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Research Article

Estimation of soil carbon pools under major cropping systems of Mayiladuthurai district of Cauvery Delta Zone, Tamil Nadu, India

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Abstract
Soil organic carbon (SOC) is a potential indicator of soil quality and ecosystem sustainability. The present study aimed to evaluate SOC pools under major cropping systems of Mayiladuthurai district of Tamil Nadu. The composite samples were collected from two depths (0-15 and 15-30 cm) by stratified random sampling and were analysed for pH, EC (Electrical conductivity), C fractions, inorganic carbon and permanganate oxidisable carbon by standard procedures. The SOC content under different land use was in the order of Forestry > Rice – pulses > Rice – cotton > Sugarcane > Uncultivated. The mean SOC content of the study area was 12.58 Mg ha^{-1}, where the majority of the area falls under low to medium rating of SOC. Hence, cultivation practices should incorporate activities that increase SOC to maintain soil quality. SOC was positively correlated with fractions of carbon – C_{VL} (r = 0.37**), C_L (r = 0.65**) and C_{LL} (r = 0.58**), indicating changes in land use would affect the carbon dynamics of the ecosystem. The root biomass, aeration status, microbial activity, nutrient reserves and inherent soil characteristics influenced SOC to decrease with depth. The PCA analysis revealed that the variation in carbon dynamics of the study area was influenced by SOC, C_{LC}, C_{LL} and non-labile carbon due to differences in land management practices. Therefore, such soil management practices will be a powerful tool to sequester carbon, which supplements climate change mitigation.

Keywords: Cauvery delta zone, Carbon dynamics, Carbon pools, Soil carbon

INTRODUCTION

Soil organic carbon (SOC) is vital in maintaining soil health and sustainability. In terrestrial land use, organic carbon supports the productivity and resilience of the ecosystem (Zeraatpisheh *et al.*, 2020). The topsoil of the terrestrial ecosystem serves as the largest sink for carbon and changes in land use will result in carbon emission as CO_2 into the atmosphere (Hoffmann *et al.*, 2017). Conversion of land use types, urbanization, and expansion of industrial activities deplete or redistribute of the global C pool in different ways. The quantity of carbon within the ecosystem is balanced between the addition of C inputs and loss through C outputs (Zhang *et al.*, 2022). SOC serves as a potential indicator of soil quality and fertility. Therefore, there is an increasing demand for information about SOC worldwide. Protecting and upscaling SOC will benefit the soil by enhancing fertility, reducing erosion and improving resilience towards climate change (Bossio *et al.*, 2020).

The diverse nature of soil management practices accompanied by differences in agricultural operations, climatic conditions, land cover and topography, impacted the variation in soil organic carbon and other soil properties (Tajik *et al.*, 2020). Intensive agriculture practices greatly rely on tillage, machinery, agrochemicals and land use changes to obtain maximum crop production potential. Consequently, it seriously threatens SOC reserve, which triggers biodiversity loss. The differential nature of land use patterns and carbon mineralisation rate significantly affect soil carbon's biogeochemical cycle. Adopting cropping practices that supplement soil carbon sequestration may help reduce greenhouse gas emission into the atmosphere (Mirchooli *et al.*, 2020). Further, weathering of minerals, soil acidity or alkalinity, accumulation of contaminants, nutrient reserves, microbial diversity and soil inherent characteristics influence the soil carbon reserves within the ecosystem (Bhattacharya *et al.*, 2016).

Knowing the spatial variation of SOC is very important in rectifying the land management and agricultural practices, enabling the ecosystem's sustainability. The spatial variation of soil carbon pools would help in enabling suitable management practices (Reza *et al.*, 2017). The study on the correlation of spatial distribution of SOC pools is of great significance, which supports the assessment of carbon reserves. Information on the depth-wise distribution of soil organic carbon fractions will aid in budgeting carbon in any land use.

However, details about the distribution of soil organic carbon pools under different cropping systems in intensively cultivated areas are limited. Hence, the present study was undertaken to compute the soil carbon pools under major cropping systems in Mayiladuthurai district of Cauvery Delta Zone, Tamil Nadu.

