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Article

Carbon variability in the soil of a rice field in Costa Rica

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Abstract

Knowledge of the soil carbon stock (SCS) is vital for appropriate farming practices management, ie. tillage and to monitor SCS changes as mitigation strategies of carbon footprint. This study aims to quantify the variability and spatial distribution of the SCS. In an area of 1 ha 45 micro-pit (1 x 0.8 x 1 m) were divided into four strata. Vertical distribution of soil carbon was quantified along with other chemical and physical soil properties that affect rice production in Parrita, Costa Rica. A map of spatial prediction of the distribution and goodness-of-prediction values were calculated to estimate the effectiveness of the SCS prediction when different numbers of sampling points were used 45, 27, 15 and 7 microplots. As accurate measurements, the Mean Absolute Error and the Mean Square Error were calculated. In this study, the SCS was 85.8 (±2.6) Mg C ha^{-1}, into the total profile (0-100 cm), where the first 30 cm represented 46.2%. Prediction of the spatial distribution suggests that in annual agricultural crops, with tillage systems 15 sampling points ha^{-1} a can effectively estimate the SCS.

Keywords:

climate change mitigation, geostatistical interpolation, kriging method, soil mapping.

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Introduction

Soils are critical for climate change mitigation as they represent the largest carbon (C) reservoir in the terrestrial biosphere (Zomer *et al*., 2017). While initiatives promoting soil C sequestration are emerging (FAO, 2019), tree-based C fixation dominates C credit markets (Valderrama *et al*., 2018). These markets, shaped by voluntary programs and policies such as the EU emissions trading scheme, the Paris Agreement, and 4 per 1 000 initiative (Lal, 2016), require robust platforms for soil C monitoring and verification at scale (Smith *et al*., 2020).

Accurate soil carbon stock (SCS) estimation demands appropriate spatial and temporal resolutions, along with standardized global protocols (FAO, 2020). Understanding C and nitrogen (N) stock variability is essential to analyse how agricultural practices, particularly tillage, impact soil properties. This enables the identification of optimal soil management strategies to enhance crop production while preserving soil health. Determining initial soil C levels is crucial for establishing baseline conditions to assess C changes, retention, and loss (Nayak *et al*., 2019).

Soil C distribution within the profile is heterogeneous (Jandl *et al*., 2014), influenced by factors like root distribution, land use, and soil properties (Yu *et al*., 2019). While C accumulates in deeper layers (30-100 cm) (Aguilera *et al*., 2013; Oliveira *et al*., 2016), common sampling depths (20-40 cm) may be insufficient for accurate C monitoring (FAO, 2019). Shallow sampling can lead to inaccurate assessments, particularly regarding erosion (Davis *et al*., 2018). In Costa Rica, the Recsoil initiative, focusing on livestock and coffee sectors, utilizes 30 cm sampling depth. However, the applicability of this protocol in annual cropping systems requires further evaluation for broader implementation (FAO, 2024).

Appropriate sampling depth increments are crucial for accurately quantifying C changes. Common techniques include sampling by soil horizon, which can be challenging due to varying soil taxonomy guidelines or by fixed depth (Davis *et al*., 2018). To account for spatial variability, sampling methodologies must consider factors such as sampling point distance and depth. Geostatistical methods, such as Kriging, are effective for quantifying spatial distribution and predicting soil C (Wen *et al*., 2015; Ahmed *et al*., 2022).

The objectives of this study were quantifying the vertical distribution of soil C across the soil profile (0-100 cm) and determine the optimal number of samplings to quantify SCS by the spatial interpolation technique. We hypothesize that soil properties, such as C content, can be predicted through the combined use of statistical and geostatistical methods. This approach aims to determine the optimal number of sampling points required to capture spatial variability (fewer than 15 points per hectare), thereby optimizing resources and improving sampling efficiency.

Material and methods

Study site

The study was carried out in the Costa Rican Central Pacific, at the experimental farm of the National Rice Corporation in Parrita, Puntarenas (9° 30' 55.02" N, 84° 22' 2.56" W). The area classified as a Tropical Humid Forest (L. Holdridge life zone system) presents an average annual temperature of 27 °C (max. 32.5 °C and min. of 22.5 °C), with average annual precipitation of 2 000 to 3 000 mm year^{-1} (Alvarado-Velas *et al*., 2021).

The soil was classified as *Fluventic Haplustepts* with a medium coarse texture. It is an alluvial Inceptisol, characterized by being colluvial from the Pirris River, with an ustic climatic regime, low organic matter, medium to high fertility, medium to fine surface granulometry in depth and the presence of rocky outcrops, for agricultural use see other soil properties on supplementary material (Table 1).

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Table 1. Physical and chemical characteristics of the soil of the experimental plot located in the Conarroz Experimental Farm, Parrita, Costa Rica (n= 9).

