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Oxalate-extractable aluminium is a key predictor of organic carbon content in Swedish agricultural topsoils

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ABSTRACT

Previous research has shown the importance of oxalate-extractable aluminium (Alox) for predicting soil organic carbon (SOC) contents across diverse geographical regions. However, studies using data from humid continental climates are scarce, and the data used in these studies have not been statistically representative for larger scales. Our study aimed to 1) evaluate the influence of soil physical and geochemical properties (specifically Alox), farm management, and climate on the spatial distribution and storage potential of SOC in Swedish agricultural soils and 2) to assess whether estimates of aggregation, assumed to influence the protection of soil organic matter, could improve predictions. We analyzed a statistically representative subset of mineral soils with pH < 7 from the Swedish soil and crop monitoring program, which covers the country's agricultural land. We identified the most important predictors for topsoil SOC contents using a random forest model. We employed partial dependence plots to visualize and interpret the interactions between key variables and SOC contents. Results showed that Alox was the most important predictor for SOC contents, as evidenced by its high relative importance score and the increased out-of-bag error when removed from the model. Notably, SOC content reached a plateau at Alox contents of about 3.5 g kg^{-1}, suggesting the possibility of SOC under-saturation. Climatic variables were of secondary importance, while farm management did not emerge as a significant predictor. Surprisingly, silt-sized aggregation was not identified as an important variable for predicting SOC content. Our findings emphasize the importance of incorporating geochemical properties, particularly Alox, in addition to soil texture, in predictive modelling and monitoring efforts for enhanced soil carbon management in humid climates.

1. Introduction

Carbon storage in agricultural soils may help mitigate climate change and, at the same time, make soils more adapted to a changing climate (Lal, 2008; Sanderman et al., 2017). Soil is the largest terrestrial soil organic carbon (SOC) pool. About 65 % of this SOC is considered to be contained in mineral-associated organic matter and thereby partly protected from microbial decomposition (Heckman et al., 2022; Sokol et al., 2022). The clay fraction (<2 μm) has often been considered an indicator of SOC storage capacity in mineral soils (Feng et al., 2013; Salonen et al., 2024; Solly et al., 2020; Wiesmeier et al., 2019). Finer particles, such as clay, have a larger specific surface area and, therefore, a large capacity to adsorb soil organic matter (SOM) (Rabot et al., 2018; Sollins et al., 1996). Based on this understanding, it has been suggested that soils have a finite capacity to store SOC and that this storage capacity depends on the clay content (Feng et al., 2013; Hassink and Whitmore, 1997; Salonen et al., 2024). The point at which this capacity is reached has been referred to as '*carbon saturation*' (Hassink, 1997). When soils are not saturated, soil and crop management changes that increase organic matter inputs can increase the mineral-associated SOC pool (Castellano et al., 2015; Guillaume et al., 2022; Hassink, 1997). Agricultural soils, especially deeper soil layers, are typically '*carbon under-saturated*' (Georgiou et al., 2022; Sanderman et al., 2017).

According to the Swedish soil and crop monitoring program (SMP; accessible at https://miljodata.slu.se/mvm/aker), there has been an increase in SOC concentrations in Swedish agricultural soils, equivalent

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to a relative increase of 0.38 % yr^{-1} during the last decades (Henryson et al., 2022; Poeplau et al., 2015). This increase has been attributed to changes in land use, with an increase in the area under ley and a corresponding decrease in annual crops as the main driver (Henryson et al., 2022; Poeplau et al., 2015). Data from the same monitoring program and data from the Swedish Farm Register also showed that SOC contents were larger in dairy farms than in arable farms (Henryson et al., 2022). These changes were attributed to a larger proportion of ley and higher use of animal manure in dairy farms (Henryson et al., 2022; Poeplau et al., 2015). This shows that Swedish agricultural soils may have the potential to store more SOC.

However, clay content alone does not determine SOC storage since it does not fully account for the surface area or presence and abundance of reactive minerals (Bailey et al., 2018; Farrar and Coleman, 1967; Rasmussen et al., 2018; Totsche et al., 2018). Other soil properties besides clay content, are needed to estimate a soil's SOC storage capacity (Bailey et al., 2018; Solly et al., 2020), and the clay saturation concept could be replaced by a soil's mineralogical capacity to store SOC (Poeplau et al., 2024). The mineralogical capacity should not be viewed as a threshold since a soil's capacity to store SOC can also be influenced by management and climate (i.e. the '*ecosystem capacity*' (Poeplau et al., 2024)).

In order to explain the mineralogical capacity, reactive mineral phases containing Al and Fe can be leveraged since they are considered to associate with SOM through organo-metal complexation and/or co-precipitation and thereby regulate microbial and enzymatic accessibility SOM (Kleber et al., 2015). It has also been suggested that interactions between clay, reactive metal phases, and SOM facilitate soil aggregation (Schlüter et al., 2022; Tisdall and Oades, 1982; Totsche et al., 2018). Aggregates are assumed to protect SOM by physically limiting microbial and enzymatic accessibility (Hall and Thompson, 2021; Matus et al., 2014). Since SOC is mainly associated with the silt and clay fraction, aggregation in silt- and/or clay sizes may be more important than macro-aggregation for SOM protection (Totsche et al., 2018; Wiesmeier et al., 2019). Furthermore, SOC has been shown to correlate with the volume of released clay particles upon SOM removal (Jensen et al., 2019; Fukumasu et al., 2021).

Indeed, positive correlations between oxalate-extractable aluminium (Alox) and iron (Feox) (assumed to represent the reactive mineral fraction of these metals) and SOC contents have been reported on national scales in the United States, New Zealand, and Chile in different climates (Beare et al., 2014; Hall and Thompson, 2021; Matus et al., 2006; Rasmussen et al., 2018). For example, Rasmussen et al. (2018) showed, using data from the U.S. Department of Agriculture's National Cooperative Soil Survey, that SOC contents increased with increasing Alox and Feox under humid conditions in acidic to neutral soils. Fukumasu et al. (2021) showed for a limited dataset from the Nordic countries and Canada that Alox was positively correlated with topsoil SOC contents. Alox was also the strongest predictor for topsoil SOC for a dataset of arable soils from southern Finland (Salonen et al., 2024). However, it is unclear how statistically representative these datasets are for Sweden and other regions with humid continental climates and soils formed from quaternary deposits.

