Soil Organic Carbon in the Anthropocene: A Global Meta-analysis

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Abstract

Anthropogenic activities have a significant impact on soil organic carbon (SOC), affecting its contribution to ecosystem services, including climate regulation. We conducted a systematic investigation and comparison of the effect of land use changes, land management practices, and climate change on SOC in mineral and non-permafrost soils worldwide. Our review of 230 meta-analyses revealed that (i) any conversion to croplands leads to high SOC loss, which can be partially restored through land management practices, with the introduction of trees and the addition of exogenous carbon being the most effective, (ii) most land management practices that affect established forests deplete SOC, and (iii) indirect effects of climate change, such as wildfires, have a greater impact on SOC than direct effects (e.g. rising temperatures). Our study provides consolidated evidence that can assist decision-makers in safeguarding existing SOC stocks, promoting SOC-friendly agricultural practices, and guiding scientists in addressing knowledge gaps.

Keywords: meta-analysis, carbon sequestration, climate change mitigation, research synthesis, systematic review

Main

Soil organic matter (SOM), mainly composed of carbon, is a critical component of soils[1]. It plays a major role in regulating soil health[2,3] and other ecosystem services such as biodiversity conservation, and food production[4]. Moreover, it is a key contributor to the global carbon cycle and climate regulation[5]. The global soil organic carbon (SOC) stocks to 2 m of soil depth are estimated at approximately 2400 Gt C[6], which is three times the amount of carbon in the atmosphere[7]. Small changes in SOC stocks can, therefore, significantly impact atmospheric carbon dioxide levels and climate change[8,9].

Achieving global net zero CO_2 emissions by 2050 is crucial for limiting global warming to 1.5°C by the end of the century[10]. This requires avoiding, reducing, and offsetting greenhouse gas (GHG) emissions in all sectors, including the agriculture, forestry, and other land-uses (AFOLU) sector[11]. For instance, it is critical to preserve carbon-rich ecosystems like peatlands, old-growth forests, wetlands, and mangroves, which hold at least 260 Gt of 'irrecoverable' carbon[12]. On the other hand, negative emission technologies can offset excess GHG emissions[10], and natural climate solutions such as SOC restoration can play a crucial role in this process, while also offering additional benefits such as biodiversity conservation[13–15]. SOC preservation and restoration alone can contribute up to 25% of the potential of natural climate solutions, with 40% of this potential coming from SOC preservation and 60% from the restoration of depleted SOC stocks[16].

Numerous factors, herein referred to as 'drivers', directly or indirectly impact SOC levels. Land-use change is a major SOC driver at the global scale[17,18]. According to Winkler et al. (2021)[19], almost a third of the global land area has undergone land-use change in the last six decades (1960-2019). The conversion of natural ecosystems to agricultural land is estimated to have resulted in a carbon debt of 116 Gt carbon in the top 2 m soil layer[19]. For example, the conversion of primary forest to cropland caused a massive loss of SOC stocks[20]. Afforestation of cropland can partially restore these stocks[21], yet SOC restoration is generally slower than depletion. Land management is another crucial driver of SOC change, and several agricultural practices such as manure application[22], no-till farming[23,24], cover cropping[25] and agroforestry[26,27] have been proposed to increase SOC stocks[28]. Finally, climate change can also have a significant impact on global SOC stocks, by increasing SOC mineralization due to higher temperature[29], or by decreasing carbon inputs to the soil as a result of less favorable plant growth conditions linked to more variable and extreme weather events[30]. Greater efforts in land-use and land management that turn soils into future carbon sinks are therefore required[31] Thousands of experiments have investigated the impact of drivers of SOC change, and the findings are being consolidated in a growing number of meta-analyses[32,33]. Yet a comprehensive understanding of the effects of land-use change, land management, and climate change on SOC is still lacking. Each meta-analysis is restricted in its scope and often focuses on a limited number of interventions or geographical regions[34]. Furthermore, their results can be highly variable and sometimes contradictory, which to a certain extent is linked to methodological issues and the number of experiments synthesized. To gain a comprehensive and critical understanding of the drivers of SOC change and to evaluate land-use and land management options for maintaining or rebuilding SOC, a thorough and critical analysis of existing knowledge is necessary. The use of a second-order meta-analysis approach that integrates results from multiple first-order meta-analyses holds promise for enhancing statistical power by increasing sample size, while also considering the quality of the meta-analyses included. This method also allows for a more comprehensive analysis, facilitating a broader understanding of the topic. Second-order meta-analysis methods have seldom been applied to drivers of SOC change (but see Bolinder et al., 2020[35], Young et al., 2021[36], and Lessmann et al., 2020[37], on the effects of some specific interventions on SOC). A high-level synthesis of existing knowledge can facilitate evidence-based decision-making and prioritize actions to globally increase SOC[38,39]. Combined with local knowledge, it can also contribute to identifying the best practices for local implementation of SOC preservation and restoration.

Here, we conducted a comprehensive analysis that included over 220 factors of SOC change, representing the direct and indirect effects of human interventions, including land-use change (e.g., forest-to-cropland conversion), land management (e.g., mineral fertilization), and climate change (e.g., warming). Our findings are derived from 230 first-order meta-analyses (Suppl. 1), which synthesized the results of more than 25,000 papers and 190,200 paired comparison data. To select the most appropriate meta-analytical models, we evaluated the random structure of the models, the inclusion of quality scores, and the redundancy of primary studies (*see methods*). To ensure the robustness of our conclusions, we compared the estimates obtained through frequentist versus Bayesian inference methods (suppl. 2), but we present in the main text only frequentist estimates. No publication bias was detected according to the Egger's test and the trim-and-fill method (suppl 3-5). Our study considered SOC expressed as a stock (Mg C ha^{-1}) or as concentration (g C kg^{-1} soil) since the retrieved first-order meta-analyses used one of these two metrics (Supl.6).

Large yet variable impacts of land use change and land management, small and uncertain impact of climate change

Our results revealed that the overall effects of land-use change and land management on SOC were 7-10 times larger than the direct effects of climate change (i.e. excluding the indirect effects of wildfire and freeze/thaw Figure 1). Both negative and positive effects of land-use change and land management practices were found, thereby highlighting the opportunities of increasing SOC but also the risks of its depletion.

