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Abstract

This work aimed at appraising the changes and responses of soil organic carbon (SOC) stocks to the dynamics in agriculture and other land use between 2001–2030 in São Paulo State, Brazil. This is the first time a study of this kind was conducted at State-scale and in Brazil based on a long-term dataset. Also, the first time the application of InVEST model in land use-carbon dynamics studies was performed in a State-scale. InVEST provides the potential to integrate carbon stocks from other soil components (e.g., biogenic sources) than other models. Soil data were sourced from Soilgrid, and Brazilian soil legacy data. Land use-cover data were collected from the Brazilian Institutes (IBGE and MapBiomas), which was classified into 13 classes including cropland, and others. The result revealed that cropland increased by approx. 70,000–90,000 km^2 (i.e., 20% increase), forest increased by approx. 20,000–45,000 km^2 (i.e., 15% increase), while other land use either decreased or had insignificant increase. Regarding SOC stocks, the decadal changes in SOC stocks between 2001–2010, 2010–2020, and 2020–2030 were respectively 1.88 t ha^{-1} (7.1%), 0.71 t ha^{-1} (2.5%), and 0.95 t ha^{-1} (3.3%) for forests, and 1.66 t ha^{-1} (78.7%), 1.51 t ha^{-1} (40.1%), and 3.17 t ha^{-1} (60%) for croplands. Forest had the highest percentage of SOC per hectare (30.07%), but in terms of decadal changes in SOC stocks, cropland had the highest rates of positive increase (i.e., 6.34%). Consequently, these SOC accumulations have helped to mitigate climate change by storing C and reducing atmospheric CO_2. Therefore, this research would provide a vital insight into farming and policymaking on climate change-agriculture sustainability initiatives as a valuable foundation to optimize organized efforts for promoting SOC stocks without compromising environmental safety and food security.

1. Introduction

Globally, anthropogenic activities increased atmospheric CO_2 contents by 0.41% (1.7 parts per million, ppm) between 2022 and 2023 (NOAA 2023a, 2023b), while surface temperature exceeded 1.1 °C between 1900–2020 (IPCC 2023). Particularly, forest degradation and deforestation increased with anthropogenic activities which became the indirect drivers of rises in global surface temperature and global atmospheric CO_2 (Nyarko *et al* 2023, Chervier *et al* 2024). Yet, forest systems such as tropical forests play a key role in climate change and carbon sequestration (Lal 2004a). Soil is not only the most significant component of the global carbon cycle but also forms the largest terrestrial carbon pool (Nwaogu *et al* 2024), accounting for about 2500 Gt of total carbon stocks (Lal 2004a, Hou *et al* 2020), of which soil organic and inorganic carbon composed approximately 1550 Gt and 950 Gt, respectively (Lal 2004b). Soil organic carbon (SOC) is a vital component of the soil that performs essential function in soil fertility, soil health, ecosystem productivity, food security, planetary health, and the global carbon cycle (Nwaogu *et al* 2024). Studies have confirmed that an infinitesimal loss or release from this vast SOC stock would trigger a substantial effect on future atmospheric CO_2 content (Smith *et al* 2008). Therefore, soil as a primary reservoir of terrestrial carbon is becoming a prime focus in carbon storage and sequestration. In recent past, there has been increased efforts by governments and many institutions, groups, and individuals to create awareness aimed at improving SOC stocks and sequestration to mitigate climate change caused by elevated atmospheric CO_2 concentrations (Nwaogu *et al* 2024).

Studies have shown that there is a link between changes in soil organic carbon pools and land use-land cover (LULC) (Wiesmeier *et al* 2019). Globally, it is estimated that land use and land cover including agriculture, forestry, and other land uses (AFOLU) account for 22% of greenhouse gas (GHG) emissions (IPCC 2023). However, this scenario contrasts with the situation in Brazil where in 2021, AFOLU represented 74% of national emissions (49% LULC, and 25% agriculture) (SEEG 2021). The potential of soil profiles in SOC concentrations is vital in agroecosystems, and many studies have demonstrated the critical need to have a good knowledge of SOC dynamics and regulations on carbon sequestration within soil horizons as prerequisites to predict the impacts of land use changes on general soil health and carbon emissions (Camacho *et al* 2023, Damian *et al* 2023).

The spatio-temporal distribution and variability of SOC requires tools that will promote effective investigation under the different land use. Therefore, remote sensing and geospatial technologies have proved effective in studying soil and many other environmental conditions (Xu *et al* 2023, Mahmood *et al* 2024, Ashraf *et al* 2024), and over large land areas (Chen *et al* 2019).

Spatial and vertical distribution of SOC concentration and stocks are controlled by multiple factors including soil properties (e.g., soil texture and bulk density) (Reichenbach *et al* 2023), environmental phenomena (e.g., climate and topography) (Odebiri *et al* 2024, Wang and Huang 2023) and anthropogenic drivers (e.g., human activities, population, and policies) (Nwaogu *et al* 2018). The main drivers of SOC vary significantly at different spatial scales because of the intricate dynamics in the socioeconomic and environmental parameters (Wiesmeier *et al* 2019).

It is well-known that agricultural production pioneered by extensification, and intensification ranks high among the human activities that have significant effects on land use change (Franzluebbers 2023), consequently changes in SOC stocks (Nwaogu *et al* 2018, Oliveira *et al* 2022). This is especially pronounced in the high populated and population growing countries like Brazil where there has been intensive deforestation due to demand for food, energy, and agricultural products (Cherubin *et al* 2015, Oliveira *et al* 2022). In addition, land use-cover spatio-temporal dynamics have profound impacts on the spatio-temporal distribution of SOC (Nwaogu *et al* 2018, Prakash and Shimrah 2023). Although studies have reported diverse findings, there is a consensus that under similar climate conditions, SOC are found more in the forests, pasturelands, and grasslands relative to croplands (Padbhushan *et al* 2022, Damian *et al* 2023, Franzluebbers 2023). Recently, this general notion is becoming obsolete and questionable as it is not realistic in every geographical location, because improvements in agronomic and farm management systems are contributing positively to SOC stocks in croplands (Cherubin *et al* 2015, Oliveira *et al* 2023). In Brazil for example, several agricultural policies have been introduced to enhance SOC through agriculture. Among the programs include the RenovaBio program (a federal biofuel policy), that certifies producers to receive C credits (CBIOs) (Cherubin *et al* 2021), and the low-carbon agricultural policy (ABC plan). These diversified agricultural management systems in Brazil are achieving great feats in repositioning the farmlands to accumulate and stabilize more carbon, and with higher yields.

Top among the Brazilian States which serve as agricultural hubs is São Paulo State. The State is prominent in the productions of sugarcane, soybeans, corn, wheat, and beans (CONAB 2020, Danelon *et al* 2023). In recent decades, agricultural intensification and extensification have become popular in the State with substantial reduction in pasture areas and a significant increase in croplands (Ogura *et al* 2022). São Paulo State became a crucial study area because of its importance in crop cultivation especially for accounting for more than 50% of sugarcane production in Brazil. Sugarcane is a major source of biofuel (ethanol) in Brazil (Ogura *et al* 2022). Thus, significant land use changes have become a norm in the State, and this consequently has substantial implications on the SOC stock vis-à-vis climate change mitigation. However, the potential of cropland expansion in São Paulo State for food and bioenergy has been defined by many authors (Cherubin *et al* 2021), but its associated benefits and challenges need to be assessed.

Although São Paulo as a State in southeastern Brazil is among the top agricultural regions in the country, there is dearth of information on the influence of different LULC (including different agricultural practices) on SOC sequestration. This is because many of the existing studies are limited in either geographical area or temporal extent, thus lack accurate conclusions about variability and changes in SOC stocks since such study requires longer years of investigation. Assad *et al* (2013), Groppo *et al* (2015), and Menezes *et al* (2021) have performed similar studies in same region, but this is the first time a study with a long-term dataset (3 decades:

i.e., 2001–2030) was performed at State-scale in Brazil. The application of the InVEST model in land use-carbon dynamics studies in São Paulo State is also seen as a novelty. InVEST model has an edge over other models in this study because it provided the opportunity to combine carbon stocks from other soil compartments such as biogenic components. However, some previous studies in the region have applied the InVEST model that focused on smaller areas not as large as a State-scale (Bacani *et al* 2024, Santana *et al* 2025, Felix *et al* 2022, Pavani *et al* 2018). For example, in the Três Lagoas municipality of Eastern State of Mato Grosso do Sul (Bacani *et al* 2024), in the Alfenas Municipality of Minas Gerais state (Santana *et al* 2025), Itaperuna Municipality of northwest Rio de Janeiro (Felix *et al* 2022), and in the Northern Coast of São Paulo State (Pavani *et al* 2018), InVEST model was used to assess and quantify SOC sequestrations in different small-scaled land use in Brazil.

Additional novelty of this paper could be defined by the attempt to acquire and integrate soil data from soilgrid, and Brazilian soil legacy data in mapping SOC in different land use. Further, the potential of croplands in accruing more SOC over time under sustainably conservative agriculture was observed, and this could be a part of the novelty of the study because many studies discredited this propensity of croplands. This might be attributed to many factors including short-term study and inclusion of farming systems devoid of sustainable practices. Brazil has recently become famous among the countries that have adopted improved agronomic and conservative agricultural production systems such as crop-livestock-forestry, crop-livestock, livestock-forestry, and other integrated agricultural systems. Thus, these improved farming practices have strong support for the promotion of carbon stocks, and a reduction in carbon emissions.

This study evaluated the changes in agricultural and other land uses as an indicator for changes in SOC in São Paulo State, Brazil. The specific objectives are to: (i) investigate the effect of different land uses on SOC stock; (ii) identify land use system(s) with positive or negative changes in SOC stocks; and (iii) establish the land use with promising support for SOC sequestration in future. Therefore, it is hypothesized that SOC stock is significantly influenced by changes in land use, especially conversion to agriculture. The work will contribute to address the ongoing concern on whether 'croplands have the potential to enhance SOC stocks overtime, if sustainably managed?' The study will provide important insight into the roles of different land uses on soil carbon stock and therefore help scientists, decision-makers, environmental managers, and government agencies to formulate policies for climate-agriculture sustainability. These policies will serve as valuable steps for mitigating climate change and improving food security by implementing sustainable farming systems for promoting soil health via SOC sequestration in agricultural-frontier States like São Paulo and other regions.

2. Materials and methods

2.1. Study area

The study area, São Paulo State is in the Southeastern Region of Brazil (figure 1). The State covers an area of 248,219.481 km^2 and occupies parts of the Atlantic Forest and Cerrado biomes with severe changes in LULC due to changes in agricultural land use and policies (IBGE 2011). The state is characterized by different climate types (Köppen) namely, tropical wet and dry, and humid subtropical (Alvares *et al* 2013, Alvares *et al* 2022). The tropical wet and dry are mostly from March to August, while the humid subtropical are commonly from September to February. The average temperature ranges between 24 °C and 26 °C, while annual rainfall ranges from 1000 to 1400 mm with the highest precipitation occurring between October to March, while June to August records the least amount of precipitation (Vera *et al* 2006, Medeiros *et al* 2016). The annual mean humidity is 74.3% (do Nascimento *et al* 2022). The natural forest vegetation consists of the Atlantic Rainforest along the shore, and at the edges of the plateau. Other zones are dominated by the Cerrado ecosystems. The principal soil types include *Latossolos* (Oxisols) and *Argissolos* (Ultisols and Alfisols) which are dominant and are distributed across the highlands and surrounding lowlands. In the mountainous region, the Pseudo-developed *Cambissolos* (Inceptisols) and *Neossolos Litólicos* (Entisols) are prevalent. Along the rivers' banks, are found *Gleissolos* (Aquents, Aqualfs, Aquepts), *Organossolos* (Histosols), and *Neossolos Flúvicos* (Entsols/Fluvents) (Oliveira *et al* 1999).