Depth (cm)	Bult density	Ksat	C	pH	EC	Sand	Clay	Silt
10	1.2 ±0.02	0.14 ±0.02	1.24 ±0.03	5.86 ±0.06	0.16 ±0.01	33 ±2.87	30.04 ±1.52	37.09 ±2.46
30	1.26 ±0.01	0.1 ±0.02	0.83 ±0.04	6.2 ±0.04	0.14 ±0.01	35.58 ±2.97	32.24 ±1.81	32.38 ±2.29
50	1.28 ±0.01	0.07 ±0.02	0.63 ±0.03	6.37 ±0.04	0.13 ±0.01	37.67 ±2.85	32.64 ±1.94	29.89 ±2.44
80	1.27 ±0.01	0.05 ±0.01	0.39 ±0.02	6.33 ±0.04	0.13 ±0.01	41.36 ±2.91	29.64 ±1.45	29.11 ±2.57

Experimental design

In 2019, 45 sampling points were established across a 1 ha area with approximately 15 m spacing to assess spatial soil property variability. A 1 x 0.8 x 1 m pit was made at each point. The pit was divided into four strata: 0 to 20 cm, 20 to 40 cm, 40 to 60 cm and 60 to 100 cm, with samples taken in the middle of each profile (10, 30, 50 and 80 cm) for chemical and physical analysis. To calculate de SCS we use the strata 0-30, 30-60 and 60 to 100 cm according to FAO (2020) and to ease comparison with other schemes that use 0-30 depth, values were interpolated from the original strata concentrations.

Physical and chemical properties

Texture analysis was done using the modified hydrometer method. Bulk density was determined with undisturbed samples, for which 8 x 5 cm, cylinders were used. The saturated hydraulic conductivity (HC) was determined through the constant water column method, in 8 x 5 cm cylinders. pH and electrical conductivity (EC) (Mettler Toledo brand, SevenGo Duo pro model) were measured in 1:1 H_2O.

Total C and N content were determined by dry combustion (Duma's method) using a vario Macro cube CN analysers (Elementar Analyse Systeme GmbH, Germany). As the data was not normally distributed, differences among depths for all the measured variables were tested for significance using the non-parametric Kruskall-Wallis H-test, and when there was a significant (*p* value 0.05) Tukey-Kramer test.

The Pearson correlations significance levels was determinate to find relationship between pairs of variables. All statistical analyses were performed in the R Studio program version 1.1.463 interface (RStudio Team, 2020). Moran's, I index with nominal values of 10 cm, 30 cm, 50 cm, and 80 cm was used to analyse the degree of spatial autocorrelation of the variables. This index examines the location of each observation based on a comparison with its neighbouring observations (Wu *et al*., 2024).

Soil carbon and soil total nitrogen (STN stocks

Stocks were estimated based on C and N concentrations and the volume and density of each soil layer according to FAO (2022). Differences in the effect of depth on SCS and STN were evaluated through a separation of the total stock (measured at 100 cm) in three measurement strata. We examined the differences between measurement strata using a one-way Anova and when there was a significant (*p* value= 0.05), an analysis with the Tukey's honest significant difference's function was performed.

Optimization of soil sampling by geostatistical analysis and prediction comparison

The spatial distribution of soil C and N stock was examined by interpolation maps with ArcMap 10.5 and QGIS 3.12.3 with Grass 7.8.3 software, using the geostatistical interpolation ordinary kriging.

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It is assumed that the data closer to a point of interest have greater weight or influence on the interpolation, this method is widely used when the sampling intensity is high, and it is also a good option when there is a minimum distance in the data (Bhunia *et al*., 2018).

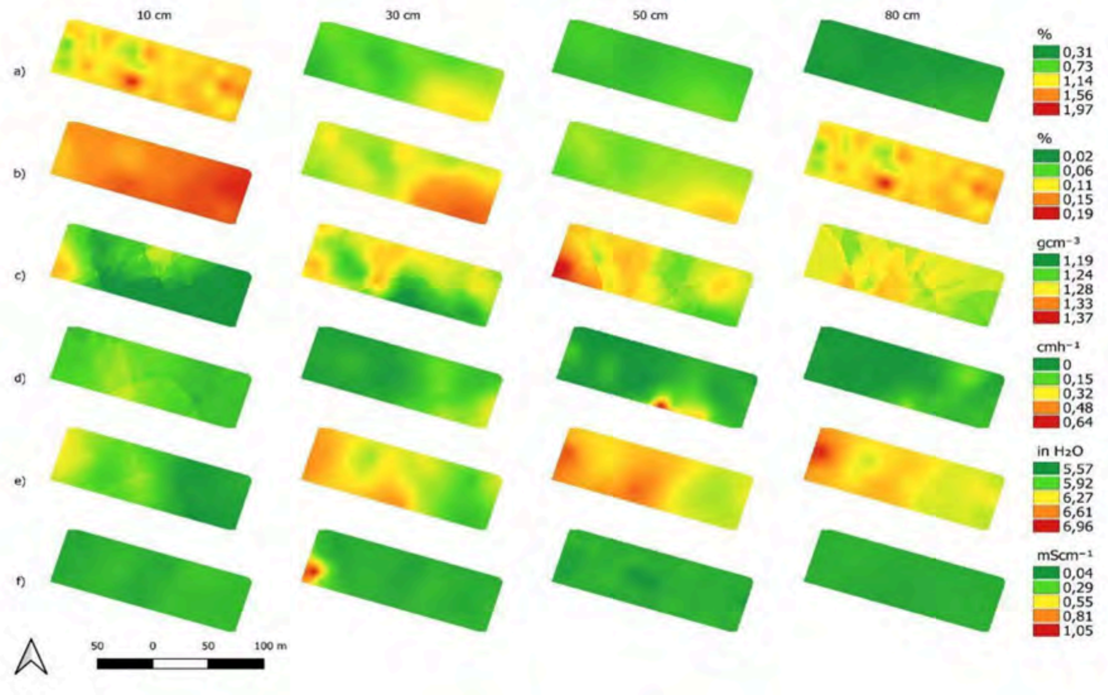
A map of prediction of spatial distribution of soil C was made with differences in the number of sampling points: 45, 27, 15 and 7. Comparison of predictions was based on measures of accuracy: the mean absolute error (MAE), the mean squared error (MSE) and the goodness-of-prediction (G) (Schloeder *et al*., 2001).

