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Soil properties override climate controls on global soil organic carbon stocks

Running title: Controls on global soil carbon stocks

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Abstract

Soil organic carbon (SOC) accounts for two-thirds of terrestrial carbon. Yet, the role of soil physiochemical properties in regulating SOC stocks is unclear, inhibiting reliable SOC predictions under land use and climatic changes. Using legacy observations from 141,584 soil profiles worldwide, we disentangle the effects of biotic, climatic and edaphic factors (a total of 30 variables) on the global spatial distribution of SOC stocks in four sequential soil layers down to 2 m. The results indicate that the 30 variables can explain 70-80% of the global variance of SOC in the four layers, to which edaphic properties contribute ~60%. Soil lower limit is the most important individual soil properties, positively associated with SOC in all layers, while climatic variables are secondary. This dominant effect of soil properties challenges current climate-driven framework of SOC dynamics, and need to be considered to reliably project SOC changes for effective carbon management and climate change mitigation.

Introduction

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Soil organic carbon (SOC) represents the largest pool of terrestrial carbon (Le Quéré et al., 2016; Batjes, 2016) and plays a key role in combating climate change and ensuring soil productivity. To better manage land for maintaining SOC levels or enhancing carbon sequestration, it is vital to elucidate controlling factors of SOC stabilization and stock. As an important soil property, it is reasonable to expect that SOC might be integrally influenced by five predominant factors controlling soil development and formation; namely, climate, organisms, topography, parent materials, and time (Jenny, 1994). However, climate is usually prioritized and considered to be critical (Carvalhais et al., 2014) because of its direct effect on soil carbon inputs via photosynthetic carbon assimilation, and output via microbial decomposition. But climate-driven predictions of SOC dynamics (e.g., using Earth system models) remain largely uncertain, particularly across large extents (Todd-Brown et al., 2013; Bradford et al., 2016).

A primary source of the uncertainty is our poor understanding of how edaphic properties regulate SOC stabilization and stock in soil (Davidson and Janssens, 2006; Dungait et al., 2012). For example, SOC can be physically protected from decomposition via occlusion within soil aggregates and adsorption onto minerals (Six et al., 2000), which create physical barriers preventing microorganisms to decompose carbon sources (Doetterl et al., 2015; Schimel and Schaeffer, 2012), but how this protection influences global SOC stocks is unclear. Additionally, the soil physicochemical environment controls the supply of water, nutrients, oxygen and other resources, which are required for microbial communities to utilize SOC as well as for plant carbon assimilation to replenish soil carbon pool. Considering the large spatial variability of soil properties globally, we need to understand the edaphic controls of SOC better. By explicitly considering the effect of soil physicochemical properties, we hope to promote a review of climate-driven frameworks of SOC dynamics.

In addition to our incomplete understanding of the general importance of soil properties

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in regulating SOC stocks, whether and how their effects vary with soil depth are also unclear. Most studies focus on topsoil layers (e.g., 0–30 cm), even though globally, deeper soil layers (below 30 cm) store more carbon than topsoils (Jobbágy and Jackson, 2000; Batjes, 2016). This large subsoil SOC pool may actively respond to climate and land use changes like topsoil SOC. Studies of whole soil profiles have observed increased loss of subsoil SOC under warming (Pries et al., 2017; Melillo et al., 2017; Zhou et al., 2018) as well as under additional supply of fresh carbon (Fontaine et al., 2007). Land uses such as cropping and grazing can also induce substantial subsoil SOC losses (Sanderman et al., 2017), which is concerning because of the potential adverse effect of climate and land use changes. It is therefore imperative that we better understand the controlling factors of SOC in deep soil layers as this will help to develop unbiased strategies to manage whole-soil profile carbon effectively.

