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Water productivity and footprint of major Brazilian rainfed crops – A spatially explicit analysis of crop management scenarios

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ABSTRACT

Green water is a central resource for global agricultural production. Understanding its role is fundamental to design strategies to increase global food and feed production while avoiding further land conversion, and obtaining more crop per drop. Brazil is a country with high water availability, and a major exporter of agricultural goods and virtual water. We assess here water use and water productivity in Brazil for four major rainfed crops: cotton, maize, soybeans, and wheat. For this, we use the EPIC crop model to perform a spatially explicit assessment of consumptive water use and water productivity under crop management scenarios in Brazil between 1990 and 2013. We investigate four different land-water interactions: (i) water use and productivity for different management scenarios, (ii) the potential of supplemental irrigation for productivity improvement, (iii) changes in green water use throughout the study period, and finally (iv) potential reduction of land and water demand related to agricultural intensification. The results show that, for the studied crops, green water is the main resource for biomass production, and intensification can lead to great improvements in green water productivity. The results also suggest that, despite achieving higher yields, irrigation-based intensification tends to lower overall water productivity, compared to fertilizer-based intensification strategies. This is, however, regionally and crop-specific. Furthermore, due to higher yields and water productivity, producing the same amount of crop output in irrigated or rainfed intensification scenarios would result in the reduction of resource demand, in the order of 34–58 % for cropland, and 29–52 % for water.

1. Introduction

Increasing demands for food, feed, and bioenergy are a major challenge for securing water resources in the coming decades. Human activities have already overused blue water resources (i.e., liquid water in rivers, lakes, wetlands, and aquifers) worldwide (Falkenmark and Molden, 2008; Vörösmarty and Sahagian, 2000; Wada and Bierkens, 2014). Blue water scarcity limits the productivity of agricultural systems (Davis et al., 2017). On the other side, the use of green water (i.e., soil water formed by precipitation and available to plants) is about four to five times higher than blue water use in agriculture globally (Hoff et al., 2010). While water science has mostly focused on estimating and managing blue water, understanding how to make better use of green water resources is fundamental to meet future demands (Falkenmark and Rockstrom, 2006).

Water productivity is usually defined as the amount of crop yield obtained relative to the evapotranspiration of green and blue water during production. Improvement of water productivity is an important strategy to reduce the need for additional resources in both irrigated and rainfed systems (Molden et al., 2010). On a global perspective, commodity trade from areas with high water productivity to areas with lower productivity results in net water savings (Chapagain, 2006; Fader, 2011). Improving the management of green water, and increasing green water productivity, is desirable both in arid and water-abundant areas (Rockström and Barron, 2007). Higher crop yields can reduce the impact of agricultural systems by facilitating sparing of lands with high biodiversity (Phalan et al., 2011). At the same time, higher water productivities generate net water savings and reduce

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pressure in regions with higher water stress or scarcity (Fader et al., 2011).

Existing water footprint studies have largely focused on impacts of water use on the location of production, particularly in water-stressed areas. Brazil has abundant blue and green water resources, although the local availability of water is highly heterogeneous (ANA, 2013; Flach et al., 2016). As a major agricultural producer and net exporter of agricultural commodities, Brazil exports about 54.8 billion m^3 of virtual water per year, mainly to Europe (da Silva et al., 2016). Brazilian agriculture has undergone stark changes in the last decades, through horizontal expansion and intensification (Dias et al., 2016; Zalles et al., 2019). The expansion of Brazilian cropland has been connected to increasing conversion of natural ecosystems, and negative impacts to biodiversity and the water cycle (Bondeau et al., 2007; Gibbs et al., 2010; Spera et al., 2016; Zalles et al., 2019).

Previous virtual water trade analysis of Brazilian agriculture on a national scale used rather coarse datasets from available global water footprint assessments, such as the one presented in the work of Mekonnen and Hoekstra (2011) (da Silva et al., 2016; Flach et al., 2016). Other water footprint and virtual water trade studies focused on smaller scales and regional scales, mostly relying on local measurements (Albuquerque, 2013; Carvalho and Menezes, 2014; Lathuillière et al., 2018, 2014; Silva et al., 2015).

Our present study is the first to model local agricultural water footprints for Brazilian agriculture at a national scale employing a spatially explicit biophysical crop growth model at high spatial resolution with most recent input data. We analyze land and water interactions for agricultural production in the recent past, and for scenarios of agricultural management. Here we focus only on green and blue water. We aim to understand the recent changes in green water use in Brazilian agriculture, but also possibilities for the future, in particular the role that blue water can play in improving land and water productivity.

By providing spatially explicit and process-based assessments of green and blue water in agriculture, advanced crop models have enabled the progress of global water footprints and trade studies. These biophysical models applied in global water assessments include GEPIC (Liu, 2009; Liu and Yang, 2010), GCWM (Siebert and Döll, 2008), H08 (Hanasaki et al., 2013; Konar et al., 2016), LPJmL (Fader et al., 2010; Gerten et al., 2011; Rost et al., 2008), and WBMplus (Wisser et al., 2008). With the use of the EPIC biophysical crop model and high resolution soil, elevation and climate data, we simulated 24 crop cycles between 1990 and 2013 for four traditionally rainfed crops: cotton, first and second season maize, soybeans, and wheat.

First, we analyze how changes in nutrient input affect yields and water productivity, and investigate how the intensification of food production in Brazil affects agricultural water use productivity. Furthermore, we estimate the geographical distribution of irrigation potential across the country. Lastly, we analyzed the influence of agricultural intensification scenarios on the demand for water and land.

2. Materials and methods

2.1. The EPIC model

The Environmental Policy Integrated Climate (EPIC) model simulates the biological, physical and chemical processes that occur in the soil-plant-atmosphere-management system at the field scale with a daily time step (Williams et al., 2008). The model contains several modules, which simulate processes related to weather, hydrology, erosion, nutrients, soil temperature, plant growth, plant environment control, and tillage. Although originally designed to model soil erosion impacts on crop production, EPIC has been used comprehensively to simulate climate change impacts, nutrient cycling and loss, soil carbon, pesticide fate, among others (Gassman et al., 2004).