Results

Variability of physical and chemical properties

Spatial variability in C, N, pH, bulk density, HC, and EC was most pronounced in the top 10 cm (Figure 1). Total C and N contents peaked at 1.23% (±0.03) and 0.15% (±0.003) in the top 10 cm, respectively, and decreased with depth, reaching minima of 0.39% (±0.02) and 0.07% (±0.002) at the deepest stratum. C distribution was homogeneous across all strata, whereas N content varied within the plot.

Figure 1. Spatial distribution a) total carbon content (%C); b) total nitrogen content (%N); c) bulk density (g cm^{-3}); d) hydraulic conductivity (cm h^{-1}); e) pH and f) electrical conductivity (mS cm^{-1}) made by Kriging interpolation (n= 45) at Experimental Farm in Parrita, Costa Rica. Values on the top (10, 30, 50, 80 cm) are the midpoint in the soil categories sampled as previously described in the methodology.



Bulk density showed values greater than 1 g cm^{-3}, increasing from 1.2 g cm^{-3} (±0.01) at top stratum to 1.28 (±0.01) at 50 cm, the highest value recorded through the profile (Figure 1c). This stratum had high variability in the horizontal distribution. The HC decreased through the soil profile, from 0.14 cm h^{-1} (±0.02) to 0.048 cm h^{-1} (±0.01), maintaining horizontal homogeneity in the plot. At 80 cm, the distribution was uniform with values close to zero (Figure 1d).

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Soil pH increased with depth, from 5.89 (±0.06) at 10 cm to 6.33 (±0.04) at 80 cm (Figure 1e), exhibiting horizontal heterogeneity with higher values westward. EC showed uniformity across the plot, gradually decreasing with depth, from 0.16 mS cm^{-1} (±0.01) in the topsoil to 0.13 mS cm^{-1} (±0.01) (Figure 1f). Clay content initially increased from 30% (±1.5) to 32.2% (±1.8) but decreased to a minimum of 29.6% (±1.5) below 50 cm depth. Sand content exhibited a nearly linear increase from 33% (±2.9) in the topsoil to 41.4% (±2.9) in the deeper stratum.

Silt content declined with depth (37.1 ±2.5% at 10 cm versus 29.1 ±2.6% at 80 cm depth). HC exhibited the highest correlation with other variables supplementary material (Table 2), showing positive correlations with C, N, EC, and clay. Sand content correlated positively with bulk density (r=0.306, p< 0.01), pH (r= 0.464, p< 0.01) and EC (r= 0.053, p< 0.05). As anticipated, the strongest Pearson correlation was between C and N (r= 0.957, p< 0.01).

Table 2. Analysis of the Pearson correlation coefficient between soil parameters at the Conarroz Experimental Farm in Parrita, Costa Rica.

	Bult density	HC	Carbono	Nitrógeno	pH	EC	Sand	Clay	Silt
Bult density	1								
HC	-0.195**	1							
Carbon	-0.498***	0.329***	1						
Nitrogen	-0.484***	0.34***	0.957***	1					
pH	0.356***	-0.217**	-0.599***	-0.6***	1				
EC	-0.002*	0.041*	0.054*	0.097	-0.048*	1			
Sand	0.306***	-0.238**	-0.342***	-0.392***	0.464***	0.053*	1		
Clay	-0.096*	0.038*	0.126*	0.161*	-0.195**	-0.006	-0.531***	1	
Silt	-0.293***	0.252***	0.316***	0.35***	-0.414***	-0.058	-0.816***	-0.056*	1

* = significance level at 5%; **= significance level at 1%; ***= significance level at 0.1%; HC= hydraulic conductivity; EC= electrical conductivity.

Regarding to global Moran's index spatial autocorrelation, C, N, HC and pH, exhibited weak spatial association in the first 10 cm (C: 0.34, N: 0.34, HC: -0.11 and pH: 0.29), reached the strongest spatial autocorrelation at 30 cm (C: 0.64, N: 0.69, HC: 0.32, pH: 0.49), variables that diminishes again at 50 cm and 80 cm depths, as indicated by a low Z value (Z value <4.02).

Bulk density and EC exhibited consistently low spatial autocorrelation across all soil strata. Bulk density autocorrelation values ranging from 0.26 to -0.18, peaking at 50 cm (0.26) yet remaining insufficient for high spatial association. Similarly, EC maintained the trend of low autocorrelation in all depths with values ranging from 0.37 to -0.03.

Soil carbon and nitrogen stocks

In the total profile (0-100 cm), the SCS was 85.8 (±2.6) Mg C ha^{-1} (Figure 2a) with a maximum C value at the first 10 cm. Soil C decreased with depth, with the highest C content (46.2%) in the top 30 cm (39.64 ±0.86 Mg C ha^{-1}), whilst 30 to 60 cm represented 24.3% (20.93 ±0.81 Mg C ha^{-1}) and 60 to 100 cm the remaining 23.1% (19.77 ±0.95 Mg C ha^{-1}) of the SCS.