Here, we aim to disentangle the relative importance of climatic, biotic and edaphic controls on SOC stocks globally in different soil layers and identify their potential interactions among them. To do so, we assessed data from 141,584 whole-soil profiles across the globe (Fig. S1) including measurements of SOC and other soil physicochemical properties (Table S1), collated by the World Soil Information Service (WoSIS) (Batjes et al., 2017) (Table S1). For each profile, 19 climate-related covariates reflecting seasonality, intra- and inter-annual variability of climate were obtained from the WorldClim database (Fick and Hijmans, 2017), the MODIS NPP (net primary productivity) product (Zhao and Running, 2010) was used to infer apparent carbon input into the soil, and the MODIS land cover product (Channan et al., 2014) to obtain land cover information. Using these data sets, we disentangled the relative importance of biotic, climatic and edaphic covariates (a total of 30 variables, Table S1) in controlling the spatial variance in SOC stocks worldwide in four sequential soil layers (i.e., 0–20, 20–50, 50–100, and 100–200 cm), and identified the correlations between SOC stock and the most important variables.

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Materials and Methods

Observed soil profile data and harmonization

The World Soil Information Service (WoSIS) collates and manages the largest database of explicit soil profile observations across the globe (Batjes et al., 2017) which forms the foundation of a series of digital soil mapping products such as the global SoilGrids (Hengl et al., 2017). The WoSIS dataset is still growing. When we visited the dataset last on 25 March 2019, there were a total of 141,584 profiles (Fig. S1) which were used in this study. These profile observations were quality-assessed and standardized, using consistent procedures (Batjes et al., 2017). In each soil profile, multiple layers were sampled for determining SOC content and/or other soil properties. A total of 48 soil properties were recorded with multiple variates of the same property (e.g., pH measured in H_2O, $CaCl_2$, KCl etc.). In the data assessment, we excluded those soil properties apparently affected by SOC content (e.g., cation exchange capacity), and only considered 9 principal soil physicochemical properties other than SOC itself in the data analysis (Table S1). Taking the advantage of all measurements, however, other soil properties were used for missing data imputation (see the section 2.2). The layer depths are inconsistent between soil profiles. We harmonized all soil properties including SOC to four standard depths (i.e., 0–20 cm, 20–50 cm, 50–100 cm, and 100–200 cm) using mass-preserving splines (Bishop et al., 1999; Malone et al., 2009). This harmonization enables the calculation of SOC stock in the defined standard layers, making it possible to directly compare among soil profiles.

SOC stock calculation and filling missing values

We calculated SOC stock (SOC_s, kg C m^{-2}) in each standard depth as:

$$SOC_s = \frac{OC}{100} \cdot D \cdot BD \cdot \left(1 - \frac{G}{100}\right), \quad (1)$$

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where *OC* is the weight percentage SOC content in the fine earth fraction <2 mm, *D* the soil depth (i.e., 0.2, 0.3, 0.5 or 1 m in this study), *BD* the bulk density of the fine earth fraction <2 mm (kg m^{-3}), and *G* the volume percentage gravel content (> 2 mm) of soil. Amongst the 141,584 soil profiles, unfortunately, only 9,672 profiles have all the measurements of *OC*, *D*, *BD* and *G* to enable direct calculation of SOC stock. We call these profiles "stock profiles".

Another 82,734 profiles have measured *OC* (i.e., the weight percentage SOC content), but *BD* and/or *G* are missing. We call these profiles "content profiles". To utilize and take advantage of all *OC* measurements, we used generalized boosted regression modelling (GBM) to perform imputations (i.e., fill missing data). As such, SOC_s can be estimated. To do so, for *BD* and *G* in each standard soil depth, GBM was developed based on all measurements of that property (e.g., BD) in the 141,584 profiles with other 45 soil properties (*OC* and total carbon which includes organic and inorganic carbon were excluded) as covariates (i.e., predictors). The final GBM model was validated using 10-fold cross-validation repeated 10 times, and applied to predict missing values of BD and G. Table S2 shows the cross-validation statistics of the GBM for predicting BD and G in each soil depth. After all, a "SOC profiles" database including "stock profiles" and "content profile" with relevant measurements of other nine soil properties (Table S1) was obtained, and used to assess the effects of various variables on SOC_s. The prediction error of the GBM were propagated into the calculation of SOC_s to account for uncertainty resulting from data imputation.