Of the 60 types of land-use change analyzed, 25% presented a decrease in SOC that was greater than 23%, while another 25% showed an increase that was higher than 16%. Among the 143 identified land management practices, 25% displayed a decrease in SOC that was greater than 4%, while another 25% presented an increase that was higher than 24%. Thus, large but at the same time highly variable impacts can be expected, with some of the considered land-use changes or land management practices proving to be highly effective in increasing SOC stocks, while others are not.

On the other hand, the direct effects of climate change (i.e. warming, drought, and CO2 enrichment) were relatively small: a 25th percentile of -2.4% SOC change and a 75th

percentile of 4.0%. The largest SOC changes were associated with the indirect effects of climate change (e.g. wildfires, snow cover decrease) (Figure 1).

The effect of land management practices varied markedly according to the land-use type: 83% of cropland management practices analyzed resulted in a significant increase in SOC, and 70% of all land management practices that lead to a significant gain in SOC occurred in croplands (Figure 2). On the other hand, in almost half of the cases where management practices were applied to forests, there was a significant decrease in SOC. Across all land-use types wetlands showed the largest decrease in SOC following management interventions (i.e. up to -60% for wetlands degradation).

Our results confirmed the high potential to rebuild SOC in croplands[40], which is, however, largely associated with the generally low initial SOC levels in croplands[17,41]. On the other hand, in the case of forest land, the challenge is to maintain SOC levels by avoiding forest conversion and degradation[13]; few solutions currently exist to increase SOC in forest lands. It should, however, be noted that there was three times less experimental data for forest land than for croplands (Figure 2). Finally, the number of studies for a given land use or land management intervention may not necessarily reflect the importance for soil carbon preservation. For example, there are relatively few studies on wetlands despite their crucial role as a major storehouse of carbon for climate change mitigation[16].

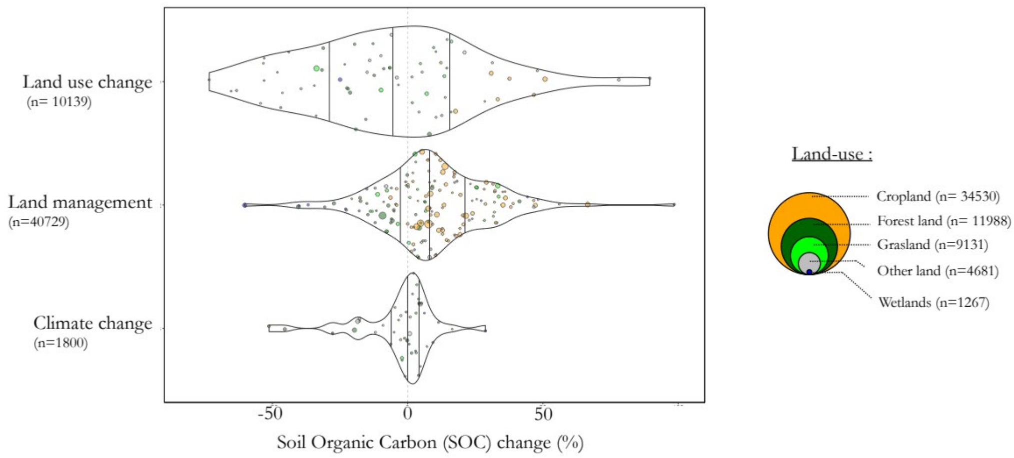

Figure 1. Distribution of soil organic carbon (SOC) change induced by land-use change, land management, and climate change. Each dot represents a mean effect of SOC change for a sub-category of each of these three main drivers per land-use type (e.g. for land management: effect of fertilization on cropland, effect of fertilization on grassland; for climate change: effect of warming on cropland, effect of an increased CO_2 concentration on grassland). Croplands are shown as orange dots, forest lands as dark green dots, grassland as light green dots, wetlands as blue dots, and other lands as gray dots. Dots of land-use change category are colored according to the initial (i.e. previous) land-use. The dot sizes are proportional to the number of paired data used to calculate the mean effect-size. Violin plots represent the distribution of values within each of the three main categories, with the 25, 50, and 75% quantiles highlighted by vertical black bars. The number of paired data ('n' in the plot) for each type of drivers and each type of land-use is shown with bubbles at the right of the plot. An interactive version of the plot is available at https://rpubs.com/dbeillouin/Figure1

The urgent need to protect carbon-rich ecosystems

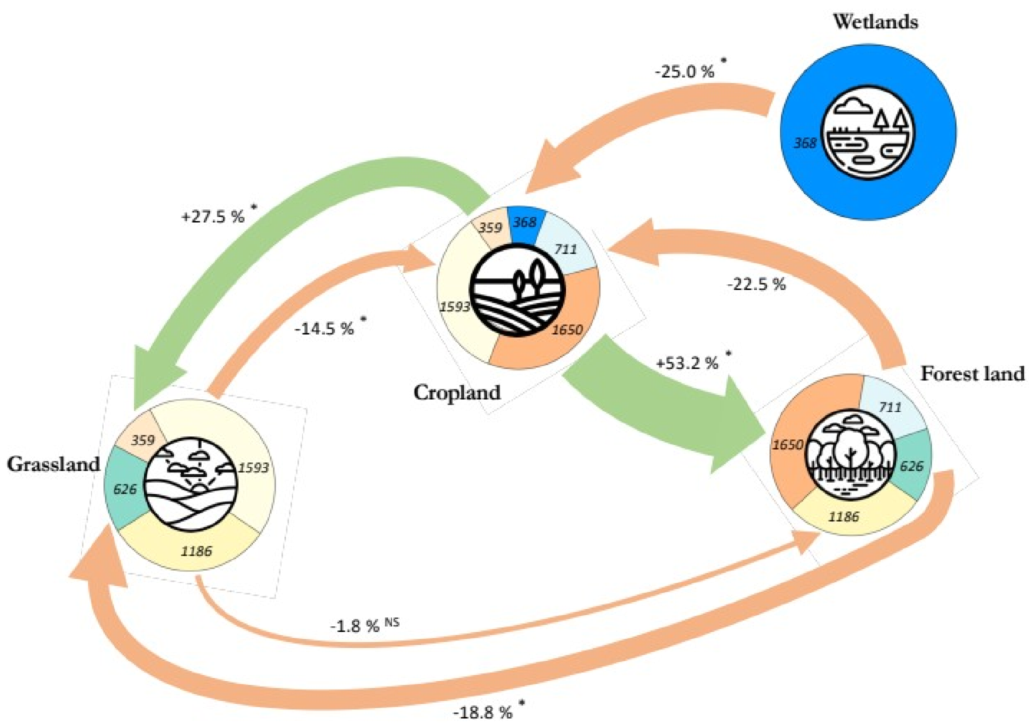

Figure 2. Impact of land-use change on soil organic carbon (SOC) in percentage change. The arrows represent the effect of a land-use change on SOC, with the final land-use on the arrowhead t side. The arrows are proportional to the SOC change, with negative effects highlighted in orange and positive effects highlighted in green. The mean SOC changes are

