Applied Geography 154 (2023) 102937

Contents lists available at ScienceDirect

Applied Geography

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

Grain-cropping suitability for evaluating the agricultural land use change in Brazil

José Lucas Safanelli [a,b,*], Rogério de Souza Nóia Júnior [c], Pedro Alves Quilici Coutinho [b], Marcela Almeida de Araujo [b], Arthur Nicolaus Fendrich [b], Rodnei Rizzo [d], Ana Letícia Sbitkowski Chamma [b], Paulo André Tavares [b], Alberto Giaroli de Oliveira Pereira Barretto [b], Rodrigo Fernando Maule [b], Klaus Reichardt [b,d], Gerd Sparovek [b], Durval Dourado Neto [b]

[a] *Woodwell Climate Research Center, Falmouth, Massachusetts, USA*
[b] *Luiz de Queiroz College of Agriculture, University of São Paulo, Piracicaba, São Paulo, Brazil*
[c] *Technical University of Munich, Department of Life Science Engineering, Freising, Bavaria, Germany*
[d] *Center for Nuclear Energy in Agriculture, University of Piracicaba, São Paulo, Brazil*

A R T I C L E I N F O

Keywords:
Agriculture sustainability
Cropland expansion
Double-cropping system

A B S T R A C T

Mapping and monitoring tools are imperative in assessing agricultural systems and guiding future decision-making to safeguard food security. Since grain-croplands are the main occupation within the Brazilian croplands that has played a substantial role in the country's land use/land cover (LULC) dynamic, this study aims at proposing a grain-cropping suitability index (CroppingSI) to support the geographical analysis of LULC agricultural trends. The proposed approach considers detailed information on climate, soils, and terrain coupled with grain-crop simulations, soil quality indexing, and terrain restrictions evaluated at the highest available resolution. With historical LULC maps (2000 and 2020), we found that terrain was the most critical factor for cropland expansion, followed by climate and soil quality. The new croplands expanded towards regions with better climate and terrain conditions while neglecting the soil quality, mostly in the Cerrado and Amazon regions. In addition, the assessment of CroppingSI was instrumental in understanding that expanding new croplands over current cleared areas (i.e., pasturelands) may expose them to marginal soil and terrain conditions. This suggests a fragility of the current expansion trend of grain-cropping systems which can substantially put food security at risk, requiring alternative strategies for maintaining or improving food through crop intensification.

1. Introduction

Agriculture intensification through the adoption of new technologies that increase crop yield and/or agriculture expansion over new areas are the main mechanisms that have been largely ensuring the increasing global production of food (Zabel et al., 2019). In turn, population growth and climate change are expected to pose new challenges to agricultural production in the next decades (Rosenzweig et al., 2014; Tilman et al., 2011; Wheeler & von Braun, 2013). This may press the current systems with additional cropland expansion over preserved lands or stimulate the development of new technologies to meet the global demand for food while maintaining sustainable development (Griggs et al., 2013; Marin et al., 2022). However, less than one-half of the world's land area is suitable for agriculture, including grazing. Nearly all of the world's productive land is already under use, while the remaining cleared land imposes several restrictions for agricultural production, putting pressure on current forests or rangelands that are also essential to sustain biodiversity and environmental services (Kendall & Pimentel, 1994; Song et al., 2021; Zabel et al., 2019). In this sense, mapping and monitoring tools are imperative to assist in the assessment of agricultural systems in order to guide future decision-making and safeguard food security (Rattis et al., 2021; Beyer et al., 2022; Schneider et al., 2022).

Among the countries that have substantial importance for global food production while having significant land use and biodiversity concerns (Beyer et al., 2022; Rodrigues et al., 2022), Brazil has

* Corresponding author. Woodwell Climate Research Center, Falmouth, MA, USA.
E-mail address: jsafanelli@woodwellclimate.org (J.L. Safanelli).

https://doi.org/10.1016/j.apgeog.2023.102937
Received 13 June 2022; Received in revised form 22 February 2023; Accepted 15 March 2023
Available online 22 March 2023
0143-6228/

experienced an increase of 170% in grain production between 2011 and 2021, reaching 270 million tones in recent years (CONAB, 2022). Such an achievement was possible mainly due to the adoption of technologies that increased crops yield in the same unit area, such as the double-cropping system, which spares land by cultivating soybean and maize in succession on the same land within the same growing season (Xu et al., 2021). Because of the changes in the agricultural production systems (high adoption of double-season crops), Brazil currently plays an important role in the global supply of soybean and maize. However, the sustainable development of Brazilian agriculture in the coming decades may still be tackled as a global challenge considering the indirect effects of soybean expansion on Amazon deforestation and the potential bottlenecks of a climate crisis (Leite-Filho et al., 2021; Rattis et al., 2021; Rodrigues et al., 2022; Song et al., 2021).

The amount of land available for cropland and double-cropping system expansion is limited, and farmers are experiencing greater competition for suitable land and water. At the same time, extreme weather conditions during growing seasons are confronting food production systems around the country (Loarie et al., 2011; Nóia Júnior et al., 2020; Rattis et al., 2021). Overarching all these issues is the threat of deforestation affecting Brazilian contribution towards global climate change mitigation and biodiversity conservation (Song et al., 2021; Tyukavina et al., 2017; Zabel et al., 2019). The challenge of increasing agricultural production by simultaneously using less land and water and emitting fewer greenhouse gases requires technological innovation and in-depth knowledge of the grain-cropping suitability across the Brazilian territory. Several studies have approached this topic and many global datasets were produced by using various model assumptions (Rosenzweig et al., 2014; Davis et al., 2017; Schneider et al., 2022). However, with the availability of new high-resolution datasets, especially those produced from big catalogs of earth observation data that detect regional or local variations (Tulbure et al., 2022; Venter et al., 2022), new opportunities emerge for mapping the grain cropping suitability at finer resolutions that would allow a simultaneous analysis with other high-resolution information. In addition, novel quantitative methods for indexing soil quality, terrain restrictions, and environmental constraints through crop simulation also offer an opportunity for improving our understanding of the variations of suitability factors over a territory (Cherubin et al., 2016; Lehmann et al., 2020; Trnka et al., 2014).

Land suitability has different interpretations according to the literature. The Food and Agriculture Organization (FAO) provided a framework for land evaluation since 1976 based on several principles, which result in a combination of land qualities that are derived by data interpretation and classification (FAO, 1976). The literature also contains several examples of crop suitability methods that can be grouped as multi-criteria evaluation systems, which are usually employed in geographical information systems (Chen et al., 2010; Alkimim et al., 2015; Mesgaran et al., 2017; Akpoti et al., 2019; Pimenta et al., 2021). Most of those methods are based on the classification of environmental layers that are further combined by rules, for example, integrating the classification of soil pH values and rainfall regimes into suitability classes (Bouman et al., 1999; Alkimim et al., 2015; Akpoti et al., 2019). The common representation of land suitability takes place in geographical units (clusters or zones), such as the Agricultural Ecological Zones (AEZ), which although straightforward and appropriate for some scales and cases, may hamper the combination with additional information on specific studies (Fischer et al., 2009). Following the principles of AEZ but representing the information in a spatially continuous form is especially useful because it allows efficient integration and analysis with external sources of information (Heuvelink & Pebesma, 1999), especially land use/land cover (LULC) maps (Tulbure et al., 2022; Venter et al., 2022).

Considering that grain-croplands are the main occupation within the Brazilian croplands that has played a substantial role in the country's LULC dynamic (Song et al., 2021; Xu et al., 2021), the present study proposes a grain-cropping suitability index (CroppingSI) to support the geographical analysis of recent LULC agricultural trends. This approach considers detailed information on climate, soils, and terrain based on grain-crop simulations, soil quality indexing, and terrain restrictions evaluated at the most available high resolution, considering also the spatial and temporal tradeoff depending on the target assessment. The resulting continuous maps allow the combination with external high-resolution LULC maps for generating quantitative evidence for understanding the agricultural expansion, mostly associated with the expansion towards the Cerrado and Amazon regions in Brazil. In addition, the proposed method is used to rank the effects of biophysical determinants on historical LULC trends.

2. Methods

The proposed method combines land attributes regarding grain crops that are harvested yearly. Intermediate components (representing the climate, soil, and terrain elements) were calculated separately and aggregated into a single variable defined as the CroppingSI. It is important to stress that the combination of the land attributes can be performed in different ways, allowing the adaption or removal of layers to align the analysis to a specific goal. Other geographical information, such as infrastructure availability or socioeconomic characteristics, for example, can be integrated as complementary data in the calculation. In this study, however, the CroppingSI calculated from climate, soil, and terrain information was used to represent the biophysical cropping potential of the Brazilian territory in order to assess the last 20 years and potential changes of the agricultural LULC. Each component of the CroppingSI and their proposed combination is fully described in the following subsections (Fig. 1).

2.1. Climate component

The climate suitability index (ClimateSI) was calculated considering the water and temperature stress that could affect grain-crop cultivation in Brazil. For this task, maize was selected as the reference crop due to several characteristics: it is cultivated from south to north in Brazil, by family smallholders and large farmers, and in different periods of the year, making possible the assessment of biophysical constraints for the whole territory. More than 98% of Brazilian maize grain production comes from two distinct growing seasons, the main season (locally known as "*milho 1^a safra*", sown from September to December) and the off-season (known as "*milho 2^a safra*", sown from January to March) maize. The main season and off-season maize sowing dates represent the most important sowing windows available for rainfed and double-grain crops in Brazil and were used for simulating the grain-crop growth potential in this study (Xu et al., 2021).

We used main-season and off-season maize cycle lengths and phenological periods defined by the official registries of grain crops cultivated in the Brazilian territory. The Ministry of Agriculture, Livestock and Food Supply (MAPA) maintains the registry of crop cultivars and hybrids that supports the agroclimatic zoning and crop insurance for different regions in Brazil. For this study, a snapshot from the official registry was collected considering the maize cultivated in the main season and off-season of 2020/2021 (MAPA, 2021a). For each federal state of Brazil, the average values of the vegetative phenological phase (days from emergence to anthesis) and total crop cycle (days from emergence to physiological maturity) were collected.