MATERIALS AND METHODS

Site description

Mayiladuthurai, a coastal district of Tamil Nadu lies between 10º 57’ 00” N to 11º 26' 00” N Latitude, 79º 31' 00” E to 79º 55' 00” E Longitude and has an aerial extent of 1172 km^2. Among the land uses, agricultural cropping covers about 753 km^2, a forest area of 198 km^2, uncultivated land use of about 117.78 km^2 and the remaining by water bodies. Sandy coastal alluvium and black soil are the major soil types that cover the study area. The major cropping systems in the study area were rice-pulses, rice-cotton and sugarcane.

Sample collection and soil analysis

The soil samples were collected using stratified random sampling from the major cropping systems, uncultivated areas, and forestry land use. The composite samples were taken from 75 georeferenced sampling points along two depths (0-15 and 15-30cm). The collected samples were air-dried, passed through 2mm and 0.2mm sieves, and used for analysis. The samples were analysed for soil reaction potentiometrically using a pH meter and electrical conductivity (EC) using (1:2.5) soil-water suspension (Jackson, 1973). The soil organic carbon was determined through wet digestion by oxidising the chromic acid produced by potassium dichromate ($K_2Cr_2O_7$) and concentrated sulphuric acid (Walkley and Black, 1934). The soil carbon fractions under different oxidising conditions were determined using 12N, 18N and 24N using sulphuric acid – aqueous solution of ratio 0.5:1, 1:1 and 2:1, respectively (Chan *et al.*, 2001).

Very labile carbon (C_{VL}) = SOC oxidizable under by 12 N H_2SO_4 Eq. 1

Labile carbon (C_L) = Difference in oxidizable OC between 18 N and 12 N H_2SO_4 Eq. 2

Less labile carbon (C_{LL}) = Difference in oxidizable OC between 24 N and 18 N H_2SO_4 Eq. 3

Soil inorganic carbon (SIC) was estimated by the rapid titration method (Richards, 1954) and $KMnO_4$ oxidizable carbon (POXC) was Spectrophotometrically measured at 550nm (Weil *et al.*, 2003). The non-labile carbon (NLC) was calculated by the difference of total soil organic carbon and POXC.

Statistical analysis

Descriptive statistics was used for summarizing the analysed data. Parameters like mean, median, minimum, maximum, standard deviation, variance, coefficient of variance, skewness and kurtosis were calculated for different soil properties.

Pearson correlation coefficient was developed for all paired combinations of response variables. Duncan’s multiple range test (DMRT) was used to compare the means and significance of the mean variations between different land uses and the statistical significance was determined at $P < 0.05$. Principal Component Analysis (PCA) was used to study variation among soil properties where multivariate data was simplified dimensionally. The statistical analyses were carried out using tools like Microsoft Office 2021, R Studio 4.2.2 and SPSS Statistics 20.0

RESULTS AND DISCUSSION

The soils under different cropping systems were alkaline in reaction with a mean varying from 7.31 to 8.12 in the topsoil and 7.32 to 8.18 in the subsurface layer (Table. 1). The mean value of soil pH of the study area was 7.56 with a coefficient of variation (CV) of 3.17%. The soils of the forest ecosystem have significantly higher (P<0.05) pH than the remaining cropping systems. Porkodi *et al.* (2022) also reported the weathering of basic natured parent material, deposition of alluvium and base accumulation from the poorly drained conditions of rice-based land use resulted in the alkaline nature of the soil pH.

The conductometric study revealed that soils were non-saline (0.33 – 0.39 dS m^{-1} in surface and 0.37 – 0.44 dS m^{-1} in subsurface layers) except the forestry land use (1.14 and 1.23 dS m^{-1} in surface and sub-surface respectively). The mean electrical conductivity (EC) value of the study area was 0.38 dS m^{-1} with a CV of 59.92% (Table 3). The EC was inversely related to the soil depth. Similarly findings were substantiated by Prusty and Farooq (2020), who noticed the intrusion of seawater from the coastal areas and accumulation of salts in the surface layers by evaporation resulted in the higher EC in the forest ecosystem. The soils having higher EC restricts the substrate availability to microbial populations, which retards the decomposition of the organic matter. The soil EC was negatively correlated with soil organic carbon (r = -0.13) (Fig. 1). Yu *et al.* (2014) implicated that the salinity disrupted the physically protected organic matter within the aggregates, leading to loss of SOC.

