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Spatiotemporal dynamics of soil organic carbon stocks due to plantation expansion and other land use changes in Kerala, India (1972–2020)

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Abstract

Increasing Soil Organic Carbon (SOC), the largest terrestrial carbon pool, through proper land management has been suggested as a nature-based solution to mitigate climate change. In this context, it is important to understand the impacts of land transformations on regional SOC stocks. The study spatially analyzed the tree plantation expansion in Kerala, India, along with other land transformations in the last five decades and its effect on surface (0–30 cm) Soil Organic Carbon (SOC) density and stocks. This study adopted a machine learning-based predictive modelling approach by combining: (1) a detailed two-time period land use map separating major plantation types; (2) legacy soil data representing ground SOC measurements for each land use category; (3) other climatic, topographic and soil variables that affect the spatial variation of SOC, in order to spatially assess the changes in SOC stocks in Kerala due to land use changes over the last five decades (1972–2020). The study highlighted significant local hotspots of losses and gains that the traditional area-based methods do not fully capture. Interestingly, although there was a large increase in the area under tree cover in the last five decades, SOC gains in certain regions were compensated by losses in other regions leading to a very small change (~ 2%) in the overall SOC pool size. Land use and soil type were the most important predictors of SOC based on the developed Random Forest model. The findings highlighted that afforestation with tree plantations might not always lead to an increase in SOC stocks at regional scales. Its effect on SOC stocks varied by plantation type and previous land use. These implications must be considered while adopting climate mitigation strategies. Also, spatially explicit evaluation of various plantation types improves SOC source sink modelling and should be considered for preparing more accurate regional & national SOC inventories.

Highlights

- Significant expansion of tree plantations & other land transformations in the last 48 years in Kerala, India, was captured spatially.
- Hotspots of SOC losses & gains due to the land transformations between 1972 and 2020 were highlighted.
- Forest loss was always associated with SOC loss; effect of conversion to tree plantations on SOC depended on plantation type and previous land use.

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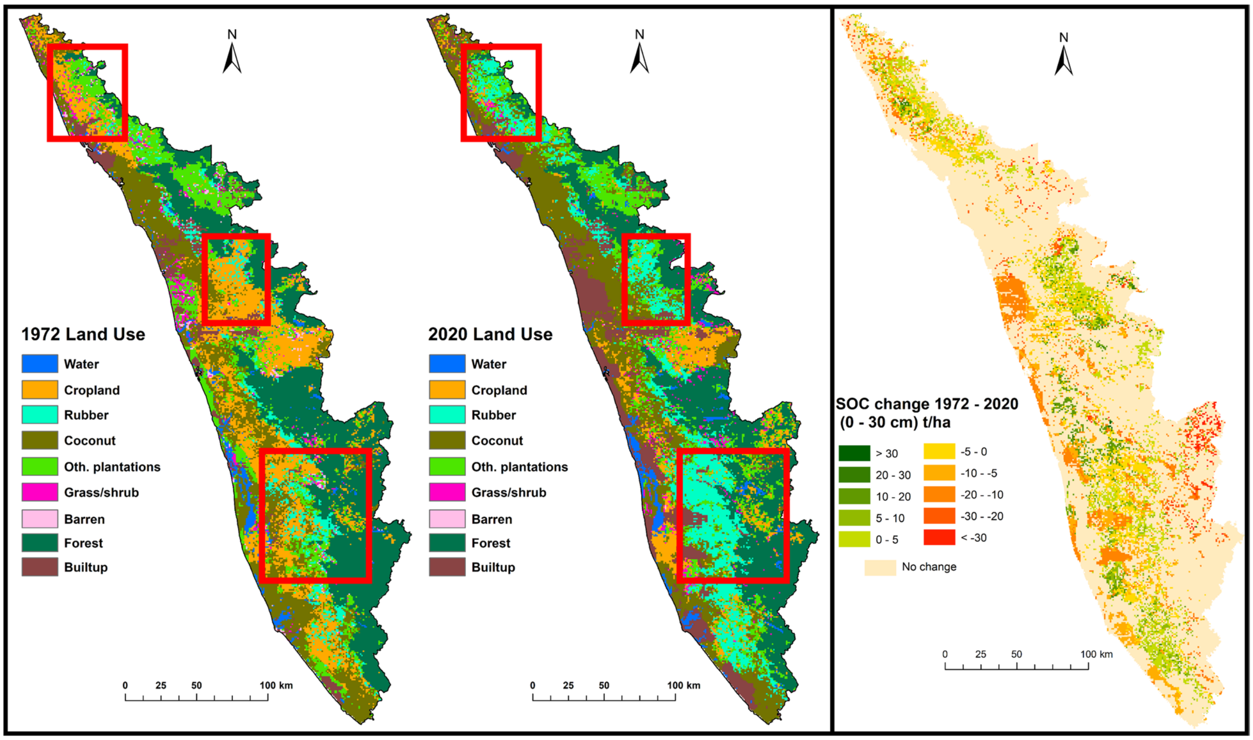
Keywords Soil organic carbon stocks, Land use change, Machine learning, Digital soil mapping, GIS, Remote sensing

Graphical Abstract



1 Introduction

Soil Organic Carbon (SOC) is the largest terrestrial pool of carbon exceeding the combined pools of atmosphere and phytomass. Its importance in climate change mitigation as well as for soil health has been widely discussed (Bossio et al. 2020; Lal 2016; Paustian et al. 2016). However, SOC estimates, especially its spatial variability, remain one of the largest sources of uncertainty in quantifying the terrestrial carbon cycle. Land Use (LU) change is a major driver of SOC and large variation in SOC densities exist amongst LU classes as well as vegetation types. Historically, the conversion of natural forests and grasslands worldwide to cultivated land has led to significant SOC losses, quantified to be around 37 Pg for the top 30 cm (Sanderman et al. 2017). Contrary to this, SOC can also increase, when degraded land is reforested, or when favorable management practices are adopted (Lal et al. 2018). For example, a recent global meta-analysis indicates that SOC can increase by up to 30% when tree plantations replace annual cropping systems (Beillouin et al. 2023).

The area under tree plantations has increased globally in the last few decades with an increasing demand for timber and commodities like rubber, coffee, tea, etc. (Fagan et al. 2022; Pendrill et al. 2022). Deforestation due to the expansion of tree plantations and its effects on various carbon stocks and fluxes have been well documented in different tropical forests (Bonini et al. 2018; Chiti et al. 2014; Guillaume et al. 2018). In the Indian context, many plantations such as rubber, tea and coffee were introduced by British colonial policies. The area under these plantations has further expanded post-independence owing to economic gains, leading to India having the second largest area under plantations (Puyravaud et al. 2010). The state of Kerala exemplifies the drastic expansion of tree plantations in India with more than one third of the total plantation area of the country currently in Kerala (Kerala State Planning Board 2022). Interestingly, unlike other tropical regions where large-scale expansion of tree plantations came at the expense of rich natural forests, plantations in Kerala have not only led to deforestation but to a large extent have also come at places where the land was already cultivated—largely to rice.

