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# Environmental factors and spatial dependence explain half of the inherent variation in carbon pools of tropical paddy soils

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ABSTRACT

The current study examined macro-environmental (climate and topography), micro-environmental (soil chemical properties) drivers, and spatially derived parameters that are significantly associated with soil carbon pools (0–15 cm) across tropical paddy-growing areas in Sri Lanka using the data from 987 sampling sites across the country. Redundancy analysis was performed to identify the relationships between the explanatory variables and the variation in different soil carbon pools i.e., total carbon (TC), Microbial Biomass Carbon (MBC), Permanganate Oxidizable Carbon (POXC), and Dissolved Organic Carbon (DOC). The spatial patterns in soil carbon pools were evaluated using Moran's eigenvector maps. Results indicated that macro, micro-environmental drivers and spatial variables explained 47% of the inherent variation of the TC, MBC, POXC and DOC. Micro-environmental drivers had a larger unique fraction relative to macro-environmental drivers (4% and 1% of the total variation, respectively). Most of the variation explained by macro-environmental drivers was shared by micro-environmental drivers (11% out of 15%). Among macro-environmental drivers, rainfall and enhanced vegetation index were more strongly related to the soil carbon pools compared to the topography-related factors. In terms of micro-environmental drivers, total N, available K, Ca, and soil pH ($H_2O$) were the best explanatory variables of soil carbon pools. Spatial patterns in soil carbon pools were largely induced by the environmental predictors that are spatially structured. Our findings provide insights into improving the reliability of spatial estimation of the soil carbon by incorporating important soil carbon preditors and quantifying the impacts of environmental changes on soil carbon pools.

## 1. Introduction

The planet is warming, and it is likely to be the most threatening and controversial environmental crisis of our century, which will cause devastating damage to the Earth's habitats and human well-being (Malhi et al., 2020; Pecl et al., 2017). Soil carbon sequestration (SCS) serves as an effective strategy for converting atmospheric $CO_2$ into a long-lived soil carbon pool and store in a form that is not easily reemitted (Lal et al., 2018). This SCS strategy aids in the reduction of anthropogenic $CO_2$ emissions while improving soil fertility and agricultural productivity (Nair et al., 2015). For example, there are many theories on soil carbon sequestration capacity, it is commonly agreed that the soil's ability to hold SOC is finite due to inherent soil properties, climate conditions, and land management practices (McNally et al., 2017). Compared to the other terrestrial ecosystems, agricultural SOC contents can be easily increased by implementing proper management practices (Lal et al., 2011).

Globally, rice is one of the leading food types consumed daily by > 50% of the world's population (Nguyen et al., 2020). About 90% of the world's rice is cultivated and consumed in the Asian continent (Muthayya et al., 2014), and approximately 80% of it is grown under submerged conditions (Bhattacharyya et al., 2014). Compared with carbon sequestration potential in upland soils, water-logged rice soils are much more efficient in preserving soil carbon (Chen et al., 2021).

Global food production primarily relies on soil fertility, and soil carbon plays a significant role in maintaining fertility status (Balesdent

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et al., 2018). In agricultural ecosystems, the carbon in-flows primarily depend on biomass decomposition, rhizodeposition, and the amount of carbon retained in soils (Zhang et al., 2021). At the same time, carbon losses are generally caused by oxidation or mineralisation and erosion and leaching processes (Zhang et al., 2021). Therefore, soil carbon vulnerability to destabilisation is an increasingly important topic in the context of global warming and SCS. As a result, studies on labile organic carbon are more beneficial for better-understanding soil carbon dynamics.

The labile forms of the soil carbon report higher inter-annual variability of the fluxes but are equally crucial for plant nutrition (Xiao et al., 2021). Further, compared to the sub-surface, a high proportion of carbon present in the soil surface exists as labile carbon pools (Marques et al., 2015). The turnover rates of these labile carbon pools could vary from days to a decade (Keskin et al., 2019). The labile pools of organic carbon and macroaggregates (>250 μm soil particles) may have considerable influence on soil quality, making them more sensitive indicators of the effects of land-use changes or management changes than the total soil carbon pool (Yang et al., 2009). These labile SOC pools mineralised fast due to the lack of chemical and physical protection (Poeplau et al., 2013) and, thus, serve as energy sources for the soil microbes and influence nutrient cycling (Hendrix et al., 2018). The main labile soil carbon pools include soil microbial biomass carbon, water-soluble organic carbon, and water-soluble carbohydrates (Rajkishore et al., 2015; Vivek, 2008).

The variation of soil carbon across space and time is modelled using two broad approaches: (a) using process-based models and (b) using empirical data-driven models. Generally, process-based models such as RothC and CENTURY and earth system models are used to quantify the variation of the soil carbon and different pools across space and time domains. Process-based models utilise conceptual pools of SOC, and mass fluxes between these pools are governed by the soil properties (e.g. clay content), climate and land management activities (Dangal et al., 2022). On the other hand, earth systems models go beyond local conditions, incorporating climatic interactions between land, atmosphere, ocean, ice and biosphere. While process-based models such as RothC (Coleman & Jenkinson, 1996) and CENTURY (Parton et al., 1988) are widely applied globally, there is an emerging interest in using earth system models. For example, Guatum et al. (2022) used a novel framework where higher resolution SOC stock was derived using a machine learning environment and then fused the outputs with earth system models to predict the decadal changes of SOC under projected climate scenarios. Under natural environmental conditions, soil functions are strongly influenced by biological organisms living in the soil, soil chemical composition, terrain attributes, and climatic conditions (Liu and Liu, 2014). There is a complex interaction of these drivers at various spatial and temporal scales (Wiesmeier et al., 2019). Therefore, analysing the relationships of different soil carbon pools with macro-environmental conditions and inheriting soil physicochemical factors is helpful in developing a predictive understanding of soil carbon dynamics. This approach is the foundation for other empirical data-driven models. The climatic, topographic variables and land use data are mainly incorporated into soil carbon prediction function using the *scorpan* approach outlined by McBratney et al. (2003). These modelling frameworks are focused on univariate estimation/prediction of the considered SOC pool. For example, Gautam et al. (2022) and Mishra et al. (2022), have utilised the proxies for the major soil forming factors (climate, vegetation, topography, and parent material) on spatial prediction of soil carbon through empirical modelling approaches. Similarly, in the Sri Lankan context, Vitharana et al. (2019) and Ratnayake et al. (2016) used empirical modelling framework to estimate the soil carbon across the country and northern paddy regions, respectively. At the regional scale, Ratnayake et al. (2016) in the Northern paddy-growing region reported the vegetation index data as a proxy for carbon inputs while, at the national scale, Vitharana et al. (2019) reported the importance of elevation, precipitation and the slope angle as the key drivers of the SOC distribution across different vegetation types.

**Table 1**
Major paddy-growing soil groups covered by the study (sources: De Alwis and Panabokke, 1972; Mapa, 2020).

| Sri Lankan great soil group | WRB (FAO) legend | USDA Soil Taxonomy Order |
|---|---|---|
| Alluvials | Fluvisols | Entisols |
| Latosols | Arenosols | Oxisols |
| Noncalcic Brown soils & Low Humic Gley | Cambisols & Gleysols | Alfisols |
| Noncalcic Brown soils & soils on old alluvium | Cambisols & Arenosols | Alfisols & Entisols |
| Reddish Brown Earths & Low Humic Gley | Luvisols & Gleysols | Alfisols |
| Reddish Brown Earths & Solodized Solonetz | Luvisols & Solonchaks | Alfisols |
| Reddish Brown Earths & Non Calcic Brown | Luvisols & Cambisols | Alfisols |
| Solodized Solonetz | Solonchaks | Alfisols |
| Bog and Half-Bog | Histosols & Histic Fluvisols | Histosols |
| Reddish Brown Latosolic | Alisols | Ultisols |
| Red-Yellow Podzolic | Acrisols | Ultisols |

Unique soil carbon controllers and their interactions should be integrated into carbon models to decrease uncertainty in predictions (Luo et al., 2020). Besides macro-environmental predictors, it is vital to identify the influence of site-specific parameters on defined soil carbon pools. This study has used a large soil carbon dataset across Sri Lanka to examine the complex interrelationships prevailing among TC (total carbon) and different soil carbon pools, namely; Microbial Biomass Carbon (MBC), Permanganate Oxidizable Carbon (POXC), Dissolved Organic Carbon (DOC), and macro and micro-environmental drivers in tropical paddy-growing soils of Sri Lanka by using constrained ordination methods. The constrained ordination methods are frequently used in ecological studies to evaluate relationships among two variable groups i.e., multivariate relationships (Cleary et al., 2022; Dray et al., 2012). Odeh et al. (1991) successfully demonstrated that such methods can be used to elucidate the complex relationships among different soil and environmental attributes. Dorji et al. (2015) applied a similar multivariate ordination approach to identify the response of different soil carbon pools to a variety of environmental predictors. The present study is aimed at simultaneously evaluating the relative roles of local climatic conditions, topographic features, vegetation index data, and site-specific soil chemical properties in influencing the spatial variation in a matrix of soil carbon pools that are often interrelated to each other. Furthermore, we applied a variation partition approach to quantify the relative importance of different predictor variable groups (macro, micro and spatial) in stabilising below-ground soil carbon pools. The proposed approach works across multivariate space, simultaneously looking into drivers of different carbon pools compared to the aforementioned univariate empirical modelling approaches.