Soil carbon fractions

The content of soil organic carbon among the different cropping systems in the study area was in the order of Forestry > Rice – pulses > Rice – cotton > Sugarcane > Uncultivated (Table 2). The mean value of soil organic carbon of the study area was 12.58 Mg ha^{-1} with CV of 11.05% (Table. 3). The significantly greater organic carbon in the agricultural cropping system than that of uncultivated land use would have arisen from the higher incorporation of stubbles and greater root residue into the soil. This was in line with Kubar *et al.* (2018), who discerned that organic C pool is influenced by the decomposition rate of crop residues which supplies the substrate to the microbial population, increasing the accumulation of SOC in the soil. The finer texture of soil under a rice-based cropping system traps the organic carbon within the clay complexes (Moharana *et al.*, 2017). The dynamics of SOC might be influenced by the quality and quantity of the carbon inputs added to the soil. Luo *et al.* (2017) reported that changes in land management practices in the cereal-based cropping system regulated the variation of SOC spatially.

The correlation matrix revealed a positive correlation of SOC with the fractions of carbon – C_{VL} (r = 0.37**), C_L (r = 0.65**), C_{LL} (r = 0.58**), indicating that changes in SOC will affect the quantity of soil carbon fractions (Fig. 1). Deshmukh *et al.* (2015) conveyed that the cultivation practices released physically protected carbon from the passive pool by increased mineralization rate which resulted in the comparatively lower SOC in the agricultural land use than that of forest ecosystem. The SOC declined with the increasing soil depth, which might have occurred from the lower microbial activity, aeration status and lower root biomass in the subsurface layer compared to topsoil.

The carbon pools largely depend upon the quantity of organic residues incorporated into the soils (Somasundaram *et al.*, 2018). The reports were similar to the work of Babu *et al.* (2020), who observed the variation in the rooting pattern, the release of root exudates and discrepancy in addition of C inputs under different cropping systems contributed to the dissimilarity in the distribution of carbon pools both quantitatively and qualitatively.

The very labile carbon fraction was significantly higher in the rice-pulses cropping system (P<0.05) and was lowest in uncultivated land use. Including legumes in the cropping sequence might have increased the labile pool of carbon in the soil, which ultimately supplies protein-rich biomass to the microbes. Similar findings were reported by Babu *et al.* (2020), who noticed the variation in the addition of root biomass under different cropping systems led to the variation of carbon fractions with depth. The mean value of C_{VL} of the study area was 4.41 Mg ha^{-1} with CV of 20.30%. The C_{VL} and C_L positively influenced crop production and affected crop yield. The higher C_{VL} in rice – pulses cropping system could be related to the secretion of more root

Table 1. Soil reaction (pH) and Electrical conductivity (EC) of the soils under major cropping systems of Mayiladuthurai district

Cropping System	pH		EC (dS m^{-1})	
	0 – 15 cm	15 – 30 cm	0 – 15 cm	15 – 30 cm
Rice – cotton	7.48 ± 0.044^{bc}	7.54 ± 0.042^{bc}	0.33 ± 0.031^{b}	0.37 ± 0.028^{b}
Rice – pulses	7.65 ± 0.044^{b}	7.68 ± 0.043^{b}	0.33 ± 0.061^{b}	0.38 ± 0.061^{b}
Sugarcane	7.31 ± 0.083^{c}	7.32 ± 0.090^{c}	0.39 ± 0.068^{b}	0.44 ± 0.075^{b}
Forestry	8.12 ± 0.017^{a}	8.18 ± 0.042^{a}	1.14 ± 0.018^{a}	1.23 ± 0.041^{a}
Uncultivated	7.52 ± 0.139^{bc}	7.57 ± 0.131^{b}	0.34 ± 0.051^{b}	0.38 ± 0.050^{b}

Data represent mean ± standard error; Means and mean variations between land uses were compared by Duncan's Multiple range test at a statistical significance of (P<0.05). The values in the same column followed by the same letter are not significantly different (P<0.05).