Significant land transformations have taken place in Kerala in the last few decades. Kerala today is among the few Indian states with a majority of its geographical area being covered by trees and the area under tree cover on the rise in the last few years (Forest Survey of India 2021). Although the forest habitats within the Western Ghats biodiversity hotspot constitute some of the tree cover within Kerala, more than half of the total tree cover in Kerala is plantations (Forest Survey of India 2021). Owing to the so called "plantation boom" in the late 1900s, most of these plantations have come up only in the last few decades. Agriculture statistics show that since the 1970s, paddy land in Kerala has decreased by more than 50%. During the same period, the area under rubber plantations increased to more than 500,000 ha from only close to 100,000 ha in the mid-1900s.

The state of Kerala presents a particular case of land transformation where, although forests have been under threat, the overall tree cover has been increasing due to the cultivation of plantation crops. Previous studies have analyzed these land transformations using historical and current crop statistics, especially its socioeconomic causes and consequences (Mohan Kumar 2005; Vijayan et al. 2024). But the understanding of its impact on SOC stocks is largely limited to a few site-level comparisons of SOC across various land use systems.

Estimating SOC stocks at regional and larger scales traditionally involved extrapolating mean values based on land use/soil type to the entire area under each of the land use/soil type (Dai et al. 2019). Such methods, however, do not capture the spatial variability within the land use/soil type. Recent advances in the Digital Soil Mapping (DSM) sphere have opened up newer avenues for mapping SOC (Minasny et al. 2013). Although ideally, due to its large spatial variability and slow rates of change, studying SOC requires large amounts of data collected repeatedly with a sufficient time gap, such measurements of SOC remain elusive to very few regions across the world. Alternatively, a space-for-time substitution method can be applied to understand the temporal dynamics of SOC (Sanderman et al. 2017). At a regional scale, such methods have been previously utilized to map SOC stocks for past land use conditions (e.g., Huang et al. 2019; Li et al. 2023; Sanderman et al. 2017) as well as for future climate/land use scenarios (Adhikari et al. 2019; Yigini and Panagos 2016). While these studies have used existing historical land cover datasets (or scenario-based projections for the future) for modeling SOC change, a major constraint in using these datasets is that they are very coarse and/or do not explicitly represent various plantation types. Previous national and global studies mapping historical land use change do not differentiate between various tree plantations, classifying them as either forests or cropland (e.g., Tian et al. 2014; Moulds et al. 2018; Hurtt et al. 2020).

Hence, we integrated Remote Sensing imagery and district-level crop statistics into the HIstoric Land Dynamics Assessment (HILDA) modeling framework (Winkler et al. 2021)—a simple framework for historical reconstruction of land use—to develop two-time period land use maps for the study area almost five decades apart. We then adopted a machine learning-based Digital Soil Mapping approach with space-for-time substitution to study changes in SOC stocks for Kerala transitioning from paddy-dominated agriculture land to tree plantations over the last five decades.

2 Materials and methods

2.1 Study area

The state of Kerala is located in the Southern part of India between the latitudes 8°17’30" N and 12°47’40" N and the longitudes 74°27’47" E and 77°37’12" E, covering an area of about 39,000 sq. km. The elevation in the region gradually increases from the western coastal belt to the high hills towards the East with a maximum elevation of over 2600 m above mean sea level (Fig. 1). The state is home to parts of the Western Ghats, world’s most densely populated biodiversity hotspot. The region is characterized by high rainfall with an average annual precipitation of 3100 mm and the state is the first to receive monsoon due to the South Western monsoon. According to the Koppen classification, Kerala is classified under the tropical monsoon climate.

2.2 Soil data compilation, harmonisation and computation of SOC density

A database of legacy soil characterization from online repositories, published reports of soil survey institutions, published literature and theses was created (Table S1). Ancillary site parameters from these publications like land use, soil type, geographic coordinates, site location information were also retained. From a total of 451 observations, using observations with SOC estimates for at least the top 30 cm and filling the gaps in geolocation from site description, 356 soil measurements were selected for SOC density modelling. These samples were collected at various time periods between 1972 and 2020. A harmonized 0–30cm SOC was estimated using an equal area smoothing spline (Bishop et al. 1999), as previously applied in the study area (Dharumarajan et al. 2021) and across other Indian regions for digital mapping of SOC at standardized depth intervals (Okonkwo et al.

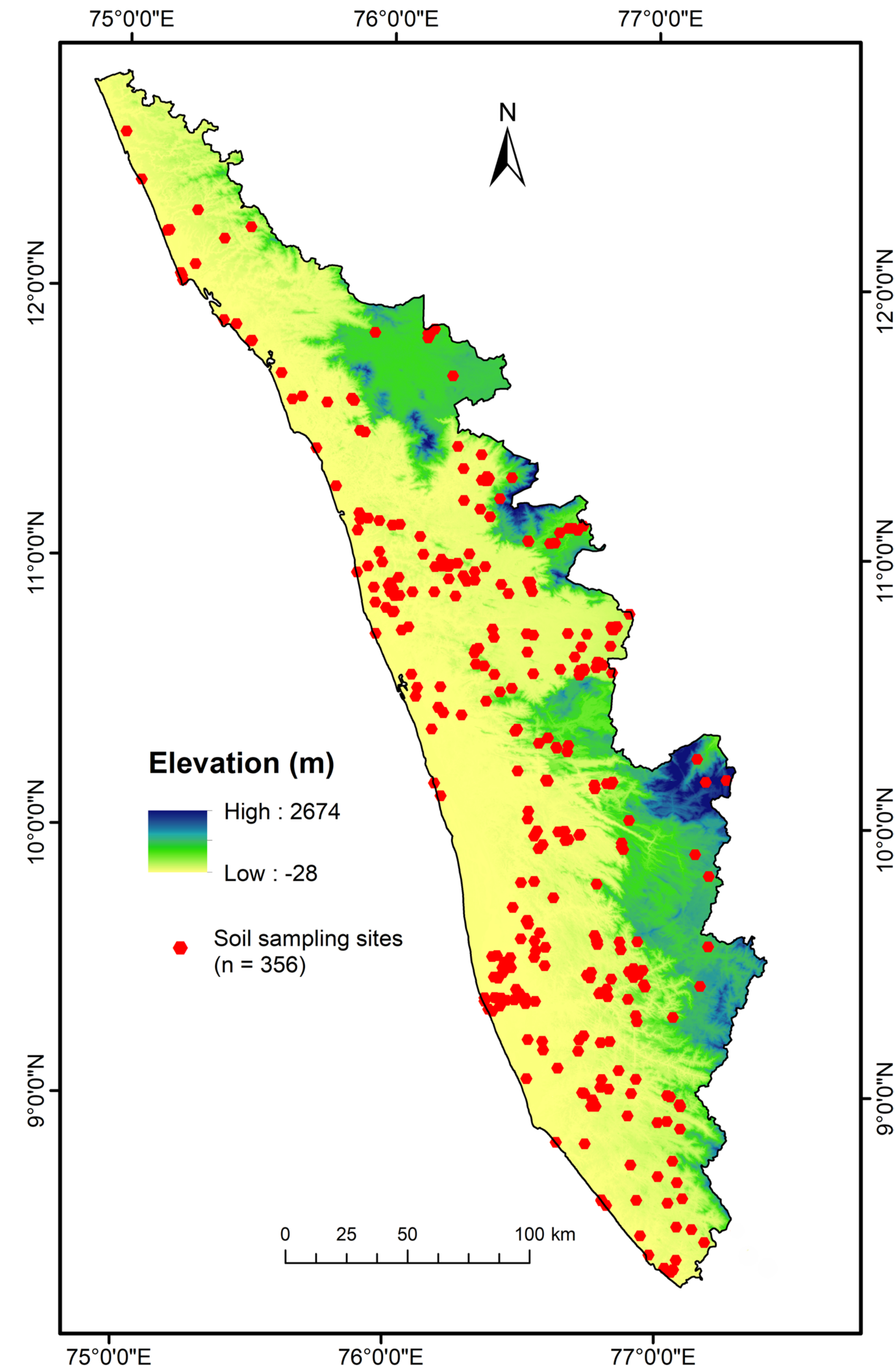


Fig. 1 Study area map with the distribution of sampling locations

2018; Santra et al. 2017). In case profile lacked bulk density measurements, pedotransfer functions (Manrique and Jones 1991) were used (MAE = 0.1; ME = −0.002) and missing gravel content values were substituted with estimates from Soil Grids (Poggio et al. 2021).

