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Soil organic carbon stock changes over 40 years in Brazil: a country-scale assessment using soil science-informed machine learning

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ABSTRACT

Brazil is at the forefront of both forest conservation and global food security, and thus, understanding the dynamics of soil organic carbon (SOC) is crucial for both. We developed a spatiotemporal model to predict national-scale changes in SOC stocks to 1 meter depth, over the last 40 years. We utilized a combination of static and dynamic environmental covariates along with more than 50,000 observation points to calibrate a machine learning model. The models achieved satisfactory accuracy, with R^2 values ranging from 0.48 to 0.88 in cross-validation and from 0.18 to 0.31 in external validation. Our findings revealed a significant reduction in SOC stocks in the North rainforest region (Amazon biome), with the largest increase in the Northeast drylands (Caatinga biome). Specifically, net SOC losses occurred in Amazon (-0.020 Pg yr^{-1}), Atlantic Forest (-0.002 Pg yr^{-1}), and Pampa (-0.0004 Pg yr^{-1}). Net gains were found in the Cerrado (0.016 Pg yr^{-1}), Caatinga (0.007 Pg yr^{-1}), and Pantanal (0.001 Pg yr^{-1}). Over the past 40 years, we estimated an absolute gain of 0.80 Pg C in Brazil. Land-use change from forests to anthropogenic uses was the primary driver of SOC stock loss, whereas conversion from pastures to croplands generally led to SOC gains. The efforts to combat climate change in Brazil require reducing deforestation and promoting sustainable agricultural intensification.

1. Introduction

Brazil plays a critical global role in both environmental conservation and food production, positioning it at the centre of the climate-agriculture nexus. Among the most pressing challenges is understanding how soil organic carbon (SOC), a key component of soil health and global carbon balance, has evolved under the dual pressures of agricultural expansion and environmental change. SOC dynamics are essential not only for climate change mitigation via carbon sequestration but also for sustaining soil functions that underpin agricultural productivity and ecological resilience (Evangelista et al., 2024; Liptzin et al., 2022). Despite this, studies in environmental and agricultural sciences have historically emphasized aboveground components, with soils receiving systematic attention only more recently (Bardgett and van der Putten, 2014; Bossio et al., 2020).

SOC is a key soil attribute that enhances the soil's multiple functions and linked to physical, chemical, and biological processes (Hoffland et al., 2020; Wiesmeier et al., 2019). As such, soil can act as either a

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carbon sink or a source, depending on land use and management practices (Smith et al., 2021; Stockmann et al., 2013). Brazil is a vast country, with a great climate, geological, pedological, and environmental diversity, composed of three major climate types (tropical, subtropical, and semi-arid) and six major biomes (Amazon, Atlantic Forest, Cerrado, Caatinga, Pantanal, and Pampa). Their SOC dynamics are influenced by interactions between soil type, land use, climate, and topography. The need for environmental conservation, such as in the Amazon, the largest tropical forest in the world, and the constant growth of the agro-industrial sector, highlight the tension between conservation and production. Brazil ranks among the world's top producers of soybeans, maize, sugar, and coffee (FAS-USDA, 2024), and grain production is projected to grow by another 24% by 2032 (MAPA, 2023b). However, climate change poses significant risks to SOC stocks, exacerbates climate instability, and threatens future yield resilience (Rattis et al., 2021).

Although studies increasingly show that sustainable intensification can reconcile agricultural production and environmental goals (Cerri et al., 2018; Marin et al., 2022; Stabile et al., 2020), national-scale monitoring of SOC dynamics remains limited. The Brazilian ABC+ Plan (MAPA, 2021), which promotes practices such as no-till, agroforestry, and pasture restoration, is expected to enhance SOC sequestration, with early estimates suggesting a 0.19 Pg C uptake from 2010 to 2020 (MAPA, 2023a; MAPA, 2024). But, to quantify the effectiveness of such policies, high-resolution, spatially explicit assessments of SOC change over time are needed.

The digital soil mapping (DSM) framework enables the generation of continuous soil information across large areas, based on soil sampling points and soil-forming factors (Ma et al., 2019). To date, DSM has been applied to generate SOC stock baselines at national (Gomes et al., 2019; Safanelli et al., 2020a), continental (Ng et al., 2025), and global (Chen et al., 2023; Poggio et al., 2021) levels. However, most maps represent a static snapshot rather than temporal dynamics. Some recent efforts have modeled annual SOC changes—e.g., Padarian et al. (2022) globally, Heuvelink et al. (2021) in Argentina, and Yang et al. (2023) in China. In Brazil, preliminary maps of SOC temporal dynamics exist only for the surface layer covering the entire territory (MapBiomas Project, 2023) and on a farm scale (dos Anjos Bartsch et al., 2025). Besides that, there is still a lack of studies to draw conclusions about the overall SOC trend across Brazil's diverse environmental conditions and land uses.

To address these gaps in SOC stock temporal information in Brazil, we developed a high-resolution (30 m) spatio-temporal model of SOC stocks to 1-meter depth across Brazil for the 1984–2023 period, calibrated with over 50,000 SOC observations and both static and dynamic covariates. Furthermore, existing machine learning approaches have often lacked explicit integration of soil process understanding; thus, we implemented, for the first time, a Soil Science-Informed Machine Learning approach (Minasny et al., 2024) for SOC spatio-temporal mapping. We investigated SOC trends across biomes, states, and land-use classes, emphasising the roles of anthropogenic and environmental drivers. Specifically, this study aims to answer: (a) Can we accurately map spatiotemporal variations in SOC stock across Brazil using machine learning informed by soil science? and (b) What have been the impacts of anthropogenic land-use change on SOC stocks over the past four decades? By answering these questions, we can provide foundational data to support evidence-based climate policy, low-carbon agriculture, and sustainable land management in Brazil and other tropical regions.

2. Materials and methods

2.1. Study area

We studied the Brazilian territory, a large area with about 8.8 million km^2, divided into 26 States (Fig. 1). Brazil has great geological, climatic, topographic, pedological, and ecological diversity, which makes it ideal for studying SOC stock spatio-temporal trends. Besides that, it is at the centre of discussions on global environmental conservation and food

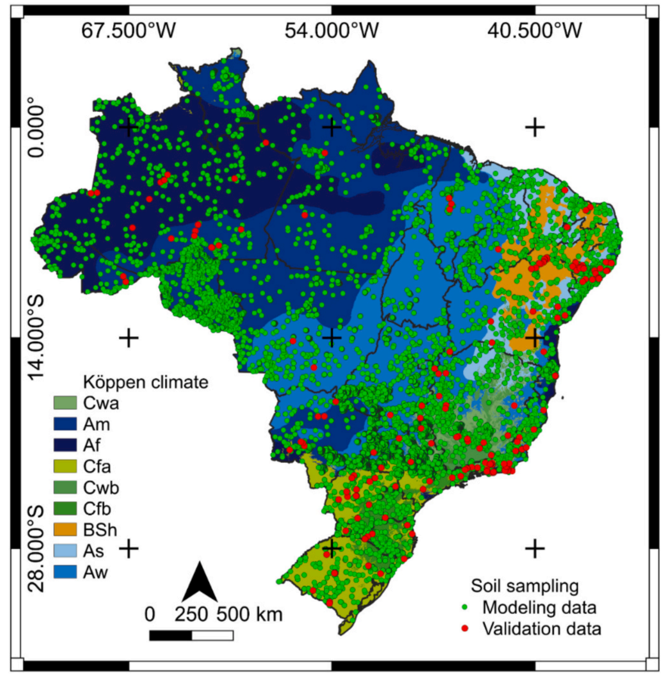

Fig. 1. Study area and soil dataset. The screened points represent the 0-20 cm layer.

production. Its geology is varied and comprises several types of sedimentary, igneous, and metamorphic rocks (Gómez et al., 2019). The climate is predominantly tropical (81.4%), with also subtropical (13.7%) and dry (4.9%) areas (Alvares et al., 2013) (Fig. 1). The relief is mainly between 200 and 400 m above sea level, and the land is slightly sloped as a result of low volcanic activity (Ross, 2013). The area presents great pedological variability, mainly covered by Ferralsols and Lixisols, which comprise more than 60% of the territory (IBGE, 2001; Santos et al., 2018; Soil Survey Staff, 2014). Brazil has six biomes: rainforests (Amazon and Mata Atlântica), savannas (Cerrado), wetlands (Pantanal), grasslands (Pampa), and drylands (Caatinga) (Gomes et al., 2019). Amazon (49%) and Cerrado (22%) are the largest biomes of the country.

