Agricultural Systems xxx (xxxx) 103174

Contents lists available at ScienceDirect

Agricultural Systems

journal homepage: www.elsevier.com/locate/agsy

Short Communication

Impact assessment of common bean availability in Brazil under climate change scenarios

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ARTICLE INFO

Editor: Dr Jagadish Timsina

Keywords:
Food security
Crop modeling
Climate change
Agricultural impacts
Common beans

ABSTRACT

CONTEXT: Brazil is one of the main producers of common beans (*Phaseolus vulgaris* L.), which have high nutritional value as human food. The climate changes predicted in the 21st century might be a possible threat to the planet's food security, given the expected population increase, and hence, increased demand for food.

OBJECTIVE: This study aimed to project the impact of climate change on common bean cropping systems using an upscaling climate approach and crop modeling to represent the Brazilian production regions.

METHODS: We considered the representative CO_2 concentration pathway scenarios (RCPs) 4.5 and 8.5 presented by the 5th IPCC Assessment Report from 20 atmospheric global circulation models covering the main bean-producing region in Brazil. The well-calibrated CROPGRO-Drybean crop model simulated two representative cultivars of the "black" and "colors" types and three cropping seasons applied by Brazilian farmers.

RESULTS AND CONCLUSIONS: On average, we found that yield increased by 5.56% and 9.12% for the RCP 4.5 and 8.5 scenarios, respectively. Increased photosynthetic efficiency due to the increased atmospheric CO_2 concentration was identified as the main cause of this yield increase. Crop respiration rates increased due to the raised air temperature, and were responsible for increasing the probability (production risk) of not meeting the future domestic demands for grains to 10.13% and 8.34% for the RCP 4.5 and 8.5 scenarios, respectively. For the national supply of grains, estimates pointed to a future in which crop production will probably rely more on area expansion than yield gains by crop intensification.

SIGNIFICANCE: Our findings emphasize the need for new policies for land utilization and investments in scientific research programs aimed towards genetic adaptation in all main Brazilian crops in the face of potential climate change.

1. Introduction

The impacts of climate change on food crops have been addressed by several scientific papers in recent years, focusing on the political, economic, social, and environmental aspects related to climate change (Cramer et al., 2001; Shogren and Toman, 2010). In developing countries, which are usually highly dependent on the agricultural sector, the effects of an adverse climate on non-adapted cropping systems would imply a relevant transformation of such agricultural scenarios (Howden et al., 2007; Mendelsohn and Dinar, 1999).

As a reliable source of vegetable protein and the most important food legume for direct human consumption worldwide, the common bean (*Phaseolus vulgaris* L.) is part of the daily diet in the majority of populations in developing countries (CIAT, 2016; Pachico, 1989). The wide range of genetic material growing across the globe (Burle et al., 2010; Rodriguez et al., 2016) allows its cultivation in a large range of environments and seasons.

Among the world's major common bean producers, Brazil is ranked in third position in terms of grain production (ca. 3 million metric tons of grains; FAOSTAT, 2018) and second in terms of harvested area (ca. 2.8 million ha planted). In Brazil, the common bean cropping system encompasses three major sowing seasons (CONAB, 2018a)() as an important strategy to control market price and to maintain food protein availability (de Portes, 2012). Brazilian common bean crops are found in the majority of the country's regions, illustrating not only their eco-

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https://doi.org/10.1016/j.agsy.2021.103174
Received 8 December 2020; Received in revised form 7 April 2021; Accepted 7 May 2021

nomic importance but also their social relevance (Fuscaldi and Prado, 2005).

For developing countries with a high rate of poverty, common beans have a major role in human nutrition. Thirty, 16, and 15% of protein intake in Niger, Sudan, and Mali respectively comes from protein-rich leguminous plants (FAOSTAT, 2013; GPC, 2020). Latin America and Sub-Saharan Africa consume ca. 10.7 and 4.5 kg of common beans per capita per year (Nedumaran et al., 2015), respectively, showing an increasing trend in recent years (Akibode and Mywish, 2012). Many of the world's largest common bean consuming countries are also enlisted in UN efforts to eradicate hunger by the mid-century (United Nations, 2015), highlighting concerns about maintaining the increase in consumption rate in order to fulfill this goal.

Beebe et al. (2011) and McClean et al. (2011) highlighted the need for studies on climate change impacts on common bean crops for developing countries and proposed a multidisciplinary agenda with the main goal of increasing crop yields. Godfray et al. (2010) and Wheeler and von Braun (2013) emphasized the importance of quantifying risks associated with common bean yields in a world expected to have more than 9 billion inhabitants by 2050. In Brazil, Heinemann et al. (2017) performed an analysis of water stress due to low relative air humidity and predicted increased water stress for common beans in the future.

The complexity of common bean cropping systems in Brazil makes their in silico representation a complex task and demands a large amount of basic data. Brazil currently has the data required for this analysis, such as cropping system data (area, yield, sowing dates, and genotypes) over a range of climates (Alvares et al., 2013) and soils (Santos et al., 2018). Despite the importance of crop production to assure the country's food security and recent policies that might increase common bean exports from Brazil (MAPA, 2018), we are not aware of any study investigating the future prospects under climate change scenarios for common beans in the existing crop area in Brazil using a robust simulation framework that includes the diversity of cropping systems, climates, and soil types across the country.

