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No more double cropping in Mato Grosso, Brazil? Evaluating the potential impact of climate change on the profitability of farm systems

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ABSTRACT

CONTEXT: Farmers in the federal state of Mato Grosso contribute about one-third of national grain production in Brazil. Given their key role in providing food and feed for fast-growing world demand, major shocks on Mato Grosso's farm holdings can lead to devastating consequences for vulnerable consumers and producers inside and outside Brazil. Research has shown that rising temperature and water stress threaten the agricultural productivity of Mato Grosso's rain-fed farm production systems. Failure of current production systems on existing croplands may also foster agricultural expansion and increase pressure on the remaining native forest. Balancing agricultural production and environmental protection is of particular concern in Mato Grosso because more than half of its territory is in the Amazon Rainforest biome. The tight schedule of field activities within double-cropping systems reduces farmers' ability to adapt to climate change and manage shocks. The increasing uncertainty about climate change and price volatility further complicate farmers' decision-making.

OBJECTIVE: This study evaluates the impact of two climate change scenarios on the profitability of double-cropping systems, considering not only climate variability but also economic uncertainties faced at the farm level.

METHODS: Our modeling system combines future climate projections with biophysical and bioeconomic models. We used high-performance computing with many compute nodes and large shared memory to account for the large heterogeneity of possible management options and farm-gate prices.

RESULTS AND CONCLUSIONS: Simulation results indicate that farmers in Mato Grosso could be exposed to significantly lower economic returns, with a future gross margin reduction of 69% on average compared to current levels. Moreover, the number of profitable cropping alternatives could drop by 18% on average. According to our simulations, climate impacts on gross margins are likely to differ in Mato Grosso, with the Southeast macro-region being the most affected and the South Central region the least. The simulation results also revealed a higher risk of losses during the second cropping season. Double-cropping systems with cotton were the most impacted by changing climatic conditions, and sunflower the least.

SIGNIFICANCE: This study revealed that climate change might negatively affect double-cropping systems in the Southern Amazon due to reduced annual precipitation, a shortening of the rainy season, and shifts in the rainy season's onset and cessation dates. Our bioeconomic simulations further suggest that farmers in Mato Grosso could lose one of their most significant comparative advantages, namely the possibility of harvesting two crops in one cropping season.

1. Introduction

Brazil is an important player for global food security (FAO, 2020) being a major producer and exporter of food and agricultural products. Accordingly, any shock to national agricultural production will likely affect worldwide supply and world market prices with potentially devastating consequences for vulnerable consumers and producers inside and outside Brazil. Given the high share of unskilled labor in the

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country's agricultural sector (Ferreira-Filho and Horridge, 2016), such a shock would also adversely affect the wealth distribution in Brazil.

Mato Grosso, covering an area of France and Germany combined, is Brazil's most important federal state in terms of agricultural production (CONAB—Companhia Nacional de Abastecimento, 2020). Currently, it leads the national production of soybean, maize, cotton, and sunflower and holds the largest cattle herd in the country (CONAB—Companhia Nacional de Abastecimento, 2020; IBGE—Instituto Brasileiro de Geografia e Estatística, 2020). Mato Grosso's agricultural productivity and its rain-fed production systems are threatened by rising temperatures, a lengthening of the dry season and changes in the spatial and temporal distribution of precipitation due to global climate change (Arvor et al., 2014; Boisier et al., 2015; Fu et al., 2013; Gil et al., 2018; Nobre et al., 2016).

Mato Grosso is also a hotspot of biodiversity with three biomes, the Cerrado with its savannah vegetation, the wetlands of Pantanal, and the Amazon Rainforest, which covers 54% of its territory. This unique biodiversity, however, is endangered through the ongoing conversion of native vegetation into pasture and cropland over the past years (Ferrante and Fearnside, 2019; IBGE, 2018; Schielein and Börner, 2018). Crop failure on existing farmland due to climate change might trigger further expansion of the agricultural frontier onto native forestland (Arvor et al., 2014).

Climate impact studies tend to use standard crop management practices, ignoring local farmer adaptations under price uncertainty (Berger and Troost, 2014; Holman et al., 2019). As argued by Lobell (2014), not fully capturing the benefits of farmer adaptation in crop management will systematically cause studies to overestimate the adverse effects of climate change. When facing lower crop yields and uncertain returns, farmers usually adapt their farm systems by changing crop mixes as well as input and output levels. Examples for this type of bioeconomic analysis incorporating farmer adaptation are Lehmann et al. (2013), who combined a crop growth model with an economic decision model to simulate winter wheat and maize production in Switzerland. Troost et al. (2015) and Troost and Berger (2015) applied agent-based simulation combined with crop-growth modeling for an agricultural region in southwest Germany, while Briner et al. (2012) simulated climate change impacts in a Swiss mountainous region using an aggregate mathematical programming model. Mittenzwei et al. (2017) applied a bioeconomic partial-equilibrium model to analyze the impact of climate change on Norway's agricultural sector considering climate and policy uncertainty.

Mato Grosso therefore deserves special attention when analyzing the future effects of climate change on Brazil's agricultural production. Recently, Hampf et al. (2020) carried out a simulation study to evaluate future impacts of climate change on temperature, precipitation, and crop yields for typical production systems in Mato Grosso. The authors found that even with adaptation of sowing dates to changes in the onset of the rainy season, climate change is likely to decrease maize and cotton yields by 28% and 17%, respectively, due to less precipitation and higher temperatures.

A second study by Brumatti et al. (2020) examined whether different adaptation measures (delay in sowing dates and adoption of short cycle cultivars) could maintain economic viability of standard double-cropping systems under future climate change, assuming fixed planted areas and fixed commodity prices. Depicting the heterogeneity of the farm production practices, however, is especially important in Mato Grosso, where the sowing window usually takes more than one month. Given the large size of farm holdings and their endowments of machinery, labor, and capital, farmers need to split the sowing campaign over many weeks, employing different applications of fertilizers and pesticides.

Addressing the knowledge gap regarding future double-cropping systems in Mato Grosso, this study's objectives are: (i) to assess the impact of climate change on farm system profitability, (ii) to identify crop adaptation options for farmers in Mato Grosso, and (iii) support farmers and policy decision-makers with farm-level planning information. The methodological approach taken in this study integrates future climate scenarios with biophysical and bioeconomic simulation models: First, crop yields were simulated with the dynamic crop growth model MONICA in response to various management practices per crop. Second, we introduced sunflower as a novel crop that can potentially reduce the adverse impacts of climate change. Third, we carried out an in-depth investigation of projected climate change effects by analyzing precipitation patterns and the rainy season's sub-regional duration. Fourth, we combined simulated crop yields with farm-gate prices and costs to calculate the gross margins of farm production systems. Fifth, by combining the simulated crop gross margins with sub-regional crop calendars and specific data of field operations, we estimated the resulting profitability of double-cropping systems. Sixth, we conducted extensive uncertainty analysis using high-performance computing to check the robustness of our simulations.

2. Data and methods

2.1. Study region and farm production systems

Mato Grosso's agricultural production takes place almost entirely in five of the seven macro-regions defined by the Mato Grosso Institute of Agricultural Economics (IMEA). Using the sampling procedure of IMEA (2010), we parameterized our simulation models for these five macro-regions (Mid-North, Northeast, South Central, Southeast, and West). The terrain in Mato Grosso is mainly flat, and the rainy season is usually well-defined, starting from September or October and extending into April or May. The prevalent farm systems consist of large-scale operations employing double-cropping rotation of soybean followed by maize or cotton. The production of sunflower after soybean is a recent cropping alternative that started around a processing facility established by a group of farmers in *Campo Novo dos Parecis* in the western part of Mato Grosso (Oliveira de Sousa et al., 2018).