For the main season and off-season cropping systems, four main phenological periods were determined: establishment (from emergence [time 0] to 16% of the total cycle); vegetative growth (from time 16% of the total cycle to anthesis); reproductive stage (flowering and grain filling, from anthesis to 76% of the total cycle); and maturation (from 76% of the total cycle to physiological maturity). When missing information was detected for a federal state, the crop parameters were filled up with the major regional mean. This step was performed to guarantee a complete list of parameters that are required for running the crop cycle

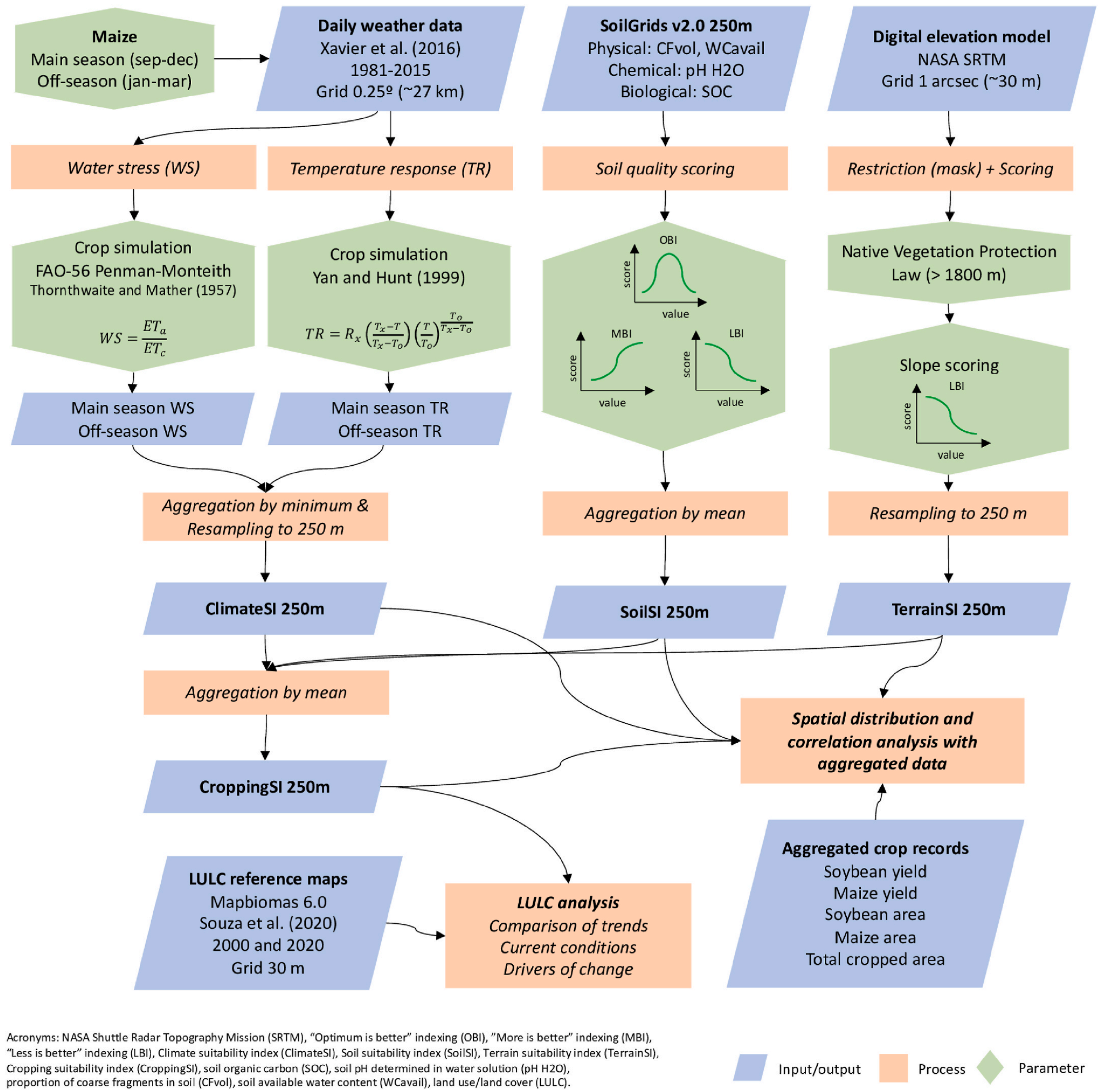

Fig. 1. Flowchart describing the datasets, processing steps, and outputs of this study.

simulations across the whole Brazilian territory (Table SM1).

In addition to crop growth parameters, the most representative sowing dates for both cropping systems were determined considering the historical weather conditions. According to the technical information detailed in the agroclimatic zoning of MAPA (MAPA, 2021b), the sowing dates should ideally occur when the average ratio between actual (ET_a) and maximum (ET_c) crop evapotranspiration (ET_a/ ET_c) is the highest during the critical phenological phase (flowering and grain filling), i.e. when the water stress is minimal. Thus, we considered as the most representative sowing date of each weather grid cell and each cropping system the one with the highest average of ET_a/ ET_c. The ET_a/ ET_c was estimated daily for 36 cultivation years with simulations from September 1st to December 21st (for the main cropping system) and from January 1st to March 21st (for the off-season cropping system), both with intervals of 10 days. The ET_c was calculated according to the FAO-56 Penman-Monteith method (Allen et al., 1998), while ET_a was estimated as a result of the soil water balance (Thornthwaite & Mather, 1955, 1957). Daily historical meteorological variables, from 1981 to 2015, were used as input and sourced from (Xavier et al., 2016). This dataset was selected due to its high-density, well-distributed, and consistent historical weather data series with a daily time interval. These characteristics are extremely important for crop simulation and several studies have tested and recommended them for new studies developed in the Brazilian territory (Battisti et al., 2019; Duarte & Sentelhas, 2020; Dias & Sentelhas, 2021). Additional information about crop coefficients and phenological periods is provided in Table SM2. In the end, the most representative sowing date for each weather grid cell was used in a final simulation to estimate the water and temperature stress of the two crop cycles cultivated during the main and off-season cropping systems.

Water stress (*WS*) was defined as the averaged ET_a/ ET_c ratio (Equation (1)) for the complete crop cycle in both cropping systems using the reference sowing dates. Then, the historical estimates were aggregated by their mean statistic. The results that varied between 0 and 1 were transformed to a scale between 0 and 100 using the multiplicative factor of 100. Similarly, the temperature response was estimated by mapping a function to the daily mean temperatures within the crop cycles, which were aggregated by the mean and letter averaged across the years. This method employs a general equation that can simulate the temperature response (*TR*) of plants based on optimum temperature (T_o), maximum temperature (T_x), and maximum rate of growth (R_x) (Equation (2)) (Yan & Hunt, 1999). The values of 26 °C, 41 °C, and 100% were set as T_o, T_x, and R_x, respectively, for both cropping systems.

$$WS = \frac{ET_a}{ET_c} \tag{1}$$

$$TR = R_x\left(\frac{T_x - T}{T_x - T_o}\right)\left(\frac{T}{T_o}\right)^{\frac{T_o}{T_x - T_o}} \tag{2}$$

In the end, each intermediate result could be assessed individually in terms of water or temperature stress for the two separate cropping systems. However, a single climate product is mandatory to be integrated with the soil and terrain suitability components. In this final step, the minimum value of the four layers (water and temperature stress of the main and off-season cropping systems) at each grid pixel was determined as the ClimateSI, following the principle of Liebig's Law of the minimum. Reducing the grid layers by their minimum value highlights which climate component can be the limiting factor for the grain-crop growth, i.e., either the water or the temperature stress, considering at the same time, the two most important cultivation windows. In the end, the results with a spatial resolution of 0.25° per pixel (i.e., approx. 27.75 km at the Equator) were downscaled to 250 m using the inverse of the weighted distance (IDW) interpolation algorithm. The maximum range and raising power interpolation parameters were set as 100 km and 0.5, respectively. We only downscaled the ClimateSI using IDW to produce a smooth transition between the pixel grid centroids and avoid the generation of spatial artifacts when combined with the other higher-resolution datasets. IDW is a deterministic method (exact interpolator) that will not produce new information at the subpixel level and was originally tested and highlighted as a good interpolation method in the paper of Xavier et al. (2016), where we sourced the climate data for this study.

2.2. Soil component

The soil suitability index (SoilSI) was developed considering the soil quality literature and indexing methods (Cherubin et al., 2016; Lehmann et al., 2020). The availability of the gridded and standardized soil layers with 250 m pixel resolution from SoilGrids, version 2 (Poggio et al., 2021), allowed the representation of physical, chemical, and (potentially) biological variations across the Brazilian territory. For calculating SoilSI, the soil organic carbon (SOC), pH determined in water solution (pH H_2O), the proportion of coarse fragments (CFvol), and available water content (WCavail) were employed. These attributes represent the major physical, chemical, and biological factors governing the natural soil quality and are strongly related to crop cultivation performance and mechanization restriction. We expect the variations of the national soil maps to be related to natural conditions because the Brazilian dataset used for the global spatial predictions employed legacy soil samples that were surveyed decades ago before the explosion of agricultural commodities and the large geographical expansion of the Brazilian agriculture (Batjes et al., 2017; Cooper et al., 2005). In addition, they were selected based on their availability or extended estimation from SoilGrids version 2 (Simons et al., 2020; Poggio et al., 2021).

