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Soil organic carbon stocks as driven by land use in Mato Grosso State: the Brazilian Cerrado agricultural frontier

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Abstract

To address national and global demand for agro-based products, agricultural expansion has rapidly become a norm in Brazil since 1950s to date. In recent decades, agricultural expansion and technological advancement have placed the country among the top producers and exporters of agricultural products. The paradigm shifts in farming system from conventional to integrated approach has brought significant changes in land use, which consequently influenced carbon sequestration and soil organic carbon (SOC). This is more prevalent in the State of Mato Grosso, one of the most producers of food in Brazil. On this background, we hypothesized that though forests have potential for SOC stock, which decreases due to conversion to cropland but in longer-term with sustainable management, carbon might accrual significantly in cropland. Therefore, this paper aimed to unveil the nexus between long term land use and carbon stock changes and estimate future SOC stocks in Mato Grosso State of Brazil. To achieve this aim, a hybridization of machine learning and the InVEST prediction models was applied to estimate the land use changes and the SOC stocks between 1990 and 2020 and estimate for 2050. The study revealed that between 1990, 2020, and 2050, croplands increased significantly by at least 78%, pastures decreased by 32%, while forests decreased marginally by about 4% due to agricultural expansions. However, in 1990 and 2020, the SOC stock was slightly up to 147.34 Mg ha^{-1}, it recorded an increase after a longer-time (i.e., in 2050). This increase was substantially under the forests, and marginally in the croplands. Climate-smart agricultural systems such as crop-livestock forest, integrated crop-livestock, and other conservation agricultural practices have great potential to contribute to sustainable development by increasing the levels of carbon in agricultural soils especially,

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after a longer period. Therefore, agricultural policies geared towards low carbon agriculture should be fully integrated into the various government decision making processes as this will guarantee food security and maximize soil carbon sequestration and stocks in the long term. Simultaneously, it is crucial to promote the dissemination of best practices for implementing and sustaining conservation efforts, thereby safeguarding the carbon stocks established to prevent their depletion. This will also support the Brazilian government in achieving its Nationally determined contributions (NDCs) through agricultural soils.

Keywords Integrated agricultural systems · Climate-smart agriculture · MLA · InVEST · Carbon sequestration · Land use · Croplands · Food security

1 Introduction

The impacts of climate change have gained widespread attention worldwide. These concerns are mostly linked to greenhouse gases (GHG), which are mostly caused by emissions of carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O) due to increase in anthropogenic activities over time [1]. The level of CO_2 concentration has increased to about 419 parts per million in recent years (ourworldindata.org) [2]. It raises the average surface temperature globally by around 40% over preindustrial levels [3, 4]. According to the Intergovernmental Panel on Climate Change [5], high emission of CO_2 might have negative influence on the agricultural sector, which depends on climate change. Thus, CO_2 requires natural components (e.g., vegetation, soil, and ocean) to serve as sinks. Studies have established that forests contribute substantially to mitigating climate change and stocking carbon [6, 7]. It became worrisome to acknowledge that growth in population and infrastructure have led to acute deforestation and degradation of the forest ecosystem at every scale (local, regional, and global) [7, 8].

Soils have been a natural pool for terrestrial carbon even before the obvious incidents of climate change. Soil is a vital element of the global carbon cycle and represents the largest terrestrial carbon storage with an estimate of 2500 Gt (1 Gt = 109 t) of total carbon stocks [6, 9], of which soil organic had about 1550 Gt up to 1 m layer depth [10]. It has been reported that a minuscule loss or release from this large C-stock might stimulate a significant impact on future atmospheric CO_2 concentration [11]. Organic carbon is an indispensable part of the soil that enhances soil biodiversity, soil quality, soil ecosystem services, crop yields, and stabilizes global carbon cycle. In recent decades, much attention has been paid on how to promote SOC stocks to mitigate climate change, and various organizations, governments of different nations and other stakeholders have been pioneering the campaign [12].

The strong connection between land use changes and SOC sequestration can never be overemphasized [13]. According to [14], agriculture, forestry, and other land uses (AFOLU) contribute to 22% of global GHG emissions. However, Brazilian GHG accounting reported that AFOLU was responsible for 74% of national GHG emissions with deforestation (49%) and agriculture (25%) [15]. Thus, AFOLU need to be given utmost attention in a nation such as Brazil because the management of land use could either make or mar the environment. Further, SOC stocks dominate largely in the surface soil and are threatened because most anthropogenic activities, especially agriculture, are performed in this soil depth [16]. Understanding SOC dynamics and drivers of carbon sequestration within soil horizons is crucial in predicting the impacts of land use changes on overall soil quality and carbon emissions [17–19]. Therefore, an effective study about the spatio-temporal distribution and variability of SOC in distinct land use requires robust geospatial and statistical approaches including Remote sensing, Geographic Information Systems (GIS), Machine Learning Algorithms (MLA), geostatistics, and the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) models [20–25]. Random Forests (RFs) is one of the popular MLA applicable in modeling and generating spatial predictions of environmental variables including SOC [23, 26]. RFs can model nonlinear relationships using both categorical and continuous covariates and has been effectively applied globally in digital soil mapping (DSM) studies [27]. Further, RFs do not only guarantee a more accurate assessment of prediction uncertainty [28], but it also minimizes the variance relative to some common algorithms [29]. Similarly, the InVEST model has been widely used for estimating ecosystem services including carbon stocks and sequestration across natural and human altered landscapes under various land use scenarios [25], but not very common in Brazil. The InVEST model was developed by the Natural Capital Project to be applied is assessing and mapping ecosystem services including carbon sequestration under different land use over time [30].

Agricultural systems characterized by extensification, and intensification have huge impacts on changes in land use and SOC stocks [31, 32]. These impacts are typically seen in the dense population growing regions such as Brazil where there have been severe conversions from one land use to the other to increase food production [33, 34]. Generally, in similar climate conditions, SOC stocks are assumed to be higher in the forests, pasturelands, and grasslands when compared with croplands [19, 35, 36]. However, it has been shown that in most regions, enhanced agricultural system such as climate-smart agriculture (CSA) has high potential for SOC enrichment in croplands [37–39]. In Brazil for example, several agricultural policies have been introduced to enhance SOC through agriculture. Among the programs include: (i) the RenovaBio program (a federal government biofuel, environmental sustainability, and climate change mitigation policy), that certifies producers to receive C-credits (CBIOs) [40], and (ii) the ABC Plan, which is a low-carbon agricultural policy aimed at increasing SOC stock with a reduced carbon emission [41]. These integrated agricultural systems in Brazil are promoting carbon stocks and food security in most regions of Brazil especially in the agricultural frontier States such as Mato Grosso State.

As a State that contributes to about 30% of national food production [42–47], and as the 3rd largest State in Brazil, the role of Mato Grosso State in carbon balance is crucial. However, there are few studies on land use changes in the region, and this is the first time a study has been conducted focusing on longer-term spatial distribution and changes in SOC stocks as induced by changes in agricultural land use. In this context, we hypothesized that though forests have potential for SOC stock, which decreases due to conversion to croplands but in longer-term with sustainable management, carbon might accrual significantly in croplands. Therefore, this paper aimed to unveil the nexus between long term land use and carbon stock changes and estimate future SOC stocks in Mato Grosso State of Brazil.

2 Materials and methods

2.1 Study area

Mato Grosso State is located within latitude 9.4624° to 17.3142° S, and longitude 50.5144° to 59.2244° W, in the Central West region of Brazil (Fig. 1). The State is among the largest States in Brazil. It has an area of 903 k km^2 and a population of 3.66 million in 2022. If Mato Grosso State was a country, it would be the world's 33rd largest country, being almost as large as Venezuela and Nigeria [48]. Mato Grosso State spans its territory between Tropical Central Brazil and Equatorial. It is the only State in Brazil which has Amazon, Cerrado, Atlantic Forests, and Pantanal, representing four of the six biomes in Brazil. Mato Grosso State is the most geographically dynamic region within South America because it has diverse agro-ecological features including vegetation, land use, climate, and altitude (which ranged from 24 to 1000 m above sea level) [21]. The average annual precipitation is 1700 mm, which ranges between 1200 and 2000 mm [49]. Mato Grosso state is a major Brazilian agricultural producer in several supply chains, such as cotton, meat, and grains (corn and soybean). The 2020/2021 harvest in this State estimated soybean production at 36 million tons, approximately 30% of national production [42–44].

2.2 Data collection, organization, and analysis

Figure 2 shows the flowchart of the research methodology applied in the study. The soil data were acquired from a soil survey data from Department of Soil Sciences, Luiz de Queiroz College of Agriculture, University of São Paulo (ESALQ-USP), which is a subset of a full dataset of the Brazilian soil legacy data (Table 1). The soil survey covered sixty-one sites with 693 samples in 1990, and 572 samples in 2020. The synthesized baseline SOC data is summarized in Table 2.

The baseline dataset used as the predictor in this analysis consisted of SOC measurements from field (as shown in the soil sampling points in Fig. 1). The data allowed for the establishment of a ground truth that served as both the model input and the basis for evaluating the predictive models. The sampling points were strategically distributed across the study region ensuring representation of diverse soil types and land cover characteristics. The Brazilian SOC sampling dataset was used to produce a subset to Mato Grosso State (which is our specific study area), and the data was converted to a geospatial format from a tabular data in CSV format.