We hypothesise that different macro- and micro-environmental predictors structured within the space influence spatial variation in soil carbon. The results of the current research could provide necessary information on important soil carbon determinants. Our findings provide insights into sustainable utilisation of resources to enhance ecosystem services through climate change mitigation and soil fertility enhancement.

## 2. Materials and methods

### 2.1. Study area

The study area, Sri Lanka, is located in the Indian Ocean, a tropical island specifically at the geographical coordinates of 5° 54′ and 9° 52′ from the North and 79° 39′ and 81° 53′ from the East. The area extent is nearly 64, 610 $km^2$, which experiences diverse climatic and topographical conditions. The annual mean temperature range is 15 °C–30 °C, and the total annual precipitation varies from 600 mm (in dry, arid regions) to 6000 mm (in wet regions). The elevation gradient directed mean sea level (MSL) to nearly 2575 m height in high massif areas. Compared to other paddy-growing countries, Sri Lanka cultivates paddy under various hydrogeological regimes. The hydromorphic combinations of all its great soil groups in Sri Lanka are utilised for paddy cultivation (Panabokke, 1996). According to the soil map of Sri Lanka, published by De Alwis and Panabokke (1972), the Great soil groups of Sri Lanka covered by the study and their World Reference Base (WRB) legend and United States Department of Agriculture (USDA) taxonomical order are shown in Table 1.

Rice is the principal food type of the country, grown as a wetland crop that represents a large portion of cultivated lands (34%) (Ratnayake et al., 2016). Therefore, there is excellent potential in storing and maintaining carbon in the paddy fields of Sri Lanka. The paddy-growing regions are located in every administrative unit of the country, and relatively flat terrain areas are utilised for its cultivation. Presently, about 708,000 ha of land are devoted to rice cultivation (Dammalage et al., 2018).

## 2.2. Soil sampling

### 2.2.1. Sampling design

Nine hundred and eighty seven soil samples were collected and quantified across the three major climatic regions (wet, intermediate, and dry) in the paddy-growing soils of Sri Lanka. The sampling approaches aided for the current study were mainly designed to capture the spatial variability of soil carbon across the landscape using modelling and mapping techniques. Therefore, soil sampling was purposely conducted using Conditional Latin Hypercubic Sampling design (cLHS) and Stratified Random Sampling (SRS). The cLHS was adapted to determine calibration sampling locations, whereas the SRS was used to determine the fully independent validation sampling locations. While two sampling designs were adopted to collect the samples to satisfy the broader objectives of the project, for this particular analysis merged dataset was used. A brief description of the cLHS and SRS are provided below.

The cLHS algorithm provides an efficient way of sampling from the multivariate distribution of the environmental covariates. It identifies a set of values from several covariates that satisfy the Latin hypercube requirement of only one sample in each row and column in n dimensions (Minasny and McBratney, 2006). Further, in the SRS design, the same environmental covariates used to develop cLHS were aided in creating the strata using the K-means clustering algorithm before randomly allocating sample locations. The environmental covariates used to develop the two sampling schemes are described below.

*2.2.1.1. Climate, topographic and vegetation index data.* The climate data (mean annual rainfall, temperature (annual average mean, annual average maximum, annual average minimum), and vapour pressure deficient (VPD)) were obtained through the wordclim database (Wordclimhttp://https://www.worldclim.org/). The elevation data was acquired through NASA SRTM data (https://www.cgiar-csi.org/data/srtm-90m-digital-elevation-databasev4-1). The SAGA Wetness Index (WI) (secondary terrain attribute) and slope (primary terrain attribute) were also derived through NASA SRTM data. Finally, the MODIS Enhanced Vegetation Index (EVI) data was derived from taking mean annual EVI data from 2005 to 2014 (NASAhttps://modis.gsfc.nasa.gov/data/dataprod/mod13.php.). All environmental covariates were standardised to 100 m spatial resolution prior to use in the analysis. A detailed description on the preparation of the climate and topographic datasets is provided in Rajapaksha et al. (2020).

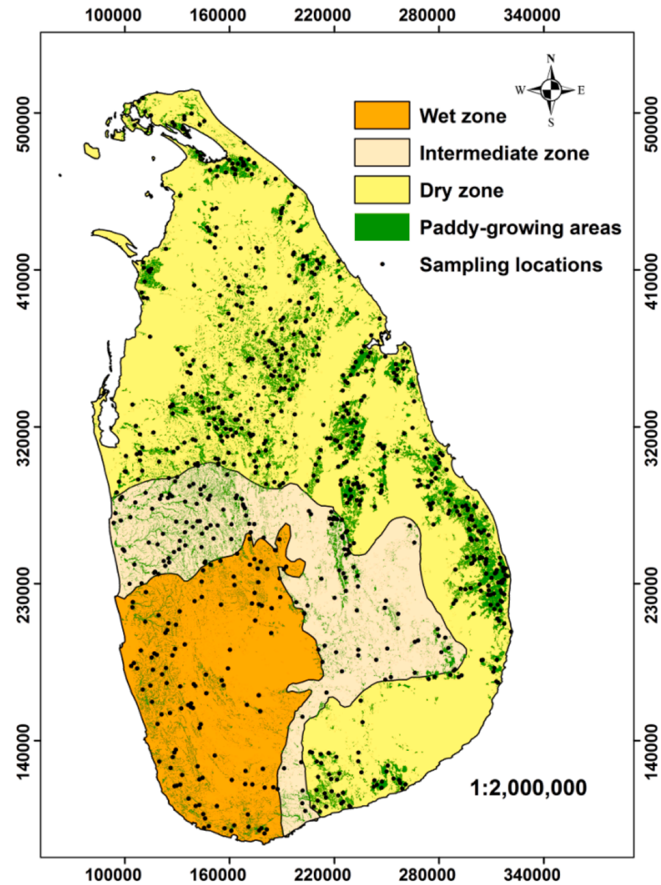


**Fig. 1.** Map of Sri Lanka showing the distribution of paddy-growing areas and soil sampling locations with overlapped climatic zones: (Coordinate system: *Kandawala*Sri Lanka Grid).

### 2.2.2. Soil sampling

To find the precise sampling location of GPS locations generated using cLHS and SRS sampling strategies; sample locations were inserted into a GPS receiver (Garmin eTrex 30x) and navigated to the location in the field. A soil augur of 5 cm width was used for the sampling. In each site, three soil samples were taken and then pooled to form composite samples at a depth between 0 and 15 cm. The distribution of paddy-growing regions and the sampling locations within the country are shown in Fig. 1.

## 2.3. Soil sample preparation and chemical analyses

Initially, all visible organic debris, plant roots, and stones were removed by handpicking. Then the soil samples were air-dried at room temperature and sieved through a 2 mm mesh sieve. The chloroform fumigation and extraction method was used to determine MBC content (Anderson and Ingram, 1993). Further, the fresh soil samples were analysed for soil pH (1:2.5 soil: water suspension) and Electric conductivity (EC) (1:5 soil: water suspension) (Anderson and Ingram, 1993). Available Phosphorous (Bicarbonate Extractable Phosphate ($PO_4^{3-}$)) content was determined using Molybdenum Blue Method (Watanabe and Olsen, 1965). Available nitrate ($N:NO_3^-$) (Cataldo et al., 1975) and ammonium ($N:NH_4^+$) (Lenore et al., 1989) contents of the soil were also detected colorimetrically by using the UV spectrophotometer.

A subset of soil samples was ground to a less than 0.15 mm powder for the dry soil analyses. The Permanganate Oxidizable Carbon (POXC) pool was estimated by the Modified $KMnO_4$ oxidizable carbon method (Weil et al., 2003), and the Dissolved Organic Carbon (DOC) pool was determined using the titration method using acidified ferrous

**Table 2**
Descriptive statistical analysis of soil parameters (n = 987).

| Parameter | Minimum | Maximum | Mean | Median | SD | CV % | Skewness | Kurtosis |
|---|---|---|---|---|---|---|---|---|
| Total C % | 0.30 | 17.9 | 2.44 | 2.04 | 1.73 | 71 | 3.52 | 20 |
| MBC % | 0.001 | 0.40 | 0.03 | 0.02 | 0.03 | 100 | 3.81 | 25 |
| POXC % | 0.001 | 0.09 | 0.06 | 0.06 | 0.02 | 33 | −1.27 | 1 |
| DOC % | 0.001 | 0.88 | 0.03 | 0.01 | 0.04 | 133 | 11.5 | 221 |
| pH | 3.67 | 9.30 | 6.45 | 6.51 | 1.04 | 16 | −0.08 | −0.6 |
| EC (dS $m^{-1}$) | 0.01 | 9.67 | 0.32 | 0.06 | 0.09 | 28 | 5.85 | 43 |
| Total N (%) | 0.01 | 1.83 | 0.26 | 0.21 | 0.22 | 84 | 2.25 | 8 |
| $PO_4^{3-}$ (mg $kg^{-1}$) | 0.02 | 242 | 17.8 | 10.6 | 23.4 | 131 | 4.26 | 27 |
| N:$NH_4^+$ (mg $kg^{-1}$) | 0.02 | 39.8 | 6.01 | 4.27 | 5.65 | 94 | 2.01 | 5 |
| N:$NO_3^-$ (mg $kg^{-1}$) | 0.02 | 71.8 | 3.65 | 2.14 | 5.33 | 146 | 6.72 | 66 |
| Available $K^+$ (mg $kg^{-1}$) | 0.64 | 596 | 85.7 | 57.0 | 86.7 | 101 | 2.39 | 7 |
| Available $Ca^{2+}$ (mg $kg^{-1}$) | 16.0 | 16181 | 1238 | 973 | 1206 | 97 | 5.32 | 52 |
| Available $Mg^{2+}$ (mg $kg^{-1}$) | 6.40 | 2072 | 260 | 195 | 225 | 86 | 2.27 | 9 |