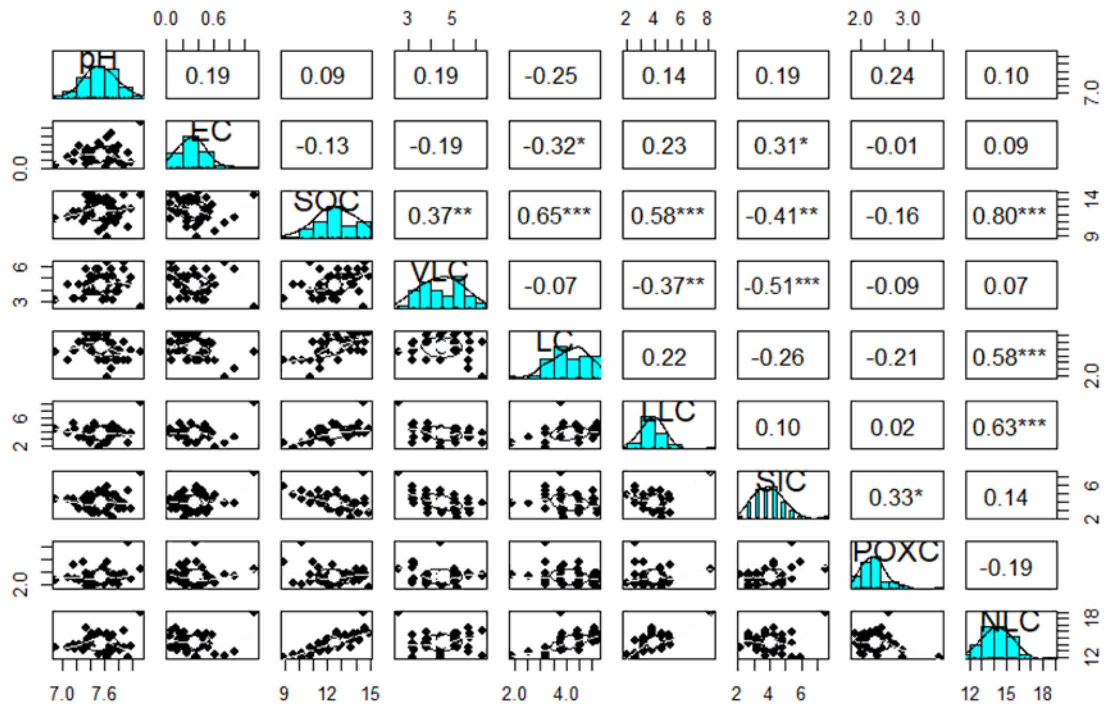

Fig. 1. *Correlation coefficient matrix between the soil carbon fractions*

exudates from the tap root system of legumes compared to other crops.

The mean value of C_L of the study area was 4.11 Mg ha^{-1} with CV of 18.04% (Table. 3). C_{VL} and C_L pool are highly susceptible to oxidation of organic carbon. The findings of Mishra and Sarkar (2020) depicted the rapid decomposition of organic matter under uncultivated areas containing open soil surfaces might have afforded the lower content of labile fractions. The mean value of C_{LL} of the study area was 4.06 Mg ha^{-1} with CV of 21.19%. Dixit *et al.* (2020) portrayed that the comparatively higher C_{LL} fraction of the carbon influenced the soil properties like cation exchange capacity, which ultimately affected the stabilization of carbon in soil.

The active carbon pool comprising of very labile (CVL) and labile carbon fraction (CL) was comparatively higher (P<0.05) in agricultural land uses than that of uncultivated and forestry land uses (Table 2). The active pool was significantly affected by the variation in the cropping system. The dominance of carbon in the active pool might be due to the influence of microbial population, incorporation of residues, application of fertilizers and oxidation of carbon in organic matter which enhances the root biomass yield (Nandan *et al.*, 2019). The root system supports the carbon cycle through the exudation of labile carbon compounds. Sahoo *et al.* (2019) substantiated that the active pool of carbon is more readily influenced by management practices compared to the passive carbon pools. The passive pool comprising of recalcitrant carbon fraction and less labile carbon was highest in forestry ecosystem and followed by uncultivated land use. The passive pool contributes to the stabilization of carbon in the tropical ecosystem. Xiang *et al.* (2015) reported a higher passive pool of carbon in forestry land use resulting from higher litter fall, which stabilized the carbon fractions in the soil. Among the agricultural land use, rice - cotton (7.78 Mg ha^{-1}) cropping system had a comparatively higher passive pool (Table 2).