In addition to the baseline dataset, various predictive factors, including Average Land Surface Temperature (LST), Rainfall, Elevation, Slope, Normalized Difference Vegetation Index (NDVI), Bare Soil Index (BSI), and Land use, were also adopted (Table 3). These factors were selected based on their relevance to SOC dynamics, and from previous research conducted in different locations, which highlighted their potential as predictors for SOC levels. Similarly, LULC

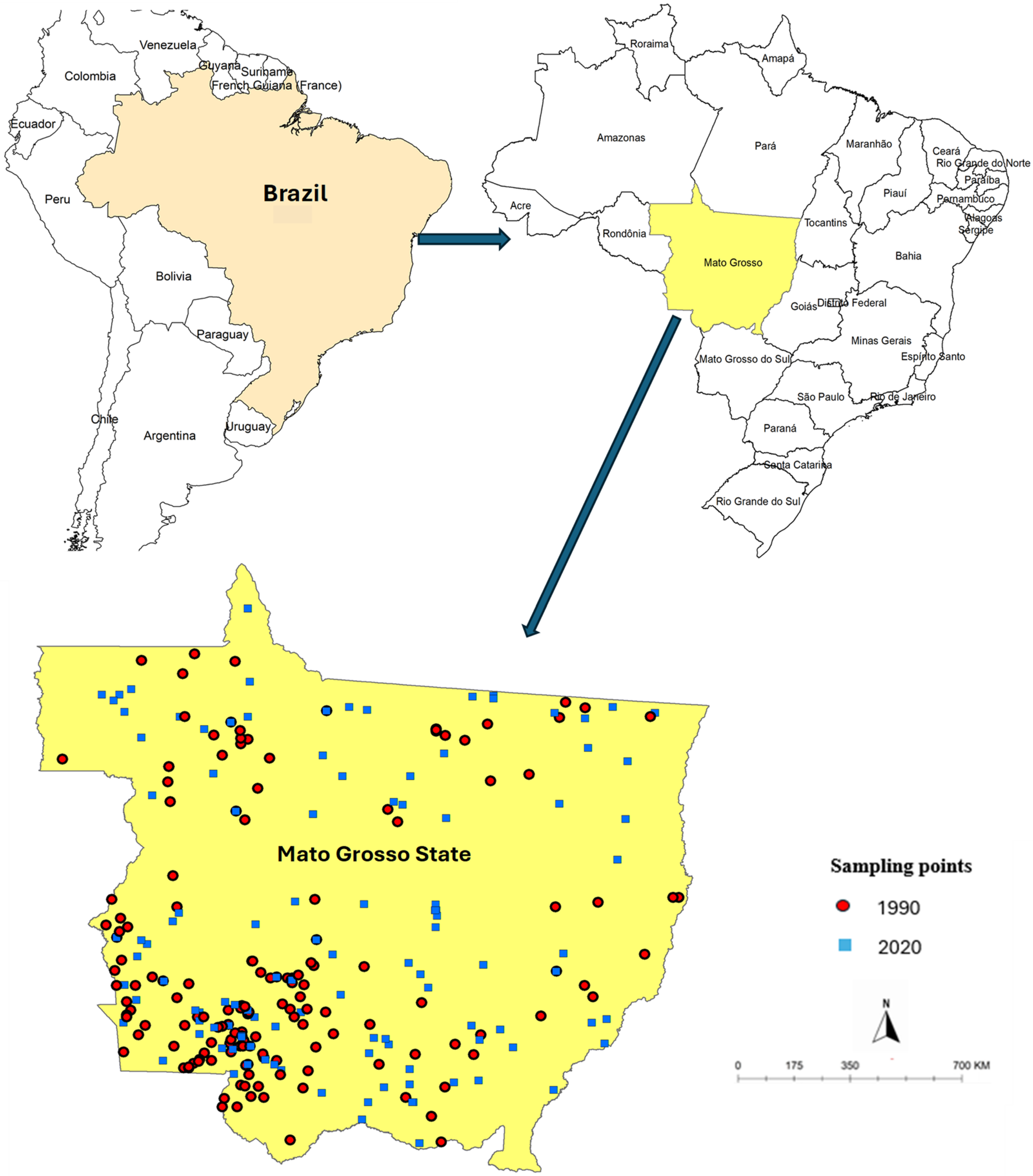


Fig. 1 Map of South America showing Brazil (top left), and Brazil showing Mato Grosso State (top right), and Mato Grosso State, the study area with the sample points for 1990 and 2020 (bottom)

classification was performed based on the information from published literature in the study area on LULC classification (Table 3).

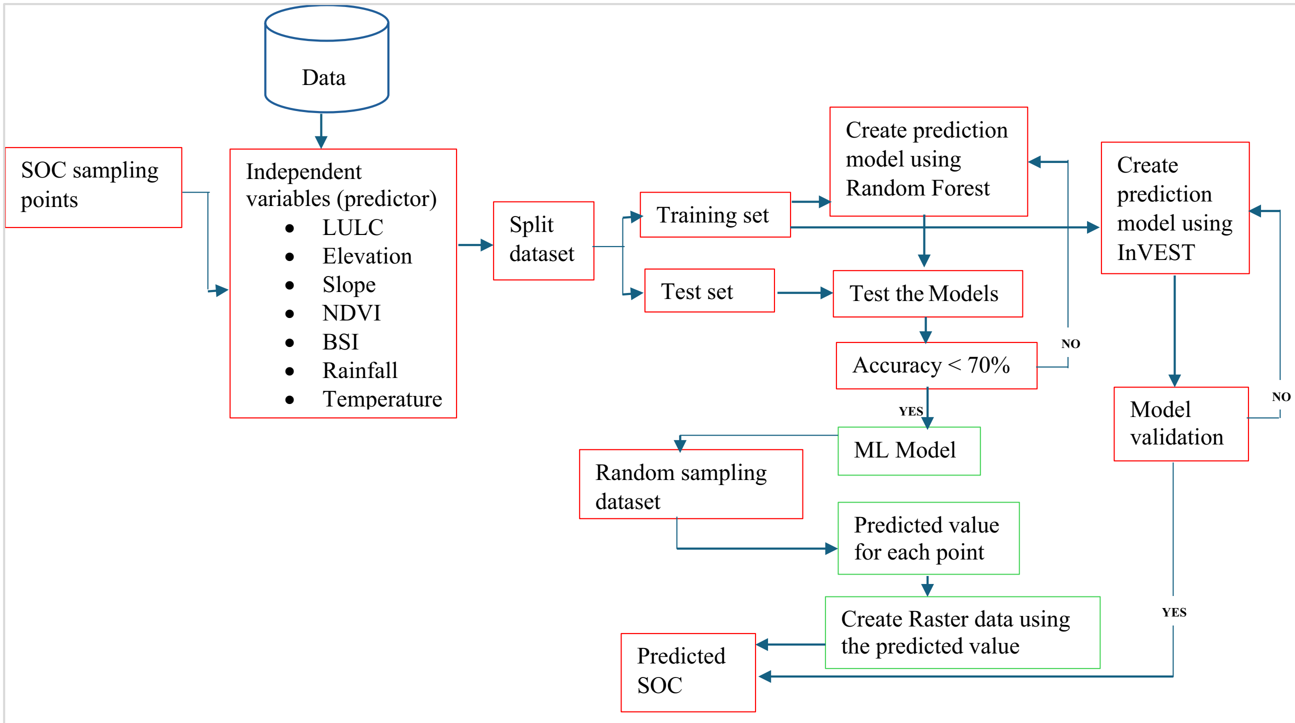


Fig. 2 Flowchart of research methodology

2.2.1 Soil data collection and organization

The scientific inquiry began with the careful collection and preparation of data. Soil Organic Carbon (SOC) measurements spanning 1990 and 2020 constitute the focal point of this investigation. Though, the soil data covered broad areas of Brazil for many years and recorded different profile depths ranging from 0 to 100 cm. This study considered only data with the profile depth of 0–30 cm, and within Mata Grosso State, the study area. In scenarios where there were missing soil data, for example SOC stocks, or bulk density, the Pedo-Transfer Functions (PTFs) established for the tropical areas were applied for the estimation following Eqs. (1) and (2) by [50]. It is pertinent to mention that the percent of stoniness was not considered for the SOC stocks computations because our soil datasets did not contain such information since it is negligible in the soils under the study area.

$$SOC\ stocks_j = \left(SOC_j * BD_j * L_j\right) * 10 \tag{1}$$

where $SOC\ stocks_j$ denotes the soil organic carbon stocks (gm^{-2}) for layer$_j$, SOC_j is the content of soil organic carbon (g kg^{-1}) for layer $_j$, BD_j is bulk density (g cm^{-3}) for layer$_{j,}$ and L_j is soil thickness layer$_j$ (cm). In this study layer$_j$ is the soil profile depth ranging between 0 and 30 cm.

Where the soil bulk density is missing, the PTFs through the following Eq. (2) was applied for the estimation of the bulk density values in the dataset:

$$\text{Bulk density } \left(BD_j\right) = 1.32\text{–}0.73 * \sqrt{SOC_j}\left(\mathrm{R}^2 = 0.73,\ \mathrm{P} < 0.001\right). \tag{2}$$

where BD_j is bulk density (g cm^{-3}) for layer$_j$; SOC_j is the content of soil organic carbon (g kg^{-1}) for layer$_j$; while, in this study layer$_j$ is the soil profile depth ranging between 0 and 30 cm.

In the absence of comprehensive statewide data, this study meticulously utilized measurements gathered at various points to model the relationship and predict SOC dynamics for these two pivotal years. By employing advanced statistical methodologies and machine learning, this study analyzed the interplay between SOC and environmental parameters to derive robust insights for both 1990 and 2020.