To fill the knowledge gap about climate change effects on common beans in Brazil, we used a well-calibrated process-based crop model to simulate future crop availability by the mid-century (2040–2070) based on climate scenarios provided by the AgMIP (Agricultural Model Intercomparison and Improvement Project) (Rosenzweig et al., 2018). Additionally, we used the approach proposed by Aggarwal et al. (2019) to take into account the technological trends that might also affect yield through the same timeline analyzed by climate change, thus making our projections closer to reality.

2. Material & Methods

2.1. Experimental data and model calibration

Three experiments were performed in distinct seasons, at two locations, with the commercial “black” and “colors” common bean cultivars “BRS Esplendor” and “Pérola”. The main purpose of these trials was to calibrate and quantify the crop model uncertainty over genotypes and environments. These experiments were conducted with cultivars that commercially represent 81.2% of all Brazilian common bean production (CONAB, 2018a, 2018b). One experiment (E1) was conducted during the winter season (irrigated) in the Midwest region, at Goiás (Latitude 16° 28′ 01″ S, Longitude 49° 16′ 59″ W), which is considered a tropical zone, Aw (dry winter), according to the Koppen climate classification. The second and third experiments (E2 and E3) were conducted in the Southeast region, in São Paulo (Latitude 22° 42′ 32″ S, Longitude 47° 37′ 45″ W), which is considered a humid subtropical zone, Cw, according to the Koppen climate classification (Alvares et al., 2013) during the summer and winter seasons.

We applied the CROPGRO model (Boote et al., 1997) to simulate crop growth and development. This crop model is a generic legume model that contains a dry bean module (Heinemann et al., 2017) adapted from the BEANGRO model (Hoogenboom et al., 1994) and is available in the DSSAT platform (Jones et al., 2003). Previous studies on wheat (Martre et al., 2015) , maize (Bassu et al., 2014) and sugarcane (Marin et al., 2015) reported that yield assessments at large (country or global) scales might have their uncertainty reduced by using ensembles of multiple crop models, resulting in a more feasible prediction for climate change scenarios related to agriculture aspects, as pointed out by Rosenzweig et al. (2018) and Tao et al. (2018). For common beans, we are not aware of any study showing that this ensemble strategy would benefit the quality of the assessment by reducing the uncertainty of crop yield predictions. Besides, we are not aware of any other process-based crop model fully available for use in such an ensemble strategy, besides the CROPGRO-Dry bean model.

To quantify the model uncertainty, we compared the observed data with simulations of leaf area index (LAI), top weights, and grain weights, using the root mean square error (RMSE), mean absolute error (MAE) (Loague and Green, 1991), the index of agreement (d) (Willmott et al., 2012), and the Nash-Sutcliffe efficiency index (NS), as measures of goodness-of-fit.

2.2. Cropped areas

In Brazil, common beans are grown in many locations (South, Southeast, Midwest, and Northeast Brazilian regions), being sown in up to three seasons, mainly in the Midwest region, where the first and second seasons (wet and dry seasons) are rainfed and the third season (winter season) is irrigated (Wander, 2007). Based on the sowing seasons for regions, and on official statistics from national crop surveys, we selected data from at least 80% of the common bean production regions for our simulations, considering only the main commercial groups “black” and “color” in the last 5 years (CONAB, 2018a, 2018b). Data at the municipality scale (IBGE, 2019a) was used to select only counties with historically important common bean yields, excluding those where the yield was below 10 Mg per year in the last 5 years.

After defining the regions, we classified similar regions regarding their environmental features into agroclimatic homogeneous zones (HZ) (Van Wart et al., 2013). Similarities between zones are indicated by an index number, which describes a given region by characteristics such as growing degree-days of a standard crop, temperature and evapotranspiration seasonality, and an annual aridity index. For each HZ, we collected daily weather data from NASAPOWER API Client (Sparks, 2018) from 1988 to 2019.

For soil representation, we extracted data from the Brazilian Soil Map (EMBRAPA, 2014) and crossed it with each HZ. Soils were filtered by their relative presence in a given zone, selecting only soils with the highest coverage. Thus, each HZ is represented by its weather station and its most important soil profile.

2.3. Future climate scenarios

Following van Vuuren et al. (2011) and Shindell (2013), for our simulations we considered two representative concentration pathways (RCP) for atmospheric CO_2 [CO_2]: RCP 4.5, the lower concentration pathway (526 ppm following Clarke et al. (2007), Smith and Wigley (2006), and Wise et al. (2009)), and RCP 8.5, the higher concentration pathway (628 ppm following Riahi et al. (2011) and Moss et al. (2010)). The reported [CO_2] values from both RCPs were inputted in the crop model as environmental variables representing future scenarios.

Future daily weather data for the 2040–2070 period was generated from downscaled datasets of 20 global circulation models (GCMs) using a tool provided by the Agricultural Model Intercomparison and Improvement Project (AgMIP, www.agmip.org), which in turn followed the assumptions and protocols of the fifth phase of the Coupled Model

Intercomparison Project (CMIP5) (Taylor et al., 2012). Detailed descriptions about each GCM used for climate projections can be found in Ruane et al. (2015).