São Paulo State has the most developed economy in Brazil, spread over diversified sectors. The total estimated population of the State is 44.42 million (https://censo2022.ibge.gov.br/panorama, 2022), and one of the largest agricultural productive States in Brazil. In addition to crops cultivation, the practice of silvopasture (i.e., crop-livestock systems), and climate-smart agricultural systems (e.g., integrated crop-livestock-forestry) has been common in São Paulo State. Agricultural intensification and extensification have become a tradition, especially in the last 2–3 decades as pasture conversion to cropland has been dominant in the area. Approximately 53.5% reduction in pasture areas and a 143.8% increase in cropland particularly sugarcane cultivation has been reported (Ogura *et al* 2022). Sugarcane is the major source of biofuel (ethanol) in Brazil, and São Paulo State is the top producer with more than 54% of the total production in the country (Ogura *et al* 2022).

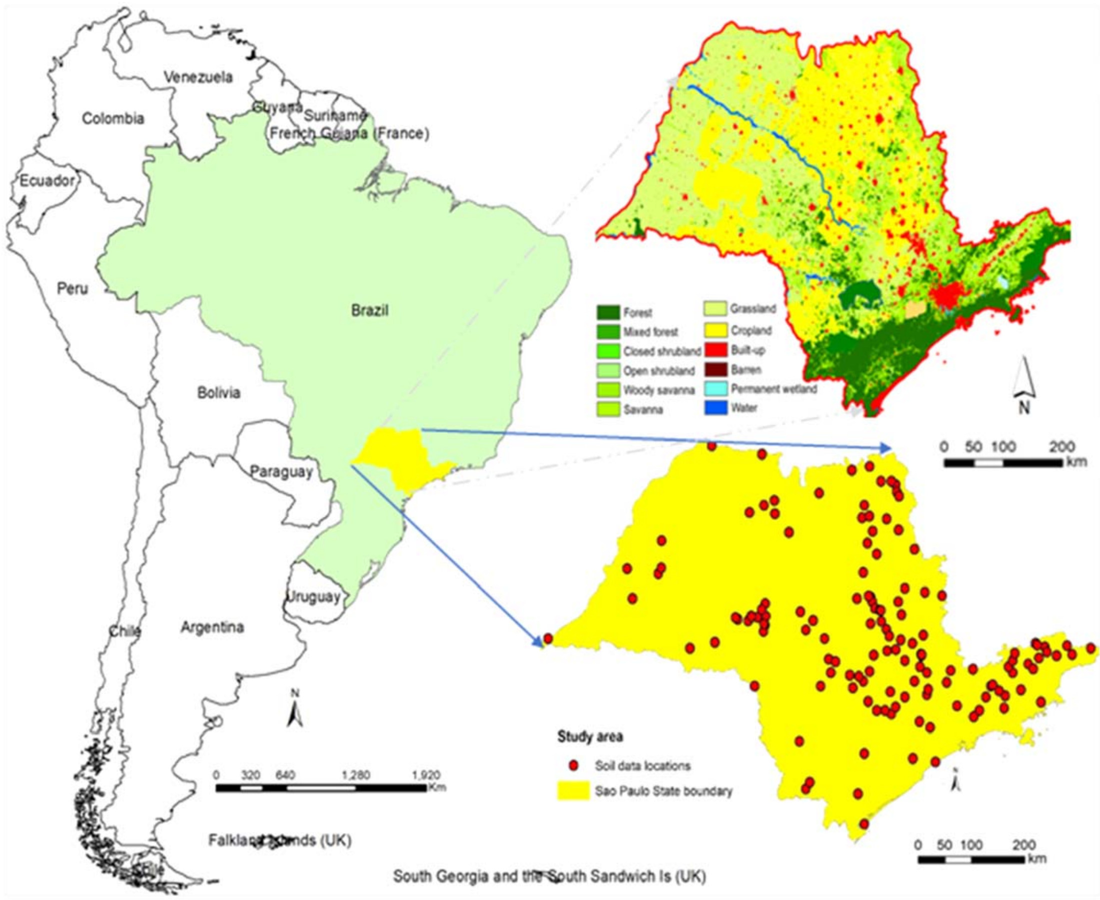

Figure 1. Study area: Brazil in South America, and São Paulo State with land use map (*top right*) and locations for the soil data (*bottom right*). The total number of soil data locations is 154, total number of samples (N) was 462 for the three decades.

2.2. Data collections and analysis

The methodological technique applied in this study followed different procedures including pre-processing of the satellite imageries, image classification, accuracy assessment, LULC change detection, and modelling and prediction of LULC using the CA–Markov chain model (figure 2).

To investigate the changes in different LULC and their effects on selected soil properties including SOC stock, different data from various sources were used (table 1), and these datasets together with information from published literature on the study area were used for the LULC classification (table 2).

2.2.1. LULC: image processing, classification, accuracy assessment, and change detection.

Satellite imageries come with some errors and distortions as well as different resolutions which were rectified, enhanced, harmonized, and managed using the geo-preprocessing tools of ArcGIS10.7, and ENVI 5.3 software and ground control points through pre-processing of the images (such as georeferencing, geometric correction, radiometric calibration, atmospheric correction, and image enhancement). Images with different resolutions were managed by creating a mosaic dataset using appropriate ArcGIS tools (e.g., the Mosaic Dataset toolset in the Data Management toolbox). In this study the maximum likelihood classifier (also known as the Bayesian decision rule) of supervised classification was used in classifying the acquired satellite images.

The input bands employed to generate false-color composite maps were bands 4, 3, and 2 (for Landsat 4 TM and 7 ETM+), and bands 5, 4, and 3, (for Landsat 8 OLI) respectively. 30 m was the spatial resolution for every band in the harmonized dataset. We believe that at this resolution, the evaluation yielded better results (Nguyen *et al* 2020). The spectral identity of each image pixel was harmonized with the training samples of the study area. After that the images were classified into 13 LULC classes, including cropland, forest, grassland/pasture, and others as listed and described in Supplementary table 1. The image classification procedure involved the generation of 180 training samples for each satellite image by applying the region of interest (ROI) tool in the ENVI 5.3 image processing software. Furthermore, existing base LULC maps obtained from the State (such as MAPBIOMAS) and Google Earth maps were also used to support the creation of 60 validation samples used to assess the accuracy of the image classification. The maximum likelihood (Li) of unknown measurement vector

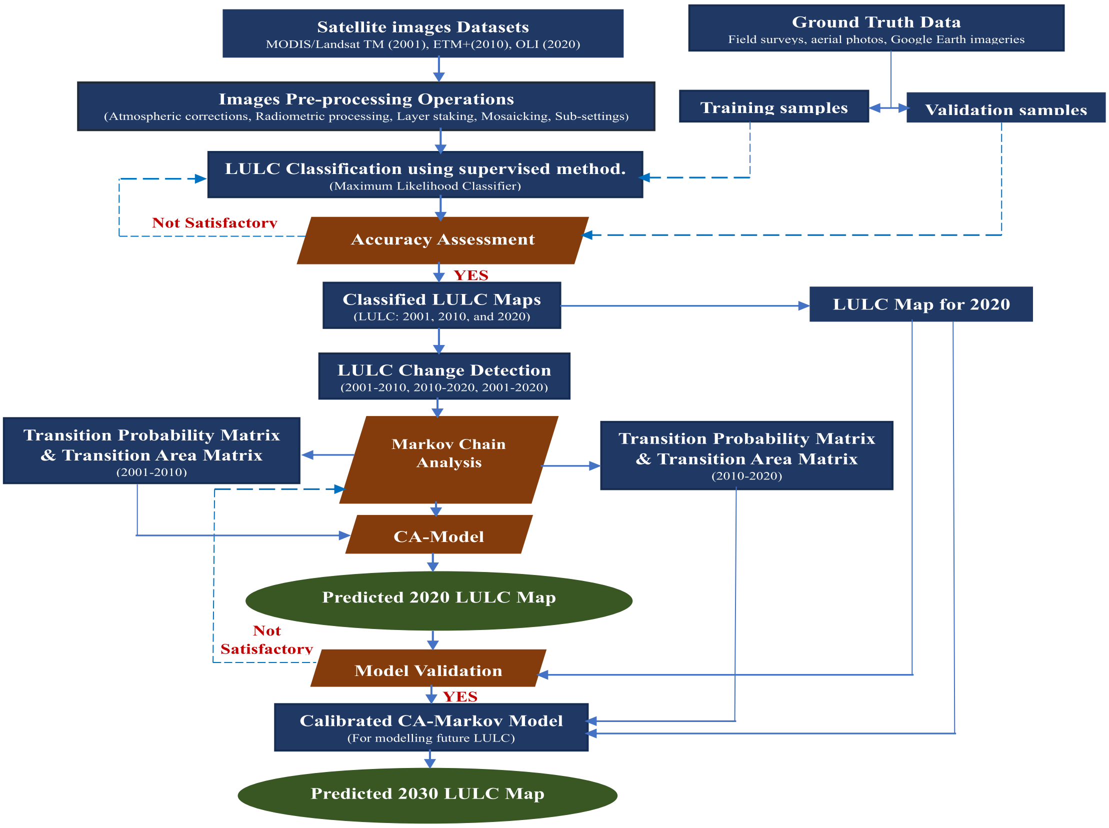

Figure 2. Flowchart of the research methodology.

(x), belonging to one of the known LULC classes (Mc), was derived following the Bayesian equation (equation (1)) (Shivakumar and Rajashekararadhya 2018):

$$Li(x) = \ln p(a_c) - [0.5\ln(|Cov_c|)] - [0.5(X - M_c)T(Cov_c - 1)(X - M_c)] \quad (1)$$

where the discriminant function in the maximum likelihood algorithm is $Li(x)$. The class is a_c, 'i' = 1, 2, 3, 4, M. 'M' is the total class number. 'X' is the n-dimensional pixel of a vector. 'n' represents the number of bands. '$p(a_c)$' is the probability of the exact class at position 'X' in 'a_c' for a pixel. The determinant of the covariance matrix of the data in class 'a_c' is $|Cov_c|$. The inverse of the covariance matrix is 'Cov_c' while the mean vector is 'M_c'.

To determine the reliability and accuracy of the image classification methods, the confusion (error) matrix technique was adopted, and an accuracy level (of > 86%) was considered as excellent and reliable for LULC classification (Ikiel *et al* 2012). The 'producer's accuracy' is defined as the probability of a reference pixel being correctly classified while, 'user's accuracy' represents the probability that a pixel classified on the map represents that category on the ground (Ikiel *et al* 2012, Fung and LeDrew 1988). To realize the average accuracies, the producer and user accuracies were estimated (Fung and LeDrew 1988). The confusion matrix has two main assessment indicators namely, the overall accuracy (OA) and kappa coefficient (K_p) (Kohavi and Provost 1998) as shown in equations (2) and (3). K_p value ranges between −1 and 1 though mostly lies between 0 and 1. Kappa coefficient (K_p) value has the following interpretations: between 0 and 0.20 = indicates slight correlation; 0.21 and 0.40 = fair agreement; 0.41 and 0.60 = moderate correlation; 0.41 and 0.60 = substantial agreement; and 0.81 to 1 defines an almost perfect correlation (Zanotta *et al* 2018).