To measure the correlation between the predictive variables and the predictors, a correlation analysis was performed on the combined datasets. The dataset was then split into training and testing datasets. The training dataset was used

Table 1 Description of the datasets, source, and their characteristics

S/No.	Data type	Data sensor/type	Cloud cover (%)	Description	Year	UTM zone	Spatial resolution	Source
1	Landsat 4	TM	4.7	LULC	1990	23S	30 m	U.S. Geological Survey (https://earthexplorer.usgs.gov/
2	Landsat 8	OLI	0.3	LULC	2020	23S	30 m	U.S. Geological Survey (https://earthexplorer.usgs.gov/
3	Google Earth images	Google Earth	–	Climate (Prec and Temp)	1990, 2020		0.5–2.5 m	CHIRPS DAILY (https://www.chc.ucsb.edu/data/chirps
4	DEM	SRTM	–	Elevation	2020		30 m	http://earthexplorer.usgs.gov
5	Sentinel-2	Satellite	–	LULC, NDVI, LST	1990, 2020		10 m	Mapbiomas (https://brasil.mapbiomas.org/)
6	Soil (SOC)	Geotif	–	(GSOCmap)	2020		250 m	FAO (https://data.apps.fao.org/)
7	Soilgrid	Geotif	–		2020		250 m	soilgrids.org; WoSIS (World Soil Information Service
8	Soil properties	Excel	–	Brazil legacy data and literature	1990, 2020			http://besbbr.com.br/
9	SOC, Bulk density, etc	Field (Excel)	–	Soil survey data	2001, 2010			ESALQ, University of Sao Paulo

Table 2 Mean and standard deviation of the summarized/synthesized baseline SOC content

LULC class	N	SOC content (g kg^{-1})	
		1990	2020
Forests	413	12.72 ± 4.9	14.35 ± 7.6
Wetland	52	6.21 ± 1.5	6.58 ± 2.7
Pastures	243	9.63 ± 4.3	9.19 ± 5.0
Bareland/sparse veg.	30	0.21 ± 0.3	0.20 ± 0.2
Shrubland	66	5.45 ± 2.8	6.11 ± 3.1
Croplands	461	8.98 ± 7.4	10.30 ± 6.8

to build a model using the Random Forest machine learning algorithm. Random Forest, a powerful ensemble learning algorithm was chosen for its ability to handle complex interactions among variables and provide accurate predictions. Many previous studies have reported high performance when using Random Forest to model the relationship between predictive and predicted datasets. The testing dataset was used to evaluate the model's performance (refer to Sect. 2.5).

Furthermore, to predict SOC values across various locations where there was dearth of data, a separate set of points was generated within the study area at an interval of 100 m. These points were used to extract data from the predictive factors, and the information obtained was utilized to predict SOC values at each location.

The Random Forest algorithm used in this study can be expressed as shown in Eq. (3):

$$\mathrm{SOC} = \mathrm{f(LST,\ rainfall,\ elevation,\ slope,\ NDVI, BSI,\ land\ use)} \tag{3}$$

where SOC represents the predicted Soil Organic Carbon value, f = function, and commas represent addition (+). Meaning that SOC is dependent on the influence from the independent variables. LST represents the Average Land Surface Temperature, Rainfall represents the rainfall data, Elevation represents the elevation information, Slope represents the slope of the terrain, NDVI represents the Normalized Difference Vegetation Index, BSI represents the Bare Soil Index, and Land use represents the land use classification.

2.2.2 Land use land cover classification using machine learning

This study utilized Landsat 4 Thematic Mapper and Landsat 8 Operational Land Image to classify LULC patterns in Mato Grossa State. The imagery was categorized into eight land use classes: croplands, pastures, bare lands/sparse vegetation, forests, settlements/built-ups, shrublands, water bodies, and wetlands considering previous literature on LULC classification in the study area (see Table 3).

An ensemble learning technique called random forests is increasingly being applied in land-cover classification using multispectral [51]. The classification process involved image extraction, preprocessing, training data selection, and machine learning classification using a Random Forest algorithm in Google Earth Engine [51].

A stratified random sampling approach was employed to evaluate the general accuracy of the classification model. Eighty percent (80%) of the data was used for training, while the remaining twenty (20%) was reserved for validation. The accuracy assessment tool in Google Earth Engine compared the classified results to ground truth labels, providing a comprehensive evaluation of the model's performance. The model was iteratively trained and refined until it achieved an accuracy above 80%.

2.3 Predicting LULC changes

The Cellular Automata-Markov (CA_Markov) chain of TerraSET model was employed to predict future land use changes. The model identifies the importance of spatial distribution of transitions [52]. The Markov model is a stochastic model that predicts change probability from a given class to another, by considering the LULC changes at different time (Al-sharif and Pradhan 2014). For example, the model presumes that the transition probability (*Pij*) between state (*j*) and (*i*) is the probability in which LULC (*i* in pixels) in time (*x*) changes to LULC class (*j*) in time (*x* + 1). So, it has the assumption that the change dynamics for a particular area is dependent on the previous or current LULC condition. It is estimated by adopting Eqs. 4 and 5 [53].

Table 3 Historical LULC classes and classification

MODIS—IGBP classification scheme	MapBiomas classification scheme	This study
(1) Evergreen needleleaf forest	N/A	N/A
(2) Evergreen broadleaf forest	(1) Forest; (2) natural forest; (3) forest formation; (9) forest plantation	Forest
(3) Deciduous needleleaf forest	N/A	Forest
(4) Deciduous broadleaf forest	N/A	Forest
(5) Mixed forests	N/A	Forest
(6) Closed shrublands	(10) Non-forest natural formation	Shrubland
(7) Open shrublands	(13) Other non-forest natural formation	Shrubland
(8) Woody savannas	N/A	N/A
(9) Savannas	(4) Savanna formation	N/A
(10) Grasslands	(12) Grassland formation; (15) pasture	Pastures
(11) Permanent wetlands	(5) Mangrove; (11) wetland	Wetland
(12) Croplands	(14) Farming; (18) agriculture; (19) annual and perennial crop; (20) semi-perennial crop	Croplands
(13) Urban and built-up	(24) Urban infrastructure	Settlements/builtup
(14) Cropland/natural vegetation mosaic	(21) Mosaic of agriculture and pasture	Croplands
(15) Snow and ice	N/A	N/A
(16) Barren or sparsely vegetated	(22) Non-vegetated area; (23) beach and dune; (25) other non-vegetated areas; (27) non-observed; (29) rocky outcrop; (30) mining; (32) salt flat	Bareland/sparse vegetation
(17) Water	(26) Water; (31) aquaculture; (33) river, lake, and ocean	Waterbodies
(18) Wooded tundra	N/A	N/A
(19) Mixed tundra	N/A	N/A
(20) Barren tundra	N/A	N/A
(21) Lake	N/A	N/A

N/A not available

$$L(x + 1) = Pij\_L(x) \tag{4}$$

The transition probabilities are generated from the transition samples ocurring during a given time frame El-Alfy et al. [53] and represented in the transition matrix (P).

$$P_{ij} = \begin{vmatrix} P_{11} & P_{12} & P_{13} & \dots & P_{1m} \\ P_{21} & P_{22} & P_{23} & \dots & P_{2m} \\ P_{31} & P_{32} & P_{33} & \dots & P_{3m} \\ P_{m1} & P_{m2} & \dots & \dots & P_{mm} \end{vmatrix} \tag{5}$$

where $L(x+1)$ and $L(x)$ are the LULC status at time $(x+1)$ and (x), respectively.

$0 \leq Pij < 1$ and $\sum(j=1)^\wedge m\ Pij = 1$, $(i, j = 1, 2, 3, \dots, m)$ is the transition probability matrix.

A Markov chain model was applied to generate the transition matrix of the LULC change and the probabilities of change from 1990 to 2020, 2020 to 2050, and 1990 to 2050. The transition matrix provided the key for projecting future LULC change dynamics [54]. On the same hand, the CA model is commonly applied in LULC prediction because of its spatial potential to modify and control processes of complex distributed scenarios. The CA model involves the cell, cell space, neighbor, time and rule, and describes the current structure of LULC, considering the condition of preceding neighborhood cells [55]. The integration of CA–Markov model is paramount for valid dynamic LULC spatial analysis [53].

We adopted the land change modeler (LCM) in IDRISI-TerrSet v.17 to investigate and model the possible LULC change dynamics in 2050. The procedures/steges used in running the CA–Markov in LCM are explained as follows:

Stage I: Creation of the transition probability matrix, and transition area matrix, and transition suitability maps by running different models with the LULC maps of 1990 and 2020.

Stage II: Introduction of a standard contiguity filter of 5 × 5 to determine and form each cell's neighborhoods and produce the spatially explicit weighing factors. After calibrating the model, the scenario-bound method was adopted to simulate the possible LULC pattern in the final process. The procedure included employing the classified LULC maps of 1990 and 2020 to calibrate and refine the Markov chain model. The earliest year (i.e., 1990) was applied as time 1, while the later year (i.e., 2020) was introduced as time 2. The transition probabilities between time 1 and 2 were utilized to simulate the LULC structure in 2050. We validated the CA–Markov algorithm to find the prediction accuracy of 2020 LULC change. The study employed kappa statistics tool to estimate the degree of unison between the projected and the actual LULC maps for the years. Conclusively, the classified 2020 LULC map was utilized as a base map to predict the potential LULC in 2050 by using the transition probabilities of 1990 and 2020.

2.4 Estimation/prediction of SOC

2.4.1 Ordinary least square (OLS)

Ordinary Least Squares (OLS) is a statistical method used to estimate the linear relationship between a dependent (SOC) variable and one or more independent variables by minimizing the sum of squared differences between observed and predicted values. The OLS model assumes linearity, independence of observations, homoscedasticity (constant variance of errors), normality of residuals, and no multicollinearity among predictors [56]. The process involves estimating regression coefficients that best fit the data by minimizing the residual sum of squares. These coefficients represent the expected change in the dependent variable for a one-unit change in each independent variable, while holding other variables constant [56]. Model evaluation is done using metrics like R-squared, adjusted R-squared, and p-values, alongside residual analysis to check for model assumption validity.

2.4.2 SOC estimation using random forests (RFs) model

Random Forests (RFs), a powerful machine learning technique known for its ability to capture intricate relationships in data, are particularly well-suited for estimating SOC levels. Due to bootstrapping and random feature selection, RFs are less prone to overfitting, which allows them to generalize well to unseen data, such as SOC levels projected for 2050 [27]. Additionally, RFs often achieve higher accuracy compared to individual decision trees [27].