Note: SD- Standard Deviation, CV- Coefficient of Variation.

ammonium sulphate (Anderson and Ingram, 1993). The available nutrient cations ($Ca^{2+}$, $Mg^{2+}$ and $K^+$) were determined using Atomic Absorption Spectrophotometer (GBC 933 AA), and the cations were extracted using the Morgan extraction method (McIntosh, 1969). Another portion of < 0.15 mm powder was again ground and sieved through a 42-μm mesh sieve followed by TC and total nitrogen (TN) contents were analysed by automated combustion using a 2400 Series II CHN Elemental Analyser (Fadeeva et al., 2008; Skeen, 1994).

### 2.4. Statistical analyses

The soil analytical values were analysed using descriptive statistics. Multivariate analyses, including detrended correspondence analysis (DCA) and redundancy analysis (RDA), were conducted to investigate the effects of macro-environments and micro-soil parameters on soil carbon pools using the vegan R package (Oksanen et al., 2015). Statistical analyses were conducted using R software version 4.1.1 (R Core Team, 2021).

In the first step, DCA was used to analyse the soil carbon data and assess the gradient lengths of the ordination axes. In cases where the gradient length of the first axis is less than 3 SDs (standard deviation units), a linear model with RDA is the best option, while a unimodal model with CCA is recommended over 4 SDs. Both models can be beneficial for intermediate lengths (Ter Braak and Prentice, 2004). In the current study, the gradient lengths of the axes were found as less than 3 SD. Thus, we selected the linear model with RDA as the appropriate ordination method for direct gradient analysis over CCA.

By using the RDA, the correlations between different soil carbon pools and the macro-environmental drivers (climate, vegetation, and topographic variables) and micro-environmental drivers (soil chemical properties) were analysed. Nine macro-environmental drivers were included in this analysis: mean annual rainfall (RF), annual average maximum temperature (MXT), annual average minimum temperature (MIT), annual average mean temperature(MT), Vapour Pressure Deficient (VPD), Enhanced Vegetation Index (EVI), Elevation, Wetness Index (WI), slope angle (SL). Moreover, nine micro-environmental drivers were included i.e., soil pH, EC, TN, $PO_4^{3-}$, N:$NH_4^+$, N:$NO_3^-$, $K^+$, $Ca^{2+}$, and $Mg^{2+}$. The four different soil carbon pools included were TC, MBC, POXC, and DOC. The RDA is allowed to explain the influence of each macro-environmental variable and micro-environmental variable on soil carbon variations and examine the association between response data and explanatory variables (Wang et al., 2016). Prior to the RDA analysis, the correlations among explanatory variables were checked to avoid severe multicollinearity issues. Additionally, a forward selection was also carried out to choose the variables that significantly influence soil carbon pool variations. The Forward selection step in RDA analysis with a double-stopping criterion is helpful to fit the most parsimonious model.

Further, the collinearity between explanatory variables of the fitted model was measured using the variance inflation factor (VIF). The significance level of the fitted model, model parameters, and axis significance were evaluated at the 0.05 probability level. Finally, the adjusted $R^2$ value of the final model was calculated to assess the model performance.

An eigenvector-based spatial modelling approach was used to identify spatial patterns in different soil carbon pools (Griffith and Peres-Neto, 2006; Peres-Neto and Legendre, 2010). Briefly, this method extracts eigenvectors of a connectivity matrix among sampling units (i.e., graph-based Moran's eigenvector maps; gb-MEM) describing all possible mutually orthogonal map patterns of the study area, which are then used as additional predictors of the response variables (Griffith and Peres-Neto 2006). For a detailed procedure for extracting and selecting an optimum subset of gb-MEM variables, we referred to Bauman et al. (2018). The R packages adespatial (Dray et al., 2018) and spdep (Bivand et al., 2015) were used for gb-MEM variable generation and for subset selection of the parameters.

The variation partitioning was performed on RDA to estimate the proportions of variation in different soil carbon pools explained by macro, micro, and spatially structured variable groups, jointly and independently. The results were expressed in terms of adjusted $R^2$ value as it is an unbiased estimate of explained variation, accounting for a number of explanatory variables and sample size (Peres-Neto et al., 2006). The relative importance of each explanatory variable group was determined based on its unique proportional contribution (i.e., variation not shared with other explanatory variable groups (Peres-Neto et al., 2006; Peres-Neto and Legendre, 2010).

## 3. Results and discussion

### 3.1. Descriptive analysis

Different soil carbon pools showed varying distribution patterns (Table 2). Significant differences between the minimum and maximum values were detected for soil carbon pools across the landscape. The coefficient of variation (CV) for the response variables of MBC, DOC (>100%), and TC (71%) indicated higher variability of those parameters. At the same time, POXC exhibited a low CV (33%) compared to the other soil carbon pools. The CV results suggested that the concentrations of soil carbon data vary strongly, and this may be due to the influence of macro-environmental factors, site-specific characteristics of the soil, or any other long-term effect of agricultural management practices.

The soil pH conditions varied from strongly acidic to basic conditions within the range of 3.67 to 9.3. The mean pH value was recorded as 6.45 ± 1.04, which was within the optimum range for plant nutrient availability. Electric conductivity (EC) measures salt content in the soil, and higher salinity makes it more difficult for plants to absorb moisture. The EC values ranged from 0.01 dS $m^{-1}$ (non-saline) to 9.67 dS $m^{-1}$(saline). A soil having a salt concentration exceeding an EC value of

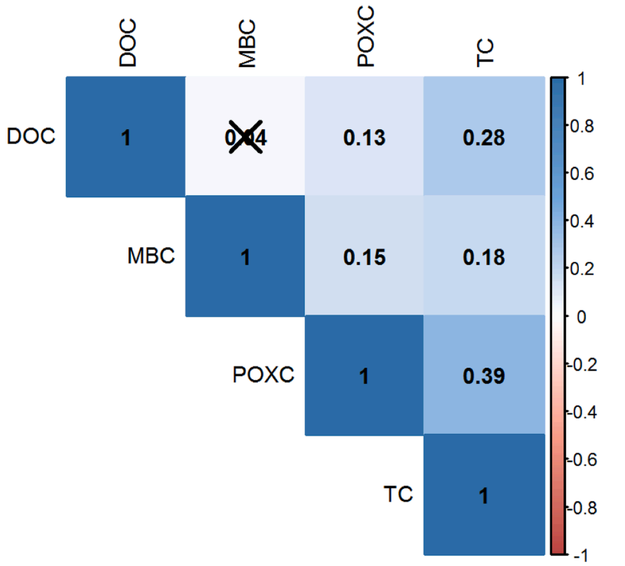


**Fig. 2.** Pearson correlation coefficient matrix of response variables. *Abbreviations*: DOC: Dissolved Organic Carbon, MBC: Microbial Biomass Carbon, POXC: Permanganate Oxidizable Carbon, TC: Total Carbon: Statistically insignificant ($p > 0.05$) coefficients are marked by a cross sign (X).

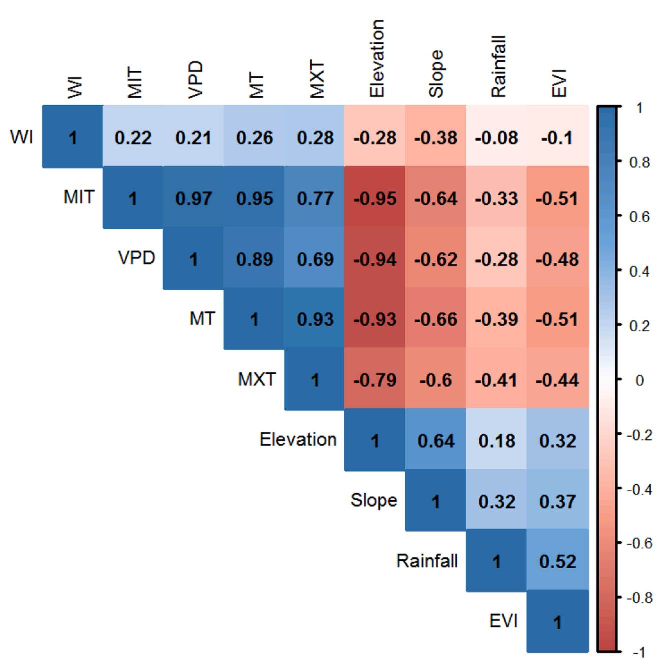


**Fig. 3.** Pearson correlation coefficient matrix of macro-environmental drivers. *Abbreviations*: WI: SAGA Wetness Index, MIT: annual average minimum temperature, VDP: Vapour pressure Deficient, MT: annual average mean temperature, MXT: annual average maximum temperature, rainfall: mean annual rainfall, EVI: MODIS Enhanced Vegetation Index: all the coefficients are statistically significant ($p < 0.05$).