2.2. Environmental covariates

The Digital Soil Mapping (DSM) approach considers that a given soil attribute is a function of the scorpan factors (s = soil, c = climate, o = organisms, r = relief, p = parent material, a = age and n = geographic position) that can be represented by environmental covariates (McBratney et al., 2003). In this way, a set of environmental covariates representing long-term soil variation (soil formation) is used for mapping soil classes or attributes. However, when aiming to make a temporal DSM, the covariates should be divided into static and dynamic components. The static covariates are assumed not to change over the study period and are used exclusively to explain long-term variations. On the other hand, the dynamic ones change over time and are used to represent short-term variations in space, depth, and time, and are obtained for 8 periods from 1984 to 2023.

The selection of covariates was guided by soil science knowledge, the literature, spatial resolution requirements, and data availability. We reviewed studies on temporal mapping of SOC stocks (Yang et al., 2023; Heuvelink et al., 2021; MapBiomas Project, 2023), as well as other DSM studies conducted in Brazil (Gomes et al., 2019; Rosin et al., 2023), to identify relevant static and dynamic environmental covariates. All covariates were retrieved and processed using Google Earth Engine (Gorelick et al., 2017). Preliminary analyses were conducted to evaluate their predictive performance, improve model accuracy, and minimize potential spatial artifacts.

We used the annual mean temperature from the climatological normal (1970-2000), seven relief attributes, and soil mineralogic indexes as static covariates. Annual mean temperature was obtained from WorldClim 2 (Fick and Hijmans, 2017) at a native spatial resolution of 1 km and resampled to 30 m using bilinear interpolation. It was treated as a static covariate because its 30-year climatological temporal resolution was incompatible with the temporal resolution of this study and introduced artifacts during preliminary testing. The seven relief attributes were derived from ALOS Global Digital Surface Model ALOS (JAEA, 2021) by using the Terrain Analysis in Google Earth Engine (TAGEE) method (Safanelli et al., 2020b). The mineralogy indexes were obtained from a digital soil mapping study of Rosin et al. (2023), with a resolution of 30m.

We used spatially continuous dynamic covariates including three vegetation indices, land use and land cover (LULC) and a synthetic soil-vegetation image (SySVI). These temporal covariates were obtained from Landsat satellites (Landsat 5, 7, 8 and 9), with native spatial resolution of 30m and native temporal resolution of 16 days. We averaged vegetation indices and SySVI every five years, while we computed the mode of LULC for the same periods. These temporal covariates were obtained from Landsat time series images (Landsat 5, 7, 8, and 9), covering all periods of study (1984-2023), with a spatial resolution of 30m and a native temporal resolution of 16 days. The vegetation indices were calculated according to Rouse et al. (1973) and Huete (1988) and Huete (1997). The LULC was generated annually by supervised machine learning by MapBiomas Project (2024).

The SySIVI image (Poppiel et al., 2025) has 6 spectral bands and comprehends the bare soil reflectance obtained by a data mining procedure developed by Demattê et al. (2018) plus vegetation reflectance in regions without soil exposure over time. We averaged vegetation indices and SySVI every five years, while we computed the mode of LULC for the same periods. The complete list of environmental covariates can be found in Table 1.

Table 1
Environmental covariates employed for SOC stock modeling.

Type	SCORPAN	Predictor name	Source/reference
Static	Climate	Annual Mean Temperature***	Fick and Hijmans (2017)
	Relief	Elevation Slope Northness Eastness Horizontal curvature Vertical curvature Shape index	ALOS (JAEA, 2021): obtained by TAGEE (Safanelli et al., 2020b)
	Soil**	Hematite / Hematite + Goethite Kaolinite / Kaolinite + Gibbsite	Rosin et al. (2023)
Dynamic*	Organisms	NDVI	Rouse et al. (1973)
		EVI	Huete (1997)
		SAVI	Huete (1988)
		LULC	MapBiomas Project (2024), described in Souza et al., 2020)
	Soil, organisms, parent material and time	SySIVI blue (450-520 nm) SySIVI green (520-600 nm) SySIVI red (630-690 nm) SySIVI NIR (760-900 nm) SySIVI SWIR1 (1550-1750 nm) SySIVI SWIR2 (2080-2350 nm)	Poppiel et al. (2025): Adapted from GEOS3 Demattê et al. (2018)

SCORPAN = SCORPAN factors; NDVI = Normalized Difference Vegetation Index; EVI = Enhanced Vegetation Index; SAVI = Soil-Adjusted Vegetation Index; NIR = near-infrared; SWIR = short wave infrared; SySIVI = bare soil and vegetation image.; ALOS = Advanced Land Observing Satellite; TAGEE = Terrain Analyses in Google Earth Engine; GEOS3 = Geospatial soil Sensing System. *The dynamic covariates were obtained for eight periods of five years from 1984 to 2023. **The soil attributes maps were generated for the layers 0-20, 20-40, 40-60, 60-80 and 80-100cm. ***The annual mean temperature was resampled from 1000m to 30m.

2.3. SOC stock data

We compiled a legacy dataset from an open-source national dataset (Samuel-Rosa et al., 2020) and from the Brazilian Soil Spectral Library (Demattê et al., 2019). We merged the datasets, selected the variables soil organic carbon (SOC), sand, silt, clay, and bulk density (BD), and checked their consistency using a set of functions for missing data, overlapping depths, and positional errors (less than 100 m). The row depth dataset (n = 377,637) was harmonized using equal area spline interpolation (Bishop et al., 1999; Malone et al., 2009) up to 1 m, using the GSIF R package (Hengl and MacMillan, 2019). We obtained a harmonized database with the following layers and number of samples: 0-20 cm = 60,860, 20-40 cm = 56,830, 40-60 cm = 50,183, 60-80 cm = 49,179 and 80-100 cm = 49,088. These depths of intervals were chosen because a considerable part of the dataset originally had some of these layers, reducing uncertainty in the spline procedure, as described in Rosin et al. (2023).

After the spline interpolation, we predicted missing soil BD values using a pedotransfer function developed with the Cubist algorithm (Quinlan, 1992). The model was calibrated using 70% of the samples with real BD (n = 2644) and validated with the remaining 30% (n = 1132). It was used as BD predictors, the static covariates along with measured clay, silt, and sand content.

The SOC stock was calculated using real or predicted BD by the equation: SOC stock (Mg ha^{-1}) = SOC (g kg^{-1}) x BD (g cm^{-3}) x depth (cm) / 10. The dataset used for validation was kept out of the training process (Section 2.5), being used as an independent validation dataset (Section 2.6). The remaining samples, with SOC stock calculated from predicted or observed BD, were used in the spatial modelling. The total modelling dataset (all time periods) and the independent validation dataset sample distribution can be visualized in Fig. 1.

2.4. Data preparation for soil science-informed machine learning

Soil science-informed machine learning consists of incorporating soil science knowledge into machine learning models, thereby increasing accuracy and interpretability (Minasny et al., 2024). As the data points are sparse in time for natural areas (unaffected by anthropogenic land use and land cover changes), we included observational priors, which augment the training data to reflect underlying knowledge about the subject, thereby enhancing the robustness of our model and allowing for more reliable predictions across different time intervals. In the current study, since we assumed the long-term climate to be static, we assumed that SOC stocks in natural areas have reached a steady state and do not vary significantly over the study period. Accordingly, we flagged the data points in these areas and incorporated them repeatedly for each of the eight time periods. This approach compels the model to predict consistent SOC stock values across all periods for these areas.

The modelling dataset was flagged as belonging to 2 classes according to LULC: natural observation points, consisting of points in areas without anthropic LULC in the period of study (n = from 1179 to 1815), and anthropic observation points, consisting of points in areas with anthropic LULC in at least one period of 5 years. The observations of anthropic observations were grouped into 8 periods: 1984-1988 (n = from 2190 to 2224, considering that collected before 1984 were aggregated in this period), 1989-1993 (n = from 4 to 5), 1994-1998 (n =

from 159 to 233), 1999-2003 (n = from 2671 to 2810), 2004-2008 (n = from 7541 to 7694), 2009-2013 (n = from 15194 to 15235), 2014-2018 (n = from 11234 to 11912), 2019-2023 (n = from 8916 to 18933) (Fig. S1). We choose to map the SOC stock over 5-year periods based on temporal data coverage and agreed with previous studies (Yang et al., 2023). The observation points on natural sites were assumed to remain constant over the study period (disregarding any possible changes in natural areas, such as climate change). In this way, these points were duplicated 8 times and combined with the anthropic observation points for each period. After that, covariates were extracted for the points in the respective period, and the dataset was used for soil science-informed machine learning modelling.