2.2. Integrated modeling approach

Our modeling system consists of two components: The first is the biophysical component that uses a process-based agroecosystem model to simulate crop yields and their responses to agro-climatic conditions and management practices. The second is a bioeconomic model that combines the climate scenarios and biophysical conditions with production requirements and market conditions to simulate the respective farm system's profitability. Uncertainty at the farm-level is considered as well at this point. The result is farm-level planning information that can support farmer planning decisions. Fig. 1 provides an overview of model components and workflows.[1]

2.2.1. Climate models

Future climate projections for this study were derived from Böhner et al. (2014) and Hampf et al. (2020) who employed two different climate models: the Statistical Analogue Resampling scheme (STAR) and the Weather and Research Forecasting model (WRF). The former projects drier and warmer conditions and more extreme events in the future, whereas the latter projects climate changes largely going in the same direction but with less severity from a farmer point of view. The climate variables simulated by STAR and WRF and used in this study are the maximum and minimum air temperature, effective sunshine hours, precipitation, and wind speed. The models provided climate projections for representative survey sites in the five IMEA macro-regions in Mato

[1] To facilitate double-blind review, model documentation including the R scripts, input and output files used in this study can be downloaded anonymously from the MPMAS developer websitehttps://www.uni-hohenheim.de/mas/software/BrazilClimateChangeSupplement.tar.gz

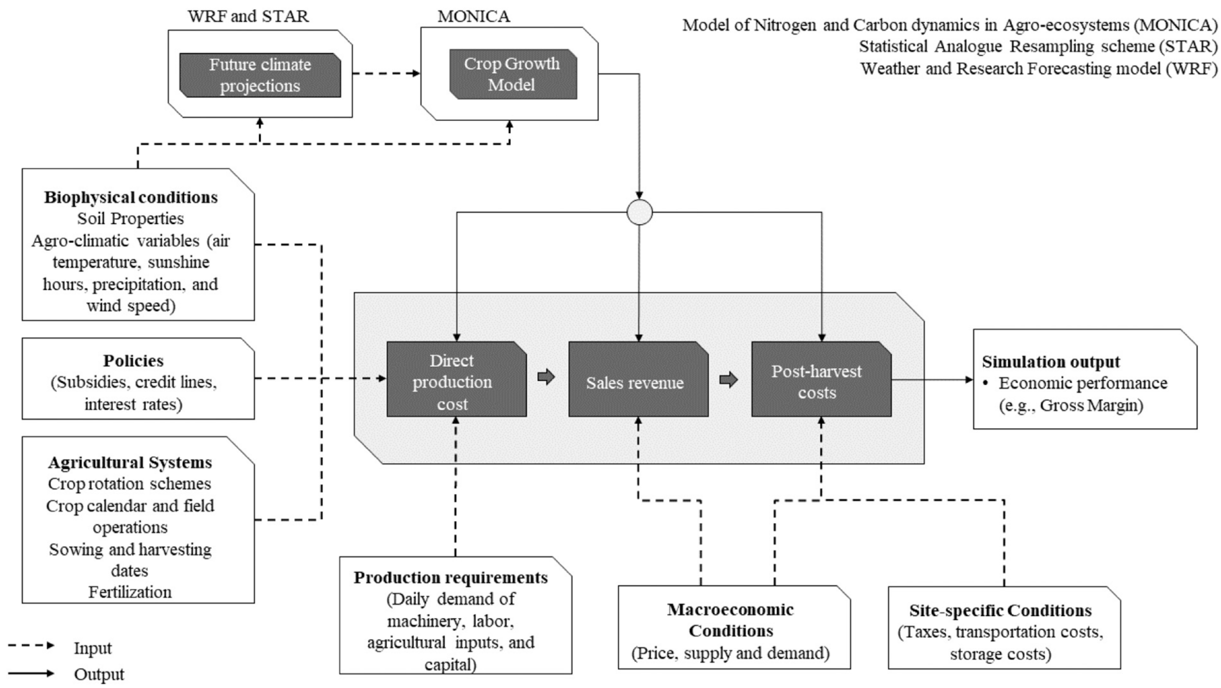

Fig. 1. Flow chart of our modeling system.

Grosso in a daily resolution up to the year 2040; the present paper uses the periods of 2020–24 and 2035–39 for comparison. Both climate models used the ECHAM5 A1B scenario from the Special Report on Emissions Scenarios (SRES) of the Intergovernmental Panel on Climate Change (IPCC). That scenario assumes further economic growth, global population peaking in mid-century, and rapid introduction of new and more efficient technologies (IPCC—Intergovernmental Panel on Climate Change, 2007).

Beyond rising temperatures and altered precipitation patterns, timing-related climatic factors can also affect crop yield. For example, in Mato Grosso's widely used double-cropping systems, delays of the rainy season's onset or its early cessation can directly impact farm net production. We therefore estimated the onset and cessation of the rainy season following Dunning et al. (2016), who proposed a two-step approach for locations such as Mato Grosso with a rainy season spanning over two calendar years. The first step consisted of calculating the climatological cumulative daily rainfall anomaly C on day d with the following equation:

$$C(d) = \sum_{i=1}^{d} Q_i - \overline{Q}$$

where Q_i is the climatological mean rainfall for each individual day of the calendar year (calculated over a period of several years), $\overline{Q}$ is the climatological daily mean rainfall, and i ranges from day 1 (i.e., 1st of January) until day d. The beginning of the climatological water season d_s is marked by the day of minimum C, and the end of the season d_e is marked by the day of maximum C. In a second step, we estimated the specific onset and cessation dates for each rainy season using the previous step's estimates as a reference. The daily cumulative rainfall anomaly A is calculated for each day in each year from $d_s - 50$ to $d_e + 50$ using the following equation:

$$A(d) = \sum_{j=d_s-50}^{d} R_j - \overline{Q}$$

where R_j is the rainfall on day j. The day after the minimum daily cumulative rainfall anomaly is defined as the onset date of the yearly rainy season, and the day after the maximum is defined as its cessation date.

2.2.2. Biophysical model component

Crop yield simulations in the biophysical component of our modeling system were carried out with the Model for Nitrogen and Carbon in Agroecosystems (MONICA) (Nendel et al., 2011). With MONICA, we simulated the response of soybean, maize, cotton and sunflower yields to different sowing dates, nitrogen fertilization rates, soybean maturity groups, soil characteristics, and climatic conditions. MONICA has already been used in Mato Grosso to simulate green financing policies (Carauta et al., 2017), sustainable measures for yield gap closure (Hampf et al., 2018), and the impact of climate change and technological development on crop yields (Hampf et al., 2020). For a detailed description of MONICA and its specification, see Nendel et al. (2011).

MONICA was parameterized in this study for five survey sites that are representative for their macro-regions following the classification of IMEA (2010). We accounted for four different soil types (acrisol, arenosol, ferrasol, plinthosol) and selected soil properties (e.g., silt, sand, and clay content, C/N ratio, bulk density) that were taken from the soil database of Cooper et al. (2005). The distribution of soil types for each macro-region was retrieved from the soil maps published by Mato Grosso's State Secretary of Planning (SEPLAN—Secretaria de Estado de Planejamento e Coordenação Geral de Mato Grosso, 2011).

The agro-climatic output variables of the climate projections from 2020 to 2040 generated with STAR and WRF—explained in section 2.2.1—were used as input for MONICA to simulate crop yields in a daily resolution for each macro-region and climate projection.

We considered an extended number of crop management options for this study, consisting of multiple sowing dates, nitrogen (N) fertilization rates, and crop maturing cycles. As shown in Table 1, we considered four sowing dates and five N fertilization rates for maize; four sowing dates and three different maturity groups for soybean; five sowing dates and seven N fertilization rates for cotton; and five sowing dates and five N fertilization rates for sunflower. Table 1 summarizes the crop-related variables used in our simulations. Crop yields were simulated within a double-cropping rotation scheme, composed of soybean or cover crop (sorghum) followed by maize, cotton, sunflower, or cover crop. In total, we simulated 960 combinations of sowing dates, fertilization rates,

Table 1
Characteristics of farm production systems analyzed in our simulations.

Crop	Sowing dates	Cycle (days)	Nitrogen fertilization (kg ha^{-1})
Cotton	15 Dec, 30 Dec, 15 Jan, 30 Jan, 15 Feb	172	0, 90, 140, 185, 230, 280, 450
Maize	20 Jan, 06 Feb, 20 Feb, 06 Mar	140	0, 40, 80, 120, 160
Soybean	01 Oct, 15 Oct, 01 Nov, 15 Nov	95, 110, 128	–
Sunflower	01 Feb, 15 Feb, 01 Mar, 15 Mar, 01 Apr	110	0, 30, 60, 90, 120

maturing cycles, and crop rotations for each site, soil type and cropping season.