EPIC has been used to model processes on regional and global scales via coupling with spatial data organized either within regular geographical grid (e.g. GEPIC, documented in Liu (2009) or with the use of homogeneous response unit approaches (e.g. in EPIC-IIASA, documented in Balkovič et al., 2014)). Previous studies have assessed impacts of crop management on yields and externalities across a range of management systems ranging from smallholder agriculture (Folberth et al., 2012) to high-input systems (Balkovič et al., 2014) and has frequently been used to study crop-water relations (Chun and Li, 2010; Liu, 2009; Liu et al., 2007; Liu and Yang, 2010). The model has been validated across scales from the field to continental (Balkovič et al., 2018; Folberth et al., 2012) and global studies (Müller et al., 2017). EPIC has also been previously shown to be suitable to model Brazilian agriculture (Barros et al., 2005, 2004; Gaiser et al., 2010).

Here the 0810 version of the model source code in FORTRAN was compiled and modified for parallel processing in a Linux environment, to make it capable of iterative simulations over a large number of parameter settings.

2.2. General modeling framework

The EPIC model contains a large number of crop and model parameters. It requires detailed input data on weather, topography, soil, crop, and crop management. The calibration and validation of the model over large areas is a challenge, since (i) there are usually no comprehensive experimental or independent data available that allow testing of the entire set of variables represented in the model for full range of conditions, and (ii) aggregated data from regional statistics are usually insufficient as they do not represent field-scale conditions (Balkovič et al., 2013).

We used an approach based on the methodology used in Balkovič et al. (2013), in which (i) the default biophysical process parameter values in EPIC were adopted with minor adjustments, (ii) reviewed crop parameters based on average cultivar characteristics for the selected crops were used for the entire study area, and (iii) sensitivity analysis and adjustment for main management parameters, namely sowing dates, length of growing season, and potential heat units, were performed to handle main sources of uncertainty. This methodology ensured that the plasticity of the results we obtained were driven by crop management, and not by improper setting of basic condition for crop growth. This was achieved by reflecting the consistency between potential heat unit (PHU) and planting/harvesting dates, and placing vegetation season to suitable parts of year with sufficient temperature sum for the crop. As a result, low yields are a result of low inputs or overall poor agro-environmental (climate and soil) conditions, not because of not reaching expected PHUs.

While data on fertilizer use has become more abundant and spatially explicit in recent years, it is still limited in terms of temporal evolution. For this reason, we chose a scenario approach in our methodology, which is described in Section 2.5. When it comes to cultivar development and characteristics, the availability of standardized, documented data becomes even more limited, especially considering the changes that have taken place during the study period. Adding a spatial and temporal cultivar component could have a great amount of uncertainty, and our chosen approach was to apply homogeneous cultivar parameters based on values found in the literature, while considering the use of regional cultivar maturity classes reflected in reported growing periods. Finally, to reduce aggregation errors related to the biophysical input data, we applied a homogeneous response unit approach, described in further detail in Section 2.3.

The crop and model parameters used in the model runs, as well as the homogeneous response units and the aggregated input data, are available for download at https://edmond.mpdl.mpg.de/imeji/collection/5xrED7T4lL4R_A0m (DOI: 10.17617/3.27).

2.3. Study area and simulation units

We focused on four of Brazil's most important crops regarding consumptive water use and production: cotton, maize, soybeans, and wheat. These four crops are among the ten most important crops in terms of harvested area and total production in Brazil. They covered approximately 70 % of the total harvested area in Brazil in 2017 (IBGE, 2018). We present further background information on agro-hydro-climatic conditions in Brazil in Figures A1 to A5 in the Supplementary Material.

Irrigated agriculture in Brazil is mostly connected to production of rice and sugarcane, which together are responsible for 51 % of total irrigated area. The share of irrigated area relative to the total harvested area for soybean, wheat, maize and cotton are of 3.7, 4.2, 4.3, and 6.5 %, respectively (FAO, 2017). Here we first assumed the selected crops as produced solely in rainfed systems, and on a later stage estimated how much blue water would be necessary to meet the crops' water requirements with supplemental irrigation.

We modeled maize twice, to represent two production systems: the main maize crop, and second maize crop, called *safrinha* in Brazil. Brazilian farmers commonly plant *safrinha* maize as a second crop after soybeans, and therefore second season maize has a different calendar from main season maize. Our model setup does not simulate double-cropping, and instead simulates second season maize separately, as a fifth crop. The yield of maize, soybeans and wheat correspond to the seed yield, while the cotton yield corresponds to the sum of the lint and seed yields.

We simulated soil and water processes associated with crop growth in Brazil between 1990 and 2013. The simulated area comprises only areas classified as cropland during the study period (see Fig. 1).

For this study, the EPIC model was setup and run for more than 8×10^4 simulation units. These units were classified primarily in terms of their biophysical homogeneity, and then further delimited based on municipality administrative boundaries. The procedure for delimitation of the simulation units was adapted from the methodology developed for the GEOBENE global database for biophysical modeling (Skalsky et al., 2008). First, a homogeneous response unit (HRU) is an area with similar soil, topography and climate characteristics. For delimitation of the HRUs, we classified the soil and topography databases based on predetermined thresholds (see detailed description and thresholds in Supplementary Material. The final boundaries of the simulation units resulted from the overlap of the climate dataset grid, the municipality boundaries, and the boundaries of the previously delimited HRUs. The resolution of the datasets used to delimitate the simulation units ranged from the 300 m resolution land use maps (ESA, 2017), 1 km resolution soil and topography datasets (Hengl et al., 2014; Jarvis et al., 2008), and the 0.25 degrees climate grid (Xavier et al., 2016). The municipal boundary shapefile divides the Brazilian territory in approximately 6000 municipalities.