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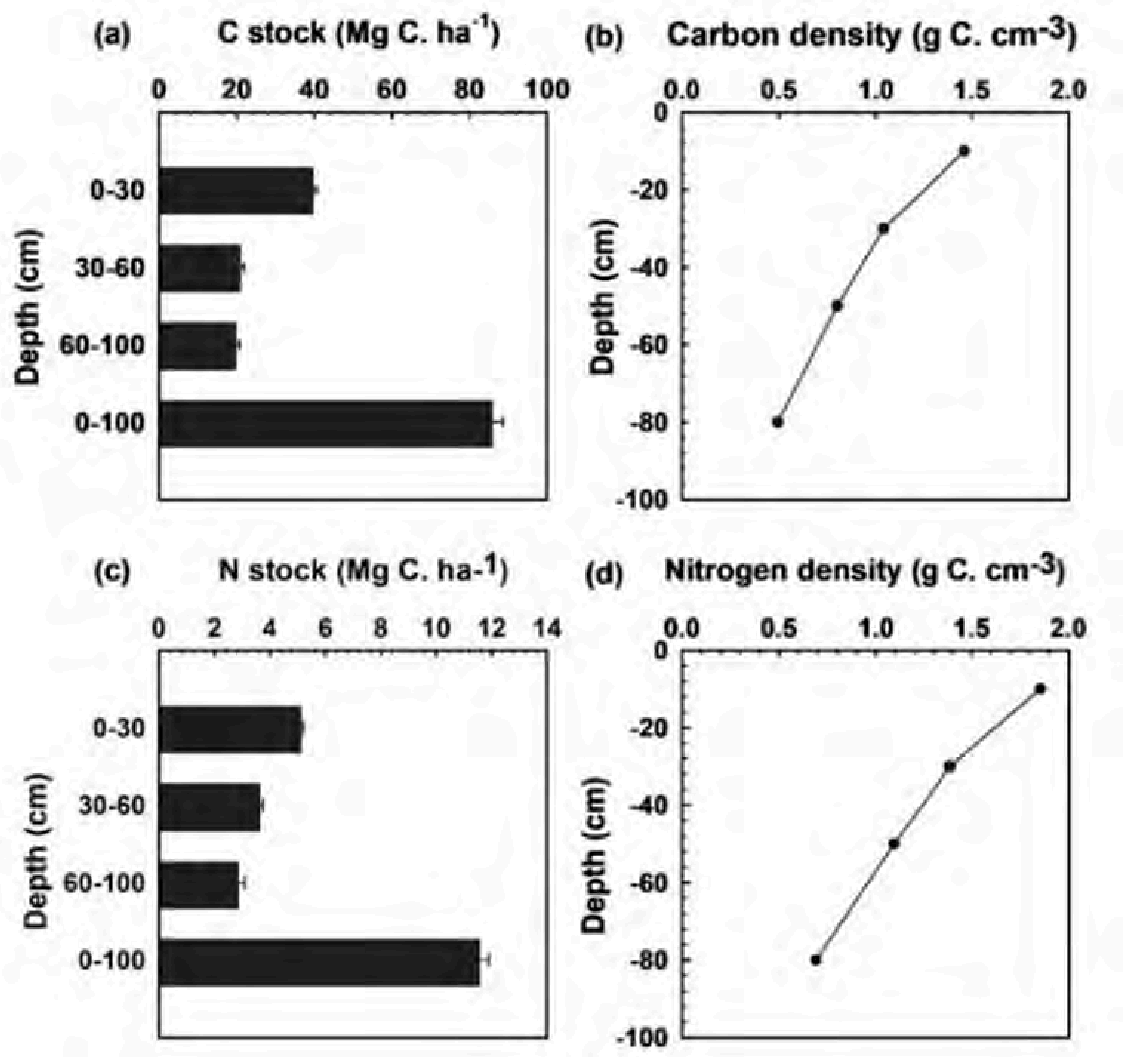
Figure 2. a) soil carbon stock (Mg C ha^{-1}); b) soil carbon density (g C cm^{-3}); c) nitrogen stock (Mg N ha^{-1}) and d) nitrogen density (g C cm^{-3}) at 30, 60 and 100 cm depth at Experimental Farm in Parrita, Costa Rica (n= 15).



The STN stock was 11.54 (±0.36) Mg N ha^{-1} (Figure 2c). As expected, the STN stock decreases more lineally with depth than soil C. The STN content showed a significant difference between strata, 0 to 30 cm accounted for 44.2% (3.52 ±0.12 Mg N ha^{-1}), 30 to 60 cm represented 31.3% (5.1 ±0.09) Mg N ha^{-1} and 60 to 100 cm represented 24.9% (2.87 ±0.2 Mg N ha^{-1}).

The C and N densities were estimated to avoid the effect of soil layer thickness on the stock assessment. Both C and N densities decreased with depth (Figure 2b; 2d) from a maximum of 1.46 g C cm^{-3} (±0.026) and 1.85 g N cm^{-3} (±0.029) at 10 cm, respectively to a minimum value of 0.49 g C cm^{-3} (±0.02) and 0.69 g N cm^{-3} (±0.06) at 80 cm depth.

Optimization of sampling effort

The effect of sampling effort on SCS predictions showed an important reduction when samples were reduced from 45 to 27, but the variability prediction did not change with 15 or 7 samples. SCS distribution kept constant at 0-100 cm when reducing the number of samples from 45 to 7 (Figure 3).