Each attribute was transformed to a scale varying between 0 and 100 using scoring functions (Cherubin et al., 2016). Before the transformation, SoilGrids layers were averaged to the depth of 0–60 cm using a simple weighted mean. The scoring functions were divided into three types: 'more is better' index (*MBI*, upper asymptote sigmoid curve), which means that higher values of the soil attribute indicate better soil quality; 'less is better' index (*LBI*, lower asymptote sigmoid curve), with lower values considered of higher soil quality; and 'optimum mid-point' (*OMI*, Gaussian shape), where an intermediate value indicates a superior soil condition. CFvol was scored using *LBI* (Equation (3)), SOC, and WCavail using *MBI* (Equation (4)), and only pH H_2O was scored using *OMI* (Equation (5)). As each soil attribute must be parametrized for its scoring, the baselines, limits, and optimal values were determined by statistical estimates (percentiles) obtained considering the whole territory (Table SM3). This approach was used to constrain the function parameters to the ranges of the SoilGrids attributes, as these layers contain uncertainty levels in their predictions, and external thresholds could yield unrealistic results. After scoring the soil attributes to the same scale range between 0 and 100, the results were simply averaged to represent the SoilSI, which is an aggregation method suggested by Cherubin et al. (2016).

$$MBI = \frac{a}{\left[100 - \left(\frac{B-UL}{x-UL}\right)^S\right]} \tag{3}$$

$$LBI = \frac{a}{\left[100 - \left(\frac{B-LL}{x-LL}\right)^S\right]} \tag{4}$$

$$OMI = \begin{cases} \dfrac{a}{\left[100 - \left(\dfrac{B_L - O}{x - O}\right)^S\right]} & if\ x < O \\ \dfrac{a}{\left[100 - \left(\dfrac{B_U - O}{x - O}\right)^S\right]} & if\ x > O \end{cases} \tag{5}$$

where a is the maximum scoring value (100%), S is the slope of the equation, set as −2.5; B is the baseline value which has a score of 50%; UL is the upper limit of the soil attribute values; LL is the lower limit of the soil attribute values; B_L is the lower baseline of the 'optimal mid-point' curve, having a score of 50%; B_U is the upper baseline of the 'optimal mid-point' curve, having a score of 50%; O is the optimum score value, equals 100%; and x is the actual soil attribute value.

2.3. Terrain component

The terrain suitability index (TerrainSI) was calculated considering the terrain slope and elevation. Remarkably highly-elevated areas (in Brazil, >1800 m) are considered protected environments according to the Native Vegetation Protection Law (12651/2012), thus, they are classified as inapt for agriculture (TerrainSI = 0). In turn, the terrain slope was mapped by a nonlinear function similar to the soil attributes. The LBI scoring function (Equation (4)) was applied with a baseline of 8% and a lower limit of 0%. According to the slope classification system from the Brazilian Soil Classification System (Santos et al., 2018), the places with more than 8% slope are categorized as rolling slopes. Sloped areas hinder crop mechanization, and the soil erosion processes can be intensified (Guerra et al., 2017; Jasinski et al., 2005). The NASA SRTM DEM with 1 arcsec of pixel resolution (~30 m at the Equator) was employed in this analysis and the TerrainSI was further resampled (mean aggregation) to match 250 m of pixel resolution.

2.4. Cropping suitability and statistical analysis

For aggregating the climate, soil, and terrain suitability indices into a single variable (i.e., the CroppingSI), the average value between the three components (TerrainSI, SoilSI, and ClimateSI) was calculated at the pixel level. The purpose of using a simple mean is to avoid including some arbitrary decision that may not represent well the geographical dissimilarities of the Brazilian territory. For this paper, which is a general assessment of the grain cropping suitability coupled with an agricultural LULC analysis, we considered the same importance weight for climate, soil, and terrain components. However, other aggregation methods can be further tested to assess the suitability restrictions across the Brazilian territory.

The CroppingSI and its three components were employed in a statistical evaluation with historical municipality-level records. For this task, all the cropping suitability variables with 250 m pixel resolution were averaged within each polygon of the Brazilian municipalities. Comparing variables with different spatial supports, i.e., cropping statistics aggregated at the municipality level with the suitability maps produced at 250 m, may certainly impact the analysis. This is a suboptimal evaluation and many aspects such as the aggregation method can hamper the results. However, there exists a lack of cropping statistics at higher resolutions compatible with the maps so this comparison was still employed to check the general associations. This analysis may not represent a true validation but yet a complementary analysis that considered the availability of public and official cropping records.

In the first step, the pairwise Pearson's correlation between each suitability component was tested to check the associations among them. Further, the cropping suitability indices were tested with municipality-level crop statistics using Pearson's correlation, which included the 2015–2019 mean yield of soybean and maize (SoybeanYield and MaizeYield, respectively), 2015–2019 mean relative cropped area (percentage relative to the municipality area) of soybean and maize (SoybeanCroppedArea and MaizeCroppedArea, respectively), and the 2015–2019 mean relative cropped area (percentage relative to the municipality area) of all the temporary crops that are harvested annually (TotalCroppedArea). We used the relative cropping area to avoid the impact of large municipality areas on the correlation analysis. The historical yields and areas were retrieved from the Brazilian Institute of Geography and Statistics – IBGE. The statistical correlation coefficients were tested at the significance level of 95%. The processing of geospatial data was performed within the Google Earth Engine cloud-based platform (Gorelick et al., 2017). Only the crop-growth simulations were run separately on the high-performance computing cluster of the Center for Mathematical Sciences Applied to Industry (CeMEAI), University of São Paulo. All the statistical evaluations and graphical analyses were performed using the R statistical programming (R Core Team, 2021).

2.5. Cropping suitability and the agricultural land-use/land-cover

The CroppingSI was compared within and among the main agricultural LULC maps from two years (2000 and 2020) produced by an external source. Croplands, composed of temporary or yearly-harvested crops including soybean and maize (pixel IDs 39 and 41); pasture & rangelands, mostly destined for livestock (pixel ID 15); and other LULC (all the other IDs) were prepared from a three-decade 30-m LULC map developed by MapBiomas Collection 6.0 (Souza et al., 2020). The three LULC classes were selected for the years 2000 and 2020, making possible the assessment of the recent changes in CroppingSI among agricultural LULC classes. For trend analysis, twelve subclasses were defined: (a) cropland available in 2000; (b) cropland available in 2020; (c) pasture/rangeland available in 2000; (d) pasture/rangeland available in 2020; (e) other LULC available in 2020; (f) other LULC available in 2020; (g) croplands available either in 2000 or 2020 (no-change); (h) new cropland (2020) expanded over pasture/rangeland from 2000 (new cover); (i) new cropland (2020) expanded over other LULC from 2000 (new use); (j) pasture/rangeland available either in 2000 or 2020 (no-change); (k) new pasture/rangeland (2020) expanded over cropland from 2000 (new cover); (l) new pasture/rangeland (2020) expanded over other LULC from 2000 (new use).

These LULC subclasses allowed the comparison and analysis of LULC trends. In this analysis, the CroppingSI was masked for each LULC subclass and extracted using a fixed-length histogram (98 bins ranging from 1 to 99) for estimating the probability density function (PDF) across the Brazilian territory. The PDFs were used to reconstruct the sample distribution of the CroppingSI and perform statistical comparisons between the subclasses. The samples were reconstructed using a wider size ($n = 10.000$) and a non-parametric permutation test (with 100 replicates) was employed for the comparison analysis (Higgins, 2004). In addition, the area (hectares), 25% (first quantile), 50% (median), and 75% (third quantile) percentiles of each subclass were also estimated for descriptive analysis.

3. Results

3.1. Climate, terrain, and soil suitability indices

ClimateSI, TerrainSI, and SoilSI vary considerably across the Brazilian territory (Fig. 2). ClimateSI presents the highest values (>75) in the central-north region of Brazil (states of Goiás, Mato Grosso, Tocantins, Maranhão, Pará, Amazonas, and Acre), and at the coast of the south-central regions (right border, Fig. 2a). The lowest values of ClimateSI (<40) were obtained in the Northeastern region (Bahia, Sergipe, Alagoas, Pernambuco, Paraíba e Rio Grande do Norte states) and the northernmost (Roraima state) of Brazil. The central-south region of the country (Mato Grosso do Sul, São Paulo, Minas Gerais, Paraná, Santa Catarina, and the Rio Grande do Sul states) present intermediate values of ClimateSI. Considering their intercorrelations and complementary representation, a negative correlation was found for TerrainSI with SoilSI (−0.32), while positive correlations were identified for TerrainSI with ClimateSI (0.05), and SoilSI with ClimateSI (0.52) (Fig. 3). These results demonstrate that these components, when evaluated separately, can highlight either contrasting and complementary information for analyzing the territory or confirm, to some extent, an expected association. SoilSI correlation with ClimateSI, for instance, confirms that climate is an important forming factor conditioning the variability of soil quality across the national extent.

TerrainSI presented the smallest spatial contrast among the three calculated components (Fig. 2b). Most of the Brazilian territory presents a TerrainSI close to 100, i.e., with no restriction to grain-cropping. On the other hand, the regions situated in steeper slopes or mountainous areas, such as those from the central-south coast of Brazil (right border) present intermediate to low values (<50) for TerrainSI. Southern Brazil presents the highest values of the SoilSI, particularly in the state of Santa Catarina (Fig. 2c). Also, some regions on the Brazilian coast (right border) and in the north of the country present high values of SoilSI (>60). The negative correlation of SoilSI with TerrainSI (Fig. 3) can be possibly explained by the occurrence of high-quality soils in more undulating terrains due to the intensive soil processes and formation over unstable surfaces (young and fertile soils). In addition, most of the Brazilian tropical soils are located in relatively stable and flat landforms that are poorer in plant nutrients and organic carbon. On the other hand, although most of the central north of Brazil close to the Amazon basin presents high values of SoilSI, this region has relatively highly evolved tropical soils that present superior physical characteristics determined by a low fraction of rock fragments and deep soil profiles, although containing high concentrations of toxic aluminum and low pH.