The SOC density for each profile was then calculated using the following equation:

$$\mathrm{SOCd} = \mathrm{OC} \times \mathrm{BD} \times \left(1 - \frac{G}{100}\right) \times d$$

SOCd—SOC density (t/ha)
OC—SOC content (%)
BD—Bulk Density (g/cc)
G—Gravel content (%)
d—depth (cm) = 30cm

Box plots showing the spread of field observations of SOC density ($n = 356$) for land cover and plantation categories adopted in this study (Forest-55, Rubber-131, Coconut-44, Other plantations-33, Cropland-87, Grass/shrub-6) is shown in Fig. 2.

2.3 Preparation of two time period LULC

Historical mapping of land use land cover can be a challenging task that requires incorporation of data from diverse sources. We adopted a methodology similar to the HILDA land change modelling framework (Fuchs et al. 2013; Winkler et al. 2021) for the reconstruction of past land cover in Kerala. The HILDA methodology requires: (1) a base LULC dataset of current year which will be used for back-casting; (2) LU inventories showing the changes in area under each LU category; (3) a gridded suitability/probability layer for each LU class that forms the basis for allocating LU change.

Here, a base LU layer for 2020 was prepared by combining multiple remote sensing based LU datasets into a 1 km × 1 km grid based on the majority class within each grid. The proportion of each class occupied within the grids was taken as the probability layer with greater proportion indicating higher probability. Change extents for each class were derived from district-level statistics for 2020 & 1972 (DES (Department of Economics & Statistics, Government of Kerala), 2022) and they were spatially allocated based on the suitability layers. For example, if there is an increase in the area of a class, grids with the highest probability within the district were allocated to that class first. During the

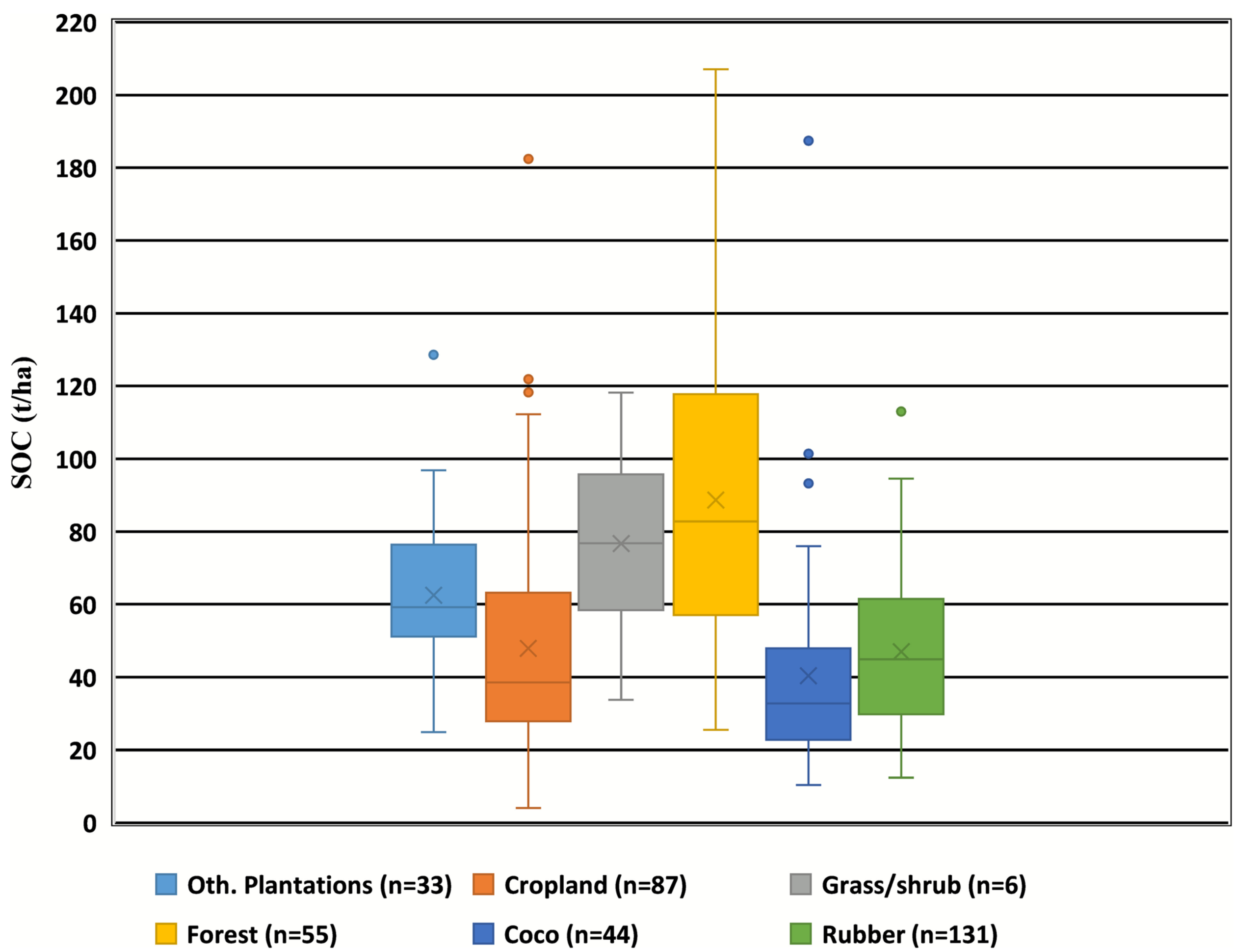


Fig. 2 Spread of SOC values (0–30 cm) for the LULC categories used in this study (Lower and upper ends of the boxes show the 25th and 75th percentile, respectively; while the extent of whiskers represent 1.5 times the Inter-quartile range. The line inside the boxes represents the median value, while the 'x' symbol represents mean)

spatial allocation process, built up class was generated first, followed by rubber, coconut, other plantations, cropland, grass/shrub, barren, water in that order. Forest change was based on a previous long-term deforestation study by Reddy et al. (2016). For the built-up class, probability was based on a time-series of gridded population density dataset (GPW v4).

