006). Hence, from October to March of each growing season, we selected the lowest SPI value (using the SPI-scale 1) for every municipality and combined the data into a single vector (i.e., shapefile) file. As a result, the 'SPI composite' data generated indicates if a given municipality experienced at least one month of drought during the critical months of the growing season. We present three key reasons supporting our use of the 'SPI composite' data. First, soybean is highly sensitive to short-term droughts (lasting less than a month), which can significantly threaten production outcomes (Medeiros et al., 2015; Cardoso et al., 2020; Ferreira et al., 2020). A higher likelihood of vulnerability to short-term droughts has also been reported for other crops worldwide (Haqiqi et al., 2023), while the World Meteorological Organization has pointed out that SPI-scale 1 better reflects short-term conditions, which negatively impact crop production (WMO, 2012). Second, short-term droughts during Brazil's soybean growing season (i.e., *veranicos*) are becoming more frequent and are projected to increase in occurrence between 2021 and 2050 (Magalhães et al., 2019). Finally, our approach provides valuable insights not only for agribusiness but also for government agencies and policymakers. By focusing on a type of climate extreme that is expected to become more frequent, our analysis offers crucial information to support decision-making and adaptation strategies for soybean production.

In addition to the timing and length of each drought event, we also evaluated its intensity by classifying the SPI values into moderate (-1.00 to -1.49), severe (-1.50 to -1.99) or extreme (≤ -2.00), following a widely used drought classification approach (McKee et al., 1993). Leng and Hall (2019) demonstrated for Brazil that the risk of soybean production losses is significantly higher in areas under severe to extreme droughts—for instance droughts are the major concern among soybean producers leading to production losses of up to 12 % (Dou et al., 2023). We applied *Mann-Kendall* statistical tests (Gocic and Trajkovic, 2013) to analyze monotonic trends in the times series of SPI values throughout the study period (1990–2022). As a final step, we also evaluated the impacts of droughts by using different standard SPI time scales for the growing seasons of 2018 and 2022, for comparability (sensitivity analysis) with our 'SPI composite', evaluating not only the statistical significance (p-value), but also the Akaike Information Criterion (AIC) for model fit. Hence, we looked at SPI scale 3 (from October to

December), and scale 6 (from October to March) of both growing seasons. These two growing seasons were selected because the exhibited droughts (evaluated using our 'SPI composite') with significant impacts on soybean outcomes, with 2022 exhibiting stronger effects (which corresponded to a very strong drought season) than 2018 (when no strong droughts where observed).

2.3. Soybean yield and total production

Since the 1990s the soybean production throughout Brazil has followed a steady pattern of increase in two indicators: total production (tons) and yield (kg^{-ha}) (Silva et al., 2020b). These trends have been attributed to several causes, including the growing international demand for soybean, developments in agricultural technology, increases in commodity prices, and national politics favoring the formation of large production regions in agricultural frontiers (Silva et al., 2020b). Hence, from the perspective of major stakeholders in agribusiness (e.g., traders, producers, public agents), soybean production needs to follow a steady growth if major factors (e.g., prices, demand) stay constant (Dou et al., 2020; Millington et al., 2021; LSPA/IBGE, 2023). In this study we adopted the interannual changes in total production and yield as the variables of interest (i.e., used as dependent variables in our spatial regression models, Section 2.4), which is a standard practice of interannual crop evaluation by the Brazilian Institute of Geography and Statistics (IBGE, 2024). Thus, we assessed the changes in total production and yield from one growing season to the next [e.g., interannual change in total production in municipality *a* from 2000 to 2001 ($\Delta = t_{2001} - t_{2000}$)].

2.4. Spatially dependent regression models

Spatially dependent regression models were applied to explore the association between droughts and soybean yield and production changes from 1990 to 2022, and to assess their potential interactions with COVID-19. We chose to use spatially dependent regression models since climate patterns may have clear spatial dependency (e.g., their effects at local and regional scales is influenced by their effects in neighboring regions), while also may tend to form spatial clusters (e.g., neighboring regions tend to exhibit similar patterns). This is aligned with Tobler's first law of geography ["everything is related to everything else, but near things are more related than distant things." (Tobler, 1970)]. Therefore, our modeling approach considered the spatial process as part of the phenomenon studied and was adopted using a spatial LAG regression model, following Eq. (1):

$$\begin{aligned} \boldsymbol{y} &= \rho \boldsymbol{W}\boldsymbol{y} + \boldsymbol{X}\boldsymbol{\beta} + \varepsilon \\ \varepsilon &\sim N\left(0, \sigma_\varepsilon^2 I_N\right) \end{aligned} \tag{1}$$

where $\boldsymbol{W}$ is the weighted matrix to compute spatial dependency among the data, $\boldsymbol{y}$ is the vector of the dependent variable values, ρ the spatial lag coefficient (rho)—which is determined by the model based on the empirical data, $\boldsymbol{X\beta}$ is the direct effect in a given municipality (i.e., effects on soybean production change given a change in the independent variable), and $\boldsymbol{\varepsilon}$ the error term. The $\boldsymbol{W}$ matrix is designed as a first-order queen contiguity style (LeSage, 2014). To confirm the necessity of spatial regression models instead of Ordinary Least Squared (OLS) regressions, we applied the Global Morans' I test on the residuals of an OLS, to evaluate spatial autocorrelation among observations (Cliff and Ord, 1981). The decision to use a first-order matrix was based on two main criteria. First, the substantial variation in the size of soybean production municipalities (ranging from 44 sq. km to 159,533 sq. km) suggests that adjacent and diffusion effects will vary depending on municipality size. Thus, we argue that a lower-order matrix would provide a more conservative estimate of diffusion effects. The ρ (rho) reflects the significance and strength of spatial dependence, so it is intrinsically related to the order contiguity defined in the spatial weights matrix. Hence, we tested second- and third-order weight matrices and compared the results using the AIC for model fit. For this test we ran both, the drought (Section 2.5) and the interaction (Section 2.7) models for the growing season of 2022.