Biotic and climatic covariates

For each "SOC profile", NPP was extracted from MODIS NPP product (Zhao and Running, 2010). The NPP product includes the annual NPP from 2001 to 2015 at the resolution of 1 km^2, which were estimated by analysing satellite data from MODIS using the global MODIS NPP algorithm (Zhao et al., 2005; Zhao and Running, 2010). NPP is the net carbon gained by plants (i.e., the difference between gross primary productivity and autotrophic respiration). If assuming a steady state of the vegetation (i.e., no long-term directional change of carbon biomass in plants), NPP will end up in soil via rhizodeposition and litter fall, and equals to total carbon input into soil. Here we calculated the average NPP based on the data from 2001 to 2015, and called this average NPP the apparent carbon input to soil, acknowledging that not all ecosystems are at the strict steady state, particularly those ecosystems (e.g., croplands) actively interact with human activities. The MODIS land cover map (Channan et al., 2014) at the same resolution of NPP databases was also used to extract the land cover information for each soil profile.

In addition to NPP and land cover type, 19 climatic variables (Table S1) for each "SOC profile" were obtained from the WorldClim version 2 (Fick and Hijmans, 2017). The WorldClim version 2 calculates biologically meaningful variables using monthly temperature and precipitation during the period 1970-2000. The data at the same spatial resolution of the NPP data (i.e., ~1 km^2) was used in this study. Eleven of the19 climatic variables are temperature-related (Table S1), and eight are precipitation-related (Table S1). These variables reflect the seasonality, intra- and inter-annual variability of climate, which would have both direct (via decomposition) and indirect (via carbon assimilation) effect on SOC stock.

Data analysis

A machine learning-based statistical model - boosted regression trees (BRT) – was performed to explain the variability of SOC_s across the globe and identify important controlling factors. A big advantage of the BRT model is its ability to model high-dimensional data set, taking into account nonlinearities and interplay (Elith et al., 2008). Using the BRT model, we modelled SOC_s in each standard depth as a function of edaphic variables in that depth, climatic and biotic variables (Table S1):

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$$SOC_s = f(edaphic, climatic, biotic). \quad (2)$$

We used a 10-fold cross-validation to constrain the BRT model in R 3.6.1 (R Core Team 2019) using algorithms implemented in the R package *dismo*. The amount of variance in SOC_s explained by the model was assessed by the coefficient of determination (R^2). To assess the potential uncertainty induced by the imputation of missing BD and G for estimating SOC_s, we conducted 200 Monte Carlo simulations. For each Monte Carlo simulation, SOC_s, if BD and G are missing, was recalculated using BD and G imputed by GBM plus an error randomly sampled from the distribution of imputation error. Using the new SOC_s estimations, then, a new BRT model was fitted.

The BRT model allows the estimation of the relative influence of each individual variables in predicting SOC_s, i.e., the percentage contribution of variables in the model. The relative influence is calculated based on the times a variable selected for splitting when growing a tree, weighted by squared model improvement due to that splitting, and then averaged over all fitted trees (Elith et al., 2008; Friedman and Meulman, 2003). As such, the larger the relative influence of a variable is, the stronger the effect on SOC_s is. To ease interpretation, the relative influence of each variable is at last scaled so that the sum is equal to 100. The overall relative influences of edaphic (i.e., the sum relative importance of all soil-related variables), climatic (i.e., the sum relative importance of all climate-related variables), as well as biotic (i.e., NPP and land cover type) variables were also calculated and compared. As we have 200 BRT estimations (i.e., 200 Monte Carlo simulations) of the relative influence, we calculated a weighted average relative influence for each variable with weights based on the R^2 of the BRT model. The partial dependence of SOC_s on individual variables was estimated for the two most important variables and the variables with a relative influence of > 10%. It reveals the marginal effect of a particular variable on SOC_s after accounting for the average effect of all other variables (Elith et al., 2008; Friedman and Meulman, 2003).