2.4 Environmental covariates for modelling SOC

Climatic, topographic and soil-related covariates were taken apart from LULC information in the soil database to develop a model for predicting SOC density across the study area. A 90 m Digital Elevation Model (DEM) was obtained from SRTM and three other covariates, slope, aspect and TWI, were generated from DEM in QGIS. A total of 19 bioclimatic variables provided by WorldClim (Fick and Hijmans 2017) were obtained to represent the climatic patterns in the study area. Soil type was taken based on the dominant soil subgroup in each mapping unit from the 1:500,000 soil association map prepared by the National Bureau of Soil Survey & Land Use Planning (NBSSLUP) which was obtained from the ESDAC website (https://esdac.jrc.ec.europa.eu/).

These covariates were resampled by using either their mean value or majority at 1 km for the spatial prediction of SOC as mentioned in Table 1.

2.5 Modelling and mapping SOC

Random Forest (RF), a decision tree-based machine learning algorithm, was used for modelling SOC (Breiman 2001). RF models use an ensemble of decision trees where each decision tree is trained on a different subset of the training dataset (using a technique called bagging or bootstrap aggregating) preventing the risk of overfitting. RF has been widely used for mapping SOC over Indian regions (Sreenivas et al. 2016) as well as across the world due to its ability to capture the complex non-linear

Table 1 List of covariates used for modelling SOC

Sr. no	Covariate	Original spatial resolution/scale	Categorical (C)/Numeric (N)	Resampling to 1 km	Source
1	Elevation	90 m	N	Mean	Farr et al. (2007)
2	Slope	90 m	N	Mean	Derived from DEM
3	Aspect	90 m	N	Mean	Derived from DEM
4	TWI	90 m	N	Mean	Derived from DEM
5	Soil type	1: 500,000	C	Majority	NBSSLUP
6	LULC	1 km	C	-	This study
7	Annual Mean Temperature	1 km	N	-	Fick and Hijmans (2017)
8	Mean Diurnal Range (Mean of monthly (max temp—min temp))	1 km	N	-	
9	Isothermality	1 km	N	-	
10	Temperature Seasonality (standard deviation × 100)	1 km	N	-	
11	Max Temperature of Warmest Month	1 km	N	-	
12	Min Temperature of Coldest Month	1 km	N	-	
13	Temperature Annual Range (BIO5-BIO6)	1 km	N	-	
14	Mean Temperature of Wettest Quarter	1 km	N	-	
15	Mean Temperature of Driest Quarter	1 km	N	-	
16	Mean Temperature of Warmest Quarter	1 km	N	-	
17	Mean Temperature of Coldest Quarter	1 km	N	-	
18	Annual Precipitation	1 km	N	-	
19	Precipitation of Wettest Month	1 km	N	-	
20	Precipitation of Driest Month	1 km	N	-	
21	Precipitation Seasonality (Coefficient of Variation)	1 km	N	-	
22	Precipitation of Wettest Quarter	1 km	N	-	
23	Precipitation of Driest Quarter	1 km	N	-	
24	Precipitation of Warmest Quarter	1 km	N	-	
25	Precipitation of Coldest Quarter	1 km	N	-	

relationships between SOC and environmental covariates (Lamichhane et al. 2019).

An RF regression model was initially used to develop a relationship between SOC density and environmental covariates. The developed model was used to predict SOC across a 1 km × 1 km spatial grid using all the environmental covariates. LULC maps for 1972 and 2020 were used for prediction to generate two-time period SOC maps while keeping soil type, topography and climate constant. This would hold true for soil type and landform that change over geological timescales. For climate, the small changes and the associated effects on SOC would be undetectable. The analysis was performed on R using the '*randomforest*' package (ntree = 500, mtry = 5, nodesize = 5).

2.6 Cross-validation and model evaluation

The final soil database was divided into training (85%) and testing (15%) subsets. A scatterplot of observed and predicted values was created and R^2 and RMSE metrics were calculated for both training and test dataset. To give a more objective assessment of the model performance by reducing any bias that might arise due to a single data split, we also adopted a tenfold cross-validation. In this, the dataset was divided into 10 equal parts (termed as folds). One of the folds was held back to test the performance of model training using the remaining nine folds and this process was repeated 10 times. By giving evaluation metrics as the mean of these 10 different runs, this procedure reduces any bias that might arise in case of a single data split. 'Caret' library in R was used to perform cross validation.

3 Results

3.1 LULC changes between 1972 and 2020

Kerala saw significant increases in the area under rubber plantations and built-up land. On the contrary, land under annual crop cultivation was significantly reduced during the study period while some deforestation was also observed. Our analysis showed that more than 4000 sq.km of land under annual crop in 1972 was converted to rubber, coconut, and the other plantation category. Likewise, forest loss was close to 1500 sq.km owing to the cultivation of various annual as well as tree crops. A major increase was seen in rubber plantations which is clearly visible in the maps showing the spatial patterns of various land use categories in 1972 and 2020 (Fig. 3). This vast increase in rubber plantations in Kerala has led to the state currently being responsible for more than two-thirds of the country's overall rubber production.

In broad-level land use classification systems, these plantations are usually categorized into forests or into arable/cropland. Hence, previous global and national-level spatial datasets that have tried to reconstruct historical land use changes (Moulds et al. 2018; Tian et al. 2014) did not represent these land conversions—thereby limiting any research on the effects of these land conversions on regional SOC stocks.

Apart from the changes involving rubber and other plantations, a major expansion of built-up land was visible, especially in the western and central part of the state. This sprawl is clearly visible in the major urban centers of Trivandrum and Ernakulam. Overall, the built-up area in the state increased from 1873 sq.km. in 1972 to 4867 sq. km. in 2020.

While the plantations expansion also led to grassland loss, the overall area under the grassland/shrub class did not change significantly due to increase in other regions. This could be attributed to the recent grassland restoration schemes in the region.

3.2 Variable importance and RF model performance for SOC prediction

Land use and soil type were the two most important predictors of SOC density as per the developed RF model (Fig. 4). The model performance was evaluated using the R^2 and RMSE metrics computed from the prediction residuals. The model performance was very good on the training dataset ($R^2 = 0.91$; RMSE = 9.21 t/ha) and was acceptable on the test dataset ($R^2 = 0.53$; RMSE = 19.2 t/ha). These numbers were comparable to many regional, national as well as global studies of SOC (further discussed in the discussion section). Likewise, the tenfold cross-validation showed similar model performance with an R^2 of 0.51 and an RMSE of 23.2 t/ha.

3.3 Spatial prediction maps and changes in SOC stocks over 48 years

The spatial patterns of SOC stocks largely mimicked the underlying land use patterns (Fig. 5). The highest SOC density (> 150 t/ha) was found in the east part of the state which has patches of dense forests within the Western Ghats biodiversity hotspot. These regions are also located at a higher elevation compared to the coastal and central regions. The western and central part of the state, where most of the lowlands and midlands were cultivated with annual crops or plantations, the SOC density ranged from 20 t/ha to 100 t/ha.