The LAG-models were used when the results suggested a possible diffusion process (e.g., a given soybean production outcome, such as a decrease due to drought in one municipality, is associated with a similar production outcome in neighboring municipalities, indicating a spatial dependence effect). Therefore, the dependent variable in one municipality is not just affected by its own independent variables but also by the dependent variable in its neighbors (i.e., the lagged dependent variable) through a spatial process captured by the spatial weights matrix (Silva et al., 2021; Silva et al., 2023; Perosa et al., 2024).

2.5. LAG-models for assessing the relationship between drought and soybean production

LAG-models were applied to evaluate the relationship between drought and the changes in soybean production and yield. We applied univariate spatial LAG-models (i.e., changes in soybean production or yield, as the dependent variables, and drought as the independent variable) for every period of change, i.e., from one growing season to the next, beginning with 1989—1990 and ending with 2021—2022. These analyses show the temporal association, at the municipality scale, between the occurrence and intensity of a drought event and the observed change in soybean production or yield of the corresponding growing season. The coefficient of determination (i.e., r-squared) of the LAG-models were used as surrogates of the magnitude of the association between drought and the change in soybean production/yield.

2.6. LAG-models for assessing the relationship between multiple droughts in sequential years and soybean production

To evaluate if consecutive years of severe/extreme droughts occurring in a given municipality are associated with larger changes in soybean production/yield, we evaluated the two-year periods in which droughts occurred (Fig. 2). For every two-years analyzed, each municipality was classified according to the occurrence and intensity of droughts as 1 = no or moderate drought, 2 = one year of severe or extreme drought, or 3 = two-years of severe or extreme drought. Changes in soybean production/yield were then evaluated by the cumulative change in the period comprehended by two successive growing seasons of interest through spatial LAG models.

2.7. LAG-models to assess the interaction between COVID-19 and droughts

To assess the relationship between COVID-19 with the changes in soybean production, and potential interactions with drought, we used the number of deaths attributed to COVID-19 per one thousand inhabitants in each municipality, as a surrogate. For the growing season of 2021, the model used data on deaths due to COVID-19 between February 2020 (first confirmed death case) and March 2021 (end of soybean harvesting period in 2021), together with the SPI composite data for the growing season of 2021. For the growing season of 2022, the model used data on deaths due to COVID-19 between February 2020 and March 2022, together with the SPI composite data for the growing season of 2022 (i.e., one model for each growing season). The dependent variable was the change in soybean production (tons) from 2020 to 2021 ($\Delta = t_{2021} - t_{2020}$) and from 2021 to 2022 ($\Delta = t_{2022} - t_{2021}$). As our major goal was to test if there was a significant interaction between drought and COVID-19 at the municipality scale, we used an interaction term (variable SPI composite * COVID-19 death records) in the LAG-model. Since the model carries both variables plus their interaction term (i.e., which constitutes an additional independent variable), to avoid multicollinearity we mean-centered the COVID-19 variable before creating the interaction term. This modification decreases the correlation among independent variables (Iacobucci et al., 2016). Two additional independent variables were also included. The first variable was rural labor per municipality, which represents an important social dimension that was significantly affected by COVID-19 (Castro and Barros, 2020). The second variable included was a crop diversity index, which corresponds to an area-weighted number of crops planted per municipality. Calculated using the Shannon Diversity Index (Aguilar et al., 2015), this index, applied to all crops planted in a given municipality, considered the planted area of each crop in 2021 and 2022 (one index for the respective growing season/model), following the same approach proposed by Silva et al. (2020a). This index has been used to demonstrate that soybean dominated landscapes tend to exhibit less diverse agricultural portfolios (Silva et al., 2020a).

3. Results

3.1. Effect of droughts on soybean production at the municipality scale

Between 1990 and 2022, the number of soybean production municipalities (those having a minimum of 300 ha of soybean planted) increased from 971 to 2213 (Fig. 1a). Furthermore, the average number of municipalities affected by droughts (using our SPI composite index) during the soybean growing season (which goes from October to March) was 1290 or 23 % of the total number of municipalities. However, while we found 1214 municipalities in 1990 (21 %), the number was 3773 in 2022 (67 %) (Fig. 1a). The soybean growing seasons of 2021 and 2022 (in this study, a soybean growing season is identified by the year when the harvest occurs) exhibited the largest number of municipalities affected by droughts (3828 and 3773 municipalities, respectively), among which 1608 and 1690, respectively, were soybean production municipalities (Fig. 1a). In contrast, 1995 was the least affected year, with only 362 municipalities affected by droughts, among which 98 were soybean production municipalities (Fig. 1a). Using a *Mann-Kendall* test we found a significant ($S = 528$, $\tau = 0.265$, $p < 0.05$) trend of increase in the number of soybean production municipalities affected by droughts over the study period (Fig. 1a)—important to note that the total number of municipalities affected by droughts increased over time, not just the soybean production municipalities. Central and Southern Brazil (regions that concentrate most of the soybean production in the

