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Authors	Castellón Meyrat, Alex;O'Sullivan, Lilian;Holloway, Paul;Wall, David;Bondi, Giulia
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Impact of management intensity of agricultural systems and soil intrinsic characteristics on soil organic carbon stocks

Alex Castellón Meyrat^{a,b,c,1,*}, Lilian O'Sullivan^a, Paul Holloway^{b,c}, David Wall^a, Giulia Bondi^a

^a TEAGASC, Crops Environment and Land Use Programme, Johnstown Castle, Wexford Y35 TC97, Ireland

^b Department of Geography, University College Cork, Cork, Ireland

^c Sustainability Institute, University College Cork, Cork, Ireland

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ABSTRACT

Enhancing carbon in soils is crucial for improving soil health and building sustainable agroecosystems. Inherent SOC stocks are site-specific and vary due to complex interactions between climate, soils, land use, and management practices. However, the coupled effects of these factors on SOC dynamics are not fully understood. This research aimed to evaluate the impact of different management regimes and intrinsic soil characteristics on SOC stocks and identify pathways that can boost carbon sequestration in agricultural soils. This study relied on data of 143 soil profiles distributed across the south of Ireland. Each site was sampled at four depths (0–15, 15–30, 30–45, and 45–60 cm) and characterized according to the land use and management practices implemented over the past five years. A Regression Tree (RT) model was employed to estimate the single and combined contribution of key soil properties and management practices on SOC stocks. Overall, intrinsic soil characteristics, especially the presence of humic layers and clay, are decisive to determine the SOC storage potential in soils. Land use and management practices primarily impact the top 15 cm, and their accumulated effect (e.g. stocking rates in grassland systems) can shift SOC stocks trends over time. Finally, the heterogeneity in subsoils controls the variability of SOC stocks in depth. The outcomes of this study can help tailor carbon farming strategies to boost carbon sequestration accounting for specific soil conditions.

1. Introduction

Carbon (C) is a dynamic element that continuously cycles between different pools (Fung, 2003). In the atmosphere, it exists primarily as carbon dioxide (CO₂), the most prevalent and long-lasting greenhouse gas (GHG) emitted by human activities (Lynch and Garnett, 2021; Villarino et al., 2014). As a result, increasing C sequestration in soils is crucial to counteract global warming. Soil constitutes the largest pool of C in terrestrial ecosystems, storing twice as much C as the atmosphere and four times more than plants (Moinet et al., 2023; Tuohy et al., 2021). Soil organic carbon (SOC) and its stocks are built up through the successive decomposition and stabilization of dead organic matter (Don et al., 2023). These stocks not only improve overall soil health but also play an essential role in climate regulation (Lorenz et al., 2019; Magdoff and van Es, 2021; Moinet et al., 2023; Paustian, et al., 1997). Therefore, preserving and enhancing SOC stocks contributes to fostering conditions conducive for sustainable and climate-resilient agriculture.

However, land use changes and intensive agriculture are disturbing natural sinks, turning soils into a source of GHG (Don et al., 2023; Haddaway et al., 2015). This has raised the concern about the impact of agriculture on SOC stocks and the cascading consequences for soil health, climate change, and sustainable food production. In response, EU governments have committed to enhancing SOC stocks and to reducing emissions with multiple initiatives. At pan-European level, the Land Use, Land Use Change and Forestry regulations binds EU Member States to a net removal target of 310 Mt of CO₂e from the atmosphere by 2030 (OJ, 2023). This represents a significant challenge, especially for Ireland, where emissions are primarily driven by peatlands being drained to expand agricultural grassland areas (Müller et al., 2025; Renou-Wilson et al., 2022); and the relatively limited forest cover in the country (11%) which constrains the potential for C sequestration in biomass (DAFM, 2023b). In addition, Ireland has committed to reduce emissions from the agricultural sector by 25% by 2030 relative to the 2018 baseline (DCEE, 2023). In light of these challenges, EU Member

* Corresponding author at: TEAGASC, Crops Environment and Land Use Programme, Johnstown Castle, Wexford Y35 TC97, Ireland.

E-mail address: alex.meyrat@teagasc.ie (A. Castellón Meyrat).

¹ ORCID ID: 0000-0003-2867-4237

States are putting in place soil sampling campaigns to quantify and monitor SOC stocks and SOC sequestration in agricultural soils (Smith et al., 2020). These initiatives highlight that agricultural land management is a key element in improving SOC stocks and meeting climate targets.

Nevertheless, the dynamics of SOC in agroecosystems depend on multiple factors which are not fully understood. Overall, intensive systems such as tillage operations (e.g. crops as grains, brassicas, tubers, etc.) are associated with SOC stock losses due to intensive ploughing and trafficking, lack of vegetation cover, and high erosion rates (Juricová et al., 2022; Juricová et al., 2025; Paustian et al., 1997; Prasuhn, 2012; Zhang et al., 2012). In contrast, more extensive systems (e.g. grasslands for grazing) are reported to preserve or enhance SOC stocks thanks to minimum soil disturbance, permanent living vegetation, abundant below-ground biomass, and returns of organic matter by animal dung (Emde, et al., 2024; Magdoff and van Es, 2021; Paustian et al., 1997). However, quantifying the impact of each land management practice (e.g. ploughing, crop rotations, use of cover crops, silage cuts, grazing, stocking rates, nitrogen chemical fertilization, organic fertilization, etc.) and their combined effects on SOC stocks, represents a challenging task because of the countless combinations and potential trade-offs between them.

In addition, the impact of these practices may vary depending on site-specific conditions. Although topsoil SOC stocks are strongly influenced by management practices, they are also shaped by intrinsic characteristics such as the legacy of native organic matter and prevailing climatic and soil-forming (pedogenic) conditions (Vogel et al., 2019). For example, poorly drained soils in temperate regions can accumulate important amounts of SOC in surface soil layers due to the slow decomposition of organic matter under water-saturated environments and low temperatures (Tuohy et al., 2021). Heavy soils can sequester more carbon at depth than sandy or stony soils, especially in subsoils due to the occlusion of SOC within illuviated clay particles (Torres-Sallan et al., 2017; Tuohy et al., 2021). These examples indicate that SOC stocks depend heavily on complex interactions between soils and management regimes and raise the question of the level of contribution of both factors (management activities and intrinsic soil properties) in determining SOC stocks.

Researchers have studied the relationship between soil properties, land uses, and environmental variables with SOC stocks, explaining the impact of predictors primarily through classical statistical methods, including correlations, regressions, ANOVA, PCA or by pedo-transfer functions (Fenton et al., 2024; Khalil et al., 2013; Paltineanu et al., 2024; Skadell et al., 2023; Kenfack et al., 2024; Torres-Sallan et al., 2017). While these methods are suitable for identifying positive or negative relationships between predictors and SOC stocks, they do not sufficiently examine the mechanisms underlying SOC dynamics. The present study aims to address these gaps by focusing on soil-management interactions and soil intrinsic characteristics as driving mechanisms that promote SOC accumulation and by ranking these predictors according to their relative contribution to SOC stocks, thereby assessing whether management practices or inherent soil properties exert greater influence.

To tackle such complex problems, machine learning techniques have been increasingly used in research. Classification and Regression Trees (CART) (Breiman et al., 1984), stand out as suitable methods for modelling non-linear interactions between multiple factors (especially in the presence of multiple categorical variables) even when the data is skewed (Kebonye et al., 2023; Paez-Trujillo et al., 2023) and contain missing values (Borcard et al., 2018). CARTs have been implemented in soil science for addressing a wide range of topics, including anthropogenic soil contamination, heavy metal dynamics and plant uptake, assessing soil quality parameters, or evaluating trade-offs between ecosystem services (Bondi et al., 2018; Obiang-Ndong et al., 2021; Tian et al., 2024; Zhang et al., 2008). However, their potential for assessing soil C patterns at national scales, particularly in relation to management

practices, remains underexplored, highlighting a need for further research in this direction.