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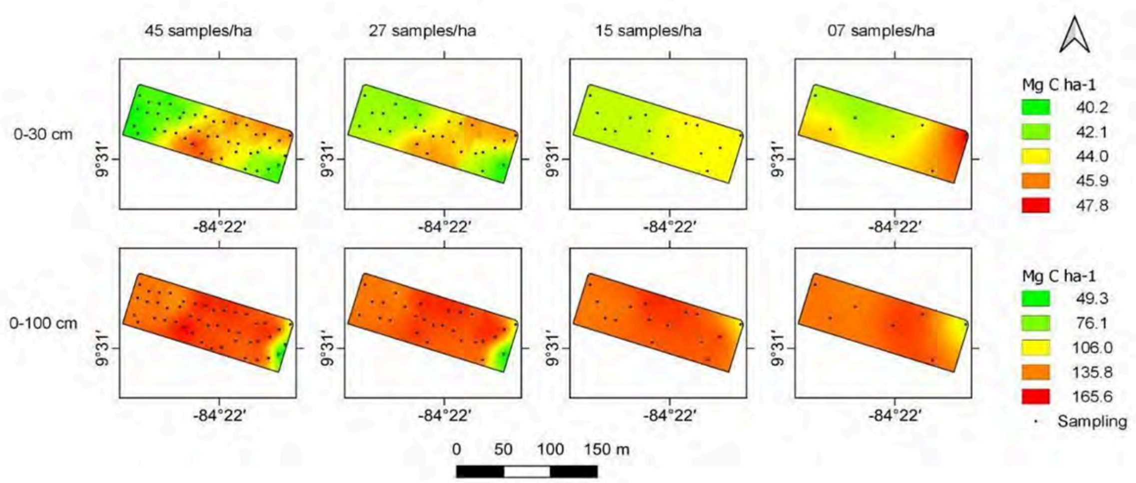
Figure 3. Spatial distribution of soil carbon stocks (Mg C ha^{-1}) by interpolation using Kriging method (n= 45, n= 27, n= 15 and n= 7) at Experimental Farm in Parrita, Costa Rica.



For SCS at 0-30 cm and 0-100 cm soil profiles, 20 m between sampling points (ie. 15) reached a prediction effectiveness of 99.38 and 99.98, respectively, given almost a perfect prediction. For a lower distance (15 m) between sampling points (ie. 45) the values turn negative (-5.83 and 61.52 at 0-30 cm and 0-100 cm, respectively) showing that it would have been better to use the general mean than the prediction supplementary material (Table 3).

Table 3. Prediction effectiveness of distance values (G %), using the ordinary Kriging method for soil carbon stocks of 0-30 cm and 0-100 cm with differences between sampling points (45, 27, 15 and 7).

Sampling points	Distance between points (m)	G (%)	
		0-30 cm	0-100 cm
45	15	-5.83	61.52
27	17	69.92	84.98
15	20	99.38	99.97
7	45	0.01	5.12

Discussion

Variability of physical and chemical properties

Distribution at different soil depths and can be differentially affected by factors such the texture. Our study, like Chatterjee *et al*. (2020), suggest the silt and clay content in soil had a relation with the soil C, supported by a positive Pearson correlation of C with these textural elements particularly with silt (Augustin and Cihacek, 2016; Matus *et al*., 2021).

According to Zhong *et al*., (2018), changes in SCS and clay dynamics in a smaller scale may be related to vegetation and soil nutrient dynamics. The correlations observed between the variable's supplementary material (Table 2) are somehow masked by the effect of the agricultural practices. As expected, C and N have a strong and positive correlation (0.957), but the correlations between the physical and chemical variables are less clear.

Correlations between HC, C, N and clay could have to do with the effect that these elements have on the aggregation of soils and their structure formation. Interestingly, N, pH and bulk

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density exhibit homogeneity in the upper layer but significant variability deeper, suggesting that surface homogeneity is likely influenced by management practices such as fertilization and tillage (Lawrence *et al*., 2020).

Soil carbon and nitrogen stocks

While SCS has been studied across various land uses in Costa Rica (Chacón *et al*., 2015; Sherman and Brye, 2019; Chatterjee *et al*., 2020), research on upland rice systems is limited. Our results show that the highest total C and N accumulation occurs in the topsoil and decreases rapidly with depth at a rate of 0.01% C cm^{-1}. In particular, the C stock at 0-30 cm (39.64 ±0.86 Mg C ha^{-1}) is lower than the one observed by Xu *et al*. (2013) (59.7 Mg C ha^{-1} 0-20 cm), but comparable to Chen *et al*. (2021) (13.7 Mg C ha^{-1} 0-15 cm) and Anantha *et al*. (2018) (20.7 Mg C ha^{-1} 0-15 cm) in upland rice systems.

For upland rice farms, the 0-30 cm depth, utilized by Recsoil (FAO, 2019) constitutes 46.2% of the 1 m stock. Our results confirm that in uniformly managed fields, most of the SCS is located within the topsoil (0-30 cm), the primary zone for crop roots, nutrient cycling and water use efficiency (Gregory *et al*., 2016).

So, it is likely that working at a 30 cm depth is enough for rice, given its shallow root systems primarily distributed within the 0-20 cm layer, especially in 0-10 cm layer, where root biomass constitutes over 80% of the whole biomass (Li *et al*., 2020), particularly in the presence of a compacted layer, as observed in this productive system (Figure 1c).