Permanganate oxidisable carbon (POXC) is very sensitive to changes in management practices carried out during cultivation than other soil C fractions because of its easily oxidizable nature (Culman *et al.*, 2021). This suggests POXC is a potential indicator for assessing changes in SOC induced by management practices (Bolan *et al.*, 2011). The mean value of POXC of the study area was 2.32 Mg ha^{-1} with CV of 13.36% (Table 3). The uncultivated soils had significantly higher (P<0.05) permanganate oxidisable carbon than the remaining land uses.

The soil inorganic carbon (SIC) was significantly higher in forestry land use. It was in the order of Forestry (7.53 Mg ha^{-1}) > Uncultivated (5.05 Mg ha^{-1}) > Sugarcane (4.19 Mg ha^{-1}) > Rice-cotton (3.91 Mg ha^{-1}) > Rice – pulses (3.39 Mg ha^{-1}) (Table. 2). The mean value of soil inorganic carbon of the study area was 4.10 Mg ha^{-1} with CV of 23.48%. The occurrence of carbonates in the mangrove ecosystem under forest land use would have contributed to the higher inorganic carbon content (Wei Guan 2018). Soil inorganic carbon was negatively

Table 2. Distribution of soil organic carbon pools under major cropping systems of Mayiladuthurai district

Cropping System	SOC ($Mg\ ha^{-1}$)		V.labile ($Mg\ ha^{-1}$)		Labile ($Mg\ ha^{-1}$)		L.labile ($Mg\ ha^{-1}$)	
	0 – 15 cm	15 – 30 cm	0 – 15 cm	15 – 30 cm	0 – 15 cm	15 – 30 cm	0 – 15 cm	15 – 30 cm
Rice – cotton	12.42 ± 0.224^{bc}	10.27 ± 0.157^{c}	4.22 ± 0.128^{b}	3.06 ± 0.107^{b}	4.33 ± 0.135^{a}	3.78 ± 0.126^{b}	3.87 ± 0.156^{b}	3.42 ± 0.150^{b}
Rice – pulses	13.37 ± 0.280^{ab}	11.17 ± 0.176^{b}	5.39 ± 0.144^{a}	4.11 ± 0.193^{a}	4.11 ± 0.232^{a}	3.63 ± 0.195^{b}	3.87 ± 0.138^{b}	3.43 ± 0.196^{b}
Sugarcane	11.40 ± 0.516^{cd}	9.22 ± 0.508^{d}	4.22 ± 0.313^{b}	3.07 ± 0.364^{b}	3.72 ± 0.247^{a}	3.46 ± 0.388^{b}	3.46 ± 0.442^{b}	2.69 ± 0.240^{b}
Forestry	14.45 ± 0.067^{a}	13.24 ± 0.040^{a}	3.52 ± 0.017^{d}	2.89 ± 0.041^{c}	3.78 ± 0.012^{a}	4.05 ± 0.040^{a}	6.20 ± 0.017^{a}	4.31 ± 0.041^{a}
Uncultivated	10.75 ± 0.574^{d}	8.44 ± 0.379^{d}	3.45 ± 0.252^{d}	2.17 ± 0.153^{c}	3.71 ± 0.247^{a}	3.45 ± 0.482^{b}	3.58 ± 0.528^{b}	2.81 ± 0.522^{b}