Overall Accuracy (OA)

$$OA = [(Pc) + (Nc)/(Pc) + (Fp) + (Nc) + (Fn)] \times 100\% \quad (2)$$

Kappa Coefficient (K_p)

$$K_p = [OA - P(e)]/[1 - P(e)] \quad (3)$$

where $\boldsymbol{OA}$ is the overall accuracy and percentage of correctly classified cases. $\boldsymbol{Pc}$ = the number of positive cases with correct identification. Nc = the number of negative cases that were classified correctly. $\boldsymbol{F_p}$ = the number of negative cases classified as positive incorrectly. $\boldsymbol{Fn}$ = the number of positive cases incorrectly classified as negative. $P(e)$ = the anticipated ratio by chance (that is, the proportion of the sum of marginal probabilities multiplication per class to the total class entries).

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

S/no.	Data type	Data sensor/type	Path/Row	Cloud cover (%)	Description	Year	UTM zone	Spatial resolution	Source
1	Landsat 4	TM	225/68	4.7	2001 LULC	2001	23S	30 m	U.S. Geological Survey (https://earthexplorer.usgs.gov/
2	Landsat 7	ETM+	222/71	15.2	2010 LULC	2010	23S	30 m	U.S. Geological Survey (https://earthexplorer.usgs.gov/
3	Landsat 8	OLI	221/70	0.3	2020 LULC	2020	23S	30 m	U.S. Geological Survey (https://earthexplorer.usgs.gov/
4	Google Earth images	Google Earth				2001 and 2010	23S	0.5 to 2.5 m	google earth (https://www.google.com.br/earth/)
5	Sentinel-2	Satellite		0	LULC Map	2001, 2010, 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	2001			http://besbbr.com.br/
9	SOC, Bulk density, etc	Excel			soil survey data	2001, 2010			ESALQ, University of Sao Paulo

Table 2. LULC classes and classification and sources. N/A = Not available.

MODIS—IGBP classification scheme	MapBiomas classification scheme	This study classification
(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	Mixed forest
(4) Deciduous Broadleaf Forest	N/A	Mixed forest
(5) Mixed Forests	N/A	Mixed forest
(6) Closed Shrublands	(10) Non-Forest Natural Formation	Closed Shrublands
(7) Open Shrublands	(13) Other non-forest natural formation	Open Shrublands
(8) Woody Savannas	N/A	Woody Savannas
(9) Savannas	(4) Savanna Formation	Savannas
(10) Grasslands	(12) Grassland Formation; (15) Pasture	Grasslands/pastures
(11) Permanent Wetlands	(5) Mangrove; (11) Wetland	Permanent Wetlands
(12) Croplands	(14) Farming; (18) Agriculture; (19) Annual and Perennial Crop; (20) Semi-Perennial Crop	Croplands
(13) Urban and Built-Up	(24) Urban Infrastructure	Built-Up
(14) Cropland/Natural Vegetation Mosaic	(21) Mosaic of Agriculture and Pasture	Cropland/Natural Vegetation Mosaic
(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	Barren/mining
(17) Water	(26) Water; (31) Aquaculture; (33) River, Lake, and Ocean	Water
(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

The post-classification change (PCC) detection approach was applied to derive the LULC Change detection through an overlay process in GIS which produced a two-way cross-tabulated matrix, indicating different changes in LULC classes. The change matrix generated in ENVI 5.3 extracted the overall quantitative LULC changes and the gains and losses in each LULC type from 2001 to 2020.

2.2.2. LULC prediction using CA-Markov model

The Cellular Automata-Markov (CA_Markov) chain was used as the LULC change prediction model and is a commonly used model for future land use simulation across the globe (Pechanec *et al* 2018). The model identifies the potential spatial distribution of transitions (Wang *et al* 2019). Markov model is a stochastic algorithm that predicts change probability from a given class to another, by considering the LULC changes at various time (Al-sharif and Pradhan 2014). For instance, the model assumes 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 ($x + 1$).

Therefore, it has the assumption that the change dynamics for a particular area is dependent on the previous or current LULC status. It is determined by applying equations (4) and (5) (El-Alfy *et al* 2024).

$$L(x+1) = P_{ij\,L(x)} \quad (4)$$

The transition probabilities are derived from the transition samples evolved during a given time span/interval El-Alfy *et al* (2024) and shown in the transition matrix (P).

$$\mathbf{Pij} = \begin{vmatrix} P_{11} & P_{12} & P_{1m} \\ P_{21} & P_{22} & P_{2m} \\ P_{m1} & P_{m2} & P_{mm} \end{vmatrix} \quad (5)$$

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

$$0 \leqslant P$$

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

A Markov chain model was used to derive the transition matrix of the LULC change and the probabilities of change from 2001 to 2010, 2010 to 2020, and 2020 to 2030. The transition matrix provided the key for projecting future LULC change dynamics (Halmy *et al* 2015). On the other hand, the CA model is commonly applied in LULC prediction because of its spatial potential to modify and regulate processes of complex distributed scenarios. The CA model encompasses the cell, cell space, neighbor, time and rule, and defines the current structure of LULC, in view of the condition of preceding neighborhood cells (Al-sharif and Pradhan 2014). The coupling of CA–Markov model has become important for effective dynamic LULC spatial analysis (El-Alfy *et al* 2024).

The land change modeler was adopted (LCM) in IDRISI-TerrSet v.17 to investigate and model the possible LULC change dynamics from 2020 to 2030. Various steps were applied in running the CA–Markov in LCM as described in Supplementary table 2.

2.2.3. Soil data

Soil data including SOC (e.g., from , SOM, pH, bulk density, texture, CEC, and others were derived from both secondary and primary sources including Soilgrid, Global Soil Organic Carbon Map (GSOCmap), previous published works (Bernoux *et al* 2002, Gomes *et al* 2019, Bieluczyk *et al* 2020), Brazilian soil legacy data and spectral library, and available soil survey data from Luiz de Queiroz College of Agriculture, University of São Paulo (ESALQ-USP). Though the soil data recorded different profile depths ranging from 0–100 cm, this study considered only data with the profile depth of 0–30 cm, and within the study area. The top-soil SOC stock (0–30 cm) has been the focus of this study because it has been reported that the greater proportion of carbon stored in the soil is found in this depth (Nwaogu *et al* 2024). Furthermore, this soil horizon suffers more threats due to acute land use changes and intense human activities (Leul *et al* 2023).

In relation to the point data, where there were missing soil data, for example, SOC stocks, or bulk density (BD), the Pedo-Transfer Functions (PTF) was used to estimate the BD where equation (6) as applied to calculate BD as established by previous studies (Bernoux *et al* 2002, Gomes *et al* 2019). The chemical and physical soil properties data were used to calibrate bulk density PTF based on the relationships between BD and soil properties. The PTF was calibrated using a linear model based on SOC and clay content, which generated a linear regression algorithm (equation (6)):

$$BD = 1.5701 - 0.06884(\%SOC)0.00568(\%clay) \tag{6}$$

where BD represents soil bulk density (g cm^{-3}), and SOC represents soil organic carbon content (%), while % clay represents the soil clay content in percentage.

It is pertinent to mention that the percentage of stoniness was not considered for the SOC stocks computations as the soil datasets did not contain such information since it is negligible in the soils under the study area.

$$SOC\ Stocks = (SOC_j \quad * \quad BD_j \quad * \quad L_j) \quad * \quad 10 \tag{7}$$

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 0–30 cm.

Data from previously published works (Bernoux *et al* 2002, Gomes *et al* 2019, Bieluczyk *et al* 2020) were either extracted from the tables or figures provided with the support of GetData Graph Digitizer software v2.26 (http://getdata-graphdigitizer.com/download.php). The collected data was subjected to rigorous preprocessing steps to ensure accuracy and compatibility. All datasets were spatially aligned using GIS software and R-studio including generalized least squares (GLS), Random Forest (RF) and spatial interpolation techniques applicable for digital soil mapping (DSM). These models including an equal-area spline algorithm were used for data standardization and harmonization, as well as to reduce the spatial dependency effect, and to fix depth intervals (0–5, 5–15, 15–30 cm) following the GlobalSoilMap specifications. Further, the soil dataset (especially SOC), was transformed to the same coordinate system (WGS1984). We estimated SOC_D (% ha^{-1}) for each layer using the following equation (8) and resampled them to a spatial resolution of 30″ × 30″. The transforming, estimation, and resampling were performed in ArcGIS10.7, and R-studio software packages.

$$SOC_D = SOC_c * BD * D * (1 - CF) \quad * \quad 10^{-2} \tag{8}$$

where SOC_C is SOC content (%), BD is soil bulk density (g cm^{-3}), D is soil depth (cm), and CF is the weight proportion of > 2 mm coarse fraction in soil (%). In calculating SOC_D, data of SOC_C, BD, and CF derived from the same soil dataset were used.

2.2.4. Carbon storage estimation based on the InVEST model.

The Integrated Valuation of Ecosystem Services and Tradeoffs (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 (Pechanec *et al* 2018), but not common in Brazil especially Sao Paulo State. The InVEST model was developed by the Natural Capital Project to be applied in assessing and mapping ecosystem services including carbon sequestration under different land use over time (Sharp *et al* 2018). The InVEST was chosen over other models because (i) when compared with other models, it provides the potential to integrate carbon stocks from the biomass (aboveground) and soil compartments including the biogenic sources of soil components; (ii) it has 'robust-data and other models compatibility ability', and is user-friendly and requires relatively zero or non-complex algorithmic equations when compared with other land use and SOC estimation models such as CO2FIX (Masera *et al* 2003), DNDC (Li *et al* 1997), and CENTURY (Parton 1996), (iii) it also supports policy-makers in exploring the possible outcomes of alternative management and climate scenarios by promoting the quantification of tradeoffs among various socioeconomic and environmental sectors and services (iv) it is a non-commercial model that can be accessed freely unlike other land use-carbon change models such as the Idrisi Land Change Modeler (LCM) and Geomod (Nwaogu *et al* 2018) or Soil and Water Assessment Tool (SWAT) (Cong *et al* 2020), (iv) Further, InVEST has an edge over other models because of its efficiency in the integration and quantification of the monetary values of ecosystem services in relation to SOC and social cost of carbon (though not applicable in the present study).

In this study, carbon stock was estimated through the carbon storage and sequestration module (CSSM) tool of the InVEST software using the classified (2020 LULC) to simulate future (2030 LULC) maps of the study area. The changes in carbon storage resulting from changes in LULC were calculated based on soil carbon pools (Pechanec *et al* 2018) 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 immobile 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 (Gong *et al* 2022). 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 (Lin *et al* 2022, Verma *et al* 2024). The sum of the carbon stock of the four carbon pools (if all are available) provides the value for the total carbon storage of the ecosystem in the area as was achieved using equations (9) and (10) (Li *et al* 2023, Verma *et al* 2024). Meanwhile, at least two of the four carbon pools must be used in modeling where all the four carbon pools are either not available or are not necessary. As applicable in this study, where the aboveground biomass carbon and the dead organic matter carbon are not necessary, soil organic carbon stocks and belowground biomass carbon were used (derived from the data collated from the field survey and available soil survey data from Luiz de Queiroz College of Agriculture, University of São Paulo (ESALQ-USP).

The carbon storage 'C_{mij}' for a given grid cell '(ij)' with LULC 'm' can be calculated as:

$$C_{mij} = A \quad * \quad (BGC_{mij} + SOC_{mij} \tag{9}$$

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

Thus, total carbon stocks

$$C_{tot} = \sum_{m=1}^{n} C \quad * \quad S_m \tag{10}$$

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).