2.4. Production risks

Climate change will affect crops from an economic perspective, according to the socioeconomic forcing aspects that are expected to change during the analyzed period (Fernández and Blanco, 2015). Economic aspects thus need to be combined with biophysical crop models and climate data series to allow estimates of how future variations in technological trends, together with leguminous and grain demand, will pose a risk to future food security (Islam et al., 2016). There are a few useful methods for quantifying technological trends to assist crop model projections that include inputs obtained from crop-specific and environmental variables, such as presented in Hampf et al. (2020). However, for the present study we followed a safer path, by using a model built using a more complex approach. We decided to make use of the outputs from the IMPACT model (IFPRI, 2015), which is intended for scenarios analysis, and in a modular structure integrates crop, hydrological and climate models, in addition to land use, price commodity, welfare and other prospects, in accordance with technological improvements due to genetic and management practices (Robinson et al., 2016). Estimates of 2050's grain supply and demand were used to generate production risk maps.

We defined production risk as the frequency of years in which the simulated yield was less than the minimum necessary to supply future country demands. To quantify the risks of not meeting future demand, area projections at the mid-century were not included, given that expanding production areas will be a limiting factor in an overpopulated world, and existing cropped areas, theoretically, should not change (Van Ittersum et al., 2013). Such analysis identified HZs with higher risk increases, tracking regions that will seek area expansion to fulfill future demands. This approach not only combines models from different subjects but also highlights HZs that might experience shortages, which is potentially useful information for public policies and private investments.

2.5. Model adjustments and data manipulation

To better represent the farmers' decisions when sowing, and following Müller and Robertson (2014) and Hampf et al. (2020), we created a hydrological trigger algorithm for sowing whenever there was an accumulated rainfall of at least 20 mm on three consecutive days, within the official sowing window recommended by the Ministry of Agriculture of Brazil (CONAB, 2018a, 2018b). With this procedure, the sowing date was variable for each season within the official sowing window, depending on the weather variability, avoiding situations where the model sowed during dry periods, i.e., leading to crop death, and thus bringing simulations closer to what farmers usually do in practice. In all scenarios, the simulations were carried out under potential conditions to emphasize environmental variability across regions and climate scenarios, meaning that farming limitations, such as water and nitrogen availability from the soil, were not considered in the modeling process.

Due to the high variability among common bean cropping systems in Brazil, all simulation outputs were grouped for each HZ by weighting the commercial genotypes, group (black and colors), and the proportions of sowing dates in each region according to official data (CONAB, 2018a, 2018b). The process consisted of observing how much of the common bean groups (as percentages) was cultivated as well as the yield in the sowing season for a given HZ. Common bean yields were presented as a weighted average of a commercial group and sowing seasons. This was intended to facilitate the interpretation of results for each HZ, where crops are grown across many seasons and commercial groups (Pelegrini et al., 2017).

3. Results

3.1. Model parameterization and validation

The model adjustment to observed data showed good statistical accuracy, as the Willmott's index agreement (d) (Willmott et al., 2012) and Nash-Sutcliffe (NS) efficiency (Nash and Sutcliffe, 1970) indicators presented positive values, showing that the model has better capacity to represent real data than the simple average of the observations (Fig. 1). The simulated values of grain weight for the "colors" group showed the worst performance although it was still considered satisfactory (Fig. 1 F and Table 1). Fig. 1 (C and F) showed great disparity in the adjustment of observed grain weight values from the Mid-

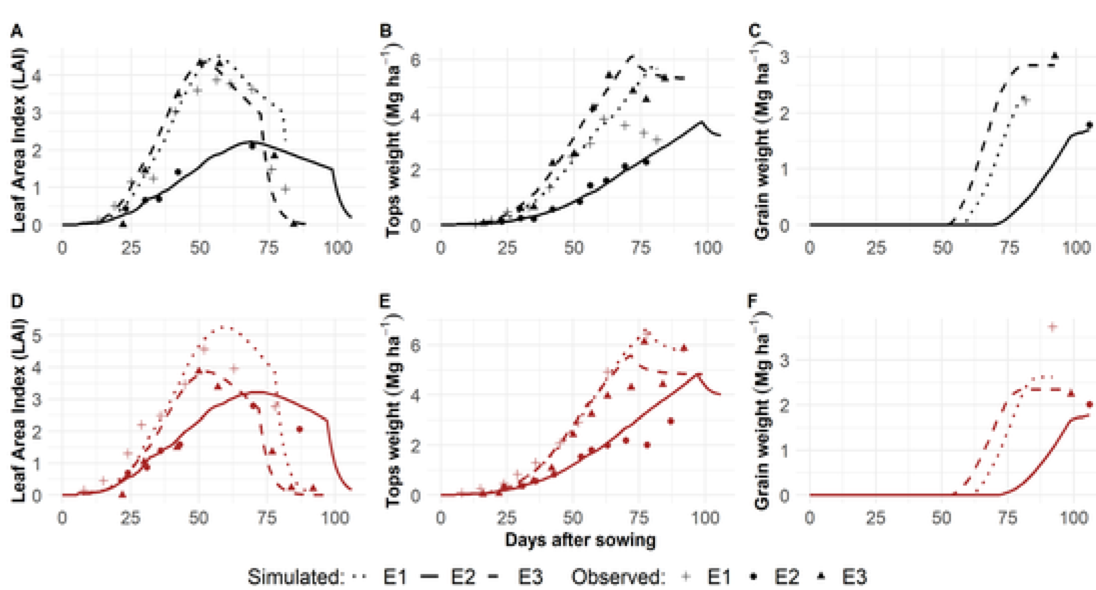

Fig. 1. Scatterplot of simulated and current datasets for model calibration. Leaf Area Index (A and D), tops weight (B and E) and grain weight (C and F), for commercial group "black" (A, B and C) and "colors" (D, E and F).