Cropping System	Active Pool ($Mg\ ha^{-1}$)		Passive Pool ($Mg\ ha^{-1}$)		SIC ($Mg\ ha^{-1}$)		POXC ($Mg\ ha^{-1}$)		NLC ($Mg\ ha^{-1}$)	
	0 – 15 cm	15 – 30 cm	0 – 15 cm	15 – 30 cm	0 – 15 cm	15 – 30 cm	0 – 15 cm	15 – 30 cm	0 – 15 cm	15 – 30 cm
Rice - cotton	8.55 ± 0.195^{b}	6.85 ± 0.173^{ab}	$7.78 \pm 0.202b^{c}$	7.94 ± 0.226^{b}	3.91 ± 0.178^{cd}	4.51 ± 0.171^{cd}	2.14 ± 0.036^{d}	1.38 ± 0.056^{c}	14.34 ± 0.170^{b}	13.57 ± 0.230^{b}
Rice – pulses	9.50 ± 0.211^{a}	7.74 ± 0.157^{a}	7.27 ± 0.158^{c}	7.33 ± 0.184^{b}	3.39 ± 0.153^{d}	3.90 ± 0.125^{d}	2.36 ± 0.031^{c}	1.54 ± 0.054^{bc}	14.57 ± 0.320^{b}	13.72 ± 0.247^{b}
Sugarcane	7.94 ± 0.312^{bc}	6.53 ± 0.359^{b}	7.66 ± 0.327^{bc}	7.64 ± 0.297^{b}	4.19 ± 0.201^{c}	4.95 ± 0.201^{bc}	2.14 ± 0.042^{d}	1.38 ± 0.112^{c}	13.59 ± 0.428^{bc}	12.57 ± 0.596^{bc}
Forestry	7.30 ± 0.028^{d}	6.93 ± 0.081^{ab}	12.72 ± 0.028^{a}	11.37 ± 0.082^{a}	6.53 ± 0.017^{a}	7.06 ± 0.041^{a}	2.60 ± 0.017^{b}	1.73 ± 0.040^{b}	18.90 ± 0.017^{a}	19.04 ± 0.040^{a}
Uncultivated	7.16 ± 0.247^{c}	5.63 ± 0.377^{c}	8.64 ± 0.440^{b}	8.51 ± 0.560^{b}	5.05 ± 0.323^{b}	5.70 ± 0.132^{b}	2.97 ± 0.176^{a}	2.35 ± 0.160^{a}	12.96 ± 0.460^{c}	11.59 ± 0.376^{c}

Data represents mean ± standard error; Means and mean variations between land uses were compared by Duncan's Multiple range test at statistical significance of ($P<0.05$). The values in the same column followed by the same letter are not significantly different ($P<0.05$).