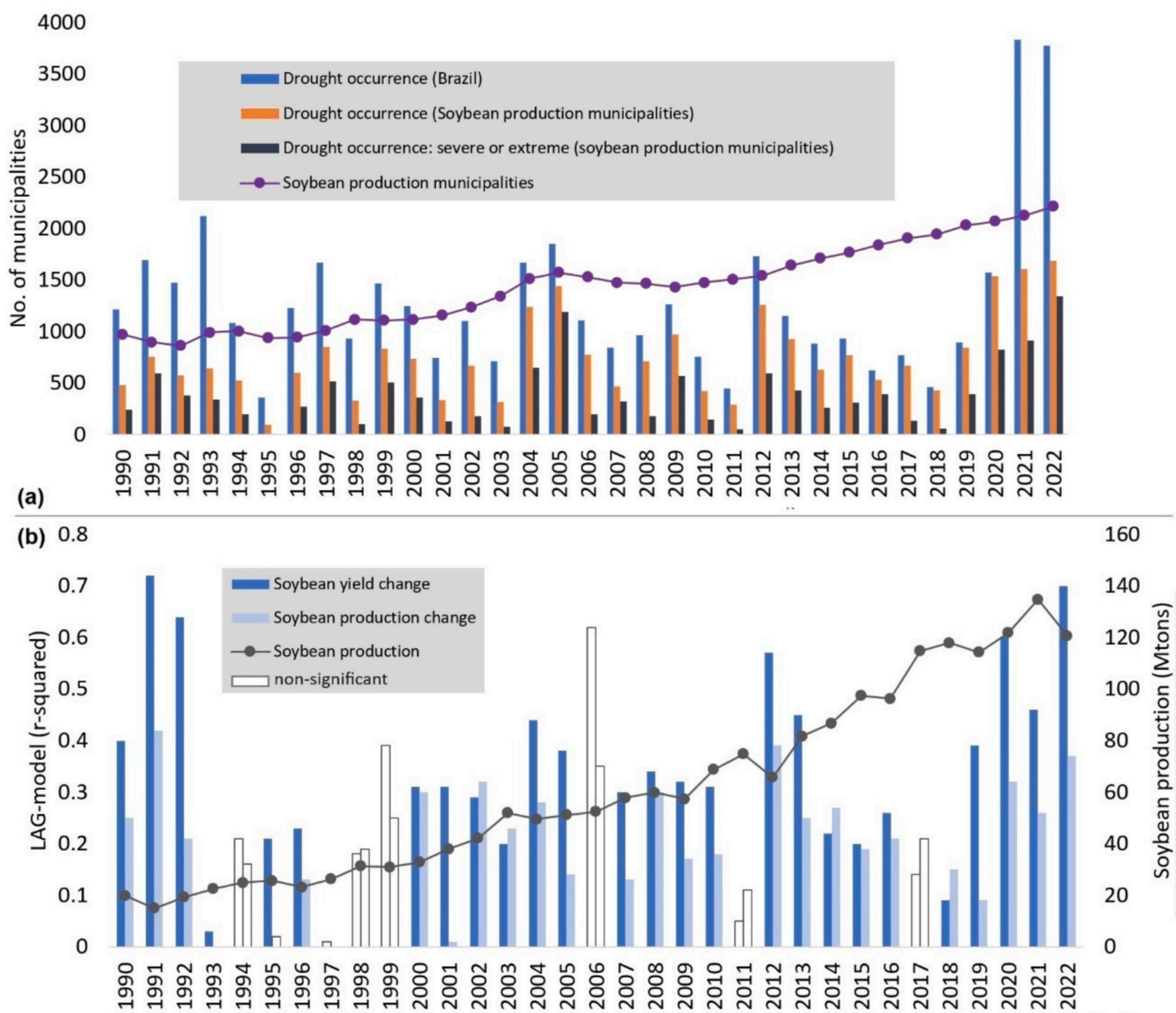

Fig. 1. (a), Drought occurrence in Brazilian municipalities, temporal changes in the number of soybean production municipalities and number of municipalities affected by severe droughts; (b), "r-squared" of univariate spatial LAG regression models for assessing the spatial effect of drought (SPI composite variable) on interannual changes in soybean yield (kg/ha) and soybean production (tons).

country) were the most affected by droughts during the 2021 and 2022 soybean growing seasons, although the 2005 and 2012 growing seasons also exhibited a large number of soybean municipalities affected by droughts, with 1442 and 1258 municipalities, respectively (Fig. 1a). It is noteworthy to mention that an average of 390 soybean production municipalities exhibited severe or extreme drought during these growing seasons (Fig. 1a).