2.5. Temporal digital soil mapping

We calibrated a multitemporal Random Forest (RF) model (Breiman, 2001) for each depth (0-20, 20-40, 40-60, 68-80, and 80-100 cm). The model was calibrated using the calibration dataset across all periods and used to predict SOC stock for the eight periods. The RF algorithm is available in GEE, allowing large area mapping with high efficiency. We used an adapted version of the Hoogen pipeline for geospatial mapping in Python, using the Google Collaborative interface coupled with GEE (van den Hoogen et al., 2021). The dataset described in the previous section, with static and dynamic covariates, was used as the training data for the temporal DSM pipeline.

The adapted pipeline constituted the following steps: a) Grid search hyperparameter tuning for the Random Forest temporal model, to choose the: number of variables per split; minimum leaf population, number maximum of leaf nodes in each tree and number of trees; b) 10-fold cross validation and calculation of performance metrics: coefficient of determination (R^2), root mean square error (RMSE) and ratio of performance of interquartile (RPIQ); c) selection of best model by the lowest RMSE; d) Spatial prediction for eight periods simultaneously with a resolution of 30 m.

2.6. External validation

For external validation, we used the independent validation dataset (described in Section 2.3) (Fig. 1), with only observations with measured BD, which were not used in the modelling procedure (Section 2.5). These samples were used to validate the final maps generated by temporal digital soil mapping, considering the respective period and depth. The R^2, RPIQ, and RMSE were also evaluated in external validation.

2.7. Interpretation

The mapping process produced 40 SOC stock maps across the eight periods and five depths. Evaluating temporal changes in SOC stocks is challenging, since spatial variations are greater than temporal variations, and sometimes a prediction for one period can conflict with the tendency in other periods. To facilitate interpretation and enhance the SOC stock trend analysis over the last 40 years, we performed a linear regression analysis pixel by pixel across the eight periods in the GEE.

$$\text{SOC stock} = a + b^{*}\text{year}$$

We used the slope of the linear regression (coefficient b) for each pixel to generate an SOC stock trend map showing rates of SOC stock gains or losses. The SOC stock slope calculation was also used in previous studies at national scales, such as Venter et al. (2021) and Chen et al. (2023). The total difference between the first and last period was also calculated.

The SOC stock annual rate of gain or loss (Mg ha^{-1} yr^{-1}) maps were then grouped into five classes according to: high loss: < -0.250; moderate loss: > -0.250 to < -0.150; no significant change: > -0.150 to < 0.150; moderate gain: > 0.150 to < 0.250; high gain: > 0.250. The rate of SOC change is based on the average value from meta-analysis studies (Guo and Gifford, 2002; Don et al., 2011).

The results were compared by land use and land cover (LULC) (MapBiomas Project, 2024) and by States, regions, and biomes (IBGE, 2006). We made three case studies, regarding consolidated cropland areas in Rio Grande do Sul State (Atlantic forest biome), areas with land use change (forest to pasture) in Rondônia State (Amazon biome) and areas with land use change (savanna to cropland) in Piauí and Maranhão States (Cerrado biome).

3. Results

3.1. Modelling

The bulk density (BD) was well estimated, yielding an R^2 of 0.43, an RMSE of 0.18 g cm3, and an RPIQ of 1.68 on the validation dataset (Table S1). Combining real SOC and predicted BD, we computed SOC stock. Comparison with observed SOC stock, our models show a very accurate prediction with an R^2 of 0.95 and RMSE of 2.63 Mg ha^{-1} on the validation dataset.

We further estimated SOC stock from 1984 to 2023, aggregating the data into 5-year intervals. The temporal mapping of SOC stock showed higher accuracy in the superficial layer than in the deeper layers, with R^2 ranging from 0.48 to 0.88, RMSE from 6.71 to 14.25 Mg ha-1, and RPIQ from 1.12 to 1.55 (Fig. 2 and Table S2). The external validation showed R^2 ranging from 0.18 to 0.31 and RMSE from 7.75 to 21.26 Mg ha^{-1}. The complete information on DSM accuracy is in Table S2, the importance of covariates is in Fig. S2, and the mean and sum values of predicted maps are in Fig. S3.

3.2. SOC stock average over the past 40 years

Across the Brazilian territory, the average SOC stock (mean for 1984–2023) was 31.72 Mg ha^{-1}, equivalent to 37.31 Pg, in the 0–20 cm soil layer. This value declined to 9.17 Mg ha^{-1} (10.77 Pg) in the 80–100 cm layer. For the 0–100 cm profile, the estimated SOC stock was 104.59 Mg ha^{-1}, corresponding to a total of 89.01 Pg (Fig. 3).

The Pampa (131.55 Mg ha^{-1}), Atlantic Forest (127.25 Mg ha^{-1}), and Pantanal (120.21 Mg ha^{-1}) biomes exhibited higher SOC stocks than the national average, while the Amazon (104.18 Mg ha^{-1}), Cerrado (100.12 Mg ha^{-1}), and Caatinga (79.56 Mg ha^{-1}) were below the average (Fig. 3a). The vertical distribution of SOC varied across biomes: the Amazon, Pampa, and Pantanal showed more pronounced declines in SOC stock from surface to subsoil, whereas the Caatinga and Cerrado exhibited relatively smaller differences with depth.

The Amazon biome, comprising 49.29% of Brazilian territory, had the largest SOC stock with 42.75 Pg at 0-100 cm depth, followed by the Cerrado biome (22% of territory) with 20.37 Pg of SOC stock and the Atlantic Forest with 14.54 Pg (Fig. 3b). The other biomes together had a total of 11.35 Pg.

3.3. SOC stock temporal changes

Our results indicate that soil organic carbon (SOC) stocks across Brazil remained relatively stable over the past four decades, with only minor fluctuations observed across soil depths and time periods (Fig. 1). For the 0–100 cm profile, the average SOC stock was 104.45 Mg ha^{-1} in the 1984–1988 period and 105.40 Mg ha^{-1} in the 2019–2023 period. The corresponding total SOC stock increased slightly from 88.90 Pg to 89.70 Pg over that period. Overall, the SOC change over the 40 years was minimal.

At the layer level, divergent trends were observed. The 0–20 cm layer showed a slight decreasing trend, with a slope of -0.005 Pg yr^{-1} (Fig. 2c). In contrast, the 20–40 cm layer exhibited an increasing trend, with a slope of 0.016 Pg yr^{-1} (Fig. 2d). The 40–60 cm and 60–80 cm layers both showed slight decline in SOC stock, with slopes of –0.005 Pg yr^{-1} and