Table 1
Statistical measures of goodness-of-fit of the crop model validation.

Commercial groups	LAI (leaf area index)					Tops weight					Grain weight				
	d	NS	MAE	RMSE	R^2	d	NS	MAE*	RMSE*	R^2	d	NS	MAE*	RMSE*	R^2
Black	0.85	0.83	0.40	0.60	0.87	0.87	0.83	0.38	0.70	0.90	0.87	0.94	0.12	0.12	0.96
Colors	0.80	0.79	0.46	0.60	0.89	0.88	0.92	0.38	0.53	0.93	0.66	0.25	0.49	0.66	0.68

d: Willmott index of agreement (Willmott et al., 2012); NS: Nash-Sutcliff index of efficiency (Nash and Sutcliffe, 1970); MAE: mean absolute error; RMSE: root mean squared error; R^2: coefficient of determination.
* Measured in Mg ha^{-1}.

west experiment (E1). This finding may explain what caused the lowest performance although the curves for the other experiments indicated a good fit for this same information.

3.2. Homogeneous zones for common beans

We found that 81% of the national common bean areas in Brazil could be represented in 24 HZs (Fig. 2). Over the last 5 years, the South and Midwest regions were the main producing states during all crop seasons. We also found that the southern part of the Northeast is responsible for 75% of common bean production in the region.

3.3. Sowing dates across Brazil

The hydrological trigger to define sowing dates across crop seasons was limited by the Brazilian sowing calendar for common beans. The result of this process, containing the intervals of possible sowing dates, is shown in Table 2.

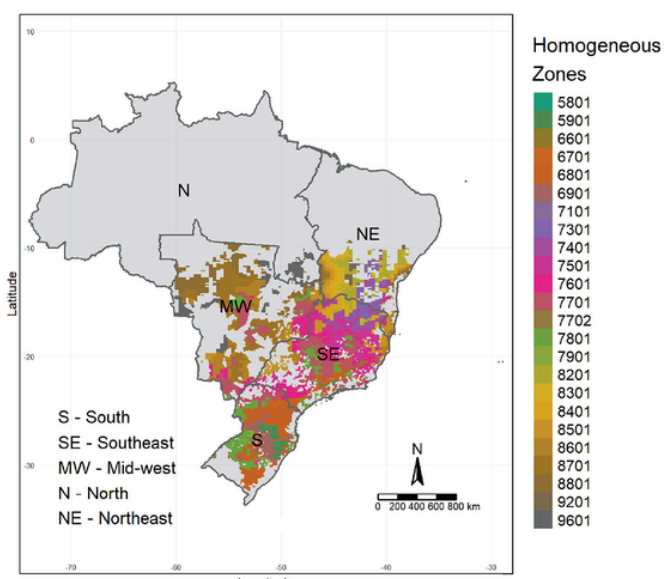

Fig. 2. Distribution of 24 Homogeneous zones, containing 81% of producing regions of common beans in Brazil. HZ are distributed by regions with social-economical similarities, according to IBGE (2019b).

Table 2
Sowing dates across seasons for common beans in Brazil.

Region	Common beans seasons 1st	2nd	3rd
Southeast	01/Oct–15/Oct	01/Feb–28/Feb	01/May–31/May
Mid-west	01/Oct–31/Oct	01/Feb–28/Feb	01/May–31/May
South	01/Sep–31/Oct	01/Jan–31/Jan	01/May–31/May*
Northeast	01/Nov–30/Nov	01/Feb–28/Feb	01/Apr–15/May

The first season in the South region starts earlier due to the consistent rainfall in mid-September. On the other hand, in the Northeast region, where sowing dates are set in November, rainfall is scarce until late October. In the third season, most cropped areas are concentrated in the Mid-west and southern Northeast regions. The sowing dates for the Southern region only represent the producers located in the northern part (i.e., Paraná). The northeast region has the shortest rainy season, thus there is a short interval between the first sowing date in the first season and the last available date in the third one.

3.4. Climate scenarios

Scenarios RCP 4.5 and 8.5 showed an increase in the average temperature in all HZs, ranging from 1.23 to 2.06 °C and from 1.75 to 2.86 °C, respectively, for RCP 4.5 and RCP 8.5 (Fig. 3). Rainfall is projected to increase at higher latitudes (between 22°S and 33°S) by 4% to 7.5%, but decrease on average by 0.5 to 7% at low latitudes (9–22° S) (Fig. 3). The HZs in the Northeast (8701, 9601, and 8801) showed higher temperature variations when compared with those in other regions, although projections showed slight changes in rainfall. Locations in South Brazil are expected to see increases in rainfall up to 7.5% when compared to the current annual accumulation. On the other hand, the Northeast and northern Southeast may see precipitation levels 6.9% lower than what is observed nowadays. A detailed description of future climate variability for each specific HZ is presented in the *Supplementary files, as* Table 1.