2.4. Simulation setup

To reduce uncertainties related to the crop calendars, an initial model run is performed to select optimal calendars, based on planting and harvesting dates available in the dataset published in Sacks et al. (2010). This dataset includes time windows for the planting and harvesting season for different areas around the country. We ran the model for non-irrigated conditions with minimized nutrient stress, for three different calendar options - early, mid and late planting and harvesting. The option with higher yields for each crop and simulation unit was chosen. We calculated the PHU for each crop, simulation unit, and planting and harvesting window.

We initialized the model by carrying out spin-up model runs for the period 1980–1990 to equilibrate the nutrient pools in soil, comprising soil organic carbon and total and organic nitrogen and phosphorous. The spin-up runs generated soil profile values that were used as inputs

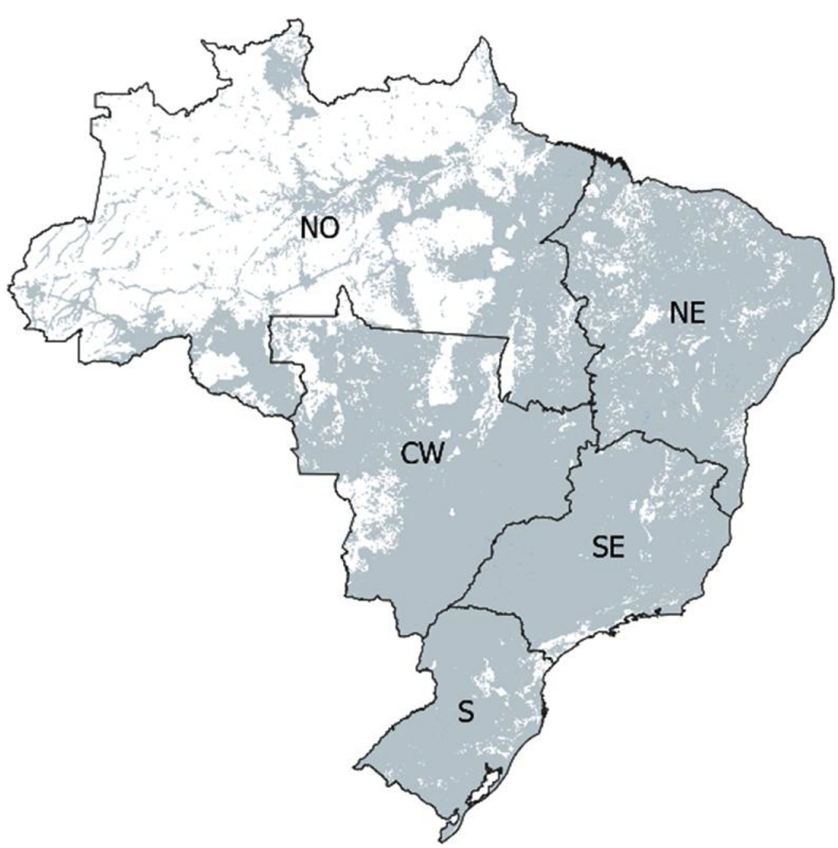

Fig. 1. Study area. Simulation units (shaded area) in the five Brazilian administrative regions (NO: North, NE: Northeast, SE: Southeast, S: South, CW: Center-West).

Table 1
General model setup for scenario runs. The values in parenthesis refer to specific application rates for soybeans.

Scenario	N Application rate (kg/ha)	P application rate (kg/ha)	Irrigation application rate (mm)
No Fertilization (N)	0	0.1	0
Low-Input (L)	25	25 (10)	0
Mid-Input Rainfed (M1)	100	100 (30)	0
Mid-Input Irrigated (M2)	100	100 (30)	2000
High-Input Rainfed (P1)	400	400	0
High-Input Irrigated (P2)	400	400	2000

to the final transient model runs. The Supplementary Material provides further detail on the methodology for PHU calculation, model initialization, and spin-up model runs (Tables A.2-A.4).

2.5. Crop management scenarios

With the lack of spatially and temporally explicit data on fertilizer use, producing a business-as-usual reconstruction of yields in the scale of this study would not be possible. Therefore, we designed water and fertilization scenarios in order to explore different outcomes within a space of possibilities for agricultural management. We assumed here that the yield changes in the scenarios developed are dependent on water and nutrient availability, and thus we designed the scenarios based on fertilizer and irrigation application. We chose to consider irrigation and fertilizer application, as these explain 60%–80% of global-yield variability for most major crops (Mueller et al., 2012). We do not consider, however, other management options like tillage, mulching, pest control, and cultivar development.

We simulated six different crop management scenarios depicting different combinations of fertilizer application and irrigation (see Table 1). The first scenario, which we named "no fertilization", assumes crop management with no additional water or fertilizer input, and aims to simulate how the production of the selected crops would be without any external input. On the other side of the spectrum, two scenarios called "high input" are designed to provide enough fertilizer input to minimize nutrient stress. Other two fertilizer scenarios were designed based on historical fertilizer application data, called "low input" and "mid input", and are intended to mimic the input level of farms with intermediate cropping intensity. The mid and high input scenarios were simulated both for irrigated and non-irrigated conditions, while the no fertilization and low input scenarios were simulated only for rainfed conditions. The application rate values for nitrogen and phosphorus for the low and mid-input scenarios were classified by identifying representative application rate values for Brazil from Mueller et al. (2012).

In the irrigation scenarios, the model supplies irrigation water on each day in which the water stress factor exceeds 20 % (water stress trigger of 0.8), thus allowing a small degree of water stress. For nitrogen application, the model was set to provide nitrogen when nitrogen stress is above 20 % (nitrogen stress trigger of 0.8), with a pre-determined application rate specific to each scenario. When it comes to phosphorus, the model was set to apply a certain application rate before planting. The fertilizer levels and stress triggers used to set up each scenario are detailed in Supplementary Material (Tables A.3 and A.4).

2.6. Water use and efficiency indicators

The model output of EPIC comprises detailed information on crop growth, water, nutrient, and carbon fluxes in daily, monthly and yearly steps. For this study, we focus on the estimated annual yield (Yd, ton/ha), the growing season evapotranspiration (GSET, mm), and the amount of water provided by irrigation annually (IR, mm).