2.2.3. Bioeconomic model component

Crop management practices adapted to the local conditions of Mato Grosso involve the use of distinct seed varieties and agricultural inputs. For instance, when farmers use crop varieties with longer maturity cycles, they typically apply more pesticides. Moreover, each agricultural practice requires different field operations, and each field operation has its own timing of input, labor, and machinery demands. To capture this heterogeneity at the farm system level, we created location-specific crop calendars in a weekly resolution for each agricultural practice and then combined this information with site-specific data on machinery and labor demands as well as on the remaining, other agricultural inputs.

We then programmed our bioeconomic model component using the R Software (R Core Team, 2020) to compute the total utilized amounts of the various production factors required to produce a crop under a specific management option. In addition to the various crop management options that were simulated in the biophysical model component MONICA, we also considered specific crop seed varieties. This level of detail was necessary because different seed varieties demand different pesticides and application quantities with noticeable implications for farm-level production costs. Moreover, our bioeconomic simulations had to cover region-specific technical and economic constraints such as different availability of machinery services, input/selling prices as well as transportation costs.

Our region-specific management schemes built on the farm survey of IMEA (2016) and were adapted to our simulation experiments with the assistance of local experts from the Brazilian Agricultural Research Corporation (EMBRAPA) and the Federal Institute of Mato Grosso (IFMT). Altogether, our production cost estimation accounted for 165 agricultural inputs (fertilizers, seeds, herbicides, insecticides, fungicides, diesel), 13 field operations (soil preparation and pH correction, sowing, spraying, harvesting), and three post-harvest activities (transporting, processing and storing).

We used crop gross margins as an indicator of farm system profitability in Mato Grosso. Gross margins are defined as sales revenue minus direct production costs such as expenses for machinery usage, labor employment and input acquisition, as well as post-harvest costs and direct taxes related to selling the produce. The sales revenue was calculated for each crop product *p* associated with a specific crop management option, denoted with the variable θ. Cotton was the only crop that generates two products, cotton lint and cotton seed. The sales revenue of a specific crop management practice θ, in macro-region *r*, with soil type *s* and in year *y* was computed as:

$$Revenue_{\theta,r,s,y} = \sum_{p=1}^{P} Yield_{\theta,p,r,s,y} \times Price_{p,r,y}$$

Machinery costs were estimated using the official documentation of the Brazilian National Food Supply Company—CONAB (CONAB—Companhia Nacional de Abastecimento, 2010). We included 16 machine types in our model simulations (various tractors, harvesters, loaders, distributors of fertilizer and pesticides, sprayers, and plows). The machinery costs comprise the expenses associated with the use of machinery (such as fuel, filters, and lubricants), plus maintenance and insurance/damage. The sum of these expenses is the resulting operating cost of using machinery and is estimated in Brazilian Reais (R$) per hour. This is then multiplied by the amount of machinery used (in hours), which is estimated on a weekly basis (w) and depended on the management option chosen and the macro-region. Accordingly, the machinery operating cost of a crop management option θ in macro-region *r* was estimated as:

$$MachineryOperatingCost_{\theta,r} = \sum_{m=1}^{M} \times \sum_{w=1}^{W} machineryUse_{\theta,m,r} \times operatingCost_{m,hp,ac}$$

where *m* is the specific machine used, *hp* is its horsepower, and *ac* its acquisition cost.

The cost of fuel per hour of use is a function of the machinery horsepower and a diesel consumption factor, which was estimated as 12% (CONAB—Companhia Nacional de Abastecimento, 2010):

$$FuelCost_m = horsePower \times dieselFactor \times dieselPrice$$

In addition, CONAB (2010) estimated the cost of filters and lubricants as 10% of the fuel cost. Maintenance cost was estimated as a fraction of the acquisition cost, which depends on the machinery type. Machinery with horsepower greater than zero has a maintenance factor of 1%. In comparison, those without horsepower (such as implements that must be towed by or mounted on the tractor) have a maintenance factor of 0.8%. The maintenance cost was expressed per hour by dividing it by the total lifetime in hours, which was also taken from CONAB (2010). Cost for insurance and machinery damage was related to the acquisition cost, which was multiplied by a factor of 0.375%, and then divided by the total lifetime.

The labor cost was estimated based on the time requirement of each crop management option in the various macro-regions. Like machinery, the labor requirements (number of hours needed) was estimated on a weekly basis considering the field operations within the crop calendar. The resulting labor cost of a crop management practice θ in the macro-region r was computed as:

$$LaborCost_{\theta,l,r} = \sum_{w=1}^{W} laborRequirement_{\theta,l,r} \times (wage_l + taxes\ and\ contributions)$$

where *l* is the labor type (such as manager, driver, or field assistant). Wages for each labor type were taken from the IMEA database and then converted to hourly figures (IMEA—Instituto Mato-Grossense de Economia Agropecuária, 2016).The expenses related to payroll taxes and contributions were estimated according to the current legislation, which amount to approximately 48% of the wages paid.

The total amounts of remaining (other than machinery and labor) agricultural inputs *i* used in each crop production system were estimated together with local experts based on detailed data from the production cost survey of IMEA (2016). Input prices vary per macro-region and were also taken from IMEA's online database. The calculation of input costs was connected to the crop calendar and computed per crop management option and macro-region as:

$$OtherInputCost_{\theta,r} = \sum_{i=1}^{I} \sum_{w=1}^{W} inputRequirement_{\theta,i,r,w} \times inputPrice_{i,r}$$

We considered four different types of cost that farmers in Mato Grosso incur after harvest: the cost of transporting, processing, and storing the crops, plus the cost of technical assistance (extension), which were all taken from IMEA (2016) for the various macro-regions.

Processing cost was calculated as a percentage of total production cost. Storage cost was related to total production, but also on how long (in months) the product was kept in the storage facility (which varied per crop product and macro-region). Transportation cost was estimated as the distance (in kilometers) from the farm gate to the next processing facility, multiplied by the transportation fee and the amount produced. In contrast, the cost for technical assistance was calculated as a share of the crop revenue.

Finally, depending on the crops produced, farmers have to pay different types of taxes that are shown in Table 2 (Käfer et al., 2014). Some of these taxes had to be calculated as a percentage of the sales revenue, while others depended on the standard fiscal unit, or UPF (in Portuguese, *Unidade Padrão Fiscal*). The UPF value is determined by the federal state on a monthly basis.

2.3. Uncertainty analysis

Our simulation experiments were subjected to extensive model uncertainty analysis. This was necessary for two reasons: First, to produce robust and truly representative results, which are global distributions over the model parameter space (and not only point estimates). Second, to deal with the potential influence of error and uncertainty intrinsically associated with simulation models. Complex farm system models rely on many parameters, and uncertainty analysis assures that the modeling results are not significantly determined by the modeler's choice of ad hoc specific values (Berger and Troost, 2014).

A common challenge with uncertainty analysis is the considerable amount of computing power required (Troost and Berger, 2015). We addressed this issue by combining high-performance computing with an efficient experimental design. To reduce the number of necessary model evaluations, we used the Sobol' sequence (Tarantola et al., 2012). This sampling technique named after a Russian mathematician seeks to sample the parameter space efficiently by distributing the parameters' points evenly, thus offering faster convergence and stable estimates (Berger et al., 2017). Accordingly, we repeated each gross margin estimation over 100 uncertainty scenarios or design points. Each time, new values of the uncertain input variables were drawn from their respective distributions. In total, we identified 14 uncertainty parameters (described in Table 3) that can be grouped into four categories: labor requirements, crop yields, input, and selling prices. Since local prices and yields in Mato Grosso are highly correlated (due to climate conditions, supply and demand, and dependence on the US dollar exchange rate), we did not sample crop yields and prices independently. To preserve these observed correlations, we instead sampled prices and yields for a simulation period from a complete set of local market data observed in Mato Grosso (available for 2012 to 2017). The test for model convergence showed that the mean and 5th and 95th percentile of simulated gross margins rapidly converge to stable values, indicating that 100 repetitions were sufficient to generate robust results in our simulation study (Fig. 2).

The full experimental design for our study comprised 65 million data points. Each data point corresponded to the simulated gross margin of one double-cropping system under a unique combination of crop management options, Sobol's sequence design points, soil types, region-specific climatic conditions, future climate scenarios, and the period of simulation.

Table 2
Selling taxes.

Tax	Crop	Calculation
FUNRURAL	Cotton, Maize, Soybean, and Sunflower	Tax x Price x Yield
FETHAB	Soybean	Tax x UPF x Yield
FACS	Soybean	Tax x UPF x Yield
IMA-MT	Cotton	Tax x UPF x Yield

Table 3
Parameter variation in the Sobol' sample.