noted alongside the arrows. An asterisk indicates a significant effect. The numbers in the disks around each land-use represent the number of data pairs used to calculate the SOC change. Note that the mean initial SOC levels are different between the various land-uses, effect-sizes expressed in percent change should therefore be interpreted in reference to this level. Details of the information used to make this graph as well as details by sub-category of land use are available at https://rpubs.com/dbeillouin/Figure2.

Across all studies, the conversion of forest lands, grasslands, and wetlands to croplands consistently resulted in significant SOC loss, with mean values of -23% [confidence intervals (CI): -27;-17], -14% CI [-20;-9], and -25% CI [-31;-19], respectively (Figure 2). These large losses of SOC, combined with the extensive areas converted to cropland observed in the last decades (~ 1.0 million km^2 over the last 60 years[19]) have thus contributed substantially to the atmospheric CO_2 increase[2].

Our figures may, however, underestimate the actual SOC losses with regard to the conversion of forest lands because most of the underlying primary studies - and thus most of the resulting meta-analyses - quantified these losses over a period of a few years to a maximum of a few decades after conversion, whereas the time to reach a new SOC equilibrium after a land-use change is much longer (e.g. estimated to be about 80 years for grassland conversion to cropland[42]). This underlines the importance of long-term experiments and continued SOC monitoring[43]. Natural ecosystems are also known to contain more stable soil carbon stores[44], and their preservation is crucial for near-term climate change mitigation[45].

The degree of SOC loss following land conversion to croplands varied depending on the type of cropping system established, with lower SOC losses observed after forest conversion to croplands cultivated under agroforestry practices (-12%, CI [-19, -4.8]), or with perennial crops (-6.7%, CI [-14, +1.6]) compared to those cultivated with annual crops (-32%, CI [-38, -24]). Similar results were found for the conversion of grasslands to croplands, where SOC losses were higher for croplands cultivated with only annual crops (-19%, CI [-27, -10]) compared to agroforestry or the inclusion of perennial crops (+2%, CI [-6, 9] and -7%, CI [-11, -1], respectively). Introducing perennial crop species in croplands appears to be a promising approach for mitigating the negative effects of cropland expansion on SOC. Perennial crops are known to intercept higher amounts of solar radiation throughout the growing season and produce more biomass compared to annual crops[46], as well as allocate more resources to belowground plant parts and have permanent deeper root systems[47]. These characteristics make them more conducive to increase SOC compared to annual crops. In addition to their benefits for SOC accumulation, perennial crops are recognized for providing a range of other ecosystem services[48]. Yet, both the extent of SOC loss following forests or grasslands conversion to croplands and the potential mitigation effect of perennial crops depend on local pedoclimatic conditions[42,49].

The conversion of croplands to forests or grasslands resulted in significant SOC gains of +53% (CI [29,81] and +27% (CI [4;55], respectively (Figure 2). This potential for SOC increase is particularly pronounced for degraded croplands (with low SOC levels), and generally in tropical regions[50]. However, it is widely acknowledged that ecosystem restoration often fails to fully recover the functions of the undisturbed ecosystems[51,52], including soil carbon sequestration[53]. The high levels of SOC increase should therefore be interpreted with caution, as the initial levels of SOC in croplands are generally low.

Finally, the conversion of forest lands to grasslands lead to significant SOC changes (-19%, CI [-32, -2], but not the conversion of grassland to forest land: -2 CI [-16, 15]). The effect of these two types of land-use change on SOC is considered to be particularly determined by local soil and climate conditions[54].