4 dS $m^{-1}$ is classified as saline in agriculture (De Costa et al., 2012). Therefore, some places in the country have exceeded the desired level of EC, creating soil salinity problems.

### 3.2. Response variables – Different soil carbon pools

#### 3.2.1. Correlations among response variables

Pearson correlation matrix indicated that response variables were not strongly correlated to each other (Fig. 2). TC content and POXC ($r = 0.39$, $p < 0.05$) showed moderately strong positive linear relationships, while other carbon pools showed weaker correlations.

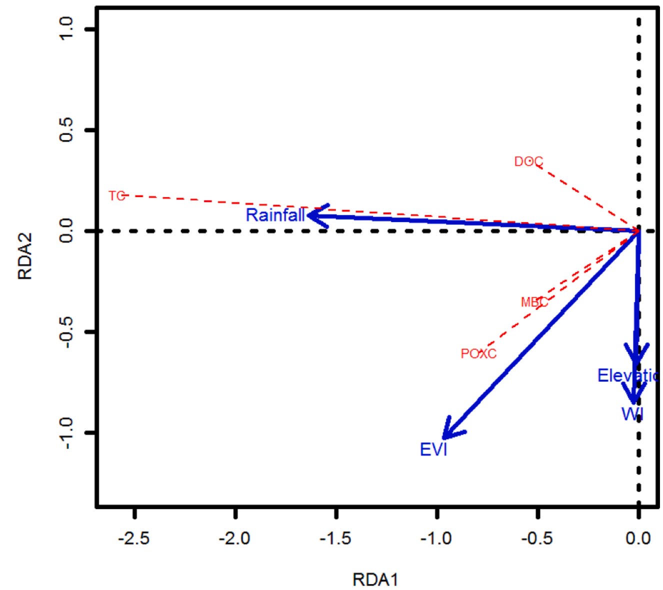


**Fig. 4.** Redundancy analysis (RDA) biplots of macro-environmental drivers versus soil carbon pools of Sri Lanka. Abbreviations: red-dashed lines represent the soil C pools, and blue arrows represent the macro-environmental drivers. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

### 3.3. Macro- environmental drivers

#### 3.3.1. Correlations among macro-environmental drivers

Mean temperature, minimum temperature, maximum temperature, and VPD and elevation are highly correlated ($r \geq 0.8$, $p < 0.05$). Therefore, mean temperature, minimum temperature, maximum temperature, and VPD parameters were removed, and elevation was retained for further analyses (Fig. 3).

#### 3.3.2. Forward selection of macro-environmental variables and fitting the most parsimonious model

According to forward selection results, rainfall, EVI, elevation, and WI were significant at 0.05 significance level ($p < 0.05$), and the slope angle was dropped because of its less influence. The VIF of the selected macro-environmental parameters varied between 1.09 and 1.47. As a rule of thumb, VIF < 10 indicates the absence of strong collinearity problems (Miles, 2014). Therefore, no multicollinearity was observed among the variables, and all the parameters were included in the model.

The RDA results indicated that several macro-environmental factors could influence the fluxes of soil carbon pools in paddy-growing soils of Sri Lanka (Fig. 2). All macro-environmental parameters together explained 13.34% of the soil carbon variation. The first two axes were significant at the 0.05 significance level. In the fitted model for macro-environmental variables, the first and the second constrained axes (RDA 1, RDA 2) explain 12.2% and 1% of the variation, respectively. Accordingly, the importance of the rainfall and vegetation index data on soil carbon fluctuations was higher than those of the topographic factors of elevation and WI (related to soil moisture). Several studies have been concluded similar results. For example, Liu et al. (2015) indicated that the distribution of soil carbon was significantly affected by climatic variables, vegetation biomass, and soil moisture. The work carried out by Zhou et al. (2020) in north-western China identified precipitation, elevation, and temperature as the most critical environmental covariates explaining SOC variation.

RDA also illustrated the relationships among the different soil carbon

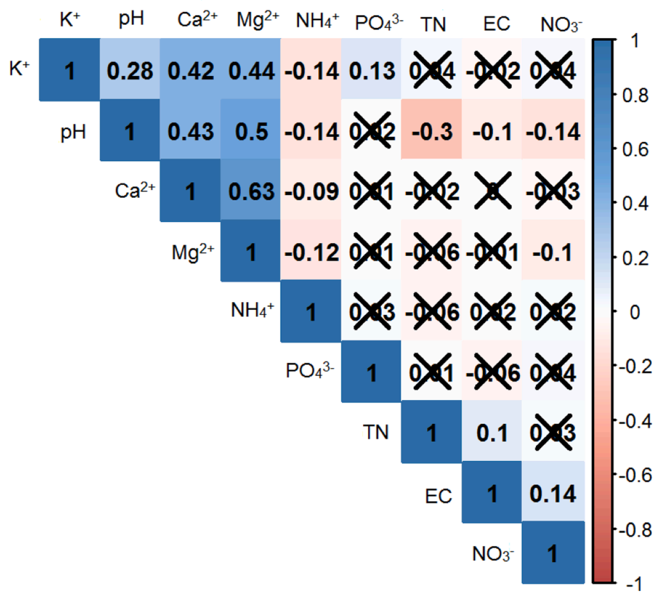


**Fig. 5.** Pearson correlation coefficient matrix of micro-environmental drivers. *Abbreviations*: EC: Electric Conductivity: Statistically insignificant ($p > 0.05$) coefficients are marked by a cross sign (X).

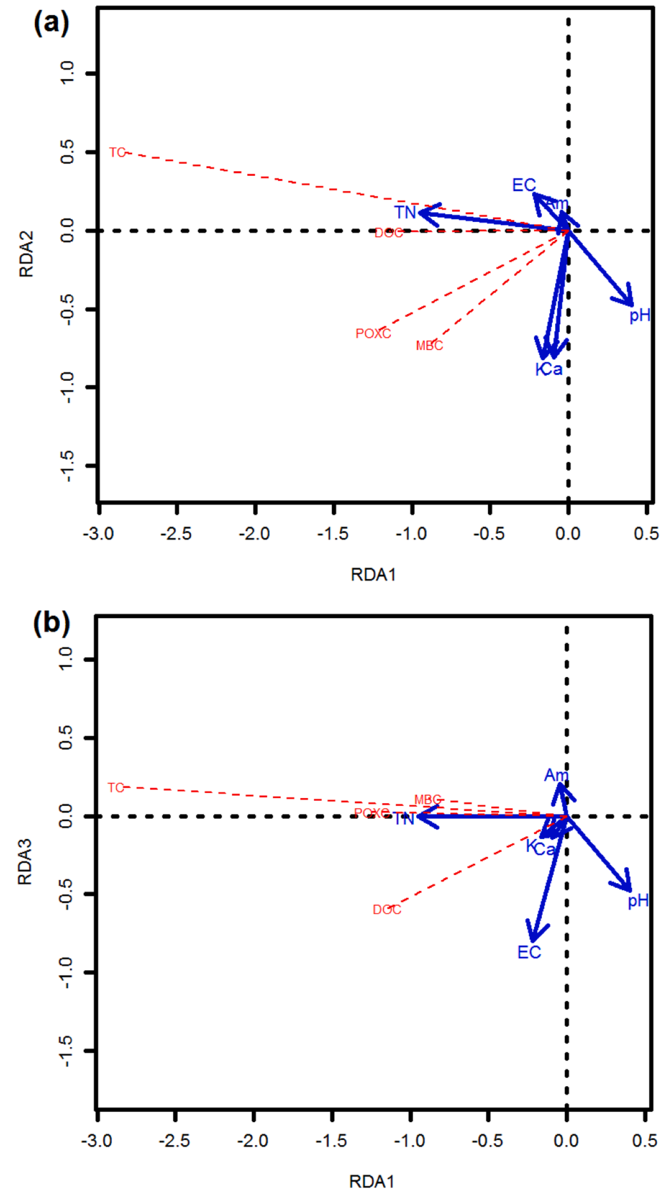


**Fig. 6.** Redundancy analysis (RDA) biplots of micro-environmental drivers versus soil carbon pools of Sri Lanka: (a) RDA biplot of axis 1 vs axis 2 (b) RDA biplot of axis 1 vs axis 3. *Abbreviations*: red dashed-lines represent the soil carbon pools, and blue arrows represent the micro-environmental drivers. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

pools and environmental drivers (Fig. 4). Accordingly, the rainfall and EVI were positively correlated with TC content and DOC, MBC, and POXC contents. It is clearly highlighted the prevailing solid correlation between the annual rainfall and TC pool rather than other soil carbon pools. Further, the conspicuous affinity between POXC and MBC with the vegetation index data (related to productivity and soil fertility) was depicted. The WI and elevation showed positive correlations with MBC and POXC while negatively affecting DOC content. The elevation controls the micro-environmental conditions (mainly temperature and hydrological characteristics of land) that possibly influence on microbial activity, thereby affecting the breakdown and transformation of different soil carbon pools (Martin et al., 2014; Tsui et al., 2013). Meanwhile, WI derived from Digital Elevation Model (DEM) as a secondary terrain attribute is crucial for soil carbon dynamics. In areas of high WI and potentially high- water content, the decaying rate of residual plant materials decreases, and the plant growth increases, which ultimately enhances SOC input and accretion (Li and McCarty, 2019). As a result, the simultaneous increment of MBC and POXC pools could be expected.