Predicting SOC for the year 2050 involved leveraging historical SOC data from 1990 and 2020, alongside various environmental parameters such as slope (×1), elevation (×2), Land use (×3), BSI (×4), rainfall (×5), LST (×6), and NDVI (×7). Utilizing a RFs model, with the aim to capture the intricate relationships between these parameters and SOC dynamics to forecast SOC levels for the future. We bootstrap samples from the historical SOC dataset combined with the environmental parameters (×1,×2,….×7). Each tree is constructed using a subset of the available data through a process known as bootstrap aggregating, or bagging [57]. Moreover, a random selection of features from the total set of environmental parameters (slope, elevation, land use and others) is used to build these trees. For each bootstrap sample, grow a decision tree (T*i*) to its maximum depth without pruning. At each node in the tree, randomly select a subset of features (e.g., 3 out of the 7 features). Mathematically, the prediction for a new sample (*x*) using Random Forest regression can be calculated as shown in Eq. (6):

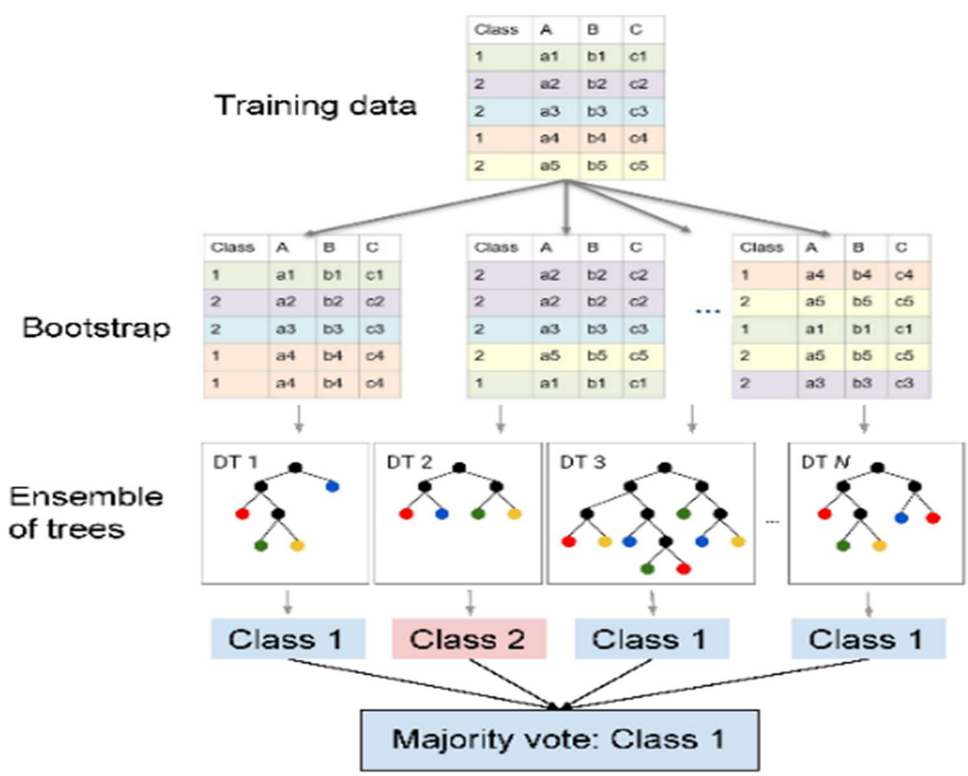
$$\hat{y} = \sum_{i=1}^{I} T_i(x) \tag{6}$$

y^ is the predicted value. *Ti*(x) is the prediction of the i-th decision tree for the input *x*. *I* is the total number of trees in the forest.

Bootstrapping helps us to prevent overfitting by generating multiple training datasets from our original data (Fig. 3). We created each dataset by randomly sampling data points with replacement, meaning a data point can appear multiple times in a single training set. This approach ensures that each tree learns from a slightly different perspective of the data, thereby improving generalizability [57]. At each decision node within a tree, rather than considering all environmental parameters, only a random subset is evaluated [27]. This mechanism forces the tree to identify diverse splitting rules and prevents it from becoming overly reliant on any single feature, which leads to more robust models.

Further, each decision tree in the forest learns by partitioning the data into branches based on specific environmental parameters. These partitions aim to maximize the separation between data points with different SOC values in our study. The tree continues to split until it reaches a stopping criterion, such as a minimum number of data points in a branch. Essentially, each tree creates a series of 'yes/no' questions based on the environmental features, ultimately predicting the SOC level for our data point [58]. Random Forests provide insights into the relative importance of each environmental parameter for predicting SOC levels, aiding in understanding the key drivers of soil carbon dynamics [59].

Fig. 3 Random forests-Bootstrap model demonstration chain and principles



The final prediction for a new data point is not made by a single tree. Instead, all the trees in the forest make their individual predictions based on their learned decision rules. The final SOC level prediction in this study becomes the average of the individual tree predictions, a method known as ensemble voting [27]. This ensemble approach leverages the strengths of each tree while mitigating potential weaknesses, resulting in a more robust and accurate SOC prediction in this our study.

2.4.3 Carbon stock estimation based on The InVEST model

To consolidate the results from the RFs model, the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) model was also applied in predicting the SOC stocks. Carbon stocks were estimated using the carbon storage and sequestration module (CSSM) tool of the InVEST software. The changes in carbon storage resulting from changes in LULC were calculated based on carbon pools [25] to determine the current and predicted future changes in carbon stock. The primary assumption of the CSSM states that the amount of the carbon content of a given LULC is either at a steady state or fixed, and the carbon stock of that specific LULC can be derived by multiplying the amount of carbon content by that of the land area/landmass [60]. The carbon stock module in the CSSM of InVEST model splits the ecosystem carbon pool into four basic carbon sinks consisting of aboveground biomass (i.e., aerial vegetation), belowground biomass (biogenic/roots), soil carbon, and dead organic matter carbon [61, 62]. The sum of the carbon stock of the four carbon pools provides the value for the total carbon storage of the ecosystem in the area, and this could be achieved using Eqs. (7) and (8) [62, 63].

The carbon storage 'Cm,i,j' for a given grid cell '(i,j)' with LULC 'm' can be calculated as:

$$\mathrm{Cm.i.j} = \mathrm{A} * (\mathrm{AGCm,i,j} + \mathrm{BGCm,i,j} + \mathrm{SOCm,i,j} + \mathrm{DOCm,i,j}) \tag{7}$$

where A represents the area (of the cell). AGCm,i,j, BGCm,i,j, SOCm,i,j and DOCm,i,j are the aboveground biomass carbon, belowground biomass carbon, soil organic carbon, and dead organic matter carbon stocks for the given cell (x, y) with LULC 'm' respectively and at a particular time.

$$\text{Thus, total carbon stocks (Ctot)} = \sum_{m=1}^{n} Cm, i, j * Sm \tag{8}$$

Ctot means the total carbon stock (or storage) in the area (given cell); *Sm* signifies the area of the LULC type m; n denotes the total number of LULC types. The carbon in water bodies was assumed to be zero (0).

Consequently, in this study, changes in carbon stock were estimated based on the average values reported in relevant literature in the study region [64–68], and data from the national legacy/inventory [69, 70]. The inVEST model has a limitation of relying on average values, thereby not permitting the use of minimum or maximum values to determine changes in carbon stocks. This limitation notwithstanding, it is efficient in the estimation of SOC stocks.

2.5 Models' validation

The LULC for 2020 was validated by comparing the observed LULC classification for 2020 and simulated LULC using Land Change Modeler for 2020 (as described in Sect. 2.3). Techniques applied in validating the SOC results/models were as shown in Eqs. 9, 10, and 11 [71]. The methods include R-squared (R^2), Mean Squared Error (MSE), and Mean Absolute Error (MAE). The R-squared (R^2) value was used to assess the proportion of variance in SOC explained by the model, with higher R^2 values indicating better model performance. Mean Squared Error (MSE) was employed to calculate the average squared difference between observed and predicted SOC values, with lower MSE values indicating more accurate predictions. Mean Absolute Error (MAE) was also used to measure the average magnitude of prediction errors, providing a straightforward interpretation of model accuracy. The model with the best performance, as determined by the highest R^2 and accuracy score, and the lowest MSE and MAE was selected for final SOC prediction and mapping.

$$\mathrm{MSE} = \sum \left(\mathrm{Y_i} - \hat{\mathrm{Y}}_i\right)^2 / \mathrm{n} \tag{9}$$

$$R^2 = \left[\sum_i \left(\hat{Y}_i - Y_i\right)^2\right] / \left[\sum_i \left(Y_i - \hat{Y}_i\right)^2\right] \tag{10}$$

$$\text{MAE} = \left[\sum |Y_i - \hat{Y}_i|\right]/n \tag{11}$$

where Σ is a symbol that means "sum", Y_i is the observed value for the ith observation, $\hat{Y}_i$ is the predicted value for the ith observation, and n is the sample size for the prediction.

3 Results and discussion

3.1 Models' evaluation/performance

Table 4 indicates the derived accuracy and comparison between observed and simulated data for the LULC prediction. The results show the producer and user accuracies, overall accuracy, and kappa statistics for the LULC classification. The results revealed that the overall accuracy was 85.34% for 1990, and 88.17% for 2020, while the kappa index was 0.84 (i.e. 84%), and 0.85 (85%) for 1990 and 2020 respectively. For the SOC, the evaluation produced a high accuracy of 91.7%, and the model's predictive errors were measured using MAE, which was 4.04, and MSE, calculated at 0.0443, and both showed a low level of error in the predictions.

3.2 Land use

Significant changes in land use were observed between 1990, 2020, and 2050 (Table 5, and Fig. 4). Croplands had the highest positive change by recording a significant increase of 77.6% between 2020 and 2050, and 128% between 1990 and 2050. In contrast, pasture recorded the highest negative change with a significant decrease of 32% between 2020 and 2050, and 38% between 1990 and 2050. On the other hand, settlement increased marginally by 8.1% and 9.5% between 2020 and 2050, and between 1990 and 2050 respectively. Meanwhile, pasture, forests, shrubland, wetland, and water bodies decreased marginally between 1990 and 2050. Brazil is the world's largest producer of many foods such as cotton, meat, corn, sugar cane and soybean (accounting for about 34% of the world total). The State of Mato Grosso is a major Brazilian agricultural producing State and ranks the largest in the production of most of the crop-based foods [72]. The State records a high rate of annual growth, largest cropland expansion and more than 28% of the national soybean production [45]. The 2020/2021 harvest estimated for soybean production in the State was at 36 million tons [42–44]. In recent decades, Mato Grosso and other Brazilian States have increased their agricultural production exponentially to become one of the main global producer and exporter of food, feed, fiber, and fuel [46]. This therefore explains the reason croplands significantly increased between 2020 and 2050 while the pastures and forests decreased as observed in this study. In affirmation to the findings of this study, the report by [47] demonstrated that Mato Grosso State had the largest crop area of 11.78 Mha (i.e.,19.3%) of the total Brazil's crop area in 2022, and followed by Rio Grande do Sul which had 8.92 Mha (14.6%). It was further reported that the agricultural crop expansion potential area of Mato Grosso State is 5.12 Mha, and this value is more than 10 times when compared with most of the other Brazilian States including Rio Grande do Sul which has 0.35 Mha [47].