Maximizing soil organic carbon through best land management practices

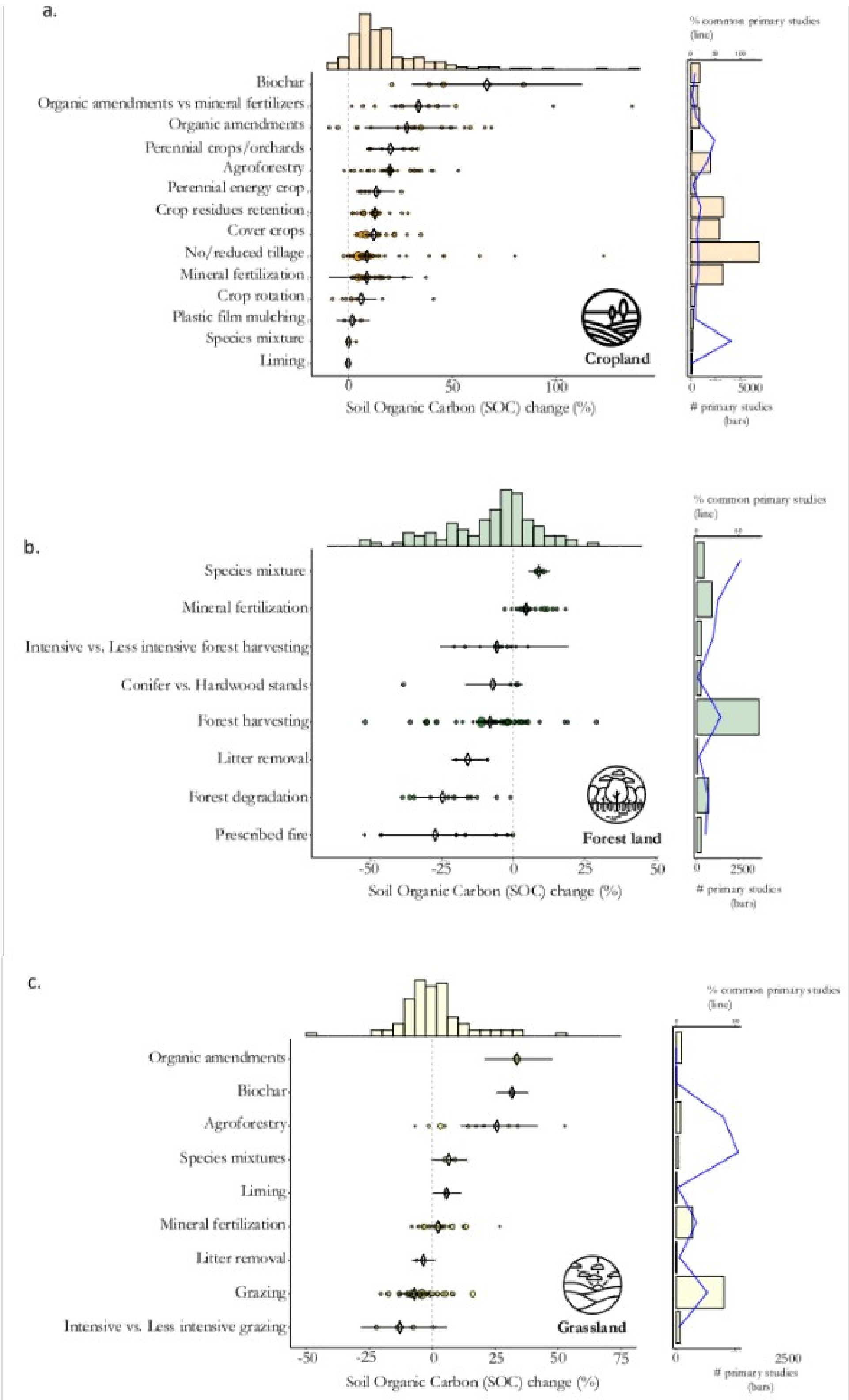

Figure 3. Impacts of various cropland (a.), forest land (b.), and grassland (c.) management practices (vs. the non-application of the management practice) on soil organic carbon (SOC) in percentage change. Diamonds and lines of the main plots represent the median summary effect and 95% confidence intervals (CIs) of the SOC change, respectively. The dot size are proportional to the number of paired data. The histograms above each of the plots represent

the probability distribution of effects for all practices combined. The barplots on the right of each main plot represent the number of data for each practice (bars) and the % of primary studies used by at least 2 meta-analyses (lines). Grazing type compares high grazing intensity versus low grazing intensity. Forest degradation includes the change of primary forest to secondary forest and secondary forest to plantation forest. Details of the information used to make this graph as well as details by sub-category of land use management are available at https://rpubs.com/dbeillouin/Figure3.

Exogenous carbon inputs to resulted in the largest increases in SOC in cropland and grassland. Biochar showing a SOC gain of +66%, CI [31, 112] in cropland and of +31% CI [26;38] in grassland. Organic amendments applied on cropland resulted in a SOC gain of +28%, CI [8, 52], and of +33% CI [20;47] in grassland (Figure 3, see details by sub-types of amendment in the online table associated to Figure 3 and in Suppl. 7). Biochar application is regarded as having a high climate change mitigation potential[55], which is supported by our findings. We also show the large variability of the effect of biochar which could probably be explained, among other factors, by very different application rates and physicochemical properties of biochars[52]. The long-lasting effects of biochar, which persists for a longer period than the biomass it is derived from, amount for most of the CO_2 removal benefits associated with its application, even when considering GHG emissions resulting from its production and handling[56]. Yet the scarcity of biomass in some regions, or competition with livestock feeding in most sub-Sahara African countries[57], can hamper the large-scale production of biochar. Besides, possible adverse effects of biochar on soil properties and biodiversity should be considered. Moreover, the extent of exogenous carbon inputs impact on climate change mitigation may be limited depending on the alternative fate of the amendments[58,59], and the availability to produce these amendments. On the other hand, enhanced soil health and plant productivity resulting from organic amendments can further increase carbon input and reinforce the positive effect on SOC. Similar mechanisms could applied for mineral fertilizers; yet, our results show that application of mineral fertilizer resulted in non-significant effect on SOC: +9% CI [-9;31] for cropland and +2 CI [-0;5] in grassland. Fertilizer input is considered by some authors as a main contributor to soil carbon sequestration (up to 70–88 Mt C yr^{-1} SOC increase globally estimated in Lessmann et al. (2022)[35]), especially in low fertile soils[60]. Interestingly, our study shows that partial or total substitution of mineral fertilization with organic amendments leads to increased SOC by +34% CI [20, 49].

Agroforestry and the use of perennial crops significantly increased SOC in croplands by +20%, CI [17, 23] and +20%, CI [9, 33], respectively. The incorporation of trees in croplands resulted in an average SOC increase of 33% CI [24;43] for multi-strata systems, 32% CI [9;60] for parklands, and 21% CI [17;23] for alley cropping, 19% CI [-5;50] for improved fallows, 17% CI [12;22] for hedgerows (see online interactive table associated to Figure 3). Growing trees in grasslands (i.e. silvopasture) also resulted in a significant SOC increase of +25%, CI [+0, 41]). The inclusion of agroforestry practices is regularly brought up by policymakers, e.g. 40% of the 147 non-Annex I countries under the Kyoto Protocol propose agroforestry as a solution in their Nationally Determined Contributions[61]. Yet much of the SOC storage potential associated with the integration of trees in croplands and grasslands occur in countries where agroforestry is not considered as a climate change mitigation option[62]. Moreover, including trees in croplands could increase competition for resources with crops and often requires supplementary nutrient inputs in the short term[63]. It is worth noting that other types of crop diversification had limited effects on SOC in croplands. For instance, crop rotation had a mean effect of 6%, CI [-1, 14], and variety mixture had a mean effect of 0%, CI [-1, 1]. Interestingly, replacing a monospecific forest with a mixture of tree species resulted in a significant 9.0% SOC increase (CI [5, 133]). The number of meta-analyses investigating some of the above-mentioned on SOC stocks is limited (e.g. the effect of mixed species forests).