In this study, we used a statistically representative sub-sample of the data contained in the SMP, which covers all agricultural land in Sweden, to identify the strongest predictors for SOC contents across a humidity gradient. These data were combined with new measurements of oxalate extractable Al, Fe and P and silt-sized aggregation. Our objectives were i) to quantify the relationships between soil physical and geochemical properties, farm management, climatic variables, and topsoil SOC contents in Sweden and ii) to assess whether estimates of aggregation, assumed to influence the protection of SOM, could improve predictions.

2. Methods and materials

2.1. Inventory design and data sets

We used stored topsoil samples from the Swedish soil and crop monitoring program (SMP) of arable land (Eriksson, 2021). The SMP includes measured data on soil chemical and physical variables and information on farm type and is, therefore, suitable for gaining insights into which variables best explain variations in soil organic carbon (SOC) contents. Soil samples have been collected repeatedly from these sites since 1988, with sampling occurring every ten years. For this study, we exclusively utilized data from the third inventory cycle (Inventory III), which was conducted between 2011 and 2017. After sampling, the samples were air-dried, sieved through a 2-mm sieve, and stored in airtight plastic containers in a temperature-controlled room. All soil samples from the SMP had previously been analyzed for the variables listed in Table S1. We only used the SOC content, texture, pH and exchangeable cations (Ca, K, Mg, and Na) (Eriksson, 2021). We selected these variables based on evidence from large-scale studies, which have demonstrated their significant influence on SOC contents (Rasmussen et al., 2018; von Fromm et al., 2025) and to limit overfitting and avoid adding noise. Element concentrations were analyzed using the 200.8 method (ICP SFMS). Soil pH (H_2O) was determined according to SS-ISO 10390. Carbon content was determined using a LECO Trumac CN analyzer according to SS-ISO 10694. Soil texture was analyzed using the pipette method after organic matter oxidation (Messing et al., 2024).

2.2. Selection of sampling points

To limit the number of samples used for further chemical analysis, we selected 100 samples from the 2039 topsoil samples contained in Inventory III. Since SOC has previously been shown to correlate with the contents of short-range order (SRO) phases and organo-metal complexes (i.e. the reactive mineral fraction estimated from Alox and Feox) for mineral acidic soils (Fukumasu et al., 2021; Hall and Thompson, 2021), we selected samples that represented mineral acidic soils. We first excluded samples with pH >7 ($n = 258$). In line with previous studies distinguishing between mineral and organic soils, we excluded organic soils, defined as those with SOC content greater than 70 g kg^{-1} ($n = 147$), from our analysis (Andrén et al., 2008; Poeplau et al., 2015). The pH of the remaining samples ($n = 1624$) was between 4.5 and 6.9, and SOC content was between 10 and 70 g kg^{-1} soil. To obtain a representative sub-sample, we stratified the remaining samples into four groups: high pH-high SOC ($n = 276$), high pH-low SOC ($n = 477$), low pH-high SOC (n = 477) and low pH-low SOC ($n = 394$). The first twenty-five samples were selected from each group after randomization. The amount of soil left in storage was insufficient for one of the selected samples. This sample was replaced by the 26th sample from the same group. In this manner, we merged the advantages of ensuring representation across key subgroups through stratification with the statistical benefits of random sampling within each stratum (Neyman, 1992).

The geographical distribution of the sampling locations for the selected samples was checked against the distribution of locations for the whole dataset (Fig. 1A). Distributions of SOC content and pH for our subsample were representative of the distributions for all data from Inventory III, again excluding samples with SOC contents >70 g kg^{-1} and pH >7 (Fig. 1B and C). The density curves were achieved using the Kernel density estimation, which produced smooth curves of pH and SOC (Wickham and Wickham, 2016). Fig. S1 shows that our subsample was also representative of the SMP concerning soil and crop farm management.

2.3. Oxalate extraction

In addition to the variables selected in the SMP, we carried out ammonium oxalate extractions to estimate Alox, Feox and Pox contents.

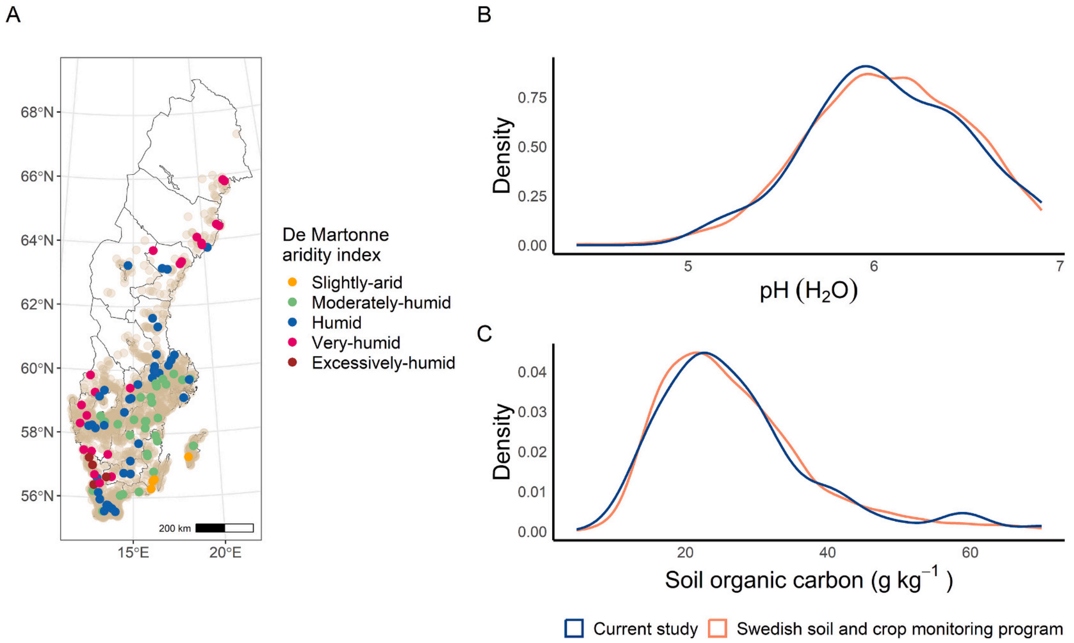

Fig. 1. A) The geographical distribution of sampling points in the Swedish soil and crop monitoring program (SMP) brown and the selected sampling points for the current study visualized according to the De Martonnes aridity index, B) Distributions of soil pH and C), soil organic carbon content at 0–20 cm depth for samples from the SMP and the sub-sample used in this study. Samples with pH > 7 and SOC contents >70 g kg^{-1} were excluded for both cases.