We chose to use the Hargreaves method in the EPIC Model for estimating evapotranspiration (Hargreaves and Samani, 1985). The blue water corresponds to the IR parameter, and the green water corresponds to the total growing season evapotranspiration (GSET), minus the water application through irrigation.

$$Green\ Water\ (mm) = GSET\ (mm) - IR\ (mm)$$

The consumptive water use (CWU, m^3/yr), crop water productivity (WP, kg/m^3) and virtual water content (VWC, m^3/kg) in a certain area are defined and calculated as follows. In the main body of this article, we analyze only consumptive water use and water productivity values. In the Supplementary Material we also present the values of virtual water content, for comparison with values previously reported in the literature.

$$CWU\left(\frac{m^3}{yr}\right) = 10 * \sum GSET\left(\frac{mm}{yr}\right) * Area_{\ SimU}(\text{ha})$$

$$WP\ (kg/m^3) = 100 * \frac{Yd\ (ton/ha)}{GSET\ (mm)}$$

$$VWC\ (m^3/ton) = 10 * \frac{GSET\ (mm)}{Yd\ (ton/ha)}$$

We aggregated the yields and water productivities from the simulation unit to the municipal level, by calculating the weighted averages using the simulation unit area divided by the total simulation unit area in each municipality as weights. We then aggregated them to the regional level, using the harvested area per municipality divided by the total harvested area per region as weights.

To estimate the consumptive water use and water productivity for the historical scenario, we used the simulated growing season evapotranspiration from the high-input rainfed scenario aggregated at the municipal level, and the reported yields between 1990 and 2013 (IBGE, 2018). Therefore, we assume that the water use for production in this period comprises only rainfed agriculture, and accounts only for green water use.

We calculated the potential for implementation of irrigation infrastructure (IP) using two different approaches. First, the potential for irrigation is described as the rate of yield increase between the irrigated and rainfed high-input scenario (IP1), as an indicator of the potential of supplemental irrigation to increase local crop productivity.

$$IP1(\%) = 100 * \frac{Yd_{HI,IRR}(\frac{ton}{ha}) - Yd_{HI,RF}(\frac{ton}{ha})}{Yd_{HI,RF}(\frac{ton}{ha})}$$

In a second approach, we assume that the more of blue water is necessary to meet the crop water requirements, the higher the likelihood that farmers will make the choice to implement irrigation systems (IP2). It is common to assume that irrigation systems will be implemented if the rate between blue and total water use is above a certain threshold, usually around 10 % (Dell'Angelo et al., 2018; Rosa et al., 2018). Accordingly, we further estimate the potential for implementation of irrigation (IP2) as the rate between blue and total consumptive water use during the cropping season.

$$IP2\,(\%) = 100 * \frac{IR_{HI,IRR}(mm)}{GSET_{\ HI,IRR}(mm)}$$

With the use of the estimated land and water productivity, we calculated how much water and land would be necessary for each

Table 2
Average yields (ton/ha, above) and maximum and minimum regional averages productivity (kg/m^3, below) estimated in this study, for every crop and scenario.

Scenario	Cotton	Maize	Second Season maize	Soybean	Wheat
Average yields (ton/ha), national					
No Fertilization (N)	1.2	1.2	1.0	1.0	0.6
Low-Input (L)	1.9	2.2	1.9	1.9	1.4
Mid-Input Rainfed (M1)	3.9	4.7	4.5	3.4	2.7
Mid-Input Irrigated (M2)	4.1	4.9	4.8	3.7	2.8
High-Input Rainfed (P1)	5.1	5.5	5.1	3.6	2.8
High-Input Irrigated (P2)	5.9	5.8	5.8	3.9	2.9
Water productivity (kg/m^3), regional range					
No Fertilization (N)	0.09–0.17	0.2–0.49	0.18–0.55	0.15–0.37	0.18–0.29
Low-Input (L)	0.16–0.24	0.38–0.87	0.49–0.79	0.34–0.6	0.39–0.62
Mid-Input Rainfed (M1)	0.33–0.53	0.9–1.61	1.34–1.54	0.66–0.74	0.85–1.11
Mid-Input Irrigated (M2)	0.32–0.42	0.88–1.34	1.3–1.53	0.66–0.74	0.82–1.13
High-Input Rainfed (P1)	0.47–0.64	1.12–1.63	1.38–1.71	0.70–0.75	0.85–1.11
High-Input Irrigated (P2)	0.46–0.62	1.11–1.37	1.39–1.85	0.47–0.63	0.85–1.13

municipality to produce the same amount of crop output reported during the study period ($P_{Reported}$, $kg/year$) for each scenario. The reported production between 1990 and 2013 was obtained from IBGE (2017). We calculated first the necessary area and consumptive water use for each municipality, and then aggregated it to the national level. The area was calculated with the use of the yields estimated by the model for each scenario, while the consumptive water use relies on the water productivity levels estimated by the model for each scenario.

$$CWU_{Scenario}\left(\frac{m^3}{yr}\right) = \sum \frac{P_{Reported}\ (kg/yr)}{WP_{\ Scenario}(kg/m^3)}$$

$$HA_{Scenario}\left(\frac{ha}{yr}\right) = \sum \frac{P_{Reported}\ (kg/yr)}{Yd_{\ Scenario}(kg/ha)}$$

By computing the difference between the water and land demand in each scenario and the actual water and land requirements, we estimated the water and land demand reduction potential of each scenario.

$$Demand\ Reduction_{Scenario}\ (\%) = 100 * \frac{HA_{Scenario} - HA_{Reported}}{HA_{Reported}}$$

$$or\ 100 * \frac{CWU_{Scenario} - CWU_{Historical}}{CWU_{Historical}}$$

2.7. Data

Soil parameters of soil depth, percent sand, silt and clay, bulk density, pH, and organic carbon content are obtained from the SoilGrids database (Hengl et al., 2014). These parameters are available for five soil layers (0–5, 5–15, 15–30, 30–60, 60 − 100 cm), with a resolution of 1 km. The soil hydraulic properties, of saturated water content and saturated water conductivity, were obtained from the HiHydroSoil Soil Map of Hydraulic Properties (Boer, 2015), with a resolution of 1 km.