This research aimed to assess the impact of land management regimes and soil intrinsic characteristics on SOC stocks across different soil types and depths. To achieve this goal, a Regression Tree (RT) approach was implemented to model and interpret the relationship between soil intrinsic characteristics, agricultural activities, and SOC stocks. This study addressed the following questions:

- (i) What is the level of contribution of soil intrinsic characteristics and management regimes in determining the SOC stocks?
- (ii) Which soil / management paths enhance SOC stocks across soil profiles?

In this research we have hypothesized that:

- i) Land use and / or management regimes exert a greater influence on SOC stocks than soil intrinsic characteristics across different soil types and depths.
- ii) Interactions between selected soil intrinsic characteristics and management practices enhance SOC storage.

2. Methods

2.1. Signpost programme: Deep soil sampling campaign

The study was carried out under the Signpost Programme, a multi-annual deep soil sampling campaign investigating the carbon sequestration potential of agricultural soils in Ireland and aiming to set the baselines of SOC stocks in soils at national level (Murphy et al., 2024; Bondi et al., 2024). This study relied on the data collected in 37 farms distributed across 11 counties in the South-East region of the country (Fig. 1). Most of the farms were located within agroclimatic regions 1 and 2, sharing similar climatic conditions including warm temperatures (mean annual temperature 7–11 °C) and relatively dry to average rainfall (mean annual precipitation 600–1800 mm) (Coonan et al., 2024a and 2024b; Holden and Brereton, 2004). Farm selection was guided by land uses and management regimes representative of typical Irish farming systems. As a result, grasslands and tillage farms accounted for approximately 70% and 30% of the selected farms respectively, resembling national land use patterns in agricultural soils in Ireland (Copernicus Land Monitoring Service, 2018). This selection included 10

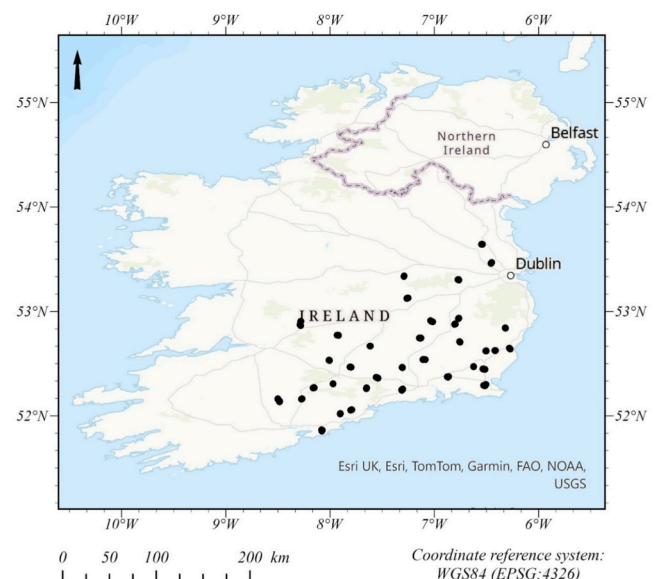


Fig. 1. Location of sampling sites across Ireland.

tillage crops farms, 25 grasslands farms (14 dairy, 6 beef, 4 dairy-beef, and 1 beef-sheep systems), and 2 mixed farms where tillage and grasslands operations were carried out equally. On each farm, a maximum of four fields were selected for soil sampling, considering their position on the slope and capturing the maximum possible combination between soil types and management regimes. A total of 143 sites were sampled encompassing scenarios from soils under intensive management to soils under extensive regimes across contrasting soil types. This approach enabled us to link the impact of management practices and intrinsic soil characteristics on SOC stocks.

2.1.1. Management data

Sites selected were representative of the average farm management over the past five years. For each of the 143 fields, detailed information on agricultural activities was collected through surveys to capture the range of practices that could influence SOC stocks. These data included land use (e.g. grassland, tillage), farming system type (e.g. dairy, beef, mixed), and specific management practices such as livestock type, grazing stocking rate, nitrogen input rates, crop rotations, traffic patterns, last ploughing date, straw incorporation, and application of organic amendments. This comprehensive dataset allowed observed soil characteristics and SOC stocks to be directly associated with the management practices applied on each field. A summary of the farm activity information collected is presented in Table 1.

2.1.2. Soil classification and soil sampling

In spring 2023, a pedological survey was conducted to classify and sample 143 fields (Bondi et al., 2024). Within each selected field, a representative area of approximately 30×30 m (~ 900 m²) was delineated, and a soil profile pit was excavated at its center, with the location recorded using GPS coordinates. Soils were classified according to the Irish Soil Information System at both great group and subgroup levels (Simo et al., 2008) and World Reference Base (WRB) system (IUSS Working Group WRB, 2022) (Table 1), capturing a wide range of soil types, including Brown Earth (Cambisol, $n = 68$), Luvisol ($n = 29$), Brown Podzolic ($n = 8$), Surface-water Gley (Stagnosol, $n = 23$), Groundwater Gley (Gleysol, $n = 7$), and Alluvial soils ($n = 8$). During classification, soil descriptors capturing the intrinsic properties of the soil, were systematically recorded for each horizon within the profile. A standardized procedure was followed, with the same team of surveyors ensuring consistency across all fields. In each profile pit, soil samples of approximately 1 kg were collected from four fixed depth intervals up to 60 cm depth (0–15 cm, 15–30 cm, 30–45 cm, and 45–60 cm). This sampling depth captures the majority of SOC pools affected by agricultural management in Irish farming systems while sufficiently aligning with the IPCC's standard framework recommendations for monitoring SOC stocks (Peng and Van Eerd, 2024; Poeplau and Don, 2013; Raffield et al., 2024; Skadell et al., 2023; Torres-Sallan et al., 2017, Torres-Sallan et al., 2018; Tuohy et al., 2021). Three bulk density rings per defined depth were also collected and all samples transported to the Teagasc laboratory facilities in Johnstown Castle for processing. Altogether, soil descriptors and samples were collected for 572 depth intervals using this profile-based approach.

2.1.3. Lab analysis

Soil characterization consisted of multiple agronomic parameters including pH, clay, silt, sand, and macro (N, K, P, C, Ca, Mg) and micronutrients (Fe, Al) estimated by different laboratory techniques. Soil pH was determined using a 1:2.5 soil-to-water ratio. Total nitrogen (N_{tot}), total carbon (C_{tot}), soil inorganic carbon (SIC), and soil organic carbon (SOC) were determined by dry combustion using a CN LECO FP 2000 analyzer (LECO Corp.). SOC corresponds to the difference between C_{tot} and SIC. Morgan's extractable P and K (P_{mor} and K_{mor}) were determined at a 1:5 (v/v) soil to Morgan's solution ratio (10% NaOAc pH 4.8). Mehlich-3 extractable aluminium (Al_{M3}), iron (Fe_{M3}), calcium (Ca_{M3}), magnesium (Mg_{M3}), potassium (K_{M3}) and phosphorus

Table 1

Predictors for building a Regression Tree of SOC stocks dynamics in agricultural soils.