The Al and Fe extracted with oxalate originate from short-range order (SRO) aluminosilicates, poorly crystalline hydrous oxides and organic-mineral complexes (Hall and Thompson, 2021; Matus et al., 2008). The Pox would represent extracted inorganic and organic phosphorus fractions (Fransson, 2001). Approximately one gram of air-dried soil, sieved through a 2-mm mesh, was mixed with 100 mL of 0.2 mol L^{-1} acid ammonium oxalate solution. This solution was prepared by combining diammonium oxalate monohydrate ($[NH_4]_2C_2O_4 \cdot H_2O$) and oxalic acid dihydrate ($C_2H_2O_4 \cdot 2H_2O$), with the pH adjusted to 3.0. The mixture was shaken for four hours on an orbital shaker (GFL orbital shaker, Vortexers, *Germany*) with as little exposure to light as possible to minimize photochemical oxidation. The suspension was centrifuged for 15 min at 4000 rpm. The supernatant was then filtered through a 0.2 μm micro filter (Sarstedt™, *Germany*) using a syringe, again with as little exposure to light as possible. The filtrate was diluted with water at a 1:3 ratio. Alox, Feox and Pox concentrations were analyzed using Inductively Coupled Plasma Optical Emission Spectroscopy (ICP-OES) on a Perkin Elmer 5300 DV instrument (*Ontario, Canada*).

2.4. Silt-sized soil aggregation

The volume of (<2 μm) particles released upon chemical dispersion of the silt-sized aggregates was used as a measure of soil aggregation (Fukumasu et al., 2021). This volume was estimated from the difference in the volume of clay-sized particles after chemical dispersion and mechanical dispersion. Mechanically dispersed soil was assumed to contain primary particles and micro-aggregates, while chemically dispersed soil contained only primary particles.

For mechanical dispersion, 5 g of air-dried soil was mixed with water, shaken overnight, and sieved through a 63-μm sieve. The particle size distribution of the suspension was then determined using the methods described by Svensson et al., 2022. For chemical dispersion, the soil was treated with hydrogen peroxide, boiled, cooled, and rinsed. Then 1 mL of a chemical dispersant (sodium carbonate, Na_2CO_3 7 g L^{-1} and sodium metaphosphate, $(NaO_3P)_n$ 33 g L^{-1}) and distilled water were added, resulting in a final volume of ca. 40 mL. The mixture was shaken overnight and sieved before analyzing the particle size distributions. Particle size distributions for chemical dispersion and mechanical dispersion were determined through laser diffraction measurements using a Horiba Partica LA-90 V2 (Svensson et al. (2022).

2.5. Statistical analysis

We used a random forest model (RFM) to predict SOC contents for selected explanatory variables (Friedman, 2001). The selected explanatory variables included four categorical farm management variables, nine geochemical variables, measured concentrations of Alox, Feox and Pox, three measured physical properties and three climatic variables (Table 1). The weather data was obtained by averaging observed records from 1961 to 2017 provided by the Swedish Meteorological and Hydrological Institute (Swedish Meteorological and Hydrological Institute, 2025). These data were derived from gridded analysis models, which interpolate observed climate records for enhanced spatial accuracy. From these data, we calculated the De Martonne aridity index (DMAI), a measure of humidity and aridity (De Martonne, 1925):

$$\mathrm{DMAI} = \frac{\mathrm{MAP}}{\mathrm{MAT} + 10} \tag{1}$$

where MAP (mm) is the mean annual precipitation and MAT (°C) is the mean annual temperature. For visualization purposes, DMAI was divided into seven classes (Table S2) (Pellicone et al., 2019).

We selected the most influential variables based on previous knowledge related to SOC predictions (Solly et al., 2020; Von Fromm et al., 2021; Yu et al., 2021). Summary statistics for all included variables are presented in Table S3. Note that all variables were logarithmically transformed in the analysis to reduce skewness. MAT was first transformed by subtracting each value from the maximum MAT value and adding 1 to ensure that all values were positive before the logarithmic transformation. All farm management variables were included as categorical variables (yes/no), according to the answers in an SMP farmer questionnaire.

Initial data exploration was conducted using Spearman's rank correlation coefficients (ρ) to examine pairwise relationships between all untransformed non-normal variables. In cases where tied ranks occurred, p-values were approximated as exact computation is not possible with ties. From the RFM, we determined the variable

Table 1

Variables used for the Random forest analysis. SMHI is the Swedish meteorological and hydrological institute. SMP is the Swedish soil and crop monitoring program.

Type	Variable	Unit	Abbreviation	Source
Climate	Mean annual temperature (1961–2017)	°C	MAT	SMHI
	Mean annual precipitation (1961–2017)	mm	MAP	SMHI
	De Martonne aridity index	–	DMAI	De Martonne (1925); SMHI
Geochemical properties	pH (H_2O)	–	pH	SMP
	Exchangeable magnesium	g kg^{-1} soil	Mg	SMP
	Exchangeable manganese	g kg^{-1} soil	Mn	SMP
	Exchangeable calcium	g kg^{-1} soil	Ca	SMP
	Exchangeable potassium	g kg^{-1} soil	K	SMP
	Oxalate extracted aluminium	g kg^{-1} soil	Alox	Ammonium oxalate extraction
	Oxalate extracted iron	g kg^{-1} soil	Feox	Ammonium oxalate extraction
	Oxalate extracted phosphorus	g kg^{-1} soil	Pox	Ammonium oxalate extraction
Soil physical properties	Clay (<2 µm)	%	Clay	Chemical dispersion
	Silt (2–63 µm)	%	Silt	Chemical dispersion
	Silt-sized aggregation (Volume of primary particles in aggregates)	% of <2 µm particles in <63 µm aggregates	Aggregation	Chemical and mechanical dispersion
Farm management	Practice	–	I. Organic (Yes/No) II. Conventional (Yes/No)	SMP
	Operation	–	I. Crop (Yes/No) II. Mixed (Yes/No) III. Animal (Yes/No) IV. No.farming (Yes/No)	SMP
	Rotation	–	I. Mostly.crops.without.ley (Yes/No) II. Crops.and.several.years.of.ley (Yes/No) III. Almost.only.ley (Yes/No) IV. Other.rotation (Yes/No)	SMP
	Manuring	–	I. Regular.manure.application (Yes/No)	SMP