### 3.4. Micro-environnemental drivers

#### 3.4.1. Corrélations between micro-environnemental drivers

The soil pH showed moderately strong positive relationships with available $Mg^{2+}$, $Ca^{2+}$, and $K^{+}$ contents ($0.3 < r < 0.5$, $p < 0.05$; Fig. 5). Also, soil pH depicted a moderately strong negative relationship with the total soil N content ($r = -0.3$, $p < 0.05$). Further, the $K^{+}$, $Ca^{2+}$, and $Mg^{2+}$ ions also showed positive affinities with each other ($0.42 < r < 0.63$, $p < 0.05$). And the correlations that prevail among other parameters were relatively weak. Therefore, all the variables were kept for the model execution purpose.

#### 3.4.2. Forward selection of micro-environmental parameters and fitting the most parsimonious model

As a result of forward selection, soil $NO_3^-$, $PO_4^{3-}$ and $Mg^{2+}$ contents were removed due to their less influence on considered soil carbon pools, and other parameters (TN, $K^{+}$, pH, $Ca^{2+}$, EC and $NH_4^+$) were retained for the model execution purpose. The VIF of the selected micro-environmental parameters varied between 1.02 and 1.43, and the collinearity problem was not observed among the variables. Further, the fitted model for the micro-environmental variables was significant at a 0.05 significance level.

The micro-environmental parameters explained 21.46% of the soil carbon variation. The first three axes are significant at the 0.05 significance level. Accordingly, the first, second, and third constrained axes (RDA 1, RDA 2, and RDA 3) explain 18.6%, 1.88%, and 0.61% of the variation, respectively. The total N, available $K^{+}$, $Ca^{2+}$, and soil pH were the best explanatory variables for soil carbon pools, followed by soil EC and $NH_4^+$ content. Interestingly, the factors that are related to MBC were more or less similar to that of POXC, indicating similar driving forces for both pools. Usually, the MBC and the POXC carbon contents are interdependent as microbes utilise the oxidizable carbon as a readily available energy source (Lucas and Weil, 2012).

The prevailing relationships among soil carbon pools and other micro-environmental variables were illustrated in Fig. 6. Significant negative trends were observed between TC and other pools with the soil pH. Different organic acids are liberated during the organic matter decomposition and decrease soil pH, thereby accelerating the intensity of soil reduction (Dhaliwal et al., 2019). At low pH, the inhibitory effect of organic acids such as formic, acetic, and propionic acid can decline organic matter degradation in wetland soils (Stevenson, 1967), which mimics made wetland-like ecosystem in the majority of paddy production systems in Sri Lanka. At a higher soil pH, the bonds between organic constituents and clay particles in the soil could be easily broken (Neina, 2019), leading to an increase in mineralisable pools of C and N. In addition, Andersson et al. (2000) have demonstrated the effect of basic soil pH conditions on removing DOC from the system. Additionally, one of the main factors influencing soluble and plant-accessible metal concentrations in the soil is pH. Positive trends were observed between $K^+$, $Ca^{2+}$, and $Mg^{2+}$ with the soil pH (Fig. 5). Therefore, to some extent, soil acidification may negatively affect soil fertility because it depletes $Mg^{2+}$, $Ca^{2+}$, and $K^+$ base cations. Mainly, the leaching of basic cations could be observed in areas experiencing low pH values (White, 2013).

Further, a highly positive linear relationship was found between TC and TN concentrations. A collective effect of fresh organic carbon input and low soil N availability leads to a higher SOC mineralisation rate and a lower soil carbon storage potential (Fang et al., 2018). Hence, carbon storage capacity enhances at high N concentrations. Also, significant positive trends were observed between TN content and POXC, MBC, and DOC pools. Zhang et al. (2020) highlighted that N substantially affects the labile organic carbon pools of the soil, likely because N can promote the growth of both above and below-ground crop biomass while hastening crop litter decomposition. Furthermore, increased root biomass could have also resulted in the greater release of labile root exudates (Zhang et al., 2020). Soil N is essential to maintain better carbon inflows to the soil ecosystem.

The available $K^+$ and $Ca^{2+}$ nutrient cations showed positive trends with TC, DOC, MBC, and POXC pools. During the degradation of plant-derived material, microbial-derived inputs closely interact with mineral particles to form an organo-mineral complex structure which is a primary cause of soil carbon stabilisation (Plaza et al., 2013). Even though available $Ca^{2+}$ ions in the soil tend to improve microbial growth, the ability of $Ca^{2+}$ to attach to negatively charged organic surfaces is more likely responsible for Ca-mediated SOC stabilisation (Rowley et al., 2018). The oxidizable C pool consists of simple organic compounds, including amino acids and other simple carbohydrates (Zhong et al., 2015). The $Ca^{2+}$ can readily exchange its hydration shell and create inner and outer-sphere complexes with organic functional groups such as carboxyl and phenols (Rowley et al., 2018). Hence, oxidizable carbon stabilises within the soil by bonding with $Ca^{2+}$ ions. Minick et al. (2017) revealed that high $Ca^{2+}$ availability reduces the mineralisation of $^{13}C$-depleted SOC and stabilises oxidizable SOC that exists in relatively fresh substrates. Further, monovalent $K^+$ ions in the soil form organic ionic bonds in the interlayers of certain phyllosilicates, which also could lead to reduced SOC degradation (Solly et al., 2020). More importantly, Masek et al. (2019) demonstrated that K-enriched biochar amendments could significantly improve soil carbon sequestration potential partly because of the additive effect of K ions on biochar to enhance stable carbon pool.

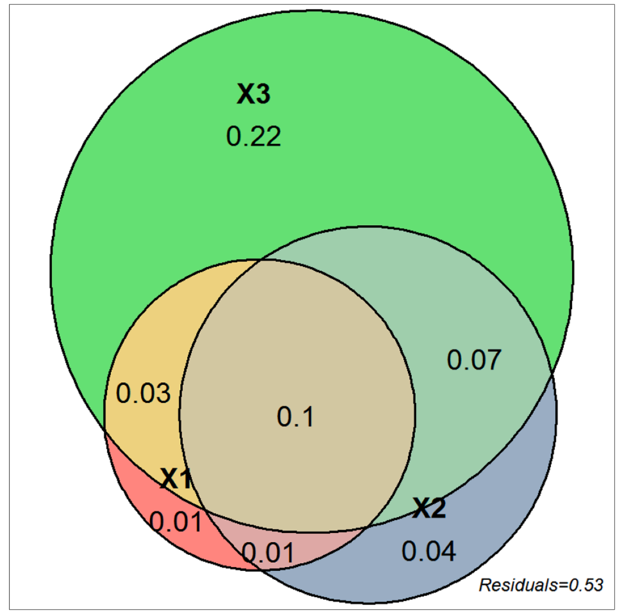


**Fig. 7.** Area-proportional Euler-Venn diagram, Explanatory drivers: X1: Macro-environmental drivers (Rainfall, EVI, Elevation, WI), X2: Micro-environmental drivers (pH, TN, $K^+$, $Ca^{2+}$, EC, $NH_4^+$), X3: Spatial parameters (significant Morgan eigen vector maps), the overlap represents shared variation among explanatory drivers.

### *3.5. Evaluation of spatial parameters by using spatially derived Morgan vector maps (MEMs)*

The RDA model for the selected spatial variables was fitted by using significant MEMs at a 0.05 significance level. Some of the plot connectivity spatial matrices used to generate MEMs are depicted in Appendix A (e.g., Distance-based, Relative, and Gabriel). All of the spatial MEMs together explained nearly 42% of the soil carbon variation.

### *3.6. Variance partitioning based on selected macro, micro, and spatial drivers*

The macro-environmental, micro-environment and spatial parameters together explained 47% of the variation in soil carbon pools (Fig. 7). Variance partitioning showed that unique fractions of all three variable groups were statistically significant ($p < 0.05$), indicating that their contributions are important for explaining variation in soil carbon pools. Micro-environmental factors had a larger unique fraction relative to macro-environmental variable groups (4% and 1% of the total variation, respectively). Usually, soil carbon flows and stabilisation mechanisms are directly controlled by microbial functions in the soil. Meanwhile, Zech et al. (1997) reported that the micro-environmental variables that modulate microbial habitat and activities, such as soil nutrients, pH, and water content, are closely associated with soil carbon dynamics. Compared to that, the influence of large-scale variations of macro-environmental variables on microbial functions is relatively less, which will, in turn, impact soil carbon dynamics. Thus, site-specific micro-environmental variables are more important in explaining variation in different soil carbon pools than macro-environmental variables considered in the study as they are more representative of natural landscapes (Mishra and Riley, 2015).