Meanwhile, it is important to mention here that 2030 was chosen for the prediction as to have a short-term knowledge about the likely status of SOC stock in the study area. This was ultimately decided considering the United Nations' SGDs 2030 agenda (especially SDG 2-Zero hunger, and SDG 13-Climate action) and the Nationally Determined Contributions (NDCs) agreement by the Brazilian government to reduce carbon emissions and increase C-sequestration through agricultural soils systems.

2.2.5. Models' validation

The models/results were evaluated using some key validation and performance methods as in equations (11)–(13) (Duarte *et al* 2022, Obidike-Ugwu *et al* 2023). 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.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(yi - \hat{y}i)^2 \tag{11}$$

$$R^2 = \frac{1}{n} - \sum_{i=1}^{n}\frac{(yi - \hat{y}i)^2}{(yi - yi)^2} \tag{12}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|yi - \hat{y}i| \tag{13}$$

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.

2.2.6. The limitations or uncertainties of using remote sensing data for SOC estimation

Despite the enormous advantages of applying Remote sensing data for SOC estimations, it also has associated limitations or uncertainties such as (i) errors that emanate from multiple data sources which have different formats, units, and resolutions, thus needs rigorous processes to be harmonized and integrated before usage (Stumpf *et al* 2018, Nieto *et al* 2024), (ii) inconsistency or low consensus in sampling depth and density, (iii) inadequacy in the desired level of informativeness and lack of a standard laboratory procedure and statistical methodology (Takoutsing *et al* 2022), (iv) absence of details on imagery pre-processing or information on the spectral attributes of the targeted soils (Nieto *et al* 2024). Poor precision in the measurement methods and the adoption of small training sample sizes which could increase the prediction errors (Schmidinger and Heuvelink 2024). Additional limitations or uncertainty might originate from the fact that Remote sensing data could lack the granularity to differentiate between varying SOC quantities on the ground, hence this kind of pixel combination may cause inaccurate estimations (Zhou *et al* 2021). Also, the challenges of calibration and validation of satellite data, considering local-regional or global scale factors and site-specific features (Abdelmajeed and Juszczak 2024). In as much as some of these limitations can never ruled-out in the study as obtainable in other studies, we effectively managed them to achieve the optimal goals of the study.

2.2.7. Statistical analysis

The descriptive statistics and correlations of the selected soil properties were calculated using the STATISTICA version 13.0 software package (Statsoft, Tulsa, OK, USA). Soil properties were ordinated by redundancy analysis (RDA) using the multivariate CANOCO version 5.0 statistical package. In this constrained ordination, variables used were the land use-cover classes and the soil properties (SOM, Bulk density, pH, clay, sand, silt, K, Na, Al, CEC, and base sum-SB) as explanatory variables while SOC was the response variable. The data were scaled because the indicators were diverged in measurement units, and subsequently the stepwise selection was adopted to reduce the number of explanatory variables by eliminating collinearity. Finally, in the RDA, the permutation test function was performed with 999 permutations. ANOVA was also applied to determine the mean differences in SOC between the decades and land use, while correlation analysis was performed to ascertain the relationships between SOC and the other soil variables.

3. Results and discussion

3.1. Land use-land cover (LULC) and the changes

The LULC of the study area was classified into 13 classes as shown in table 3. The classified LULC maps of 2001, 2010, and 2020 were produced by applying the supervised maximum likelihood classification. The overall accuracy results obtained from the classified LULC maps for 2001, 2010, and 2020 were 86.72%, 89.03% and 92.11%, while the kappa statistics were 0.82, 0.85, and 0.88, respectively (table 3). This revealed a reliable, accurate, and valid classification of images for evaluating LULC change (Ikiel *et al* 2012).

The LULC was dominated by forest, cropland, grassland/pasture, savanna, mixed-forest which had the highest coverage between 2001–2030 (figures 3(a)–(d)). Some LULC classes have significant changes (e.g., cropland and pastures) while others did not (e.g., open and closed shrublands). Regarding spatial distribution during the 30 years of study, the forest is primarily found in the south and south-eastern part of the study area while, grassland/pasture predominated west and north-western part. On the other hand, cropland is extensively found in the entire area though mainly in the north, north-east, south-west, and central parts (figures 3(a)–(d).

The State of São Paulo is predominantly grassland or pasture during the period of this study (2001–2030). Grassland/pasture accounted for about 40% of the landscape in 2001 but steadily declined over the years. The predicted extent of grassland in 2030 is 29% (table 4). In contrast, cropland, savanna, and forest gradually increased across the study area between 2001–2030. Cropland increased from 21% in 2001 to 25% in 2020, and it is estimated to be about 30% in 2030, and this was predominantly due to sugarcane expansion. Savanna and forest increased slightly between 2001 and 2020. Forest is expected to rise slightly (approx. 15.8%) in 2030.

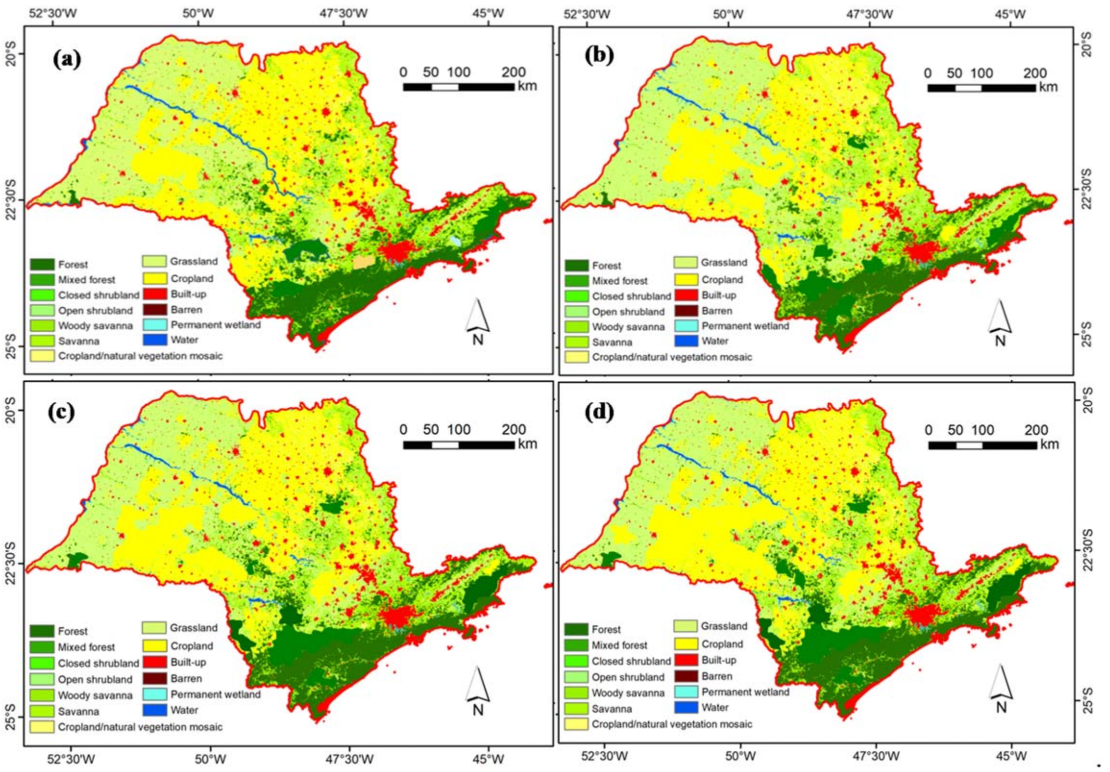

Figure 3. Land use and land cover classification in São Paulo State (Brazil) from 2001 to 2030, showing significant cropland expansion and forest regrowth in certain regions. (a) 2001 (b) 2010 (c) 2020 (d) 2030.

Table 3. Classification accuracy assessment.

S/no.	LULC class	2001 Accuracy (%)			2010 Accuracy (%)			2020 Accuracy (%)		
		Producer's	User's	Kp	Producer's	User's	Kp	Producer's	User's	Kp
1	Forest	85.09	91.47	89.32	77.24	81.67	80.15	81.92	94.06	87.27
2	Mixed forest	93.14	85.66	90.07	73.51	80.99	76.01	92.45	87.97	85.14
3	Closed shrublands	80.27	92.81	82.89	85.61	85.28	84.99	94.33	92.65	93.61
4	Open shrublands	93.11	74.05	86.45	95.01	92.45	90.67	90.26	91.17	90.23
5	Woody savanna	80.75	88.25	83.61	99.26	89.62	91.11	100.0	78.83	95.77
6	Savanna	98.43	96.61	85.95	80.93	97.55	87.83	91.09	96.34	90.48
7	Grassland/pastures	91.97	69.82	80.84	90.62	70.89	86.52	94.38	88.75	89.05
8	Permanent wetlands	78.95	87.55	75.53	85.27	92.41	88.09	87.43	91.26	84.63
9	Cropland	86.04	90.17	84.29	96.74	93.16	92.57	88.94	94.36	87.18
10	Built-up	91.72	100.0	100.0	78.43	87.95	80.91	93.35	75.52	88.99
11	Crop & nat veg mosaic	82.65	89.67	85.44	92.21	99.53	92.75	90.07	85.49	86.25
12	Barren & mining lands	69.88	92.35	80.91	84.68	96.23	91.62	89.95	97.74	83.34
13	Waterbody	84.34	90.44	82.28	91.15	100.0	99.97	71.93	93.41	86.68
	Overall accuracy (OA)	86.72%			89.03%			92.11%		
	Overall kappa stat (Kp)	0.82 (82%)			0.85 (85%)			0.88 (88%)		

Forest dominated the south and south-eastern part of the study area because of the tropical and Atlantic Ocean environment and landscape which have almost 100% Atlantic Forest vegetation and contributed to the Cerrado ecosystems. Grassland/pastures prevail in the western and north-western parts which are historically dominated by ranching. However, in recent years, diversified crop cultivation including specialized and integrated farming systems tend to be replacing pastures with palisade grass (*Urochloa brizantha cv. Marandu*) thus, cropland became widespread in the study area (Danelon *et al* 2023).

Most of the LULC had negative changes in coverage during the 30-years of investigation except the cropland and forest which had a continuous increase throughout the study periods (table 4). For example, cropland increased by 0.89% (between 2001 and 2010), 3.10% (2010–2020), and 4.65% (2020–2030), while forest increased by 1.19% (2001–2010), 0.74% (2010–2020), and 0.30% (2020–2030) respectively. On the other hand,

Table 4. Land use-land cover (LULC) classes and changes in % from 2001–2030.

Land use class	2001	2010	2020	2030	2001–2010	2010–2020	2020–2030
	Land use land cover (%)				Land use land cover change (%)		
Forest	13.574	14.767	15.512	15.811	1.193	0.744	0.300
Mixed forest	0.004	0.004	0.008	0.156	0.000	0.004	0.148
Closed shrublands	0.015	0.012	0.010	0.006	−0.003	−0.002	−0.005
Open shrublands	0.011	0.006	0.004	0.003	−0.005	−0.002	−0.001
Woody savanna	2.546	2.455	2.444	2.318	−0.091	−0.011	−0.126
Savanna	14.246	16.892	16.401	15.240	2.646	−0.439	−1.212
Grassland/pasture	38.476	33.665	31.121	28.648	−4.811	−2.545	−2.473
Permanent wetlands	0.940	0.954	0.845	0.929	0.014	−0.109	0.084
Cropland	20.999	21.884	24.982	29.633	0.885	3.098	4.651
Built-up	4.146	4.128	4.186	4.243	−0.018	0.066	0.057
Crop/natural vegetation mosaic	3.972	4.100	3.392	1.942	0.128	−0.708	−1.450
Barren/mining lands	0.016	0.024	0.017	0.009	0.009	−0.007	−0.008
Water	1.054	1.108	1.078	1.062	0.054	−0.090	−0.016

Table 5. Estimated percentage of SOC (per hectare) in different Land use in 0–30 cm depth.