importance based on the increase in the mean square error (IMSE) when a variable was removed from the model. We used the Boruta algorithm to select the relevant variables with respect to the response variable (Kursa and Rudnicki, 2010). In addition, we used partial dependency plots (PDP) to illustrate how individual explanatory variables contributed to the variation in SOC while other variables were kept constant (Friedman, 2001; Pearson, 2017). The model performance was evaluated using the out-of-bag (OOB) error (OOBE), which is the mean square error for the data points not included in each bootstrap sample. This estimate provides internal validation without requiring a separate test set to mitigate the risk of overfitting (Breiman, 2001).

We compared the RFM with the results of a linear regression model (LRM) as a benchmark model. We used the method of comparing the RFM and the LRM described by Jeong et al. (2016) to ensure that the two models were comparative. We trained an optimized RFM (based on the Boruta feature selection algorithm) and LRM (based on a backward selection using the model with the lowest Akaike information criterion score) on 50 % of the data and tested both models on the remaining data. We used the root mean square error (RMSE) to assess how well the model fitted the measured data.

Data processing and analysis were carried out using R version 4.3.1 (R Core Team, 2023). We used the “RandomForest” R package (Friedman, 2001; Liaw and Wiener, 2002) and the “partial” function in the “PDP” R package to determine the partial dependence of each variable (Greenwell, 2017). The LRM analysis was conducted with the “lm” function in R (R Core Team, 2023) and the “relaimpo” R package (Groemping, 2006) to show the relative variable importance in the LRM. In addition, we also used the packages “ggplot2” (Wickham, 2016), “ggspatial” (Dunnington, 2023) and “ggtern” (Hamilton & Ferry, 2018) for graphical and geographic illustrations. The base shape files used for the maps to create Swedish administrative borders were from the 2011 annual stock block data from the Swedish Board of Agriculture (Jordbruksverket, 2025).

3. Results

3.1. SOC content in relation to geochemical and physical properties, farm management and climate

Soil organic carbon content was between 10 and 70 g kg^{-1} (Table S3) with a mean C:N ratio of 11.5 ± 2.7. Alox and Feox concentrations were 0.4 to 4.3 g kg^{-1} and 1.2 to 13 g kg^{-1} soil, respectively (Table S3). Soil texture covered ten different classes, with clay contents in the range of 1.4–52 % and silt contents in the range of 9.6–95 % (Fig. S1). The fraction of clay contained in silt-sized aggregates was between 0 and 38 %. Climate data indicated conditions from slightly arid ($30 \leq \mathrm{DMAI} \leq 35$; Table S2) to excessively humid ($60 \leq \mathrm{DMAI} \leq 187$; Table S2) (Fig. 1A). The northern parts of Sweden were characterized by very humid to humid conditions, while the southern parts were slightly arid to excessively humid. The central regions were characterized by moderately humid ($35 \leq \mathrm{DMAI} \leq 40$; Table S2) to humid conditions ($40 \leq \mathrm{DMAI} \leq 50$).Of the selected samples, 43 % were from crop farms, 31 % from animal farms, 24 % from mixed farms, and 2 % reported no specific farming activities (Fig. S1). Forty-six percent of the samples were from fields where manure was regularly applied. Additionally, 34 % of the samples were from fields with annual crops without ley, 31 % annual crops with several years of ley, and 27 % almost exclusively ley.

The geographical distributions of SOC content co-varied with Alox concentrations (Fig. S2) but not with Feox concentrations or pH (Fig. S3). The clay content was generally higher in the central part of Sweden compared to the southern and northern parts (Fig. S5), whereas the silt content was higher in the northern parts compared to the central and southern parts of Sweden (Fig. S5). Spearman rank correlation coefficients (ρ) confirmed the above-described relationships (Fig. 2). The strongest correlation with SOC content was found for Alox (ρ = 0.6) (Fig. 2). SOC content was not significantly correlated with Feox or clay content but weakly positively correlated with other geochemical variables (exchangable Ca and Pox) and climatic variables (DMAI). SOC content was also weakly positively correlated with regular application of manure and mixed framing. Notably, DMAI was high when the rotation was dominated by ley (ρ = 0.29) and low when the rotation was dominated by annual crops without ley. Silt-sized aggregation was strongly positively correlated with clay content (ρ = 0.7).

3.2. Key predictors of SOC across a humidity gradient

The random forest model (RFM) reproduced the measured SOC contents (RMSE = 0.32 g kg^{-1}) slightly better than the linear regression model (LRM) (RMSE = 0.34 g kg^{-1}; Fig. S5). Our model showed that Alox was the most important predictor, with an increase in mean square error (MSE) of approximately 21 % when excluded from the RFM, followed by DMAI with an increase in MSE of approximately 9 %. Other important variables selected by the Boruta algorithm were Mn, Pox, Silt, exchangable Ca, MAT and MAP, with an increase in MSE ranging from 6 to 9 % when excluded from the model.

The RFM with all relevant variables included (Fig. 4A) had a lower prediction error than the model without Alox (Fig. 4B). Excluding Alox from the RFM increased the OOBE with 10 % compared to the model containing all key predictors (Fig. 4). Both models underestimated SOC contents for values larger than 40 g kg-1, while values smaller than approximately 20 g kg^{-1} were overestimated. Both models showed a greater propensity for underestimation than overestimation.