3.5. Production scenarios

The central region of Brazil (Midwest, Northeast, and northern Southeast) showed the worst scenarios for future grain yield, mainly in RCP 4.5. Among the seasons in this region, the third season experienced the highest impact, considering that in the first and second seasons the beans are mainly planted alongside soybean crops. In addition, the region is home to the highest producing counties (e.g., Cristalina/GO and Unaí/MG), with an average increase ranging from 2.5 to 5% for RCP 8.5 (Fig. 4).

The Brazilian South region had the highest average yield for both scenarios. It is expected that with the future projected climate, the region will have better environmental conditions for crop growth and development. Projections of black bean production in Brazil, which is mainly concentrated in the southern states, showed increases from 5 to 15% in comparison with current yield levels (Fig. 4).

In general, in the Mid-west and Northeast of Brazil, we observed mostly no change or negative yields when compared with the current yield; also, this region presented the largest variations around the projected mean yield in both scenarios, showing the highest level of uncertainty relative to the Southern areas (Fig. 4). A detailed description of future yield variability for each specific HZ is presented in the *Supplementary files*, as Table 2.

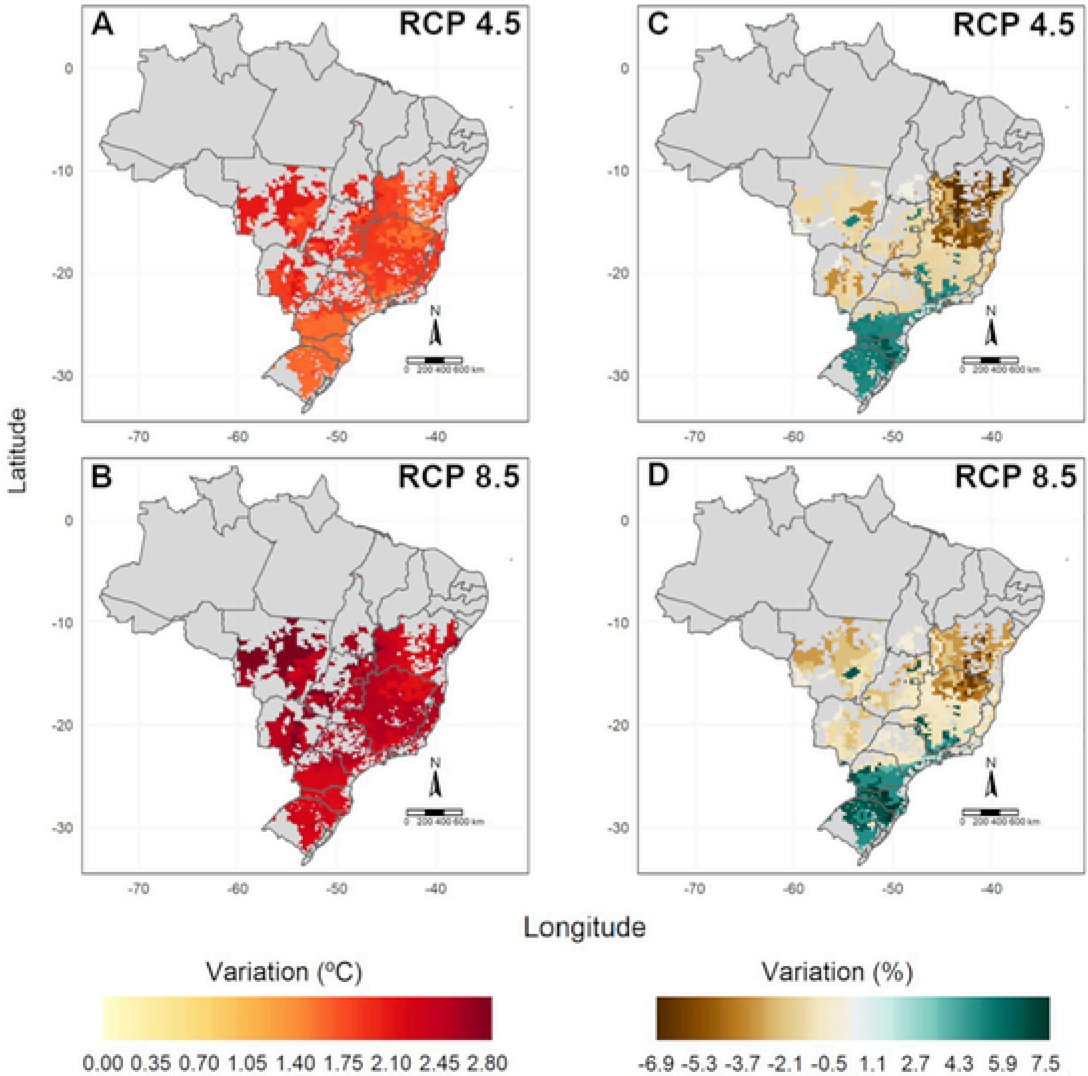

Fig. 3. Projected variation for the average period from 2040 to 2070 for air temperature (A and B) and rainfall (C and D) for RCP 4.5 (A, C) and RCP 8.5 (B, D).