The changes in SOC between 1972 and 2020 can be better visualized in Fig. 6. As seen in the figure, significant changes, other than the losses due to urban expansion near the coastal regions, came in the central part. The expansion of plantations and built-up land in these parts, as visualized in Fig. 3, led to major changes in SOC density. While the conversion of annual crop to plantations led to some gains in SOC, deforestation and urban

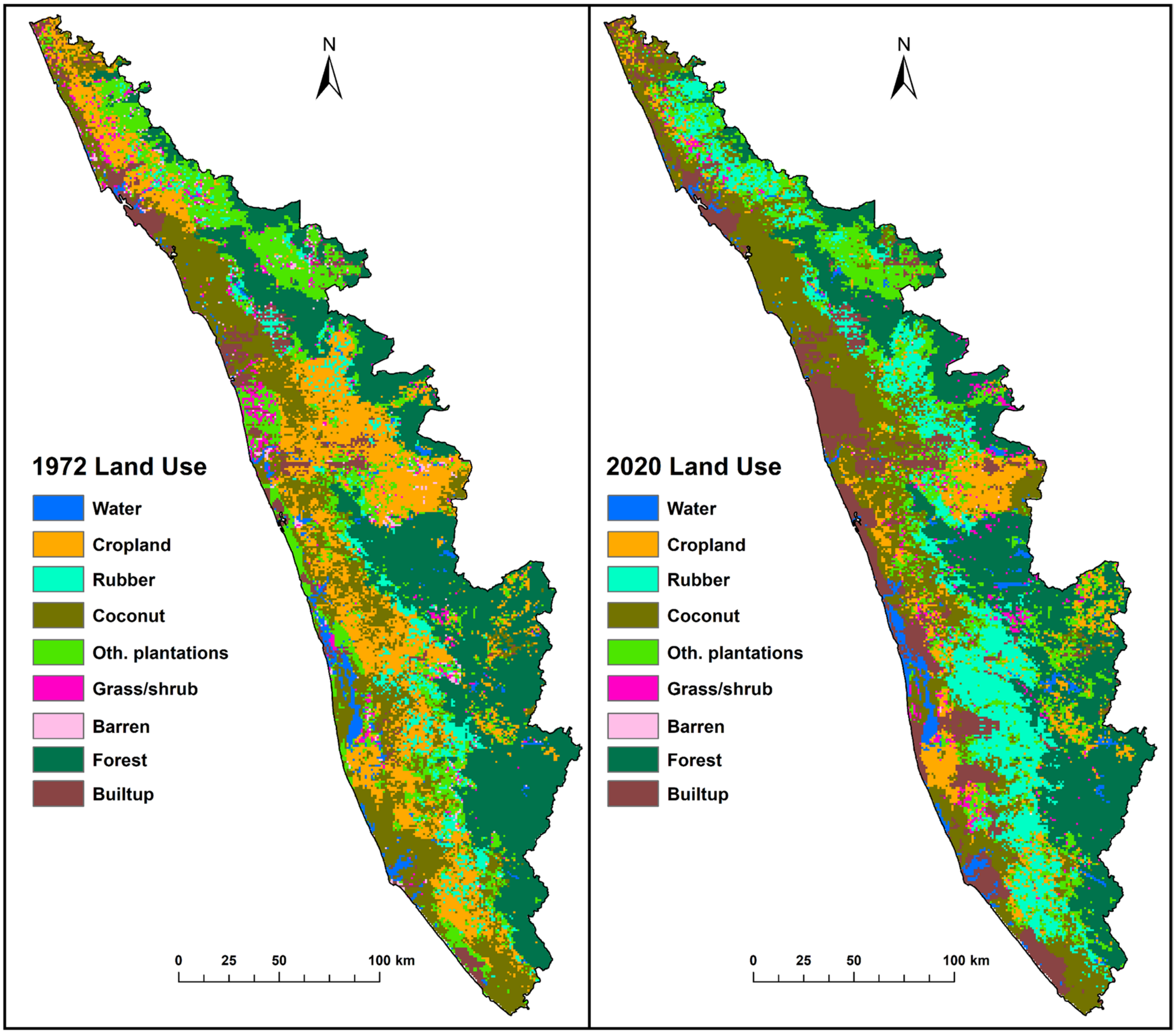


Fig. 3 Land use maps for 1972 (left) and 2020 (right)

expansion have led to SOC losses. The mean SOC losses/gains due to major land conversions are shown in Table 2. Forest conversion to annual crop, coconut, other plantations, and rubber classes led to mean SOC losses of 25, 19, 18 and 8 t/ha respectively. On the other hand, the conversion of annual crop to the other plantations led to SOC gains (mean increase of 7.75 t/ha) while the mean SOC change due to the conversion of annual crop to rubber and coconut remained close to zero.

During the study period, the state of Kerala also saw large increases in built up land. For our analysis, due to a lack of local data over SOC changes due to the expansion of built-up land, we used the default IPCC value of a 20% loss of SOC due to the conversion to built-up land (IPCC 2006). This resulted in an estimated overall loss of 0.28 million tonnes of carbon due to urbanization.

Lastly, we computed the overall change in the SOC stocks for the state of Kerala. Table 3 shows SOC stock values under each land use category for 1972 and 2020 and the change between the two years. As seen in the table, the change in total SOC stocks of the region was very small. The results show that the losses in SOC due to land transformations like deforestation were offset by SOC gains due to the cultivation/plantation expansion in regions that previously supported low SOC stocks. In terms of the total SOC stocks, these observations were similar to those from a previous study in the northern part of Western Ghats (Lo Seen et al. 2010).

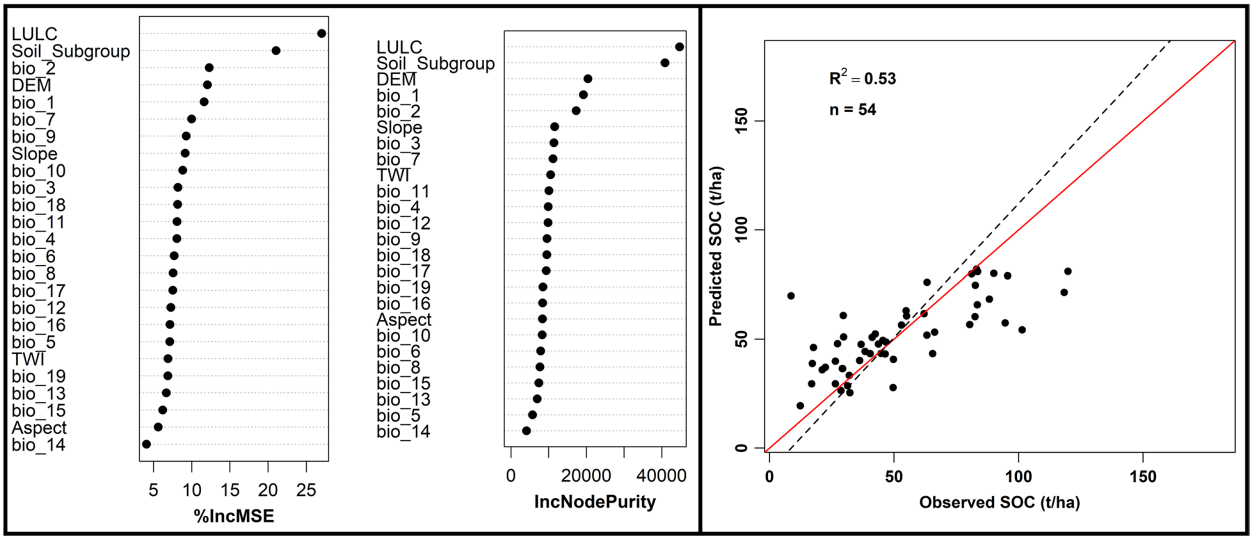


Fig. 4 Variable importance (left) and Scatterplot of observed vs predicted SOC (t/ha). (bio_1 to bio_19 are the 19 bioclimatic variables—described in Supplementary information). %IncMSE & IncNodePurity in the variable importance plot show the variable importance based on percent increase in Mean Squared Error and Node Purity without each variable respectively