The partial dependence plots (PDPs) in Fig. 5A illustrate that predicted SOC content increase with higher Alox concentrations, with the largest increases observed between 2 and 3.5 g kg^{-1}. Further increases in Alox beyond this range had a limited effect on predicted SOC content. Similar trends were observed for DMAI and Pox, where SOC content increased and then plateaued at higher values of these variables (Fig. 5B, C). For DMAI, this plateau was evident under very humid ($50 \leq$ DMAI ≤ 60) and excessively humid ($60 \leq$ DMAI ≤ 187) conditions. Predicted SOC generally decreased with increasing exchangable Mn (Fig. 5D) but increased with higher proportions of silt-sized particles, and exchangable Ca (Fig. 5E, F). MAT and MAP had opposing effects. MAT decreased with predicted SOC content (Fig. 5G). For MAP, predicted SOC contentwas lowest at values around 600–700 mm, increased with higher MAP, and plateaued above approximately 800 mm (Fig. 5H).

4. Discussion

4.1. General modelling results

The random forest model generally reproduced the measured SOC contents better compared to the LRM. The RFM was more robust and better at capturing the complex relationships between the predictors and SOC contents. In both models, oxalate-extractable aluminium (Alox) was the most important predictor (Fig. 3, S6). However, SOC contents in the RFM were overestimated for values smaller than 20 g kg^{-1}, while values larger than 40 g kg^{-1} were underestimated. Only 11 and 26 % of the samples had SOC contents <20 and > 40 g kg^{-1}, respectively. This imbalance could have resulted in overfitting in the 20–40 g kg^{-1} range at the expense of poorer fit to measured data at lower and higher SOC contents. Expanding the dataset for these ranges might have improved model performance, as was the case for Jeong et al. (2016). Even though RFM can sometimes be overly specialized to training data, which potentially leads to overfitting, using out-of-bag error (OOBE) helps to reduce this risk.

4.2. Geochemical predictors of spatial variation in SOC contents in Swedish agricultural soils

Geochemical properties, particularly Alox, emerged from the RFM model as the most important predictors for SOC contents for Swedish agricultural soils with pH lower than 7. This was shown both by the relative importance scores and the fact that the model, by including Alox, resulted in smaller out-of-box errors (OOBE; Fig. 4). This result is in line with previous studies in temperate and humid climatic zones such

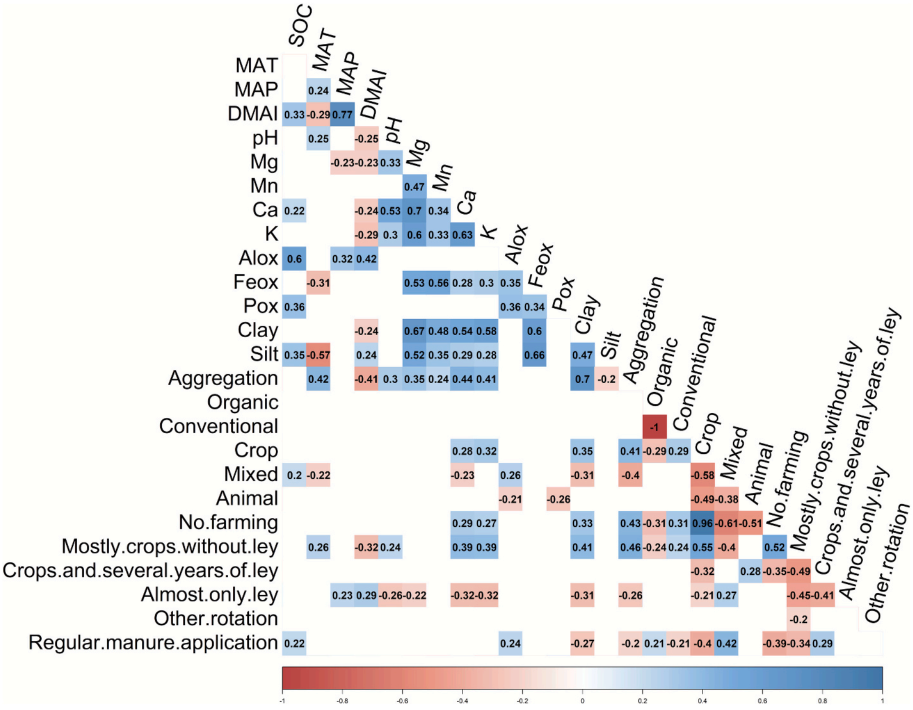

Fig. 2. Spearman rank correlation coefficients (ρ) for the relationships between all variables. Correlations with *p*-values below 0.05 are shown.

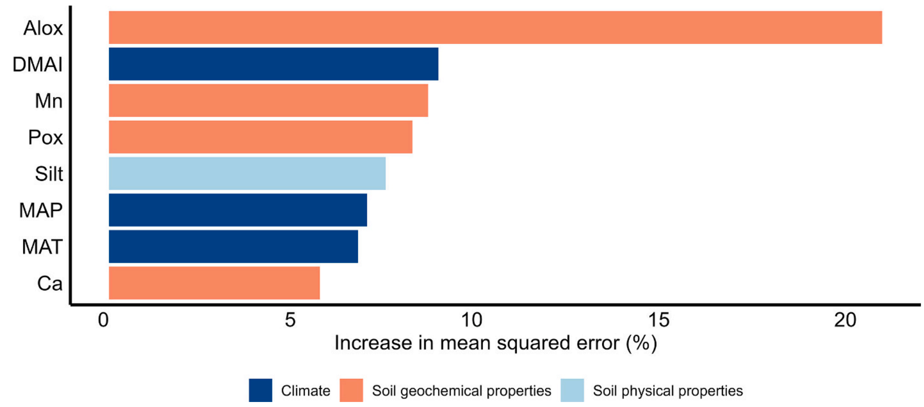

Fig. 3. Variable importance, expressed as the increase in mean squared error (MSE) upon removal of each predictor from the random forest model for soil organic carbon (SOC) content. Variables are grouped by category: climate, soil geochemical properties, and soil physical properties.