Table 4 Accuracy assessment of the LULC classification

S/No.	LULC class	1990		2020	
		Producer's	User's	Producer's	User's
1	Forest	90.24	89.95	87.11	84.7
2	Shrublands	86.51	91.07	88.25	79.32
3	Pastures	93.02	73.16	89.54	71.48
4	Wetlands	75.49	81.67	86.03	91.26
5	Croplands	92.53	91.44	90.18	89.51
6	Settlements/built-up	76.99	95.01	88.69	75.36
7	Breland/sparse vegetation	68.17	90.32	81.25	93.04
8	Waterbodies	84.55	95.14	96.07	99.15
	Overall accuracy (OA)	85.34%		88.17%	
	Overall kappa (Kp)	0.84		0.85	

Table 5 Mato Grosso State Land use, and change information in 1990, 2020, and 2050

Land use	1990		2020		2050		Change 1990-2020	Change 2020-2050	Change 1990-2050	Remarks
	Area (km^2)	%	Area (km^2)	%	Area (km^2)	%	[in area(%)]	[in area(%)]	[in area(%)]	
Bareland /Spare Vegetation	187	0.02	184	0.02	181	0.02	3 (1.6)	3 (1.6)	6 (3.2)	-(Decreased very slightly)
Settlement	865	0.09	876	0.09	947	0.1	11 (1.3)	71 (8.1)	82 (9.5)	+ (Increased marginally)
Water Bodies	4,003	0.43	3,996	0.43	3,994	0.43	7 (0.2)	2 (0.1)	9 (0.2)	- (Decreased slightly)
Wetland	22,919	2.45	22,885	2.45	22,761	2.44	34 (0.1)	124 (0.5)	158 (0.7)	- (Decreased slightly)
Shrubland	29,804	3.19	29,755	3.18	28,613	3.06	49 (0.2)	1,142 (3.8)	1,191 (3.9)	- (Decreased marginally)
Croplands	100,622	10.77	129,714	13.88	230,317	24.64	29,092(28.9)	100,603 (77.6)	129,695(128)	+ (Increased significantly
Pasture	267,053	28.57	242,417	25.94	165,835	17.84	24,636(9.2)	76,582 (31.6)	101,218(37.9)	- (Decreased significantly)
Forests	509,199	54.48	504,825	54.01	482,004	51.47	4,374 (0.9)	22,821 (4.5)	27,195 (5.3)	- (Decreased marginally)
TOTAL	**934,652**	**100**	**934,652**	**100**	**934,652**	**100**				

The colour indications are for land use. Grey = Bareland/sparse vegetation; Red = Settlement; Navy blue = Water bodies; Light blue = Wetland; Brown = Shrubland; Yellow = Croplands; Light green = Pasture; and Deep/Dark green = Forests

The bold in the table represents the total area (in kmsq and %) of the land use in 1990, 2020, and 2050

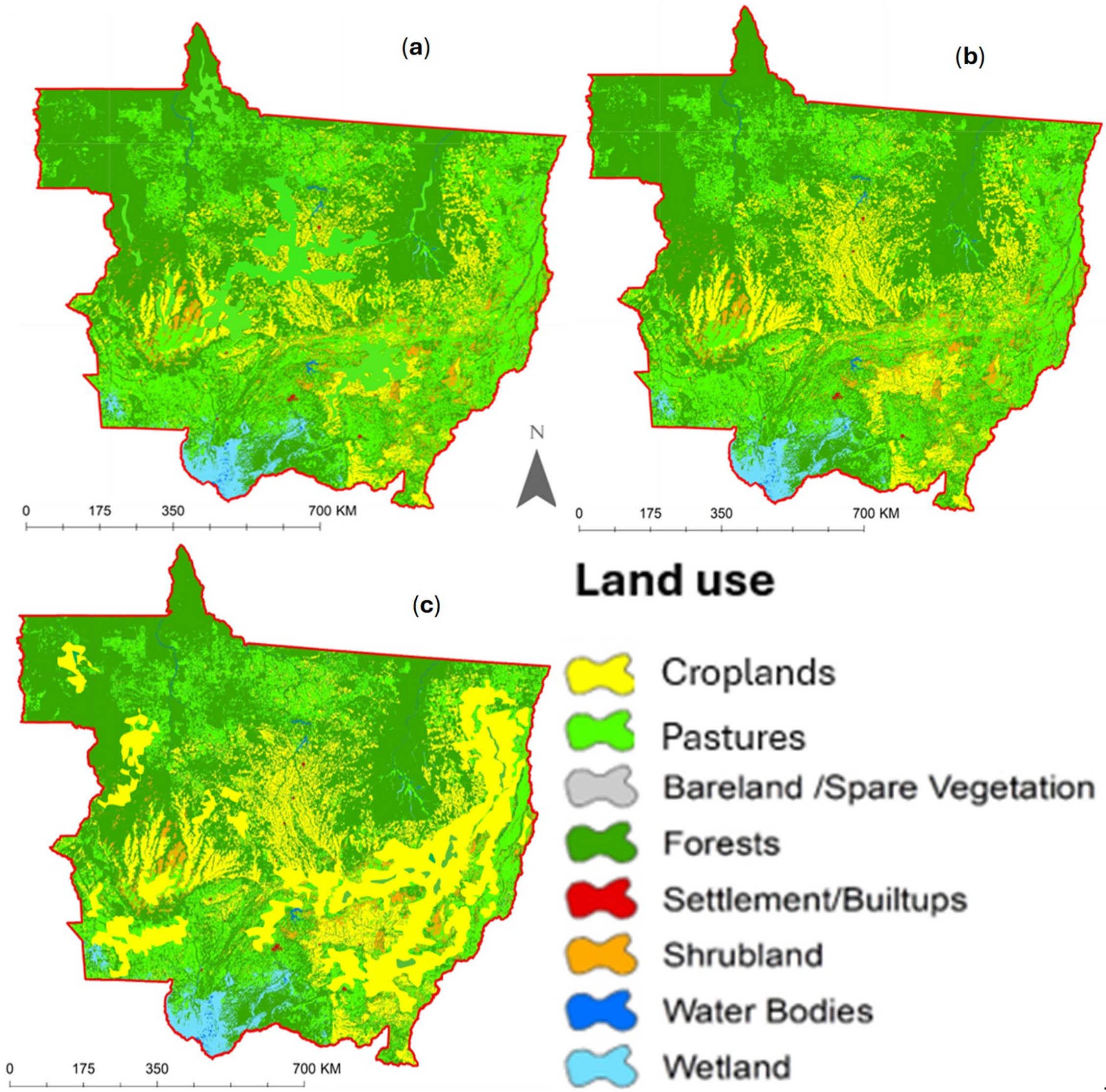


Fig. 4 Land use in Mato Grosso State for **a** 1990 **b** 2020, and **c** 2050

3.3 Soil organic carbon (SOC) stocks

SOC stocks revealed high variability in area and in time during the study period (Figs. 5 and 6). For example, in 1990 fewer areas had the SOC stocks of 147.34 Mg ha^{-1} while in 2020, the SOC stocks had more areas that recorded higher amount of SOC stocks (Fig. 5a and b). On the other hand, estimated values in 2050 were substantially higher above the values for either 1990 or 2020 (Fig. 6). In terms of spatial variability and distribution, the central areas of the State showed the highest SOC stocks when compared with either the Northeast or Southern part. According to Teodoro et al. [21], and da Silva Souza et al. [73], spatio-temporal dynamics in SOC stocks could be attributed to many factors including (i) land use and its changes, (ii) anthropogenic activities and agricultural intensifications and management systems, (iii) environmental drivers (e.g., climate vegetation and elevation), as well as (iv) climate-smart farming policies.

It is important to state that only forests, pastures, and croplands showed significant impacts on the SOC stocks (Table 6), and forests had the highest SOC stocks in all the study years including the predicted year. The increase in forests might not be a surprise because of the recent policies introduced for forest management which support forest under-growth, litter, and microbial biomass activities. The study also observed a marginal increase in SOC stocks under