All of the 947 soybean production municipalities located in the Southern region of Brazil (map of soybean production regions, Supplementary Information—Fig. SI1), which represented 20 % of the national soybean production in 2022, were affected by droughts in 2022 (908 experienced severe or extreme drought). Between 1990 and 2022, the total annual soybean production in Brazil increased from 19.9 Mtons to 120.7 Mtons (i.e., 500 %; Fig. 1b). Over the same period the average yield increased from 1732 kg^{-ha} to 2951 kg^{-ha}. However, the growing seasons of 1991, 1996, 1999, 2004, 2009, 2012, 2016, 2019, and 2022 showed decreases in total production (tons) with respect to the previous year, with 2022 exhibiting the largest decrease (a drop of 14 Mtons or 10.5 %). It is noteworthy to mention that the mean composite Standardized Precipitation Index (SPI) value observed in 2022 (−1.69) was the second lowest after the one observed in 2005 (−2.03). Considering that the average value of the SPI composite over the entire study period was −1.08, this shows that drought in 2022 was 63 % more intense than the average over the study period.

We applied LAG-models to assess the relationship between droughts and changes in soybean production and yield (Supplementary

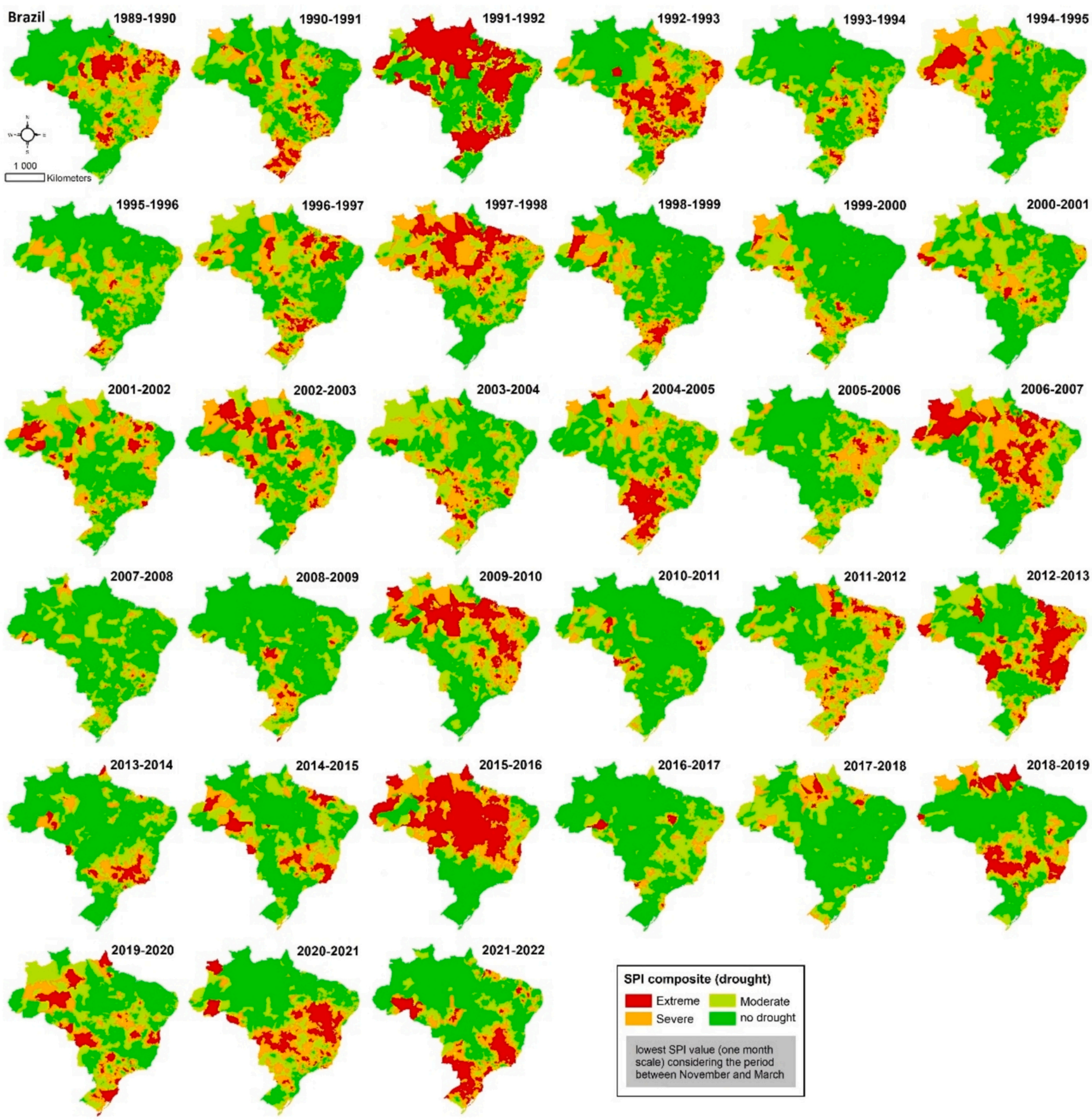

Fig. 2. Spatiotemporal drought occurrence (according to the SPI composite) across Brazil during the growing seasons of 1990 to 2022.