Source	Predictor	Type	Description	Categories
Soil properties	SOC stocks	Numerical	Response variable	Continuous
	Clay %	Numerical	Percentage of clay content (%)	Continuous
	Depth	Categorical	Fixed sampling depth each 15 cm.	0-15, 15-30, 30-45, 45-60
	Diagnostic feature	Categorical	Diagnostic features or horizons based on Irish soil taxonomy system	humic, stagnic, gleyic, typic
Management data	Soil type	Categorical	Soil groups or first order of classification based in the Irish soil taxonomy system	Alluvial, Groundwater Gley, Surface-water Gley, Luvisol, Brown Earth, Brown podzolic
	Land use	Categorical	General land use at landscape or regional scale	Arable crop, Grassland, Fallow
	Farming system	Categorical	Specific farming system at local scale. A hierarchical subdivision of land use.	Fallow, Grassland (permanent), Grassland (improved), Grain crop, Grain crop + Legumes, Brassicas, Legumes, Tubers
	Farm management	Categorical	Specific land management practices implemented in farming systems	Fallow, Grass: Grazing only, Grass: 1 Cut + Grazing, Grass: 2 Cut + Grazing, Grass: Silage only (3 cut), Grazing (2/3 Fert), Tillage no till, Tillage min till, Tillage plough based
	Livestock type	Categorical	Main livestock in grassland systems	Dairy, Beef, Sheep
	Grazing stocking rate	Categorical	Ranges of organic nitrogen (ON) in kg/ha/yr	0, < 100, 101-130, 131-150, 151-170, 171-190, 191-210, 211-230, 231-250
	Nitrogen input rate	Categorical	Ranges of N inputs in kg/ha/yr	0-50, 50-100, 100-150, 150-200, 200-250, 250-300, > 300
	Crop rotation	Categorical	Crop rotation over the year	forage - forage, grain - cover crop, grain - grain, brassica - brassica, tuber - bare soil
	Trafficking	Categorical	Number of trafficking	4, 8
				(continued on next page)

Table 1 (continued)

Source	Predictor	Type	Description	Categories
	Last plough	Categorical	activities during the year Number of years since the last plough	1, 3, 10, 15, 20
	Straw incorporation	Binary	Straw incorporation after the harvest	Yes, No
	Organic amendments	Binary	Addition of organic manure, slurry, or compost	Yes, No

(P_M3) were measured by Varian VISTA Inductively coupled plasma-optical emission spectroscopy (ICP-OES) (Varian). Clay, silt and sand were estimated through models derived from spectroscopy (de Santana et al., 2023). A summary of most of these properties is reported in Table 1 in the Supplementary material.

Bulk density and coarse fragments were calculated based on the ISO 11272:2017 (ISO, 2017) (Equation 1).

$$BD = \frac{M_d - M_s}{V - V_s} \quad (1)$$

Where, BD is the soil dry bulk density (Mg m^{-3}), M_d is the oven-dry soil material weight (g), M_s is the oven-dry stone weight (g), V is the volume of soil core (cm^{-3}), and V_s is the volume of stones (mL)

SOC stocks were estimated using the method proposed by Fenton et al. (2024), (Table 1).

$$SOCs_i = SOC_i \times BD_i \times D_i \times (1 - CF_i) \quad (2)$$

$SOCs_i$ is the SOC stock (t C ha^{-1}), SOC_i is the soil organic carbon mass proportion in the soil fraction $< 2 \text{ mm}$ (g kg^{-1}), BD_i is the soil bulk density calculated for the whole sample (g cm^{-3}), D_i is the soil layer thickness (cm) associated to sampling depths, and $(1 - CF_i)$ is the mass proportion of coarse fragments $> 2 \text{ mm}$ to the whole soil (g kg^{-1}).

2.2. SOC and management information dataset for model application

This research aimed to assess the impact of soil management regimes and soil intrinsic characteristics on SOC stocks across different soil types and depths. To achieve this goal, a Regression Tree (RT) approach was implemented to model the relationship between soil-intrinsic characteristics, agricultural practices, and SOC stocks; quantify the relative contribution of predictors; and interpret the interactions among key drivers. To build the RT model, 143 soil profiles, representing 572 layers with soil properties and unique soil and management observations were used. SOC stock was defined as the response variable, while other soil and management properties (1 numerical, 12 categorical, and 2 binary) were used as predictors (Table 1). Categories of management data are consistent with typical management practices implemented in Irish farming systems based on farmer surveys and guidelines described in current advisory handbooks (Lalor et al., 2016; Wall and Plunkett, 2020). Before fitting the model, data from 572 soil layers were reviewed and missing values in SOC stocks (8 layers, $\sim 1.35\%$) and Clay (83 layers, $\sim 14\%$) were detected. These data were imputed using the median of corresponding soil groups and depth ranges to preserve dataset integrity (Alam et al., 2023). Results indicate no substantial differences in the distribution of data values before and after the median-based imputation (Figures S1a and S1b).

2.3. Model framework

2.3.1. Model overview

To explore the factors influencing SOC stocks, a Regression Tree (RT) method was implemented. This approach is suitable for modelling complex environmental problems such as SOC dynamics in agro-ecosystems, as it can capture nonlinear interactions between multiple factors (numerical and categorical) without previous parametric assumptions on data distribution (Kebonye et al., 2023; Paez-Trujillo et al., 2023). In addition, it can handle missing data through imputation techniques such as using the mean or median to fill gaps (Borcard et al., 2018). RTs rely on recursive partitioning, which splits the observations based on predictors to create data nodes with maximum homogeneity in the response variable. This process is repeated iteratively until no observation can be relocated to a new node (Gözükara and Altay, 2021; Pinheiro et al., 2018). The nodes conform to a tree structure that is grown, tuned, and pruned until a balance between accuracy and interpretability of the branches or decision rules is achieved (Obiang-Ndong et al., 2021). The model was developed at the soil-layer level, rather than for the entire profiles (0–60 cm), to allow greater flexibility in the splitting of attributes and to capture depth-specific variations in SOC stocks.

2.3.2. Model construction

To build the RT, three parameters were required: i) the Complexity Parameter (CP), which controls the tree size (the smaller the value the bigger the tree), ii) the minimum number of observations in a split node (minsplit), and the minimum number of observations in terminal nodes (minbucket) (Therneau and Atkinson, 2023). The initial model was designed using a low $CP = 0.001$ to maximize the number of branches and broadly inspect all possible interactions between predictors and SOC stocks across the tree structure. A minsplit of 30 ($\sim 5\%$ of the dataset) was used to ensure statistical power and reduce unrepresentative partitioning at the node level. A minbucket of 10 ($\sim 2\%$ of the dataset) was implemented – following the “1/3 minsplit ratio” recommended by default in the rpart package (Therneau and Atkinson, 2023) – in order to reduce noise in the rules. This resulted in a tree with 21 partitions and 22 terminal nodes.

2.3.3. Assessment of performance and optimization

A 10-fold cross-validation process was implemented to assess overall performance of the model and identify the optimal CP for fine-tuning and pruning the tree to its optimal size. Based on the results, the RT was pruned using a CP of 0.004939. The optimized tree presented 8 partitions with 9 terminal nodes and reported a minimum cross-validated error of 0.33, equivalent to a predictive performance of 67% (Table 2, Fig. 4). Additionally, the robustness of the RT structure was evaluated with non-parametric statistical methods. Significant differences among terminal nodes or rules were detected using the Kruskal–Wallis test ($\chi^2(8) = 420.17$, $p < 2.2 \times 10^{-16}$). Post-hoc pairwise comparisons using the Wilcoxon rank-sum test with Benjamini–Hochberg correction revealed significant differences across most terminal nodes (Figure S2). The performance at each terminal node is reported using Root Mean Squared Error (RMSE), which quantifies the average magnitude of errors between observed and simulated values (Therneau and Atkinson, 2023). This metric varies from 0 to $+\infty$ and the smaller the value the better the predictions (Kouzehgar and Eslamian, 2023). Additional metrics were estimated to describe the quality of the predictions, and these are reported in supplementary materials (Table S3). The Variable Importance (VI) was calculated to rank the predictors based on their influence on the model construction (Fig. 3). The VI represents the total contribution of the variables to reduce the impurity or errors in the split nodes of the tree (Therneau and Atkinson, 2023). The RT model was interpreted based on rules or collection of paths from the initial to the terminal nodes, which describe the relationship between different predictors and SOC stocks (Table 3, Fig. 4).