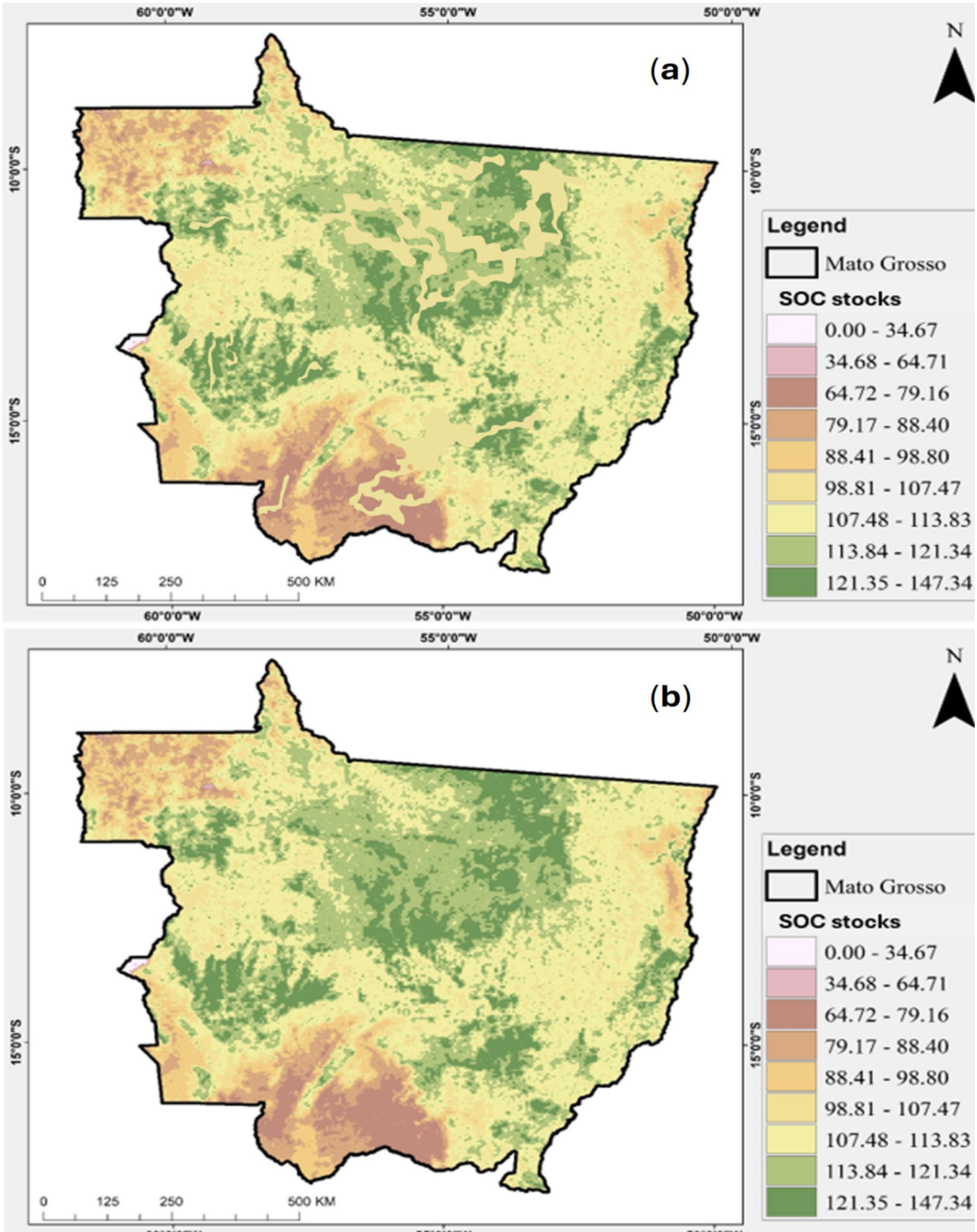


Fig. 5 SOC stocks (Mg ha^{-1}) in Mato Grosso State in **a** 1990 **b** 2020

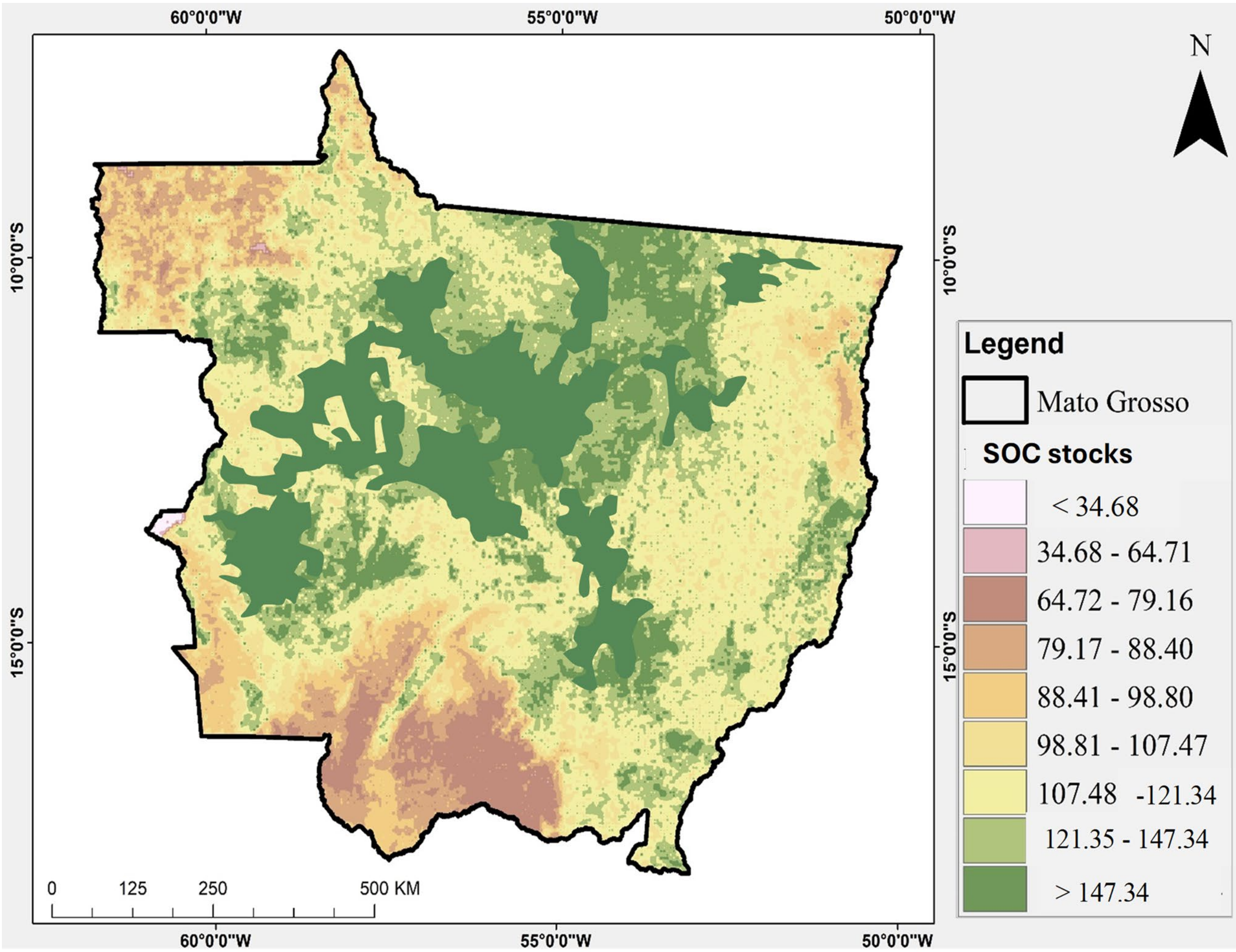


Fig. 6 Predicted SOC stocks (Mg ha^{-1}) for 2050

Table 6 Change in SOC stocks under the different land use in the study years

Land use	SOC stocks (Mg ha^{-1})			Change in value (%)		
	1990	2020	2050	1990–2020	2020–2050	1990–2050
Forests	130.15	141.9	153.08	11.8(9%)	11.2 (8%)	22.9 (18%)
Pastures	112.48	109.5	103.8	2.9 (3%)	5.8 (5%)	8.7 (8%)
Croplands	94.55	113.8	121.34	19.3 (20%)	7.5 (7%)	26.8 (28%)
Shrubland	73.61	72.95	72.88	0.66 (0.8%)*	0.07 (0.1%)*	0.73(1%)*
Wetland	59.32	58.89	59.06	0.43 (0.7%)*	0.17 (0.2%)*	0.26 (0.4%)*
Bareland/sparse vegetation	1.53	1.52	1.52	0.01 (0.6%)*	0	0.01 (0.6%)*

*Change in SOC stocks (in %) were very insignificant and negligible in shrubland, wetland, and bareland/sparse vegetation when compared to forests, pastures, and croplands

the croplands in the predicted year (2050). For instance, in 1990 and 2020, the highest SOC stock under the croplands was 113.83 Mg ha^{-1}, and this value increased by 6.2% (that is 7.51 Mg ha^{-1}) in 2050 particularly in the Cerrado.

Though increasing the croplands by converting some forests and pastures to croplands reduced the total SOC stocks in the study area but over time the croplands might accumulate more carbon (especially in the Cerrado) following a sustainable practice. The adoption of good agricultural land use management is of great benefit for both economic and ecological sectors. For example, previous studies in the country have established that a 1% increase in land productivity led to a 0.0043% reduction in GHG emissions for all Brazilian regions [74, 75]. The prospects of croplands and the Cerrado biome to sequestrate excess CO_2 have been established in previous studies. According to Toloi et al. [2], the Cerrado biome's sequestration potential (3.99E + 07 tons of CO_2eq) is four times higher than its actual emissions, and this neutralizes the impact caused by CO_2 emissions. In addition, the soil C stocks in the topsoil under no-till cropping system was found to have a generally higher C storage compared to native Cerrado and conventional tillage soils in Cerrado [76]. It was also observed that in a-23 year of commercial grain cultivation, there was a SOC stock increase under the cropland compared to the native Cerrado soil [77]. Other authors reported that conversion of low-productivity pasture into CSA (e.g., agrosilvopastoral) and actively managed pasture systems enhanced soil C and N stocks in the Brazilian Cerrado [78]. Further, a recent meta-data analysis by Oliveira et al. [79] also affirmed that sustainable agricultural management such as CSA increased SOC in Cerrado in the long run. Considering these findings coupled with our result, it could be assumed that over time the croplands might accumulate more carbon (especially in the Cerrado) following a sustainable practice, though the contrasting phyto-physiognomies of the region is also an important determinant.

3.4 SOC stocks, land use, other environmental drivers, and soil physical properties

The correlation result reveals notable interrelationships between the drivers of SOC stocks (Fig. 7). For example, soil organic carbon per hectare (Mg ha^{-1}) exhibited a strong positive correlation with land use ($r = 0.643$), and elevation ($r = 0.556$), whereas a moderate positive correlation with rainfall ($r = 0.398$), normalized difference vegetation index (NDVI) ($r = 0.397$), bare soil index (BSI) ($r = 0.395$), and land surface temperature (LST) ($r = 0.398$). SOC showed a weak positive correlation with slope ($r = 0.067$). Rainfall revealed a strong positive correlation with NDVI ($r = 0.919$), BSI ($r = 0.939$), and LST ($r = 0.999$), indicating a robust relationship between higher rainfall and increased vegetation density which consequently enhanced vegetation health and surface temperature.