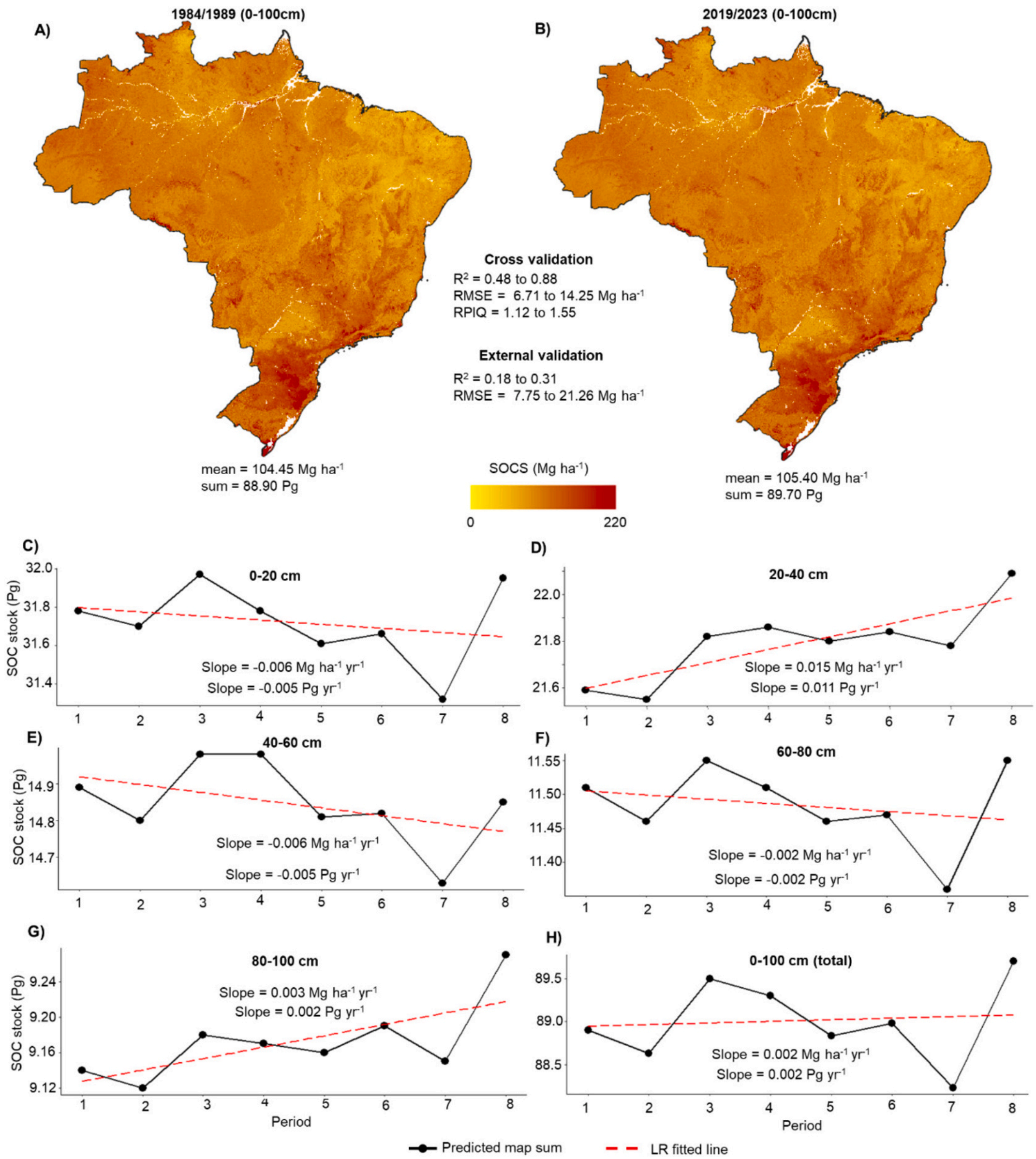

Fig. 2. Soil organic carbon (SOC) stock maps 0-100 cm, for the initial - 1984-1989 (A) and last - 2019-2023 (B) period and the SOC stock trend over time for all depths (C, D, E, F, G and H). LR = linear regression

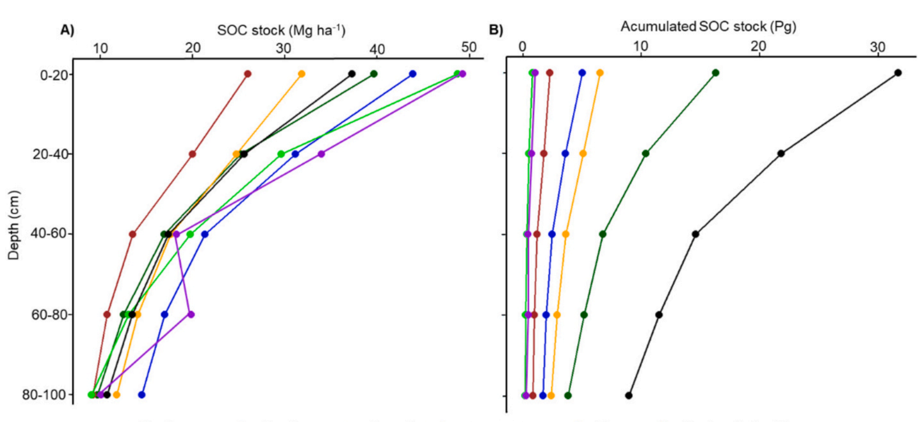

Fig. 3. Average soil organic carbon (SOC) stock by biomes in Brazil. SOC values are presented relative to area (A) and the total for the biome territory (B)

–0.002 Pg yr^{-1}, respectively (Fig. 2e,f). The deepest layer, 80–100 cm, showed a modest increasing trend, with a slope of 0.002 Pg yr^{-1} (Fig. 2g). When considering all layers together (0–100 cm), SOC stock had a slight increasing trend, with a slope of 0.002 Pg yr^{-1} (Fig. 2h).

3.3.1. LULC changes and its influence on SOC stock

Land use and land cover (LULC) change had a great effect on SOC stock dynamics (Fig. 4). First, considering the cases of study, we observed distinct SOC stock trends in cropland areas of Rio Grande do

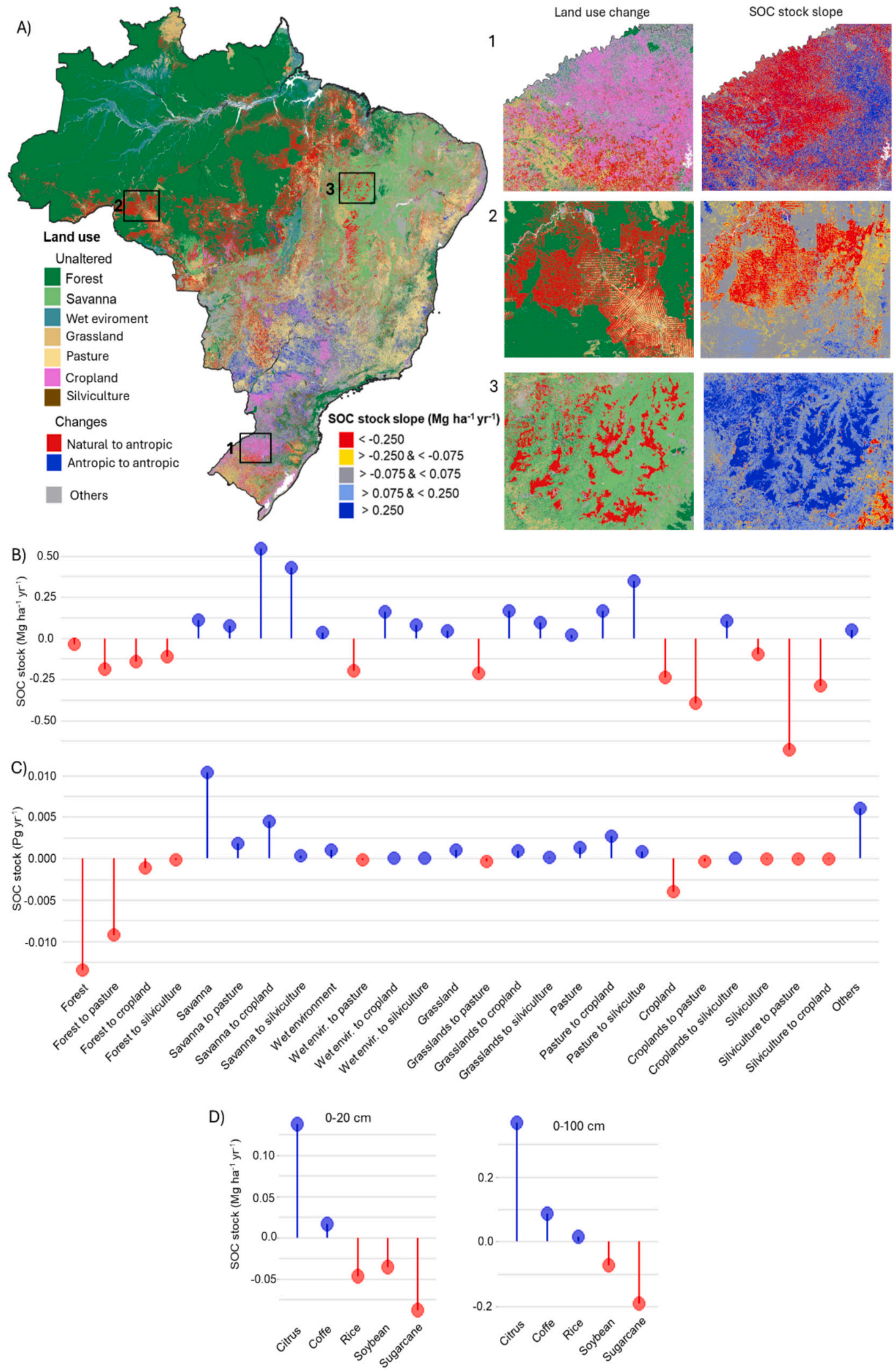

Fig. 4. Land use and land cover map and case of studies (A) and soil organic carbon (SOC) stock slope by land use and land use changes (B,C and D).