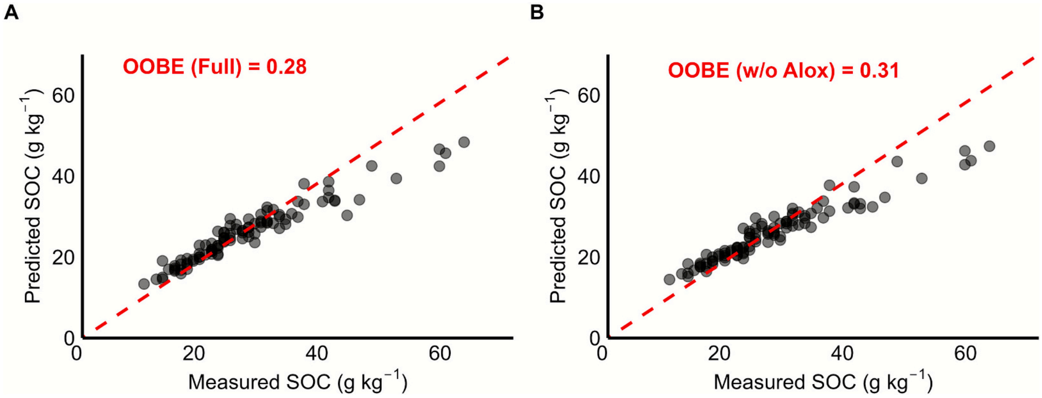

Fig. 4. Predicted soil organic carbon (SOC) contents from the random forest model plotted against measured SOC contents for A) all predictor variables selected by the Boruta algorithm and B) all predictor variables except Alox. OOBE is the out-of-bag error.

as those in New Zealand, the United States and Finland (Beare et al., 2014; Hall and Thompson, 2021; Salonen et al., 2024). For example, Hall and Thompson (2021) demonstrated that Alox was the strongest predictor for SOC contents in climates ranging from temperate to tropical in North America, Puerto Rico, Alaska, and Hawaii (NEON, 2020; Yu, 2021). We, thereby, confirmed results from studies based on smaller datasets or with more limited geographical coverage for humid continental climates (Fukumasu et al., 2021; Salonen et al., 2024). For example, Salonen et al. (2024), found that Alox explained 21 % of the variation in SOC contents in Finnish arable soils with clay contents between 2 and 68 %.

The underlying mechanisms behind our findings likely involve: (1) Sorption: Short-range order mineral phases represented in Alox provide abundant reactive surfaces for the sorption (via hydrogen bonds and covalent bonds (Ahmad and Martsinovich, 2023)) of organic carbon compounds (e.g., carboxylic acids and cellulose), hereby, also promoting aggregation (Kleber et al., 2021; von Fromm, 2025). This reduces the accessibility of SOC to microbial decomposition, thereby increasing SOC persistence in soil. (2) Formation of organometal co-precipitates and complexes: Aluminium oxides can form strong complexes with organic matter, particularly with ligands containing carboxyl and phenolic groups. These complexes decrease the solubility and mobility of organic carbon, further promoting SOC retention (Hall & Thompson, 2025). In our study, the measurement of total Alox encompasses both short-range order mineral phases and organometal complexes, making it difficult to distinguish the specific contributions of each to SOC stabilization. However, the role of Alox in aggregation as suggested in the first mechanism is questionable, as aggregation was not correlated with Alox (Fig. 2).

Exchangeable cations can act as binding agents for SOC and are closely associated with enhanced aggregate stability, thereby contributing to SOC stabilization (Bronick and Lal, 2005; Phocharoen et al., 2018; Slimani et al., 2022; Totsche et al., 2018). This stabilization may be partly attributed to the formation of cation bridges with SOC (Huang et al., 2019) and ionic bonds with organic substrates, resulting in immobilisation and stabilization of SOC (Solly et al., 2020; Kunhi Mouvenchery et al., 2012). Our findings support this mechanism, as we observed increased SOC concentrations with higher levels of exchangeable Ca (Fig. 5F) and a positive correlation between exchangeable Ca and Aggregation ($\rho = 0.44$; Fig. 2). The abundance of Ca cations in Swedish agricultural soils likely reflects the widespread presence of lime-rich glaciofluvial deposits and calcareous soils, particularly in Götaland, as well as in the western, southern, and central regions of Sweden, and in southwestern mountainous areas under cultivation (Clason & Granström, 1992). In contrast, the decrease in SOC content with increasing exchangeable Mn concentration (Fig. 5D) may be related to the catalytic role of Mn in SOM decomposition, where Mn facilitates the breakdown of complex organic molecules into simpler compounds (Li et al., 2021).

Rasmussen et al. (2018) proposed that the principal controls on SOC storage are determined by soil pH and water availability. Specifically, in water-limited, alkaline soils, calcium, and to a lesser extent, clay content, are the dominant factors influencing SOC storage. In contrast, in more humid and acidic environments, iron and aluminium minerals, particularly their complexes and oxyhydroxides, play a greater role. Based on these findings, it is plausible that under less humid conditions, exchangeable Ca is the most important factor for SOC stabilization, whereas under more humid conditions, oxalate-extractable aluminium