The study also observed a strong relationship between SOC stocks and clay content ($r = 0.5646$; $p < 0.01$), while SOC stocks decreased with increase in bulk density ($r^2 = 0.4125$; $p < 0.01$) (Fig. 8). These findings highlighted the interlinks among the variables and provided insights into their associations. For instance, strong relationships have been demonstrated between average rainfall, average LST, and NDVI (see Fig. A1), which showed that the northern part of Mato Grosso State had higher values compared to the south. In addition to land use, the variability in the environmental covariables influenced the distribution of SOC stocks in the study area. Many studies have reported strong relationships between SOC and land use in Brazil [21, 73], and globally [20, 80, 81]. In a global scale, it has been reported that if the SOC content in the topsoil under cropland increased from 0.27% to 0.54%, a stock ranging from 0.56 to 1.15 t C.ha.yr^{-1} could be sequestered, and this could represent 0.90 to 1.85 Pg C yr^{-1} for at least a continuous 20 years of the sequestration [80]. Meanwhile, contrary to the findings in our study, a recent study in China concluded that conversion from grassland to cropland produced a negative SOC stock [81]. This could be explained by the short duration of the experiment and other environmental and management factors because a positive result could be achieved over a longer period and not in a short period. Further, the influence of other variables such as soil texture could be substantial. For instance, some studies within and outside Brazil have reported significant relationships between SOC and clay contents [81–84]. Meanwhile, our study observed a significant interaction between SOC stocks and soil physical properties (especially clay and bulk density). As affirmed in a recent study by Mao et al. [83] who established that clay and silt do not only protect microbial

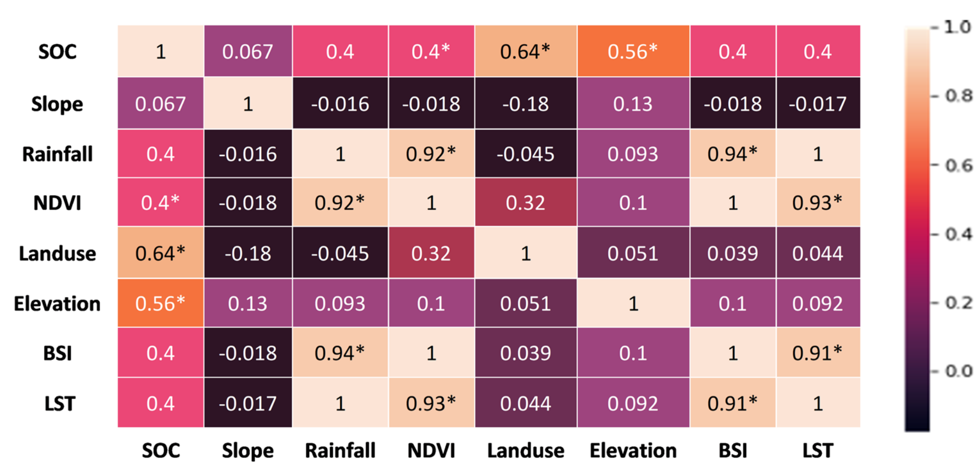


Fig. 7 Summary of the correlation between SOC stocks and other environmental drivers

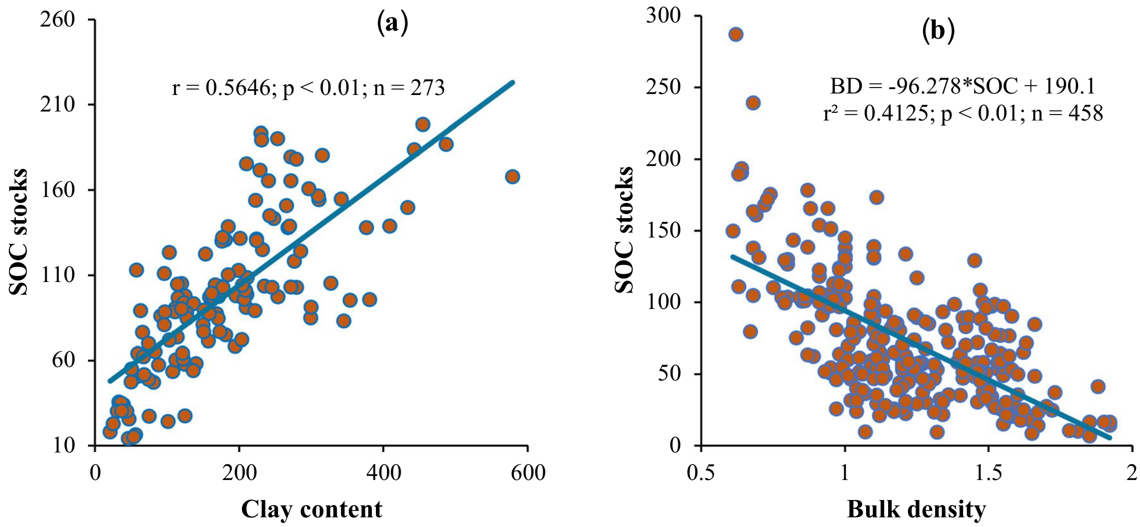


Fig. 8 Relationships between soil organic carbon (SOC) stocks (Mg ha^{-1}) and **a** clay content (g kg^{-1}), and **b** bulk density (g cm^{-3}) in soils from the study area (Mato Grosso State) during the study period. r: Pearson's correlation coefficient, statistically significant at 1% level. n: number of samples

carbon from decomposition but also enhance its production which consequently increased SOC stocks in the dryland soils of Northern Arizona, USA. Similarly, in Brazil, SOC stock was found to have increased with an increase in clay content but decreased with an increase in bulk density [84].

The OLS regression analysis was conducted with a dataset consisting of 2,607 observations (Table 7). The model yielded an R-squared value of 0.708, indicating that approximately 70.8% of the variability in the dependent variable (SOC Mg ha^{-1}) can be explained by the independent variables included in the model (Table 7). The adjusted R-squared value was 0.707, suggesting that the model's predictive power remains consistent even after accounting for the number

Table 7 Summarized ordinary least squares (OLS) regression results used for model validation