Sul State within the Atlantic Forest biome, where one part exhibited significant SOC stock loss while another showed a substantial increase (case study 1) as depicted in Fig. 4a. Additionally, a considerable decrease in SOC stock due to deforestation (from natural to anthropogenic land use) was observed in Rondônia State, in the Amazon biome (case study 2 in Fig. 4a). Lastly, there was a significant increase in SOC stock associated with the conversion of savanna to agriculture (from natural to anthropic land use) in the Cerrado biome in Piauí and Maranhão States (case study 3 in Fig. 4a).

The greatest relative loss of soil organic carbon (SOC) stock was observed in the conversion of silviculture to pasture (-0.68 Mg ha^{-1} yr^{-1}), followed by the transitions from croplands to pasture (-0.39 Mg ha^{-1} yr^{-}

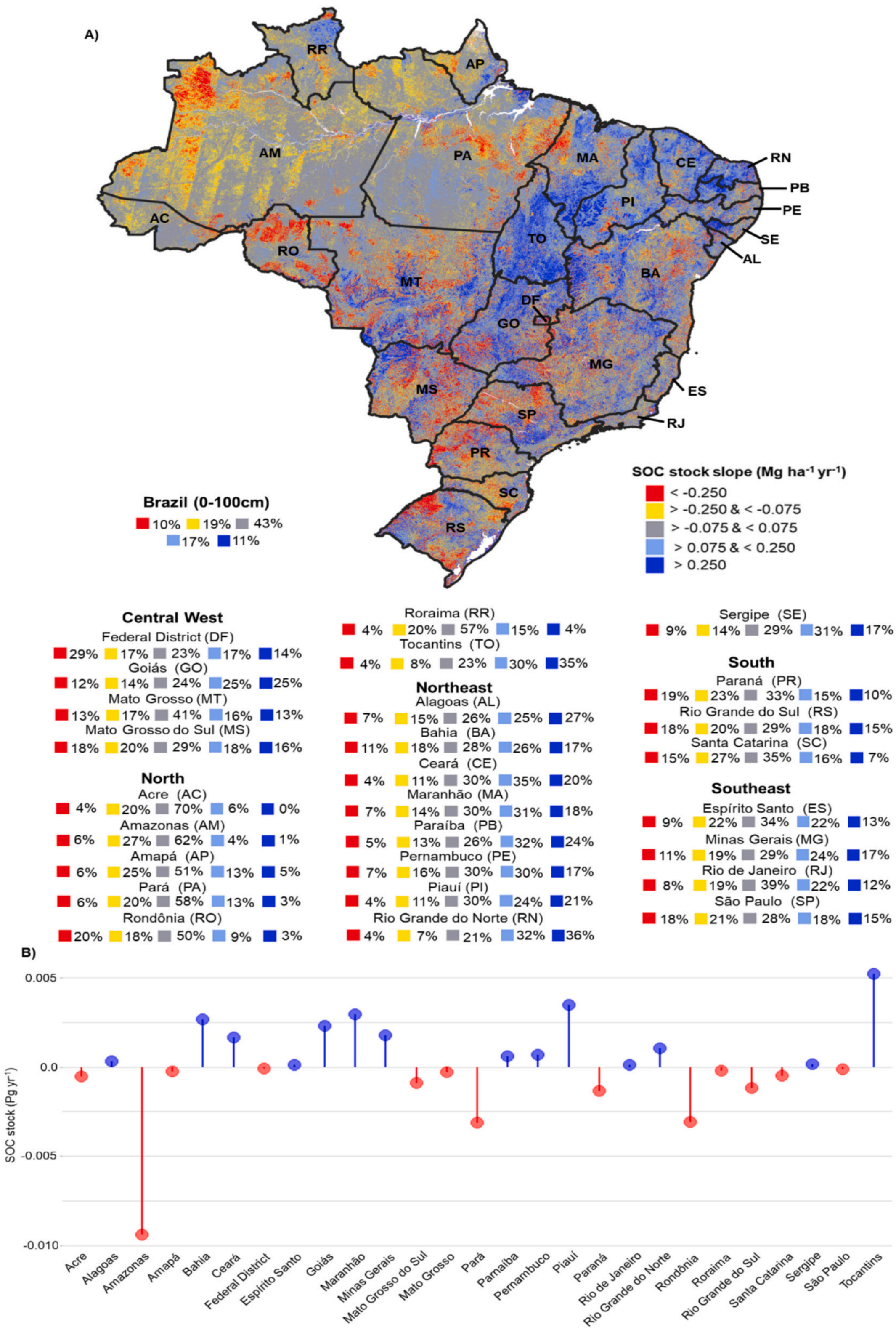

Fig. 5. Brazilian map of soil organic carbon (SOC) stock changes over 40 years, divided by State level (A), and average value of SOC changes per State (B).

^{1}) and silviculture to croplands (-0.29 Mg ha^{-1} yr^{-1}) (Fig. 4b). Other transitions associated with significant SOC losses included grassland (natural grasslands) to pasture (anthropogenic grasslands), wetlands to pasture, forest to pasture, forest to croplands, and forest to silviculture. Areas that remained under the same land use type, specifically croplands. experienced SOC losses (-0.24 Mg ha^{-1} yr^{-1}).

In contrast, the largest relative SOC gain occurred with the conversion of savanna to croplands (0.54 Mg ha^{-1} yr^{-1}), followed by savanna to silviculture (0.42 Mg ha^{-1} yr^{-1}) and pasture to silviculture (0.35 Mg ha^{-1} yr^{-1}). Transitions from pasture to croplands and grasslands to croplands also resulted in notable increases in SOC accumulation rates.

The absolute change in SOC stock is strongly influenced by the area extent of each LULC category. Consequently, unchanged land uses contributed the most to the overall SOC change (Fig. 4c). Among these, forests exhibited the largest absolute SOC loss (-0.0135 Pg yr^{-1}), whereas savannas showed the greatest SOC gain (0.0104 Pg yr^{-1}).

Among LULC transitions, the conversion of forest to pasture resulted in the greatest SOC loss (-0.0104 Pg yr^{-1}). In contrast, the conversion of savanna to pasture led to the highest SOC gain (0.0044 Pg yr^{-1}), closely followed by pasture to cropland conversion, which also showed a gain of 0.0044 Pg yr^{-1}. Despite gains in some areas, croplands overall experienced a notable loss in SOC stock (-0.0040 Pg yr^{-1}). Detailed SOC stock values by LULC across all soil depths are provided in Fig. S4.

At the crop level, sugarcane exhibited the steepest relative SOC decline, with losses of -0.09 Mg ha^{-1} yr^{-1} in the 0–20 cm layer and -0.19 Mg ha^{-1} yr^{-1} over the 0–100 cm profile (Fig. 4d). Soybean also showed SOC decline. In contrast, citrus cultivation resulted in the highest SOC gain. Coffee cultivation led to an increase in SOC, while rice showed a mixed pattern—SOC loss in the 0–20 cm layer but a gain in the 80–100 cm layer.

3.3.2. SOC stock rate of change by States and regions

Considering the entire Brazilian territory, SOC stock remained stable across 43% of the area (Fig. 5a). However, 29% of the territory experienced a decline in SOC stock, with 10% showing high losses and 19% showing moderate losses. In contrast, 28% of the area saw an increase in SOC stock over time, with 11% showing high gains and 17% showing moderate gains. The Northern region exhibited the largest absolute SOC stock losses, particularly in the states of Amazonas (-0.0085 Pg yr^{-1}, with 33% of the area experiencing losses), Rondônia (-0.003 Pg yr^{-1}, with 38% of the area experiencing losses), and Pará (-0.0027 Pg yr^{-1}, with 26% of the area experiencing losses) (Fig. 5). The notable exception in this region was the state of Tocantins, which showed an increase in SOC stock (+0.0049 Pg yr^{-1}, with 38% of the area experiencing gains), bordering both the Cerrado biome in the Central West and the Caatinga biome in the Northeast.

