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The economics of farming expansion in the Brazilian Cerrado under possible effects of climate change

RESEARCH ARTICLE

Henrique Monaco[a,b], Carlos Ortiz[c], Lilian Caetano[d], Christoph Müller[e] and Jonas Jägermeyr[f,g]

[a]*Ph.D. Student, University of Illinois at Urbana Champaign, 1301 W Gregory Drive, Urbana, IL, 61801, USA*

[b]*Consultant,* [c]*Senior Associate, Centrec Consulting Group, 3 College Park Ct, Savoy, IL, 61874, USA*

[d]*M.Sc. Student, University of Sao Paulo, Luiz de Queiroz College of Agriculture (ESALQ), Av. Pádua Dias 235, Agronomia, Piracicaba, SP 13418-900, Brazil*

[e]*Working group leader at PIK, Potsdam Institute for Climate Impacts Research (PIK), Member of the Leibniz Association, Telegrafenberg A31, 14473 Potsdam, Germany*

[f]*Associate Research Scientist, Climate School, Columbia University, 2880 Broadway, New York, NY 10025, USA*

[g]*Associate Research Scientist, NASA Goddard Institute for Space Studies, 2880 Broadway, New York, NY 10025, USA*

Abstract

This analysis assesses the financial viability of legally investing in native Cerrado vegetation deforestation for crop production, considering climate change. The study uses data from twelve different crop models based on three different climate models to predict potential future crop yields in cleared land for growing soy and maize. The outcomes show that in many micro-regions, investments in clearing land for crop production would destroy economic value, that is, generate a negative net present value because of low/negative and volatile cashflows driven primarily by future yields as affected by climate. Our analysis was carried out based on present agricultural practices and technology. As climate changes, farmers may adapt their practices, which can lead to more resilient and productive crops, or grow different crops, which could provide better returns on investment in clearing land than the ones resulting from our analysis. Despite various uncertainties, farmers, policy makers and financial institutions should be aware of the climatic and financial risks associated with land clearing in Brazil, mainly in micro-regions in which all scenarios resulted in negative outcomes in the investment analysis.

Keywords: agricultural expansion, climate change, deforestation, economic feasibility, investments in land conversion

JEL code: Q15

Corresponding author: hc30@illinois.edu

1. Introduction and literature review

Brazil's Central and Northwestern regions tend to feature flatland and large tables with deep soils, suitable to agriculture with proper fertility adjustments (Silva *et al.*, 2021), on which the native vegetation is known as Cerrado, hence the region's name: the "Cerrados" (Ferraz-Almeida *et al.*, 2021).

The Cerrados in Brazil have an important environmental value. Its deforestation is already bringing several unbalances, among which extreme heat affecting landscape, populations, and crops. A recent study concluded that the value of the various ecosystem services, including water and climate regulation, is estimated at US$5310/ha in present value in 2005's prices, at 10% cost of capital (Flach *et al.*, 2021).

Most of Brazil's agricultural and cattle production expansion have happened on the Cerrado Biome during the past four decades (Rada, 2013). This expansion has accelerated, given the profitability obtained by farmers, and (Daldegan *et al.*, 2019) shows that soy production increased by 9.6 million ha or 128% between 2000 and 2017. Approximately 38% of soy harvested in the 2016–2017 cycle came from land that had once been covered by native vegetation in 1999. The MATOPIBA subregion has been the most affected by this trend.

Although most of the recent expansion has happened on degraded, overgrazed pastureland, there is still a strong activity of converting land under native vegetation into cropland (Daldegan *et al.*, 2019), partly into pastures, given the expansion of agriculture over pastures (Picoli *at al.*, 2020).

Of particular concern are native vegetation plots within crop farms that exceed the minimum conservation (set-aside) requirement by the Brazilian Forest Code that could be legally cleared, of which up to 2.2 million ha are projected to be converted by 2030 (Soterroni *et al.*, 2019).

Commodity production farmers must constantly pursue economies of scale and gains of productivity to remain competitive, as real commodity prices tend to decline over time in high competition markets. This is known as "Cochrane's agricultural treadmill" (Howard, 2009).

Grain and oilseeds demand has been growing following the population growth (Nepstad *et al.*, 2014) and with rising income pulling the demand for animal protein, and demand for feed as consequence (Umberger, 2015). This has sustained farmers' profitability, which has led to expansion in the last agricultural frontiers of the Cerrados.

The deforestation behind this expansion has been associated with shortening of the rainy season (Pires *et al.*, 2016), decline in water soil penetration and retention, rising local temperature and more erratic rainfall. (Flach *et al.*, 2021) show that continuous clearing of natural vegetation in the Cerrados will continue to negatively change regional climate, negatively affecting crop yields, reducing farmers' profitability.

There are interactions between land-use change and environmental conditions as (Lucas *et al.*, 2023) point, concluding that the increase in the loss of global natural areas in recent years could potentially lead to unprecedented levels of deforestation and loss of species if this trend continues. However, these authors also highlight that technological developments can contribute to mitigating negative impacts to biodiversity.

The preservation of natural areas and native species depends directly on the possible increase in yields on currently farmed cropland by effectively harnessing natural resources through scientific knowledge (Lamb *et al*., 2016).

There is considerable uncertainty related to climate change impacts on global agriculture, their extent, effects, and the adaptation alternatives farmers may utilize. Climate change has already been affecting agricultural yields around the world because of changes in rainfall patterns and temperatures (Jägermeyr *et al.*, 2021).

Based on latest global gridded crop models, the study shows that soybeans and maize are negatively affected by climate change across the major production regions in the United States, in Brazil, and in Southeast Asia.

Crops, such as grains, oilseeds, or grass, have been adapted to a certain range of temperatures and require a certain amount of rainfall. Possible changes in climate affecting temperature and rainfall patterns may not only affect crop yields but increase pest and disease incidence (Chaloner *et al.*, 2021; Zandalinas *et al.*, 2021), which would impact crop production costs.

The double-cropping system (meaning two crops grown each year, of which soybeans and maize are the most prevalent) may also be hindered because of changes in rainfall patterns and smaller sowing window (Andrea *et al.*, 2020).

Crop yields and costs are basic drivers of farmers' cash flow, which should compensate for farmers' capital expenditures related to the land acquisition, vegetation clearing, soil fertility adjustments, infrastructure, working capital and the risks involved (Spicka *et al.*, 2019).

The impact of climate change on agriculture is expected to be geographically uneven (Goulart *et al.*, 2023), therefore not leading to compensatory commodity price rises, resulting in negative economic impacts in affected regions. Moreover, demand growth for grains and oilseeds is not likely to generate higher average real prices in the decade ahead, which could otherwise enhance farmers' profitability. According to FAO's Outlook (FAO, 2023) per capita consumption of vegetable oil for food is projected to grow by 0.1% p.a., considerably less than the 0.8% p.a. increase observed during 2013–2022, while protein meal is projected to grow at 0.9% p.a., also below the 2.9% p.a. of the last decade.

Farmers affected by climate change may face reduced profitability and increased financial risks. Moreover, further vegetation clearing in the Cerrados can create feedback effects that might further accelerate climate change with additional adverse effects for yields (Pires *et al.*, 2016), reducing the economic feasibility of expanding farming on natural vegetation.

As climate may change, it may generate volatility in agricultural yields, increasing risks, negatively affecting economic profits from farming as well as land value, challenging farmers' perspective of gains from expansion investments.

2. Hypothesis and research questions

Given the discussed challenges associated with expanding production in the Cerrados native vegetation, this paper aims at quantifying the economic value added of expanding crop production over native vegetation in the Brazilian Cerrado given possible climate change scenarios and current local production characteristics. We rely on assumptions such as expenditures, prices, capital costs, production system and we model yields based on different climate change scenarios. If yields are negatively affected by climate events, not compensated by price rises, farmers' cash generation would also be negatively affected, and so would the feasibility of land conversion in the region.