Considering the potential collinearity in the 19 climatic variables, we conducted another set of BRT modelling using their principle components. Before fitting the BRT model, a principle component analysis (PCA) was performed to eliminate potential correlations in the 19 bioclimatic variables. Only were important principal components (PCs) with variances of greater than 1retained based on Kaiser's criterion (Kaiser 1960). The PCA was performed using the function prcomp in the package stats in R 3.6.1 (R Core Team, 2019). All other settings of BRT modelling were the same to that using all 19 climatic variables. Here, it should be noted that, in terms of interpretability, the results of climatic PCs are more difficult to explain as they mask the effect and relative importance of individual climatic variables, which is one of the key questions our study aims to address and also very important to understand the role of climate variability and seasonality. So the main texts will focus on the results using all 19 individual climatic variables, if the modelling results are not markedly different from that using climatic PCs.

Results

Our results indicate that the 30 biotic, climatic and edaphic variables can explain 80%, 73%, 69%, and 73% of the variance of SOC stocks in the four soil layers across the globe, respectively (Fig. 1). This result is similar to that using four principle components representing the 19 climatic variables (Fig. S2 and S3). Edaphic variables are consistently the most important controls of SOC stocks in the four soil layers, albeit both the leading edaphic variable and relative influence of individual variables are distinct among soil depths (Fig. 2 and S4). Soil lower limit (LL15, i.e., soil water content obtained at a matric potential of 1,500 kPa) is the most important in the 0–20, 20–50, and 50–100 cm soil layers, alone contributing 34.1%, 30.5% and 29% to the explained variance, respectively (Fig. 2 and S4). In the 100–200 cm soil depth, the most important variable is sand content which alone contributes 15% to the explained variance and LL15 is the second most important contributing 8.2% to the explained variance.

The second most important parameter is the maximum temperature of warmest month (T5), contributing 11.1% to the explained variance) in the 0–20 cm layer, while NPP is the second most important in the deeper two layers (e.g., 20–50 cm and 50–100 cm), contributing 8.9% and 8% to the explained variance, respectively (Fig. 2). The individual contribution of all other variables is less than 10%, while the unique contribution of most variables is less than 5% (Fig. 2). Our predictions of bulk density (BD) and gravel content (G), which we used to estimate SOC stocks were accurate (Table S2). Hence, the uncertainty of the models to explain global SOC stocks in different soil layers was relatively small (Fig. S5).

Summing the relative importance of individual variables, the overall effect of soil properties is quite consistent among the four layers, accounting for 54.6%, 52.6%, 56.8% and 51.2% of the overall influence of all assessed variables respectively. Overall, climatic variables account for 35.6%, 37.3%, 34% and 43.3% in the four layers, respectively (Fig. 3). The two biotic variables (i.e., NPP and land cover type) overall only accounts for only 9.8%, 10.1%, 9.2% and 5.5% in the four layers, respectively (Fig. 3). Using four climatic PCs, the relative importance of edaphic, climatic and biotic variables shows the similar importance to that using 19 individual climatic variables (Fig. S6 vs Fig. 3). These results demonstrate the dominant control of soil properties on global SOC stocks.

Fig. 4 shows the marginal effects of the two most important variables controlling SOC stock after taking into account the average effects of all other predictors. Generally, SOC stock increases with LL15 in all four soil depths until reaching a plateau when LL15 is relatively high (Fig. 4A, C, E and H). In the 0–20 cm depth layer, T5 has a negative effect, particularly under warmer conditions (Fig. 4B). In cooler conditions, the effect of T5 is generally neutral. Although NPP is the second most important parameter in the middle two layers, its effect is divergent depending on NPP level (Fig. 4D and F). In the 100–200 cm depth, sand as the most important variable has negative effect on SOC stock (Fig. 4G).