Notably, most of the variation explained by macro-environmental factors was shared by micro-environmental factors (11% out of 15%). In the context of Sri Lanka, the major climatic zones (wet, intermediate, and dry) across the country have been predominantly defined by the variation in annual rainfall. The subsequent temperature changes and associated evapotranspiration rates also differ among these primary climatic zones. Hence, the nature of major soil types i.e., mineral composition and texture, vary among those climatic zones as they are highly influenced by the primary climatic conditions of the area (Indraratne, 2020), whereas the availability of predominant nutrients that affect soil carbon dynamics (total N, $Ca^{2+}$ and $K^{+}$) (Fig. 6) usually rely on the soil conditions. For instance, the particle size distribution and chemical composition of clay minerals impact the K content in the soil (Raheb and Heidari, 2011). The Ca concentrations in various soil types greatly vary, mainly due to parent material and the degree of weathering and leaching processes (Mengel and Kirkby, 2012). Further, N fixed on clays can significantly contribute to subsurface soil N storage (Stevenson, 1986). Therefore, macro-environmental factors can indirectly influence soil carbon pools through effects on micro-environmental factors (Luo et al., 2017).

Nearly half of the variation explained by spatial factors (~20% of total variation) was shared by other variable groups, indicating that spatially-structured macro and micro-environmental factors may have induced similar spatial patterns in soil carbon pools across the country. In general, the distribution of soil carbon pools is affected by changes in environmental factors, such as climatic variables, land productivity-related vegetation index data, topographic characteristics (Fig. 4), and soil types that are structured in space which in turn generate spatially associated structures with soil carbon pools across the landscape.

Additionally, the unique fraction explained by spatial factors (22% of total variation) may be attributed to variation in soil carbon pools related to potential predictors that were not considered in the study (e.g., soil texture information and different clay minerals). For instance, Dan-Dan et al. (2010) showed that city- or country-scale soil texture is more important than climatic variables in explaining soil carbon distribution. Besides, several studies have reported the usefulness of soil clay content as a proxy for assessing both labile (Kölbl and Kögel-Knabner, 2004) and total soil carbon (Gómez-Guerrero and Doane, 2018) pools.

## 4. Caveats

In this study, TC content was analysed by automated combustion, and the soils were not treated with acid to remove inorganic carbon prior to the instrumental analysis. Therefore, small quantities of inorganic carbon could have been remained in some soil samples leading to some uncertainties in the estimates. However, it is reported that the quantity of carbonates in agricultural soils is significantly low compared to the organic carbon fraction (Tao et al., 2022; Raza et al., 2021), and therefore, such effect is likely negligible. In addition, unexplained variation in soil carbon pools could be related to the site-specific information that was not incorporated in the present study, such as soil physical characteristics (e.g. texture data) and the clay mineralogical composition that influence the stabilisation of some SOC pools.

## 5. Conclusions

The findings of the current study provide firsthand information that is vital to the soil carbon management of under-studied tropical paddy-growing soils to enhance ecosystem services that mainly associate with climate change mitigation and soil fertility enhancement. For this purpose, a combination of direct gradient analysis (RDA), Moran's Eigenvector Maps (MEMs), and variation partitioning analysis were used to quantify the influence of macro and micro-environmental factors on the spatial variation in soil carbon pools. It was found that nearly half of the soil carbon variation (47%) was significantly explained by a combination of macro, micro, and spatial factors, while micro-environmental conditions were more important than macro-environmental factors. Most of the soil carbon pools were highly spatially structured, as the controlling environmental predictors are spatially structured. Our findings provide insights into improving the reliability of future spatial soil carbon predictions by incorporating important soil carbon predictors.

Further, agricultural soil carbon management is an approved Greenhouse Gas compensation strategy. Even though improving the SOC status of the tropical ecosystems, including Sri Lanka, is not easy compared to the temperate region, as the climatic conditions of the tropics are favourable for the rapid decomposition of SOC. Therefore, the direct changes in soil carbon pools due to the influence by macro-environmental conditions are beyond our control. The study showed that soil carbon could be manipulated by micro-environment controllers such as TN, $K^{+}$, $Ca^{2+}$, and pH. Hence, micro-environmental controllers that significantly influence soil carbon pools can be considered when designing site-specific land management strategies in agricultural soils, which in turn are useful for paddy growth and productivity. Having a solid understanding of the stabilisation mechanisms of soil carbon and the influencing factors will assist in implementing effective management strategies leading to precise fertilisation, environmental protection and food security.

## 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.

## Data availability

Data will be made available on request.

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## Appendix A

See Fig. A1.

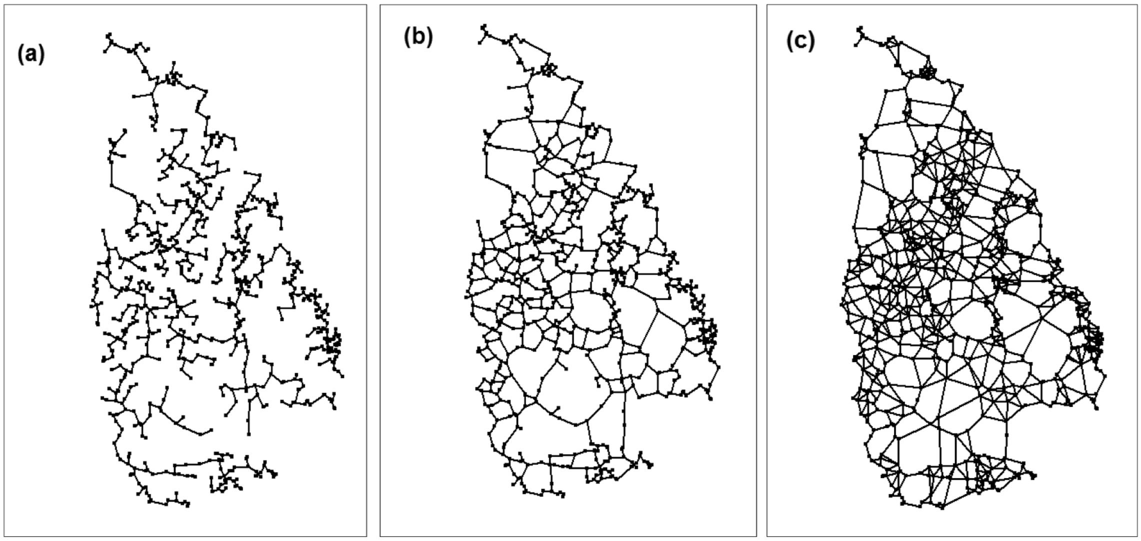


**Fig. A1.** Plot connectivity spatial metrices, (a) Distance based plot, (b) Relative plot, (c) Gabriel plot.

## Appendix B. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.catena.2023.107278. These data include Google maps of the most important areas described in this article.

## References


Anderson, J., Ingram, J., 1993. Tropical soil biological and fertility: a handbook of methods, 2ed. Wallingford: CAB International, 221p.

Andersson, S., Nilsson, S.I., Saetre, P., 2000. Leaching of dissolved organic carbon (DOC) and dissolved organic nitrogen (DON) in mor humus as affected by temperature and pH. Soil Biol. Biochem. 32, 1–10.

Balesdent, J., Basile-Doelsch, I., Chadoeuf, J., Cornu, S., Derrien, D., Fekiacova, Z., Hatte, C., 2018. Atmosphere–soil carbon transfer as a function of soil depth. Nature 559, 599–602.

Bauman, D., Drouet, T., Fortin, M.J., Dray, S., 2018. Optimizing the choice of a spatial weighting matrix in eigenvector-based methods. Ecology 99, 2159–2166.

Bhattacharyya, P., Neogi, S., Roy, K., Dash, P.K., Nayak, A., Mohapatra, T., 2014. Tropical low land rice ecosystem is a net carbon sink. Agr. Ecosyst. Environ. 189, 127–135.

Bivand, R., Altman, M., Anselin, L., Assuncao, R., Berke, O., Bernat, A., Blanchet, G., 2015. Package 'spdep'. The Comprehensive R Archive Network.

Cataldo, D., Maroon, M., Schrader, L.E., Youngs, V.L., 1975. Rapid colorimetric determination of nitrate in plant tissue by nitration of salicylic acid. Commun. Soil Sci. Plant Anal. 6, 71–80.

Chen, X., Hu, Y., Xia, Y., Zheng, S., Ma, C., Rui, Y., He, H., Huang, D., Zhang, Z., Ge, T., 2021. Contrasting pathways of carbon sequestration in paddy and upland soils. Glob. Chang. Biol. 27, 2478–2490.

Cleary, D.F., Polonia, A.R., Swierts, T., Coelho, F.J., de Voogd, N.J., Gomes, N.C., 2022. Spatial and environmental variables structure sponge symbiont communities. Mol. Ecol. 31 (19), 4932–4948.