Our hypothesis is that farmers expanding into native vegetation, and employing substantial capital to do so, may be destroying economic value (generating a negative net present value on the investment) in some regions of the Cerrado because of yield volatility under climate change.

3. Data and methods

To assess the economic feasibility of agricultural expansion in the Cerrado Biome, we first derived yields according to different climate scenarios (details in yields modelling section). A climate scenario represents the combination of climate variables (i.e. rainfall and temperature) and yield responses based on crop models that take into account projected atmospheric carbon concentration levels. The resulting yield projections were used as input in an economic model to analyze the feasibility of agricultural investments in clearing land.

To account for the uncertainty associated with climate change, yields were derived from two scenarios of carbon concentration projection: a less severe scenario (RCP2.6) and a more severe scenario (RCP8.5). This was done across three different global climate models, resulting in a total of six different future yield projections.

For the various Cerrado regions, their respective projected annual yields, production costs, prices, and capital expenditures were the inputs to an economic model that simulates future cash flows. These cash flows were discounted at an assumed cost of capital to assess net present value (NPV) of the investments in converting natural vegetation into cropland (details in economic model section). A negative NPV infers that the cash flow would be insufficient to cover the expenditures and the risks associated with the investments in clearing and exploring the land.

The overall representation of the analysis process can be seen in Figure 1 and will be detailed in the next sections.

3.1 Area of study and double-crop regions

This study examines the Brazilian Cerrado biome, which covers 21% of Brazil's land area and has faced significant deforestation from the expansion of agriculture. It accounted for 44% of the 3.4 Mha forest-to-soy conversion from 2001 to 2016 (Song *et al.*, 2021). The biome includes 13 Brazilian states, as highlighted in Figure 2. Economic analysis focused solely on states where the Cerrado covers at 25% of their respective area.

In a great portion of the Cerrados, two crops can be grown annually, mainly soybeans early in the summer and corn later in the summer in well-developed soils. Therefore, our simulation involves growing soybeans followed by corn after the third season on cleared land if local rainfall patterns allow. The study sourced actual yield data from the Produção Agrícola Municipal (PAM/IBGE). Recent yields from 2019 to 2021 were used to assess whether the rainfall pattern allowed for double-crop cultivation. Figure 3 shows regions suitable for single or double-crop cultivation.

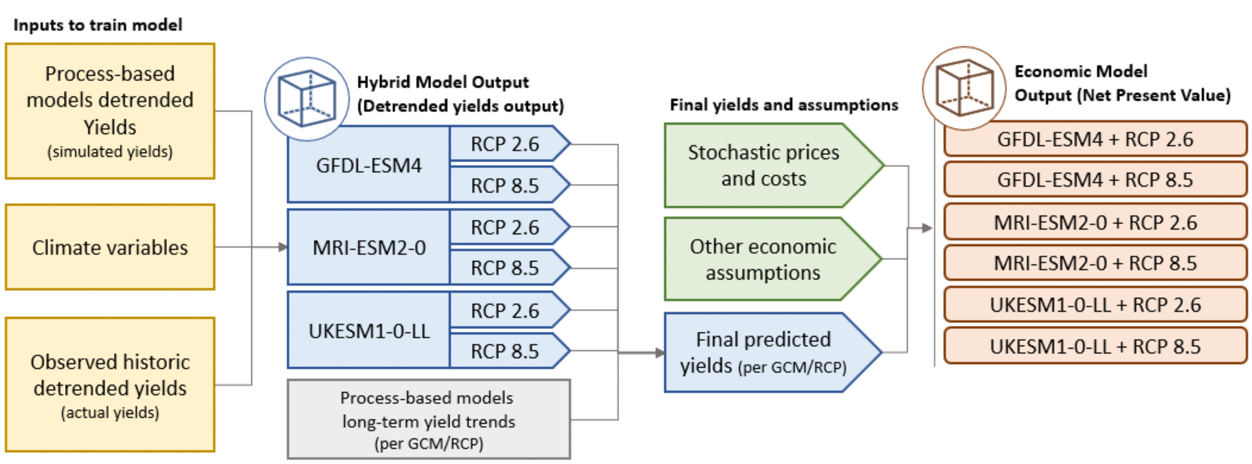

Figure 1. Representation of the analysis process.

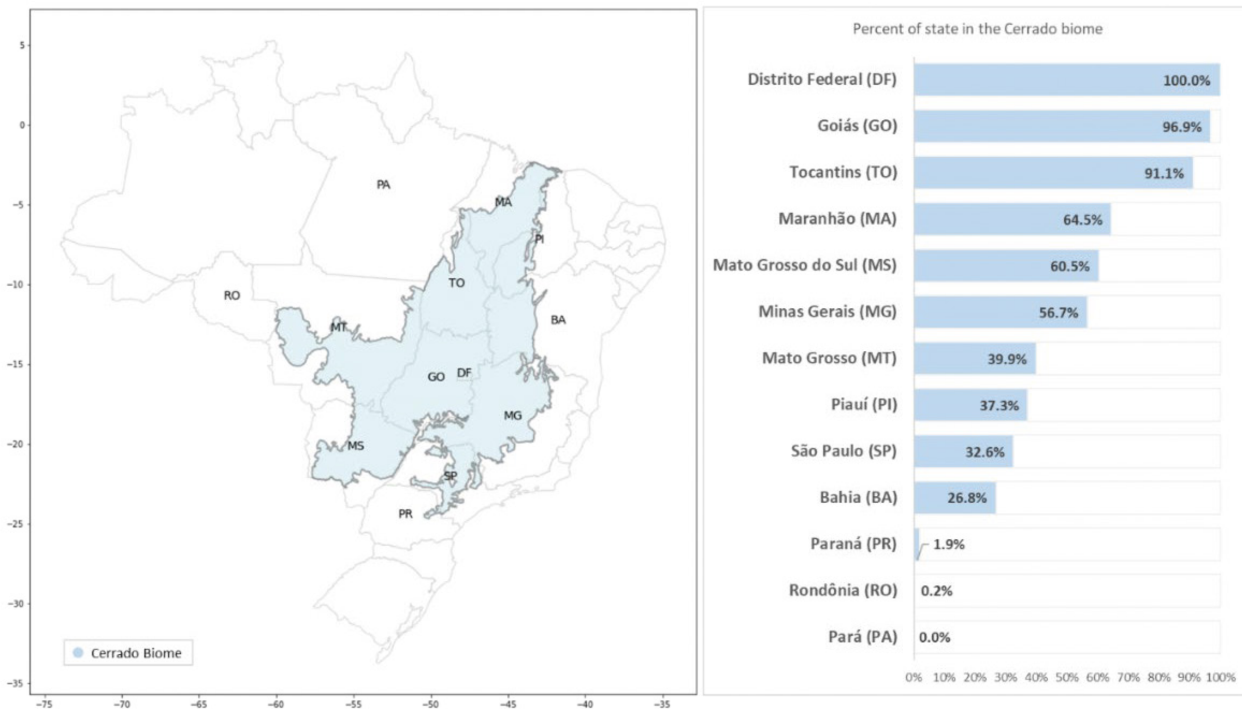

Figure 2. Cerrado Biome in Brazil with states territories in Cerrado.

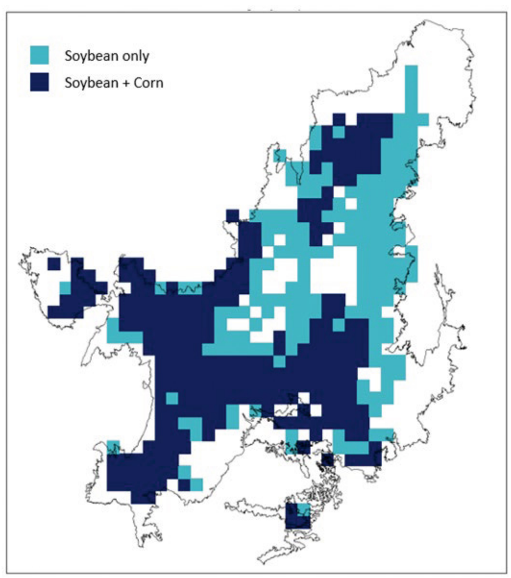

Figure 3. Cerrado areas with either single-crop (soybean only) or double-crop (soybean followed by corn as a second crop).