Table 2

Overall RT model performance. Identification of optimal Complex Parameter (CP) to prune the tree accounting for minimum number of splits with the lowest 10-fold cross-validated error. The Complexity Parameter (CP) penalize the RT structure based on the number of splits. The relative error (R_E) represents the prediction error compared to the null model (zero nodes) and it quantifies the reduction in prediction error as the number of splits increases. The 10-fold cross-validation error (CV_E) is the mean prediction error obtained across the 10 validation folds. The Predictive Performance ($1 - CV_E$) and it is reported in decimal and percentage units.

Complexity Parameter (CP)	Number of splits	Relative Error (R_E)	10-fold cross-validation error (CV_E)	Predictive Performance ($1 - CV_E$)	Predictive Performance (%)
0.448831	0	1.0000	1.0024	-0.0024	-0.24
0.177400	1	0.5512	0.5571	0.4429	44.29
0.043612	2	0.3738	0.3926	0.6074	60.74
0.014858	3	0.3302	0.3489	0.6512	65.12
0.014111	4	0.3153	0.3485	0.6515	65.15
0.008562	5	0.3012	0.3381	0.6619	66.19
0.007269	6	0.2926	0.3334	0.6666	66.66
0.007059	7	0.2854	0.3287	0.6713	67.13
0.004939	8	0.2783	0.3252	0.6748	67.48
0.003885	9	0.2734	0.3320	0.6681	66.81
0.003705	10	0.2695	0.3388	0.6612	66.12
0.003520	11	0.2658	0.3392	0.6608	66.08
0.003325	12	0.2623	0.3374	0.6626	66.26
0.003106	13	0.2589	0.3375	0.6625	66.25
0.002691	14	0.2558	0.3363	0.6637	66.37
0.002517	15	0.2531	0.3333	0.6667	66.67
0.002343	16	0.2506	0.3338	0.6662	66.62
0.002268	17	0.2483	0.3337	0.6663	66.63
0.001326	18	0.2460	0.3308	0.6692	66.92
0.001262	19	0.2447	0.3323	0.6677	66.77
0.001000	21	0.2422	0.3322	0.6678	66.78

Table 3

Matrix of RT including hierarchical level and rules.

Description of levels (L) and rules (R)	SOC stock (t C ha ⁻¹)	
1. Diagnostic soil property		
L1. Depth (cm): 0-30		
L2. Humic layer: Yes	R1	79 (n = 22, RMSE=29.70)
2. Land use effect		
L1. Depth (cm): 0-30		
L2. Humic layer: No		
L3. Depth (cm): 0-15		
L4. Land use: Fallow, Grassland		
L5. Stocking rates: Moderate	R2A	48 (n = 49, RMSE=10.17)
L5. Stocking rates: Low, High	R2B	41 (n = 43, RMSE=10.25)
L4. Land use: Tillage crops	R2C	34 (n = 40, RMSE=7.96)
3. Textural class		
L1. Depth (cm): 0-30		
L2. Humic layer: No		
L3. Depth (cm): 15-30		
L4. Clay %: > 22%	R3A	32 (n = 83, RMSE=10.63)
L4. Clay %: < 22%	R3B	25 (n = 49, RMSE=8.20)
4. Subsoil heterogeneity		
L1. Depth (cm): 30-60		
L2. Soil group: Alluvial = Yes	R4	26 (n = 16, RMSE=21.08)
5. Subsoil heterogeneity		
L1. Depth: 30-45, 45-60		
L2. Soil group: Alluvial = No		
L3. Depth (cm): 30-45	R5A	15 (n = 135, RMSE=6.89)
L3. Depth (cm): 45-60	R5B	9 (n = 135, RMSE=4.83)

3. Results and discussion

3.1. Variations of SOC stocks at depth (0-60 cm) across different soil types

Soil types presented different ranges in SOC stocks accumulated within 0–60 cm depth (Fig. 2). Overall, soils influenced by water such as Gleys and Alluvial presented the highest SOC stocks values (>200 t C ha⁻¹) and a large variability (coefficient of variation (CV) = 31–52%) (Fig. 2, Table S2), mainly explained by the presence of humic topsoils, or carbon-enriched horizons formed due to the slow decomposition of organic matter under water saturated environments (Simo et al., 2008). These soils are commonly managed as grasslands rather than arable land, which means the carbon losses typically associated with intensive tillage are relatively limited in these soil types (Bondi et al., 2020). These findings highlight the importance of soil formation processes and intrinsic characteristics as key determinants in defining the SOC storage capacity (Vogel et al., 2019).

In contrast, free to moderately drained mineral soils, such as Brown Earth (93 t C ha⁻¹), Luvisol (97 t C ha⁻¹), and Brown Podzolic (110 t C ha⁻¹) presented lower stocks and less variability (Fig. 2, Table S2). Brown Earths are young soils with relatively uniform profiles where SOC

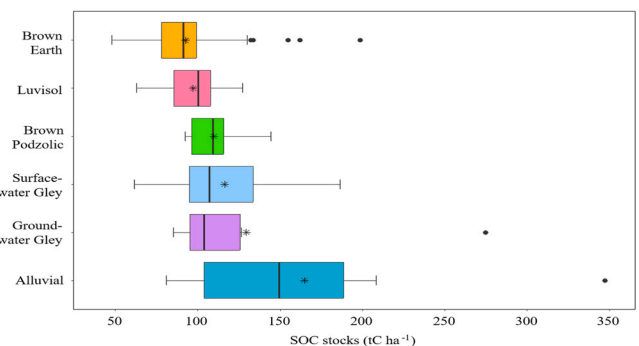


Fig. 2. SOC stocks across different soil types. (*) The asterisk represents mean values (|) Vertical line inside the boxplots represents the median, (●) Black dots represent exceptional values. Brown Earth (n = 68), Luvisol (n = 29), Brown Podzolic (n = 8), Surface-water Gley (n = 23), Groundwater Gley (n = 7), Alluvial (n = 8).

is predominantly stored in the upper 30 cm (Simo et al., 2008; IUSS Working Group WRB, 2022). SOC is occluded within macroaggregates that are easily degradable by soil disturbances, making SOC stocks sensitive to tillage activities (Torres-Sallan et al., 2017). These soils presented a moderate variability ($CV = 26\%$) and a large range ($48\text{--}189 \text{ t C ha}^{-1}$) (Table S2) more likely explained by changes in management regimes rather than intrinsic characteristics (Simo et al., 2008; IUSS Working Group WRB, 2022; Torres-Sallan et al., 2017). The lowest SOC stocks were recorded in potato systems ($\sim 50 \text{ t C ha}^{-1}$) where it is known that intensive operations substantially reduce soil carbon (Prasuhn, 2012), while highest values (above 120 t C ha^{-1}) occurred in more extensively managed grasslands (Fig. 2). This pattern reflects the heterogeneous nature of tillage practices compared with the more homogeneous management of grasslands, which are more standardised across the farming community and tend to sustain higher SOC levels (Bondi et al., 2020). Luvisols showed slight increases in the stocks due to the clay stabilization effects on SOC, especially in depth (Fig. 2, Table S2) (Torres-Sallan et al., 2017; Paltineanu et al., 2024) and Brown Podzolics showed higher values primarily driven by SOC accumulation in the topsoils due to slow organic matter decomposition rates and acidic conditions (Fig. 2, Table S2) (Sandborn et al., 2011; Sauer et al., 2007). Even though Brown Podzolic soils reflect high SOC stocks, these soils require a management regime that optimize fertility due to an intrinsic propensity for degradation associated with acidity and Fe accumulation (Sauer et al., 2007).