Coleman, K., Jenkinson, D., 1996. RothC-26.3-A Model for the turnover of carbon in soil, Evaluation of soil organic matter models: using existing long-term datasets. Springer, pp. 237–246.

Dammalage, T.L., Sirisena, T., Susaki, J., 2018. MODIS Satellite Data Based Rice Yield-Forecasting Model for Sri Lanka: A Pilot Study on Kurunegala District. Asian J. Geoinform. 17.

Dan-Dan, W., Xue-Zheng, S., Hong-Jie, W., Weindorf, D., Dong-Sheng, Y., Wei-Xia, S., Hong-Yan, R., Yong-Cun, Z., 2010. Scale effect of climate and soil texture on soil organic carbon in the uplands of Northeast China. Pedosphere 20, 525–535.

Dangal, S.R., Schwalm, C., Cavigelli, M.A., Gollany, H.T., Jin, V.L., Sanderman, J., 2022. Improving soil carbon estimates by linking conceptual pools against measurable carbon fractions in the DAYCENT Model Version 4.5. J. Adv. Model. Earth Syst. 14 (5) e2021MS002622.

De Alwis, K.A., Panabokke, C.R., 1972. The soils of Sri Lanka. Soil Sci. Soc. Sri Lanka 2, 17–83.

De Costa, W., Wijeratne, M., De Costa, D., Zahra, A., 2012. Determination of the appropriate level of salinity for screening of hydroponically grown rice for salt tolerance. J. Natl. Sci. Found. 40.

Dhaliwal, S., Naresh, R., Mandal, A., Singh, R., Dhaliwal, M., 2019. Dynamics and transformations of micronutrients in agricultural soils as influenced by organic matter build-up: A review. Environ. Sustain. Indicators 1, 100007.

Dorji, T., Odeh, I.O., Field, D.J., 2015. Elucidating the complex interrelationships of soil organic carbon fractions with land use/land cover types and landform attributes in a montane ecosystem. J. Soil. Sediment. 15, 1039–1054.

Dray, S., Blanchet, G., Borcard, D., Guenard, G., Jombart, T., Larocque, G., Legendre, P., Madi, N., Wagner, H.H., Dray, M.S., 2018. Package 'adespatial'. R Package, 2018, 3-8.

Dray, S., Pelissier, R., Couteron, P., Fortin, M.-J., Legendre, P., Peres-Neto, P.R., Bellier, E., Bivand, R., Blanchet, F.G., De Caceres, M., 2012. Community ecology in the age of multivariate multiscale spatial analysis. Ecol. Monogr. 82 (3), 257–275.

Fadeeva, V., Tikhova, V., Nikulicheva, O., 2008. Elemental analysis of organic compounds with the use of automated CHNS analyzers. J. Anal. Chem. 63, 1094–1106.

Fang, Y., Singh, B.P., Collins, D., Li, B., Zhu, J., Tavakkoli, E., 2018. Nutrient supply enhanced wheat residue-carbon mineralization, microbial growth, and microbial carbon-use efficiency when residues were supplied at high rate in contrasting soils. Soil Biol. Biochem. 126, 168–178.

Gautam, S., Mishra, U., Scown, C.D., Wills, S.A., Adhikari, A., Drewniak, B.A., 2022. Continental United States may lose 1.8 petagrams of soil organic carbon under climate change by 2100. Glob. Ecol. Biogeogr. 31, 1147–1160.

Gómez-Guerrero, A., Doane, T., 2018. The response of forest ecosystems to climate change. Develop. Soil Sci. Elsevier 185–206.

Griffith, D.A., Peres-Neto, P.R., 2006. Spatial modeling in ecology: the flexibility of eigenfunction spatial analyses. Ecology 87, 2603–2613.

Hendrix, P.F., Coleman, D.C., Crossley, D., 2018. Using knowledge of soil nutrient cycling processes to design sustainable agriculture, Integrating Sustainable Agriculture, Ecology, and Environmental Policy. Routledge 63–82.

Indraratne, S., 2020. Soil Mineralogy, The Soils of Sri Lanka. Springer, pp. 35-47.

Keskin, H., Grunwald, S., Harris, W.G., 2019. Digital mapping of soil carbon fractions with machine learning. Geoderma 339, 40–58.

Kölbl, A., Kögel-Knabner, I., 2004. Content and composition of free and occluded particulate organic matter in a differently textured arable Cambisol as revealed by solid-state 13C NMR spectroscopy. J. Plant Nutr. Soil Sci. 167, 45–53.

Lal, R., Delgado, J., Groffman, P., Millar, N., Dell, C., Rotz, A., 2011. Management to mitigate and adapt to climate change. J. Soil Water Conserv. 66, 276–285.

Lal, R., Smith, P., Jungkunst, H.F., Mitsch, W.J., Lehmann, J., Nair, P.R., McBratney, A. B., de Moraes Sa, J.C., Schneider, J., Zinn, Y.L., 2018. The carbon sequestration potential of terrestrial ecosystems. J. Soil Water Conserv. 73, 145A–152A.

Lenore, S., Clesceri, A., Rhodes, R., 1989. Trussell Standard Methods for the Examination of Water and Wastewater. American Public Health Association.

Li, X., McCarty, G.W., 2019. Application of topographic analyses for mapping spatial patterns of soil properties, Geospatial Analyses of Earth Observation (EO) data. IntechOpen.

Liu, S., An, N., Yang, J., Dong, S., Wang, C., Yin, Y., 2015. Prediction of soil organic matter variability associated with different land use types in mountainous landscape in southwestern Yunnan province, China. Catena 133, 137–144.

Liu, Z., Liu, Q., 2014. Magnetic properties of two soil profiles from Yan'an, Shaanxi Province and their implications for paleorainfall reconstruction. Sci. China Earth Sci. 57, 719–728.

Lucas, S., Weil, R., 2012. Can a labile carbon test be used to predict crop responses to improve soil organic matter management? Agron. J. 104, 1160–1170.

Luo, Z., Feng, W., Luo, Y., Baldock, J., Wang, E., 2017. Soil organic carbon dynamics jointly controlled by climate, carbon inputs, soil properties and soil carbon fractions. Glob. Chang. Biol. 23, 4430–4439.

Luo, Z., Viscarra Rossel, R.A., Shi, Z., 2020. Distinct controls over the temporal dynamics of soil carbon fractions after land use change. Glob. Chang. Biol. 26, 4614–4625.