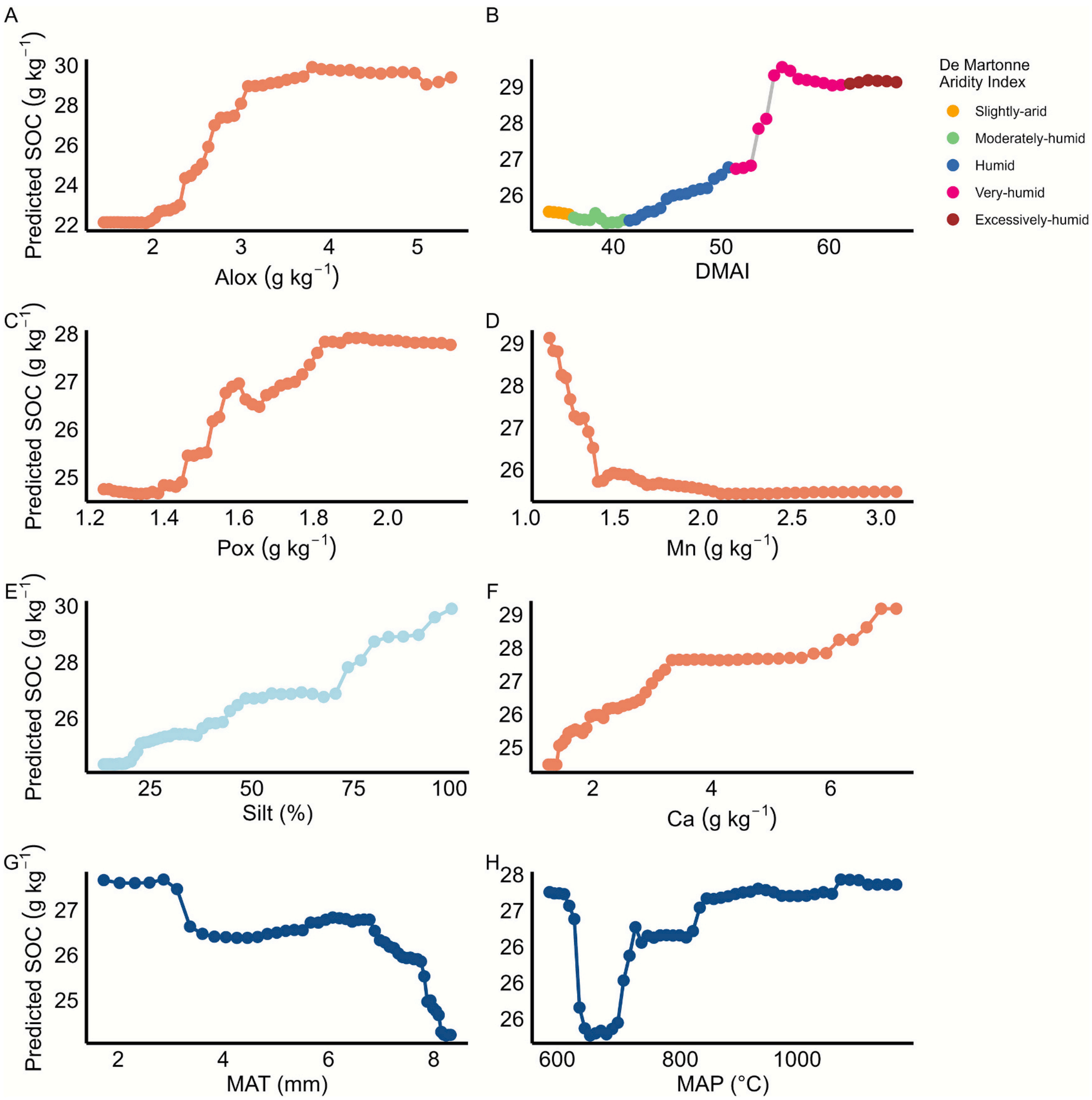

Fig. 5. Partial dependence plots (PDPs) for the predictor variables with the highest relative importance scores, as identified by the Boruta algorithm, in the random forest model (RFM) for soil organic carbon (SOC). A) oxalate-extractable aluminium (Alox), B) De Martonne aridity index (DMAI), C) oxalate-extractable phosphorus (Pox), D) exchangeable manganese (Mn), E) silt-sized soil particles (2–63 μm), F) mean annual temperature (MAT), G) exchangeable calcium (Ca), and H) mean annual precipitation (MAP).

(Alox) may assume greater importance.

Surprisingly, in contrast to the findings of Fukumasu et al. (2021), who reported that SOC stabilization via physical protection was associated with silt-sized aggregates and particles in the topsoil of Swedish agricultural fields, our study found that silt-sized aggregation was not a strong predictor of SOC content. This suggests that aggregation played a relatively minor role in protecting SOM from microbial decomposition in the soils we examined. Notably, silt-sized aggregation was positively correlated with clay content (Fig. 2), consistent with the well-documented influence of clay on soil aggregation (Boix-Fayos et al., 2001; Kemper and Koch, 1966; Rivera and Bonilla, 2020). Clay content is frequently incorporated into pedotransfer functions to predict aggregate stability (Wu et al., 2017). Beyond the sorption of SOM onto clay surfaces, aggregates smaller than 20 μm are thought to consist of flocculated clay particles held together by van der Waals forces, hydrogen bonding, and Coulombic interactions (Tisdall and Oades, 1982).

The observed increase in predicted SOC content with increasing Pox can be attributed to the intrinsic properties of SOM. A substantial proportion of organic phosphorus is associated with SOM (Kleber et al., 2007; Spohn, 2020). Organic phosphorus compounds, which typically contain one or more phosphate groups, exhibit a high affinity for adsorption to mineral surfaces (Spohn, 2024). Accordingly, Pox is expected to correlate positively with both SOC and Alox, which was confirmed in our study (Fig. 2, Fig. 5C). Pox also includes a fraction of inorganic phosphorus forms, often associated with Alox and Feox in acidic soils (Fransson, 2001). The combined contributions of organic and inorganic phosphorus to Pox likely explain the similar trends observed in the PDPs for Alox and Pox (Fig. 5A, C), as well as its positive correlation with SOC (ρ = 0.36; Fig. 2).

In contrast to our results, Feox content was a significant predictor in the regression models used by Salonen et al. (2024), and the sum of clay and silt contents was a significant predictor in one of their models. However, the effect of Feox was insignificant for soils with clay content smaller than 30 %. In our data, the range of clay contents was not as wide (1–52 %), and 75 % of the samples had clay contents smaller than 30 %. It is possible that the limited effects of soil texture and Feox contents in our dataset compared to Salonen et al. (2024) were due to these differences in soil texture. Another possibility is that the effects of increased surface area with increasing clay content were cancelled out by increased soil moisture. Soils with high clay content are more prone to create partially anaerobic microsites, which limits microbial degradation (Keiluweit et al., 2017; Noël et al., 2024). Also, Feox, which was positively correlated with clay content (Fig. 2), may have been affected by soil moisture. Under anaerobic conditions, Fe(III) may be reduced to Fe(II), which is a less reactive form of iron (Chen et al., 2020; Fukumasu et al., 2021). Nonetheless, our findings agreed well with previous large-scale studies (e.g., Hall & Thompson 2022; Rasmussen et al., 2018; von Fromm et al., 2025; Yu et al., 2021).