Several other land management practices showed smaller but significant positive changes in SOC, including no-till farming (+9%, CI [5, 13]- see online interactive table associated to Figure 3), reduced tillage intensity (+11%, CI [+0, 24], crop residues retention (+13%, CI [10, 16]), and perennial energy crop (+13, CI [5;22]). Several of the above practices are frequently implemented in combination, such as reduced tillage, crop residue retention, and crop diversification being principles of conservation agriculture. However, the number of first-order meta-analyses dealing with these combined and more complex agricultural practices remains limited (suppl. 9). Similarly, organic agriculture could include at different levels organic amendments and crop diversification, among others. Our results indicate a large effect of this agricultural system on SOC (+35% CI [11;64]).

On the contrary, some other practices had significant negative effects on SOC, such as prescribed fire in forest land (-27%, CI [-47, -0]). Note that prescribed burning is sometimes recommended to reduce carbon losses from future potential wildfires, but its direct and indirect carbon costs (e.g. greenhouse gases emission, reduced SOC stock, …) may outweigh the benefits in emissions reduction[64]. Forest degradation (i.e. converting secondary forest to plantation; -24%, CI [-35, -13%]), forest harvesting (-8.5%, CI [-11.4, -3.2]), and forest litter removal (-16%, CI [-21, -10]), also negatively impact SOC. For grassland, grazing (i.e. intense vs. less intense grazing (-12% CI [-28;6]) and grazing vs. no grazing : -7% CI[-13;-0]) had negative impacts on SOC.

Indirect effects of climate change could have a marked negative effect on SOC

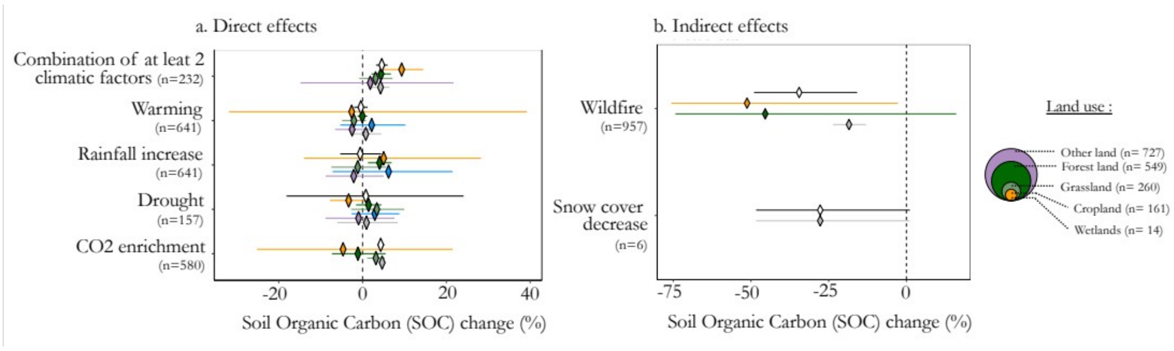

Figure 4. Impact of direct (a) and indirect effects (b) of climate change on soil organic carbon (SOC). Diamonds and lines represent the estimated median summary effect and the 95% confidence intervals (CIs) of the SOC change (%), respectively. Details of the information used to make this graph as well as details by sub-category of climate change are available at https://rpubs.com/dbeillouin/Figure4.

Direct effects of climate change such as warming, drought or rainfall increase had either uncertain and small impacts on SOC change in mineral and non-permafrost soils when analyzed individually (Figure 4). Specifically, drought did not significantly affect SOC (global effect across all land-uses type: 0.8%, CI [-18.2, +24.1]), the same was observed for warming (-0.4%, CI [-2.0, +1.2]), and rainfall increase: -0.6%, CI [-5.3, +4.4]). CO_2 enrichment, on the contrary had a significant effect for two of the four land-use type analyzed, and a mean effect of +4%, CI [3, 5]) % across all land-use.

When considered in combination, direct effects of climate change had a significant positive effect on SOC change, with a mean effect of + 4.5% [3.2; 6.0]. This effect could be driven by CO_2 enrichment, which was present in most of the combination examined. Available data on the individual and combined direct effects of climate change on SOC are, however, very limited. Further studies are needed to better understand the individual and combined effects of climate change on SOC[65], especially in the different land-use types and under different climatic conditions. This would allow to refine our understanding of the mechanisms driving SOC dynamics and develop more accurate projections of SOC changes in response to global climate change. In particular, it could be important to refine the responses of the various SOC fractions responses to climate change drivers[43] (and see suppl. 8) and the various confounding factors affecting SOC decomposition rates[66]. For example, climate change simultaneously affects SOC input through plant biomass production and SOC decomposition, e.g. warming can increase plant biomass, but also enhance decomposition[14]; elevated CO_2 can stimulate plant growth while having a weak effect on SOC decomposition[67].

On the other hand, our findings indicate that indirect effects associated with climate change, such as wildfire or snow cover decrease, may have a more substantial impact on SOC than direct climate change effects. The underlying database is, however, also very small and the results should be confirmed in further experimental studies. Note, however, that the effect of wildfire remains consistent with the large and significant impact observed for prescribed fires in forested areas (as shown in Figure 3), as well as for fires of non-classified types (as detailed in online table associated to Figure 4). These indirect effects should not be overlooked, given that, for instance, the occurrence of forest fires has doubled in the last 40 years[68] , and has notably increased in many biomes[69]. Other indirect effects of climate change, such as the impacts of flooding and the freeze/thaw effect, have yet received limited or no synthesis in existing meta-analyses.

In summary, our second-order meta-analysis, which examined more than 220 types of land-use change, management practice, or climate change that affect SOC, identified the main factors leading to SOC loss, but also options for maintaining or increasing SOC levels worldwide. Protecting natural ecosystems and introducing perennial crops in agricultural lands could efficiently preserve SOC. Efforts to preserve SOC worldwide may face local threats from the indirect effects of climate change, which appear to have a greater impact than direct effects. We have also identified key knowledge gaps that demand further research, especially in neglected areas such as wetlands and the impact of climate change on SOC. Our global second-order meta-analysis is a valuable tool for scientists conducting future research. The results, which include a ranking of the best practices to protect or increase SOC, could serve as a background reference for decision-makers on climate change mitigation. The implementation of our results in local contexts, however, must be carried out with care because of the particular pedo-climatic context and the lack of representativeness of our results in certain environments.