Information—Table SI1). Regarding the changes in soybean yields, results of the LAG-models show that large and significant r-squared values were obtained at the beginning and at the end of the study period, while low and/or non-significant r-squared values were obtained during the mid-1990s and 2010s (a large but non-significant value was observed in 2006; Fig. 1b). The two highest r-squared values, indicating a relationship explaining >70 % of the variance observed in soybean yields, were obtained in 1991 and 2022, years that also exhibited quite large reductions in soybean production (Fig. 1b). With respect to changes in soybean production, no clear trend over time was observed (Fig. 1b). However, the largest and significant r-squared values occurred in 1991, 2012, and 2022, which coincide with those obtained for soybean yields (Fig. 1b). For the drought model of 2022, we also tested two additional weights matrices of second- and third-order of contiguity. While the AIC for the first-order was 52,024.3, second- and third-order were 52,257.3, and 52,382.9, respectively—indicating that the first-order was more suitable. In addition, the two different SPI scales (3-month, and 6-month) tested resulted in a significant association between drought and soybean production outcomes for the growing season of 2022, but with a lower AIC observed for the model with the 'SPI composite' (i.e., reflecting the lowest SPI 1-month observed during the growing season) and a slightly higher r-squared value. However, for the drought model of 2018, while a significant association between drought and soybean outcomes were observed for the 'SPI composite', no significant results were observed for SPI scales 3 and 6—showing that the SPI based on 1-month scale was more sensitive to capturing the effects of drought on soybean production in years of more regular precipitation (Fig. 2).

3.2. Association between multiple droughts and soybean production

We evaluated the cumulative change in soybean production for the growing seasons of 2021 and 2022 (the two sequential growing seasons with the largest number of municipalities affected by drought). Among 2213 soybean production municipalities, the average cumulative production change exhibited a reduction of 450 tons (with a yield reduction of 0.23 kg^{-ha}). However, municipalities that did not experience a drought during any of these two growing seasons exhibited an average increase in the cumulative soybean production change of 9770 tons (with a yield increase of 0.27 kg^{-ha}), while those affected by severe or extreme droughts in both years exhibited an average reduction of 9442 tons (with a yield reduction of 0.71 kg^{-ha}). In addition, municipalities that experienced a severe or extreme drought in only one of these two growing seasons exhibited an average reduction in cumulative soybean production change of 1554 tons (with a yield reduction of 0.10 kg^{-ha}). Furthermore, municipalities that experienced multiple droughts exhibited an average cumulative production change that was 21 times lower than the average for all soybean production municipalities (SI—Table SI2).

We also tested other sequential periods, besides 2021—2022, marked by droughts affecting a large number of municipalities (Fig. 1a, b). For the periods 1991—1992, 2004—2005, 2008—2009, and 2021—2022 results of LAG-models showed that municipalities affected by multiple droughts exhibited a significantly lower soybean production compared to municipalities that did not experience them (SI—Table SI3). In contrast, for the periods 2007—2008, 2012—2013, 2015—2016, and 2020—2021 the LAG-models showed non-significant results (SI—Table SI3). Finally, for the period 2021—2022, the cumulative production change for municipalities affected by multiple droughts showed: (*i*) larger decreases as compared to municipalities affected by multiple droughts occurring during prior periods, and (*ii*) the largest decrease in soybean production compared to municipalities affected by just one severe or extreme drought in all periods analyzed.

3.3. Interaction between COVID-19 and droughts

Between February 2020 and March 2021, soybean production municipalities reported 95,607 deaths due to the COVID-19 pandemic. This represented around 30 % of the total number of deaths due to the pandemic (321,515) reported for the same period throughout Brazil. By the end of March 2022, the number of deaths due to the pandemic in the soybean production municipalities was reported to be 219,262 (Fig. 3a). This figure represented around 33 % of the total number of deaths reported throughout the country due to the pandemic (659,757 deaths reported by March 31, 2022). In soybean production municipalities, the average number of deaths per thousand inhabitants between March 2020 and March 2022 was 2.88, while it was 1.18 between the beginning of the pandemic and March 2021. In addition to the dramatic loss of human life, by the second year after the onset of the pandemic, COVID-19 was exerting significant negative impacts on social life (e.g., lockdowns, overwhelmed health systems) and the economy (e.g., disruptions to supply chains). For instance, by March 2021, global soybean prices increased 54 %, as compared to the previous year, while low fluctuations were observed in the price of agricultural inputs (Fig. 3b). However, from March 2021 to March 2022, while the global soybean price increased just 15 %, the price of major agricultural inputs, such as phosphate and potassium fertilizers, exhibited increases of 32 % and 58 %, respectively (Fig. 3b). These numbers suggest that COVID-19 seemed to exert an effect on not only the global prices of agricultural commodities such as soybean, but also on the global price of agricultural inputs, including fertilizers, particularly during 2022 (Fig. 3b,c). Such effects coincided with the occurrence of extreme droughts associated with lower soybean production and yield (Fig. 1). Fig. 3c shows that soybean inflation-adjusted production costs per hectare in the growing season of 2022 were on average 71 % higher than those in 2021, and 90 % higher than those in 2010. The increase in the price of fertilizers observed between 2021 and 2022 exerted the largest effect on this compounded soybean production cost per hectare, switching from an average of 20 % of the production costs in 2021 to 31 % in 2022.

We applied LAG-models to assess the potential interaction between COVID-19 (using deaths per municipality as a surrogate) and droughts, for the growing seasons of 2021 and 2022. Results of these LAG-models showed that 2021 exhibited no significant interaction, while 2022 exhibited a significant ($p < 0.01$) and positive interaction (SI—Table SI4, Fig. SI2). Hence, results from this model indicate that municipalities under severe drought conditions and with higher COVID-19 death cases where more associated to decreases in soybean production (SI—Fig. SI2). Furthermore, an additional independent variable used in the models, 'rural labor', exhibited a significant negative coefficient in the 2022 model, indicating that larger losses in soybean production occurred in municipalities with a lower number of rural laborers. Similarly, the variable 'crop diversity' exhibited a significant positive coefficient in the 2022 model, indicating that larger losses in soybean production occurred in municipalities with a lower diversity of crops (i.e., municipalities producing, on average, more soybean than other crops). The 2022 model also showed a significant ($p < 0.001$) spatial lag term "W" of the dependent variable, indicating spatial dependence. This suggests that changes in soybean production in a given municipality are also influenced by the dynamics observed in neighboring municipalities.