Despite the potential of subsoil to protect C from losses (Tautges *et al*., 2019), soil C measurement depths below 30-40 cm are uncommon (Tautges *et al*., 2019). While the estimation of SCS to 1 m in the subsoil is often presumed stable, it can hold importance in long-term management experiments (Gregory *et al*., 2016). Nitrogen stock is overlooked due to its strong correlation with C content (Averill and Waring, 2018; Li *et al*., 2023).

Nevertheless, it is notable that at our site, the N stock from 0-30 cm is only 30% higher than the one from 30-60 cm and the one from 60-100 cm. This could be attributed to N fertilization that impact the top layer, and the tendency for N to move in the profile, less influenced by root growth compared to C movement (Börjesson *et al*., 2018; Ojeda *et al*., 2018), particularly beyond the compacted layer.

Optimization of sampling effort

Determining the appropriate sample size is crucial for accurate and precise field study (Nayak *et al*., 2019; Lawrence *et al*., 2020). The results for the interpolation using the kriging method have proven to be effective in interpolating C soil, leading to 66% reduction in sampling with 15 samples ha^{-1}. Kriging effectively interpolated soil C, allowing a 66% reduction in sampling from 45 to 15 samples ha^{-1} in our small, homogeneous area, particularly when considering the 1 m depth profile. Bogunovic *et al*. (2017) propose similar reductions (50 to 70 %) using co-kriging with auxiliary variables.

Low autocorrelation observed for C, N, HC, and pH in the top 10 cm reflects their high variability and susceptibility to agricultural practices (Usowicz and Lipiec, 2021), what is curious about this result is that this autocorrelation decreases at 30 cm and increases again at 50-60, this could suggest an effect of mechanization since these soils are characterized by serious compaction at around 20 cm.

Sampling intensity should vary based on the variable and study objectives (Nayak *et al*., 2019). Topsoil requires denser sampling due to its sensitivity to inputs. However, for less spatially variable parameters like HC and EC, sampling intensity can be reduced (Usowicz and Lipiec, 2021).

Conclusions

Kriging effectively interpolated C stock, enabling a 66% reduction in sampling effort to 15 samples ha^{-1} for 1 m depth estimations. Physical variables exhibit lower spatial variability, allowing for reduced sampling compared to chemical variables. Our findings demonstrate significant potential

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for reducing human effort and associated costs in SCS estimation. For small, homogeneous fields, the use of composite samples warrants further investigation as a potential alternative to individual samples.

Bibliography

1 Aguilera, E.; Lassaletta, L.; Gattinger, A. and Gimeno, B. S. 2013. Managing soil carbon for climate change mitigation and adaptation in mediterranean cropping systems: a meta-analysis. Agriculture, Ecosystems and Environment. 168:25-36. https://doi.org/10.1016/j.agee.2013.02.003.

2 Ahmed, I. S.; Hassan, F. A.; Sulieman, M. M.; Keshavarzi, A.; Elmobarak, A. A.; Yousif, K. M. and Brevik, E. C. 2022. Using environmental covariates to predict soil organic carbon stocks in Vertisols of Sudan. Geoderma Regional. 31(e00578):1-16. https://doi.org/10.1016/j.geodrs.2022.e00578.

3 Alvarado-Velas, M.; Monge-Cordero, M.; Arias-Fernández, M.; Chinchilla-Cortés, J.; Briones-Cambronero, K.; and Alfaro-Martínez, A. 2021. Estudio hidrogeológico de los acuíferos del Pacífico Central, provincias de Puntarenas y San José, Costa Rica, América Central (Informe técnico). Dirección de Investigación y Gestión Hídrica, Unidad de Investigación Hidrogeológica. SENARA. 12-246 pp.

4 Anantha, K. C.; Majumder, S. P.; Padhan, D.; Badole, S.; Datta, A.; Mandal, B. and Gade, K. R. 2018. Carbon dynamics, potential and cost of carbon sequestration in double rice cropping system in semiarid southern India. Journal of Soil Science and Plant Nutrition. 18(2):418-434. https://doi.org/10.4067/S0718-95162018005001302.

5 Augustin, C. and Cihacek, L. J. 2016. relationships between soil carbon and soil texture in the northern great plains. Soil Science. 181(8):386-392. Doi: https://doi.org/10.1097/SS.0000000000000173.

6 Averill, C. and Waring, B. 2018. Nitrogen limitation of decomposition and decay: How can it occur?. Global Change Biology. 24(4):1417-1427. https://doi.org/10.1111/gcb.13980.

7 Bhunia, G. S.; Shit, P. K. and Maiti, R. 2018. Comparison of GIS-based interpolation methods for spatial distribution of soil organic carbon (SOC). Journal of the Saudi Society of Agricultural Sciences. 17(2):114-126. https://doi.org/10.1016/j.jssas.2016.02.001.

8 Bogunovic, I.; Kisic, I.; Mesic, M.; Percin, A.; Zgorelec, Z.; Bilandžija, D.; Jonjic, A. and Pereira, P. 2017. Reducing sampling intensity in order to investigate spatial variability of soil pH, organic matter and available phosphorus using co-kriging techniques. A case study of acid soils in Eastern Croatia. Archives of Agronomy and Soil Science. 63(13):1852-1863. https://doi.org/10.1080/03650340.2017.1311013.