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Discussion

The dominant role of soil properties

Our results demonstrate the dominant control of soil properties on SOC stocks in the whole-soil profile. Soil physical and chemical properties directly determine the activity of decomposer community which mediates the decomposition of soil carbon (Derrien et al., 2014; Foesel et al., 2014; Bernard et al., 2012). More importantly, soil carbon can be physically protected from decomposition via occlusion with soil aggregates and binding with minerals (Lehmann and Kleber, 2015; Dungait et al., 2012; Schmidt et al., 2011), while the protection capacity is largely determined by soil physiochemical properties (Six *et al.* 2000). These physical protection processes may lead to soil-dependent stabilization/destabilization of different soil carbon substrates (Waldrop and Firestone, 2004; Keiluweit et al., 2015; Six et al., 2002).

Few studies have paid particular attention to the dynamics of SOC in subsoils across large scales. We find that the overall influence of climatic variables on SOC stock is similar in all soil layers. In a forest soil, a recent study found that SOC in the whole soil profile down to 1 m is sensitive to warming (Melillo et al., 2017). This sensitivity may be general across the globe. One might expect greater importance of climate in surface soils as topsoil is at the frontline of interacting with the atmosphere. But our results do not show a clearly decreasing importance of climate with soil depth. As might be expected, however, the smallest influence of climate is in the 100–200 cm layer. Field observations are certainly needed to verify this finding as it may have significant implications on the fate of deep soil carbon under global climate warming. These results suggested that the final importance of climate for SOC storage is diluted by its effects on other controls which directly or indirectly affect SOC in opposite direction to the effect of climate, mechanistically supporting the growing appreciation that the impact of climate on SOC dynamics is overestimated.

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The importance of soil hydraulic properties and texture

Soil LL15 is consistently one of the two most important individual variables in all soil layers positively affecting SOC stock. Although SOC may have positive effect on LL15, particularly when SOC is high (Hudson 1994), more importantly, the importance of LL15 may be attributed to its effect on plant growth. Theoretically, LL15 is close to the minimal soil moisture required a plant not to wilt, it thus may strongly regulate plant growth therefore carbon inputs into soil and final SOC stock. Together with DUL (i.e., drained upper limit – soil water content obtained at the matric potential of 33 kPa), in addition, LL15 determines the available water capacity of soil (AWC, i.e., the difference between DUL and LL15) and thus LL15 would affect SOC stock indirectly via its determination on soil AWC. The available water capacity of soil is associated with water dynamics and soil porosity and thus may largely regulate oxygen availability for microorganisms to utilize SOC as well as soil thermal regimes. In addition, AWC couples with a series of soil hydrological processes such as runoff and drainage, which have direct effects on the vertical/horizontal translocation of SOC, particularly in the surface soil layer. In the 100–200 cm soil layer, soil LL15 plays a less important role, which may due to that waterlogging and low oxygen are universal in subsoil. Rather, factors influencing water and oxygen diffusion may be more important in deeper layers, such as soil texture. In line with this proposition, our results show that the overall importance of soil texture (i.e., the sum of the relative influence of clay, silt and sand contents) increases with increasing soil depth (Fig. 2).

Minor role of carbon inputs in determining spatial variability of SOC stocks

The effect of apparent carbon input, NPP, on SOC stock is small, particularly in deeper soil layers (Fig. 2). The importance of NPP may largely depend on how much NPP ends up in the soil and how it is translocated to different depths. Total NPP may not be a useful indicator of actual carbon inputs into different soil depths, particularly in deeper layers. Subsoils may be subject to greater environmental constrains than topsoils, such as water logging and low oxygen level. These environmental constrains may result in more complex SOC stabilization processes and divergent behaviour of decomposer community (Keiluweit et al., 2017), therefore diluting the effect of NPP on SOC stock in deeper soil layers. However, here we must to point out that the minor role of carbon inputs in determining the global spatial distribution of SOC stocks does not mean that they are not important for local carbon management. Under the same climatic and edaphic conditions, indeed, carbon inputs should be the predominant factor controlling if the soil is a carbon sink or source.