The topography maps for the area were obtained from the NASA Shuttle Radar Topographic Mission (SRTM) 90 m Digital Elevation Database (v4.1), available through the Consortium for Spatial Information (CGIAR-CSI) of the Consultative Group for International Agricultural Research (CGIAR) (Jarvis et al., 2008). The CGIAR-CSI SRTM Digital Elevation Models have a resolution of 90 m at the equator.

Daily climate data on maximum and minimum temperature, precipitation, wind speed, relative humidity, and solar radiation between 1980 and 2013 for Brazil were obtained from the database of daily gridded meteorological variables for Brazil (Xavier et al., 2016), with a spatial resolution of 15 arcminutes.

The mapping of cropland and harvested areas were obtained from two data sources. The area delimited for cropland in general was based on the European Space Agency's Climate Change Initiative Land Cover Maps (ESA-CCI LC maps) at the resolution of 1 km (ESA, 2017). The harvested area and crop production per Brazilian municipality were obtained from the Brazilian Statistics Bureau (IBGE, 2018) for around 5500 municipalities and all crops of interest, between 1990 and 2015. The crop calendars were based on the publicly available data set of global planting date patterns developed by Sacks et al. (2010).

We overlaid the datasets with classes of soil texture, cropland area, slope, and altitude at the 1 km resolution to delimitate the simulation units, which became the spatial units on which the model is run. The crop calendars and weather data were used to calculate the PHUs necessary for the model setup. The datasets of soil, altitude, crop calendar, and weather were averaged by simulation unit area in order to produce the input files for the model.

3. Results

3.1. Yields and water productivity

The following section describes our results for consumptive water use, and water productivities. A detailed comparison of these results with previous studies and with reported data is provided in the Supplementary Material (Tables A.6–A.11).

As expected, higher nutrient and water application rates resulted in consistently higher simulated crop yields, and higher water productivity values (Table 2). The average water productivity of irrigation scenarios is slightly lower than the water productivity of equivalent, i.e., high-input, rainfed scenarios. Thus, increased water input is likely to increase the amount of water per unit of output.

To assess the space for improvements in crop yields and water productivity, we computed the yield difference between simulations of high-input systems and reported municipal averages for entire Brazil in the period 1990–2013. For the estimation of water productivity, we used an average of the modelled growing season evapotranspiration, for rainfed scenarios. Table 3 shows the spatial and temporal average of the growing season evapotranspiration for all crops, for irrigated and rainfed scenarios. The evapotranspiration of rainfed scenarios includes only green water, while irrigated scenario footprints include both green and blue water.

Fig. 2 shows the simulated impacts of water and nutrient

Table 3
Average growing season evapotranspiration (mm/yr) for irrigated and non-irrigated scenarios, for every crop.

	Cotton	Maize	Second season maize	Soybeans	Wheat
Rainfed Scenarios	607	425	323	501	285
Irrigated Scenarios	713	467	349	551	300