4 Discussion

4.1 Comparison of model performance and SOC prediction with other studies

Machine learning algorithms have been shown to capture the complex non-linear relationships between SOC and environmental covariates (Wadoux et al. 2020). In our study, using the Random Forest algorithm, the obtained R^2 of 0.53 between the observed and predicted SOC for the validation dataset ($n = 54$) was comparable to many typical DSM studies predicting SOC density for the top 30 cm at regional to national scales (e.g., Area = 169,639 km^2, $n_{train} = 385$, $n_{val} = 165$, $R^2_{val} = 0.48$, ME = 0.62 (Huang et al. 2019); Area = 169,640 km^2, $n_{train} = 210$, $n_{val} = 70$, $R^2_{val} = 0.38$, $R^2_{train} = 0.76$ (Adhikari et al. 2019); Area = 149,997 km2, $n_{train} = 470$, $n_{val} = 157$, $R^2_{val} = 0.56$, $R^2_{train} = 0.91$, $RMSE_{val} = 19.32$ t/ha (Li et al. 2023)). The R^2 obtained in the study was also more than that of a previous DSM study in the region using RF albeit the models were developed for different depth layers (Dharumarajan et al. 2021). Nonetheless, this study used more than twice as many soil samples as in the previous study. Moreover, developing a remote sensing derived LU map in this study enabled the use of land use as a covariate as LU plays an important role in the soil carbon cycling processes. This was also visible in the variable importance metric where Land Use was found to be the most important variable to predict SOC (Fig. 4).

In this study, the total SOC stock of Kerala for the top 30 cm was estimated to be 227 Tg and 222 Tg for 1972 and 2020, respectively. This was similar to the 386 Pg reported by Dharumarajan et al. (2021) for the 0–30 cm layer, whose study area consisted of four additional districts from neighboring states, leading to an overall area that was around 45% more than the area in this study. Furthermore, we compared the SOC stocks of Kerala from this study to a previous national study by Sreenivas et al. 2016. The data from that study was publicly available aggregated to 5 km x 5 km grid through the Bhuvan portal (https://bhuvan-app3.nrsc.gov.in/data/download/index.php?c=p&s=NICES&g=OS&p=slp). From the downloaded dataset, the SOC stocks for Kerala was calculated as 567.77 Tg for a soil layer of 0–1 m depth. The SOC stocks for the 0–30 cm from this study was around 40% of the SOC stocks for 0–1 m from the dataset in Bhuvan.

Although a number of studies have used DSM for mapping SOC in India at national (Sreenivas et al. 2016), regional (Dharumarajan et al. 2021), as well as subwatershed scales (Kumar et al. 2018), the temporal dynamics of SOC at larger spatial scales has been neglected. Using a process-based ecosystem model, a previous national scale study estimated that LU changes in India over the past century have increased the SOC stocks by 1.7 Pg (Banger et al. 2015). However, the study had used coarse-resolution historical LU data that does not distinguish among various plantations, thereby limiting any further analyses on the changes in SOC due to land transformations involving tree plantations. Calibrating such a model for each plantation/crop type still remains a challenge. Using a space-for-time substitution assumption along with a detailed LU map as a dynamic covariate in DSM, the method adopted in this study provides an effective

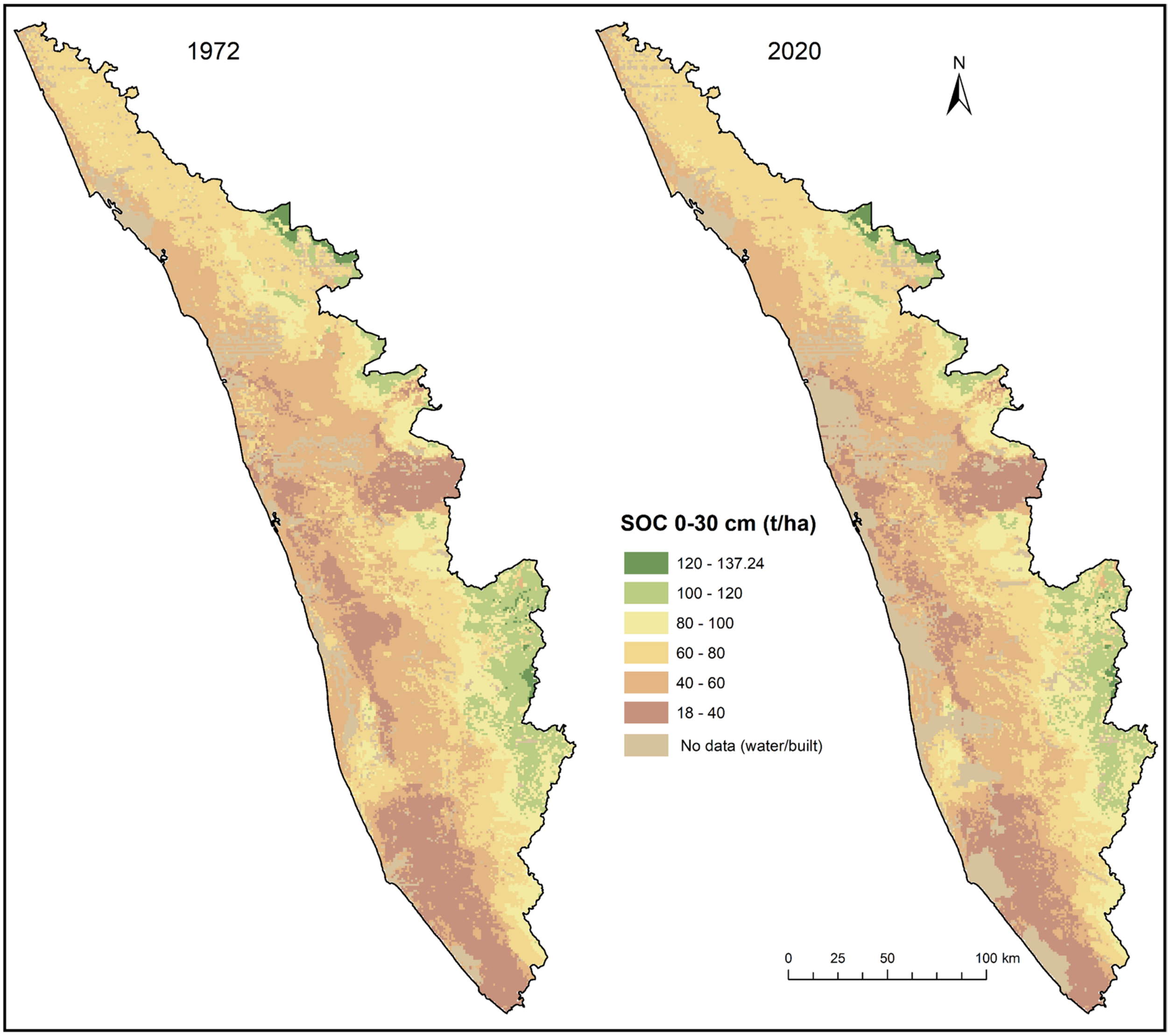


Fig. 5 Top soil (0–30 cm) SOC density (t/ha) for 1972 (left) and 2020 (right)

strategy to assess the impact of large-scale land transformations on SOC stocks in a spatially explicit manner (Li et al. 2023; Sanderman et al. 2017).