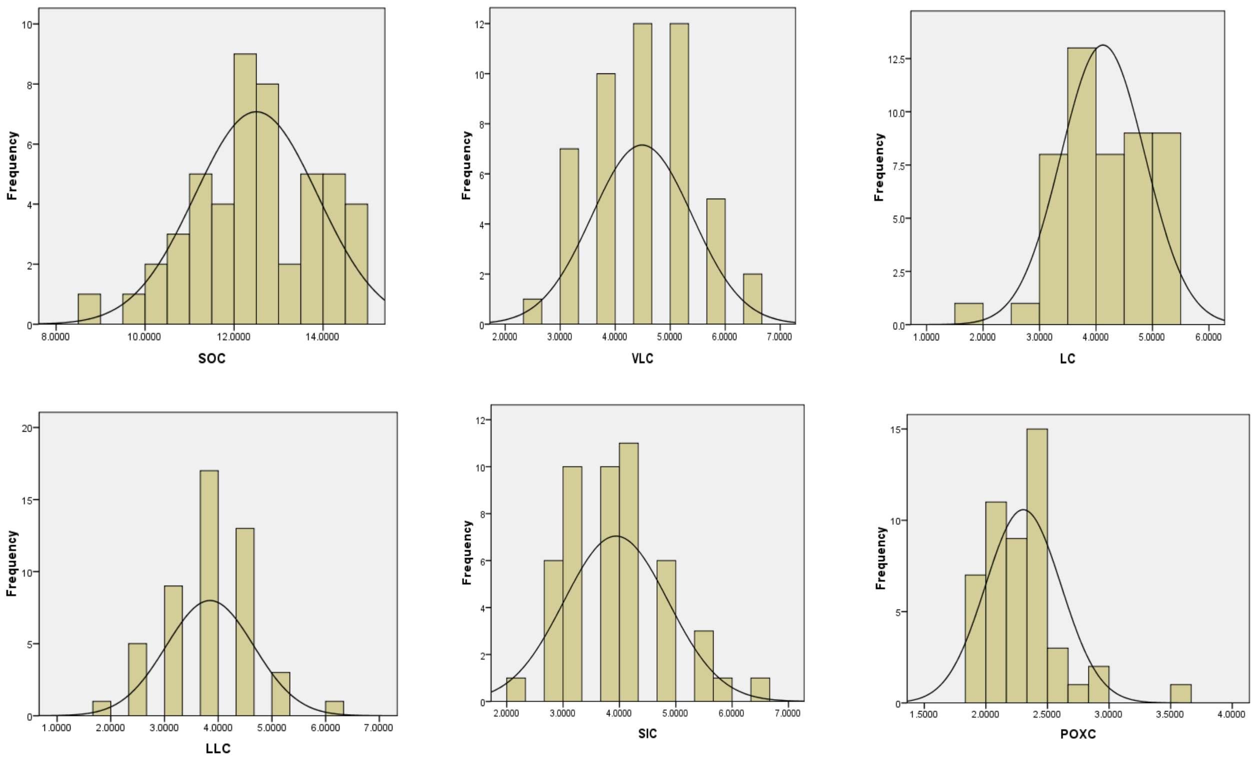

Fig. 2. *Histograms of soil carbon pools (a) soil organic carbon (b) very labile carbon (c) labile carbon (d) less labile carbon (e) soil inorganic carbon (f) permanganate oxidisable carbon (POXC)*

Table 3. Descriptive statistics of carbon fractions under major cropping systems of Mayiladuthurai district

Parameter	Minimum	Maximum	Mean	Median	SD	Variance	CV	Skewness	Kurtosis
pH	6.90	8.12	7.56	7.54	0.26	0.07	3.17	0.17	0.25
EC	0.04	1.14	0.38	0.36	0.26	0.07	59.92	1.51	2.65
SOC	8.92	14.93	12.58	12.62	1.41	1.99	11.05	-0.36	-0.23
C_{VL}	2.52	6.37	4.41	4.46	0.97	0.95	20.30	-0.07	-0.58
C_L	1.91	5.19	4.11	4.42	0.73	0.54	18.04	-0.58	0.36
C_{LL}	1.91	8.20	4.06	3.82	1.27	1.62	21.19	1.88	4.91
SIC	2.15	7.53	4.10	3.76	1.20	1.43	23.48	1.26	2.06
POXC	1.87	3.65	2.32	2.31	0.31	0.09	13.36	1.81	6.02
NLC	11.92	18.90	14.47	14.20	1.55	2.41	9.01	1.13	2.10

correlated with the soil organic carbon (r = -0.41**) (Fig. 1). Saderne *et al.* (2019) also observed a negative relation of SIC with the SOC indicating the increase in SIC will affect the concentration of soil organic carbon. Song *et al.* (2022) reported that the dissolution of carbonates by acidic reverberations occurred during crop cultivation led to decreased SIC in agricultural land use. The mean value of non-labile carbon of the study area was 14.47 Mg ha^{-1} with CV of 9.01%. Similar phenomenon was shown by Babu *et al.* (2020) who observed comparatively higher fraction of non-labile carbon in the rice based cropping sequences resulting from the conversion of labile C fractions, root biomass and residues into recalcitrant form of carbon. Leno *et al.* (2021) noticed the chemical stabilization of labile C with clay and silt fractions resulted in the transformation of labile C into non-labile carbon.

The summary statistics revealed the variations of soil carbon fractions among the different land uses with in the study area (Table. 3). The mean value of the soil properties like soil reaction (pH), Electrical conductivity (EC), soil organic carbon (SOC), very labile, labile, less labile carbon, soil inorganic carbon (SIC), permanganate oxidisable carbon (POXC) and non-labile carbon were 7.56, 0.38 dS m^{-1}, 12.58 Mg ha^{-1}, 4.41 Mg ha^{-1}, 4.11 Mg ha^{-1}, 4.06 Mg ha^{-1}, 4.10 Mg ha^{-1}, 2.32 Mg ha^{-1}