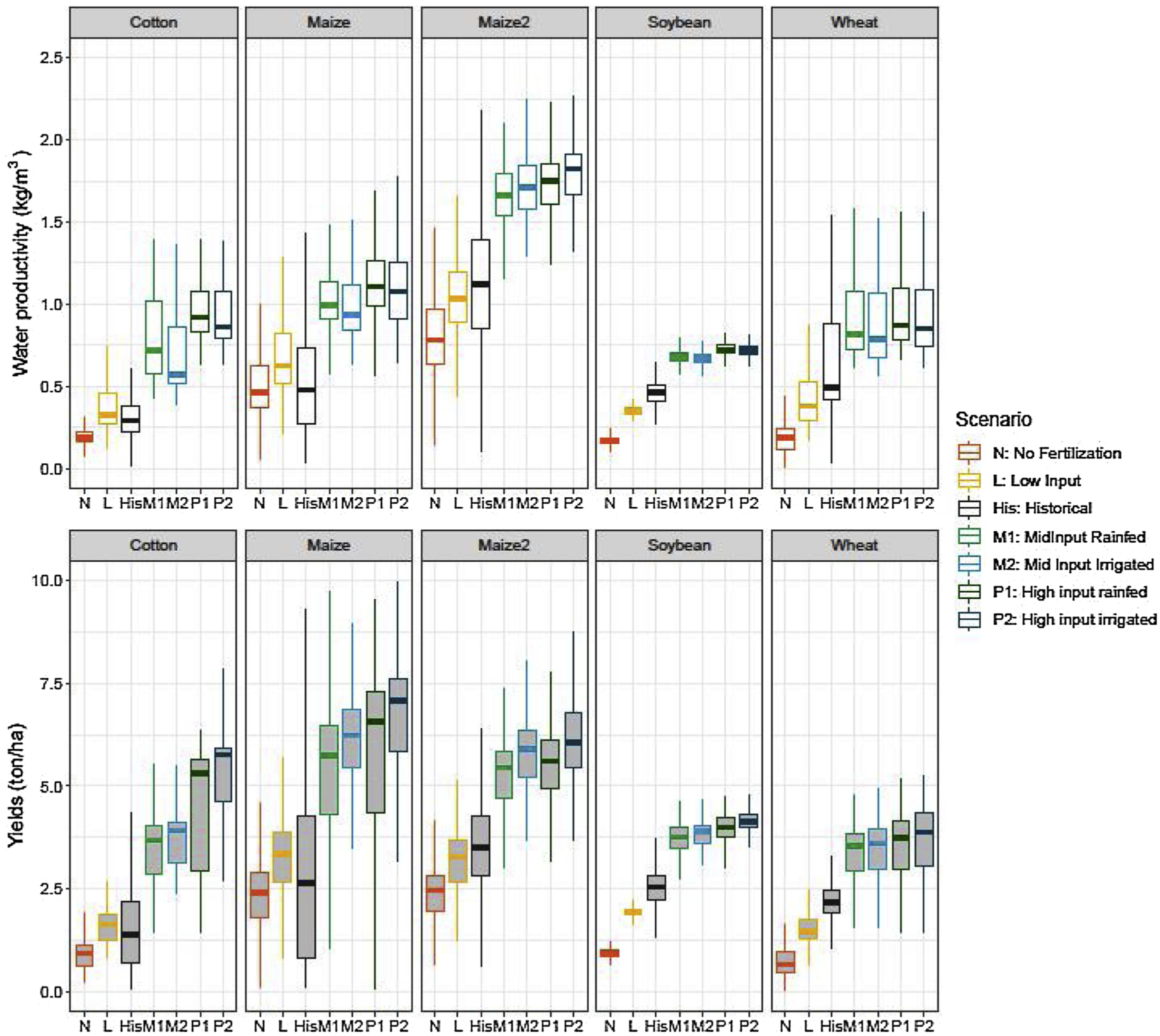

Fig. 2. Water productivity and yields. Water productivity (above, kg/m^3) and yields (below, ton/ha) statistics per municipality, related to historical data and management scenarios, for all crops and scenarios.

management on crop yields and water productivity. Supplementary irrigation leads to much smaller yield increases than supplementary fertilization. For maize and wheat, the average yield improvements of supplemental irrigation are mostly negligible. However, when analyzing the same data regionally, we observe higher changes in the south and southeast regions for soybeans and in the northeast region for cotton (see Figs. B.4-B.5). On the other hand, we find that second-season maize greatly increases yields across the territory, which indicates that water availability could be one of the main limitations for double-cropping expansion (see Figs. 2 and B.3).

While the average water productivities are smaller for irrigated scenarios compared to the corresponding rainfed scenario with the same level of fertilization, in some cases irrigated yields are much higher (e.g. cotton, Fig. B.1). The highest yield increases for cotton occur in the Northeast region. This region also shows the steepest decreases in water productivities for both main and second season maize (see Figs. B.2-B.3).

For most crops, the range of scenario results adequately covers the observed variability of the reported yields during the study period. This agreement is especially noticeable for crops with moderate spatial variability such as wheat and cotton, or presents reported and simulated homogeneous yield values, such as soybeans. On the other hand, the high spatial variability of reported maize yields is not fully reproduced in our simulations (Fig. 2). Maize production is dispersed across a much larger number of municipalities and includes both smallholder and commercial farming.

3.2. Feasibility of supplemental irrigation

The scenario results indicate that fertilization is generally more important for improving crop yields than irrigation. However, the benefits of supplemental irrigation and its influence on annual water use differ greatly between crops and locations. In this section, we analyze which crops and areas of the country could benefit more from additional blue water, as well as where blue water would make up a larger share of total water demand.

Fig. 3 shows spatial differences between high-input non-irrigated and high-input irrigated scenarios. The ratio between blue and total water use depicts the share of irrigation water necessary for optimal plant growth (Fig. 3a). The potential yield changes (Fig. 3b) indicate regions that would benefit the most from supplemental irrigation. To illustrate the potential pressure of irrigation on blue water resources, we included in Fig. 3c a modified map from the Brazilian Water Agency showing blue water stress (total water demand, divided by total water availability) per micro-basin (ANA, 2013).

The area where both most blue water use and yield increase because of irrigation happens is the northeast area of the country, an area known for high levels of water stress due to its semi-arid climate. While the share of blue water in total water use is also high in southern areas of the country, the higher water use does not translate to higher yields

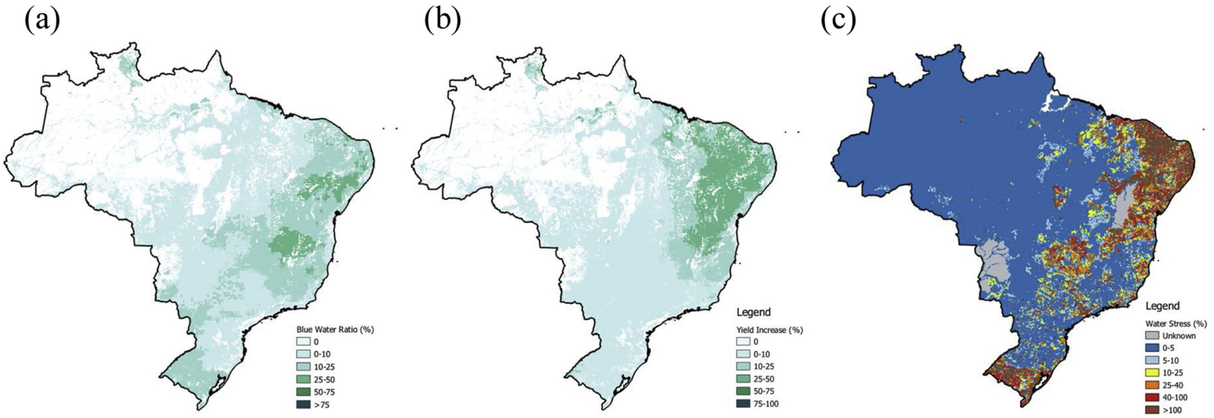

Fig. 3. Irrigation potential and blue water stress. Ratio between blue and total water use in the irrigation scenarios, averaged for all crops (%) (a); Average yield increase from water-stressed to irrigation scenario, averaged for all crops (%) (b); and blue water stress, defined as the total water use in a basin divided by the total water availability (%), adapted from (ANA, 2013) (c) (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

for the crops analyzed in this study. These two areas - northeast and outmost south - are also areas known for high levels of water stress resulting from low local water availability (Fig. 3c).

The areas with high blue water ratio in Fig. 3a, but low yield increase in Fig. 3b, are the areas in which there is a sizable increase of consumptive water use by the addition of irrigation, but without a corresponding increase in productivity. These are the areas where most of the reduction of water productivity from one scenario to the other happens. The areas that could benefit the most from irrigation are those with high yield increase (Fig. 3b), but low rates of blue water (Figure b).