Table 1. Summary of data sources for yields and climate data.

Simulated data			**Observed historic data**
Yields	**Climate variables**	**SSP/RCP**	**Yields**
Ensemble means of 12 crop models	GFDL-ESM4, MRI-ESM2-0 and UKESM1-0-LL	SSP1-2.6 SSP5-8.5	PAM/IBGE

3.2 Yields modelling

To predict corn and soy yields variability over time, we deployed a hybrid model, which combines (i) climate variables, (ii) crop-model generated yields and (iii) actual yields. This approach aims at enhancing the representation of year-to-year variability in crop yields, which was found less pronounced in process-based models (see Appendix A). The resulting detrended yields were integrated with long-term trend estimates which had been obtained from different crop-models and climate scenarios. This process was outlined in Figure 1. Hybrid models have been utilized before in similar settings and shown to outperform process-based or simple climate-based models based on RMSE and MAE (Feng *et al.*, 2019; Goulart *et al.*, 2023; Shahhosseini *et al.*, 2021).

Table 1 summarizes climate and yields data utilized. The combination of datasets and models utilized allowed for 6 different projected yield scenarios per crop. The datasets and model are discussed in more detail in the next sections.

Data sources

Climate variables

The climate variables include monthly maximum, minimum, and average temperatures, as well as average rainfall. The months of October through February were chosen to represent the soybean growing season, while February through July were selected for corn as a second crop.

The simulated climate data was obtained from the sixth phase of the Coupled Model Intercomparison Project (CMIP6). For the historical run spanning from 1988 to 2015, the GSWP3-W5E5 dataset was employed. This dataset combines two global datasets, namely GSWP3 (Global Soil Wetness Project Phase 3, Kim, 2017) and W5E5 (WFDE5 over land merged with ERA5 over the ocean, Lange *et al.*, 2021). It integrates reanalysis and gridded field observations to ensure a comprehensive and reliable representation of the data at a 0.5° × 0.5° spatial resolution at a daily frequency. For the projected climate data (2015–2060) we utilized three global climate models, or climate forcings, (GCMs): GFDL-ESM4, MRI-ESM2-0 and UKESM1-0-LL. The climate models were chosen because of their sensitivities to CO_2 concentrations. In addition, we used two Shared Socioeconomic Pathways (SSPs) and Representative Concentration Pathway (RCP) combinations: SSP1-2.6 and SSP5-8.5.

Different SSPs and RCPs combination represent different assumptions of future carbon concentration in the atmosphere, which would reflect in temperatures raising by a certain magnitude above its historical average. For the climate models considered, the RCP SSP 1-2.6 and 5-8.5 represent a more conservative and a more aggressive increase in atmospheric temperature given carbon levels, respectively. For more details about the climate forcing and RCPs see (Jägermeyr *et al.*, 2021).

Simulated yields from crop models

Process-based models simulate photosynthesis, crop biology, and phenology, capturing the direct effects of CO_2 fertilization on plant development. The simulated yields were obtained from the Global Gridded Crop Model Intercomparison initiative (Jägermeyr *et al*., 2021), which ensures consistency in modeling inputs such as climate data, land use, fertilizer input, and soil information across different research sectors. Ensemble means of 12 different crop models (ACEA, CROVER, CYGMA1p74, DSSAT−Pythia, EPIC−IIASA, ISAM, LandscapeDNDC, LPJmL, pDSSAT, PEPIC, PROMET and SIMPLACE−LINTUL5) utilizing the same modeling protocol, climate forcings and RCPs mentioned above were utilized.

To ensure that simulated corn yields referred to corn as a second crop, only yields from corn sown during the initial three months of each year were considered, based on the planting date calendar from the dataset. All simulated yields were detrended utilizing a polynomial regression of second degree. Long-term trends were utilized to generate the final projections (Figure 4).

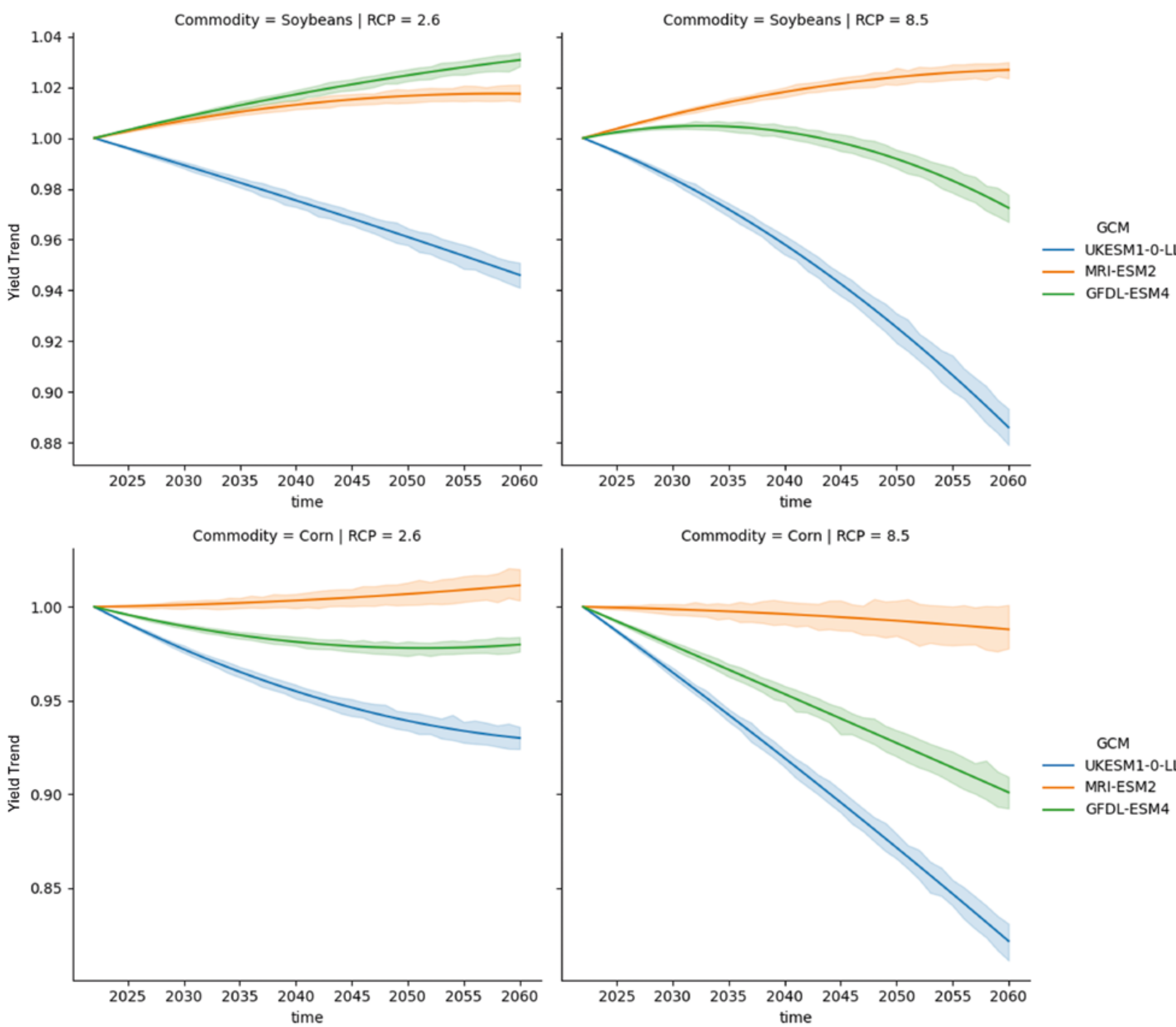

Figure 4. Long-term trends in yields according to each GCM and RCP combination.