When the suitability components were compared with the overall CroppingSI, ClimateSI presented the highest correlation (0.85), followed by SoilSI and TerrainSI. The CroppingSI has a high variation across the Brazilian territory and indicates the major limitations for agricultural practices (Fig. 2d). The highest values of CroppingSI were obtained in

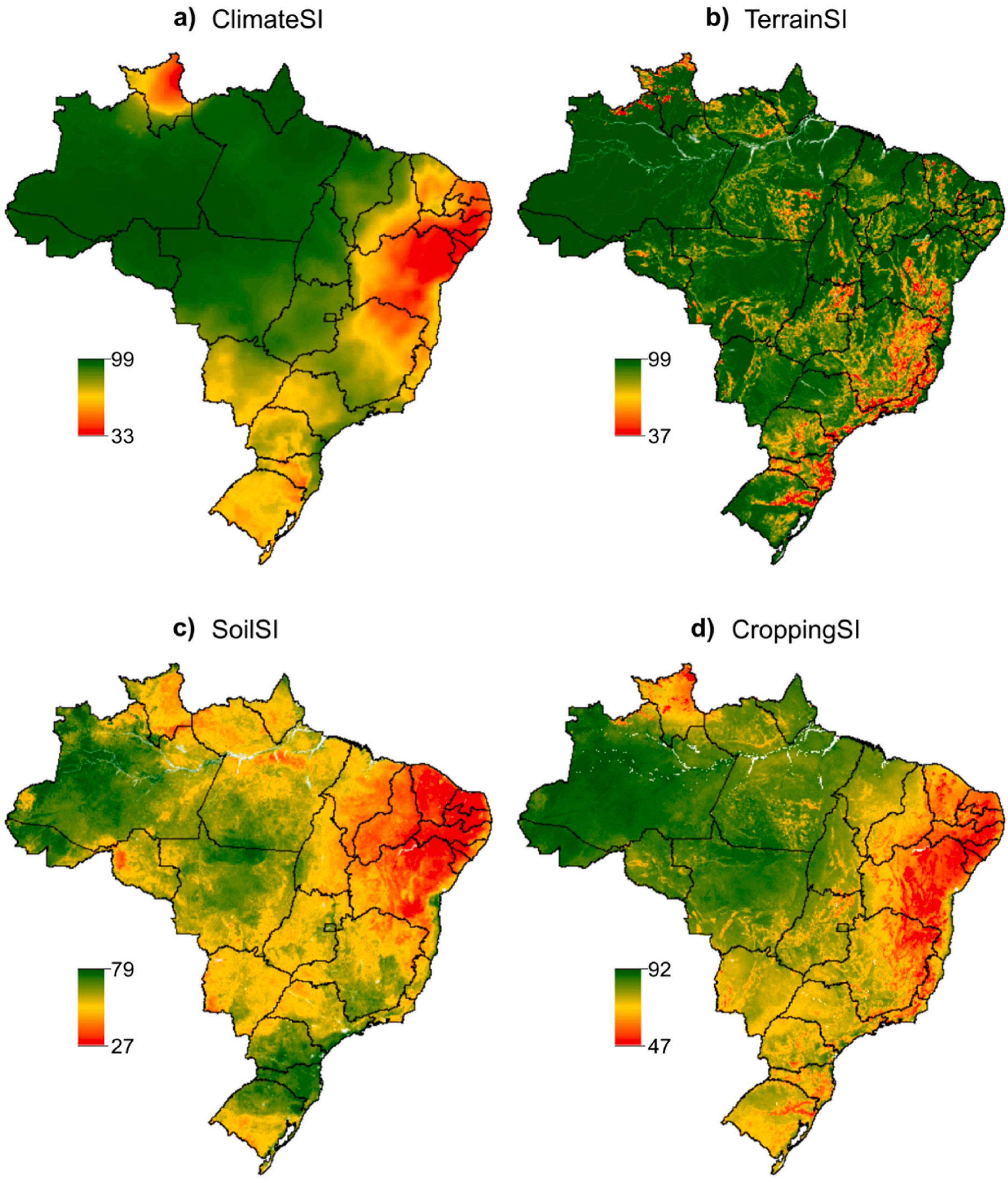

Fig. 2. Grain cropping suitability index and its components in Brazil. a) climate (ClimateSI), b) terrain (TerrainSI), c) soil (SoilSI), d) and the average cropping suitability (CroppingSI).

the central north of Brazil, near the Amazon region, with a few minor spots concentrated in other regions. On average, less suitable sites are found in the northeast of Brazil and in mountainous terrains. Most of the central region of Brazilian territory, where recent croplands expanded over the Cerrado biome, present intermediate to high CroppingSI values (Fig. 2d).

The resulting maps had a significant agreement with historical crop production statistics (Fig. 3b). SoilSI had positive correlations with all the crop statistics, with the highest correlation found for maize (0.75) and soybean yield (0.43), confirming the overall importance of soil quality for crop yield performance. For TerrainSI, a negative correlation was found for soybean and maize crop yields (although inferior to SoilSI), while the association with the relative cropped areas was positive. The positive correlations of the terrain quality with the relative cropped area can be explained by the preferable cultivation of crops on flatter terrains. ClimateSI had diverging results with crop production statistics, with a negative and very low correlation with soybean yield (−0.04), and a positive and moderate correlation with maize yield (0.32). This indicates that while maize yields may be linked to climate favorability, soybean cultivation might be less sensitive to this factor. The negative correlation with soybean relative cropped area (−0.24) may indicate that external factors also play a stronger influence on the cultivation decision. This can be potentially linked to the significant density of soybean in regions with variable weather conditions, as this

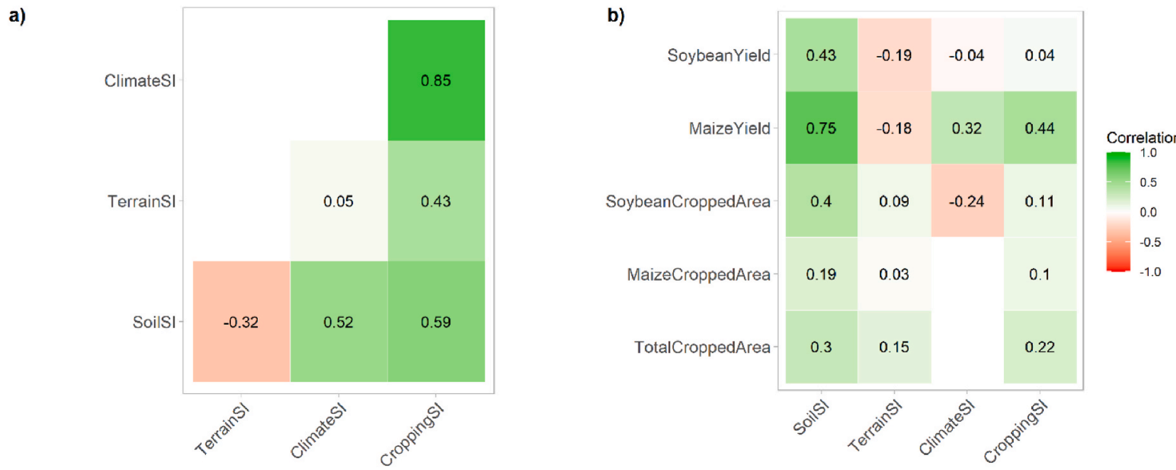

Fig. 3. Statistical evaluation of the climate (ClimateSI), terrain (TerrainSI), soil (SoilSI), and cropping suitability indices (CroppingSI). a) Pairwise Pearson's correlation between suitability indices. b) Pairwise correlations of suitability indices with municipality-level crop statistics. SoybeanYield and MaizeYield: 2015–2019 mean yield of soybean and maize, respectively. SoybeanCroppedArea and MaizeCroppedArea: 2015–2019 mean relative cropped area (percentage relative to the municipality area) of soybean and maize, respectively. TotalCroppedArea: 2015–2019 mean relative cropped area (percentage relative to the municipality area) of all the temporary crops that are harvested annually. Blank squares refer to repeated or not significant (5% error probability) correlation coefficients.

crop has a widespread distribution across the Brazilian territory. For CroppingSI, which takes into consideration the average of the intermediate components, the positive and significant correlations confirm a possible consistency of this product for representing major geographical patterns related to grain-crops production.

3.2. Cropping suitability and the agricultural land use/land cover trend

When the suitability components were assessed considering the occupation of temporary grain crops, a slight increase in TerrainSI and ClimateSI was revealed over the last 20 years (Fig. 4). This result is the opposite of SoilSI, where a decreasing trend was found. In addition, the temporal analysis of these components revealed that, among them, on average, TerrainSI presents the highest estimates followed by ClimateSI and SoilSI. This result demonstrates that grain crops, the most representative type of cropland that is responsible for the largest changes in agricultural LULC (excluding pasture), have been expanding towards regions with better terrain and climate quality and neglecting soil quality.

In Brazil, pasture/rangeland and cropland occupied together about 201 million ha in 2020. From 2000 to 2020, cropland increased by 79%, i.e., from 24 to 43 million ha. From the 43 million ha occupied with cropland, 25% was previously destined to pasture/rangeland, and the remaining 75% came from other uses, such as native or commercial forests, grasslands, coffee, orange, sugarcane, regions with an undistinguished mosaic of agriculture and pasture, etc. In the first case, the CroppingSI for the new croplands that expanded over pasture/rangelands is higher (median of 80) than those that remained unchanged since 2000 or that were converted by other uses (median 78 and 77, respectively). The new cropland that expanded over pasture/rangeland is

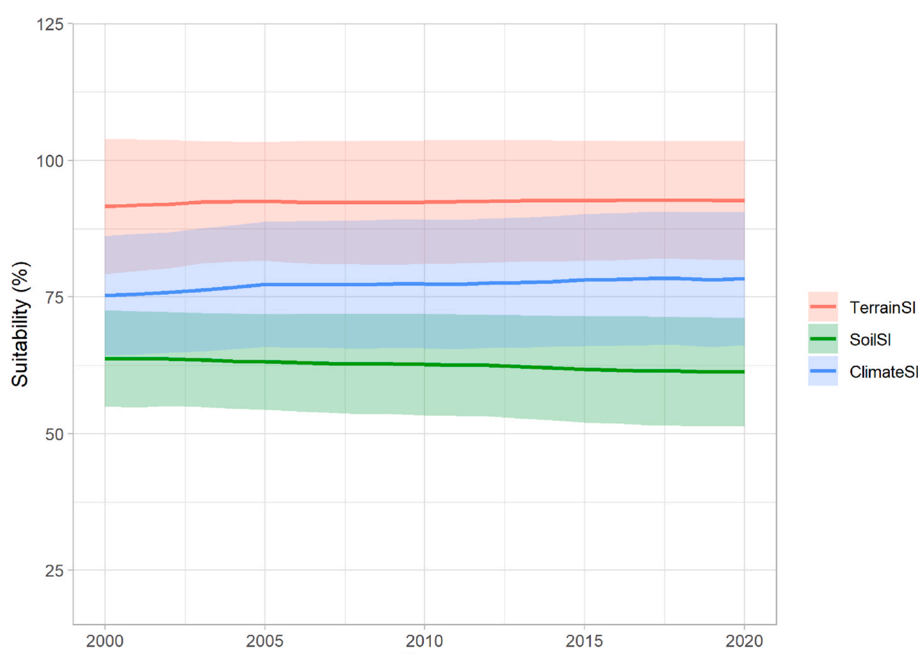

Fig. 4. Variation of the climate (ClimateSI), terrain (TerrainSI), and soil (SoilSI) suitability indices within the croplands over the last 20 years. Shaded areas represent the standard deviation of the mean (solid lines).

mainly located in the Cerrado biome, while the cropland that expanded over other uses is mostly located in the south, MATOPIBA and Legal Amazon (Fig. 5a).