For the 2022 model we also utilized weights matrices of second- and third-order, with the lowest AIC observed for the first-order at 51996.6, while 52,233.4, and 52,352.7 for the second- and third-order, respectively. For all the univariate drought, multiple droughts, and interaction models applied in this study, we found significant Moran's I values ($p < 0.05$), indicating the presence of spatial autocorrelation, which was also confirmed by the significance ($p < 0.05$) of the spatial lag term "W" and its associated lag coefficient ρ (rho) (SI—Table SI1, Table SI3, and Table SI4).

4. Discussion

Our study sheds light on the complex interactions between multiple

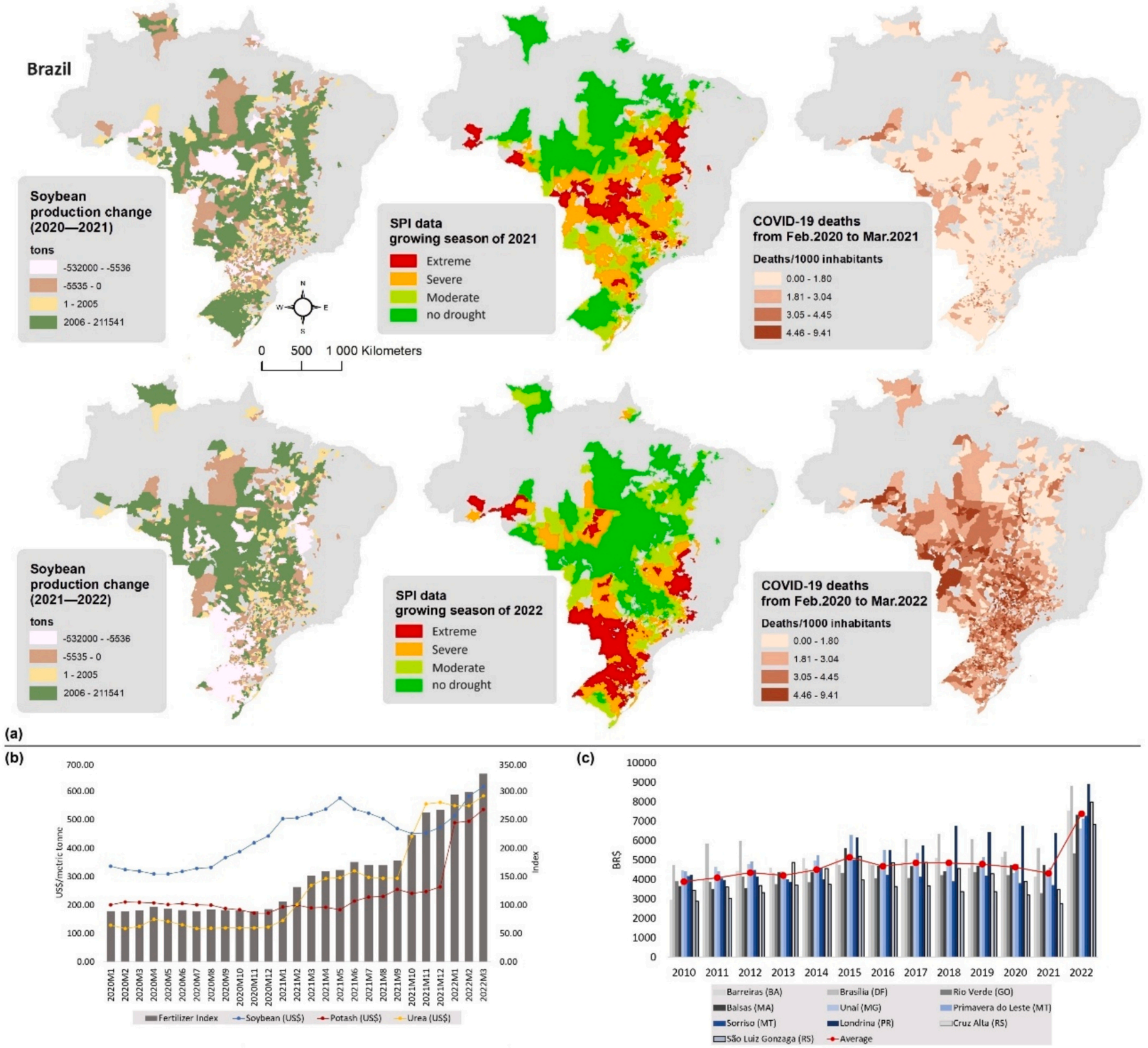

Fig. 3. (a), Spatial patterns of soybean production change (tons) for the growing seasons of 2021 and 2022 along with maps exhibiting the spatial patterns of drought and COVID-19 deaths per thousand inhabitants; (b), economic indicators of the soybean supply chain considering the grain price, and prices for major inputs; (c), Economic indicators of the soybean production costs in major production municipalities between 2010 and 2022.