Variable	Distribution or sampling method	Min	Max
Soybean price	RS	0.96	1.15
Maize price	RS	0.85	1.19
Cotton price	RS	0.91	1.04
Sunflower price	RS	0.98	1.05
Fertilizers price	RS	0.99	1.07
Herbicides price	RS	0.92	1.04
Fungicides price	RS	0.75	1.09
Insecticides price	RS	0.99	1.05
Seed price	RS	0.95	1.17
Soybean yield	RS	0.97	1.03
Maize yield	RS	0.91	1.13
Cotton yield	RS	0.94	1.05
Sunflower yield	RS	0.96	1.09
Labor requirement	Triangle	0.84	1.18

Note: "RS" means randomly sampled from vector of local market prices and yields.
The modus from triangle distributions as well as RS variables equal to unity.

2.4. Model validation

Following the approach of Berger and Troost (2014), we conducted many structured verification tests during the modeling stage to check whether our modeling system was free of programming errors and truly performed as intended. In addition, we arranged face validation of model and simulation results with local experts and professionals at key institutions in Mato Grosso, such as EMBRAPA, IMEA, IFMT, and the Federal University of Mato Grosso (UFMT).

Furthermore, we carried out model validation tests to evaluate how well simulated values of yields and gross margins matched with corresponding observed values. To that end, we simulated crop yields using observed climate data from the Brazilian National Institute of Meteorology (INMET) for five different locations in Mato Grosso. Based on these, we simulated the gross margins of typical production systems and compared them with those estimated by IMEA in their production cost survey (IMEA—Instituto Mato-Grossense de Economia Agropecuária, 2016). Since gross margins are reported only for the most typical production systems of each macro-region in the IMEA survey (and are not estimated by the Brazilian Institute of Geography and Statistics (IBGE)), only 13 observed data-points were available for validation: five for soybean and maize, and three for cotton (cotton was not cultivated in the South Central and Northeast regions).

Fig. 3 summarizes the validation tests using the performance indicators suggested by Berger et al. (2017). We achieved a Nash-Sutcliffe (NSE) model efficiency of 0.65, where unity means a perfect match, zero means that model prediction is as good as the mean of observed data, and negative values indicate that the mean is a better predictor than the model. Our current analysis achieved a standardized absolute error (ESAE) of 0.67 as a goodness-of-fit, compared to 0.47 in Carauta et al. (2017), who simulated farmer land use in Mato Grosso with a bio-economic model. Because our current model simulates gross margins (that are independent of each other), compared to the categorical land uses of the aforementioned authors, we chose to use NSE over ESAE as a performance evaluation method in this study; the latter is provided only for comparison. For details about the validation of the biophysical model component, see the supplementary material.

3. Results

3.1. Changes in duration of the rainy season and precipitation patterns

Fig. 4 presents the estimated onset and cessation dates in the two comparison periods (2020–24 and 2035–39) for two climate scenarios and five macro-regions. The variation in both the onset and cessation dates was higher for the STAR scenario in 2035–39 compared to

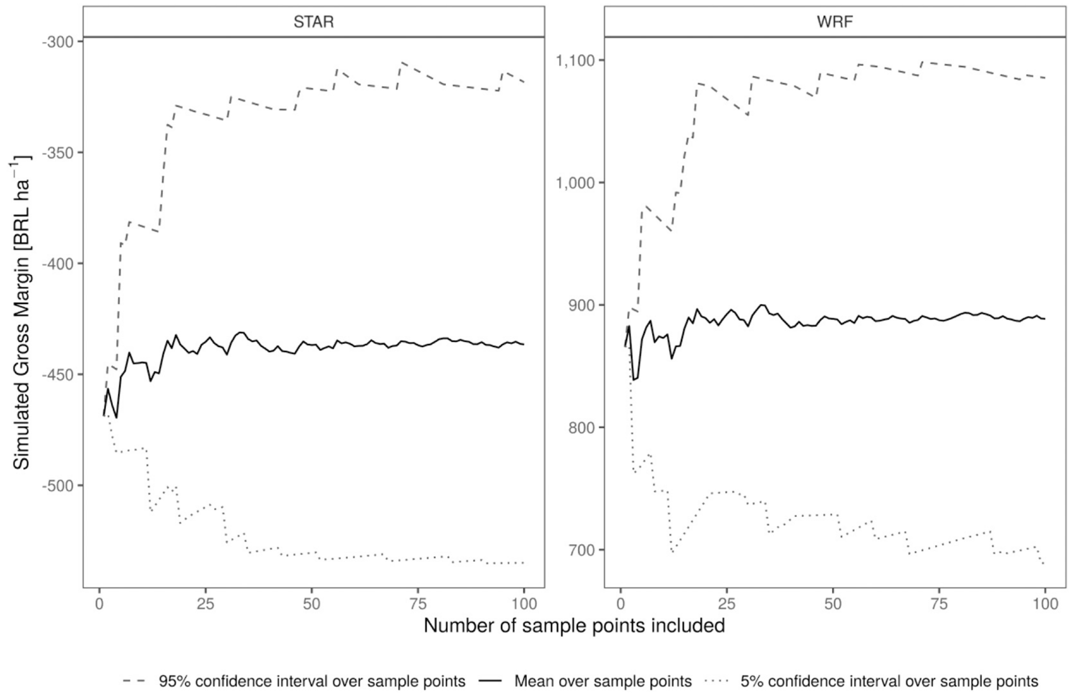

Fig. 2. Convergence of Mato Grosso's weighted gross margins for 2035–39 over sample points of the Sobol' sequence.

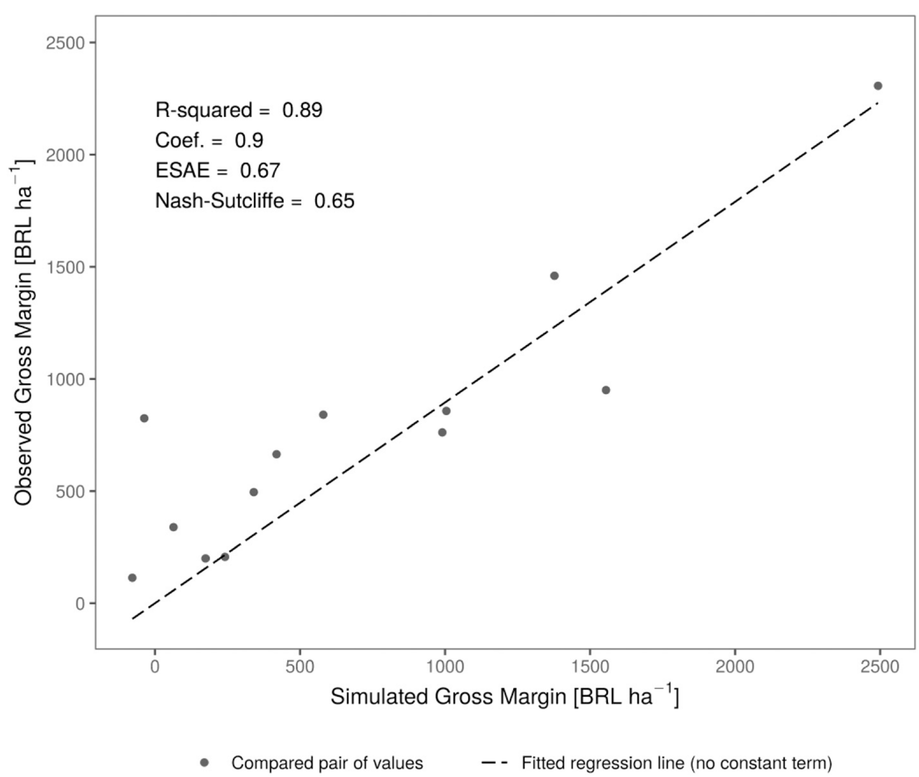

Fig. 3. Model validation at the farm level for typical agricultural systems. The dashed line indicates a regression line between the simulated and observed gross margins. Coef. = coefficient of the regression line with no constant term. ESAE = standardized absolute errors.

2020–24. Conversely, for the WRF climate scenario, the variation was lower in the onset but higher in the cessation dates in the later period. Comparing the rainy season's median duration (number of days between the onset and cessation dates) between the two periods shows a reduced span in almost all regions (except for the South Central region in the WRF scenario). The median decrease was 53 days in the STAR scenario, 5 days in the WRF scenario.