Methods

We conducted a second-order meta-analysis to examine the impact of drivers of SOC change, namely land-use change, land management, and climate change, across various land-use types. Our analysis synthesized the findings of 230 first-order meta-analyses on SOC that were conducted globally (see Suppl. 1 for details) on croplands, forest lands, grasslands, wetlands, and other lands. We assessed the quality of the meta-analysis and the potential overlap of primary studies between the meta-analyses to produce reliable estimates of effects. Further details on the methodological framework can be found in an associated data paper[34] and in an evidence map[33].

Systematic literature search

We conducted a systematic search for peer-reviewed meta-analyses on bulk SOC stocks or concentrations using various databases, including the Web of Science Core Collection, Scopus, CAB Abstracts, and Agricola (through the OVID platform) and the Google Scholar search engine. The search was performed on January 9th, 2020, and updated in July 2022, using the following search string : ("meta*analysis" OR "systematic review") AND ("soil organic carbon" OR "SOC" OR "soil organic matter" OR "SOM" OR "soil carbon") in 'topic words', i.e. titles, abstracts, and keyword fields. We screened the titles and abstracts of the 1,005 identified papers for their potential inclusion. To be included, a paper had to i) analyze the effect of one or several drivers on bulk SOC stock or concentration, ii) present a statistical formal analysis of at least two primary studies on SOC, iii) present indicators of precision of the effect-sizes (standard errors or confidence intervals). The full text of the studies was then independently reviewed by at least two co-authors of this study.

Data extraction and coding

All the effect-sizes of the 230 meta-analyses that met the above inclusion–exclusion criteria were extracted from the text, tables, or figures (using Plot Digitizer http://plotdigitizer.sourceforge.net/) and recorded in an Excel file. The land-use type associated with each effect-size was documented according to IPCC standards[70]. We also extracted the metrics (e.g. ratio, percentage change), possible transformations (e.g. log values), confidence intervals or other indicators of dispersion, and the number of primary studies and observations that were used to calculate the effect-sizes. The list of original studies (and their DOIs, when available) used in each meta-analysis was retrieved, thereby allowing us to identify the number of common original studies between each pair of meta-analyses. Finally, we characterized the retrieved meta-analyses by eight quality criteria related to the literature search, statistical analyses, and potential bias analysis (see Beillouin et al, 2021[34] for a precise description of the criteria). A poor methodology used to retrieve the primary study and analyze the data can indeed result in biased and misleading results[71].

Effect-sizes (and confidence intervals) expressed as standardized mean differences or percentage changes were converted into ratios to ensure the comparability of the results between the meta-analyses[72] and were then log-transformed to ensure normality. Once the models were applied, we transformed the log ratios and their associated confidence intervals and expressed them in percent change to facilitate interpretation. We then categorized the drivers of SOC change reported in the meta-analyses into three main categories: land-use change, land management, or climate change. In case a meta-analysis presented subgroup analyses, only independent effect-sizes, i.e. based on different sets of primary studies, were retained.

Pairwise meta-analysis

To estimate the effect of practices on the SOC, we tested several meta-analytical models, varying in the structure of their random effects, the inclusion or not of the quality score of the meta-analyses, and of the redundancy of the primary studies between the meta-analyses. The best model for each factor (i.e. the one whose results are presented in the main text) was then chosen based on the AIC. The most complex model is a three-level meta-analytical model, including a variance-covariance matrix considering both the precision, the quality, and the redundancy of the meta-analyses. The model is written as follows :

$$\log\left(Y_{ij}\right)=\mu+b_i+\varphi_{ij}+\varepsilon_{ij} \qquad (1)$$

$$\text{with } b_i \;\; N\left(0,\tau^2\right),\ \varphi_{ij} \;\; N\left(0,\upsilon^2\right) \text{ and } \varepsilon_{ij} \;\; N\left(0,\sigma_{ij}{}^2\right),$$

where $Y_{ij}$is the j^th^ effect-size of the i^th^ meta-analysis (one meta-analysis could present several effect-sizes), $\mu$is the mean estimated effect (i.e. diamonds in the above plots),b_i is the random effect of the i^th^ meta-analysis effect (i.e. between-cluster heterogeneity),φ_{ij} is the random effect-size effect within the i^th^ meta-analysis (i.e. within-cluster heterogeneity, and ε_{ij} is the random estimation errors associated with the j^{th} effect size of the i^{th} meta-analysis (i.e. the sampling error). Here, the clusters are represented by the meta-analyses included in our study. This three-level model implies the estimation of two heterogeneity variance parameters (here noted τ^2 and υ^2).

We weighted each effect-size by the inverse of its variance, as recommended by Marín-Martínez and Sánchez-Meca (2010) . We then reduced the weight of the lower-quality meta-analyses according to Doi et al. (2015)[73,74]. As a quality proxy, we used the percentage of the eight quality criteria met by a meta-analysis (see Beillouin et al., 2022[33] for a detailed explanation of the criteria). We also considered the non-independence between the effect-sizes of different meta-analyses by calculating a variance-covariance matrix based on a pseudo correlation between meta-analyses[75]. The proxy of the correlation between each pair of meta-analyses was estimated as $(2\times m) / (n_1+n_2)$, where m is the number of common primary studies between each pair of meta-analyses, and n_1 and n_2 represent the total number of primary studies in the two respective meta-analyses.

The other models tested corresponded to i) a model with a simplified random structure, i.e. without the between-cluster heterogeneity (b_i); ii) a three-level hierarchical model without considering the redundancy of primary studies, iii) a three-level hierarchical model without considering both the redundancy and of primary studies and the quality of the meta-analyses.

Analysis of the results and sensitivity analyses

The model results were summarized by the median as a point estimate and the 95% confidence interval as a measure of uncertainty of the point estimate. The potential publication biases were assessed with funnel plots and Egger's test[76]. The funnel plots assume that studies with high precision will be plotted near the average mean effect, and studies with low precision will be spread evenly on both sides. Egger's test gives the degree of funnel plot asymmetry as measured by the intercept from regression of standard normal deviates against precision. The sensitivity of the results against publication bias was tested with the Rosenthal fail-safe number, i.e. the number of additional studies with a mean null result necessary to provide a non-significant global estimated effect (see suppl 3-5). We also estimated the mean effect considering the missing studies based on the trim-and-fill methodology[77].