years of drought and the global effects of the COVID-19 pandemic on Brazil's soybean production. In recent years, Brazil has been impacted by numerous drought events, with the number of affected municipalities significantly increasing during the 2020s—soybean producers in Central Brazil have also noted changes in precipitation patterns in recent years negatively impacting production (Dou et al., 2023). We also found new evidence showing that although drought events may occur in sequential years, their cumulative impacts are not always significant, but are more likely to occur—i.e., five out of eight sequential growing seasons analyzed exhibited significant impacts. These cumulative effects were demonstrated by our analysis of the association between the sequential occurrence of multiple droughts and soybean outputs, which were observed with higher intensity in the growing seasons of 2021 and 2022, both of which coincided with the occurrence of La Niña. These results suggest that La Niña seems to have a larger effect during the rainy season in Brazil, thus influencing more the summer crop agriculture (Cirino et al., 2015). This provides crucial information for policymaking and agricultural management (e.g., planting) decisions.

Simultaneously with extreme and prolonged droughts in Brazil's soybean producing regions, the COVID-19 pandemic unfolded on a global scale, affecting human societies in varied forms and with different intensities (Berry, 2023), increasing the risks for society due to multiple crises (Quigley et al., 2020; Vyas et al., 2021). While the first cases of COVID-19 in Brazil were reported in February of 2020, the year 2021 exhibited the largest number of COVID-related deaths, accounting for around 75 % of the total deaths reported between 2020 and 2023 (WHO COVID-19 Dashboard, 2020). Using the number of COVID-related deaths as a surrogate, we found a significant interaction between droughts and COVID-19 but only during the growing season of 2022 (SI—Table SI4). However, these results did not establish any direct causal relationship between droughts and the pandemic, or a direct causal effect of COVID-19 on soybean production, given the high degree of mechanization utilized for soybean production, together with low labor demands, and the fact that the population cohort most linked with soybean production (e.g., rural laborers) were less affected by COVID-19 (SI—Table SI4; Derin et al., 2024). Therefore, the disruptions caused by COVID-19 on soybean production in Brazil were manifested through other channels, such as the increase in the price of agricultural inputs (Fig. 3b), which cascaded into the soybean production costs (Fig. 3c) but were not followed by comparable increases in soybean prices (Fig. 3b). For instance, a survey in Pakistan showed that 72 % of farmers observed high spikes in input prices due to COVID-19 effects on supply chains, putting pressure on their production capacity (Hussain et al., 2023). Here, it is crucial to underline Brazil's reliance on fertilizers supplied by global markets, which poses a significant vulnerability to its agricultural sector (Liu et al., 2018).

In the 2022 growing season, COVID-induced disruptions had already permeated global agricultural supply chains (Meier and Pinto, 2024), increasing the prices of agricultural inputs (Menezes et al., 2023) that have not returned to pre-COVID-19 levels (IMF, 2024). Over the short term, this effect was, to a certain extent, mitigated by the increase in soybean demand, mainly from China, reducing some of the short-term economic burdens imposed by the increase in production costs (Jank et al., 2023). Nevertheless, this is not sustainable over longer periods, partly because soybean prices started to fall faster than production costs (Torres et al., 2024). In addition, while the economic impact of droughts on soybean producers is significant (Carvalho et al., 2020), the burdens due to consecutive years of drought are even more stringent, as they impact the investment capacity of producers, reducing their ability to carry out management practices that help maintain or increase productivity (Lisboa and Nakamura, 2023; Fantin and Beledeli, 2024). For example, the positive effects of fertilizer applications on soybean yields tends to be short-lived (i.e., they do not carry over to the following growing season), thus continuous fertilizer applications are necessary to sustain high yields (Martha Jr. et al., 2010) but require high economic investments every growing season. This outcome, combined with the fact that Brazilian agriculture operates with low incentive levels [support of producers constitutes <3 % of the average gross farm receipts at the farm-gate level (OECD, 2023)], results in a reduced capacity of producers to adopt capital-intensive agricultural practices (Barros et al., 2004). Consequently, under the high prices of agricultural inputs induced by the COVID-19 pandemic, particularly in 2022, farmers decreased their utilization, further reducing the soybean yields that were already burdened by the successive droughts of 2021 and 2022.

Since the 1990's, soybean producers have been trying to adapt to adverse climate conditions. For instance, production tends to increase reliance on technological developments of seed varieties of undetermined cycle (Dou et al., 2023), which increases tolerance to water stress and is becoming the preferable type of soybean cycle among Brazilian producers (Dall'Agnol, 2017). Although a useful strategy, irrigation in soybean production represents <10 % of its total planting area (Goulart, 2023) and implementation costs prevent its expansion at larger scales. Conservation soil management practices, such as non-tillage along with plant diversification/rotation, have been implemented in production areas over the last decades given support to cope with water shortages (Debiasi et al., 2022). National level monitoring systems—e.g., the *Agricultural Zoning for Climate Risk* (ZARC) also have an important role in helping producers to decide the best planting window in every growing season, which is additionally contributing to avoid agricultural losses (Santos and Martins, 2016). In addition, producers have already demonstrated some degree of flexibility and change production strategies to avoid low fertile areas (e.g., high sand content), thus decreasing vulnerability to drought, as those areas seem to have lower capacity to buffer water shortages during the growing season (Silva et al., 2020b).