Table 4. Principal Component analysis (PCA) of the soil carbon fractions

Principal Component	Initial Eigenvalues		
	Total	% of Variance	Cumulative %
PC 1	2.89	32.12	32.12
PC 2	2.09	23.19	55.32
PC 3	1.41	15.68	71.00
PC 4	1.03	11.48	82.48
PC 5	0.64	7.10	89.58
PC 6	0.54	5.95	95.53
PC 7	0.39	4.29	99.81
PC 8	0.02	0.18	99.99
PC 9	0.01	0.01	100.00

Component Matrix				
	Principal Components			
	PC 1	PC 2	PC 3	PC 4
pH	-0.040	0.346	0.791	0.071
EC	-0.170	0.586	0.163	-0.634
SOC	0.961	-0.009	0.233	0.053
C_{VL}	0.203	-0.610	0.684	-0.093
C_L	0.774	-0.118	-0.363	0.259
C_{LL}	0.584	0.651	-0.032	-0.036
SIC	-0.365	0.749	-0.117	0.172
POXC	-0.327	0.312	0.296	0.719
NLC	0.846	0.393	0.060	-0.021

Extraction Method: Principal Component Analysis.
(4 components extracted)

and 14.47 Mg ha^{-1}. The development of histograms helped identify each parameter's distribution over the study area and the normal distribution curve indicated the symmetrical plot of each parameter (Fig. 2).

The soil properties like electrical conductivity, very labile carbon, labile carbon pool, less labile carbon pool, and soil inorganic carbon had more coefficient of variation compared to soil pH, soil organic carbon, permanganate oxidisable carbon and non-labile carbon pool (Table 3). Sarkar *et al.* (2022) expounded the representation of pH values in the log scales of proton concentration resulted in the lower variability of soil pH in the cropping system. The high coefficient of variation (CV) of EC, SOC, C_{LL} and SIC indicates the spatial variation within the study area.

Principal component analysis (PCA) was conducted to assess the variation of the soil properties using multivariate data analysis. In total, 9 components were generated through PCA analysis. Out of which, 4 principal components had eigen values more than 1 indicating the variability of soil carbon fractions. The cumulative contribution of variability by the first four principal components was 82.48%. The principal component 1 (PC1) contributed a variability of 32.12% dominated by the loading of SOC, C_{LC}, C_{LL} and non-labile carbon (Fig. 3). The variability of PC 2, PC 3 and PC 4 were 23.19%, 15.68% and 11.48% respectively (Table 4). Teferi *et al.,* (2016) noticed four principal components over Eigen value of 1 with the variation of soil carbon content occurring from the difference in amount of organic matter, pH and clay content in the soil. The PCA clearly interprets that different management practices under different cropping systems influenced the variation in soil carbon fractions in the study area.

Conclusion

The present study concluded that the changes in the cropping system influenced the size of the soil carbon pools under major cropping systems of Mayiladuthurai district of Cauvery Delta Zone, Tamil Nadu. The crop residues were prerequisites for SOC pool and the incorporation of both autochthonous and allochthonous means reflected on the SOC content with depth. Even a slight change in SOC content largely affected the stability of carbon within the aggregates. The SOC content under different land uses was in the following order: Forestry> rice-pulses > rice-cotton> sugarcane > uncultivated in the study area. The SOC content varied from 10.75 to 14.45 Mg ha^{-1}, where the majority of the area fell under low to medium rating of SOC. Hence, cultivation practices should incorporate activities that increase SOC to maintain soil quality. In all land use types, the proportion of active carbon pools was higher than passive pools, indicating easy loss of accumulated carbon under land use changes. However, forestry land use reported a higher proportion of passive pool, indicating a more stable nature of the accumulated SOC. The correlation matrix depicted the strong relation between carbon fractions, where changes in land use will definitely affect the carbon dynamics. The PCA analysis revealed that the variation in carbon dynamics of the study area was influenced by SOC, C_{LC}, C_{LL} and non-labile carbon due to differences in land management practices. Therefore, soil management practices are a powerful tool to sequester carbon which supplements climate change mitigation.

Conflict of interest

The authors declare that they have no conflict of interest.

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