All crop models simulating yields have kept technology and management practices constant at 2015 levels, assuming that current practices and technology will remain unchanged over time to isolate the climate effect on yields. While this is a common practice, it's worth noting that future yields may potentially be higher due to the implementation of new or adapted management practices, and of technological advancements in farming.

Observed (actual) historical yields

Observed yields from PAM/IBGE were utilized to train the model, which worked as a bias correction mechanism. Only municipalities that offered data for 7 or more consecutive years were considered. The datasets were resampled to a 0.5° × 0.5° grid to match the spatial resolution of climate and simulated yields data using the first order conservative remapping scheme (Goulart *et al.*, 2023). All yields were converted to kg per hectare for the future yield estimates. Historical yields for soybeans were measured between 1988–2015, and for corn as a second crop, from 2003–2015.

Yields interannual variability model

To model the interannual variability of yields, this analysis employed a multi-layer perceptron (MLP) model, which is composed of individual models, or neurons, organized into layers with the Relu activation function. MLPs have previously been utilized for yield modelling with climate indexes (Goulart *et al.*, 2023). The input layer of the MLP reads the data, the hidden layers process them, and the output layer provides the results. Each neuron in the MLP has an activation function, which processes the data, and associated weights that determine their importance to the network. To develop the MLP, the Keras package based on the TensorFlow platform was utilized (Abadi *et al.*, 2016).

Detrended yields were utilized to predict interannual variability, excluding the effects of management practices, technology, and CO_2 levels. Latitude and longitude inputs were also considered to capture regional interactions with climate variables. Detrending was applied to both simulated and observed yields, employing a second-degree polynomial specific to each latitude × longitude combination within the region. Furthermore, distinct series were utilized for process-based simulated yields, reflecting their dependence on diverse climate forcings.

A cross-validation scheme (*K*-fold with 5 splits) was used to compute performance scores and avoid overfitting. The performance measures selected were *R*-squared (R^2, equation 1), mean absolute error (MAE, equation 2) and root-mean-square error (RMSE, equation 3).

$$R\text{-squared } (R^2) = 1 - \frac{\sum_{i=1}^{n}\left(\text{Observed value}_i - \text{Predicted value}_i\right)^2}{\sum_{i=1}^{n}\left(\text{Mean of observed values} - \text{Predicted value}_i\right)^2} \tag{1}$$

$$\text{Mean Absolute Error (MAE)} = \frac{\sum_{i=1}^{n}\left|\text{Observed value}_i - \text{Predicted value}_i\right|}{n} \tag{2}$$

$$\text{Root Mean Squared Error (RMSE)} = \sqrt{\frac{\sum_{i=1}^{n}\left(\text{Observed value}_i - \text{Predicted value}_i\right)^2}{n}} \tag{3}$$

These results were subsequently combined with the long-term trends of simulated yields across the GCM-RCP scenarios, resulting in projected soybean and second crop corn yields for each grid cell from 2022 through 2060.

3.3 Economic model

The economic model calculates the Net Present Value (NPV) of the cash flow generated from investing in soybean and corn production on cleared native vegetation over 30 years, incorporating yields estimates as described above.

Model description and assumptions

The economic model mirrors the investments in farming on a 10,000-hectare plot of land, which is representative of stand-alone conversion projects, cleared in 5 years, at a rate of 20% per year (2000 ha land/year). The land would be cleared, prepared for farming soy and corn as a second crop in perpetuity. The future stream of cash flows generated by the project were discounted at a weighted average cost of capital. The resulting stream of discounted cash flows determines the Net Present Value (NPV) for each climate scenario.

$$\text{Net Present Value (NPV)} = \sum_{t=1}^{n-1} \frac{\text{CF}_t}{(1+r)^t} + \frac{\text{CF}_{\text{perp}}}{(1+r)^{30}} \tag{4}$$

where: CF_t = Free cashflow in period t, r = discount rate, t = time-period and CF_{perp} = cashflow in perpetuity.

Net Present Value (NPV) is a financial metric used in capital budgeting to evaluate the profitability of an investment by comparing the present value of expected cash inflows with the present value of expected cash outflows over a specified period (Brigham *et al.*, 2019).

$$\text{CF}_t = (\text{Revenues}_t - \text{Costs}_t) * (1 - \text{Effective Tax Rate}_t) + \text{Depreciation and Amortizations} - \text{Net CAPEX}_t + \text{Working Capital Change}_t \tag{5}$$

$$\text{Revenues}_t = 0.98 * \Sigma_i \text{ Yield}_{it} * \delta_{it} * \text{Area in production}_t * I_{it} * \text{Price}_{it} \tag{6}$$

for $i \in$ {soybeans, corn}, I_{it} represents if the region is a doubled cropped region and if corn as a second crop is being considered (after 3rd year). Revenues are assumed to have a 2% discount.

Area in production follows the clearing pattern described above. Finally, the model incorporates a gradual increase in soybean yields over the initial seven years, the δ factor, which reaches a mature yield level at the 7th year of farming, which mirror practices described by interviewed farmers and are consistent to other studies (Daldegan, G. *et al.*, 2019). In year 2 through year 7, the yield was assumed to be 85%, 88%, 92%, 95%, 97% and 100% of the yields projected according to the climate scenarios described earlier. As for corn, it begins at the mature yield level (100%) in year 3 from clearing. The assumed prices per unit of soybean or corn will be described in the next section.

$$\text{Costs}_t = \Sigma_i \text{ Direct Costs per hectare}_{it} * \text{Area in production}_t * I_{it} + \text{SG and A expenses}_t - \text{Depreciation and Amortizations}_t \tag{7}$$

For Machinery and Equipments (M&E) a depreciation schedule was assumed as linear, mirroring a useful life of 10 years and a 10% salvage values. No salvage value was assumed for the investments in clearing and soil improvements. Sales, general and administrative (SG&A) expenses were obtained from reports issued by the Companhia Nacional de Abastecimento (CONAB, 2022) and were assumed to be BRL100 per ha in the first year and BRL300 per ha for each subsequent year. Production costs will be described in the next section.

$$\text{Effective Tax Rate}_t = \frac{\max\{(\text{Costs}_t - \text{Depreciation and Amortizations}_t - \text{Interest Expense}_t), 0\} * 0.275}{(\text{Costs}_t - \text{Depreciation and Amortizations}_t)} \tag{8}$$

The capital structure was assumed to be equivalent to 60% Debt-to-Asset, with a net cost of debt equivalent to 8% per year. The tax bracket was assumed as being 27.5%, generating taxes expenses in case of positive Earnings before Taxes (EBT).

$$\text{Net Capex}_t = (\text{Clearing costs}_t + \text{New M\&E investments}_t) * \text{Cleared area}_t + \text{M\&E replacement rate} * \text{M\&E value}_t + \text{Soil maintenance rate} * \text{Clearing investments value}_t \quad (9)$$

Clearing costs represent the necessary investment (with permits, operations and administrative expenses) to convert native vegetation into cropland. New machinery and equipment along with clearing costs are incurred with the clearing pace. There were no public sources for land clearing and capital expenditures required for establishing a farming operation, therefore we have resorted to interviews with five farmers who had been involved with legal land clearing recently to obtain reasonable estimates of such expenditures (details can be provided by the authors upon request). Clearing costs (expenditures for clearing) were assumed to be BRL 8920 per ha cleared and new M&E investments to be BRL 8000 per ha cleared. M&E replacement rate was assumed to be 5% and Soil maintenance rate to be 3%.

$$\text{Working capital change} = \text{Working capital}_t - \text{Working capital}_{t-1} \quad (10)$$

$$\text{Working capital}_t = \text{Direct costs}_t * 285/360 \quad (11)$$

The working capital refers to the cash necessary for the business operations within a specific year. In our analysis, we consider that the farmer must cover 285 days of direct costs out of 360. This implies that for each additional BRL 1 incurred in direct costs, farmers need to finance approximately 80% of it. The change in working capital is calculated as the difference between consecutive years. As the farmer expands operations and clears parcels of native vegetation, substantial amounts of working capital are required and must be accounted for in the analysis.

$$\text{CF}_{\text{perp}} = \left(\frac{1}{5} * \sum_{t=26}^{30} \text{CF}_t\right) * \frac{(1+g)}{r-g} \quad (12)$$

The cash flow in perpetuity, or terminal value, was calculated as the average of the last 5 years of free cash flows, with a perpetual growth (g) of 2% and discounted by the discount rate minus the growth rate.