4.2 Impact of cropping pattern shift and other land transitions on SOC

Consistent with previous studies, our analysis showed a decrease in SOC stocks due to the conversion of forest to cropland. To further understand the patterns of SOC change and how it is affected by various land conversions, we divided cropland into annual crop, rubber, coconut and other tree plantations. The mean SOC loss of around 25 t/ha (~ 24% in relative terms to initial SOC) due to the conversion of forests to annual crop cultivation from this study was within the range from previous meta-analyses (Don et al. 2011; Guo and Gifford 2002). Among the tree crops, forest conversion to coconut and the other plantations category showed larger losses (mean losses of 18.9 and 17.6 t/ha, respectively) in comparison with forest conversion to rubber plantations (mean loss of 7.97 t/ha). Using a calibrated RothC model, Paramesha et al. (2025) also found that forest conversion to coconut plantations would lead to a loss of 21 t/ha in the top 30 cm of soils in the Western Indian state of Goa. Meanwhile, in the North Eastern part of India, by using the RothC model, Mishra et al. (2021) simulated a loss of around 16 t/ha in the

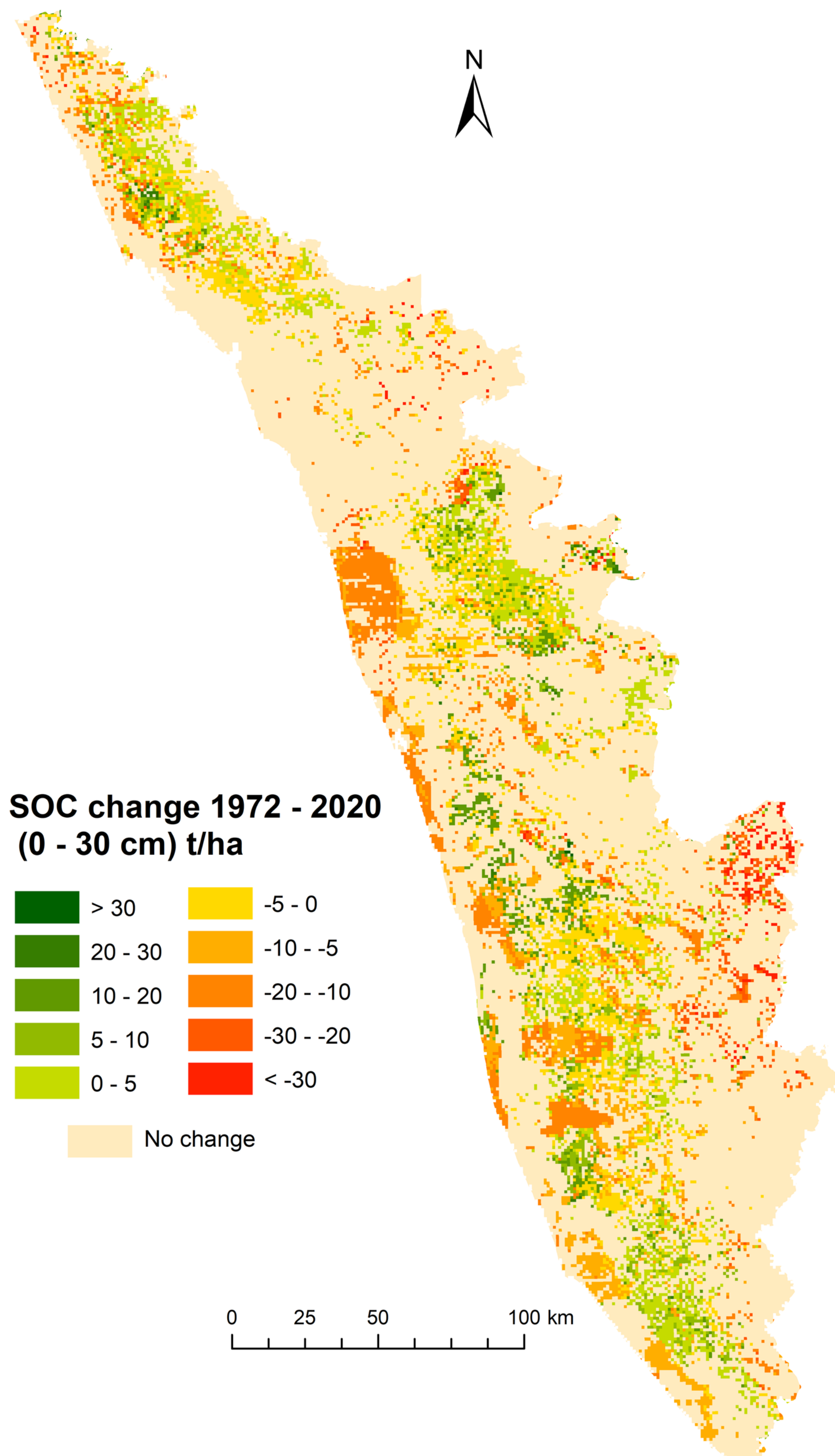


Fig. 6 Areas with gains and losses in the topsoil (0–30 cm) SOC in Kerala between 1972 and 2020

Table 2 Mean SOC changes due to major LU changes in the study area

LU change	Area (sq.km.)	Mean percent SOC change	Mean SOC change (t/ha)
Forest to other plantation	779	−18.34	−17.63
Forest to annual crop	303	−23.98	−24.9
Forest to grassland	256	−6.37	−5.9
Forest to rubber	294	−10.2	−7.97
Forest to coconut	52	−21.52	−18.98
Annual crop to other plantation	1431	18.22	7.75
Annual crop to rubber	1718	−0.29	−0.19
Annual crop to coconut	1193	−2.61	−1.27

0–30 cm soil layer due to the conversion of forests to rubber plantations.

Other studies around the world have also found decreases in SOC stocks following the conversion of forests to rubber plantations computed at different depths but the magnitude of loss varied by location. For instance, van Straaten et al. (2015) analyzed paired observations from various tropical regions and found that SOC loss due to forest conversion to rubber plantations ranged from 7 t/ha in Indonesia to 41 t/ha in Cameroon in the top 1 m of mineral soils. Similarly, Blécourt et al. (2013) reported a decrease of 37 t/ha to a depth of 1.2 m in Southern China.

As discussed earlier, in other global and national land cover datasets that map historical land use, tree plantations are usually classified either as cropland or as forest—limiting any regional scale efforts to study the effect of land conversions involving tree plantations on SOC. Government policies in the region over the last few decades have encouraged planting trees like rubber. This has seen a considerable increase in the area under rubber plantations in the last few decades. Although planting perennial tree crops has been suggested as an option to increase carbon stocks in agricultural land (Glover et al. 2010), the understanding of such land use change effects on SOC, like much of the SOC dynamics, remain highly uncertain. This study shows the variable response of SOC density upon the conversion of annual crops to tree plantations with different tree species. It is important to note that while forest conversion to cropland in Kerala was always associated with a loss in SOC (mean loss of 25 t/ha), the expansion of tree plantations didn't necessarily lead to significant gains in SOC (Table 2).