According to the first hypothesis, it was expected that land use and/or management regimes exert a greater influence on SOC stocks than soil intrinsic characteristics across different soil types and depths. However, results reject this hypothesis and demonstrate that intrinsic characteristics determine the potential of SOC storage capacity up to 60 cm, while management contributes towards shifting trends towards the upper or lower boundaries of the potential range. These findings are aligned with Vogel et al. (2019) who emphasize that the potential of soil functions is governed mainly by intrinsic soil characteristics, with management practices influencing short-term changes. Results are also consistent with studies that indicate that management influence decreases with depth and that deep soil carbon is largely governed by the inherent soil characteristics (Skadell et al., 2023; Torres-Sallan et al., 2017; Torres-Sallan et al., 2018; Tuohy et al., 2021). A possible explanation is that SOC stocks represent the SOC that has accumulated, stabilized, and reached a relative equilibrium within the agroecosystem (Caruso et al., 2018). Management practices clearly induce SOC changes in the short-term, but these changes are relatively small compared to the entire stocks (Skadell et al., 2023), and SOC stocks in temperate soils respond slowly, requiring decades to reach a new equilibrium (Emde et al., 2024).

3.2. Regression Tree performance and hierarchical levels / hierarchy of factors

A regression Tree method based on the CART approach (Breiman et al., 1984) was implemented to analyse the effect of agricultural activities on SOC stocks across different soil types. The initial model showed an overall predictive performance of $\sim 72\%$ ($R_E \sim 28$) (Table 2). After a 10-fold cross-validation the tree was pruned to its optimal size (Table 2). The resulting RT was structured into 5 levels of depth, with 8 splitting nodes, and 9 rules with a predictive performance of 67% (Table 2). Any additional splitting would penalize the accuracy; therefore, this represented the optimal tree structure.

Predictors of high importance informing the RT structure including depth, diagnostic feature, soil type, clay content, land use, and grazing stocking rates were flagged by the model as the main explanatory factors of SOC stocks in agroecosystems and contributed to defining the tree structure. Factors such as farming systems, farm management, livestock type, nitrogen input rate, crop rotation, trafficking, last date of plough, straw, and organic amendments incorporation did not have or had very

little influence on the RT performance and the model construction (Figs. 3 and 4). The hierarchy of the tree can be summarised in next levels:

- Level 1: Depth
- Level 2: Diagnostic feature / Soil type
- Level 3: Depth
- Level 4: Land use / Clay content
- Level 5: Grazing stocking rates

The upper part of the RT is dominated by intrinsic soil characteristics. Soil depth controls the range of two high hierarchical levels (1 and 3), emphasizing its relevance for the distribution of SOC along soil profiles, especially between topsoil and the subsoil. Soil type heterogeneity and the presence of diagnostic features (i.e. humic layers) were highlighted by the model at level 2, indicating the dominant role of native organic matter in SOC stocks. These results suggest that inherent properties are primarily responsible of the SOC storage potential in soils.

The lower part of the RT is influenced by a combination of intrinsic soil characteristic and management regimes. Level 4 characterizes the influence of clay content and land use on SOC stocks and establishes that both factors have a similar level of contribution to SOC storage capacity. Level 5 highlights the potential of animal grazing to shift SOC stocks trends within grassland systems (Table 3, Fig. 4). The RT model did not flag out other management practices as a relevant factor (Figs. 3 and 4). The rank of most relevant factors detected by the RT is provided in Fig. 3.

In our first hypothesis, we stated that land use and management practices exert greater influence on SOC stocks compared to intrinsic soil characteristics. However, the hierarchical relationship between predictors revealed the opposite, indicating that intrinsic characteristics largely determine the current SOC stocks and distribution up to 60 cm, while land uses and management practices act as modifiers, shifting trends within potential ranges (Table 3, Fig. 4). This suggests that management practices have little short-term impact, but their long-term cumulative effect is crucial in shifting trends in SOC stocks over time. Significant enhancements in SOC stocks based on management practices are achievable in the long-term but the maximum storage capacity will be ultimately determined by inherent soil characteristics.

3.3. Regression Tree analysis

To understand the interaction between predictors and SOC stocks, the RT model was interpreted based on rules, or paths connecting the

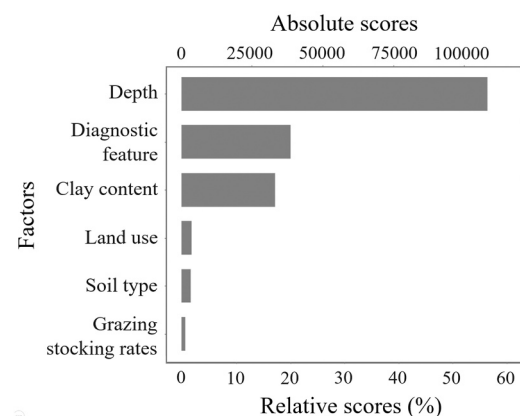


Fig. 3. Rank of factors based on the Variable Importance (VI). Absolute scores quantify the overall contribution of each factor in defining nodes or reducing uncertainties within the RT structure. Relative scores express these contributions as percentages, rescaled the sum to 100%. Factors with a contribution of less than 1% were omitted.

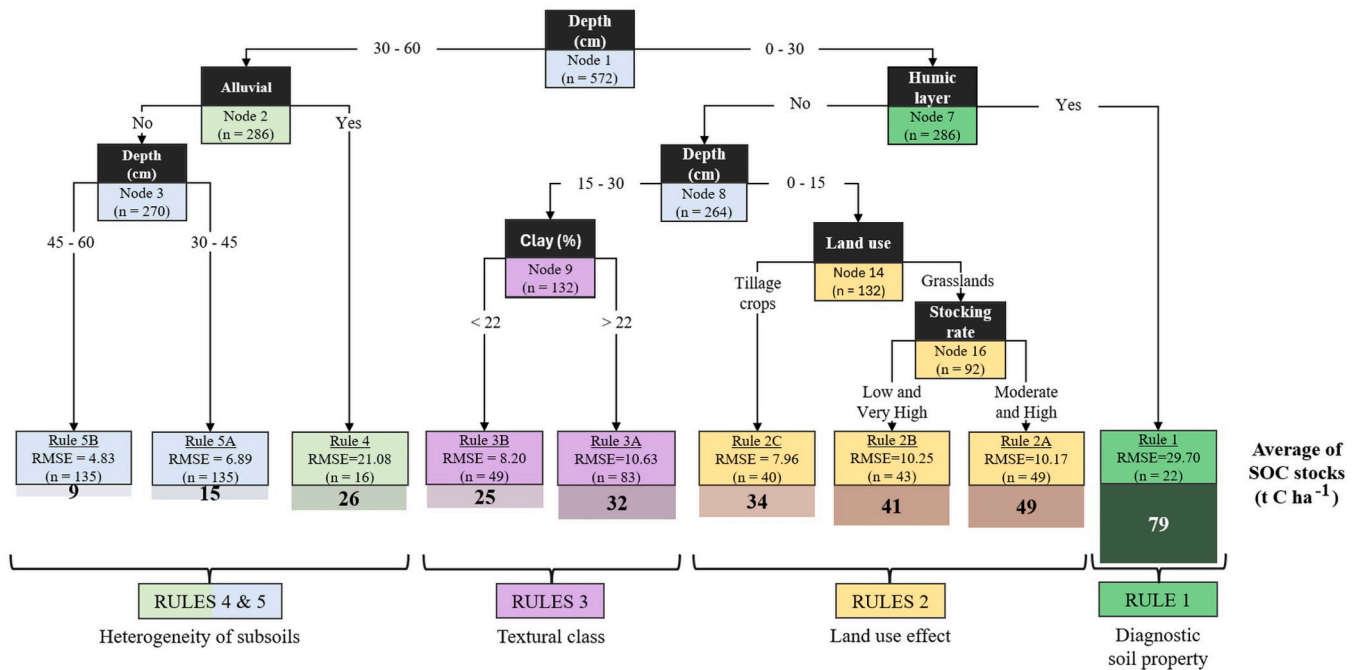


Fig. 4. Regression Tree of SOC stock dynamics across tillage crops and grassland systems.