3.3. Water and land use under management scenarios

During the period between 1990 and 2013, the production of the four selected crops grew from 46 thousand to 171 thousand tons per year. In the same period, the corresponding harvested area grew from 26 to 46 million hectares (IBGE, 2018). Assuming rainfed conditions for all crops, we estimated the water use in the period 1990–2013 for all crops, as shown in Fig. 4. As the share of harvested area for main and second season is not known for the entire study period, we assumed all maize was planted as a single crop, and therefore we multiplied the total measured harvested area for maize by the consumptive water use estimated for main season maize.

Soybeans use the highest amount of water because of greater harvested area, which has been expanding across the Brazilian territory steadily in the last decades. Lathuillière et al. (2014) estimated that the total green water use for soybean production in the state of Mato Grosso (the state with the highest soybean production in Brazil) in 2004 was 28 km^3, while we estimate here a close value of 30 km^3 in the same year, reaching 45 km^3 in 2013. The observed increase in water footprints for maize and soybeans is directly related to increases in harvested area reported during this period.

We estimated the amount of resources necessary to obtain the same crop output during this period, under the conditions simulated in the rainfed and irrigated high-input scenarios. When estimating changes in resource demand, we assume that land sparing happens because of increase in land productivity, and reduction of water demand because of reduction of cropland area and increase in water productivity. In this context, we define land and water demand reduction here as the percentage difference between the scenario-derived and the actual cropland area and water use. As seen in Table 4, the average percentage of land demand reduction is higher in the irrigated scenario for all crops. However, the reduction in water demand are not necessarily higher in the irrigated scenario.

In Fig. 5 we show the amount of cropland and total water use required to produce the reported crop output in Brazil for 1990–2013 for this study's selected crops. The 'historical' line refers to the amount of resources necessary to produce these crops under normal conditions, the other lines refer to the amount of resources needed if they were

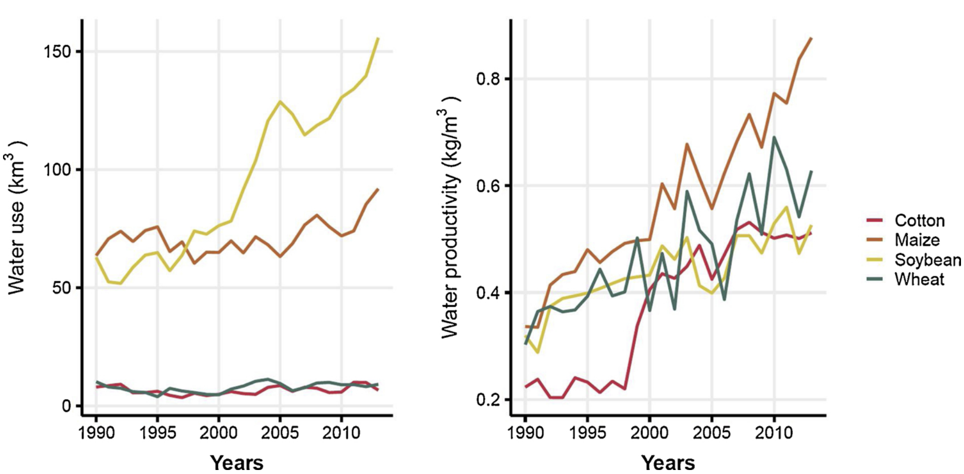

Fig. 4. Evolution of consumptive water use and water productivity. Total consumptive water use per crop (km^3, left) and water productivity (kg/m^3, right) in the period 1990–2013, considering reported harvested area and crop production per municipality.

Table 4
Prospective average land and water demand reduction (%) for production of selected crops for 1990–2013, for rainfed and irrigated potential scenarios.

	High-input rainfed	High-input irrigated
	Land demand reduction (%)	Land demand reduction (%)
Cotton	52	58
Maize – main season	34	49
Maize – 2 season	38	42
Soybean	36	40
Wheat	45	47
	Water demand reduction (%)	Water demand reduction (%)
Cotton	52	50
Maize – main season	29	41
Maize – 2 season	38	40
Soybean	37	36
Wheat	46	44

produced with the productivity and resource use levels connected to the high-input rainfed and irrigated scenarios. Results show that the gap between the actual and potential land and water use has decreased through the years, as improved agricultural management and higher crop productivity becomes widespread in the country.

While in the irrigated scenario higher productivity requires less cropland and therefore lower green water use, it also results in lower water productivity and the addition of blue water use (as seen in Fig. 2). The amount of water used in the rainfed and irrigated scenarios (Fig. 5) is very similar because of these two opposing effects that cancel each other.

As seen in Table 4, the effects of irrigation and fertilization on water demand is highly dependent on the crop. When adding up all crops, the high-input rainfed and irrigated scenarios ultimately result in a very similar level of water requirements, even though the land requirements are a bit larger for the rainfed scenario. Independent results for each crop are presented in Figures B.8 to B.11 in the Supplementary Material.

4. Discussion

Our analysis shows a picture of the trade-offs and synergies for land and water use efficiency, looking into different scenarios of irrigation and fertilization. When it comes to changes in overall water use, we see that cropland expansion was the main cause for the general increase of green water use in Brazil, mostly for production of soybeans. The scenario analysis showed that agricultural intensification has the potential to enable the production of the same amount of output on a smaller area and with lower water requirements. The main result of our study is the observed dominance and importance of green water as a resource for agriculture in Brazil. While cropland expansion can be seen as the additional appropriation of green water, intensification can be seen as a strategy for better use of the green water available.

From the results, we can see that the implementation of supplemental irrigation did not always result in comparable increases in productivity, when compared to equivalent non-irrigated scenarios. This is due to the availability of green water during the growing season across most regions of the country, but also a result of our modeling approach, which assumed that crops were planted during that part of the year that was the least limited by lack of precipitation. The areas in which our model showed that the benefits and relative importance of irrigation would be more pronounced, are also areas known for semi-arid conditions with high-levels of blue water stress. These are also the regions where most of the current irrigation infrastructure exists (ANA, 2017).