From the 158 million ha with pasture/rangeland available in 2020, 69% remained unchanged since 2000, while the other part came mostly from other uses, different from croplands. From 2000 to 2020, pasture/rangeland expanded to 47 million ha of other uses dated in 2000. The new pasture/rangeland is mainly concentrated in the edges of the Amazon rainforest (Fig. 5a), a region with a CroppingSI (median of 81) higher than the pasture/rangeland that remained unchanged since 2000 (median of 76). It is worth noting that, despite the low amount of new pasture/rangeland that expanded over croplands (0.8 million ha), this LULC trend took place over areas with similar CroppingSI (median of 76) compared to pasture/rangeland that remained unchanged since 2000 (median of 76). This trend is the opposite of croplands, since it expanded over pasture/rangeland with more favorable conditions, with a median CroppingSI of 80, which is significantly higher compared to the croplands that remained unchanged since 2000 (median of 78). Additional information can be found in Table SM4 from supplementary material.

In this sense, the CroppingSI of 24 million ha mapped in 2000 is statistically inferior to the CroppingSI of croplands from 2020 and to the CroppingSI of the area that was converted between 2000 and 2020 (Fig. 6a). The CroppingSI of croplands that expanded in the last 20 years over other uses (new use) is statistically worse than all other cases, but the current situation was compensated by the expansion that took place over pasture/rangelands (new use). A different perspective is found for the pasture/rangelands. The recent changes that took place over croplands (new cover) contain the lowest estimates of CroppingSI. However, when the expansion of pasture/rangeland took place over other LULC (new use), the cropping suitability of these places are statistically superior.

In summary, both croplands and pasture/rangelands have been expanding towards regions with better biophysical conditions, which coincides with the Cerrado and Amazon biomes. The current conditions and equivalent trends of both pasture/rangelands and croplands were also compared (Fig. 6b). The current croplands (2020) are statistically superior to the current pasture/rangelands (2020). However, the recent changes in both of these uses favored croplands with higher CroppingSI areas, as confirmed by the statistical analysis (Fig. 6b). When both cases were compared by the expansion over other LULC, the new pasture/rangelands were favored (Fig. 6b).

4. Discussion

4.1. Cropping suitability

Southern Brazil presents the highest SoilSI suitability in the country (Fig. 2). The historical and recent agricultural performance of the farmers located in this region confirms our results. For example, the highest average soybean yield ever recorded of a predominantly non-irrigated state in Brazil was from Paraná (southern Brazil) in the 2019/2020 season, with 3925 kg ha^{-1} (CONAB, 2022). The last four winners of the national soybean yield contest before are also from southern Brazil (CESB, 2021). The high soil quality and the regular annual rainfall distribution for a single season are the key factors for the high cropping suitability in this region (Fig. 2). Yet, the interannual variability of climate imposes important limitations to double grain cropping, and the soybean and maize grain yields within the south region have already dropped by more than 50% due to extreme drought and frost events (Nóia Júnior et al., 2020), differently from the farms located in the central region with Cerrado biome (Song et al., 2021; Xu et al., 2021).

The ClimateSI is the main limitation of cropping systems in most of the northeast of Brazil (Fig. 2). The predominant climate of the central-northeast, according to Köppen's classification, is hot and semi-arid (BSh), with annual precipitation below potential evapotranspiration (Alvares et al., 2013). The region contains limited resources, farming mostly for subsistence (FAO, 2015). However, around the São Francisco River, there are sites with irrigation and high levels of technology adoption in agriculture, particularly for grape and mango production. Similarly, significant amounts of grain cropland take place in the MATOPIBA region (west border of the northeast region, closer to Amazon), with an Aw climate, i.e., tropical with dry winter (Alvares et al., 2013). In this region, as well as in other parts of the Brazilian Cerrado (e.g., in Mato Grosso and Goiás states), the main limitation to agriculture is related to soils with low natural chemical fertility (Fig. 2),

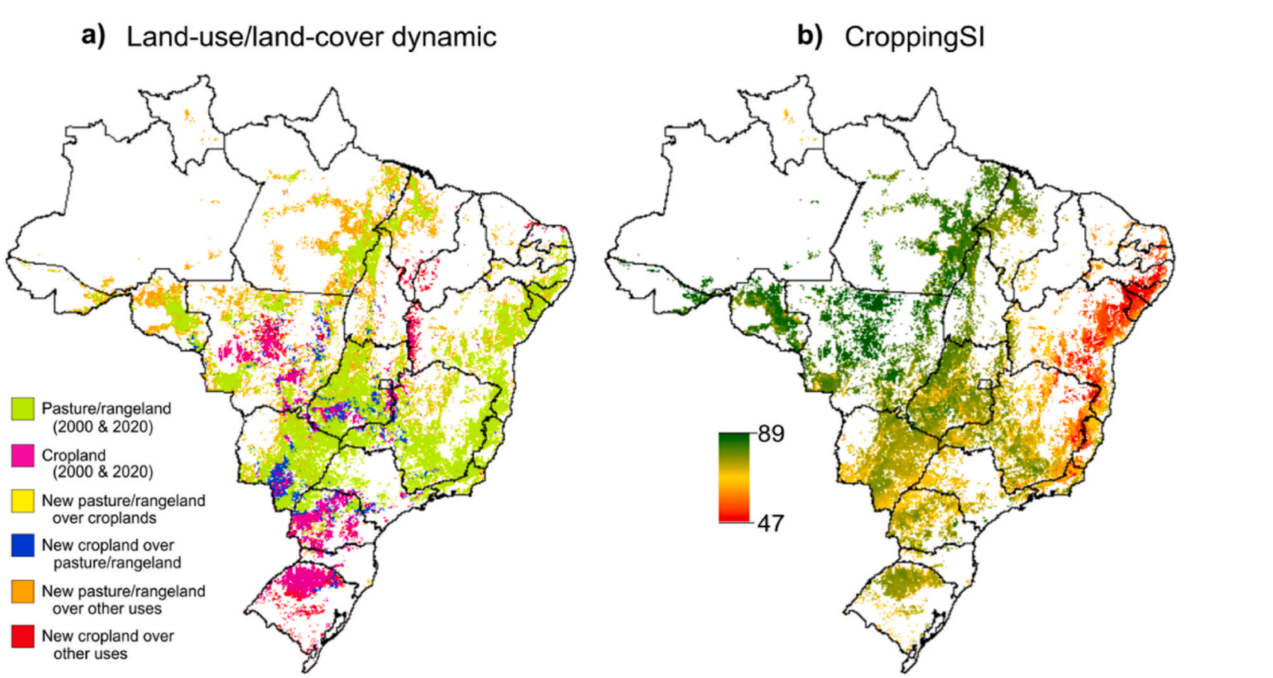

Fig. 5. Land use/land cover (LULC) dynamic and the cropping suitability index. a) Cropland, pasture/rangeland, and other LULC distribution between 2000 and 2020. b) Spatial distribution of the cropping suitability index (CroppingSI) over the cropland and pasture/rangeland areas.

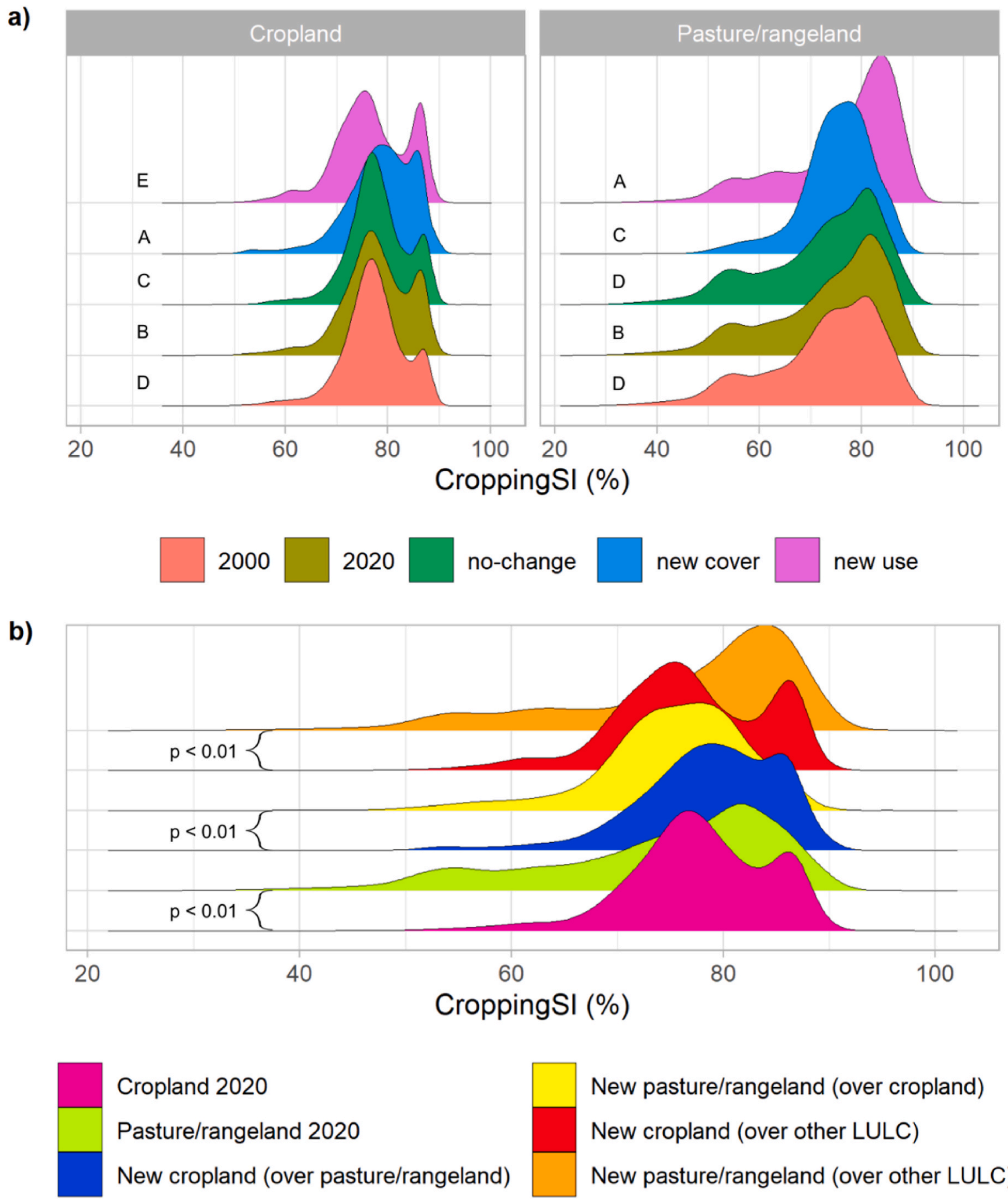

Fig. 6. Cropping suitability index (CroppingSI) statistical comparison within and among agricultural land use/land cover (LULC) classes. a) Probability density functions (PDF) of CroppingSI from croplands, pasture/rangelands, and other LULC, and their dynamics between 2000 and 2020. b) PDF of CroppingSI among LULC trends. PDFs with the same letters do not differ by a 1% probability error.