The discount rate is a crucial factor in determining the present value of a future cash flow. It is the rate at which future cash flows are discounted to determine their present value (Damodaran, 2006). The discount rate was calculated as 10.48%, representing the weighted average cost of capital, determined by the proportion of debt and equity in the company's capital structure and their respective costs. For this analysis, we assumed Debt to Asset Ratio of 60%, a cost of debt of 8% and a cost of equity of 17.5% per annum.

The cost of equity was calculated considering the risk-free rate, the country-specific premium, the historic stock market premium, and an activity premium of 4% assigned to account for the additional risk associated to a mid-size firm with low governance level, which is the case of most farming enterprises. Finally, the NPV was converted to $USD considering the exchange rate of set to 5.2 (IMEA, 2022).

Crop prices and operational costs assumptions and stochastic processes

Crop prices and operational costs assumptions were the same across all climate scenarios but different for each state in the Cerrado Biome. They were obtained from Companhia Nacional de Abastecimento (CONAB) and are illustrated in Table 2. Due to lack of data availability, corn production costs for DF were assumed to be the same as in GO; MS the same as in MT, and PI, the same as for MA.

Table 2. Initial costs and prices considered.

State	Corn		Soybean	
	Cost (BRL/ha)	**Unit price (BRL/60 kg)**	**Cost (BRL/ha)**	**Unit price (BRL/60 kg)**
BA	3641	68	5767	166
DF	5614	73	6851	163
GO	5614	69	4986	158
MA	3442	71	5455	172
MG	6159	76	5404	162
MS	4565	71	6181	168
MT	4596	64	5526	152
PI	3442	71	4730	161
TO	4098	71	5477	163
SP	5170	76	5871	167

As costs and prices are volatile and will vary over time, we utilized a stochastic approach, which generates random assumptions for prices and costs with the starting points depicted in Table 4. The analysis also assumes that prices would not suffer any real trend decline, which would otherwise be the case if trend yields were to increase over time (Howard, 2009).

The values distribution in the stochastic approach influences the results (Musshoff, 2012). In this study, we assume that prices and variable costs to be correlated and to follow a Geometric Brownian Motion (GBM). The parameters for prices and costs volatilities and for correlation were obtained respectively from a data series published by CONAB and by the Instituto Matogrossense de Economia Aplicada (IMEA) with data from 2004 through 2022. The correlation between yields and prices was found to be close to zero, therefore yields were assumed to be independent of prices.

For each variable in each state within the Cerrado, 5000 different correlated progressions were simulated. Each single progression was utilized in the economic model, creating 5000 different results (NPV) for each grid cell analyzed. By using a large number of simulations, the model is able to capture the range of possible outcomes and their probabilities, providing a more realistic representation of the risks and uncertainties associated with the project. The most likely NPV outcomes (average of 5000 NPVs) are presented as results.

4. Main results

4.1 Crop model performance

The summary of the hybrid model performance in the training dataset (based on actual yields (up to 2015) and GSWP3-W5E5) is presented in Table 3.

As an illustration of the model performance and ability to capture interannual variations, Figure 5 depicts the historical detrended data and model predictions.

Projected yields

With the respective models, we estimated projected detrended yields from 2023 through 2060, by GCM and RCP combination. The projected yields were then combined with long-term trends from crop-based models, resulting in the final yield projections. The average of the Cerrado projected yields over the years

Table 3. Summary of model performance (MAE and RSME shown as kg/ha).

	Soybean	Corn
R^2	0.763	0.724
MAE (kg/ha)	91.191	168.421
RSME (kg/ha)	138.477	267.162

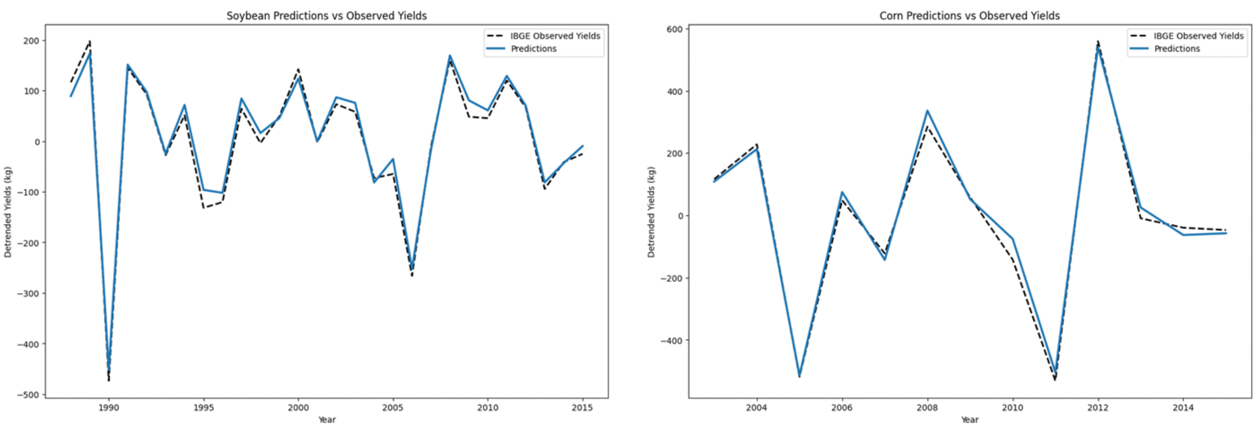

Figure 5. Historical detrended yields and model's projected yields.

is illustrated below. The shaded areas around lines in Figure 6 represent the 95% confidence interval across the Cerrado region.

Depending on the combination of GCM with RCP, the projections seem to indicate, in some cases, a slight increase in yields. However, in general, they suggest a reduction in yields due to the simulated model trends. Despite the downtrends for corn and somewhat steady trends for soybeans, we can see from the results that they are volatile over the years, with some very poor and some very good years. The charts above show a line for each combination of GCM and RCP. While the charts depict the mean values, projected yields are heterogeneous throughout the Cerrado biome.

NPV per acre

The NPV results presented here (Table 4) denote the level of economic feasibility of a potential investment in converting native Cerrado vegetation into farmland. The stochastic approach generated a series of NPV results for each combination of climate forcing and RCP generated from the yield model. The means of the distributions of NPV results from each scenario was computed and figures between parenthesis represent a negative value.

The net present value of the project, when considering the most severe scenario of climate change, or RCP 8.5, was substantially lower in the GFDL-ESM4 and UKESM1-0-LL climate forcings.

30% and 60% of results from all climate models were negative for RCPs 2.6 and 8.5 respectively. At the 8.5 RCP level, most scenarios would have a high probability of generating economically unfeasible investment projects, especially on the UKESM1-0-LL forcing. Table 5 shows the results per state and GCM/RCP combination. Values in parentheses represent negative NPV.