root to the terminal nodes (Table 3, Fig. 4). Most of the rules (6 of 9) were directly associated with soil intrinsic characteristics highlighting the role of inherent properties on SOC stocks. The RT model identified soil depth as the starting point for understanding paths of SOC stocks in agricultural soils, based on soil-management interactions. Soil depth defines two main branches. In Fig. 3 the right branch explains the dynamics of SOC stocks in the topsoil (0–30 cm), while the left branch the dynamics in the subsoil (30–60 cm). The rules that govern these paths are explained below (Fig. 4).

3.3.1. Rule 1: Diagnostic soil properties

This rule creates one of the most dominant partitions in the RT. Rule 1 ($n = 22$) consisted of a single high level hierarchy rule (Table 3, Fig. 4), where soils with the presence of humic layers within the first 30 cm, reported highest stocks in surface (79 t C ha^{-1} , $\text{RMSE} = 29.70 \text{ t C ha}^{-1}$). The Humic feature in a layer is characterized by a high carbon content between 3.5% and 20%, developed through the slow decomposition of organic matter under water-saturated environments (Simo et al., 2008). These layers can accumulate ~ 2 times more carbon than any mineral topsoils described throughout other rules. This result highlights the strong influence of a diagnostic feature such as the humic feature in predicting SOC stocks, confirming that intrinsic soil properties can exert as much impact as land management in shaping carbon storage patterns. The dominance of this rule within the RT suggests that the presence of humic features acts as a key threshold, separating soils with inherently greater SOC storage potential and enhanced resilience (Environmental Pillar, 2025; United Nations Environment Programme (UNEP), 2022). Beyond SOC accumulation, humic layers are also associated with multifunctional benefits such as improved fertility, structure, and water retention capacities (Bondi et al., 2018; Magdoff and van Es, 2021; Simo et al., 2008).

3.3.2. Rule 2: Land use effect

This block is composed of three low-hierarchy rules (Table 3) and is the only block that reaches the 5th level of hierarchy. This set of rules characterized the cumulative effect that major land uses and management practices (in grassland systems) might have on SOC stocks in mineral topsoils (Table 3, Fig. 4). Up to 15 cm depth, the path of rules is

governed by Land Use (Tillage versus Grassland) followed by grassland management, specifically stocking rates. Overall, topsoil SOC stocks tend to decrease as management intensity increases, ranging from 34 t C ha⁻¹ (RMSE = 8.27 t C ha⁻¹) for Tillage topsoil (n = 38) to 48 t C ha⁻¹ (RMSE = 10.83 t C ha⁻¹) associated with Grasslands with moderate stocking rates (n = 49). Notably, grasslands the least and most intensive systems reflected a lower SOC stock 41 t C ha⁻¹ (RMSE = 10.03 t C ha⁻¹) (Table 3, Fig. 4).

Tillage crops showed 20–30% lower SOC stocks in the top 15 cm compared to grasslands (Table 3, Fig. 4), likely as a result of recurrent physical, chemical, and biological disturbances within the systems that impede SOC accumulation in the long-term, especially in the top layers of soil (e.g., ploughing, trafficking, fertilization, harvesting, imbalances in biota, erosion, etc.) (Emde et al., 2024; Paltineanu et al., 2024). In contrast, grasslands offer more stable conditions that facilitate carbon stabilization, with permanent vegetation and manure inputs steadily increasing the SOC stocks (Dal Ferro et al., 2020; Emde et al., 2024; Magdoff and van Es, 2021). While grassland systems tend to accumulate SOC primarily in the topsoil, tillage practices tend to reduce or redistribute organic matter downward through ploughing, leading to a more heterogeneous SOC distribution within the soil profile (Alcántara et al., 2016; Burger et al., 2023; Prasuhn, 2012). Consequently, although substantial differences exist in topsoil SOC between the two systems, the total SOC stocks to 60 cm depth may be relatively similar between these systems.

Within grassland systems, differences were detected based on management intensities. Overall, Moderate to High stocking rate systems (150–230 average annual kg ON/ha) reported 15% more SOC stocks compared to Low and Very high stocking rates (0–150 and >230 average annual kg ON/ha respectively). Moderate grazing stimulates plant regrowth by removing old plants and creating conditions for new shoots, while low stocking rates are associated with limited inputs of organic matter and high stocking rates decrease aboveground and belowground biomass, present more losses of soil nitrogen and an unfavourable microbial environment that translates into lower SOC stocks (Chen et al., 2015; Tang, 2023; Wang et al., 2025). This example illustrates how the cumulative effect of little short-term accruals can shift SOC stocks trends over time due to the persistent implementation of certain management

practices, stressing the urgency of combining immediate actions to preserve current SOC stocks with measures that contribute to enhancing them in the mid and long term.

3.3.3. Rule 3: Textural class

The results suggest that soil layers between 15–30 cm depth (irrespective of each soil type) with a proportion of clay $\geq 22\%$ are capable of storing in average 7 t C ha^{-1} (30%) more than soils with clay $< 22\%$ (Table 3, Fig. 4). By definition, this is more expected to happen in Luvisols and Groundwater Gleys characterized by B horizons enriched with illuviated clay (Simo et al., 2008; Torres-Sallan et al., 2017; IUSS Working Group WRB, 2022). Clay provides physical protection to the SOC against tillage and microbial activity, stabilizing it in the long term (Torres-Sallan et al., 2017). Although the rule generalized the stabilization effect of clay between 15–30 cm, clay illuviation can occur at other depths (depending on site-specific conditions). For this reason, some soils may have the potential to store carbon beyond 30 cm depth (Paltineanu et al., 2024; Torres-Sallan et al., 2017). Therefore, optimal management of clay-enriched soils represents a key action for reducing GHG emissions in the agricultural sector. (Torres-Sallan et al., 2017; Tuohy et al., 2021).