The possible reasons for the varying behavior of different tree types could be explained by their inherent biophysical traits as well as by the human modifications to those ecosystems. For example, Mina et al. (2023) attributed lower litter content in coconut plantations for the lower SOC contents when compared to rubber plantations in a study in the southern part of Kerala. Similarly, Saha et al. (2010), comparing major plantations in central Kerala, noted that soil management disturbances like litter removal, manual weeding, are much lesser in rubber plantations leading to a greater input of C into soils. These factors could explain the larger loss of SOC due to the conversion of forests to coconut plantations in this study when compared to the conversion to rubber plantations (Table 2). Moreover, most of the plantations are planted to obtain commodities like their fruit or latex, or for timber extraction. Either way, a significant amount of the primary production is constantly extracted from the system, which could reduce the inputs to soils through litterfall and roots. For instance, Kumar et al. (2009) showed that the proportion of total dry matter of a coconut tree in its fruit ranged from 53% to 67% in three different soil types in south India. In another study in the Oceanic island country of Vanuatu, nut production represented 46% of the total NPP of a coconut tree (Roupsard 2008). Similarly, tapping of latex for rubber production could lead to an annual latex flux ranging

Table 3 SOC stocks under each LU category for 1972 and 2020

Sr. no	Land use	1972		2020		SOC stock diff (Tg)
		Area (sq.km)	SOC stock (Tg)	Area (sq.km)	SOC stock (Tg)	
1	Forest	12,165	103.18	10,282	87.02	−16.16
2	Rubber	1929	10.27	5793	30.2	19.93
3	Coconut	7744	34.78	8369	38.66	3.88
4	Other plantations	5482	32.86	5101	31.93	−0.93
5	Cropland	8082	39.56	3227	17.15	−22.41
6	Grassland/shrub	991	6.6	940	6.24	−0.36
	Total		**227.27**		**222.51***	

* Includes SOC stocks of area converted from various LU classes to built-up between 1972 & 2020 after computing a 20% loss of original SOC as per IPCC tier 1 method

from 0.7 t/ha/yr to 1.9 t/ha/yr (Blagodatsky et al. 2016). All these factors could lead to lower inputs of carbon into soils, leading to smaller SOC stocks, compared to forests.

The results of this study further emphasize the need to study plantation ecosystems and their carbon cycling processes separately. Many studies on carbon sequestration in trees concentrate only on carbon stored in above-ground and below-ground biomass (e.g., Panumonwatee et al. (2025)) without taking into account the SOC dynamics. The complexity of SOC sequestration post vegetation restoration (Deng and Shangguan 2025) needs to be considered before designing afforestation strategies. Notably, in the Indian context, many previous studies have advocated for the separation of natural forests and plantations owing to their differences in terms of biodiversity and carbon stocks (Puyravaud et al. 2010). The results from this study strengthen the argument in the context of SOC and identify the need for having different sub-classes within the "tree" layer for improved SOC and SOC change assessment.

Another reason for the lesser change in SOC could be rice being the major annual crop in the study area. Paddy fields have been documented to support greater SOC stocks due to increased fertilizer addition and/or due to the anaerobic conditions that reduce the oxidation of carbon in some waterlogged rice fields. Similar results were also observed by Muñoz-Rojas et al. (2015) albeit in the Mediterranean soils, where SOC did not increase following the conversion of rice-dominated arable land to permanent crop.

4.3 Sources of uncertainty

In this study, while the use of LU maps separating major plantations like rubber and coconut improved the spatial prediction of SOC stocks, more refined representation of LULC dynamics can further improve the accuracy of SOC stock changes. For example, at the scale of our study (1 km), it was not possible to identify and separate different land management practices like agroforestry; intercropping that can have a direct effect on SOC. Although remote sensing-based techniques exist to map the current distribution of such land uses (Sharma et al. 2023), mapping the past distribution remains extremely challenging and methods combining a variety of data sources are being explored (Pasha et al. 2024). Moreover, the "other plantations" category in the land use maps contained various plantations like mango, areca nut that covered extremely small areas. Hence, it wasn't possible to separate them at the scale of our study.

Secondly, the study considered that for each LU category, the same combination of environmental factors would lead to the same SOC stock. This approach, however, does not take into the account the effect of other change phenomenon like increasing CO_2 concentration in the atmosphere or nitrogen fertilization. Such changes could have either positive effects through increasing plant primary productivity or negative effects through increased microbial decomposition due to increasing temperatures (Smith et al. 2008). These effects, however, could not be considered using the current approach.

Owing to these unavoidable uncertainties, the regional change in SOC stocks of 4.76 Tg over the 48-year period can be considered negligible. Nonetheless, the study highlighted important local hotspots of losses and gains due to various land transformations (Fig. 6) that cannot be captured by traditional area-based non-spatial methods or static digital soil maps (e.g., Dharumarajan et al. 2021). From these hotspots, it could be clearly observed that deforestation (conversion to cropland as well as plantations) was always associated with SOC loss while plantation expansion in some croplands led to gains in SOC. Some of these changes would get lost if tree cover is not separated into forests and plantations, as is the case in existing historical land use datasets.

5 Conclusions

The study evaluated the spatial distribution of SOC density and its change over 48 years, adopting a space-for-time substitution method in a machine learning-based Digital Soil Mapping framework. Land use and soil type were the most important predictors of SOC density. Using Remote Sensing & GIS-derived LULC maps that separate major plantation types, forests and cropland, along with field SOC observations representing these categories, the study predicted SOC stocks for 1972 and 2020 and analyzed the overall changes in SOC stocks due to various land transformations.

Increasing tree cover has been suggested as a promising nature-based solution to mitigate climate change by increasing the land carbon stocks. The study highlighted the complexity of such land transformations in terms of SOC sequestration. The main conclusions from our analysis show that: (a) tree cover is not equal to forest in terms of SOC stocks; (b) spatially explicit evaluation of plantation types is necessary for an improved SOC source-sink modelling at a regional scale.

In the Indian context, while the area under tree cover has been increasing over the last few decades (Forest Survey of India 2021), its effect on the regional and national SOC pools has not been studied comprehensively. In Kerala, a major hotspot of plantation expansion, the study showed that, the change in overall SOC pool of Kerala remained very small in spite of significant land transformations.

A further look into the hotpots of SOC losses & gains revealed that while forest loss and urbanization were always associated with SOC loss in the study region, the expansion of tree plantations in certain regions led to some gains in SOC. However, the regional SOC stocks were not altered significantly as gains in SOC were compensated by losses in other regions. These implications must be considered when designing reforestation strategies and estimating regional and national SOC inventories. The method used in this study can be adopted in other regions around the world where there is a lack of repeated soil measurements or resource limitations do not allow for detailed process-based modelling, to understand the effects of large-scale land transformations on SOC stocks and move towards a better carbon source-sink modelling.

Supplementary Information

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Supplementary Material 1.

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Authors' contributions

All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by Saketh Kandadai. The first draft of the manuscript was written by Saketh Kandadai and all authors reviewed and commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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Data availability

The soil sampling data used for analysis has been retrieved from publications listed in the supplementary material. All other data sources have been mentioned in the manuscript.

Declarations

Competing interests

The authors declare no competing interests.

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