9 Börjesson, G.; Bolinder, M. A.; Kirchmann, H. and Kätterer, T. 2018. Organic carbon stocks in topsoil and subsoil in long-term ley and cereal monoculture rotations. Biology and Fertility of Soils. 54(4):549-558. https://doi.org/10.1007/s00374-018-1281-x.

10 Chacón, P.; Lorenz, K.; Lal, R.; Calhoun, F. G. and Fausey, N. 2015. Soil organic carbon in some land uses of Costa Rica. Acta Agriculturae Scandinavica Section B: soil and Plant Science. 65(4):310-320. https://doi.org/10.1080/09064710.2015.1008563.

11 Chatterjee, N.; Nair, P. K.; Nair, V. D.; Bhattacharjeem, A.; Virginio-Filho, E. M.; Muschler, R. G. and Noponen, M. R. A. 2020. Do coffee agroforestry systems always improve soil carbon stocks deeper in the soil? a case study from Turrialba, Costa Rica. Forests. 11(1):1-49. https://doi.org/10.3390/f11010049.

12 Chen, X.; Hu, Y.; Xia, Y.; Zheng, S. ; Ma, C.; Rui, Y.; He, H.; Huang, D.; Zhang, Z.; Ge, T.; Wu, J.; Guggenberger, G.; Kuzyakov, Y. and Su, Y. 2021. Contrasting pathways of carbon sequestration in paddy and upland soils. Global Change Biology. 27(11):2478-2490. https://doi.org/10.1111/gcb.15595.

DOI: https://doi.org/10.29312/remexca.v16i5.3664

13 Davis, M.; Alves, B. J.; Karlen, D. L.; Kline, K. L.; Galdos, M. and Abulebdeh, D. 2018. Review of soil organic carbon measurement protocols: a US and Brazil comparison and recommendation. Sustainability. 10(1):1-20. https://doi.org/10.3390/su10010053.

14 FAO. 2019. Food and Agriculture Organization of the United Nations. Recarbonization of global soils. A dynamic response to offset global emissions. http://www.fao.org/3/i7235en/I7235EN.pdf. 1-8 pp.

15 FAO. 2020. Food and Agriculture Organization of the United Nations. A protocol for measurement, monitoring, reporting and verification of soil organic carbon in agricultural landscapes GSOC-MRV Protocol. Rome. https://doi.org/10.4060/cb0509en.

16 FAO. 2022. Food and Agriculture Organization of the United Nations. Global Soil Organic Carbon Sequestration Potential Map GSOCseq v.1.1. Technical report. Rome. https://doi.org/10.4060/cb9002en.

17 FAO. 2024. Food and Agriculture Organization of the United Nations. Cómo la iniciativa RECSOIL impulsa el cambio en Costa Rica. FAO Global Soil Partnership. https://www.fao.org/global-soil-partnership/resources/highlights/detail/es/c/1680245/.

18 Gregory, A. S.; Dungait, J. A. J.; Watts, C. W.; Bol, R.; Dixon, E. R.; White, R. P. and Whitmore, A. P. 2016. Long-term management changes topsoil and subsoil organic carbon and nitrogen dynamics in a temperate agricultural system. European Journal of Soil Science. 67(4):421-430. https://doi.org/10.1111/ejss.12359.

19 Jandl, R.; Rodeghiero, M.; Martinez, C.; Cotrufo, M. F.; Bampa, F.; Wesemael, B.; Harrison, R. B.; Guerrini, I. A.; Richter, D. D.; Rustad, L.; Lorenz, K.; Chabbi, A. and Miglietta, F. 2014. Current status, uncertainty and future needs in soil organic carbon monitoring. Science of the Total Environment. 468-469:376-383 pp. Doi: 10.1016/j.scitotenv.2013.08.026.

20 Lal, R. 2016. Beyond COP21: potential and challenges of the ‘4 per Thousand’ initiative. Journal of Soil and Water Conservation. 71. 20A-25A pp. https://doi.org/10.2489/jswc.71.1.20A.

21 Lawrence, P. G.; Roper, W.; Morris, T. F. and Guillard, K. 2020. Guiding soil sampling strategies using classical and spatial statistics: a review. Agronomy Journal. 112(1):493-510. https://doi.org/10.1002/agj2.20048.

22 Li, C.; Wang, G.; Han, Q.; Sun, J.; Ning, H. and Feng, D. 2023. Soil moisture and water-nitrogen synergy dominate the change of soil carbon stock in farmland. Agricultural Water Management. 287(1):108-424. https://doi.org/10.1016/j.agwat.2023.108424.

23 Li, Q.; Li, A.; Dai, T.; Fan, Z.; Luo, Y.; Li, S.; Yuan, D.; Zhao, B.; Tao, Q.; Wang, C.; Li, B.; Gao, X.; Li, Y.; Li, H. and Wilson, J. P. 2020. Depth-dependent soil organic carbon dynamics of croplands across the Chengdu plain of China from the 1980s to the 2010s. Global Change Biology. 26(7):4134-4146. https://doi.org/10.1111/gcb.15110.

24 Matus, F. J. 2021.Fine silt and clay content is the main factor defining maximal C and N accumulations in soils: a meta-analysis. Sci. Rep. 11(6438):1-17. https://doi.org/10.1038/s41598-021-84821-6.

25 Nayak, A. K.; Rahman, M. M.; Naidu, R.; Dhal, B.; Swain, C. K.; Nayak, A. D.; Tripathi, R.; Shahid, M.; Islam, M. R. and Pathak, H. 2019. Current and emerging methodologies for estimating carbon sequestration in agricultural soils: a review. Science of the Total Environment. 665:890-912. https://doi.org/10.1016/j.scitotenv.2019.02.125.