despite presenting good physical conditions such as deep profiles and low proportion of rock fragments (de Assis et al., 2011; de Carvalho Mendes et al., 2012; Klamt & van Reeuwijk, 2000). The fertilizer cost in this region corresponds to up to 40% of the total grain production cost, whereas this share can decrease to 20% in southern Brazil (CONAB, 2022). Overall, high grain-crop yield in Brazil is directly related to higher soil quality, as indicated in Fig. 2.

4.2. Cropland expansion

Grain cropland has been expanding to regions with better cropping suitability (ClimateSI and TerrainSI) that were previously occupied by pasture/rangeland, particularly in the northern Cerrado and Amazon regions. These results agree with previous studies that indicated a large proportion of the expansion in Brazil takes place by first converting forests to pasture and then to cropland, particularly soybean (Song et al., 2021). While deforestation has well-known environmental and social impacts, such as loss of biodiversity and increased CO_2 emissions (Lapola et al., 2018; Zabel et al., 2019), the conversion of pasture/rangeland to intensive row cropping areas may also lead to significant impacts in the environment. The increased use of agrochemicals, machinery, and fertilizer can alter the physical and chemical properties of local soil and water systems, leading to soil erosion and water pollution, as reported in central Brazil (Hunke et al., 2015). Furthermore, advancing grain-cropland to low SoilSI areas, such as Rondônia state in the Amazon region, may lead to their abandonment in the future and potential new deforestation, as the need for high investments to build soil fertility in the long-term remains (de Sant-Anna et al., 2017; Hunke et al., 2015; Vendrame et al., 2010).

The current trend of agricultural expansion in Brazil may threaten the national economy and food security and has implications for other countries. Deforestation in the Amazon affects rainfall in Brazil, neighboring countries, and as far away as other continents (Leite-Filho et al., 2021; Marengo et al., 2018; Medvigy et al., 2013). The increase in greenhouse gas emissions may further intensify the projected increase of extreme weather events affecting agricultural production in Brazil and elsewhere (Rattis et al., 2021). Brazilian agriculture, a major global food supplier, has shown its fragility mainly in the face of recent extreme weather events. In 2020, soybean grain production in the Rio Grande do Sul state dropped by 49%, a shortfall of 8 Mt due to extreme drought during summer. In 2021, the national off-season maize production decreased by 20% due to a compound of extremes with drought events, heat, and frost, even with an additional planted area of 1 Mha (+10% compared to the previous year). These events contribute to food price spikes and farmer indebtedness, with food insecurity becoming more frequent with climate change (Rattis et al., 2021; Rodrigues et al., 2022).

Assuming that Brazil has the potential to adopt low-carbon production models and preserve natural ecosystems by cattle ranching intensification (Cohn et al., 2014; Cortner et al., 2019), which also increase the availability of already-cleared areas (pasture/rangelands) for grain-cropland expansion, the ClimateSI estimated in these remaining areas are on average, similar to the current croplands (Fig. 7). For SoilSI and TerrainSI, on the other hand, the conditions are inferior. Despite being an unrealistic scenario that goes against a sustainable development that would bring potential sanctions, the conversion of other uses (e.g., forests and natural rangelands) to cropland would be only beneficial considering the higher ClimateSI available in those areas. SoilSI and TerrainSI of the current croplands are already superior to the remaining pasture/rangeland and other uses. Nonetheless, recent studies have found that regional warming and drying already have pushed current agricultural lands out of their optimum climate space in the Amazon and Cerrado regions (Rattis et al., 2021; Rodrigues et al., 2022), with unsuitable climate conditions for grain crops expected to increase in the future.

Promoting innovation and adoption of new technologies for closing current crop yield gaps in areas with high cropping suitability (intensification) would be better suited for the country's future agricultural agenda. This opportunity represents an increase of soybean, maize, and sugarcane yield by up to 2 t ha^{-1} (Sentelhas et al., 2015), 7 t ha^{-1} (Andrea et al., 2018), and 200 t ha^{-1} (Dias & Sentelhas, 2018), respectively. A recent study has shown that about 6 Mha (1955 Mt of CO_2e) of Amazon Forest or Savannah can be spared if accelerating soybean yield improvement and expansion on already-cleared areas takes place in Brazil (Marin et al., 2022). More importantly, this would allow Brazil to increase its production to about 160 Mt, ~20% compared to 2021/2022 levels (CONAB, 2022), without new deforestation and by halting the global climate warming potential (Marin et al., 2022). Similarly, integrated systems by combining crop, livestock, and/or forestry activities in the same area are especially promising due to the synergic positive effects on soil and environment quality while promoting agricultural production (Carvalho et al., 2014; Lemaire et al., 2014; Salton et al., 2014). Therefore, the development and adoption of cropping suitability models, like the one proposed in this study, are key for supporting decision-making on future paths of Brazilian agriculture.

4.3. Limitations and improvements

We quantified the grain cropping suitability across the Brazilian territory based on detailed information on climate, soils, and relief coupled with crop simulations and quality scoring functions. The CroppingSI inputs are usually publicly available for any country in the world either from global or regional datasets, such as the SoilGrids and other gridded climate datasets, making its application and adaption elsewhere. However, all these input datasets may have associated uncertainty that can impact the derived products and the findings of this study. Special attention may also be paid to the LULC maps due to some variations that may be found with other resources (Kinnebrew et al., 2022; Winkler et al., 2021), despite all the efforts taken for selecting and defining the best source for identifying the spatial changes across the Brazilian territory. In addition, as any model is prone to biased estimation or some assumptions may not represent well the dissimilarities of a huge territory like Brazil, the readers are encouraged to consider

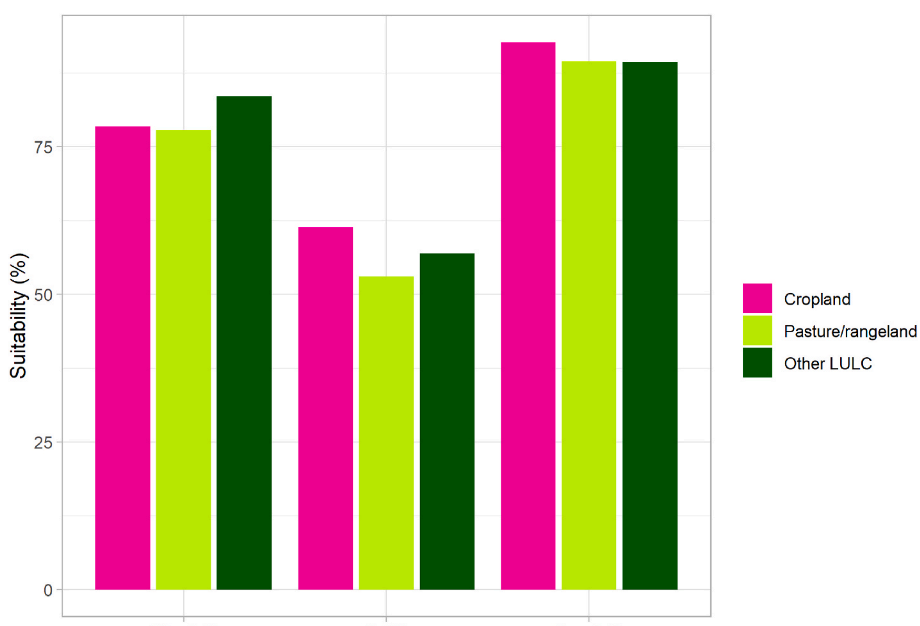

Fig. 7. Cropping suitability variation among the major land-use/land-cover (LULC) classes by 2020.

further evidence for the proposed claims. In turn, different from other initiatives that produced global datasets on coarse resolution datasets or targeted the development to other specific goals, our proposed method relied on sources with the highest available resolution recommend for Brazil, considering also the spatial and temporal tradeoff (Duarte & Sentelhas, 2020; Tulbure et al., 2022) and model assumptions that may have favored a specific LULC analysis.

Within a regional context, the agricultural suitability model proposed by Pimenta et al. (2021) for evaluating LULC change in western Bahia (MATOPIBA region), for instance, considered only rainfall and terrain slope as environmental layers. Other suitability methods employed in different studies usually lack the representation of soil, crop, and climate relationship, a connection that is well represented by crop simulation models and proposed in this study. The global inventory of suitable, cultivable, and available cropland developed by (Schneider et al., 2022), in turn, used a fuzzy logic coupled with irrigation information, historical and forecasted climate data, and several crop types, also considering crop-specific characteristics and requirements during the growing period about climate, soil and topographic conditions. Our study shared the same principles but not considered forecasted climate patterns, as other studies have explored this topic (Rattis et al., 2021; Rosenzweig et al., 2014). More importantly, our study took advantage of high-resolution datasets depicting the regional or local variations of Brazilian territory, providing the context-specificity often required for policy-making and implementation (Xavier et al., 2016; Tulbure et al., 2022). Another contrasting characteristic of the proposed method is the representation of cropping suitability as a continuous variable that allows the reconstruction of probability distribution functions and the execution of comparison tests, expanding the analysis from the conventional concept of using categorical data within multicriteria analysis (Alkimim et al., 2015; Bouman et al., 1999; Chen et al., 2010; Mesgaran et al., 2017).