We have shown that, in the case of water resources, intensification is a pathway for improving the efficiency of water use, with the consequence of sparing water use in either water-stressed, or water and biodiversity rich areas. When it comes to greenhouse gas emissions, Burney et al. (2010) showed that land sparing due to agricultural intensification outweighs the emissions related to intensification strategies. It is important to highlight, however, that the focus here is to understand trade-offs related to land and water use, and therefore discount other possible environmental impacts that might result from agricultural intensification, such as greenhouse gas emissions and water quality.

We were able to replicate the range of historical yields and observed water productivities with our setup of the EPIC model. Our results show that we have sufficient plasticity in our results to reconstruct a business-as-usual trajectory of yields. We have also demonstrated (see Supplementary Material) that the estimated values for water productivity fall within the range of previously reported values (Lathuillière, 2011; Liu and Yang, 2010; Mekonnen and Hoekstra, 2011); and the same can be said for yields (IBGE (Brazilian Institute of Geography and Statistics), 2018; Mueller et al., 2012). In the absence of spatially explicit crop-specific data on fertilizer and irrigation water use, we opted to explore a full range of possible management options.

It is important to highlight that the EPIC model lacks a lateral component, i.e., it only represents vertical relationships in one particular field, and neglects interconnection of more fields down the slope. With this limitation, it is not possible to consider any gain or loss of water due to lateral flow. All our estimates are based on water balance

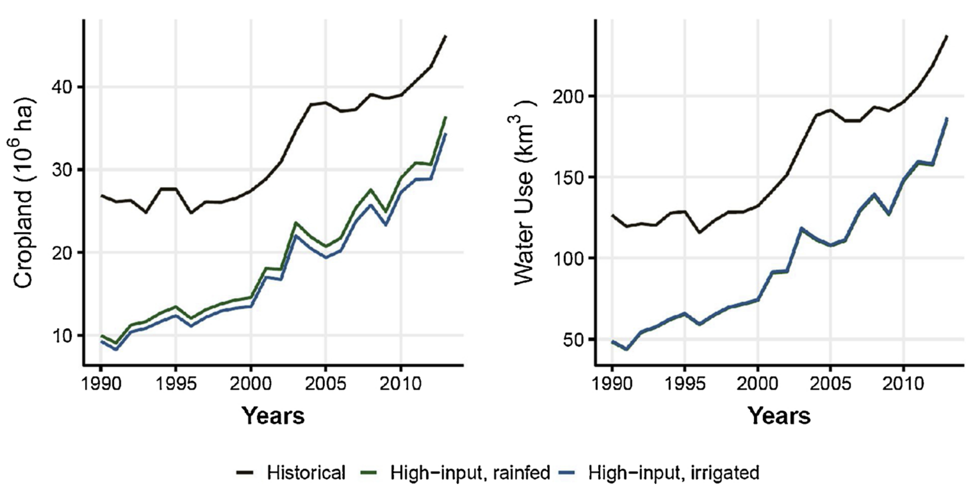

Fig. 5. Scenarios of consumptive water use. Annual cropland area (10^6 ha) and consumptive water use (km^3) required for production of reported production between 1990–2013, as well as for the high-input rainfed and irrigated scenarios.

at the site, namely evapotranspiration vs. rainfall. This approach is coherent with the spatial scale of our study, as lateral processes would have a bigger effect on the results in smaller scales.

Despite the positive evaluation of the model, several shortcomings remain in our modeling approach. Although intercropping is a common practice, our model setup reflected only single cropping. The inclusion of second season maize as a monocrop is a step towards modeling real double cropping systems, yet very simplistic. This approach can reveal certain aspects of the water consumption out of main season, as we have witnessed in the results. The modeling of double cropping is not the focus of this study, yet, it is definitely a very important aspect to be considered in future water consumption related studies.

The choice farmers make in the planting and harvesting dates, as well as the choice of which crops will be grown, depends on a series of factors that include weather, international market prices, and subsidies. We assumed here that crop calendars vary in space, but are static from year to year and are the same for all crop intensification scenarios. Yields and water footprints are particularly sensitive to start and length of the cropping season (Tuninetti et al., 2015). Our approach used documented cropping data (Sacks et al., 2010) and attempted to remove uncertainties by selecting optimal calendar options. However, an interesting avenue of investigation would be to compare results based on crop calendars with different temporal and spatial resolutions. The implementation of supplemental irrigation could also potentially extend the length of the available harvesting season, or enable an increase in cropping frequency in certain areas (Lathuillière et al., 2018). We did not consider these implications here and only focus on how productivity could change within the current average growing season.

One of the main factors that have allowed the expansion of crop cultivation to different parts of the territory and the improvement of land productivity is the development of a variety of cultivars adapted to different environments, as well as the introduction of new pest control mechanisms. Another possible limitation of our modeling approach is that our model operates only with average and conservative cultivar parameters, which are homogeneous for the study area.

5. Conclusions

With our modeling framework, we were able to replicate the range of historical yields and observed water productivities of cotton, maize, soybean, and wheat in Brazil. Green water was identified as the main water resource for the production of these crops. The results also show that the yield increase related to nutrient stress reduction have the highest potential to improve green water productivity.

There is potential for irrigation of these crops in Brazil, with yield improvement resulting from supplemental irrigation. Yet, the highest potential for irrigation mostly overlaps with areas with high levels of blue water stress. The supplemental irrigation would result, in several cases, in reduction of the overall water productivity when compared to rain-fed scenarios. On the other side, fertilizer-related intensification is shown to result in steep improvements in green water productivity. Closing the yield gap through optimal fertilization and irrigation have the potential in Brazil to reduce the demand for land and water, in order of 34–58 % of cropland area and 29–52 % of total water requirement for the selected crop production.

In consideration of the overuse of blue water worldwide, water-rich countries like Brazil act like vast reserves of green water that are available through global trade of agricultural products. Understanding the role Brazil plays in contributing to global water use, as well as the potential for reduction of water demand, was one of the motivations of this study. That is particularly important considering the extent of the recent horizontal expansion of Brazilian agriculture, which resulted in larger land and water resources use, as well as displacement of natural ecosystems. This is one of the first studies, which analyze the land and water use interactions in Brazilian agriculture at national scale.

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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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.agwat.2019.105996.

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