Significant losses were also observed in the South, particularly in Paraná, where SOC stocks decreased by -0.0015 Pg yr^{-1}, and 42% of the area experienced losses. In contrast, the Northeast region showed the largest increase in SOC stocks, particularly in Piauí (+0.0034 Pg yr^{-1}, with 45% of the area experiencing gains), Maranhão (+0.0034 Pg yr^{-1}, with 49% of the area experiencing gains), Bahia (+0.0034 Pg yr^{-1}, with 43% of the area experiencing gains), and Ceará (+0.0018 Pg yr^{-1}, with 55% of the area experiencing gains).

The West-Central region also experienced notable gains, especially in Goiás (+0.0025 Pg yr^{-1}, with 50% of the area experiencing gains) and Mato Grosso (+0.0034 Pg yr^{-1}, with 34% of the area experiencing gains). However, the Federal District showed a high rate of SOC loss (-0.0058 Pg yr^{-1}), with 46% of the area experiencing losses. The Southeast region was the most stable, with minimal changes in SOC stock. For additional details, the total SOC stock by state for all depths is shown in Fig. S4.

3.3.3. SOC stock change by biomes

The Amazon biome exhibited the greatest SOC stock loss, estimated at -0.020 Pg yr^{-1} or -0.048 Mg ha^{-1} yr^{-1}, with 8% of its area experiencing high SOC loss, while 22% showed moderate loss (Fig. 5a). The Atlantic Forest and Pampa biomes also experienced SOC decline, with losses of -0.015 Mg ha^{-1} yr^{-1} (-0.002 Pg yr^{-1}) and -0.021 Mg ha^{-1} yr^{-1} (-0.0004 Pg yr^{-1}), respectively. High SOC losses affected 14% of the Atlantic Forest and 18% of the Pampa area.

In contrast, the Cerrado biome showed the largest SOC gain, accumulating 0.016 Pg yr^{-1} (0.077 Mg ha^{-1} yr^{-1}), with 23% of the area showing high and 25% moderate gains. The Pantanal biome had the highest relative SOC gain (0.081 Mg ha^{-1} yr^{-1}), or 0.001 Pg yr^{-1}, with high and moderate gains observed in 17% and 15% of its area, respectively. The Caatinga biome also gained SOC (0.007 Pg yr^{-1}, or 0.077 Mg ha^{-1} yr^{-1}), with 7% and 15% of its area classified as high- and moderate-gain zones, respectively.

The Amazon was the only biome that had significant SOC stock losses in the surface layer (0–20 cm), whereas all other biomes showed either stability or increases in this layer (Fig. 6b–c). SOC stocks in the 20–40 cm layer were generally stable or increasing across all biomes, while deeper layers (40–60, 60–80, and 80–100 cm) showed stable trends.

4. Discussion

4.1. Modeling accuracy

The prediction of bulk density (BD) using the Cubist model achieved satisfactory accuracy (RMSE = 0.18) (Table S1), outperforming previous national-scale efforts such as Heuvelink et al. (2021) for Argentina (RMSE = 0.24). When SOC stock was calculated using predicted BD, the model's performance improved substantially (R^2 = 0.95), as SOC exhibits greater variability than BD, thereby minimizing the propagation of BD prediction errors.

Our temporal SOC stock mapping also demonstrated superior accuracy compared to prior large-scale studies. For the surface layer, our cross-validation RMSE was 14.25 Mg ha^{-1} (21.26 Mg ha^{-1} in external validation), outperforming past studies such as the MapBiomas Project (2023) in Brazil (RMSE = 36.7 Mg ha^{-1}), Heuvelink et al. (2021) in Argentina (RMSE = 20.4 Mg ha^{-1}), and Yang et al. (2023) in China (RMSE = 50.8 Mg ha^{-1}). These improvements are likely due to the larger sample size (Figs. 1 and S1) and higher-resolution covariates used in this study (Garosi et al., 2022; Sun et al., 2022). We utilized 73,695 samples for the 0–20 cm layer (0.0086 samples km^{-2}), exceeding the densities used in previous efforts. Additionally, most of our environmental covariates had a 30 m resolution (except annual mean temperature), in contrast to the coarser covariates used in earlier studies. It is necessary to note that duplicated samples from natural land use categories could artificially inflate cross-validation accuracy due to repeated data appearing in both calibration and validation folds, however they did not affect external validation.

All environmental covariates used showed some importance to the model (Fig. S2), as we conducted preliminary tests before selecting them. The static covariates showed greater importance than the dynamic ones, with higher relative importance values for annual mean temperature, elevation, and the Kaolinite + Kalinite / Gibbsite index (Fig. S2) (Tayebi et al., 2021; Wiesmeier et al., 2019). Among the dynamic covariates, LULC was a highlight, along with the SWIR bands of SySIVI. The LULC importance decreased with depth, indicating that these layers are less sensitive to anthropic influence (Luo et al., 2019; Li et al., 2023).

4.2. SOC stock spatial distribution

The overall spatial distribution of SOC stocks across the Brazilian territory (Fig. 2a,b) aligns well with patterns reported in previous studies (Gomes et al., 2019; Vasquez et al., 2017). However, our estimated SOC stocks did not always match those reported in earlier assessments. For instance, Vasquez et al. (2017) reported 36.6 Pg of SOC in the 0–30 cm layer, which is comparable to the 34.6 Pg estimated for the 0–20 cm layer in the present study. In contrast, Gomes et al. (2019)

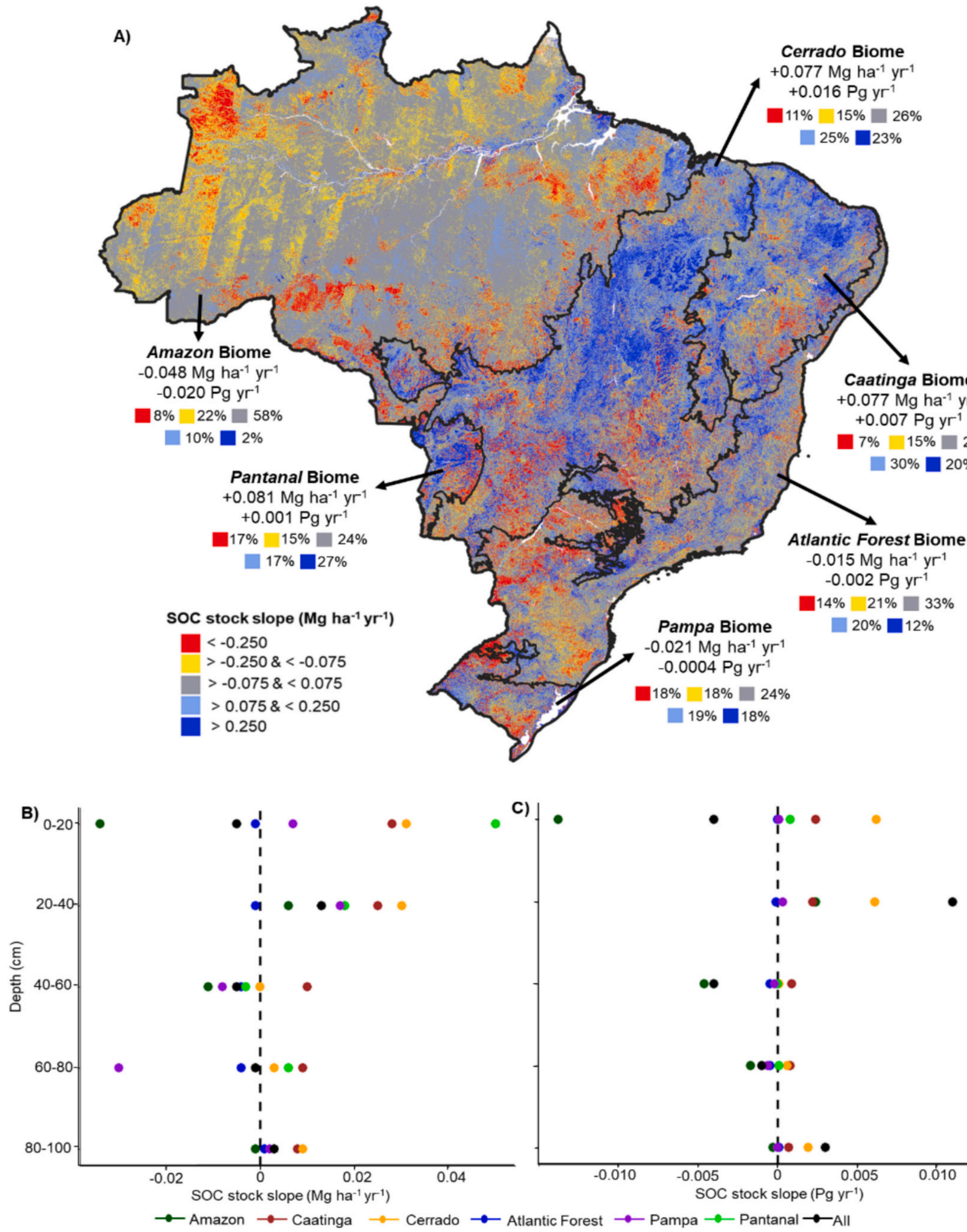

Fig. 6. Soil organic carbon (SOC) stock rate of change: (A) over Brazil and (B) grouped by biomes

estimated 71.3 Pg for the 0–100 cm layer, whereas our results indicate a higher average stock of 89.01 Pg. SOC stock estimates for Brazil have varied considerably over the past three decades of studies (Batjes, 2005; Bernoux et al., 2002; Schroeder and Winjum, 1995; Vasquez et al., 2017; Gomes et al., 2019). We believe our estimate is more accurate because of the substantially larger, more representative dataset. The distribution of sampling points can be found in Figs. 1 and S1.