3.6. Future production risks

The predictions of future demand for common beans, technological increases in yield, and crop area availability in Brazil were projected based on IMPACT model outputs. These outputs showed a trend for increasing demand with and without climate change for the 2050s. In Brazil, assuming the 2010 cropped area (4387.1 Mha) in the IMPACT model under the climate change scenario, future demand is expected to reach 4986.8 Mg, which means an increase of ca. 44% compared with current demand (3462.3 Mg). Current yields average 0.88 Mg ha^{-1}, and the IMPACT model projected a technological increase by 2050, which would leverage yields to 1.35 Mg ha^{-1}, meaning a 65.4% increase (Fig. 5).

Most HZs in Brazil showed an increased risk of not meeting future demands without expanding cropped areas or increasing investments for raising yield levels close to the yield potential (Fig. 6). The exception was the HZ in Northeast Brazil (HZ 9201, Fig. 2), where future demand is subject to a slight decrease in the risk (about 2%), despite yield projections showing a decrease in average production in both scenarios (Fig. 5). Northeast (HZ 7901, 8201, and 8301) and central areas of the South region (HZs 5801, 5901, 6701, 6801, and 7801) showed a mild risk increase (5 to 10%). Three HZs (7601, 7701, and 7702), representing key production regions in the Mid-west, Southwest, and South, were identified as the main higher-risk areas in the future, with projected risk increases close to 25%.

4. Discussion

The average air temperature increases for RCP 4.5 and 8.5 for common bean producing regions in Brazil were comparatively higher than those projected by the United Nations Intergovernmental Panel on Climate Change for Earth's surface temperature by the mid-twenty-first century (0.9 to 2.0 °C and 1.4 to 2.6 °C, respectively, for RCPs 4.5 and 8.5) (IPCC, 2014). On average, future scenarios generated by 20 GCMs have shown a slightly higher increase in maximum temperatures (2.05 ± 0.99 °C) compared to minimum temperature (1.96 ± 0.66 °C). The GCMs follow a probabilistic methodology to estimate rainfall in the chosen regions, showing an increase in locations where rainfall is well distributed throughout the year (South and Southwest), and decreasing in places where rainfall follows a different regime, such as in the Mid-west and Northeast (Alvares et al., 2013; Wilks, 2012). In agreement with Mearns et al. (2003) and Rosenzweig et al. (2018), the use of climate change models applied to agricultural studies indicated that the main differences in climate variables, air temperature, and rainfall, lie in disparities between locations at high lati-