Uncertainties and limitations

We have used a diverse and representative dataset across the globe for the analysis, however, there are still some limitations in the datasets and assessment. First, our study did not bring land use history and intensity (such as the time length of cropping and the intensity of grazing) into the analysis, which may significantly affect SOC stabilization processes and thus SOC stocks in managed landscapes (Sanderman et al., 2017). As anthropogenic land use may change from year to year, it is challenging to accurately explain SOC stock changes in those systems that experience intensive human disturbances across large extents. Second, all soil properties including SOC were treated as constant. In reality, however, some soil properties, particularly chemical variables such as pH, may actively respond to external disturbance including human activities. Treating these variables as constant may result in under- or over-estimations of the variable importance if a variable shows marked temporal variability. Third, in managed systems, the apparent carbon input represented by NPP may not accurately reflect the real carbon input into soil (Luo et al., 2018; Pausch and Kuzyakov, 2018), leading to biased estimation of the importance of C inputs. In cropping areas, for example, yield harvesting and crop residue removal certainly reduce the fraction of NPP ending up in the soil. Finally, we would like to point out that, albeit edaphic factors appear to be the dominant controls on SOC

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stock, climate might have an impact on those edaphic factors and hence SOC stocks in the long term (Jenny 1994). Indeed, Luo *et al.* (2017) have provided evidence that climate not only directly but also directly (via its effect on edaphic factors) exerts significant effect on SOC dynamics. All these limitations should be overcome to provide more robust predictions on the role of different factors in SOC stabilization and stock, which will be particularly important for understanding long-term SOC dynamics in managed systems.

Conclusions

Quantitatively, we have demonstrated the dominant role of soil properties in regulating SOC stock in the whole soil profile at the global scale. This dominance has important implications for understanding mechanisms of SOC stabilization and destabilization. Previous modelling and experimental efforts have mostly focused on climatic and biotic aspects, and many of the studies are over smaller scales. We argue that soil physicochemical characteristics define the boundary conditions for the climatic and biotic factors. That is, climatic and biotic factors (e.g., carbon inputs) can regulate the rate of SOC of shifting from one capacity to another, but a soil's physicochemical properties may inherently determine the SOC stock capacity of soil. It is thus critical to understand how soil processes mediated by different soil properties in different soil layers respond to those climatic and biotic factors and land management practices, and feed this information into the prediction of SOC stock capacity in the whole soil profile. However, individual soil variables work together involving complex interactions and non-linear relationships with each other as well as with climate to regulate SOC stock (Fig. 3 and Table S1). We need more and better quality data (e.g., following the same soil sampling and measuring procedure and using novel approach for monitoring of soil properties) and innovative methods (Viscarra Rossel et al., 2017) for representing soil heterogeneity to facilitate robust prediction of SOC dynamics over large extents.

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Results of this study further demonstrate that globally the influence of individual climatic variables on SOC stock is weaker than the influence of individual soil properties regardless of soil depth. Current Earth system models are mostly driven by climate, with few cases have approximated the regulation of soil properties on carbon decomposability (Tang and Riley, 2014; Riley et al., 2014). We find that none of the assessed climatic variables was the most important variable (Fig. 2). Undoubtedly, climate has direct effect on plant growth and thus potential carbon inputs to the soil, but our results demonstrate that the effect of climate on SOC stock is much weaker than the effect of soil properties. Our research highlights the urgent need to consider soil properties and their interactions with climate to provide more reliable predictions of SOC stock and changes under climatic and land use changes.

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Data availability

Soil data including soil organic carbon and the considered soil properties from WOSIS are available at http://www.isric.org/explore/wosis/accessing-wosis-derived-datasets. Climate data including 19 bioclimatic variables from WorldClim are available at http://worldclim.org/version2. All other data are available from the corresponding author.

Author Contribution

Z.L. conceived the study and assessed the data. Z.L interpreted the results and wrote the manuscript with the contribution of R.V.R.

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Competing interests

The authors declare no competing interests.