3.3.4. Rule 4 and 5: Subsoil heterogeneity

The influence of management decreases with depth and deep soil carbon is largely governed by the inherent soil characteristics (Skadell et al., 2023; Torres-Sallan et al., 2017; Torres-Sallan et al., 2018; Tuohy et al., 2021). Rules 4 and 5 situated in the left side of the tree (Fig. 4) are related to the distribution of SOC below 30 cm (30–60 cm) and explain the influence that heterogeneous geological depositions, stony subsoils, and weathered bedrock (parent material) have on SOC stocks in depth (Angst et al., 2018). Rule 4 consists of a single high-hierarchy rule, where the stocks are determined by the stratified layers in alluvial subsoils (Table 3, Fig. 4) achieving high averages of 26 t C ha^{-1} (RMSE of $21.08 \text{ t C ha}^{-1}$) thanks to the presence of silty and clayey subsoils (Simo et al., 2008; Paltineanu et al., 2024). In other non-Alluvial soils, SOC stocks in subsoils were lower, ranging from 9.5 t C ha^{-1} (RMSE = 4.83 t C ha^{-1}) to 15 t C ha^{-1} (RMSE = 6.92 t C ha^{-1}) depending on the depth (Table 3, Fig. 4). Although management has a limited influence below 30 cm depth, long-term effects of practices such as N or NPK fertilization, application of organic manure, straw incorporation, reduced tillage, and the inclusion of legumes in crop rotations and pasture systems can enhance SOC stocks at depth (Skadell et al., 2023). However, the RT did not identify management-related rules at these fixed depths, likely because most agricultural activities in Ireland are concentrated within the upper 20 cm of the soil profile. In addition, the strong heterogeneity of subsoil layers creates site-specific conditions that can be masking the effects from other factors on SOC stocks (Skadell et al., 2023). Overall, SOC decreased with depth, likely because conditions such as water stagnation, water table fluctuations, soil compaction, and stoniness limit the development of plant root systems, thereby reducing C inputs and SOC accumulation at depth (Börjesson et al., 2018). Although subsoils presented low values, they accumulated approximately 30% of the SOC stocks across soil profiles, a considerable amount that should not be omitted when considering how to optimize soil management for the delivery of multiple soil based ecosystem services, including climate regulation.

The second hypothesis stated that interactions between soil intrinsic characteristics and management practices enhance SOC storage. These findings lead to a partial acceptance of this hypothesis, since the combination of selected intrinsic characteristics and management practices can lead to enhanced SOC stocks but primarily in the first 15 cm of soils (Rules 2 A, 2B, and 2 C, Fig. 4). In Irish agroecosystems, most of the agricultural interventions are conducted on topsoils, causing greater impacts near the surface. However, the influence of management decreases with depth (Skadell et al., 2023), and other factors such as clay content and heterogeneity of subsoils start to play a more dominant role

(Dal Ferro et al., 2020; Torres-Sallan et al., 2017; Skadell et al., 2023).

4. Implications and limitations

This research advances the scientific understanding of SOC stock dynamics in agricultural soils. Results indicate that soil intrinsic characteristics define the SOC storage potential and the long-term effects of land use and management shift SOC stocks trends within soil types. This knowledge can help raise awareness among landowners about the SOC storage capacity of their soils (Fig. 4) and would facilitate the design of climate-smart strategies to sustain food production while increasing SOC stocks (Fig. 4). An initial characterization of the soils and their current stocks is required to establish a baseline against which the impact of a set of practices can be monitored over time. Considering that SOC accumulation is a long-term process, management strategies should prioritize the protection of existent stocks and implement soil-targeted measures to boost SOC sequestration. Such initiatives should be broadened across all farms to empower farmers to make decisions that will optimise the role of soils in relation to climate regulation (especially humic soils due to their high SOC content) while supporting long-term soil health and sustainability.

The RT provided rules with expected values of SOC stocks in response to different soil-management interactions (Fig. 4) and showed different paths to enhance SOC stocks. Overall, the RT identified that permanent living vegetation (i.e. grasslands) contributes to improvement of SOC stocks (Table 3, Fig. 4). This implies that the conversion of fallow bare lands into grasslands; the inclusion of cover crops, mixed and perennial crops in tillage systems; and the implementation of agroforestry or silvopasture that have been considered as part of the efforts to mitigate climate change elsewhere could be promising strategies to optimise carbon stocks here (Paustian et al., 1997; Poeplau and Don, 2015; Siddique et al., 2023). Furthermore, the incorporation of livestock with moderate stocking rates in grassland systems, ranging between 150 and 230 kg organic nitrogen (ON) $\text{ha}^{-1} \text{ year}^{-1}$, stand out as a promising path to contribute to climate targets. Although differences in SOC stocks between stocking rate categories were modest (7 t C ha^{-1} , corresponding to roughly 15% higher SOC under moderate stocking rates compared with low [$0\text{--}150 \text{ kg ON ha}^{-1} \text{ year}^{-1}$] and very high [$>230 \text{ kg ON ha}^{-1} \text{ year}^{-1}$] levels), the broad implementation of moderate grazing management could nonetheless make a substantial contribution to meeting national climate objectives. These examples highlight that achieving climate neutrality in the agricultural sector demands the collaboration of multiple stakeholders, through the implementation of coordinated actions across different scales. Importantly, practices such as maintaining moderate stocking rates represent an adjustment for farmers, that could contribute to national climate goals without imposing major changes to existing management systems, however, it is important that the implicit economic and environmental impacts must be considered.

The RT also provides thresholds that researchers and industry personnel could use as a benchmark to test promising methods for boosting SOC sequestration. The model identified that soils with less than 22% clay content tend to have low SOC stocks (25 t C ha^{-1}) (Table 3, Fig. 4). This 22% threshold was derived from the specific soil types and regional conditions of this study; its applicability as a universal benchmark requires further validation across a wider range of soils and climatic contexts. But overall, soils with clay content below this level are inherently more limited in their capacity to store SOC, which can guide site-specific management strategies. This threshold also provides a quantitative benchmark for prioritizing interventions, such as organic amendments applications, cover cropping, or reduced tillage, on soils where SOC sequestration potential is constrained. Moreover, it serves as a practical reference for researchers and practitioners when evaluating the effectiveness of practices aimed at enhancing carbon storage, enabling more targeted and efficient efforts to increase SOC across diverse soil types or textural classes (Gross et al., 2024; Krauss

et al., 2022; Knoblauch et al., 2021; Skadell et al., 2023; Wulannityas et al., 2021). In parallel, benchmarks could also allow policy makers to define realistic targets in incentive schemes such as the Carbon Farming Framework (Harris et al., 2024). Given the critical role of clay in SOC sequestration, linking soil-specific SOC thresholds, such as the 22% clay benchmark, to financial or technical support programmes could help prioritize interventions in soils with the greatest sequestration potential. Such benchmarks can promote the adoption of best management practices and ensure that incentive schemes, like the Carbon Farming Framework, are both effective and verifiable, ultimately enhancing the impact of climate-smart agricultural policies. This can facilitate a gradual transition from conventional to climate-neutral systems, rewarding verifiable efforts to reach higher thresholds based on soil type C storage potential.

The RT model was able to explain the SOC dynamics associated with general land uses, demonstrating its potential to capture differences in SOC stocks patterns and generate specific rules that explain trends across different agricultural systems (Table 3, Fig. 4). However, the lack of data for some systems probably limited the outcomes. For example, potato crops ($\sim 50 \text{ t C ha}^{-1}$) would be expected to report much lower SOC stocks compared to other tillage crops due to the intensive nature of the system (Prasuhn, 2012). However, it could not be discriminated by the model, possibly due to the limited number of observations ($n = 2$). Similarly, very few observations were collected for organic tillage crops and multispecies swards in grasslands, limiting the exploration of SOC dynamics in those systems. This reduced number of observations could be leading to an overgeneralization, in Rule 2 C, where all tillage operations are grouped under a single rule (Table 3, Fig. 4). Therefore, increasing the number of samples could allow the development of new rules to assess the impact of these specific systems on SOC stocks. Alternatively, it is possible that the categorical resolution of management data collected through five-year retrospective surveys was insufficient to capture the nuanced, long-term effects of these practices, or that these effects are masked by the greater variability driven by intrinsic soil properties. This also underscores the importance of long-term, standardized experiments for quantifying the impacts of specific management practices (Lorenz et al., 2025). Furthermore, the RT model was tested in a geographic region with similar climatic conditions. Variations in climate may affect the dynamics of SOC stocks, which represents a potential limitation for extrapolating the results of this research to other regions of the country, however Nowbakht et al. (2025) previously found a low modelled impact of climate conditions on the SOC estimation. As our study was restricted to the Southeast region it cannot fully address this question. Further research is required to assess the effect of climate on SOC stocks in agricultural soils.