Fig. 5 shows the simulated precipitation patterns in the STAR and WRF scenarios as daily average precipitation for both periods. Daily precipitation declined relatively sharply in the STAR scenario but showed a slight increase in the WRF scenario.

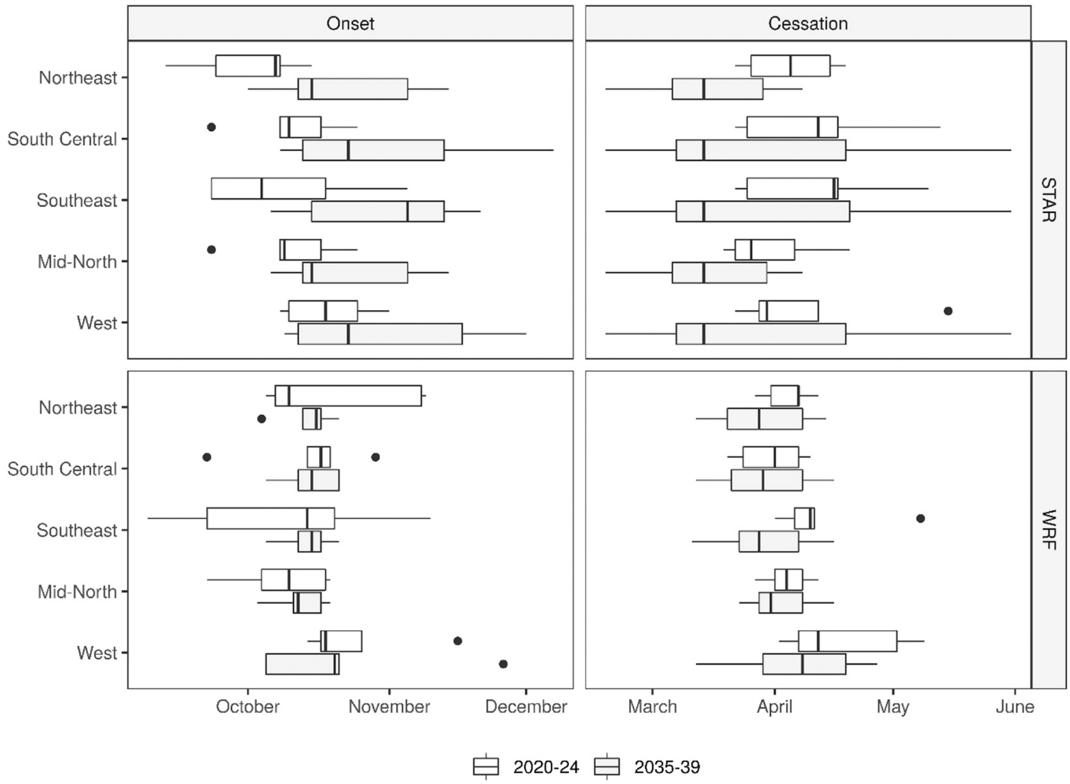

Fig. 4. Simulated rainy season's onset and cessation dates.

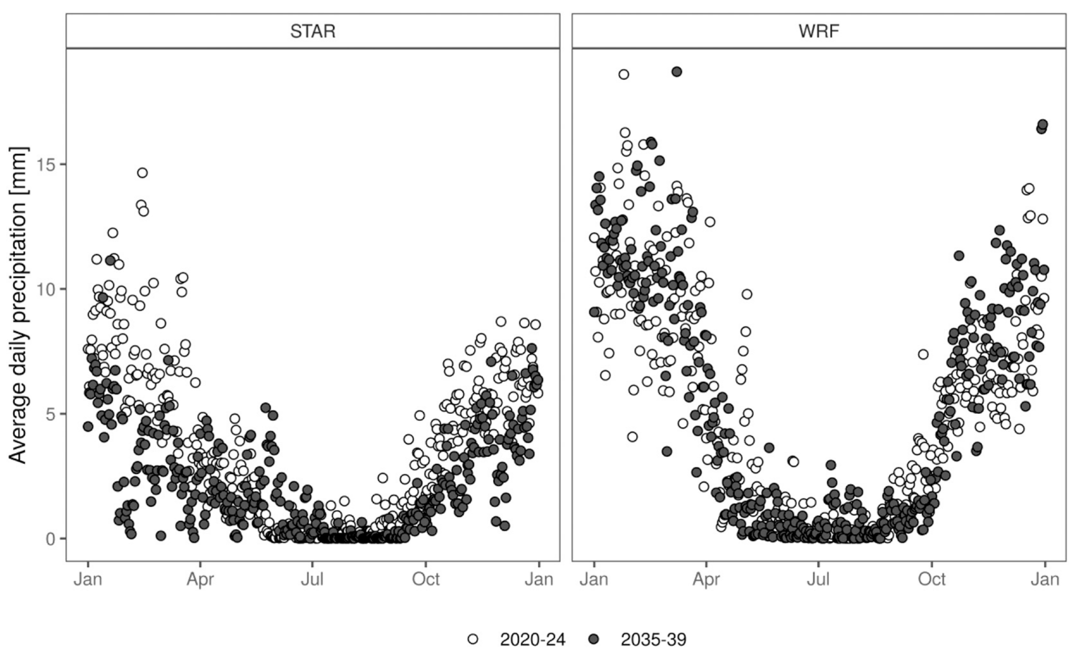

Fig. 5. Simulated average daily precipitation in Mato Grosso, Brazil.

3.2. *Impact of climate change on crop yields*

Fig. 6 displays the simulated yields of cotton, maize, soybean, and sunflower in 2020–24 and 2035–39 for the two climate scenarios. The boxplots present the full distribution of crop yield changes over many crop management options (as described in section 2.2.2), whereas the triangles reflect the median crop yield change resulting from standard management options. Thus, the latter reflect the climate change impact without farmer adaptation, the former the potential effects with farmer adaptation. The percentage change in the median results is negative for all crops in the STAR scenario and almost all crops in WRF, except for soybean.

3.3. *Impact of climate change on farm system profitability*

The simulated gross margins—in Brazilian Reais (BRL) per

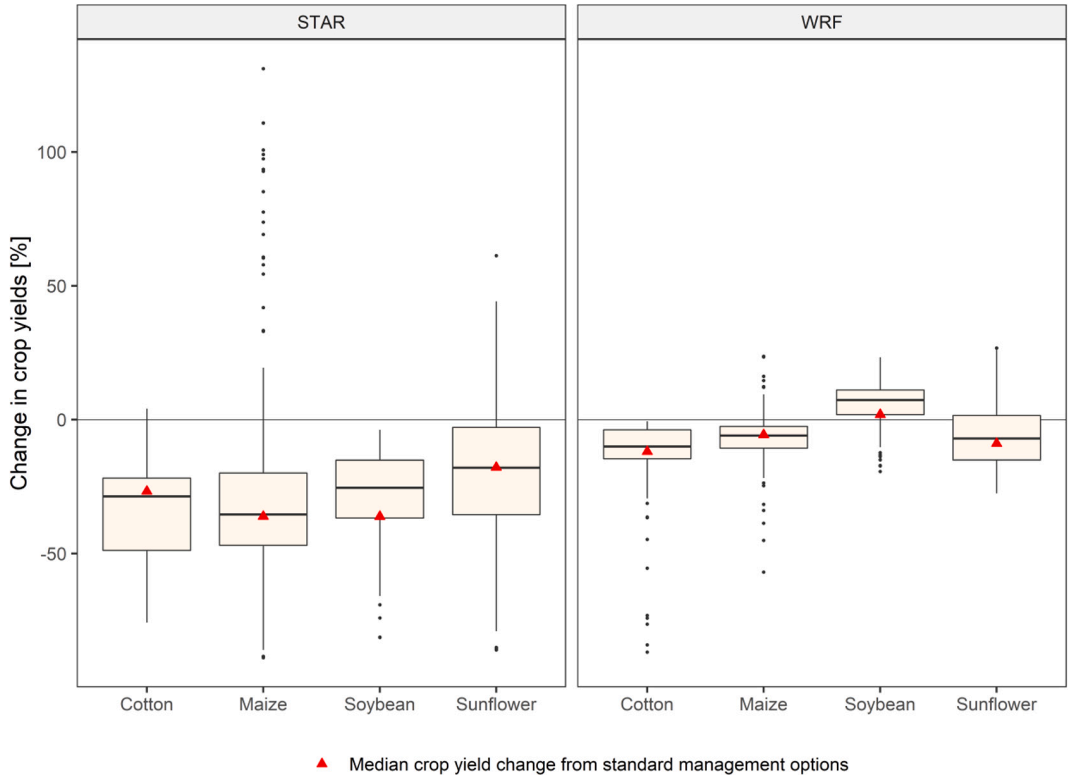

Fig. 6. Percentage change in simulated crop yields between 2020–24 and 2035–2039.

hectare—of the five major double-cropping systems in Mato Grosso for two climate projections are depicted in Fig. 7. Each panel represents the full distribution of gross margins over all Sobol' design points (or model repetitions) for 2020–24 and 2035–2039. Overall, gross margins were lower in the STAR than in the WRF scenario. The gross margins were significantly lower in the 2035–39 period in STAR, whereas only slight changes were evident in the WRF scenario. The agricultural systems with cotton experienced more occurrences of negative gross margins in both periods and scenarios.