Malhi, Y., Franklin, J., Seddon, N., Solan, M., Turner, M.G., Field, C.B., Knowlton, N., 2020. Climate change and ecosystems: Threats, opportunities and solutions. The Royal Society.
Mapa, R.B., 2020. The Soils of Sri Lanka, Springer, New York, NY, USA.
Marques, J.D.D.O., Luizao, F.J., Teixeira, W.G., Sarrazin, M., Ferreira, S.J.F., Beldini, T. P., Marques, E.M.D.A., 2015. Distribution of organic carbon in different soil fractions in ecosystems of central Amazonia. Revista Brasileira de Ciencia do Solo, 39, 232-242.
Martin, M., Orton, T., Lacarce, E., Meersmans, J., Saby, N., Paroissien, J., Jolivet, C., Boulonne, L., Arrouays, D., 2014. Evaluation of modelling approaches for predicting the spatial distribution of soil organic carbon stocks at the national scale. Geoderma 223, 97–107.
Masek, O., Buss, W., Brownsort, P., Rovere, M., Tagliaferro, A., Zhao, L., Cao, X., Xu, G., 2019. Potassium doping increases biochar carbon sequestration potential by 45%, facilitating decoupling of carbon sequestration from soil improvement. Sci. Rep. 9, 1–8.
McBratney, A.B., Santos, M.M., Minasny, B., 2003. On digital soil mapping. Geoderma 117 (1–2), 3–52.
McIntosh, J.L., 1969. Bray and Morgan soil extractants modified for testing acid soils from different parent materials 1. Agron. J. 61, 259–265.
McNally, S.R., Beare, M.H., Curtin, D., Meenken, E.D., Kelliher, F.M., Calvelo Pereira, R., Shen, Q., Baldock, J., 2017. Soil carbon sequestration potential of permanent pasture and continuous cropping soils in New Zealand. Glob. Chang. Biol. 23, 4544–4555.
Mengel, K., Kirkby, E.A., 2012. Principles of plant nutrition. Springer Science & Business Media.
Miles, J., 2014. Tolerance and variance inflation factor. Wiley StatsRef: Statistics Reference Online.
Minasny, B., McBratney, A.B., 2006. A conditioned Latin hypercube method for sampling in the presence of ancillary information. Comput. Geosci. 32, 1378–1388.
Minick, K.J., Fisk, M.C., Groffman, P.M., 2017. Soil Ca alters processes contributing to C and N retention in the Oa/A horizon of a northern hardwood forest. Biogeochemistry 132, 343–357.
Mishra, U., Riley, W., 2015. Scaling impacts on environmental controls and spatial heterogeneity of soil organic carbon stocks. Biogeosciences 12, 3993–4004.
Mishra, U., Yeo, K., Adhikari, K., Riley, W.J., Hoffman, F.M., Hudson, C., Gautam, S., 2022. Empirical relationships between environmental factors and soil organic carbon produce comparable prediction accuracy to machine learning. Soil Sci. Soc. Am. J. 86, 1611–1624.
Muthayya, S., Sugimoto, J.D., Montgomery, S., Maberly, G.F., 2014. An overview of global rice production, supply, trade, and consumption. Ann. N. Y. Acad. Sci. 1324, 7–14.
Nair, R., Mehta, C., Sharma, S., 2015. Carbon sequestration in soils-A Review. Agric. Rev. 36.
Neina, D., 2019. The role of soil pH in plant nutrition and soil remediation. Applied and Environmental Soil Science, 2019.
Nguyen, B.T., Phan, B.T., Nguyen, T.X., Nguyen, V.N., Van Tran, T., Bach, Q.V., 2020. Contrastive nutrient leaching from two differently textured paddy soils as influenced by biochar addition. J. Soil. Sediment. 20, 297–307.
Odeh, I., Chittleborough, D., McBratney, A., 1991. Elucidation of soil-landform interrelationships by canonical ordination analysis. Geoderma 49, 1–32.
Oksanen, J., Blanchet, F., Kindt, R., Legendre, P., Minchin, P., O'Hara, R., 2015. 629 vegan: community ecology package. R package 2, 1.
Panabokke, C. R., 1996. Soils and agro-ecological environments of Sri Lanka. Colombo, Sri Lanka: NARESA, xvi, 220.
Parton, W.J., Stewart, J.W., Cole, C.V., 1988. Dynamics of C, N, P and S in grassland soils: a model. Biogeochemistry 5, 109–131.
Pecl, G.T., Araujo, M.B., Bell, J.D., Blanchard, J., Bonebrake, T.C., Chen, I.C., Clark, T.D., Colwell, R.K., Danielsen, F., Evengard, B., 2017. Biodiversity redistribution under climate change: Impacts on ecosystems and human well-being. Science 355.
Peres-Neto, P.R., Legendre, P., Dray, S., Borcard, D., 2006. Variation partitioning of species data matrices: estimation and comparison of fractions. Ecology 87, 2614–2625.
Peres-Neto, P.R., Legendre, P., 2010. Estimating and controlling for spatial structure in the study of ecological communities. Glob. Ecol. Biogeogr. 19, 174–184.
Plaza, C., Courtier-Murias, D., Fernández, J.M., Polo, A., Simpson, A.J., 2013. Physical, chemical, and biochemical mechanisms of soil organic matter stabilization under conservation tillage systems: a central role for microbes and microbial by-products in C sequestration. Soil Biol. Biochem. 57, 124–134.
Poeplau, C., Don, A., Dondini, M., Leifeld, J., Nemo, R., Schumacher, J., Senapati, N., Wiesmeier, M., 2013. Reproducibility of a soil organic carbon fractionation method to derive RothC carbon pools. Eur. J. Soil Sci. 64, 735–746.
R Core Team., 2021. R: A Language and Environment for Statistical Computing (Version 4.1. 1)[Computer Software].
Raheb, A., Heidari, A., 2011. Clay mineralogy and its relationship with potassium forms in some paddy and non-paddy soils of northern Iran. Australian J. Agric. Eng. 2, 169–175.
Rajapaksha, R., Karunaratne, S., Biswas, A., Paul, K., Madawala, H., Gunathilake, S., Ratnayake, R., 2020. Identifying the spatial drivers and scale-specific variations of soil organic carbon in tropical ecosystems: A case study from Knuckles Forest Reserve in Sri Lanka. For. Ecol. Manage. 474, 118285.
Rajkishore, S., Natarajan, S., Manikandan, A., Vignesh, N., Balusamy, A., 2015. Carbon sequestration in rice soils–A review.
Ratnayake, R., Karunaratne, S., Lessels, J., Yogenthiran, N., Rajapaksha, R., Gnanavelrajah, N., 2016. Digital soil mapping of organic carbon concentration in paddy growing soils of Northern Sri Lanka. Geoderma Reg. 7, 167–176.
Raza, S., Zamanian, K., Ullah, S., Kuzyakov, Y., Virto, I., Zhou, J., 2021. Inorganic carbon losses by soil acidification jeopardize global efforts on carbon sequestration and climate change mitigation. J. Clean. Prod. 315, 128036.
Rowley, M.C., Grand, S., Verrecchia, É.P., 2018. Calcium-mediated stabilisation of soil organic carbon. Biogeochemistry 137, 27–49.
Skeen, C.J., 1994. Carbon, hydrogen, and nitrogen by a CHN elemental analyzer. Analytical methods manual for the Mineral Resource Surveys Program US Geological Survey, 186.
Solly, E.F., et al., 2020. A critical evaluation of the relationship between the effective cation exchange capacity and soil organic carbon content in Swiss forest soils. Front. Forests Global Change 3, 98.
Stevenson, F., 1967. Organic acid in soil: in Soil Biochemistry, Vol. L, AD McLaren and GH Peterson, eds. Marcel Dekker, New York.
Stevenson, F., 1986. Carbon balance of the soil and role of organic matter in soil fertility. Cycles of soil–carbon, nitrogen, phosphorus, sulfur, micronutrients.(Hrsg. Stevenson, FJ), Wiley Verlag, New York, 45-77.
Tao, J., Raza, S., Zhao, M., Cui, J., Wang, P., Sui, Y., Zamanian, K., Kuzyakov, Y., Xu, M., Chen, Z., 2022. Vulnerability and driving factors of soil inorganic carbon stocks in Chinese croplands. Sci. Total Environ. 825, 154087.
Ter Braak, C.J., Prentice, I.C., 2004. A theory of gradient analysis. Adv. Ecol. Res. 34, 235–282.
Tsui, C.C., Tsai, C.C., Chen, Z.S., 2013. Soil organic carbon stocks in relation to elevation gradients in volcanic ash soils of Taiwan. Geoderma 209, 119–127.
Vitharana, U.W.A., Mishra, U., Mapa, R.B., 2019. National soil organic carbon estimates can improve global estimates. Geoderma 337, 55–64.
Vivek, P., 2008. Carbon sequestration pattern in maize (Zea mays l.)-mycorrhizal (Glomus intraradices Schenck and Smith) system under long-term fertility gradients, TNAU, Coimbatore.
Wang, J., Wang, H., Cao, Y., Bai, Z., Qin, Q., 2016. Effects of soil and topographic factors on vegetation restoration in opencast coal mine dumps located in a loess area. Sci. Rep. 6, 1–11.
Watanabe, F., Olsen, S., 1965. Test of an ascorbic acid method for determining phosphorus in water and NaHCO3 extracts from soil. Soil Sci. Soc. Am. J. 29, 677–678.
Weil, R.R., Islam, K.R., Stine, M.A., Gruver, J.B., Samson-Liebig, S.E., 2003. Estimating active carbon for soil quality assessment: A simplified method for laboratory and field use. Am. J. Altern. Agric. 18, 3–17.
White, R.E., 2013. Principles and practice of soil science: the soil as a natural resource. John Wiley & Sons.
Wiesmeier, M., Urbanski, L., Hobley, E., Lang, B., von Lützow, M., Marin-Spiotta, E., van Wesemael, B., Rabot, E., Ließ, M., Garcia-Franco, N., 2019. Soil organic carbon storage as a key function of soils-A review of drivers and indicators at various scales. Geoderma 333, 149–162.
Xiao, Y., Huang, Z., Li, Y., Ling, Y., Xiao, H., 2021. Dynamics Variation of Soil Labile Organic Carbon Fractions in Different Wetland Types of Dongting Lake under Seasonal Water Level Fluctuation. Sustainability 13, 13836.
Yang, Y., Guo, J., Chen, G., Yin, Y., Gao, R., Lin, C., 2009. Effects of forest conversion on soil labile organic carbon fractions and aggregate stability in subtropical China. Plant and Soil 323, 153–162.
Zech, W., Senesi, N., Guggenberger, G., Kaiser, K., Lehmann, J., Miano, T.M., Miltner, A., Schroth, G., 1997. Factors controlling humification and mineralization of soil organic matter in the tropics. Geoderma 79, 117–161.
Zhang, L., Chen, X., Xu, Y., Jin, M., Ye, X., Gao, H., Chu, W., Mao, J., Thompson, M.L., 2020. Soil labile organic carbon fractions and soil enzyme activities after 10 years of continuous fertilization and wheat residue incorporation. Sci. Rep. 10, 1–10.
Zhang, K., Maltais-Landry, G., Liao, H.L., 2021. How soil biota regulate C cycling and soil C pools in diversified crop rotations. Soil Biol. Biochem. 108219.
Zhong, Y., Yan, W., Shangguan, Z., 2015. Soil carbon and nitrogen fractions in the soil profile and their response to long-term nitrogen fertilization in a wheat field. Catena 135, 38–46.
Zhou, T., Geng, Y., Chen, J., Liu, M., Haase, D., Lausch, A., 2020. Mapping soil organic carbon content using multi-source remote sensing variables in the Heihe River Basin in China. Ecol. Ind. 114, 106288.