Land use class	2001	2010	2020	2030	Samplesize
			SOC (%)		(N)
Forest	26.53	28.41	29.12	30.07	66
Mixed forest	12.41	12.75	13.01	13.14	18
Closed shrubland	10.93	8.87	9.06	9.51	15
Open shrubland	5.54	4.99	5.11	5.02	21
Woody savanna	13.63	11.64	12.25	10.35	20
Savanna	9.82	11.52	10.13	9.87	85
Grass/pastureland	8.34	7.93	5.07	2.25	117
Permanent wetland	3.27	3.18	2.34	1.96	12
Cropland	2.11	3.77	5.28	8.45	78
Crop/natural vegetation mosaic	7.41	6.94	8.63	9.38	24
Barren/mining	0.01	—	—	—	6
Built-up	—	—	—	—	—
Water	—	—	—	—	—

the grassland/pasture area decreased significantly by 4.81% (2001–2010), 2.55% (2010–2020), and 2.47% (2020–2030) (table 4). São Paulo State is in the 6th place among the States with the largest area of integrated agricultural systems (IAS) in Brazil (approx. 1.3 million ha). The State is favorable for extensive crop cultivation because of its prevailing management and environmental systems including rainfall amount ranging from about 1,000 to 1,400 mm year^{-1} (Vera *et al* 2006, Coltro *et al* 2009, Medeiros *et al* 2016). When compared with other land use, the pastureland decreased significantly during the entire study period, and this could be explained by the extensive conversion of the pastures to sugarcane (cropland) (Cherubin *et al* 2021).

3.2. Carbon stocks and land use

Across the study periods, forests accounted for the highest percentage of SOC per hectare when compared with other land use (table 5).

The result on the total C-stocks (in g m^{-2}) (figures 4(a), (b)), and the C-stock change status (figure 4(c)) revealed variations across the area. This was also established in previous studies conducted in Brazil and other regions (Ercole *et al* 2023, Sahu *et al* 2023) and this could be explained by many biophysical and human factors (Gutierrez *et al* 2023, Nwaogu *et al* 2023, Okolo *et al* 2023). In the south and south-eastern part, which is forest dominated, the total C-stock was more than 6500 g m^{-2} for 2020 and 2030 (figures 4(a), (b)). This agreed with the range found in the earlier studies by Bernoux *et al* (2002) in the same study area. Cropland, grassland/pasture, mixed forest, and shrubland areas had total SOC stocks ranging from 601–6500 g m^{-2}. Forest accounted for about 27% of SOC per hectare in 2001 and is expected to rise above 30% in 2030. This finding was consistent with the results from other studies in different tropical and subtropical regions of the world such as Nigeria (Okolo *et al* 2023), China (Yang *et al* 2023), Ethiopia (Geremew *et al* 2023), and India (Sahu *et al* 2023). This could be attributed to many reasons including control of erosion (Yang *et al* 2023), soil and vegetation

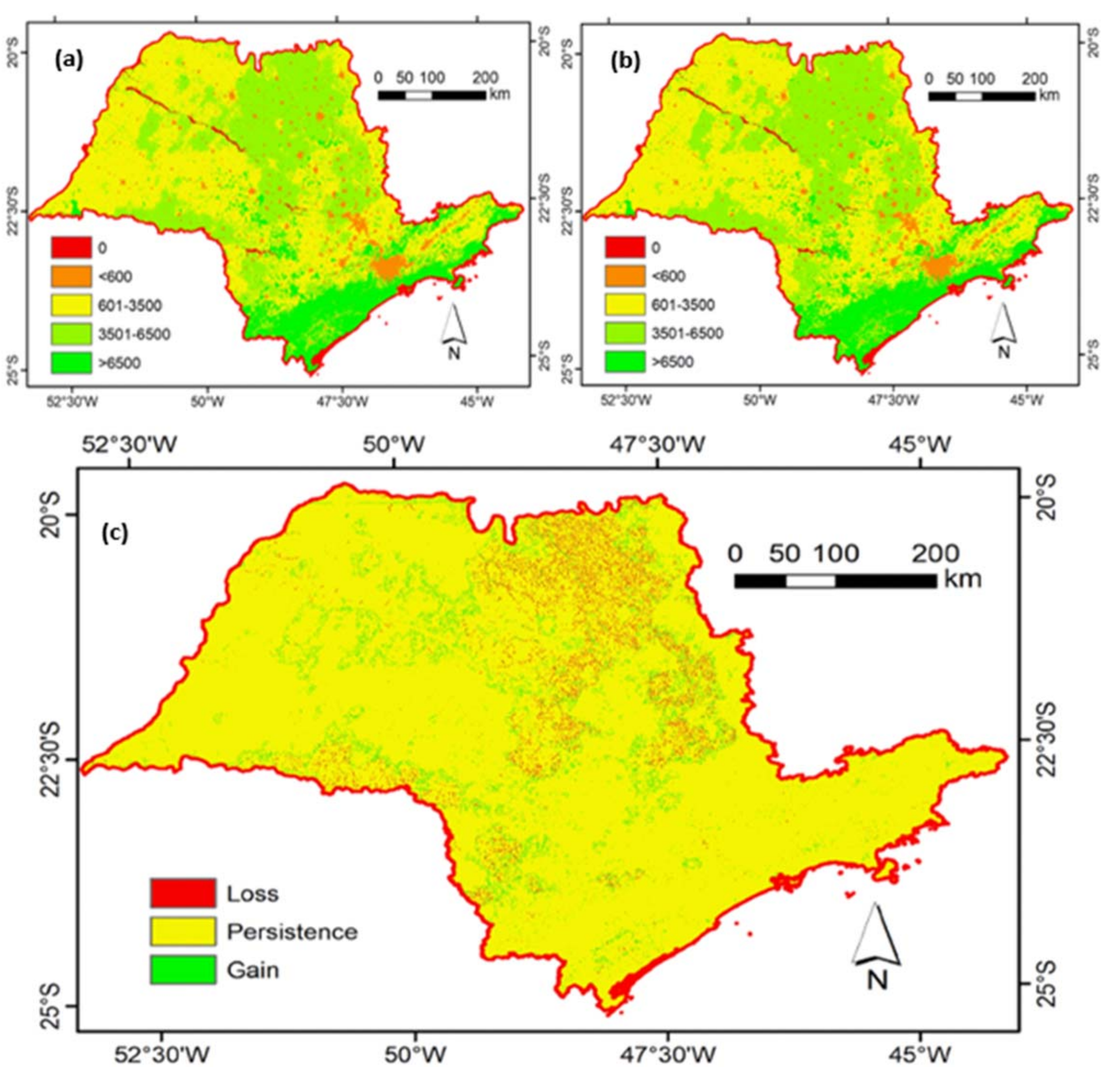

Figure 4. Total carbon stocks (g m^{-2}) estimated to (a) 2020, (b) 2030, and (c) the carbon stocks change status from 2020–2030 in the 0–30 cm depth.

characteristics (Zhao *et al* 2023), other environmental drivers (Gutierrez *et al* 2023), and human management factors (Nwaogu *et al* 2018, Nwaogu *et al* 2023).

In terms of the change status of the total C-stocks, the model result revealed a persistence status for most land use though, a significant gain was found in the central parts of the area under cropland (figure 4(c)).

Although cropland was not among the land use with the highest SOC per hectare, it had the highest positive change across the study periods in terms of the decadal changes in SOC stocks (table 6, figure 5, and figure 6). For example, between 2001 and 2010, there was an increase of 1.66 tons ha^{-1} (i.e., about 79%) of SOC stocks in cropland and 1.51 tons ha^{-1} during 2010–2020 period. Still under cropland, carbon stock is predicted to increase from 1.66 tons ha^{-1} to 3.17 tons ha^{-1} between 2001 and 2030 respectively (table 6). Other land use with continuous increase in SOC stocks from 2001–2030 were forest and mixed forest. In contrast, there was a sharp decline in SOC stocks under grassland/pasture and permanent wetlands (table 6, figure 5 and figure 6). Further, there were significant mean differences in SOC across the decades (figure 5(a)), also most of the land use revealed significant differences in SOC stocks between the decades (figure 5(b)). Substantial changes in the land use are responsible for these mean differences in SOC (Mello *et al* 2014, Cherubin *et al* 2021, Oliveira *et al* 2023). Contrary to the findings from some previous studies (Hartono *et al* 2023, Wang and Huang 2023), cropland increased in SOC, and this corresponds to the findings by other studies (Odebiri *et al* 2024, Heikkinen *et al* 2021, Wiesmeier *et al* 2019), which also revealed higher carbon levels in the topsoil of croplands. The accumulation of SOC in agricultural landscapes over longer-term might be caused by improved agricultural management systems including: (i) crop diversification and intercropping with cover crops (Locatelli 2024), (ii) organic residues, green manure and other nutrient amendments such as biochar and compost (Kumar *et al* 2025), (iii) crop rotation (Yao *et al* 2025), zero or reduced tillage (Besen *et al* 2024), and integrated agricultural systems (IAS)

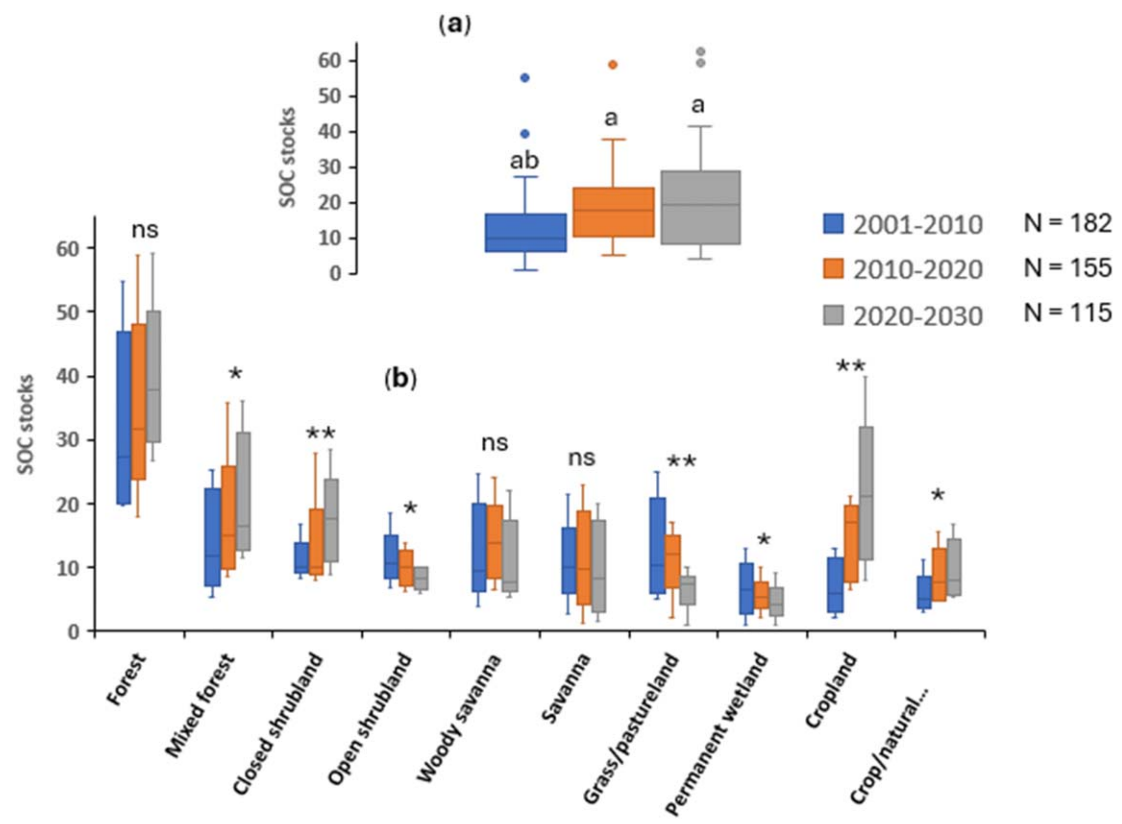

Figure 5. SOC stocks (Mg C ha^{-1}) in decades and under the different land use. Mean differences in decades of SOC stocks (a); differences based on the land use types (b). In figure 5(a), same letter indicates that there were no significant differences in SOC stocks between the decades, while in figure 5(b), the asterisk * represents significant at $p < 0.05$; ** represents significant at $p < 0.01$, and **ns** represents not significant. **N** represents the number of samples per decade. Mean differences were estimated in only ten land use types excluding barren soil/mined area, built-up, and water where no data were available. Crop/natural stands for Crop/natural vegetation mosaic.