5. Future directions, governance and policy responses

Additional efforts in the coming years are needed to broaden our understanding about the many possible ways by which extreme weather events combined with pandemics, such as COVID-19, could affect agricultural production systems. The resilience and adaptation of Brazilian agriculture to such supply shocks deserve attention, because the country's role as one of the major global food/feed suppliers is projected to strengthen in the next decade (OECD-FAO, 2023). As Brazil already contributes with around 50 % of the global soybean trade (Campeão et al., 2020), significant impacts in the country's production trigger cascade effects along the feed and animal value chains that could negatively affect supply and, ultimately, food security. Stakeholders, from farmers to private companies and policymakers, need to coordinate efforts and work together to address such vulnerabilities and potential spillovers to increase the resilience and adaptation of agricultural production systems under multiple shocks (Viña and Liu, 2023). These efforts must include intelligence and forecasting deliverables to support the public and private decision-making process, as well as knowledge and technological developments, and tailored policies, to cope with this changing environment. Intelligence and forecasting activities should encompass both the analysis of possible futures, targeting the medium- to the long-run, as well as biophysical and market monitoring and alert systems, which could provide a sound basis for operational and tactical (e.g. short- to medium-run) adjustments. The innovation system benefits from these intelligence inputs to move further forward in the design and implementation of R&D (genetics, digital transformation, management), technology transfer, and extension agendas centered on resilience, adaptation and mitigation objectives of a sustainable agriculture. Such efforts interact with economic and political realms. On the one hand, because Brazilian agriculture operates with low levels of incentives, c.a. 3 % of the farmers' gross revenue at the farm-gate level, indicating producers are likely to promptly respond to market signals. On the other hand, because policies interfere in biophysical, social, and economic outcomes through financing (credit, insurance), guidance on sustainable production approaches (soil and water conservation, reduced intensity of greenhouse gas emissions, product quality standards), market dynamics and barriers to trade (incentives and disincentives to production and consumption), and infrastructure development (transport, storage, irrigation, digital/connectivity) are necessary.

Different mitigation and prevention measures should quickly evolve and be implemented to address future shocks. It would be useful to treat Brazil as part of a metacoupled human and natural system (Liu, 2017), integrating socioeconomic and environmental conditions within Brazil as well as interactions (e.g., trade, technology transfer) with adjacent and distant countries (Liu, 2023). We provide a few suggestions that could be implemented in the short-, mid-, and long-term.

A feasible short-term response would be fostering widespread adoption of monitoring systems for assessing changes in climate regimes, biotic pressures, and abiotic stressors such as soil moisture. Digital transformation such as IoT, analytics, among others, are likely to boost the outcomes of these monitoring systems to support better decisions towards sustainable agricultural practices.

As a mid-term response, both public and private initiatives should facilitate emergency credit access in municipalities affected by extreme weather events and other stressors such as pandemics. ZARC by reducing likelihood of weather risks (Santos and Martins, 2016) offers a sound basis for expanding insurance to cope with unfavorable climate events in Brazilian agriculture. The *Agricultural Activity Guarantee Program* (Proagro) (Carvalho et al., 2020), and the *Rural Insurance Premium Subsidy Program* (PSR) (Santos et al., 2024) are examples of insurance programs benefiting from ZARC's deliverables. These strategies would help producers to implement more weather-resilient agricultural management practices. For instance, fostering adaptation/mitigation approaches, such as non-tillage and integrated crop-livestock systems, benefits soil and water conservation, increasing the agricultural systems' resilience. In addition, planting primarily on high responsive (productive) lands while sparing marginal productive areas during growing seasons forecasted to experience extreme weather events has been successfully applied by some soybean producers (Silva et al., 2020b).

Long-term responses include a strengthened R&D strategy to fuel the innovation system with knowledge and technologies such as novel crop varieties more resistant to drought (Fahad et al., 2017; Khan et al., 2024) and biotic stressors (e.g., pests and diseases), and improved management practices requiring lower inputs and conferring improved resilience to a changing climate. Infrastructure development benefits both the supply and demand sides and could reduce greenhouse gas emissions (Wang et al., 2024). Another long-term approach to potentially reduce weather and supply-chain disruption risks centers on diversifying production within Brazil (Perosa et al., 2024) and stimulating the national agricultural input industry (SAE, 2021).

While described for the soybean sector in Brazil, with proper modifications, similar actions, combined with other measures, may be implemented around the world. This will provide opportunities for building more resilient and sustainable food production systems under the context of multiple interactive shocks.

CRediT authorship contribution statement

Ramon Felipe Bicudo da Silva: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Andrés Viña:** Writing – review & editing, Writing – original draft, Validation, Supervision, Methodology, Investigation, Funding acquisition, Conceptualization. **Daniel de Castro Victoria:** Writing – review & editing, Software, Methodology, Data curation. **Mateus Batistella:** Writing – review & editing, Validation, Investigation, Conceptualization. **Geraldo B. Martha:** Writing – review & editing, Validation, Investigation, Conceptualization. **Emilio Federico Moran:** Writing – review & editing, Resources, Project administration, Conceptualization. **Jianguo Liu:** Writing – review & editing, Supervision, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare no conflict of interest.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2025.179047.

Data availability

Data will be made available on request.

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