4.3. Limited influence of climate and farm management on SOC predictions compared to geochemical properties

In line with previous studies, our results show that climate variables and farm management practices were of secondary importance to geochemical properties (Doetterl et al., 2015; Van De Vreken et al., 2016). However, previous national-scale studies, which were based, at least partly, on the same data as we used, have shown that differences in farm management also led to changes in SOC contents (Henryson et al., 2022; Poeplau et al., 2015). Furthermore, the data from Eriksson (2021) showed higher SOC contents on animal farms (Table S5) due to a higher degree of pastures, regular manure application, and crop rotations that included ley. Both Poeplau et al. (2015) and Henryson et al. (2022) used SOC data from the SMP. However, unlike the method used by Poeplau et al. (2015), who conducted their analysis at the county scale, in the approach taken here, we used data from individual fields for which the farmers reported farm management data. Henryson et al. (2022) based their farm management data on the Swedish Farm Register. The data in the Swedish Farm Register are based on information on land use and the number of animals reported by farmers to the Swedish Board of Agriculture. The data on land use are uncertain due to unclear definitions (Glimskär and Skånes, 2015). It should be noted that differences in SOC content between ley-dominated rotations and other rotations were smaller for our subset compared to the complete data from Inventory III, which may explain the differences in our results (Table S5).

Climate influences both carbon inputs to soil, via its effect on net primary productivity (NPP), and the turnover of SOM (Poeplau et al., 2024; Wiesmeier et al., 2019). Yet, the complex interactions among soil physical properties, management practices, and climate introduce uncertainty in interpreting these relationships. Despite these challenges, our findings align with global-scale analyses (Jobbágy and Jackson, 2000; Hansen et al., 2023; von Fromm, 2025).

In this study, mean annual temperature (MAT) emerged as a significant predictor of soil organic carbon (SOC), with SOC decreasing as MAT increased (Fig. 3; 5F). This contrasts with Salonen et al. (2024), who observed no significant effect of MAT in a climate similar to Sweden's, likely due to the narrower MAT range in their dataset. The relationship between predicted SOC content and mean annual precipitation (MAP) was non-linear, showing an initial sharp decrease followed by a rapid increase, which is difficult to interpret (Fig. 5D). Our study would have benefited from evaluating geochemical predictors within pedoclimatically uniform sub-regions, as demonstrated by Wenzel et al. (2024). However, when MAT and MAP were integrated into the DMAI index, a general increase in predicted SOC content was observed with increasing wetness (Fig. 5C). These results suggest that higher soil moisture and lower temperature may limit microbial turnover of SOM and/or enhance NPP, thereby increasing SOC.

4.4. Assessing the SOC saturation state in Swedish agricultural soils across a humidity gradient

The partial dependence plots (PDP) show that SOC content increased gradually until it reached a plateau at higher Alox contents (Fig. 5A). A similar pattern was observed for multiple ecosystem types for the National Ecological Observatory Network dataset with sampling points across North America (Yu et al. (2021). Yu et al. (2021) suggested that this plateau indicates a potential for further SOC accrual. In other words, soils with high Alox contents may not have reached their *mineralogical capacity*. For Sweden, previous studies on the effects of changes in farm management on SOC contents have indicated that further changes should be possible if the input of SOM were increased (Eriksson, 2021; Henryson et al., 2022; Poeplau et al., 2015). It is plausible to assume that such changes should mainly occur for soils with higher Alox contents where the *ecosystem capacity* may be a limiting factor for attaining the mineralogical capacity.

Soil organic carbon content did not continue to increase with DMAI in very humid and extremely humid conditions (DMAI>53) (Fig. 5C). Aside from the limitation on C inputs, we do acknowledge other possible mechanisms that can result in the lower protection of SOC. For instance, as Alox content increases, the dominant stabilization mechanism may shift toward surface sorption, where organic molecules adsorb directly onto metal oxide surfaces from co-precipitation, providing proportionally less carbon protection per unit of metal (Wagai and Mayer, 2007). The effect of DMAI suggests a limited influence on NPP for the two wettest humidity classes. The sampling points with higher DMAI are mainly located on the west coast in the south of Sweden and in the north of Sweden. In the north, NPP is limited due to short growing seasons. At the same time, humid conditions also promote weathering, which creates new mineral surfaces that may help to stabilize SOM and decrease soil pH, leading to slower SOM turnover (Meier and Leuschner, 2010; Doetterl et al., 2015).

5. Conclusions

We found that the variations in SOC contents in Swedish agricultural soils could mainly be predicted by soil geochemistry. Especially oxalate-extractable aluminium (Alox) emerged as a key predictor. Based on these results and previous studies highlighting the importance of reactive aluminium phases in soils for SOC stabilization, we suggest that Alox measurements should be included in future soil inventories. The relationship between SOC contents and Alox suggests a potential for additional carbon storage in Swedish arable soils with large amounts of Alox. Farm management and climate variables were of secondary importance for predicting SOC contents. This study also highlights the need to explicitly include Alox in process-based models for predicting SOC storage in humid climates rather than relying solely on clay and silt content.

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Declarative statement on the use of AI-assisted technologies

During the preparation of this work, the MC used Grammarly and Perplexity in order to improve the readability and language of the manuscript. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

CRediT authorship contribution statement

Miyanda Chilipamushi: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation. **Claudia von Brömssen:** Writing – review & editing, Validation, Supervision, Software, Methodology, Formal analysis, Conceptualization. **Tino Colombi:** Writing – review & editing, Visualization, Validation, Supervision, Conceptualization. **Thomas Kätterer:** Writing – review & editing, Validation, Supervision, Investigation, Conceptualization. **Mats Larsbo:** Writing – review & editing, Visualization, Validation, Supervision, Resources, Investigation, Funding acquisition, Formal analysis, Conceptualization.

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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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Data availability

Comprehensive data from the Swedish soil and crop monitoring program are openly available at https://miljodata.slu.se/mvm/aker. The specific dataset used in this study can be made available by the authors upon request.

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