Table 6. Decadal changes in soil organic carbon stocks (t ha^{-1}) in 0–30 cm depth.

Land use class	2001–2010	2010–2020	2020–2030
Forest	+1.88 (7.1%)	+0.71 (2.5%)	+0.95 (3.3%)
Mixed forest	+0.34 (2.7%)	+0.26 (2.0%)	+0.13 (1.0%)
Closed shrubland	−2.06 (18.8%)	+0.19 (2.0%)	+0.45 (5.0%)
Open shrubland	−0.55 (9.9%)	+0.12 (2.4%)	−0.09 (1.8%)
Woody savanna	−1.99 (14.6%)	+0.61 (5.2%)	−1.90 (15.5%)
Savanna	+1.70 (17.3%)	−1.39 (12.1%)	−0.26 (2.6%)
Grass/Pastureland	−0.41 (4.9%)	−2.86 (36.0%)	−2.82 (55.6%)
Permanent wetland	−0.09 (2.8%)	−0.84 (26.4%)	−0.38 (16.2%)
Cropland	+1.66 (78.7%)	+1.51 (40.1%)	+3.17 (60.0%)
Crop/natural vegetation mosaic	−0.47 (6.3%)	+1.69 (24.4%)	+0.75 (8.7%)

+ represents the positive changes; − indicates the negative changes.

such as crop-livestock-forestry, crop-livestock, and crop-forestry (Nwaogu and Cherubin 2024, Renwick *et al* 2025). These conservation or regenerative agricultural practices have significant potential to increase soil organic matter contents, soil microbial activities, and reduction of soil erosion which consequently increase SOC accumulation over time (Rosinger *et al* 2025). IAS which involves the application of organic residues, green manure and leguminous cover crops improves soil health through N biofixation, as well as reduces evaporation and emissions of CO_2 and other greenhouse gases (GHG) (Nwaogu and Cherubin 2024). When sustainably managed, conservation agriculture and IAS have the likelihood of sequestering 0.9 Pg of SOC yearly, which might offset 25% to 34% of the estimated 3.3 Pg yr^{-1} annual increase in atmospheric CO_2 (Nazir *et al* 2024). By covering about 30% of the soil surface with crop stubble, organic materials or cover crops, the soil moisture becomes preserved, erosion and evaporation reduced, biodiversity and microbial activities enhanced, which in turn elevates SOC accretion and decreases carbon emissions (Nwaogu and Cherubin 2024, Giongo *et al* 2020).

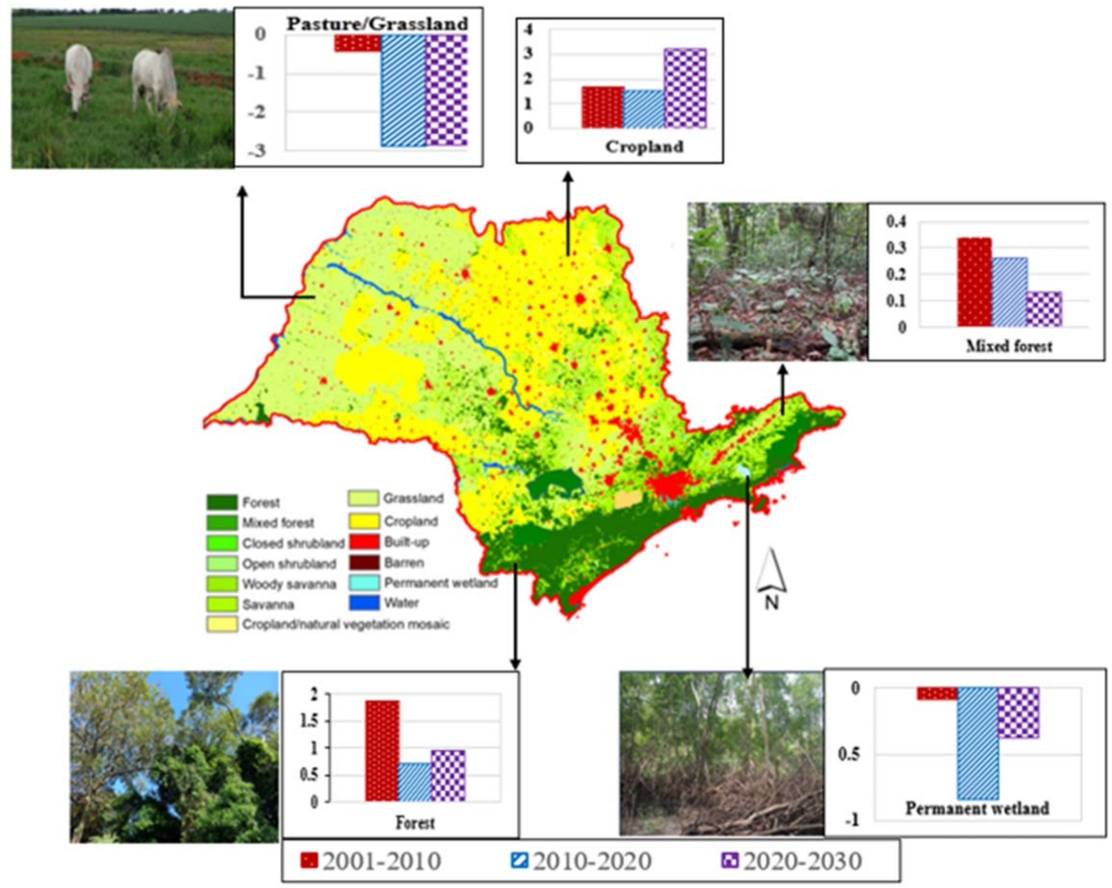

Figure 6. Agricultural and other land uses which had continuous increase and constant decrease in SOC (tons ha^{-1}) during the three decades of investigation. The unit for the *y*-axis is SOC in tons ha^{-1}, while the *x*-axis represents the years in decades (i.e., 2001–2010, 2010–2020, and 2020–2030).

SOC stock was heightened on average by 0.32tC.ha^{-1}·y^{-1} over 50years by the application of cover crops (Poeplau and Don 2015).

In addition, between 2001 and 2030 the Cropland/Natural Vegetation Mosaic was found to have increased by 1.97% though this increase was very low when compared with either the forest or cropland. The presence of trees within the crops might have supported SOC because of the trees' organic nutrients enhancements from plant litter decomposition. Another explanation for the increase in SOC in the Cropland/Natural Vegetation Mosaic could be conservation agricultural management systems such as cover cropping, crop rotation and diversification, and soil temperature modification by the natural vegetation plant species. Similarly, Odebiri *et al* (2024) observed the highest SOC stocks in Cropland and Natural vegetation in the 0–30 cm depth. The humid tropical climate and minimal soil perturbation in Natural vegetation support SOC accrual, whereas the low incidents of wildfires avert carbon loss (Chen *et al* 2018).

Spatial and temporal distributions of SOC contents and stocks are regulated by many interactions between land use (Wiesmeier *et al* 2019), plant species abundance and types (Nwaogu *et al* 2018), climate (Gomes *et al* 2019), relief (Zhu *et al* 2019), soil properties and parent material (Mao *et al* 2020), and other geographic locational-base features (Tayebi *et al* 2021). However, these driving factors vary at distinct spatial and temporal scales (Gomes *et al* 2019). Many studies in Brazil have reported higher SOC values in the surface soil layers of native forests or agroforests than in croplands, grasslands, pastures, or savanna (Mao *et al* 2020, Tayebi *et al* 2021). This could be explained by the carbon input and slower decomposition rate of soil organic matter (SOM), and deep root systems in forests relative to cropland or pasture/grasslands (Bieluczyk *et al* 2020, Franzluebbers 2023). According to the work by Bieluczyk *et al* (2020), land use for crops reduces the incorporation of carbon into the soil surface layer, but not into deeper layers.

The expansion of sugarcane in the area is the main reason for the increase in the areas for cropland. Additional reason for the increase in the cropland could be the fact that cropland has been well managed by the adoption of integrated agricultural systems (IAS) coupled with the 'ABC Plan' introduced by the Brazilian government to increase soil carbon through low-carbon agricultural practices (Brazil ABC Plan 2021, Cherubin *et al* 2021, Brasil 2022). Many studies have reported the contribution of conservation agriculture and integrated cropping systems in promoting SOC stocks at different Brazilian territories (Oliveira et al 2022, Camacho et al 2023, Damian et al 2023, Oliveira et al 2023). In support of the findings of this study, a study in the same biome revealed that though sugarcane expansion in Cerrado vegetation might reduce soil C stocks, it increases when pasture is converted to sugarcane (cropland) (Mello et al 2014).

On the other hand, this study observed a continuous decline in SOC stocks under pasture (or grassland) and permanent wetlands. The decline in SOC stocks in these land use types might be attributed to the age and management practices adopted. It has been revealed that SOC stocks tend to decrease in recently converted pasturelands and stabilize in pasturelands that have been converted for at least 30 years. This explains the loss of about 103 Mt C estimated in the Cerrado pastures in the past twenty years (Santos et al 2023). Furthermore, due to climate change and poor management, the SOC stocks in permanent wetlands tend to decrease (Kauffman et al 2018, Beloto et al 2023). Globally, many other studies have reported the influence of environmental phenomena, age and management systems on the dynamism in SOC stocks in either pasture, grassland or wetlands (FAO 2007, Franzluebbers and Stuedemann 2009, Dias Filho 2014, Soussana and Lemaire 2014, Veloso et al 2018, Oliveira et al 2022, Camacho et al 2023). In Brazil for example, non-degraded grassland with no significant management and managed pasture were found to increase SOC stocks by 15% and 8% respectively, whereas degraded pastures reduced SOC stocks by 10% (Oliveira et al 2022).