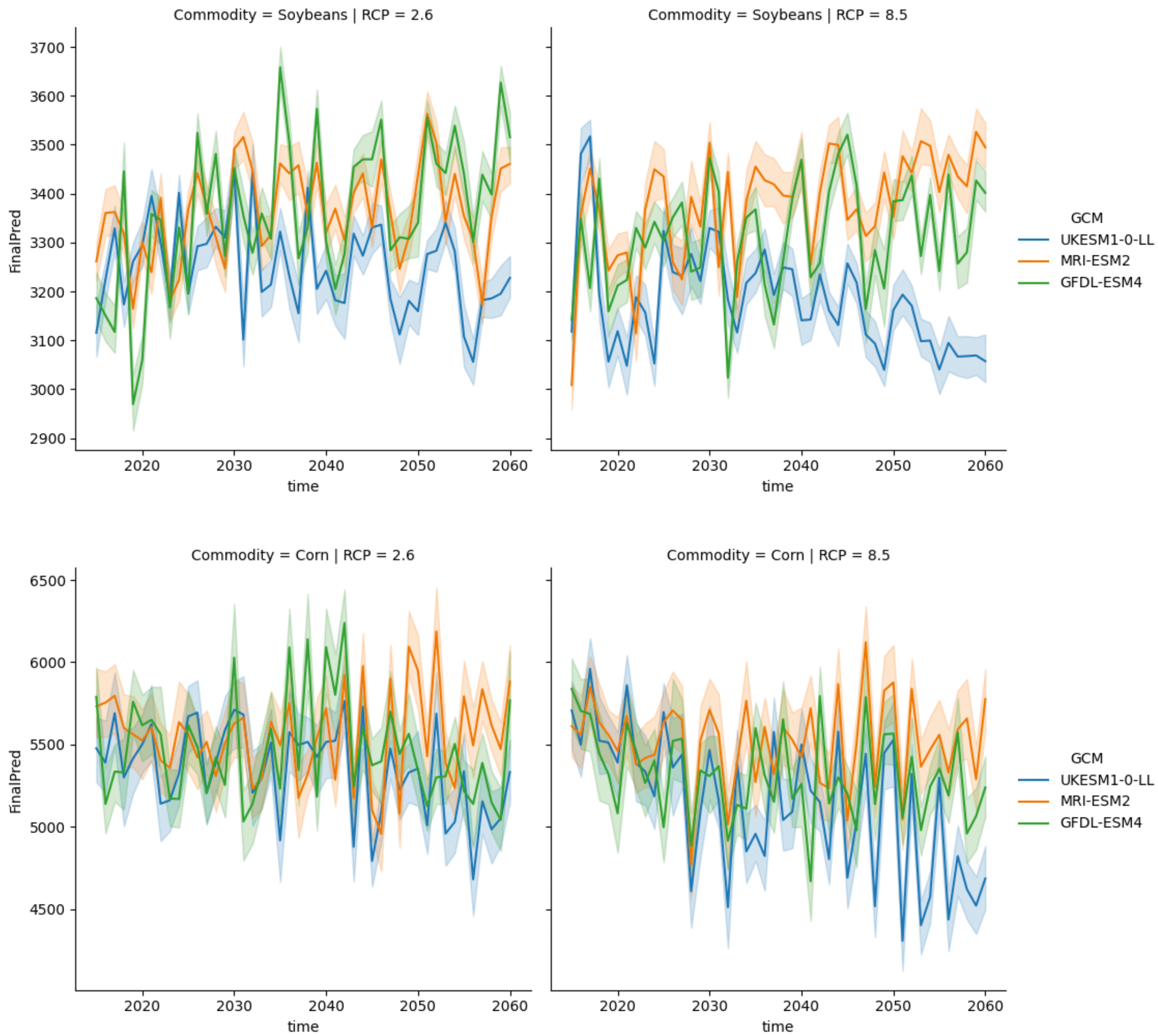

Figure 6. Projected yields for the Cerrado region according to different GCM and RCP combinations.

Table 4. Average Cerrado NPV, by climate forcing and RCP combination (US$/ha).

GCM	RCP	Mean
GFDL-ESM4	2.6	$134.4
	8.5	($13.2)
MRI-ESM2	2.6	$178.9
	8.5	$180.7
UKESM1-0-LL	2.6	$3.9
	8.5	($320.8)

Negative figures are enclosed in parentheses.

Table 5. Economic result by GCM and RCP per state (US$/ha).

GCM	RCP	States									
		BA	DF	GO	MA	MG	MS	MT	PI	SP	TO
GFDL-	2.6	$134.5	$102.9	$622.0	$200.9	$381.0	$28.0	$105.9	$96.8	($269.9)	($859.6)
ESM4	8.5	$82.9	$209.6	$550.8	$309.1	$97.0	($601.5)	($41.6)	$88.4	($435.2)	($750.7)
MRI-	2.6	$209.0	$1.5	$643.9	$84.0	$135.1	($146.6)	$417.6	$103.1	($319.8)	($659.5)
ESM2	8.5	$37.7	$20.8	$671.2	($31.0)	$265.3	($37.5)	$409.9	($3.6)	($281.0)	($747.9)
UKESM1-	2.6	$176.6	$47.4	$592.3	$76.6	$207.2	($100.6)	($142.0)	$200.4	($513.7)	($999.9)
0-LL	8.5	($15.8)	($320.2)	$321.3	($369.5)	($69.1)	($298.8)	($497.4)	($157.8)	($634.8)	($1,507.8)

Negative figures are enclosed in parentheses.

The feasibility analysis results were visually presented on a Cerrado Biome map (Figure 7). Negative net present values (NPVs) were depicted in red. Positive NPVs, in blue, indicate sub-regions with better economic feasibility in converting native vegetation to cropland. The analysis revealed that, in some micro-regions, the economic feasibility of such investments was negative across most or all three climate models. Conversely, certain regions exhibited a higher probability of providing favorable investment outcomes across most or all climate models.

5. Discussion

The results are a product of projected crop yields based on simulated yields of ensemble means of twelve crop models, three global climate models (GCMs: GFDL-ESM4, MRI-ESM2-0 and UKESM1-0-LL) and two different Representative Concentration Pathway (RCP: SSP1-2.6 and SSP5-8.5). The projected yields were then used as an input to an investment capital budget analysis evaluating the feasibility of investing in clearing land in the Cerrado Biome and farming it under different prices and costs scenarios.

The results of this spectrum of outcomes from a varying yields with climate change, and from varying price and costs scenarios show that there is a high probability that the economic results of the tested investments would be negative in some regions, while positive in some other regions of the Cerrado Biome.

In a vast area in the Cerrado, especially the ones located in the state of Tocantins, the tested investment proposition would be highly unfeasible. These micro-regions deserve attention from farmers, financial institutions financing agricultural expansion and policy makers. Farmers and policy makers should consider either maintaining the natural coverage, pursuing a different crop mix for the land to be converted or implementing technologies that potentially mitigate environmental impact (Lucas *et al*., 2023).

Even where the mean NPVs are positive, the results indicate that there might be a few years of negative cash flow, therefore farmers would have to be prepared with more liquidity and solvency to remain in business.

Climate is one of the factors affecting the resulting NPVs, along with prices, capital expenditures, and the other assumptions utilized in the economic model. An exercise aiming at providing an estimate of the magnitude of the climate effect alone on the NPV results was performed and is presented in Appendix B.

Appendix B presents the difference in NPV per region comparing projections maintaining yields at baseline level (i.e., not subject to climate influence) with projections having yields under the climate influenced scenarios (GCM/RCP). The differences are indicative of the isolated effect of climate change according to the climate models applied: NPV results were negatively affected by the climate change scenarios by at least 40.2%.