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                SOC_t_ha   R-squared:                       0.708
Model:                             OLS   Adj. R-squared:                  0.707
Method:                  Least Squares   F-statistic:                     901.1
Date:                 Sun, 02 Jul 2023   Prob (F-statistic):               0.00
Time:                         16:47:15   Log-Likelihood:                -10824.
No. Observations:                 2607   AIC:                         2.166e+04
Df Residuals:                     2599   BIC:                         2.171e+04
Df Model:                            7
Covariance Type:             nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept    482.1253     19.456     24.780      0.000     443.974     520.277
Slope         -0.0002      0.000     -0.702      0.483      -0.001       0.000
Rainfall       0.6898      0.066     21.146      0.000       1.261       1.519
NDVI           0.0590      1.197      0.049      0.961      -2.287       2.405
Land use       0.7187      0.021      0.897      0.037       0.022       0.060
Elevation      0.6679      0.002     27.645      0.000       0.063       0.073
BSI           -0.0568      1.197     -0.047      0.962      -2.403       2.290
LST           -0.1439      0.064    -21.053      0.000      -1.469      -1.219
==============================================================================
Omnibus:                      405.467   Durbin-Watson:                   0.628
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              967.009
Skew:                           0.876   Prob (JB):                   1.04e-210
Kurtosis:                       5.415   Cond. No.                     3.04e+05
==============================================================================
```

of predictors. Among the independent variables, land use, rainfall, elevation, and LST (Land Surface Temperature) were found to be statistically significant predictors of SOC. Land use, rainfall and elevations had positive coefficients of 0.7187, 0.6898, and 0.6679 respectively which implies that an increase or change in land use, rainfall, and elevations are associated with a change in SOC [21, 73, 74]. On the other hand, LST had a negative coefficient of – 0.1439, suggesting that higher LST values are associated with lower SOC values.

Across the depths, forests have the highest mean SOC stocks relative to pastures and croplands (Fig. 9). Furthermore, the topsoil layer (0–10 cm) under the forests had the largest SOC stocks (162.5 Mg ha^{-1}) in comparison with the deeper layer (133.8 Mg ha^{-1}). Pastures and croplands had higher mean SOC stocks in the deeper layer (20–30 cm) than in the superficial layers. In all the depths, there were statistically significant differences in SOC between forests and other land use, but there were no significant differences between pastures and croplands.

Higher SOC stocks at the topsoil layer of the forests might be attributed to litter [85–87]. On the other hand, low SOC at the topsoil layer under pasture and croplands could be explained by the anthropogenic disturbances [87, 88]. In consistent with our findings, Amanze et al. [87] reported that forests had the highest SOC stocks in the superficial soil layer than in the sub-layers. Meanwhile, they found that the SOC stocks in croplands and pasture decreased with increasing depth, and this contradicts with our result. Further, the results in our study differ from the report by Zhang et al. [88] who observed that though all the land use had high SOC stocks in the subsoil depths, croplands had lower SOC stocks in the topsoil layers when compared to either forest or pastures. The discrepancies in these studies could be explained by variability in cropping systems, and geographic/environmental differences (e.g., soil types, and climate).

SOC stocks in forests and croplands increased throughout the investigated years while pastures recorded a decrease (Fig. 10). The rates of change in land use were not substantial between 1990 and 2020 when compared with 1990 and 2050. The highest increase in SOC stocks were found in croplands (28%), and forests (22%) over the longer-term.

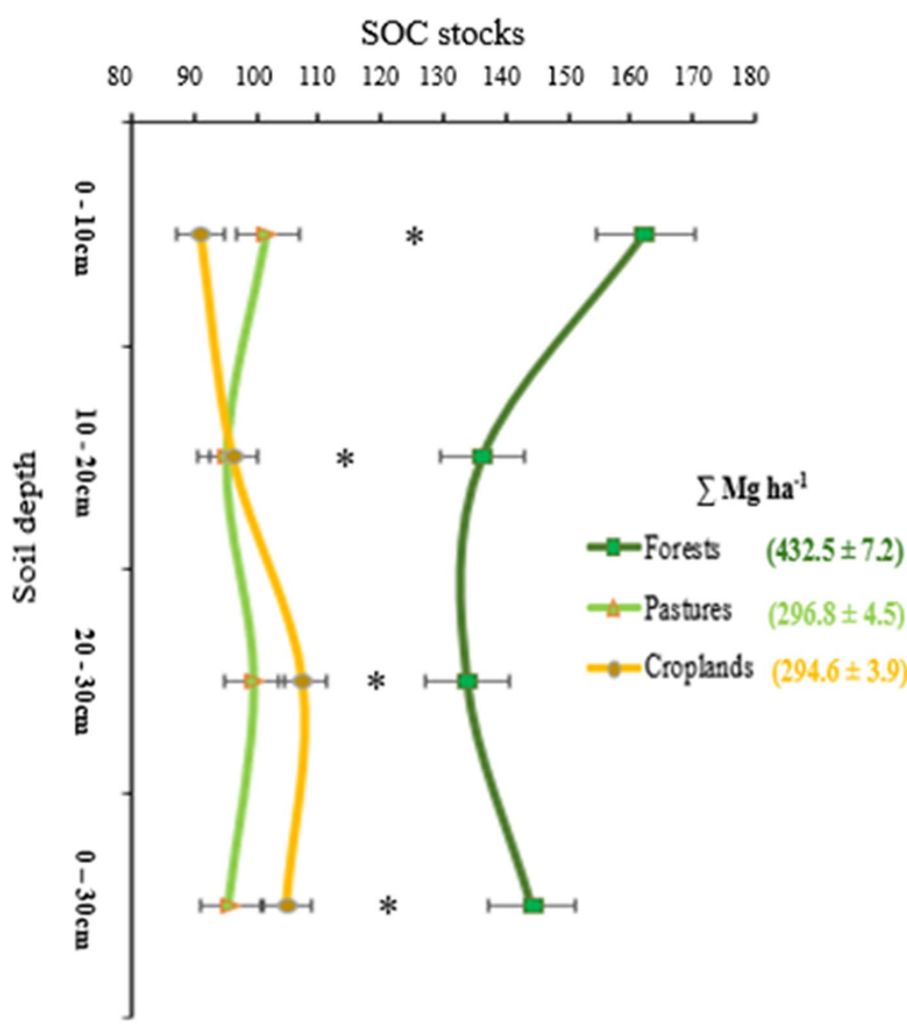


Fig. 9 Mean SOC stocks (Mg ha^{-1}) under the different land use in varying depths (0–10, 10–20, 20–30, and 0–30 cm). Asterisks (*) denote the statistically significant differences (95% confidence interval) in SOC between forests and other land use. There were no significant differences between pastures and croplands. Only three land use types (forests, pastures, and croplands) were considered in this analysis because (i) they showed the largest SOC stocks, (ii) have the most noticed impacts in SOC stocks dynamics, and (iii) occupy more than 93% of the entire area

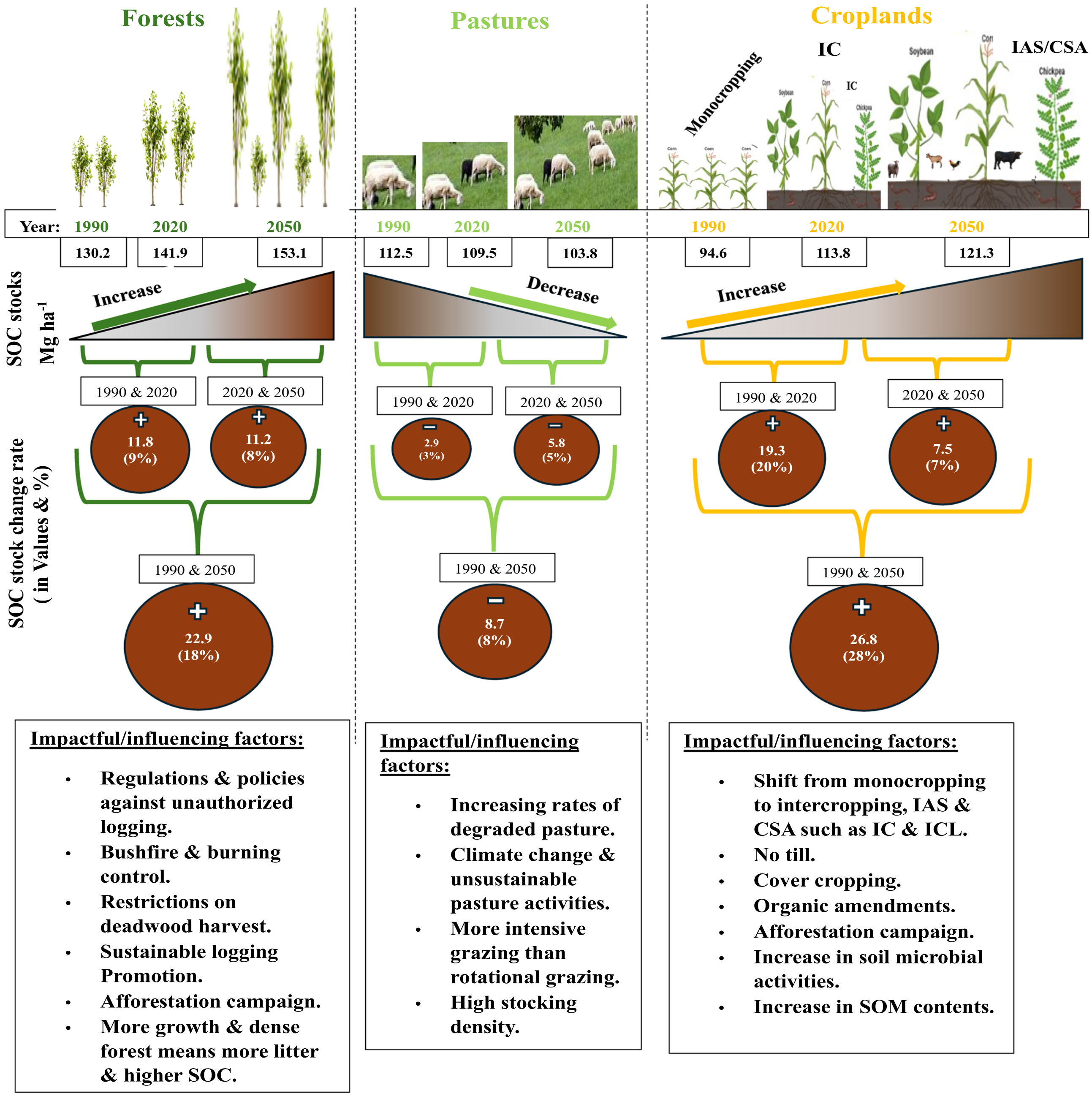


Fig. 10 SOC stocks and change rate in forests, pastures and croplands between 1990, 2020 and 2050, as well as the key drivers. Only three land use types (forests, pastures, and croplands) were considered in this analysis because (i) they showed the largest SOC stocks change, (ii) have the most noticed impacts in SOC stocks dynamics, and (iii) occupy more than 93% of the entire area. IC represents integrated cropping system; ICL represents integrated crop-livestock system; IAS indicates Integrated agricultural system; CSA means climate-smart agriculture

The relatively low change rates between 1990 and 2020 could be explained by the shorter time frame, and the early implementation period of integrated agricultural system (IAS) [89–91]. On the other hand, the long-time estimate revealed significant rates of change in forests and croplands because of the adoption of more favorable policies for sustainable forestry and farm management (see Fig. 10). Some authors have reported a high increase in SOC stocks under croplands in the longer term [91], and the practice of sustainable agricultural system was observed as one of the key drivers for the increase [92, 93]. For instance, it has been revealed that SOC for some cropping systems takes longer time ranging from 30 to 40 years to develop [91]. Furthermore, over the past 40 years, SOC has been reported to have continuously increased in croplands in the Plains of Northern China [92].

4 Conclusion

The study revealed significant changes in land use between 1990, 2020, and 2050. Croplands showed the highest positive change, whereas pastures indicated the highest negative change. Apart from croplands, settlement also increased marginally, while forests, shrubland, and wetland decreased. As obtainable in other high agricultural producing regions of Brazil, the State of Mato Grosso has been popular for the expansion of its arable lands by converting the pastures and forests to croplands. This approach has placed the State and the nation among the top producers and exporters of agricultural products used for different purposes including food, fodder, fibre, and energy (biofuel, biogas, etc.). As the demands for these products (e.g., soybean, maize, sugar cane, oil palm, cowpea, and others) continue to increase, croplands in Mato Grosso will continue to increase.

The spatio-temporal analysis demonstrated that SOC stocks had high variability across the land use, and 2050 recorded substantially higher variability (i.e., more than 50%) when compared with the stocks found in either 1990 or 2020. Strong relationship between land use and SOC can never be overemphasized especially when the topsoil layer is concerned as observed in this study. For example, the Central areas of the State prevailed with larger SOC stocks because of sustainable land use activities including intensive low-carbon agricultural practices adopted in the Cerrado. The increase in SOC stocks in the next 30 years is a promising indication that the adoption of carbon farming systems (such as integrated crop-livestock forest, and crop-livestock) in the established croplands will produce an economic and environmental sustainability in the long-term. However, in the short-term period, adoption of integrated agricultural system (IAS) might not produce a positive result, and this should not deter efforts to introduce more agendas to promote sustainable cropping systems. The current evidence that forests had higher SOC stocks than croplands should not be the basis for not increasing agricultural areas as this helps in providing food for the growing population. Meanwhile, carbon emissions and sequestration should not be treated in isolation since food security, biodiversity, the scenic beauty of the landscape, and local communities need to be considered too. The adoption of a well-managed IAS will not only support food security but will in the long run improve SOC stocks in the croplands. This study will contribute to the decision making on the need to enact more agricultural policies geared towards low carbon farming. Regarding food security, the authors argue that opening new agricultural frontiers and/or expanding cultivation areas is a viable and sustainable approach. Furthermore, findings from the study will support the Brazilian government to implement additional programs to achieve its Nationally Determined Contributions (NDCs) to the United Nations Framework Convention on Climate Change (UNFCCC) under the 2015 Paris Agreement for lower CO_2 emissions and climate change mitigation through agriculture.

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Data availability Data is provided within the manuscript or supplementary information files.

Declarations

Competing interests The authors declare no competing interests.

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