3.3. Land use, SOC, and other soil properties nexus

The multivariate ordinated redundancy analysis revealed a strong association between land use, SOC, and other soil properties during the investigation periods (figure 7). The first axis with explained variation of 47.61% had sodium (Na) relating to closed shrub and barred/mining area. The second axis with explained variation of 29.96% had a strong dominance of OM, phosphorus (P), nitrogen (N), cation exchange capacity (CEC), and silt content in forest, cropland, mixed forest, and crop/natural vegetation mosaic. The 2nd axis also showed that potassium and sandy soil had a strong relationship with open shrublands, savanna, and woody savanna. The SOC-gain cluster consisted of OM, silt, P, N, and CEC in forest, cropland, mixed forest, and crop/natural vegetation mosaic. The SOC-persistence cluster indicated that though K and sandy contents were high there was neither significant gain nor loss of SOC under savanna, open shrublands, and woody savanna. On the other hand, the SOC-loss prevailed in the grassland/pasture, barren/mining, and wetlands with higher bulk density, Al, pH, and SB (figure 7).

This study observed a strong association between land use, SOC stocks, and other soil properties. The finding is consistent with previous studies in São Paulo State (Bernoux et al 2002, Bieluczyk et al 2020), in other regions of Brazil (Camacho et al 2023, Ercole et al 2023, Damian et al 2023, Santos et al 2023), and in other countries (Nwaogu et al 2018, Franzluebbers 2023, Wang and Huang 2023). In the Brazilian Cerrado, Oliveira et al (2023) established that the adoption of a diversified and intensified agricultural practice brought an increase in SOC content and stock. Another study in the Eastern Coast of Brazil found substantial differences in SOC between forest and agricultural land but did not observe significant impacts or differences in the soil texture (Ercole et al 2023).

Cropland, forest, mixed-forest, and crop/natural vegetation mosaic were highly associated with organic matter (OM), P, N, CEC, and silt, resulting in a positive gain of SOC. On the other hand, the barred/mining areas, wetlands, and grassland/pasturelands had high Na, clay, bulk density, Al, pH, and SB which might have contributed to SOC loss. It is expected that a soil with high level of OM, P, N, CEC, and silt would promote SOC content and stocks relative to soil with high contents of bulk density, clay, SB, Al, or pH. This is because CEC, N, and P have profound support for microbial activities which increase OM and SOC. In central-southern Brazil including São Paulo State which form the main sugarcane producing region of the world, Cherubin et al (2015) observed that SOC had significant correlation with N and CEC. Moreover, availability of organic residues in forest and cropland enhances SOC relative to wetlands, grassland and/or pastures with degraded soils (Kebebew et al 2022, Padbhushan et al 2022).

In contrast to the findings of this study, some other studies found that forest or crop land use had relatively low amount of SOC, N, and CEC when compared with grasslands or pasturelands (Hartono et al 2023, Wang and Huang 2023). The dissimilarities in the results might be explained by many factors such as differences in environmental drivers (e.g., geographical location, altitude, soil types, parent materials, plants), age of the land use, and variations in management and cropping systems. For instance, the study by Wang and Huang (2023) was performed in the alpine region of Qinghai-Tibet Plateau, while the study by Hartono et al (2023) focused on only cassava and in only 15 years. These could be the reasons for the discrepancies in their findings relative to this study.

The correlation analysis between SOC and other soil properties revealed that OM ($R^2 = 0.918$), N ($R^2 = 0.627$), silt content ($R^2 = 0.720$), P ($R^2 = 0.802$), and CEC ($R^2 = 0.713$) had strong positive correlation coefficients with SOC (table 7). Though the strong relationships found between SOC and the other soil

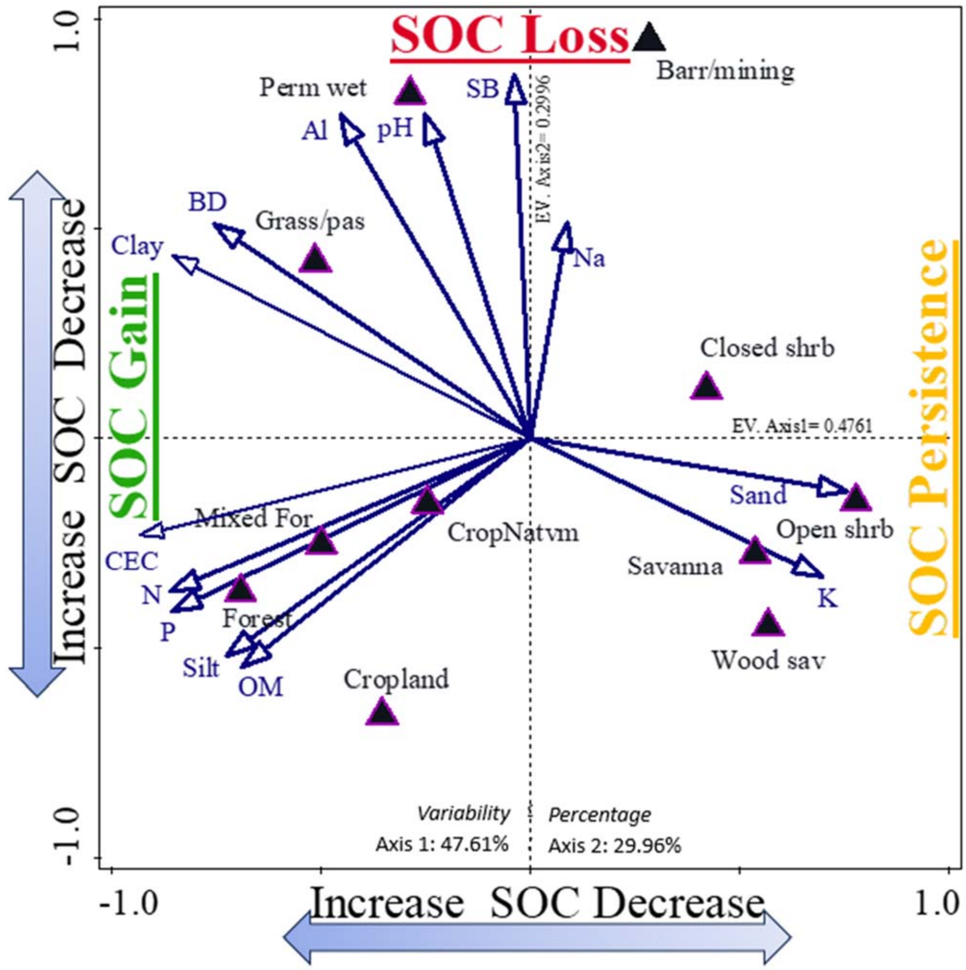

Figure 7. Multivariate ordination of redundancy analysis (RDA) on the relationships among the land use, soil properties and SOC stocks in the study area for the 3 decades. Description of abbreviations: CropNatvm = cropland/natural vegetation mosaic, Open shrb = open shrublands, Closed shrb = closed shrublands, Perm wet = permanent wetlands, Grass/pas = grassland/pasture, Wood sav = woody savanna, Mixed For = mixed forest, Barr/mining = barren/mining area. OM = soil organic matter, SB = Base saturation, BD = soil bulk density. Silt = silt content, Sand = sandy content and Clay = clay content.

properties agrees with some recent studies within and outside the study region (Kebebew *et al* 2022, Padbhushan *et al* 2022), yet it is inconsistent with the report by Recha *et al* (2022). This disparity could be attributed to complex factors including management systems, time, vegetation/crop types, soil types, topography, climate, and geographical position (Gomes *et al* 2019, Zhu *et al* 2019, Mao *et al* 2020, Tayebi *et al* 2021).

At different soil clay contents, the rates of changes for SOC stocks under the various land use were significant (figure 8). Forest ($R^2 = 0.914$; $p < 0.001$), Cropland ($R^2 = 0.904$; $P < 0.001$), Mixed Forest ($R^2 = 0.916$; $p = 0.012$), Grassland/pastures ($R^2 = 0.938$; $p = 0.027$), and Permanent wetland ($R^2 = 0.800$; $p = 0.004$). Forest, cropland, and mixed Forest displayed almost the same trend of higher SOC stocks that increased until after 30% clay contents when the SOC stocks started to diminish. This scenario could be explained by the fact that optimum clay content promotes SOC but when the clay content is higher, microbial processes and carbon storage as occluded particulate organic matter might be responsible for the decline in SOC (Liddle *et al* 2020, Schweizer *et al* 2021), consequently influencing soil cohesiveness and pore spaces (Schweizer *et al* 2021, Soinne *et al* 2023). The significant relationships between soil clay contents and SOC stocks under the different land use was also reported by other studies within and outside Brazil (Zhong *et al* 2018, Oliveira *et al* 2023). The relationship between SOC stocks and clay content depends on other factors including scale sizes, climate, and vegetation (Zhong *et al* 2018). It has been established that at regional scale with different climatic variations, the climate could play a huge role in influencing the changes in SOC and clay dynamics (Zhong *et al* 2018). However, on a local scale with no differences in climate, the changes in SOC stocks and clay content might be attributed to vegetation diversity and soil nutrient dynamics.

Table 7. Correlation coefficient and probability of error (p) between soil organic carbon and some other soil properties in the study area (0–30 cm depth) for the three decades of investigation.

Soil variables	OC	OM	N	BD	Sand	Silt	Clay	pH	P	K	Na	Al	CEC
OC	1.000												
OM	0.918**	1.000											
N	0.627*	0.773	1.000										
BD	0.18	0.384	0.003	1.000									
Sand	−0.192	−0.597	0	−0.619	1.000								
Silt	0.720*	0.833**	0.548	0.069	−0.645	1.000							
Clay	0.506	0.581	0.630*	0.717**	−0.948	0.33	1.000						
pH	−0.064	−0.089	0.001	−0.022	−0.146	0.178	0.103	1.000					
P	0.802*	0.751	0.812*	−0.534	−0.479	0.611**	0.447	0.007	1.000				
K	0.003	0.014	0.691**	−0.006	−0.028	0.004	0.011	0	0.507	1.000			
Na	0.278	0.115	0.002	−0.017	−0.012	0.009	0.025	−0.002	0.213	0.651*	1.000		
Al	−0.326*	0.328	0.000	0.074	0.008	−0.004	−0.008	−0.09	−0.478	−0.008	0.088	1.000	
CEC	0.713**	0.593*	0.557	0.141	−0.236	0.348	0.137	0.056	0.559*	0.000	0.063	0.15	1.000

* = significant at $p < 0.05$; ** = significant at $p < 0.01$. Description of the abbreviations: OC = Soil organic carbon. OM = Soil organic matter. BD = Soil bulk density. Sand = Sandy content. Silt = Silt content. Clay = Clay content. pH = Soil pH value. K = phosphorus. K = Potassium. Na = Sodium. CEC = Catio exchange capacity.