Fig. 8 compares the change in simulated gross margins of all rotation schemes and management practices in each macro-region and climate scenario. As in Fig. 6, the boxplots display the full distribution of gross margin changes, the triangles the median gross margin change resulting from current management options without farmer adaptation. The STAR scenario led to the most negative impacts in terms of gross margin, with Southeast and West being the most affected regions in STAR. In WRF, Mid-North was affected the most severely. Under STAR climate projections, the median gross margin decreased by 1670 BRL ha^{-1}, while in the WRF scenario it increased by 58 BRL ha^{-1}. The figure further shows that the simulated gross margins occasionally increased in all macro-regions under the WRF scenario.

In the STAR scenario, the double-cropping systems most negatively affected by climate change were those with early soybean sowing dates and late maize, cotton, and sunflower sowing dates. In the WRF scenario, early soybean sowing dates also presented gross margin reductions; in contrast, the gross margin increased in the combination of soybean sown on October 15 and November 1 with late sowing of maize or sunflower.

3.4. *Reduced number of profitable management practices*

In Fig. 9, we evaluated whether climate change might reduce farmer flexibility when planning their field operations and impair their ability to adapt on-farm crop management. Each bar in Fig. 9 depicts the resulting number of profitable management practices available in each climate projection period. The number of profitable alternatives was calculated by subtracting the number of cropping alternatives with negative gross margins from the number of cropping activities with positive values. On average, the number of profitable alternatives decreased by 36% in the STAR scenario, by 3% in the WRF scenario.

3.5. *Upscaled impact of climate change on farm-level profitability*

Fig. 10 evaluates the potential impact of climate change on the entire federal state by calculating Mato Grosso's total crop farm gross margin. The weighted gross margin was calculated using the simulated agent crop land uses in Carauta (2019) as a proxy for future climate impacts without farmer adaptation behavior. Each panel in Fig. 10 presents the average weighted total gross margin for crop farms in Mato Grosso for a climate scenario in two periods. Both scenarios showed a negative impact in 2035–39 compared to 2020–24, but the STAR scenario yielded a stronger reduction in gross margin.

An indication of the mean expected climate change impact on crop farm gross margins can be derived by averaging the simulation results from both climate scenarios. Accordingly, the mean expected climate impact ranged between −543 and -−436 BRL ha^{-1}, yielding an estimated average of −474. For comparison, the simulated average gross margin based on weather data from 2000 to 2015 yielded an estimate of 611 BRL ha^{-1}.

4. Discussion

This study employed bioeconomic simulation to assess ex ante the farm-level impacts of climate change in Mato Grosso, considering seasonal land-use trade-offs within double-cropping production systems. We focused on simulating the future profitability of agricultural systems and estimated the number of economically viable crop adaptation options for farmers in Mato Grosso.

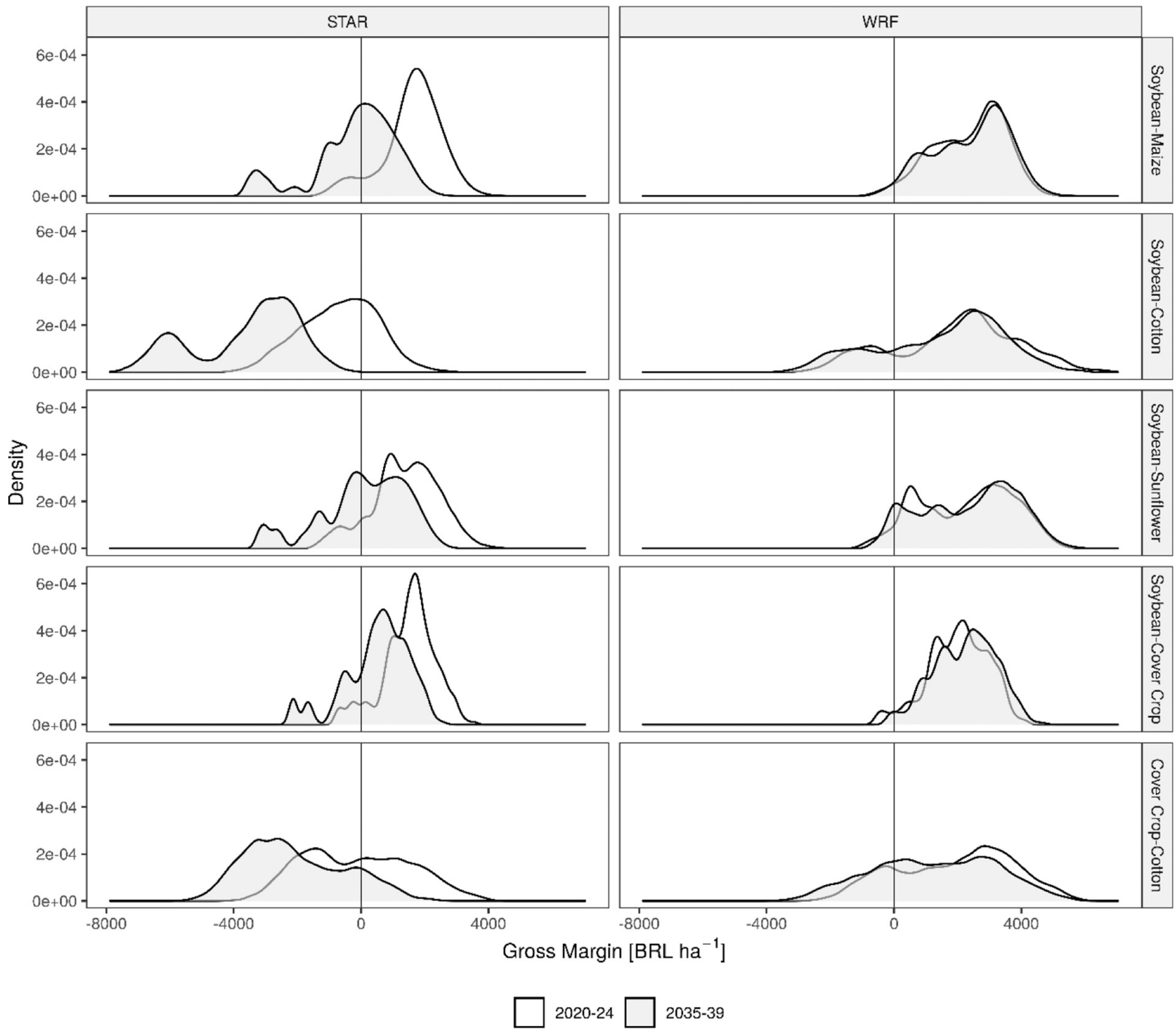

Fig. 7. Simulated gross margin of different double-cropping systems in Mato Grosso (in Brazilian Reais per hectare). Reference exchange rate of R$ 3.91/US$.

4.1. Climate change impact on precipitation and duration of the rainy season

The analysis of future precipitation patterns in Mato Grosso revealed many interesting insights when comparing the regional climate projections of STAR and WRF. For the period 2035–39 vis-à-vis the benchmark 2020–24, STAR showed a reduction in precipitation along with a shortening of the rainy season in almost all macro-regions. The rainy season started almost one month later in November and already ended in late March. STAR also yielded a less distinctive transition between the rainy and dry season, leading to significantly more precipitation in May and June (Fig. 5). This finding is in line with Ronchail et al. (2002) and Nobre et al. (2016), who associate this anomaly in precipitation with an increasing occurrence of the El Nino Southern Oscillation (ENSO). In the WRF climate scenario, the rainy season was shorter in four of the five macro-regions. In most of the cases, the cessation was anticipated to be late March or early April.