26 Oliveira, D. D.; Paustian, K.; Davies, C. A.; Cherubin, M. R.; Franco, A. L.; Cerri, C. C. and Cerri, C. E. 2016. Soil carbon changes in areas undergoing expansion of sugarcane into pastures in south-central Brazil. Agriculture, Ecosystems and Environment. 228:38-48. https://doi.org/10.1016/j.agee.2016.05.005.

27 Ojeda, J. J.; Caviglia, O. P. and Agnusdei, M. G. 2018. Vertical distribution of root biomass and soil carbon stocks in forage cropping systems. Plant and Soil. 423(1-2):175-191. https://doi.org/10.1007/s11104-017-3502-8.

DOI: https://doi.org/10.29312/remexca.v16i5.3664

28 RStudio Team. 2020. RStudio: integrated development environment for R (Version 1.3.1093) [Computer software]. RStudio, PBC. https://www.rstudio.com/.

29 Sherman, L. A. and Brye, K. R. 2019. Soil chemical property changes in response to long#term pineapple cultivation in Costa Rica. Agrosystems, Geosciences and Environment. 2(1):1-9. https://doi.org/10.2134/age2019.07.0052.

30 Schloeder, C. A.; Zimmerman, N. E. and Jacobs, M. J. 2001. Comparison of methods for interpolating soil properties using limited data. Soil Science Society of America Journal. 65(2):470-479. https://doi.org/10.2136/sssaj2001.652470x.

31 Smith, P.; Soussana, J.; Angers, D.; Schipper, L.; Chenu, C.; Rasse, D. P.; Batjes, N. H.; Egmond, F.; McNeill, S.; Kuhnert, M.; Arias#Navarro, C.; Olesen, J. E.; Chirinda, N.; Fornara, D.; Wollenberg, E.; Álvaro#Fuentes, J.; Sanz#Cobena, A. and Klumpp, K. 2020. How to measure, report and verify soil carbon change to realize the potential of soil carbon sequestration for atmospheric greenhouse gas removal. Global Change Biology. 26(1):219-241. https://doi.org/10.1111/gcb.14815

32 Tautges, N. E.; Chiartas, J. L.; Gaudin, A. C. M.; O'Geen, A. T.; Herrera, I. and Scow, K. M. 2019. Deep soil inventories reveal that impacts of cover crops and compost on soil carbon sequestration differ in surface and subsurface soils. Global Change Biology. 25(11):3753-3766. https://doi.org/10.1111/gcb.14762.

33 Usowicz, B. and Lipiec, J. 2021. Spatial variability of saturated hydraulic conductivity and its linkswith other soil properties at the regional scale. Scientific Reports. 11(1):1-12.https://doi.org/10.1038/s41598-021-86862-3.

34 Valderrama-López, C. F.; Castillo-Vargas, J. A.; Torres-Romero, J. C.; Guzmán-Lenis, A. R.; Forero-Ausique, V. F.; Duque-Chaves, C. M.; Sepúlveda-Casadiego, Y. A.; Montenegro-Gómez, S. P. 2018. Capítulo 6. Secuestro y almacenamiento de carbono: capturas de carbono por pagos de servicios ambientales. Escuela de Ciencias Agrícolas, Pecuarias y del Medio Ambiente. Universidad Nacional Abierta y a Distancia. 106-117 pp.

35 Wen, W.; Wang, Y.; Yang, L.; Liang, D.; Chen, L. D.; Liu, J. and Zhu, A. X. 2015. Mapping soil organic carbon using auxiliary environmental covariates in a typical watershed in the loess plateau of China: a comparative study based on three kriging methods and a soil land inference model (SoLIM). Environ Earth Sci. 73:239-251. https://doi.org/10.1007/s12665-014-3518-9.

36 Wu, H.; Zheng, X. Zhou, L. and Meng, Y. 2024. Spatial autocorrelation and driving factors of carbon emission density of crop production in China. Environ Sci Pollut Res. 31:27172-27191. https://doi.org/10.1007/s11356-024-32908-8.

37 Xu, S. Q.; Zhang, M. Y.; Zhang, H. L.; Chen, F.; Yang, G. L. and Xiao, X. P. 2013. Soil organic carbon stocks as affected by tillage systems in a double-cropped rice field. Pedosphere. 23(5):696-704. https://doi.org/10.1016/S1002-0160(13)60062-4.

38 Yu, H.; Zha, T.; Zhang, X. and Ma, L. 2019. Vertical distribution and influencing factors of soil organic carbon in the loess plateau, China. Science of The Total Environment. 693:133632. https://doi.org/10.1016/j.scitotenv.2019.133632.

39 Zhong, Z.; Chen, Z.; Xu, Y.; Ren, C.; Yang, G.; Han, X.; Ren, G. and Feng, Y. 2018. Relationship between soil organic carbon stocks and clay content under different climatic conditions in Central China. Forests. 9(10):1-14. https://doi.org/10.3390/f9100598.

40 Zomer, R. J.; Bossio, D. A.; Sommer, R. and Verchot, L. V. 2017. Global sequestration potential of increased organic carbon in cropland soils. Scientific Reports. 7(15554):1-8. https://doi.org/10.1038/s41598-017-15794-8.

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