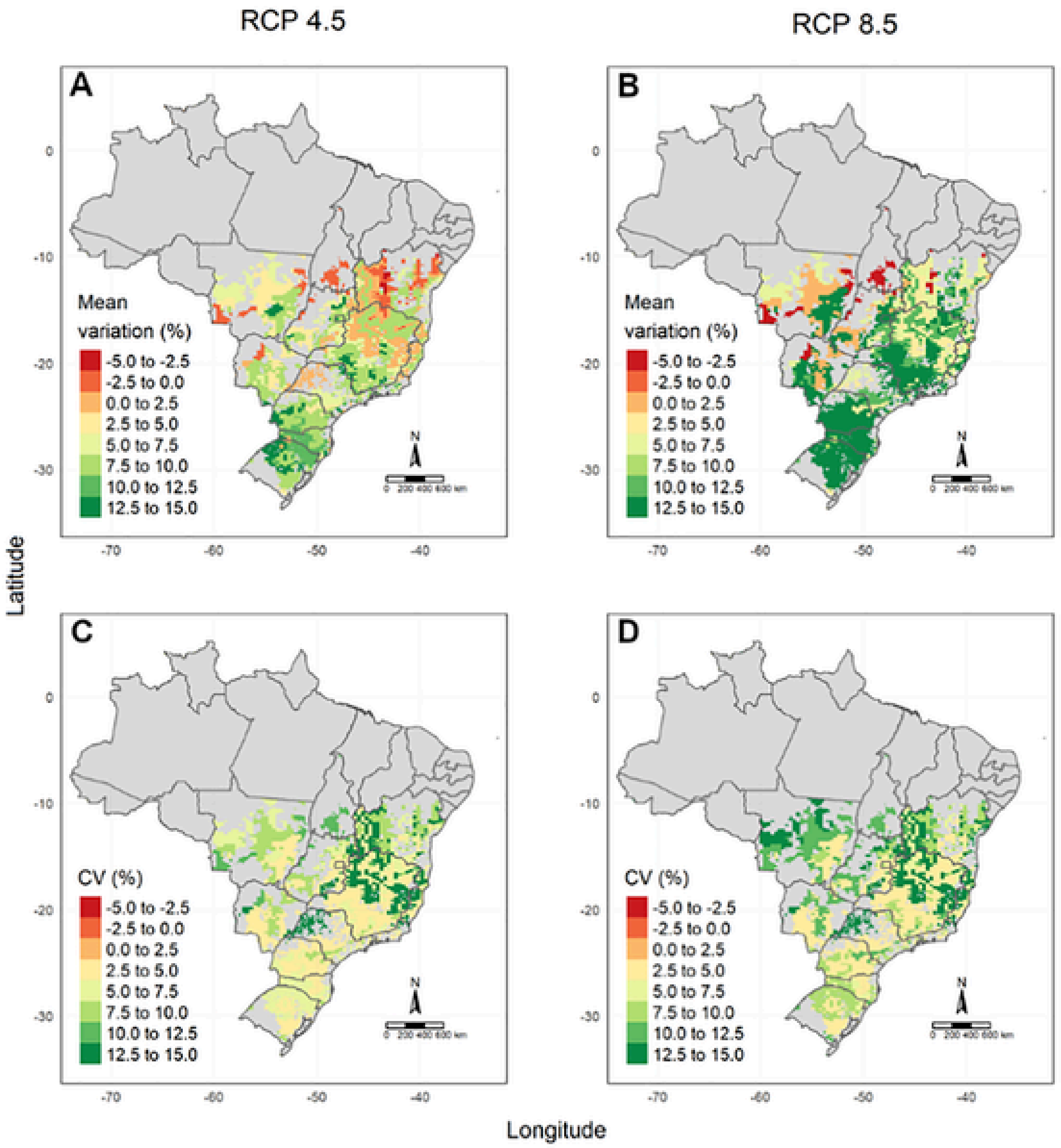

Fig. 4. Future mean variability on grain yields compared to the current mean simulated yields (A and B) and their coefficient of variation (CV) over time (C and D), on RCP 4.5 (left) and RCP 8.5 (right).

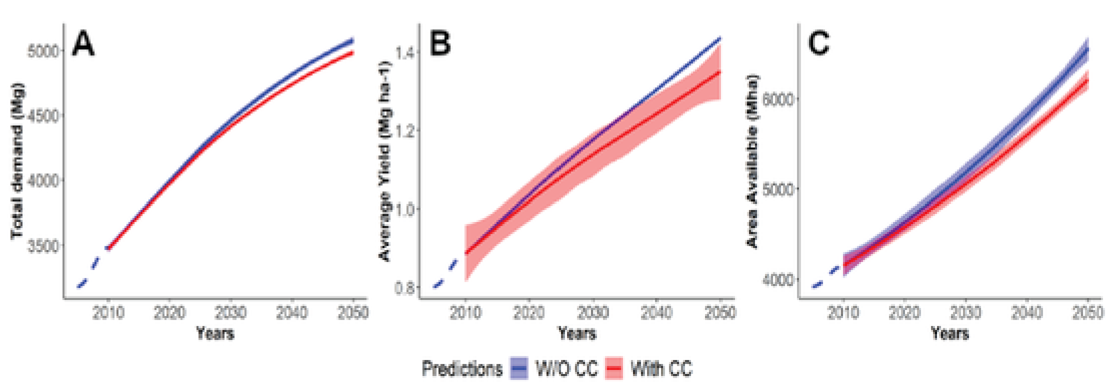

Fig. 5. Trends on total demand (A), average yield projections (B) and availability for production areas for common beans (C), until 2050's. The blue line are predictions without considering climate change, and the red ones are predictions considering climate change. Shadowed areas are errors associated with the predictions, according to IMPACT model output (IFPRI, 2015).

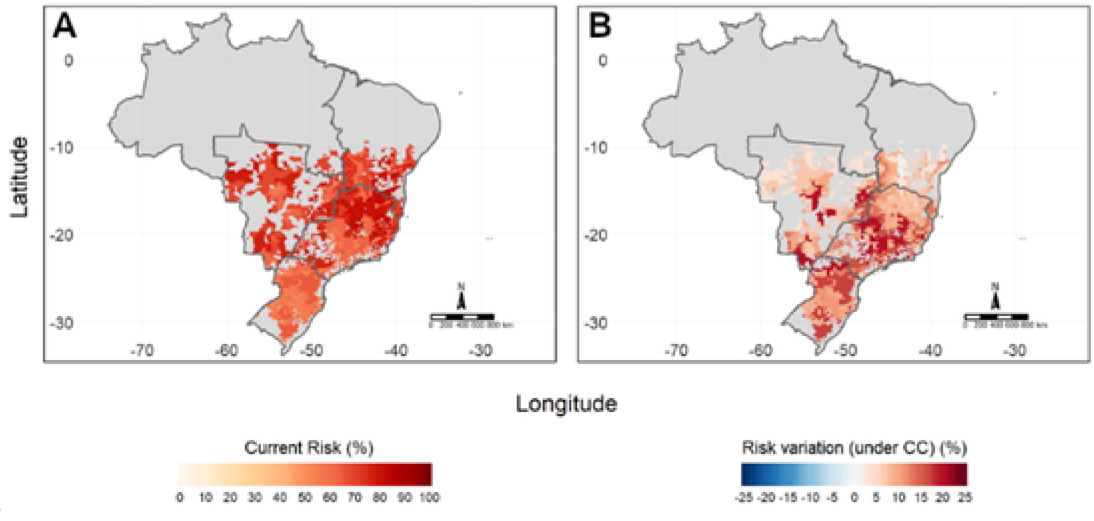

Fig. 6. Current (A) and future average variation between both scenarios (B) of risk for productions bellow the expected for demand supply, under climate change (CC) scenarios in Brazil.

tudes (higher than 22°) and low latitudes (lower than 22°) (Mearns et al., 2003; Rosenzweig et al., 2018).

Common beans are C3 metabolic pathway plants, and thus increases in [CO_2] imply a reduction in leaf conductance to gas exchange by decreasing their stomatal aperture (Boote et al., 1997; Field et al., 1995; Tubiello and Ewert, 2002). Therefore, increasing the availability of [CO_2] for photosynthesis and diminishing losses by transpiration of mesophilic water could boost crop water productivity, leading to greater grain yield gains even under events of moderate water stress (Marin et al., 2014). Hoogenboom et al. (1994) affirmed that the model used for the simulations acknowledges variations in [CO_2], interfering in photosynthesis and transpiration at the computational level, e.g. canopy and grain weight increases in response to increments in maximum leaf photosynthetic rate.