The proposed CroppingSI is a method that made possible the evaluation of biophysical factors at finer resolutions and allowed a simultaneous analysis with other high-resolution information, i.e., LULC maps. When generating the cropping suitability maps, aggregation and resampling strategies employed in this study may slightly impact the findings, but the proposed definitions were outlined to avoid some arbitrary decision that would not represent well the dissimilarities of the Brazilian territory or impact the purpose of this paper, i.e., a general assessment of the grain cropping suitability coupled with an agricultural LULC analysis. Other integration methods can be further tested to enhance or highlight the cropping suitability restrictions across the Brazilian territory. Another point worth mentioning is that cropping performance is governed not only by environmental or biophysical characteristics but also by other several factors. The crop simulations of this study were restricted to the responses of water and temperature stress for a general assessment of the Brazilian territory. Agricultural decisions and management practices are influenced by socioeconomic factors, such as credit accessibility, infrastructure availability, technological shifts, etc., so these factors may be further tested with the current implementation (Bouman et al., 1999; Alkimim et al., 2015). In fact, the modular characteristic of the proposed suitability method may allow the combination with other complementary information, making possible a flexible integration with additional variables to meet specific goals of a different analysis (Förster et al., 2015; Li et al., 2020). The proposed method can also be extended with either other high-resolution datasets that may improve the representation of biophysical characteristics or that present less associated uncertainty.

5. Conclusion

With historical land use/land cover (LULC) maps, we compared the biophysical determinants (climate, soil, and terrain) on the grain-crop area expansion in Brazil, ranking terrain as the most important factor, followed by climate and soil quality. For the first time, we show that the new croplands expanded towards regions with better climate and terrain conditions while neglecting the soil quality, which is situated mostly in the Cerrado and Amazon regions. In addition, the assessment of CroppingSI coupled with LULC maps was instrumental in understanding that expanding new croplands over current cleared areas (i.e., pastures) may expose them to marginal soil and terrain conditions. This suggests a fragility of the current expansion trend of grain-cropping systems which can substantially put at risk food security, requiring alternative strategies for maintaining or improving food production in the future, such as cropping intensification through yield gap closing or integrated production systems.

Author contributions

The research was conceived by J.L.S, R.S.N.J., P.A.Q.C., A.N.F., A.G. O.P.B, G.S. and D.D.N. Data acquisition, data processing, and statistical analysis were performed by J.L.S, R.S.N.J., P.A.Q.C., M.A.A., A.N.F., R. R., A.L.C., and P.A.T. The manuscript was written by J.L.S. and R.S.N.J. with input from all authors. All authors reviewed the final version.

Data and code availability

The datasets generated during and/or analyzed during the current study are available from the corresponding author upon reasonable request.

Acknowledgments

This research was developed using computational resources from the Center for Mathematical Sciences Applied to Industry (CeMEAI) funded by the São Paulo Research Foundation (FAPESP 2013/07375-0). The authors also thank the Public Policy Research Group from ESALQ/USP for encouraging this research.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apgeog.2023.102937.

References

Akpoti, K., Kabo-bah, A. T., & Zwart, S. J. (2019). Agricultural land suitability analysis: State-of-the-art and outlooks for integration of climate change analysis. *Agricultural Systems, 173*, 172–208. https://doi.org/10.1016/j.agsy.2019.02.013

Alkimim, A., Sparovek, G., & Clarke, K. C. (2015). Converting Brazil's pastures to cropland: An alternative way to meet sugarcane demand and to spare forestlands. *Applied Geography, 62*, 75–84. https://doi.org/10.1016/j.apgeog.2015.04.008

Allen, R. G., et al. (1998). *Crop evapotranspiration: Guidelines for computing crop water requirements*. Rome: FAO.

Alvares, C. A., et al. (2013). Köppen's climate classification map for Brazil. *Meteorologische Zeitschrift, 22*(6), 711–728. https://doi.org/10.1127/0941-2948/2013/0507

Andrea, M. C., da, S., et al. (2018). Variability and limitations of maize production in Brazil: Potential yield, water-limited yield and yield gaps. *Agricultural Systems, 165*, 264–273. https://doi.org/10.1016/j.agsy.2018.07.004

de Assis, A. C. C., et al. (2011). Water availability determines physiognomic gradient in an area of low-fertility soils under Cerrado vegetation. *Plant Ecology, 212*(7), 1135–1147. https://doi.org/10.1007/s11258-010-9893-8

Batjes, N. H., et al. (2017). WoSIS: Providing standardised soil profile data for the world. *Earth System Science Data, 9*(1), 1–14. https://doi.org/10.5194/essd-9-1-2017

Battisti, R., Bender, F. D., & Sentelhas, P. C. (2019). Assessment of different gridded weather data for soybean yield simulations in Brazil. *Theoretical and Applied Climatology, 135*(1–2), 237–247. https://doi.org/10.1007/s00704-018-2383-y

Beyer, R. M., et al. (2022). Relocating croplands could drastically reduce the environmental impacts of global food production. *Communications Earth & Environment, 3*(1), 49. https://doi.org/10.1038/s43247-022-00360-6

Bouman, B. A. M., et al. (1999). A framework for integrated biophysical and economic land use analysis at different scales. *Agriculture, Ecosystems & Environment, 75*(1–2), 55–73. https://doi.org/10.1016/S0167-8809(99)00059-6

de Carvalho Mendes, I., et al. (2012). Biological functioning of Brazilian Cerrado soils under different vegetation types. *Plant and Soil, 359*(1–2), 183–195. https://doi.org/10.1007/s11104-012-1195-6

Carvalho, J. L. N., et al. (2014). *Crop-pasture rotation: A strategy to reduce soil greenhouse gas emissions in the Brazilian Cerrado* (Vol. 183, pp. 167–175). Agriculture: Ecosystems & Environment. https://doi.org/10.1016/j.agee.2013.11.014

CESB. (2021). *Soy Brazil strategic committee*. National Soybean Yield Contest.

Chen, Y., Yu, J., & Khan, S. (2010). Spatial sensitivity analysis of multi-criteria weights in GIS-based land suitability evaluation. *Environmental Modelling & Software, 25*(12), 1582–1591. https://doi.org/10.1016/j.envsoft.2010.06.001

Cherubin, M. R., et al. (2016). Soil quality indexing strategies for evaluating sugarcane expansion in Brazil', *PLOS ONE. W. Liang, 11*(3), e0150860. https://doi.org/10.1371/journal.pone.0150860

Cohn, A. S., et al. (2014). Cattle ranching intensification in Brazil can reduce global greenhouse gas emissions by sparing land from deforestation. *Proceedings of the National Academy of Sciences, 111*(20), 7236–7241. https://doi.org/10.1073/pnas.1307163111

CONAB. (2022). National supply company: Agricultural information system. https://portaldeinformacoes.conab.gov.br/index.php/safras/safra-serie-historica.

Cooper, M., et al. (2005). A national soil profile database for Brazil available to international scientists. *Soil Science Society of America Journal, 69*(3), 649. https://doi.org/10.2136/sssaj2004.0140

Cortner, O., et al. (2019). Perceptions of integrated crop-livestock systems for sustainable intensification in the Brazilian Amazon. *Land Use Policy, 82*, 841–853. https://doi.org/10.1016/j.landusepol.2019.01.006

Davis, K. F., et al. (2017). Increased food production and reduced water use through optimized crop distribution. *Nature Geoscience, 10*(12), 919–924. https://doi.org/10.1038/s41561-017-0004-5

Dias, H. B., & Sentelhas, P. C. (2018). Sugarcane yield gap analysis in Brazil – a multi-model approach for determining magnitudes and causes. *The Science of the Total Environment, 637–638*, 1127–1136. https://doi.org/10.1016/j.scitotenv.2018.05.017

Dias, H. B., & Sentelhas, P. C. (2021). Assessing the performance of two gridded weather data for sugarcane crop simulations with a process-based model in Center-South Brazil. *International Journal of Biometeorology, 65*(11), 1881–1893. https://doi.org/10.1007/s00484-021-02145-6

Duarte, Y. C. N., & Sentelhas, P. C. (2020). NASA/POWER and DailyGridded weather datasets—how good they are for estimating maize yields in Brazil? *International Journal of Biometeorology, 64*(3), 319–329. https://doi.org/10.1007/s00484-019-01810-1

FAO. (1976). A framework for land evaluation, FAO Soils Bulletin 32. http://www.fao.org/3/x5310e/x5310e00.htm. (Accessed 7 September 2021).

FAO. (2015). *AQUASTAT country profile – Brazil*. Rome, Italy. http://www.fao.org/3/CA0213EN/ca0213en.pdf.

Fischer, G., et al. (2009). Agro-ecological zones assesment. In W. H. Verheye (Ed.), *Land use, land cover and soil Sciences - volume III: Land use planning* (pp. 61–81). EOLSS Publications.

Förster, J., Barkmann, J., Fricke, R., Hotes, S., Kleyer, M., Kobbe, S., … Wittmer, H. (2015). Assessing ecosystem services for informing land-use decisions: a problem-oriented approach. *Ecology and Society, 20*(3). https://doi.org/10.5751/ES-07804-200331.

Gorelick, N., et al. (2017). *Google earth engine: Planetary-scale geospatial analysis for everyone* (Vol. 202, pp. 18–27). Remote Sensing of Environment. https://doi.org/10.1016/J.RSE.2017.06.031

Griggs, D., et al. (2013). Sustainable development goals for people and planet. *Nature, 495*(7441), 305–307. https://doi.org/10.1038/495305a

Guerra, A. J. T., et al. (2017). Slope processes, mass movement and soil erosion: A review. *Pedosphere, 27*(1), 27–41. https://doi.org/10.1016/S1002-0160(17)60294-7

Heuvelink, G. B. M., & Pebesma, E. J. (1999). Spatial aggregation and soil process modelling. *Geoderma, 89*(1–2), 47–65. https://doi.org/10.1016/S0016-7061(98)00077-9

Higgins, J. J. (2004). *An introduction to modern nonparametric statistics*. Pacific Grove, CA: Brooks/Cole.