The shorter rainy season and changes in its precipitation patterns as highlighted in Figs. 4 and 5 have important implications for double-cropping systems here. These results are consistent with Hampf et al. (2020) and suggest that, in Mato Grosso, farmers could lose one of their most significant comparative advantages, namely the possibility of harvesting two crops in one cropping season. Without double-cropping, farmers would likely grow soybean with longer maturing cycles and late sowing dates, which would then yield the highest possible gross margin for single crops. The overall farm system gross margin, however, would be much lower than in current double-cropping systems, supporting the findings of Brumatti et al. (2020).

The potential shifts of the rainy season's onset and cessation dates highlighted in Fig. 4 provide crucial insights for farmers in their strategic development planning (scale of investment needed to cover specific machinery and labor demands). These results can guide future research regarding the most robust and profitable sowing dates and crop rotations in Mato Grosso. Given that the farmer's choice of a sowing date in a double-cropping system is intrinsically related to labor and machinery availability at the farm level, these constraints need to be captured in future investigations. For example, agent-based bioeconomic models such as in Carauta et al. (2017), could provide insights into the resulting influences on land-use change.

4.2. Direct impact on crop yields

The direct climate impact on crop yields was more severe in the STAR than in WRF scenario, corroborating the findings of Hampf et al. (2020). Interestingly—apart from soybean in WRF—climate change has the most severe negative impact on crop yields in the Southeast region. This finding suggests serious consequences for food security and economic development because the Southeast region is the second-largest

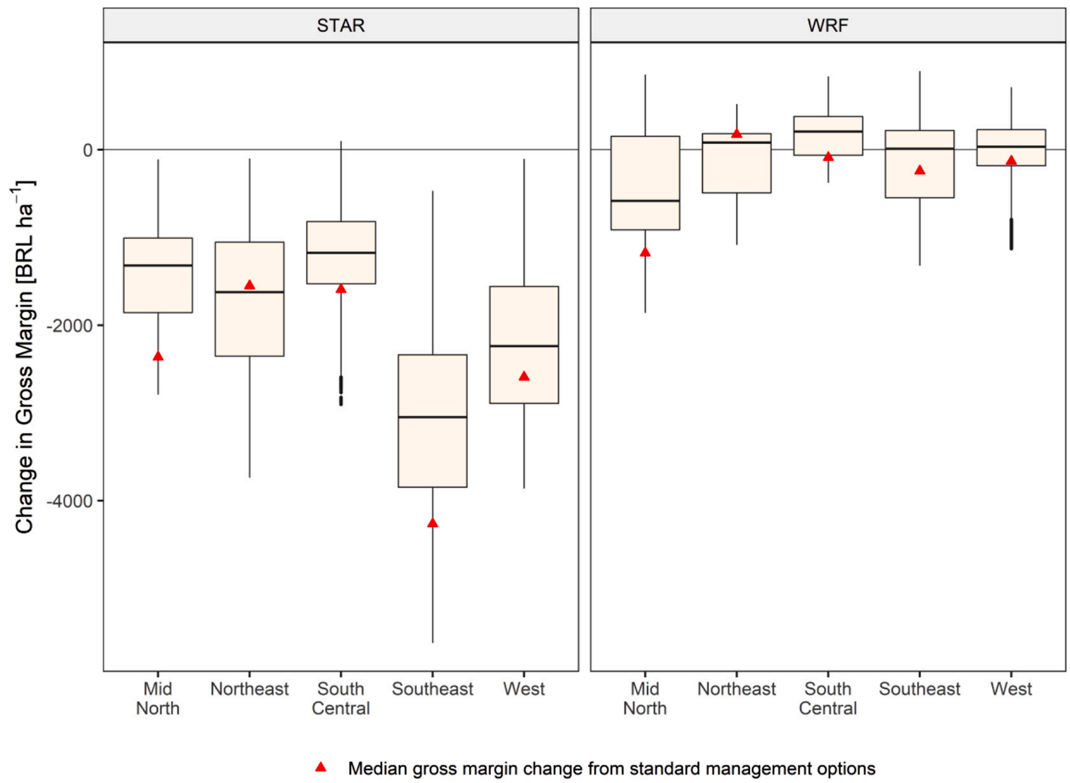

Fig. 8. Simulated change in gross margin (in Brazilian Reais per hectare) at sub-regional levels between 2020–24 and 2035–2039.

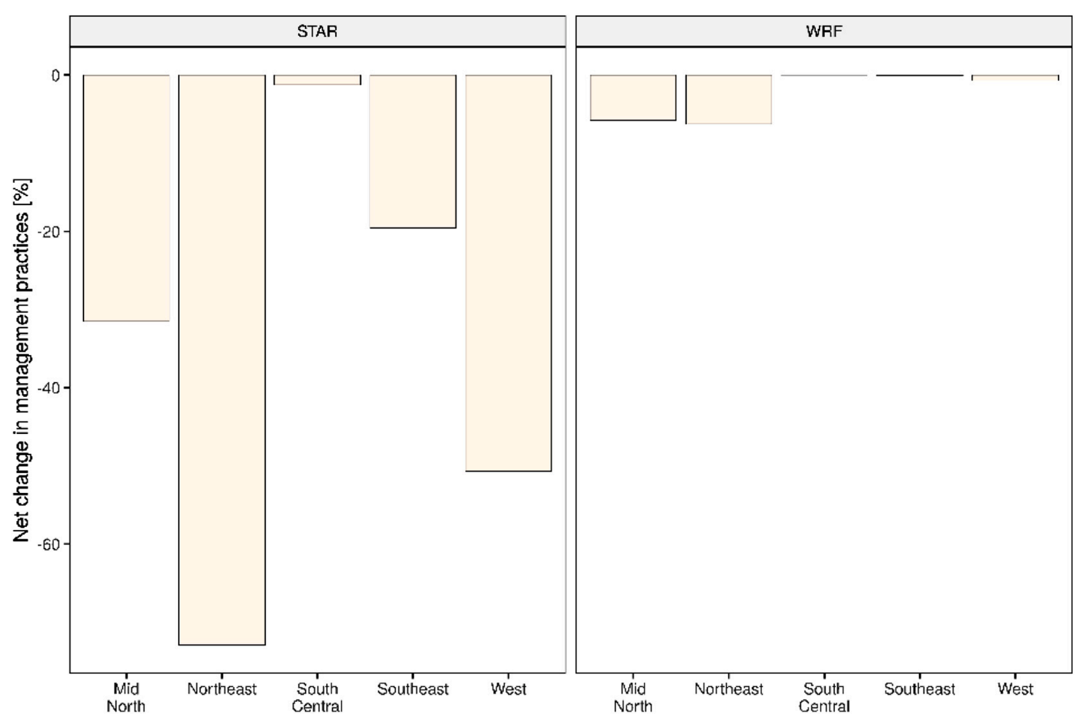

Fig. 9. Simulated net change in the number of profitable double-cropping management practices between 2020–24 and 2035–2039.

producer of soybean, maize, and cotton in Mato Grosso. Moreover, those management options of double-cropping systems which are already the least favorable in the period 2020–24 (namely, soybean early sowing dates and shorter maturing varieties) proved to be the most severely affected by climate change, making these strategies even less suitable. The result is a narrower decision space for agricultural producers. Sunflower cropping systems with late sowing dates (March 15 and April 1), in contrast, were the least impacted by climate change, highlighting this crop's potential use as a farmer adaptation strategy in Mato Grosso.