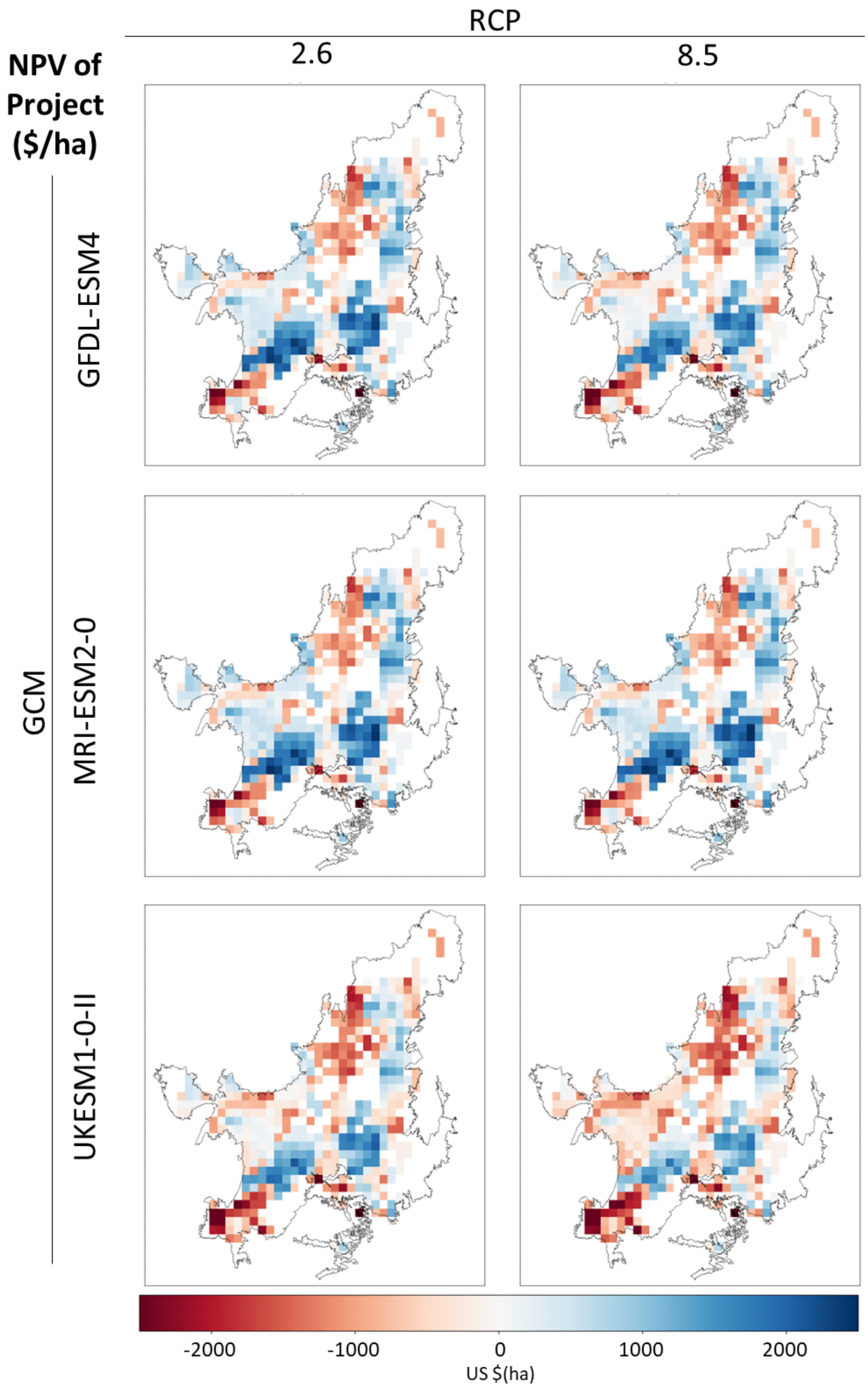

Figure 7. Geographic distribution of NPV per gridcell of the Cerrado Biome.

Besides yields, costs, prices, and cost of capital, for example, the economic feasibility of investments in land clearing tends to be positively affected by land appreciation over time. Farmers are driven by the pursuit of profits and the capital gains that can be realized by developing land pose a major obstacle to efforts to prevent deforestation. According to (Daldegan *et al*., 2019), the price differential among different land uses creates business opportunities for real estate developers seeking to profit from buying cheap land, developing it, and selling it as cleared agricultural land. The report notes that in some regions of the Cerrado, the price of a hectare of cropland was up to six times higher than the price of a hectare of native vegetation in 2016. But this assumption would only be valid if the expected stream of cash flows to be generated by farmland in these regions remain promising, growing in real terms and somewhat stable. If the effects of climate change in crop production hinder yields, expecting land appreciation might no longer be valid.

This study assumes no price increase trend because, in line with the concept of Cochrane's treadmill, in which gains of productivity in commodity production are passed downstream in the value chain, reducing real prices. As farmers adjust techniques, practices and employed technologies to enhance yields, prices would likely decrease and capture these yield gains.

Our economic analysis model does not assume possible adaptations that farmers may implement in their production models over time to cope with climate change. According to (Goulart *et al.*, 2023), effective adjustments to changes in average weather conditions have the potential to reduce the impacts of climate change on concurrent soybean crop failures throughout the Americas. However, the analysis shows that in some regions land clearing for farming tends to be a value destroying proposition, therefore while new techniques and practices for coping with climate change are not established, farmers should consider leaving the natural vegetation intact and invest elsewhere.

Widespread crop failures reduce overall supplies and result in lower inventories and higher prices. However, (Goulart *et al.*, 2023) have demonstrated that the effects of climate on yields are likely not going to be simultaneous across the major soy producing regions worldwide. Therefore, we have not accounted for the possibility that local crop yield reductions would impact prices.

Our model considers that the investor farmer would grow mainly soybeans, adding corn as a second crop whenever location allows. Therefore, the calculated stream of free cash flows only derive from this crop mix and our model may be underestimating farmers' ability to enhance their actual cash flows and the feasibility of their investments with more profitable crops, such as cotton, or with ancillary revenues from cattle, for example.

While we intended to model the currently prevalent farming practices, there would be a series of scenarios in which farmers would use more heat and drought resilient crops, change sowing dates (Fodor *et al.*, 2017; Minoli *et al.*, 2022), use new soybean cultivars (Snowdon *et al.*, 2021), which will impact yield and consequently its cash generation.

Accelerating demand for grains and oil seeds, from growing consumption of animal protein, for example, would shift prices up and enhance farmers' profitability, but studies show considerable reduction in demand growth for the coming decades (FAO, 2023).

Another limitation of our model relates to the utilization of one single discount rate, while the results show that risks vary from region to region. A more nuanced risk premium would probably have further polarized the results, as lower discount rates in lower risk regions would make local projects more feasible, and a higher rate in higher risk regions would make local projects more unfeasible. The direction of the results would probably not have changed, only their magnitude.

Although there are simplifications and limitations in this study, our results seem quite consistent and point to a direction to question further expansion of agriculture into native vegetation in the Cerrado Biome as an economically viable proposition given the variability of results and negative net present values.

6. Concluding remarks

Farmers, financial institutions, and policy makers should consider these results in their plans, as the results of our simulations have indicated that clearing Cerrado's vegetation to convert the land for farming could be economically unfeasible given possible effects of climate over the years in many micro-regions.

Conversely, as further land clearing may worsen the speed and magnitude of climate change, it seems sensible that these agents analyze alternatives such as the feasibility of recovering degraded pastures for cropland expansion instead of doing so over native vegetation.

Policy makers should consider the implementation of a series of incentives for the adoption of agricultural practices capable of mitigating environmental impacts, while also pursuing policies to avoid farming advances over native Cerrado.

In spite of the limitations of this study, the results should provide farmers and policymakers an alert to potential value destruction of expansion of agriculture on native vegetation, particularly in micro-regions to which our results were mostly negative.

Over time, as climate and technology change, and with them, global demand and prices, the economic feasibility of new agricultural investments in clearing Cerrado should be reassessed.

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Appendix A. Purpose of the hybrid model

The hybrid model aims to enhance the portrayal of annual crop yield variability, addressing the comparatively lower variability observed in process-based models' simulation data. As depicted below, process-based models' simulation data do not fully capture the interannual variability of the Cerrado region when compared with observed historical yields from IBGE, especially for soybeans. For corn, the simulated data is closer to the observed historical yields.