Hunke, P., et al. (2015). The Brazilian Cerrado: Assessment of water and soil degradation in catchments under intensive agricultural use. *Ecohydrology, 8*(6), 1154–1180. https://doi.org/10.1002/eco.1573

Jasinski, E., et al. (2005). Physical landscape correlates of the expansion of mechanized agriculture in Mato Grosso, Brazil. *Earth Interactions, 9*(16), 1–18. https://doi.org/10.1175/EI143.1

Kendall, H. W., & Pimentel, D. (1994). Constraints on the expansion of the global food supply. *Ambio, 23*(3), 198–205. http://www.jstor.org/stable/4314199.

Kinnebrew, E., et al. (2022). Biases and limitations of Global Forest Change and author-generated land cover maps in detecting deforestation in the Amazon. *PLoS One, 17*(7), e0268970. https://doi.org/10.1371/journal.pone.0268970

Klamt, E., & van Reeuwijk, L. P. (2000). Avaliação de atributos morfológicos, físicos e químicos de Ferralsolos e solos relacionados. *Revista Brasileira de Ciência do Solo, 24*(3), 573–587. https://doi.org/10.1590/S0100-06832000000300011

Lapola, D. M., et al. (2018). Limiting the high impacts of Amazon forest dieback with no-regrets science and policy action. *Proceedings of the National Academy of Sciences, 115*(46), 11671–11679. https://doi.org/10.1073/pnas.1721770115

Lehmann, J., et al. (2020). The concept and future prospects of soil health. *Nature Reviews Earth & Environment, 1*(10), 544–553. https://doi.org/10.1038/s43017-020-0080-8

Leite-Filho, A. T., et al. (2021). Deforestation reduces rainfall and agricultural revenues in the Brazilian Amazon. *Nature Communications, 12*(1), 2591. https://doi.org/10.1038/s41467-021-22840-7

Lemaire, G., et al. (2014). *Integrated crop–livestock systems: Strategies to achieve synergy between agricultural production and environmental quality* (Vol. 190, pp. 4–8). Agriculture: Ecosystems & Environment. https://doi.org/10.1016/j.agee.2013.08.009

Li, H., Zhao, Y., & Zheng, F. (2020). The framework of an agricultural land-use decision support system based on ecological environmental constraints. *Science of The Total Environment, 717*, 137149. https://doi.org/10.1016/j.scitotenv.2020.137149.

Loarie, S. R., et al. (2011). Direct impacts on local climate of sugar-cane expansion in Brazil. *Nature Climate Change, 1*(2), 105–109. https://doi.org/10.1038/nclimate1067

MAPA. (2021a). Ministry of agriculture livestock and food supply: National agricultural zoning program for climate risk. https://www.gov.br/agricultura/pt-br/assuntos/riscos-seguro/programa-nacional-de-zoneamento-agricola-de-risco-climatico/portarias.

MAPA. (2021b). SISZARC: Sistema de Zoneamento agrícola de Risco climático. http://sistemasweb.agricultura.gov.br/siszarc/base.action.

Marengo, J. A., et al. (2018). Changes in climate and land use over the Amazon region: Current and future variability and trends. In *Frontiers in earth science* (Vol. 6). https://doi.org/10.3389/feart.2018.00228

Marin, F. R., Zanon, A. J., Monzon, J. P., Andrade, J. F., Silva, E. H. F. M., Richter, G. L., … Grassini, P. (2022). Protecting the Amazon forest and reducing global warming via agricultural intensification. *Nature Sustainability, 5*(12), 1018–1026. https://doi.org/10.1038/s41893-022-00968-8.

Medvigy, D., et al. (2013). Simulated changes in northwest U.S. Climate in response to Amazon deforestation. *Journal of Climate, 26*(22), 9115–9136. https://doi.org/10.1175/JCLI-D-12-00775.1

Mesgaran, M. B., et al. (2017). Iran's land suitability for agriculture. *Scientific Reports, 7*(1), 7670. https://doi.org/10.1038/s41598-017-08066-y

Nóia Júnior, R., de, S., et al. (2020). Effects of the El Niño Southern Oscillation phenomenon and sowing dates on soybean yield and on the occurrence of extreme weather events in southern Brazil. *Agricultural and Forest Meteorology, 290*, Article 108038. https://doi.org/10.1016/j.agrformet.2020.108038

Pimenta, F. M., et al. (2021). Historical changes in land use and suitability for future agriculture expansion in western Bahia, Brazil. *Remote Sensing, 13*(6), 1088. https://doi.org/10.3390/rs13061088

Poggio, L., et al. (2021). SoilGrids 2.0: Producing soil information for the globe with quantified spatial uncertainty. *SOIL, 7*(1), 217–240. https://doi.org/10.5194/soil-7-217-2021

R Core Team. (2021). *R: A language and environment for statistical computing*. Vienna, Austria: R Foundation for Statistical Computing. https://www.r-project.org/.

Rattis, L., et al. (2021). Climatic limit for agriculture in Brazil. *Nature Climate Change, 11*(12), 1098–1104. https://doi.org/10.1038/s41558-021-01214-3

Rodrigues, A. A., et al. (2022). Cerrado deforestation threatens regional climate and water availability for agriculture and ecosystems. *Global Change Biology, 28*(22), 6807–6822. https://doi.org/10.1111/gcb.16386

Rosenzweig, C., et al. (2014). Assessing agricultural risks of climate change in the 21st century in a global gridded crop model intercomparison. *Proceedings of the National Academy of Sciences, 111*(9), 3268–3273. https://doi.org/10.1073/pnas.1222463110

Salton, J. C., et al. (2014). *Integrated crop-livestock system in tropical Brazil: Toward a sustainable production system* (Vol. 190, pp. 70–79). Agriculture, Ecosystems & Environment. https://doi.org/10.1016/j.agee.2013.09.023

de Sant-Anna, S. A. C., et al. (2017). Changes in soil organic carbon during 22 years of pastures, cropping or integrated crop/livestock systems in the Brazilian Cerrado. *Nutrient Cycling in Agroecosystems, 108*(1), 101–120. https://doi.org/10.1007/s10705-016-9812-z

Santos, H. G. dos, et al. (2018). In *Sistema brasileiro de classificação de solos* (5 ed. rev). (Brasília, DF: Embrapa).

Schneider, J. M., Zabel, F., & Mauser, W. (2022). Global inventory of suitable, cultivable and available cropland under different scenarios and policies. *Scientific Data, 9*(1), 527. https://doi.org/10.1038/s41597-022-01632-8

Sentelhas, P. C., et al. (2015). The soybean yield gap in Brazil – magnitude, causes and possible solutions for sustainable production. *The Journal of Agricultural Science, 153*(8), 1394–1411. https://doi.org/10.1017/S0021859615000313

Simons, G. W. H., Koster, R., & Droogers, P. (2020). *HiHydroSoil v2.0 – high resolution soil maps of global hydraulic properties. FutureWater Report 213* [Preprint]. www.futurewater.eu/projects/hihydrosoil

Song, X.-P., Hansen, M. C., Potapov, P., Adusei, B., Pickering, J., Adami, M., … Tyukavina, A. (2021). Massive soybean expansion in South America since 2000 and implications for conservation. *Nature Sustainability, 4*(9), 784–792. https://doi.org/10.1038/s41893-021-00729-z.

Souza, C. M., et al. (2020). Reconstructing three decades of land use and land cover changes in Brazilian biomes with landsat archive and earth engine. *Remote Sensing, 12*(17), 2735. https://doi.org/10.3390/rs12172735

Thornthwaite, C. W., & Mather, J. R. (1955). *The water balance. Centerton*. N.J.: Drexel Institute of Technology, Laboratory of Climatology.

Thornthwaite, C. W., & Mather, J. R. (1957). *Instructions and tables for computing potential evapotranspiration and the water balance* (Vol. 10, pp. 185–311). Publication in Climatology.

Tilman, D., et al. (2011). Global food demand and the sustainable intensification of agriculture. *Proceedings of the National Academy of Sciences, 108*(50), 20260–20264. https://doi.org/10.1073/pnas.1116437108

Trnka, M., et al. (2014). Adverse weather conditions for European wheat production will become more frequent with climate change. *Nature Climate Change, 4*(7), 637–643. https://doi.org/10.1038/nclimate2242

Tulbure, M. G., et al. (2022). Regional matters: On the usefulness of regional land-cover datasets in times of global change. *Remote Sensing in Ecology and Conservation, 8*(3), 272–283. https://doi.org/10.1002/rse2.248

Tyukavina, A., et al. (2017). Types and rates of forest disturbance in Brazilian Legal Amazon, 2000–2013. *Science Advances, 3*(4), e1601047. https://doi.org/10.1126/sciadv.1601047
Vendrame, P. R. S., et al. (2010). Fertility and acidity status of latossolos (oxisols) under pasture in the Brazilian Cerrado. *Anais da Academia Brasileira de Ciências, 82*(4), 1085–1094. https://doi.org/10.1590/S0001-37652010000400026
Venter, Z. S., et al. (2022). Global 10 m land use land cover datasets: A comparison of dynamic world, world cover and esri land cover. *Remote Sensing, 14*(16), 4101. https://doi.org/10.3390/rs14164101
Wheeler, T., & von Braun, J. (2013). Climate change impacts on global food security. *Science, 341*(6145), 508–513. https://doi.org/10.1126/science.1239402
Winkler, K., et al. (2021). Global land use changes are four times greater than previously estimated. *Nature Communications, 12*(1), 2501. https://doi.org/10.1038/s41467-021-22702-2
Xavier, A. C., King, C. W., & Scanlon, B. R. (2016). Daily gridded meteorological variables in Brazil (1980-2013). *International Journal of Climatology, 36*(6), 2644–2659. https://doi.org/10.1002/joc.4518
Xu, J., et al. (2021). Double cropping and cropland expansion boost grain production in Brazil. *Nature Food, 2*(4), 264–273. https://doi.org/10.1038/s43016-021-00255-3
Yan, W., & Hunt, L. A. (1999). An equation for modelling the temperature response of plants using only the cardinal temperatures. *Annals of Botany, 84*(5), 607–614. https://doi.org/10.1006/anbo.1999.0955
Zabel, F., et al. (2019). Global impacts of future cropland expansion and intensification on agricultural markets and biodiversity. *Nature Communications, 10*(1), 2844. https://doi.org/10.1038/s41467-019-10775-z