Due to its extensive land area, the Amazon biome accounts for nearly half of Brazil's total SOC stock. This carbon is predominantly concentrated in the surface layers, driven by high biomass input. In contrast to most other biomes, SOC in the Amazon declined more sharply with depth. This pattern can be attributed to climatic and edaphic conditions (Demattê and Demattê, 1993; Schaefer et al., 2008; Tognon et al., 1998). SOC is determined by biomass input, conversion of biomass to SOC, and decomposition. In Amazonian soils, the rate of biomass input is about five times greater than in the Cerrado, but decomposition rates are faster (Sanchez, 2019). Consequently, the Amazon exhibits higher SOC stocks in the surface layers due to greater biomass input, whereas the Cerrado shows relatively higher SOC stocks in subsoil layers, driven by lower decomposition rates.

The Atlantic Forest occupies a substantial portion of the Brazilian territory and exhibits SOC stock levels above the national average. A similar pattern is observed in the Pampa and Pantanal biomes, despite their relatively small territorial coverage. Much of the Atlantic Forest is located at higher elevations where lower temperatures prevail, while the Pampa lies in a subtropical climate zone, and the Pantanal is characterized by seasonal flooding. These environmental conditions contribute to reduced rates of soil organic matter (SOM) decomposition in all three biomes (Luo et al., 2017; Wiesmeier et al., 2019), thereby favoring greater SOC accumulation.

The Cerrado, a vast savanna biome situated in central Brazil, had SOC stock levels slightly below the national average. However, the Cerrado's natural vegetation is dominated by deep-rooted grasses, which facilitate SOC sequestration at deeper soil layers, more so than in the Amazon (Demattê and Demattê, 1993; Tognon et al., 1998). In contrast, the Caatinga biome, representing Brazil's semi-arid drylands, is characterized by naturally low SOC stocks. These lower values are primarily attributed to harsh climatic conditions that limit plant growth and thus reduce carbon capture and subsequent transfer to the soil (Menezes et al., 2021; Wiesmeier et al., 2019).

4.3. LULC changes time frame over last 40 years.

Before discussing the verified SOC stock changes, it is necessary to clarify the LULC changes (Fig. 4a) that occurred across different States (Fig. 5) and biomes (Fig. 6), as these were the most important factors influencing SOC stock. This kind of analysis is crucial for understanding how anthropic activities influence SOC dynamics. Agricultural areas, comprising pastures and croplands, experienced an increase of about 67% from 1985 to 2023 (MapBiomas Project, 2024). In 2023, approximately 65% of Brazilian territory was covered by natural vegetation, and about 32% was dedicated to agriculture. Fig. 4a displays the land use and land cover (LULC) map for unaltered areas alongside the LULC changes that occurred, taking into account the initial (1984-1985) and final (2019-2023) periods of the study.

Prior to 1985, agricultural areas were primarily situated in the South and Southeast regions, which were long-established cropland areas, as depicted in Fig. 4a (study case 1). The South agricultural areas were dominated by croplands, while pastures prevailed in the Southeast, with only a few agricultural sites in the Center-West and Northeast (MapBiomas Project, 2024). Croplands were mainly located in the Atlantic Forest biome, and pastures were found in the Cerrado and Pampa biomes (native grasslands).

By mid-2005, agriculture had expanded across all regions, with croplands and pastures spreading in the Center-West and pastures extending to the North and Northeast. There was notable growth of croplands and pastures in the Cerrado, pastures in the Amazon, and croplands in the Pampa biomes. The conversion of forests to pastures, and occasionally to croplands in the Amazon biome occurred in an area known as the “arc of deforestation” (Fig. 4a/study case 2).

The trends observed by mid-2005 continued, with an increase in croplands and pastures primarily in the Cerrado of the Center-West, along with more pastures in the North (Amazon biome) and more croplands in the South (mainly in the Pampa and Atlantic Forest biomes). Significant cropland expansion also occurred in the Northeast (Cerrado biome) and North (Cerrado biome) in a region known as MATOPIBA (Fig. 4a/study case 3). In addition to the conversion of natural areas to agriculture, the last 20 years saw a considerable shift from pastures to croplands in the Southeast (Atlantic Forest and Cerrado), Center-West (Cerrado), and South (Atlantic Forest). The Pantanal biome experienced minimal LULC changes.

4.4. SOC stock change

4.4.1. A modest SOC stock increase in Brazilian territory

This study presents the first SOC stock spatio-temporal dynamics up to a depth of 1m in Brazil. Our study revealed a modest increase in SOC stock in the 0-20 cm (0.17 Pg) and 0-100 cm (0.80 Pg) layers from 1984 to 2023, as indicated by SOC stock differences between the two periods. This result differs from the previous assessment performed by the MapBiomas Project (2023), which reported a stable SOC value (37.6 Pg) at 0-30 cm across the Brazilian territory from 1985 to 2021. In other countries, studies also showed small variations between the initial and final periods (Heuvelink et al., 2021; Szatmári et al., 2019; Yang et al., 2023). However, given the high spatial variation, variations within a single period may not necessarily reflect the overall trend of SOC stock over time (Fig. 3c–h).

Thus, to capture the overall trend, we fitted a linear regression of SOC stock over the whole period (Venter et al., 2021; Yang et al., 2023). We found a tendency toward SOC decrease at the surface, mixed patterns in intermediate layers, and a slight increase in deeper layers (Fig. 1c–h). MapBiomas Project (2023) did not calculate the SOC stock slope over the whole period for Brazilian territory, which makes comparasion with our results not possible. In the surface layer, SOC is more dynamic and prone to loss due to the greater influence of environmental factors (i.e., climate, vegetation) and, particularly, management practices (Tayebi et al., 2021). On the other hand, inherent soil attributes (e.g., texture and mineralogy) drive SOC stocks in the subsoil (Luo et al., 2019; Li et al., 2023). Besides, the surface layer (0-20 cm) accounted for about one-third of the SOC stock in the 0-100 cm layers (Fig. S2), exerting a strong influence on SOC variations (Fig. 2a, Fig. 3a). The trend of SOC stock at a national scale for each depth is influenced by various factors, and more precise statements can be made only by stratifying the territory.

4.4.2. LULC as the main driver of SOC stock changes

We proposed a novel interpretation of the influence of LULC, biomes, and States on SOC stock trends (Figs. 4–6). It is evident that changes in LULC were the primary factor influencing the SOC stock trends (Fig. 4) (Barakat et al., 2021; Tayebi et al., 2021). In areas with LULC changes or consistent anthropogenic use, generally higher SOC stock changes were observed; details will be provided. It is important to note that most soil observation sites were in agricultural areas or areas converted to agriculture during the study period. This may bias the results for unaltered areas under similar environmental conditions of the sampled anthropogenic areas.

Evaluating the transition from natural to anthropic land use, there was a decrease in SOC stock associated with the conversion of forests to pastures or croplands, as shown in Fig. 4b–d. This decrease is well documented in the literature (Damian et al., 2021; Fujisaki et al., 2017). This is also supported by Padarian et al. (2022), who found a reduction in SOC stocks due to deforestation in Brazil. In the case of pastures, the impact on SOC stock depends on management practices (Carvalho et al., 2010; Maia et al., 2009).