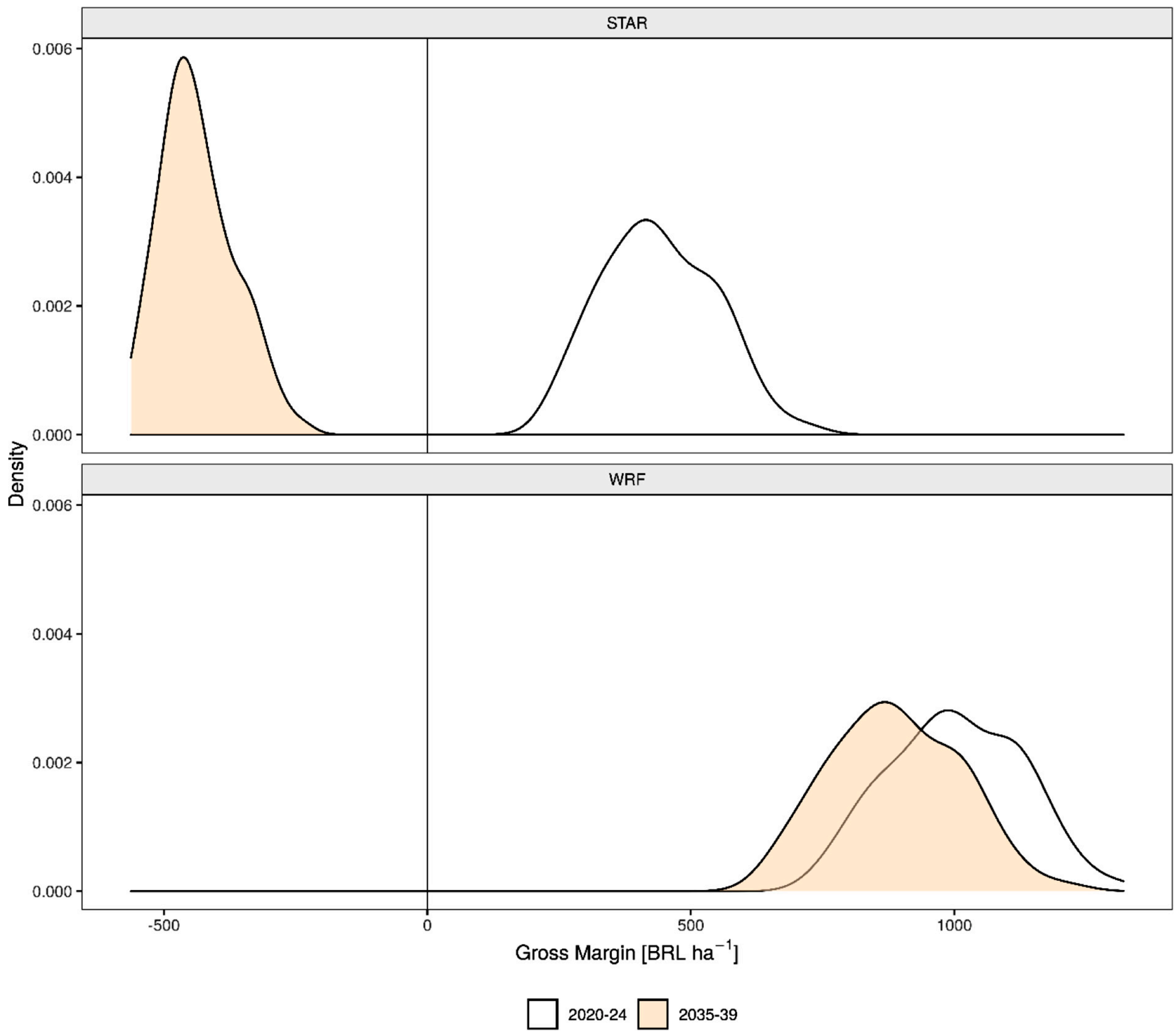

Fig. 10. Simulated averaged weighted gross margin for Mato Grosso.

4.3. Impact on crop farmer gross margins

As expected, the farm gross margins of double-cropping systems were negatively affected in our simulations in both climate projections. Nonetheless, the potential impact was more substantial in the STAR versus WRF scenario. Despite a few occurrences of a somewhat positive impact of climate change in WRF, the negative impacts on farm gross margins prevailed. Our results are therefore in accordance with Brumatti et al. (2020) who found that even with adaptation of sowing dates and adoption of short cycle cultivars, gross revenues are likely to decrease in a scenario with high deforestation rates. This would make double-cropping systems economically unfeasible.

Generally, double-cropping systems with cotton were the most negatively affected in our simulations. Traditionally seen as the most profitable system in Mato Grosso, cotton cultivation showed low profitability under both climate change scenarios, with high volatility and low returns (Fig. A. 1). Accordingly, the future introduction of drought-resistant alternatives or short maturing cultivars might compensate for potential decreases in cotton profitability. This would help prevent farmers from shifting towards less dry agricultural areas (which would likely mean further deforestation and land-use conversion).

In contrast, the novel sunflower rotation system proved to be the most resilient alternative when compared to cotton and maize. We therefore recommend further studies evaluating adequate phytosanitary management, weed control, and cultivars adapted to Mato Grosso's diverse local environments. This could help farmers make better decisions on a crop that still has low adoption rates due to high uncertainty and transaction costs (Oliveira de Sousa et al., 2018). Further studies focusing on evaluating its potential diffusion in alternative scenarios with improved infrastructure, such as additional processing facilities, could help policymakers improve the stability and efficiency of sunflower agri-food chains.

The most relevant finding in our study was that changing climatic conditions might compromise the profitability of double-cropping systems in Mato Grosso in the near future. Our results show that the weighted overall gross margin could decline by 69% on average. In comparison, soybean monocropping was the least affected by changing climate conditions. Altogether, our simulation results suggest a future backward trend from double-cropping to monocropping systems. This could have devastating consequences for farmers and the local economy because large-scale farms are highly mechanized and rely on double-cropping systems to cover their high production costs and levels of debt and obligations (de Melo and Resende Filho, 2017). Finally, a shift back to monocropping could also aggravate the environmental impacts of agriculture (e.g., erosion, soil degradation and deforestation) and could have a negative effect on the water cycle (Spera, 2017).

Our simulation experiments further revealed that some macro-regions in Mato Grosso are more vulnerable to climate change than others. Practically all crop production systems in STAR experienced an adverse outcome in the second climate comparison period 2035–39. The macro-region most affected in the WRF scenario was the Mid-North due to a combined effect of a shorter rainy season and less yearly precipitation.

This calls for more research to explore the possibilities of introducing new seed technologies and alternative management schemes in the exposed areas. The goal is to avoid a decline in production as well as to fend off a further shift of the western frontier of agricultural land-use into the rainforest and to subsequently prevent increasing deforestation rates.

4.4. Model limitations

Unfortunately, the new set of climate scenarios (IPCC—Intergovernmental Panel on Climate Change, 2014) has been released too late for inclusion into our research as part of the German-Brazilian Carbiocial project (Gerold et al., 2018). Nonetheless, we performed a comprehensive uncertainty analysis to ensure robust simulation results and examined a wide range of future climate change projections by using two contrasting climate scenarios in our model ensemble. Our findings can be interpreted as a first estimation of climate change's potential impacts, and we, therefore, recommend further studies on this pressing topic.

5. Conclusion

The future profitability of double-cropping systems in Mato Grosso may face many threats under changing climate conditions due to reduced annual precipitation, a shortening of the rainy season, and shifts in the rainy season's onset and cessation dates. Our simulation experiments further revealed that certain macro-regions in the federal state are probably more sensitive than others to climate change, underlining that these hazards might not be evenly distributed. This information can support the development of policy measures that target the interventions to each macro-region's specific needs.

Our investigation shows that climate change might severely dampen the profitability of double-cropping systems in Mato Grosso, mostly because of the shorter rainy season. This would lead to a future shift towards monocropping systems, creating additional environmental pressures on native vegetation and stresses on food production and food security.

Our bioeconomic simulations suggest that sunflower is a potential adaptation option, exhibiting resilience against changing climate compared to current farm systems with cotton and maize. Given the initial development stage of the sunflower supply chain in Mato Grosso, we recommend further investigations on the factors hindering its adoption at both farm and state levels (for example, broader and extended field trials, possible land-use trade-offs, and regional processing constraints).

Examining the simulation results under two different assumptions regarding farmer behavior (with and without farmer adaptation of crop management) demonstrated that adapted management options might help farmers buffer some of the adverse effects of climate change in Mato Grosso. Importantly, however, some of the simulated crop management alternatives will not be feasible for all farmers because their implementation depends on many other farm-level characteristics not considered in this study (e.g., machinery endowments, cash reserves, and exchange of land on land markets). Therefore, future research should consider farm agent characteristics and interactions and also investigate the role of technology diffusion on climate change adaptation.

Supplementary data to this article can be found online at https://doi.org/10.1016/j.agsy.2021.103104.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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