Finally, we tested the robustness of our results by comparing the results obtained using frequentist statistics and Bayesian statistics. Frequentist model parameters were estimated by maximum likelihood using the *metafor* R package[78]. For the Bayesian model, following the recommendations of Williams, Rast, and Bürkner (2018)[79], we used weakly informative prior scenarios. Specifically, the true pooled effect size prior was set to a normal distribution with a mean of 0 and a variance of 1. The variance priors of the models were set to a half Cauchy distribution with location parameter set at 0 and a scale parameter set at 0.5. The posterior distribution was approximated through Markov chain Monte Carlo (MCMC) simulation methods using Just Another Gibbs Sampler (JAGS) software (version 4.3.0) through the *brms* package[80]. The MCMC algorithm was run with three Markov chains, each including 20,000 iterations after a burn-in period of 8,000 iterations. In addition, the chains were thinned by storing one out of ten iterations to reduce autocorrelations in the subsequent sample. Convergence was assessed via three different criteria: (i) the potential scale reduction factor, $\hat{R}$, whose values must be equal or close to 1, (ii) the effective number of independent simulation draws, *neff*, which must be >100, (iii) graphically, by drawing trace plots and assessing whether the simulated values of the chains overlapped. All types of models above in the frequentist framework were also tested in a bayesian framework. The best Bayesian models for each practice were chosen through the wAIC[81]. Comparisons between frequentists and bayesian results are available in Suppl. 2.

All statistical analyses were conducted with R software (version 3.0.2), dplyr for data management, and ggplot2 for data visualization. All scripts used in this study are available in the MetaSynthesis R[82].

Contribution:

DB: Data retrieval, formal analysis, draft, review. MC: Data retrieval, draft, review. JD: Data retrieval, draft, review. DBerre: Data retrieval, review. AB: Data retrieval. AF: Data retrieval, review. FF: Data retrieval, review. RC: Data retrieval, draft, review.

Competing interests

The authors declare no competing interests.

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Data availability statement

The data are available under the repository https://doi.org/10.18167/DVN1/KKPLR8 and described in the corresponding DataPaper: Beillouin et al. 2021[34]

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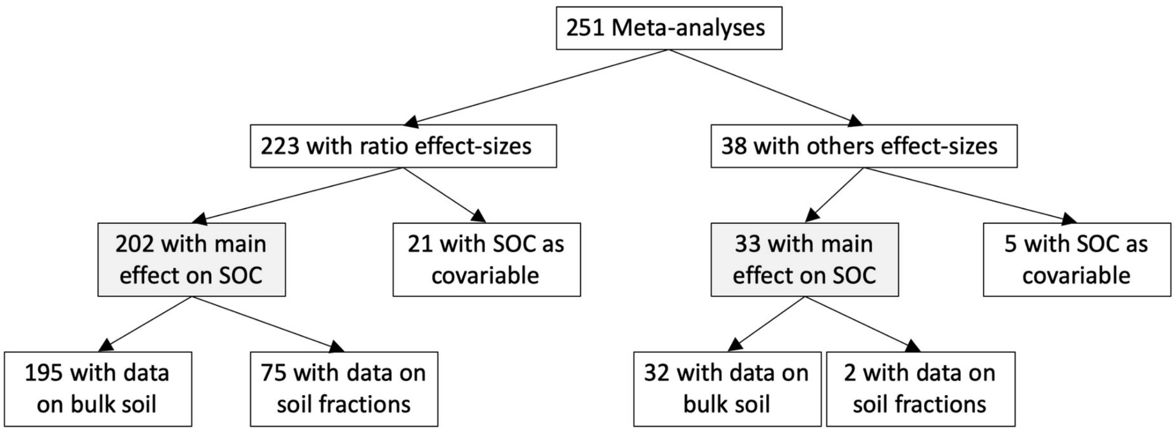
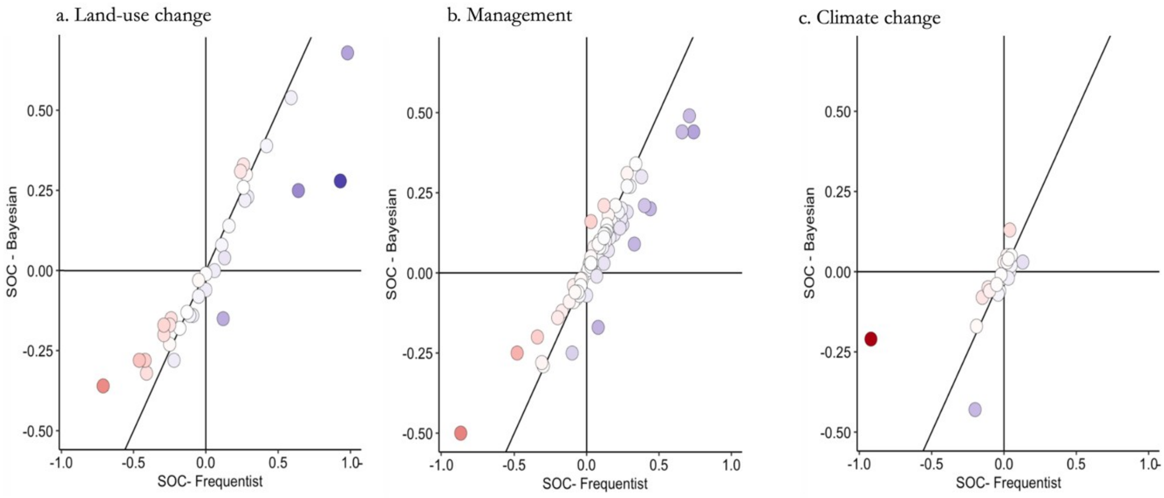
Supplementary Materials

Supplementary 1. Categorization of available meta-analyses according to the metric used to calculate the effect-size, the role of the SOC variable and the type of carbon analysed. The total number of meta-analyses with main effect on SOC is 230 (202+33 – 5 meta-analyses presenting both effect-sizes as ratio and other effect sizes).