On average, both concentration pathway scenarios showed yield gains for the majority of producing regions. Yield predictions delivered by the CROPGRO-Drybean model (Tables 1 and 2 from *Supplementary*) showed that future expected variations in rainfall and air temperature will have a minor impact on grain weight, compared to the effect of increased [CO_2]. Process-based crop models in general tend to consider biological processes when representing plant growing conditions, hence the physiological implications of greenhouse gases on crops should be included as an important factor for predictions related to major plant groups such as the Leguminosae (Ewert et al., 2007).

Although the scenarios showed increases in average crop yield, not all predictions should be considered optimistic at first sight. By comparing the risk variation of not achieving the level of production needed to meet future demands relative to current conditions, it is possible to establish a detailed projection of climate change effects in Brazilian common bean production. In terms of food security, crop seasons must be planned to fulfill future crop demands, which are expected to dramatically increase by the mid-twenty-first century (Fedoroff et al., 2010; Godfray et al., 2010). In the South region, despite a considerable predicted increase in yield under both climate change scenarios, there are projected risk increases ranging from 5 to 22%. This implies a negative impact on local farming systems, which currently account for around 27% of national common bean production (CONAB, 2018a).

The main cause of higher demand and lower yield, despite an increase in yield, is related to air temperature effects on different crop stages, which limit how much the [CO_2] elevation can contribute to yield gains. Jifon and Wolfe (2005) showed that temperatures over the optimal range (15 to 26 °C) at the final stages of the development of the common bean might result in reductions of around 18% of grain dry mass, even in environments with high [CO_2]. Prasad et al. (2002) found that increases in levels of [CO_2] do not compensate for the detrimental effects of elevated air temperature on the physiological process in reproductive stages. Similar findings were observed for soybean (*Glycine max* (L.) Merrill) (Allen et al., 1996) and peanut (*Arachis hypogaea* L.) (Prasad et al., 2003).

The Mid-west region allocates all major country cropped areas while showing higher current risks of not meeting production demands. In addition, some locations presented an increase in risks of almost 25%, meaning that production will rely mainly on area expansion and managing efforts to close the gap between current and potential grain yields, which has been the main strategy for agricultural improvements in developing countries under climate change projections (Abraham et al., 2014). This Brazilian region is of particular interest as it has at least three crop seasons. The “winter” (third) season was stimulated to take advantage of irrigated areas that produce soybean in the off-season, aiming to control prices and keep the market stable throughout the year for the final consumer (de Portes, 2012). The increasing risk of production below the expected demand may cause recurrent price fluctuations, directly affecting the demand for the product due to middlemen activities commonly practiced in grain commercialization, which in extreme cases, may force producers to replace “winter” common bean cultivation areas with more profitable crops (Yokoyama, 2002).

Current commercial genotypes may present different responses to climate change in the different locations in which common bean cultivation is practiced due to their phenotypic plasticity. Therefore, we understand that impact assessments can only be used as guidelines for national programs of plant breeding aimed at this crop in particular. Nicotra et al. (2010) reinforced that an understanding of genotype performance in the face of future climate change scenarios is crucial for developing new cultivars. Ceccarelli et al. (2010) affirmed that breeding programs consider the effects of biotic and abiotic stress, the latter being caused by environmental factors such as climate, and that studies on its changes will be essential to quantify what future genetic materials should be prepared to endure. Many other scientific efforts approaching this theme for other crops also make explicit the importance of this matter for food security in the twenty-first century (Braun et al., 2010; Chapman et al., 2012; Ortiz et al., 2008). Thus, it is expected that the results presented here will aid not only breeding programs for developing new adapted cultivars, but also public services using information to support government decisions to guarantee the availability of a cheap and reliable protein source for poor populations around the globe.

5. Conclusion

Yield projections indicate increases in the average yield of common beans in Brazil, which mostly rely on the projected increases of [CO_2] under the climate change scenarios considered herein. However, risk projections show that Brazilian production will heavily rely on area expansion in a future where suitable areas for agriculture will be a major limitation. Protecting natural ecosystems from agricultural occupation is currently the subject of intense discussion in Brazil and elsewhere, raising concerns not only about food security, but also about economic policies. Efforts in crop management to overcome yield limitations in the field and studies aimed at improving genetic adaptations for climate change must be taken into account by local governments if there is still interest in keeping common beans as a reliable protein source for poor populations with the minimum additional expansion of new areas in the mid-twenty-first century climatic scenario.

Uncited references

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.

Acknowledgments

LAS Antolin acknowledges support from “Coordenação de Aperfeiçoamento Pessoal de Nível Superior” (CAPES), due the provided master's scholarship provided for the preparation of this scientific paper.

AB Heinemann acknowledges support from “Fundação de Amparo à Pesquisa do Estado de Goiás” (FAPEG - PRONEM/FAPEG/CNPq) and “Conselho Nacional de Desenvolvimento Científico e Tecnológico” (CNPq – Edital Universal – Processo - 408025/2018-2).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.agsy.2021.103174.

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