It is also essential to expand this knowledge by analyzing the role of microbial communities in carbon sequestration, considering the seasonal, interannual, and long-term variations they experience due to changes in their environment (Bünemann et al., 2018; Madegwa and Uchida, 2021; Randall et al., 2019; Randall et al., 2020). More studies are required to incorporate a set of standardized indicators and methods that allow monitoring the role of microbes as key mediators of carbon stocks and soil health (Council of the European Union, 2024; Dundore-Arias et al., 2020).

5. Policy considerations

In a broader context, this study supports the national baseline for quantifying SOC stocks, implementing improvements in standard protocols to monitor the impact of agriculture on SOC stocks both in the topsoil and subsoil (DAFM, 2024a; Peng and Van Eerd, 2024; Poeplau and Don, 2013; Raffeld et al., 2024; Skadell et al., 2023; Torres-Sallan et al., 2017; Torres-Sallan et al., 2018; Tuohy et al., 2021). The results will support the modelling of carbon sinks and sources in Irish soils at Tier 2 level (Murphy et al., 2024). Future efforts should consider how best to account for seasonal and interannual variability, however a 5–10

year interval has been suggested as appropriate to detect SOC stock changes (Black et al., 2008). Data from this research may also contribute to soil health monitoring efforts across Europe, in line with the Soil Monitoring and Resilience Directive (Council of the European Union, 2024). This underscores the need for regular monitoring, particularly as adequate monitoring and soil information that can underpin soil management programmes has been shown to best address soil threats (Amelung et al., 2020; Smith et al., 2024).

The RT emphasizes the benefits of protecting humic soils to achieve the goals set out in the Climate Action Plan for the period 2025–2030 (DCEE, 2023). This result is consistent with the views of organizations such as the UNEP and Irish Environmental Network of NGOs Environmental Pillar which argue that carbon-enriched soils can contribute greatly to mitigate climate change (Environmental Pillar, 2025; UNEP, 2022). However, there is a gap in regulations and incentive schemes to secure humic soils. Good Agricultural and Environmental Condition (GAEC) regulations (DAFM, 2023a) designed to guarantee a minimum environmental standard in farms across Europe, offer only partial protection. GAEC 2 (Protecting Peatland and Wetland) excludes humic soils because they do not meet the criteria established for peat soils. In this regard, specialised organisations are calling for an update to the concept of peat soil to ensure the protection of more carbon-enriched soils at the national and global scale (Environmental Pillar, 2025; UNEP, 2022). GAEC 4 (Establishment of Buffer Strips Along Watercourses) encourages the conservation of some humic soils, especially Alluvials, but the economic support for farmers lasts for only five years (DAFM, 2022), compromising SOC stocks in the long-term. Another alternative is to implement a functional land management approach, which acknowledges that SOC management is central to climate-smart agriculture and requires a differentiated approach in accordance with soil type to maximize ecosystem service provision at the landscape scale (Paustian et al., 1997; Schulte et al., 2014; Schulte et al., 2016). This strategy is compatible with the European Land Use, Land Use Change and Forestry regulation (LULUCF), the EU Nature Restoration Regulation, and the Irish Afforestation Scheme 2023–2027; and provides financial support for 15–20 years, securing humic soils in the long-term (Official Journal of the European Union (OJ), 2023; OJ, 2024; DAFM, 2024b).

6. Conclusions

A RT-based model was developed to evaluate the influence of agriculture and soil intrinsic characteristics on SOC stocks. Although this RT model explains 67% of SOC stock variations across the evaluated scenarios, some important predictors may still be missing or insufficiently captured. Further investigations will be required to collect more data in order to enhance the overall performance and evaluate the influence of additional factors on SOC stocks dynamics within Irish agroecosystems. However, the utility of this model is not to predict specific values. The main value of the RT is to provide a broad overview of expected SOC storage under different scenarios, inform the baseline for SOC stock monitoring, identify soil-management combinations with the potential to enhance the stocks, and support stakeholders in designing strategies to improve SOC stocks levels across their farms. The model was built with information of 143 sites (572 soil-layer observations) including soil profile descriptors, lab analytical data, and detailed management information as inputs variables. The model distinguished and established hierarchical rules among variables, emphasizing that intrinsic characteristics determine the SOC storage potential in soils, while the cumulative effect of land use and management practices contribute to shifts in SOC stocks trends.

In total, 6 of the 9 rules depended entirely on soil intrinsic characteristics, highlighting their major influence on the SOC dynamic. The repeated occurrence of depth at different hierarchical levels of the RT emphasizes its relevance for the distribution of SOC along the soil profile. The presence (or absence) of a humic feature strongly affects the capacity of soils to store C in the first 30 cm of depth, leading to humic

soils accumulating ~2 times more SOC stocks than a soil that does not have a humic layer. Meanwhile clay content ($\geq 22\%$) plays a decisive role in SOC storage between 15–30 cm depth, turning agricultural soils above this threshold into potential sinks that can significantly contribute to the achievement of climate targets.

The fact that SOC content is highly dependent on intrinsic soil characteristics is critical, urging stakeholders to develop tailored management strategies to meet climate regulation targets in the agriculture sector, focusing primarily on protecting existing stocks (especially in humic soils) and finding innovative ways to stabilize new SOC inputs, considering site-specific conditions (e.g., soil profile texture, pH in podzolic soils, and poor drainage in heavy soils).

The influence of land use and management practices is primarily concentrated in the first 15 cm of depth. They follow a hierarchical sequence where major land uses prevail over management practices. This reinforces the idea that SOC stocks are the result of a long-term soil formation process. Overall, the model suggested that land uses with permanent vegetation cover like in grasslands and controlling grazing stocking rates contribute to increasing SOC stocks. Although the accruals due to management practices in favour of carbon sequestration are difficult to observe within the short-term, their cumulative effects have significant implications for increasing stocks in the future. From a SOC management perspective, moderate to high stocking rates in grassland systems stand out as a promising path for increasing stocks, as this management regime protects current stocks and provides the sufficient additional inputs to enhance them. However, regulating stocking rates has economic and environmental implications that need to be fully considered to optimize synergies and offset any trade-off.

Overall, the proposed RT, rather than a prescriptive tool for the achievement of very specific SOC stocks, serves more as a tool to elucidate the scenarios under which SOC stocks can be enhanced. This, in turn, provides stakeholders with guidance on how to move in the direction of increasing SOC stocks for selected scenarios essential to support a transition towards meeting both national and international climate change targets.

CRedit authorship contribution statement

Castellón Meyrat Alex Martin: Writing – review & editing, Writing – original draft, Visualization, Methodology, Data curation, Conceptualization. **Lilian O'Sullivan:** Writing – review & editing, Writing – original draft, Supervision, Resources, Project administration, Methodology, Funding acquisition. **Paul Holloway:** Writing – review & editing, Writing – original draft, Supervision, Methodology. **David Wall:** Writing – review & editing, Supervision. **Giulia Bondi:** Writing – review & editing, Writing – original draft, Resources, Project administration, Methodology, Funding acquisition, Conceptualization.

Declaration of Competing Interest

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

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at [doi:10.1016/j.agee.2026.110547](https://doi.org/10.1016/j.agee.2026.110547).

Data availability

location data of sampling sites is confidential. Soil parameter data available in supplementary information.

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