An increase in SOC stock was observed in the conversion of savannas to pastures or croplands, a finding that contradicts some studies (Carvalho et al., 2010; Santos et al., 2022). On the other hand, other research supports our findings, showing that converting savannah to croplands or pastures can indeed increase SOC stock, especially when conservation practices are employed, such as the no-tillage system (Bernoux et al., 2009; Bustamante et al., 2006; Carvalho et al., 2010; de Moraes Sá et al., 2025; Roscoe, 2003).

Analysis of transitions between different anthropogenic LULC types revealed that converting pasture to cropland or silviculture generally increases SOC stock, whereas conversions from cropland or silviculture to pasture result in SOC losses (Fig. 4b,c). These outcomes highlight the critical role of land management practices in determining SOC sequestration potential (de Oliveira et al., 2022; de Oliveira Silva et al., 2018; Freitas et al., 2020; Maia et al., 2009; Santos et al., 2023). By 2017, more than 60% of cropland in Brazil was managed under no-tillage systems, and this proportion has continued to grow annually (Fuentes-Llanillo et al., 2021). In contrast, as of 2023, only about 36% of Brazilian pastures were classified as non-degraded (Lapig, 2023), indicating widespread degradation that may hinder SOC retention.

Despite the general trend of SOC gains with pasture-to-cropland conversion, localized losses were observed, particularly where pasture was converted to sugarcane cultivation (Cherubin et al., 2016). Areas under long-term agriculture without LULC change generally experienced declines in SOC stocks, with the greatest losses observed in sugarcane systems that predominantly use conventional tillage (Fig. 4d; Cherubin et al., 2016). Soybean cultivation, although mostly managed under no-till systems, also showed SOC losses, likely due to lower biomass production compared to other crops.

In contrast, perennial cropping systems demonstrated an increase in SOC stock. This improvement is likely attributed to the absence of tillage and the integration of tropical grasses (e.g., Urochloa spp.) and other cover crops between tree rows, which help protect the soil surface and enhance overall soil health (de Sousa et al., 2024).

4.4.3. The role of states and biomes

The large area changes from forests to pasture areas in the Amazon biome (North region) resulted in the greatest reduction in SOC stock (Figs. 5–6), which occurred mainly in the surface layer, with variable tendencies at depth (Fig. S4). SOC losses induced by conversion of Amazon rainforest to agricultural land are well documented (Damian et al., 2021; Durigan et al., 2017; Fujisaki et al., 2017).

The greatest increases in SOC stock were observed in the Northeast and Tocantins State (Cerrado biome) (Figs. 5–6), affecting both surface and subsoil layers. Adopting soil conservation practices in this region's agricultural areas could mitigate losses and enhance SOC stocks. However, the significant increases observed in this study regarding the conversion of savanna to croplands were not supported by the literature (Falconeres Vogado et al., 2024; Gonçalves et al., 2024; Locatelli et al., 2022; Maia et al., 2022; Oliveira et al., 2023).

The Atlantic Forest biome experienced a loss of SOC stock in long-term cropland areas, even as some areas showed gains, likely due to different crops and management (Fig. 6). The Pampa biome (South region) experienced losses due to the conversion of natural grasslands to croplands (Fig. 5a), as recently evaluated by Ramon et al. (2024).

São Paulo and Goiás States were the only ones to show a loss of SOC with pasture-to-cropland conversion, since the cropland was sugarcane (Figs. 4–5). This observation is confirmed by Sousa et al. (2024), who reported that SOC losses were greater in São Paulo, a sugarcane producer states using conventional tillage, compared to Paraná, a state recognized as the birthplace of no-tillage in Brazil, emphasizing the importance of management systems in shaping SOC dynamics

4.5. Strengths and limitations

We conducted the first multi-depth national-scale spatio-temporal SOC stock mapping in Brazil. The 5-year temporal resolution is sufficient to assess short-term SOC changes, and the 30 m fine spatial resolution is suitable for large-area mapping. We used over 50,000 samples, exceeding the densities used in previous efforts in Brazil and other national-scale studies. Besides, most of our environmental covariates had a native resolution of 30 m, guaranteeing high quality predicted maps.

It was the first study to use soil-informed machine learning (Minasny et al., 2024) for spatio-temporal mapping of SOC stocks. For this, we included observational priors, which augment training data to reflect underlying knowledge. The use of soil-informed machine learning enhances the robustness of models, allowing more reliable predictions by providing complementary information based on underlying knowledge about the subject.

It was also the first time that the SOC trends in Brazilian territory were evaluated across the different biomes, states, and LULC classes based on continuous multitemporal predicted map data. To improve our analysis, we calculated the SOC stock slope over the last 40 years stratified by state, biome, and land use to isolate likely drivers of change.

Despite these strengths, some limitations remain. SOC mapping is challenged by the inherently low temporal variability of SOC. Besides that, we used a legacy dataset, so we had no control over sampling locations, which led to unequal sampling densities, with more samples concentrated in some regions of the study area or time periods. Most samples were from agricultural areas or areas converted to agriculture during the study period, which could introduce spatial bias, potentially leading predictions for natural areas to be biased toward the environmental conditions and soil types found in human-impacted regions. However, these limitations are difficult to overcome and can be accepted to reuse legacy data (Lagacherie et al., 2024) and the proposed soil-informed machine learning procedure helped to mitigate these issues.

One important methodological note is that the duplication samples from natural land use in the implemented soil-informed machine learning procedure may artificially inflate cross-validation accuracy due to repeated data appearing in both calibration and validation folds. However, it did not affect external validation, which showed realistic accuracy metrics. In relation to the predicted maps, some artifacts, particularly evident in SOC rate of change maps (Figs. 4–5), were linked to remote sensing covariates, especially in northern Brazil, where persistent cloud cover reduces image quality (Rosin et al., 2023).

5. Conclusions

We successfully predicted temporal SOC stocks over the last 40 years in Brazilian territory using soil science-informed machine learning, producing detailed maps (30 m resolution) for multiple layers down to 1 m. Our models achieved satisfactory accuracy, with R^2 values ranging from 0.48 to 0.88 in cross-validation and from 0.18 to 0.31 in external validation.

Evaluating the data for all territories, the SOC stock showed stability (slope = 0.002 Pg yr^{-1}) from 1984 to 2023. The absolute gain in the whole area C was 0.80 Pg across all periods (0.9%). The SOC stock changes occurred mainly in the surface layer, but significant changes were also noticed in deeper layers, down to 100 cm. It decreased in Amazon (-0.020 Pg yr^{-1}), Atlantic Forest (-0.002 Pg yr^{-1}), and Pampa (-0.0004 Pg yr^{-1}), and increased in Caatinga (0.007 Pg yr^{-1}), Cerrado (0.016 Pg yr^{-1}), and Pantanal (0.001 Pg yr^{-1}). The main losses of SOC stock are associated with the conversion of forests to pastures and croplands, whereas the conversion of savannas to these uses resulted in SOC stock gains. Agricultural intensification, through conversion from pastures to croplands or silviculture, increases SOC stocks.

Our study highlights that SOC is highly dynamic across depth and time, and that large-scale modelling approaches are critical to support investment and public policies that promote soil health, carbon farming, and actions for climate change mitigation and adaptation. SOC stock changes must be considered in governmental programs, such as Brazil's Low-Carbon Agriculture Plan (MAPA, 2021), which aims to promote sustainable intensification of agriculture and reduce deforestation across the country. Soil-informed machine learning procedure is promising for SOC stock spatio-predictions and future work should integrate process-based models to improve the interpretability and predictive power of the machine learning framework.

CRediT authorship contribution statement

Nícolas Augusto Rosin: Writing – review & editing, Writing – original draft, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **José A.M. Demattê:** Writing – review & editing, Supervision, Project administration, Conceptualization. **Budiman Minasny:** Writing – review & editing, Visualization, Validation, Methodology. **Raul Roberto Poppiel:** Writing – review & editing, Methodology, Conceptualization. **Bruno dos Anjos Bartsch:** Writing – review & editing. **Jorge Tadeu Fim Rosas:** Writing – review & editing. **Heidy Soledad Rodríguez-Albarracín:** Writing – review & editing. **Maurício R. Cherubin:** Writing – review & editing. **Carlos Eduardo Pellegrino Cerri:** Writing – review & editing. **Luis Eduardo Vicente:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.catena.2026.110155.

Data availability

Soil observation data (Reference data) (Zanodo)

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