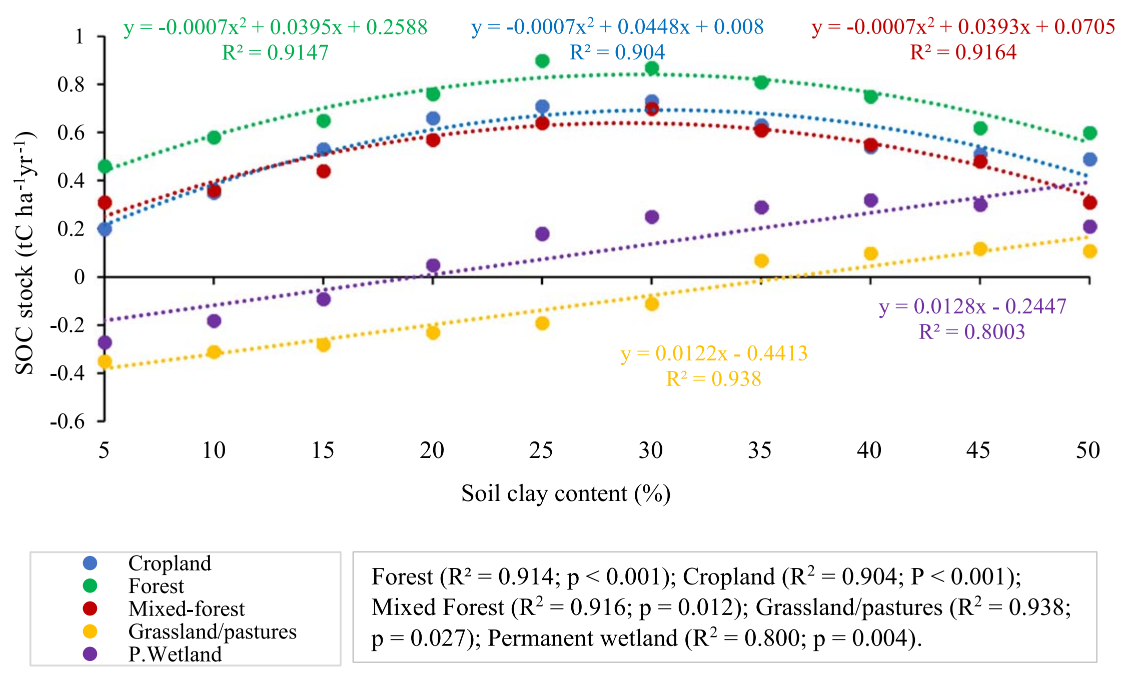

Figure 8. Estimated rates of change for SOC stocks at various clay contents under the different land use during the study period. Consideration was given to only the land use where continuous SOC stock changes were recorded.

3.4. Socioeconomic implications of increase or decrease in SOC stocks

Though there is a limited study on the influence of socioeconomic factors on SOC accretion, population density is a top socioeconomic driver of SOC stocks because it either enhances or decreases SOC cumulation, consequently supports or mars food security (figure 9). Optimal population density, especially in developing tropical regions, tends to promote SOC enrichment, increases soil health and productivity, which in turn elevates GDP and income (figure 9(a)). Rapid population growth if not well managed leads to severe land use changes such as urban expansion, deforestation, intensive pasture and cultivation which caused a decrease in some land use (e.g., pasture or croplands became degraded with low SOC leading to food insecurity, low GDP, and poor income (figure 9(b)). Many studies have examined the influence of socioeconomic variables on SOC stocks (Drechsel *et al* 2001, Duarte-Guardia *et al* 2020, Wang *et al* 2022, Jiang *et al* 2023). In sub-Saharan Africa, it was reported that about 25% of the region's GDP was affected due to depletion of SOC and other soil nutrients (Drechsel *et al* 2001). A strong negative correlation between population and GDP and SOC content was observed by Wang *et al* (2020) in Northeast China. Growing population and economic development have caused an exponential rise in land use changes (Stumpf *et al* 2018), causing substantial changes in SOC stocks, impacting the local, regional, and global climate. It was emphasized that all stakeholders including policymakers must be involved in promoting and protecting SOC pools because soil scientists and farmers can only reduce the speed of dynamism, demographic and economic policies are crucial as they are the root causes of soil carbon degradation (Drechsel *et al* 2001).

4. Limitations and way forward

Some uncertainties of using remote sensing data for SOC estimation prevailed but these were properly managed. Lack of sufficient field-based data that covered the timeframe resulted in greater dependence on remotely sensed data which required more analysis and preprocessing tasks and skills. Furthermore, studies that focus on the synergies and tradeoffs between SOC stocks and other major drivers of SOC accretion such as topography, soil microorganisms, and socioeconomic are suggested in São Paulo State, Brazil, and globally.

Though, 2030 is not a long-term from now but it is a longer-term from 2001. So, it is assumed that predicting the SOC and land use up to 2030 will give a supporting clue or an overview of the prevailing scenario in the past few decades and in the coming decades. It will help the stakeholders to acquaint themselves with the changing land use and understand the implications for SOC as well as the general soil health. It gives a crucial update that if a sustainably managed cropland could increase SOC between 2001–2030, then in a period of 50 years and above, more carbon could be sequestrated in a well adopted conservation agriculture. The significant insights for the stakeholders are to (1) fully embrace sustainable farming systems such as integrated agricultural system with

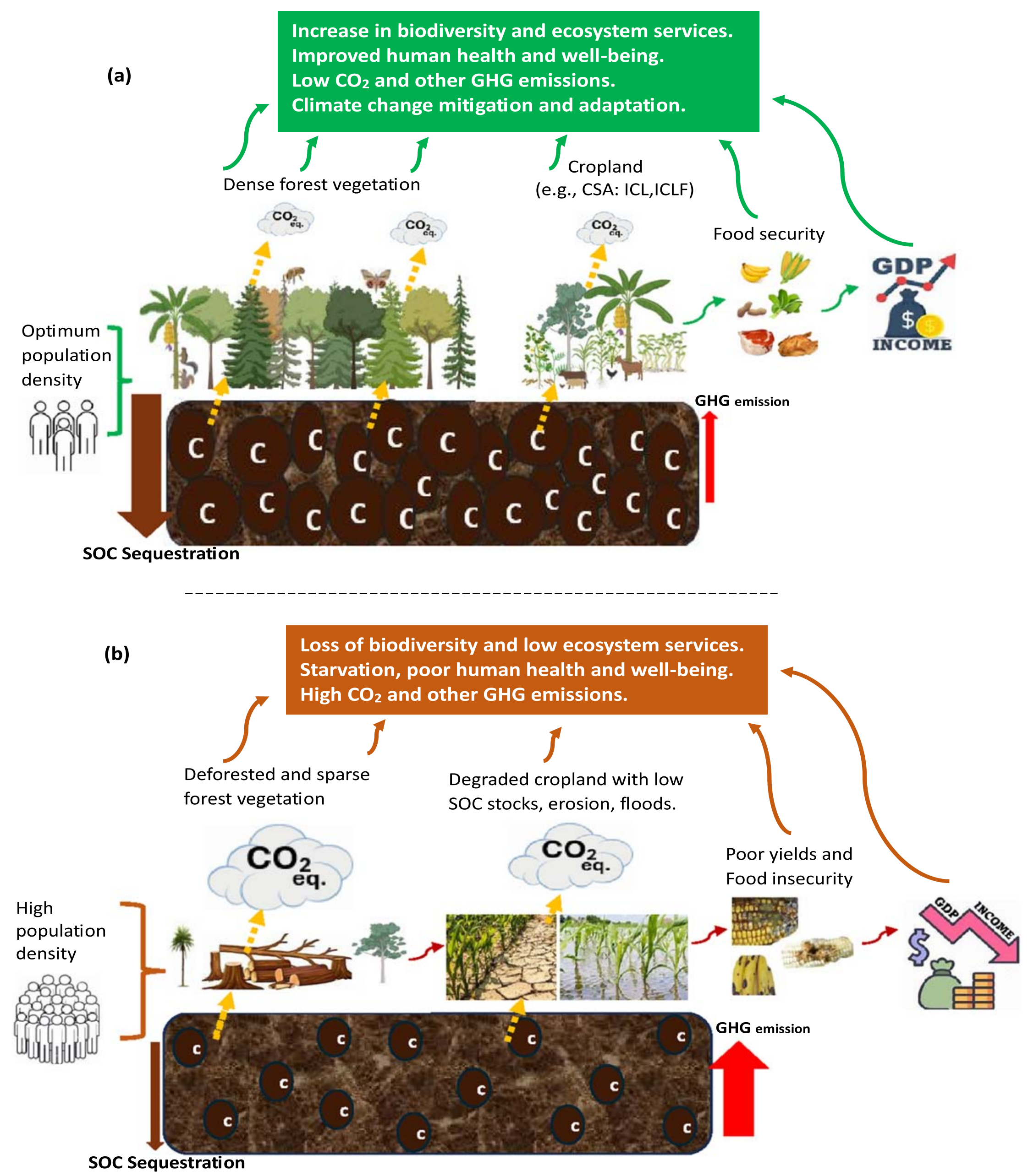

Figure 9. Conceptual framework on the socioeconomic implication of SOC stock dynamics and some of its potential and perils in areas of Sao Paulo State, Brazil. (a) Positive scenario, and (b) Negative impacts. For the abbreviations: CSA represents climate-smart agriculture, ICL represents integrated crop-livestock, ICLF represents integrated crop-livestock-forest.

crop-livestock-forest diversification, and (2) implement zero-till, organic amendments (e.g. composting, green manure, biochar, organic residue mulching), cover cropping, and crop rotations. These will contribute significantly to increasing the soil microbial activities, thus improving soil organic matter and SOC contents, and consequently enhance climate change mitigation and food security.

5. Conclusion and recommendation

Forest had the highest percentage of SOC per hectare but in terms of the decadal changes in SOC stocks, Cropland had the highest rates of increase (or positive change). This could be explained by several factors including control of erosion, improved soil, and vegetation by increased organic matter, adoption of integrated and conservative farming systems, as well as the ability of farmers to control other environmental drivers and optimize human management. A significant decrease in SOC stocks was continuously observed under grassland/pasture and permanent wetlands. Cropland revealed a positive change in SOC stocks (i.e., SOC-gain) while grassland/pastures had a negative change (i.e., SOC-loss). Therefore, cropland is observed as land use with promising support for SOC sequestration in future. It was also found that SOC stock did not only differ across the land uses but was also significantly influenced by soil properties especially soil texture, OM, N, CEC, and bulk density.

The uniqueness of this study lies in the fact that it covered a longer period than any previous study. It is also the first-time soil data from soilgrid, and Brazilian soil legacy dataset were used to map SOC under different land use in São Paulo State. Besides the novelty of applying the InVEST model in the study, decoupling the potential of croplands in accruing more SOC over time under conservative farming was remarkable for the agroecological and food production sectors. The improvement in agricultural practices plays vital roles in the promotion of carbon stocks, and a related benefit of reducing carbon emissions from the agricultural soils.

Agricultural policies that involve integrated agricultural systems, regenerative agriculture and conservation agriculture including crop species and varieties with larger and deeper root mass are recommended. We also recommend the adoption of N-fixing legumes, optimal use of cover crops especially during fallow periods, and introduction of crop rotations because these farming practices have high prospect for SOC accumulation. Increase in SOC sequestration can also be achieved through intensified organic residue retention and addition of amendments like compost and biochar and by introducing minimum or no-till. Integrating crop-livestock-forestry on the same piece of land has been established as an alternative which is sustainable in the enrichment of SOC stocks, and reduction of carbon emissions from the agroecosystems.

In addition to the environmental sector, dynamism in SOC caused by land use changes might have a significant relationship with the socioeconomic sectors of the society, and these later sectors also need to be considered in studies involving land use and SOC sequestration. We are optimistic that this research might foster a vital insight to farmers, agronomists, policymakers, and other stakeholders in climate change-agriculture sustainability initiatives as a valuable foundation to optimize organized efforts for promoting SOC stocks, environmental safety, and food security.

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Data availability statement

All data that support the findings of this study are included within the article (and any supplementary files).

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Author contributions

Conceptualization and design of the work: All authors; methodology (data collection and analysis): All authors; writing of original draft and preparation: CN and BED; writing of review and editing: All authors; Agreed to the submission of the final version and to be accountable for the integrity of the work by ensuring its accuracy: All authors.

Declarations

No potential conflict of interest was reported by the author(s).

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