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Figure Legends

Fig. 1. An example of the performance of boosted regression trees in explaining soil organic carbon stock in four standard soil depths across the globe. (A) 0–20 cm, (B) 20–50 cm, (C) 50–100 cm, and (D) 100–200 cm. The data was natural logarithm-transformed. The dashed line shows the 1:1 line. This result is one of the 200 Monte Carlo simulation results taking into account uncertainty in estimation of soil organic carbon stock. See Fig. S2 for the model performance for all 200 simulations.

Fig. 2. The relative influence of individual biotic, climatic and edaphic variables influencing global soil organic carbon stocks. The result shows the weighted average relative influence of 200 simulations. See details for the variables in Table S1.

Fig. 3. The overall relative influence of edaphic, climatic and biotic variables on soil organic carbon stock in four soil depths across the globe. The overall relative influence is calculated as the sum of the relative influence of individual variables (which is shown in Fig. 2) in each variable group (i.e., edaphic, climatic and biotic variables).

Fig. 4. Partial dependence of soil organic carbon (SOC) stock on the two most important controls. Panels from top to bottom show the results for 0–20, 20–50, 50–100, and 100–200 cm depths. Y-axes are centered over the distribution of natural logarithm-transformed SOC stock. Marks on the inside x-axis indicate the distribution of the variable in deciles. All x-axis variables are standardized. Numbers in parenthesis show the relative influence of the variable.

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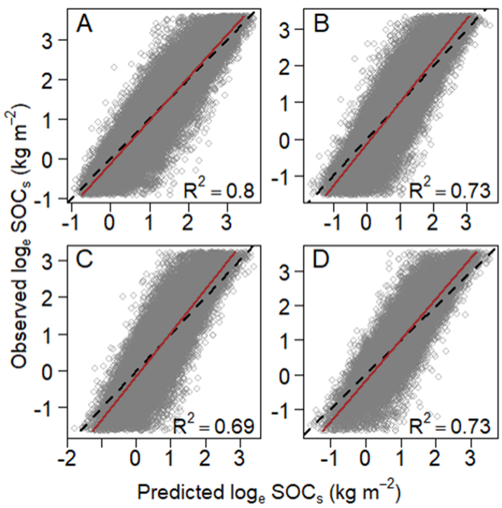
Figure 1



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478 Figure 2

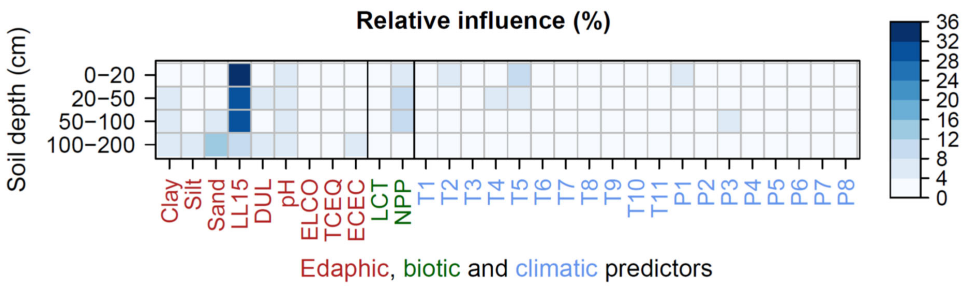

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Figure 3

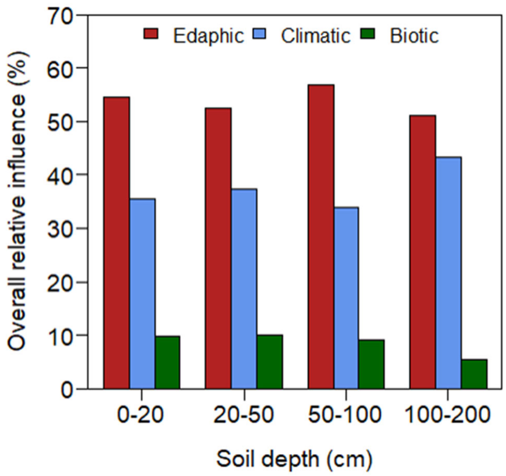

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Figure 4