As described in the result section, the hybrid model better captures the interannual variability, as shown in Figure A2 and in the comparison of the RSME in Table A.

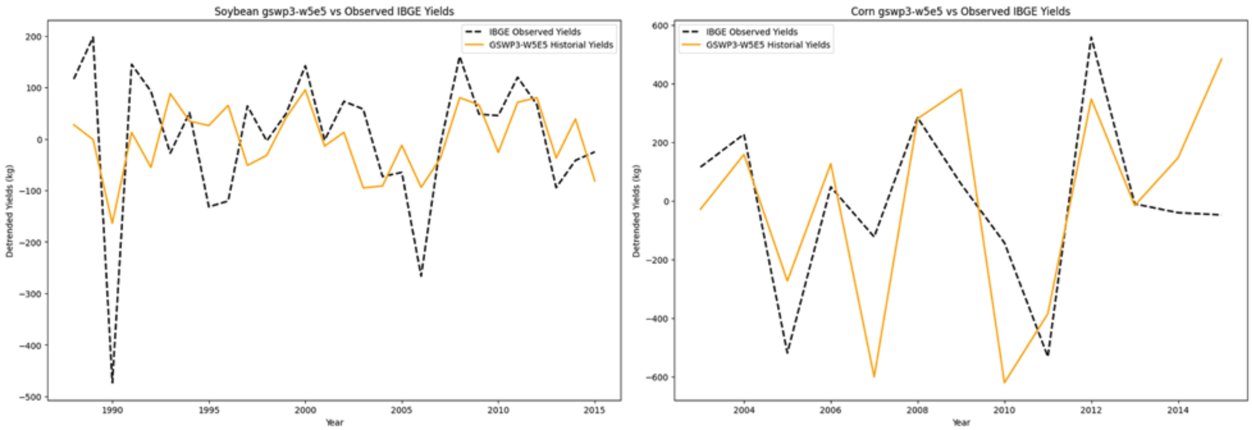

Figure A1. Interannual variability comparison between process-based model's simulation and observed data in the Cerrado region.

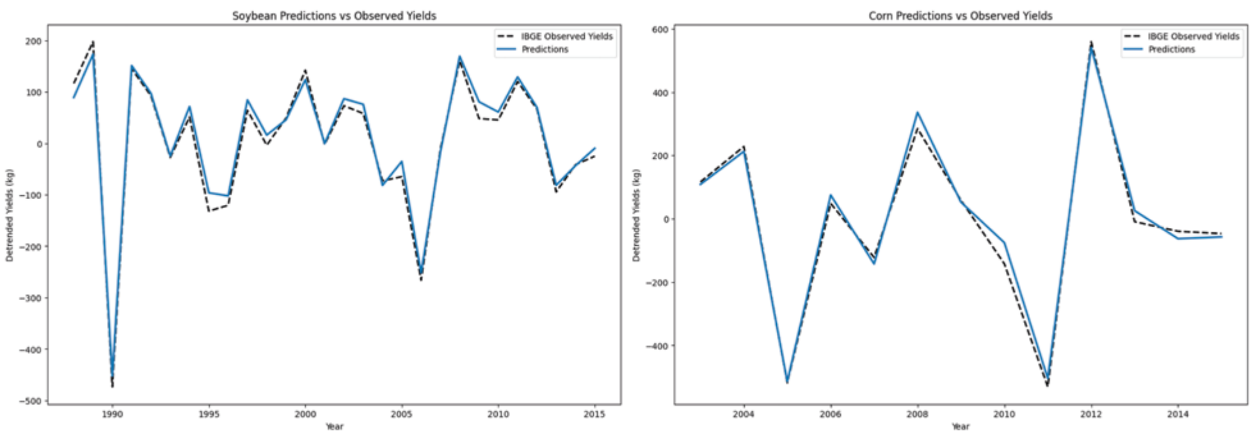

Figure A2. Interannual variability comparison between hybrid model simulation and observed data in the Cerrado region.

Table A1. Summary of hybrid model and process-based model's simulation performances (values in kg/ha).

		Process-based models	Hybrid model
MAE	Soybean	216.45	91.19
RSME		289.74	138.48
MAE	Corn	500.11	168.42
RSME		686.92	267.16

Appendix B. Isolating the climate effect in the economic analysis

The results of the economic analysis presented in this study are a function of several factors, such as costs, prices, yields, and upfront investment. Three variables utilized in the economic analysis model varied per region within the Cerrado: yields, costs and prices. All other variables were common to all regions, i.e., kept constant throughout regions.

Cost and prices were state specific, regardless of the climate forcings being applied. On the other hand, yields were climate forcing, RCP and latitude/longitude specific.

Therefore, farming in some microregions in the Cerrado might already generate low margins (due to baseline yields, cost and prices), resulting in poor investment payoff. Other regions tend to enjoy higher yields, lower costs and/or higher prices, allowing for more profitable agriculture and better chances of paying off investments in farming. That is, we cannot attribute the negative/positive NPV exclusively to yield patterns after a climate forcing and RCP.

To provide insight to the extent of the influence of climate change on the economic results of the investments in land transformation for agriculture, we have generated two sets of economic results of these investments: (a) one set assuming yields at baseline level; and (b) another set with yields obtained from the different combinations of scenarios (GCM/RCP).

The results per region of one set were subtracted from their respective region's results from the second set and the difference is presented as indicative of the isolated effect of climate change according to the climate models applied. In order to generate the first set of results, with yields assumed at baseline, with no influence from climate change, average yields from 2019, 2020 and 2021 were set constant throughout the analysis period. The results of the first set, at baseline yields, are presented in Table B1 below. Negative values are shown between parentheses.

Table B2 provides the average difference between baseline driven NPV and the NPV obtained from the climate influenced scenarios considered in this study, representing the impact of climate change on the baseline driven results.

Table B3 shows the percentage of the Cerrado in which results were negatively impacted when compared to the baseline.

Table B1. Average Result considering constant baseline yields (US$/ha).

States									
BA	**DF**	**GO**	**MA**	**MG**	**MS**	**MT**	**PI**	**SP**	**TO**
$388.1	$48.5	$675.2	$112.6	$100.2	($202.8)	$224.8	$156.0	($485.6)	($810.6)

Negative figures are enclosed in parentheses.

Table B2. Average difference in results (model results minus baseline yields results). (US $/ha).

GCM	RCP	States									
		BA	DF	GO	MA	MG	MS	MT	PI	SP	TO
GFDL-	2.6	($253.7)	$54.4	($53.2)	$88.3	$280.8	$230.8	($118.9)	($59.2)	$215.7	$32.5
ESM4	8.5	($305.2)	$161.1	($124.3)	$196.5	($3.2)	($398.7)	($266.3)	($67.6)	$50.4	($26.4)
MRI-	2.6	($179.2)	($47.0)	($31.3)	($28.6)	$34.9	$56.2	$192.9	($53.0)	$165.8	$93.7
ESM2	8.5	($350.4)	($27.7)	($4.0)	($143.6)	$165.1	$165.3	$185.2	($159.6)	$204.6	$74.0
UKESM1-	2.6	($211.5)	($1.1)	($82.9)	($36.0)	$107.0	$102.3	($366.8)	$44.4	($28.0)	($237.0)
0-LL	8.5	($404.0)	($368.7)	($353.9)	($482.1)	($169.3)	($96.0)	($722.1)	($313.8)	($149.2)	($387.0)

Negative figures are enclosed in parentheses.

Table B3. Percentage of points with a negative difference between model results and baseline results.

Model	RCP	% of negative differences
GFDL-ESM4	2.6	56.3%
	8.5	74.8%
MRI-ESM2	2.6	40.5%
	8.5	42.8%
UKESM1-0-LL	2.6	70.0%
	8.5	92.0%