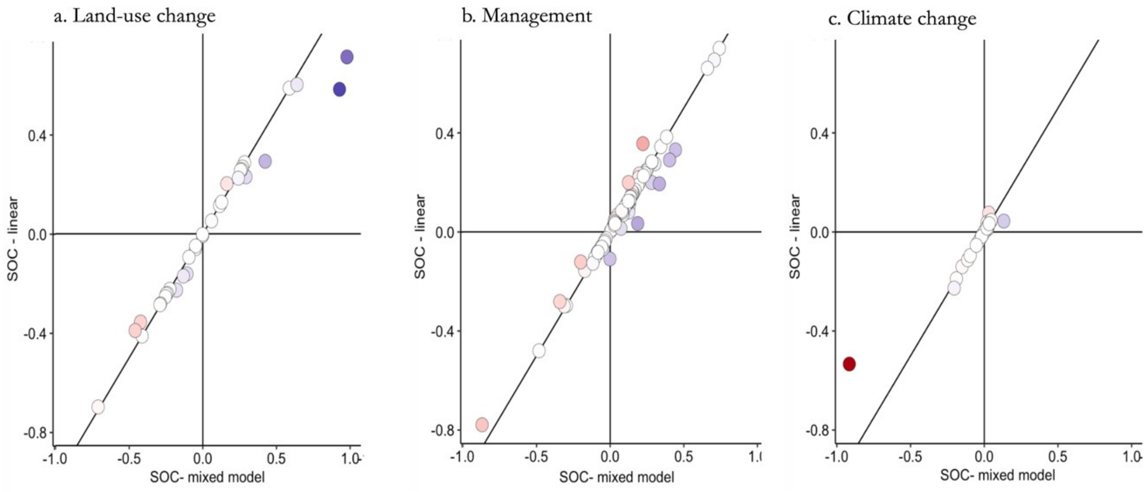


The list and characteristics of the meta-analyses is available here: https://rpubs.com/dbeillouin/List_studies

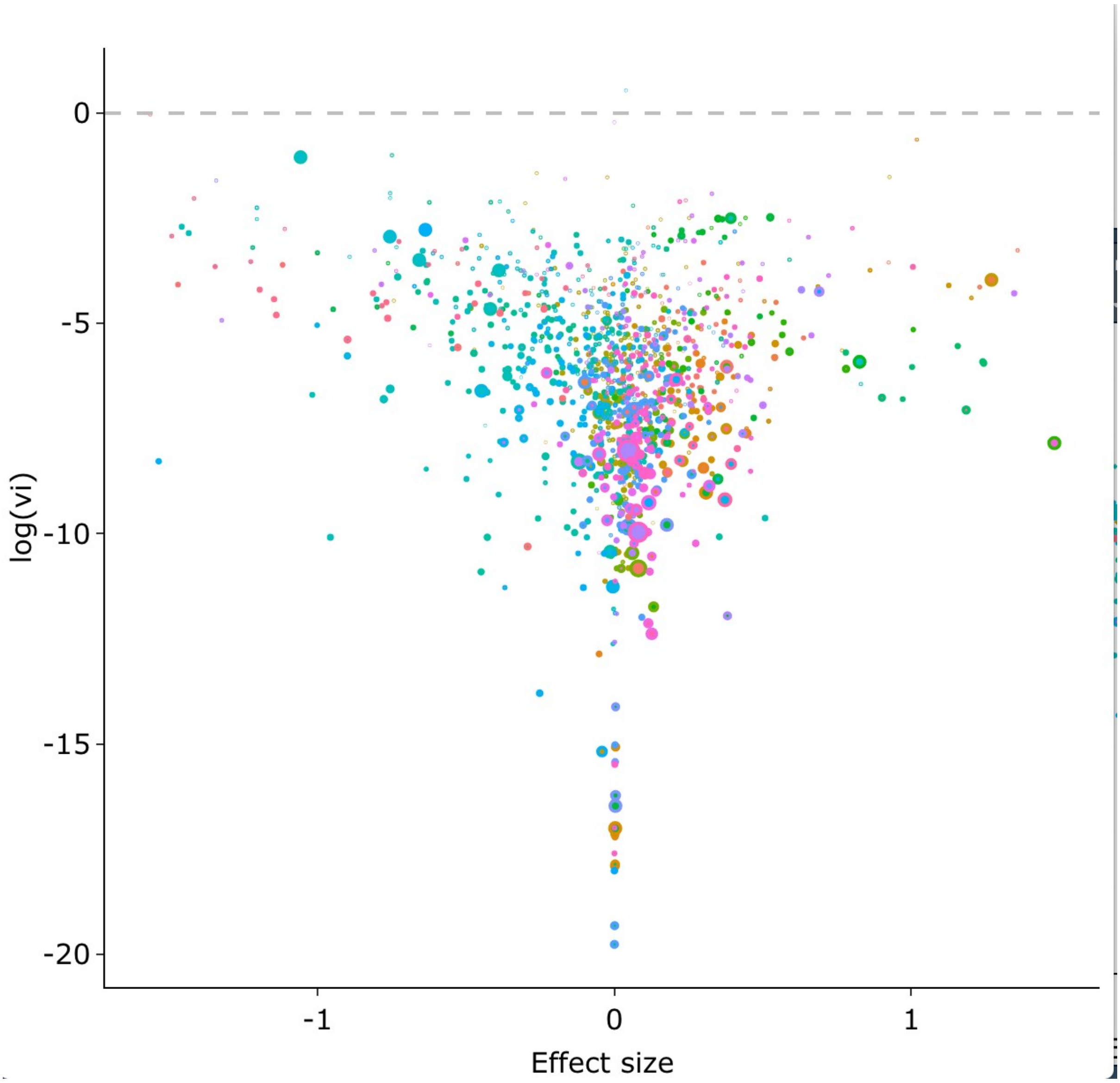
Supplementary 2. Comparisons of the results between frequentist and Bayesian inference. Best frequentist and Bayesian models were selected based on their AIC and WAIC, respectively. Each point represents a mean calculated effect-size. Colors indicate the difference between the two models.



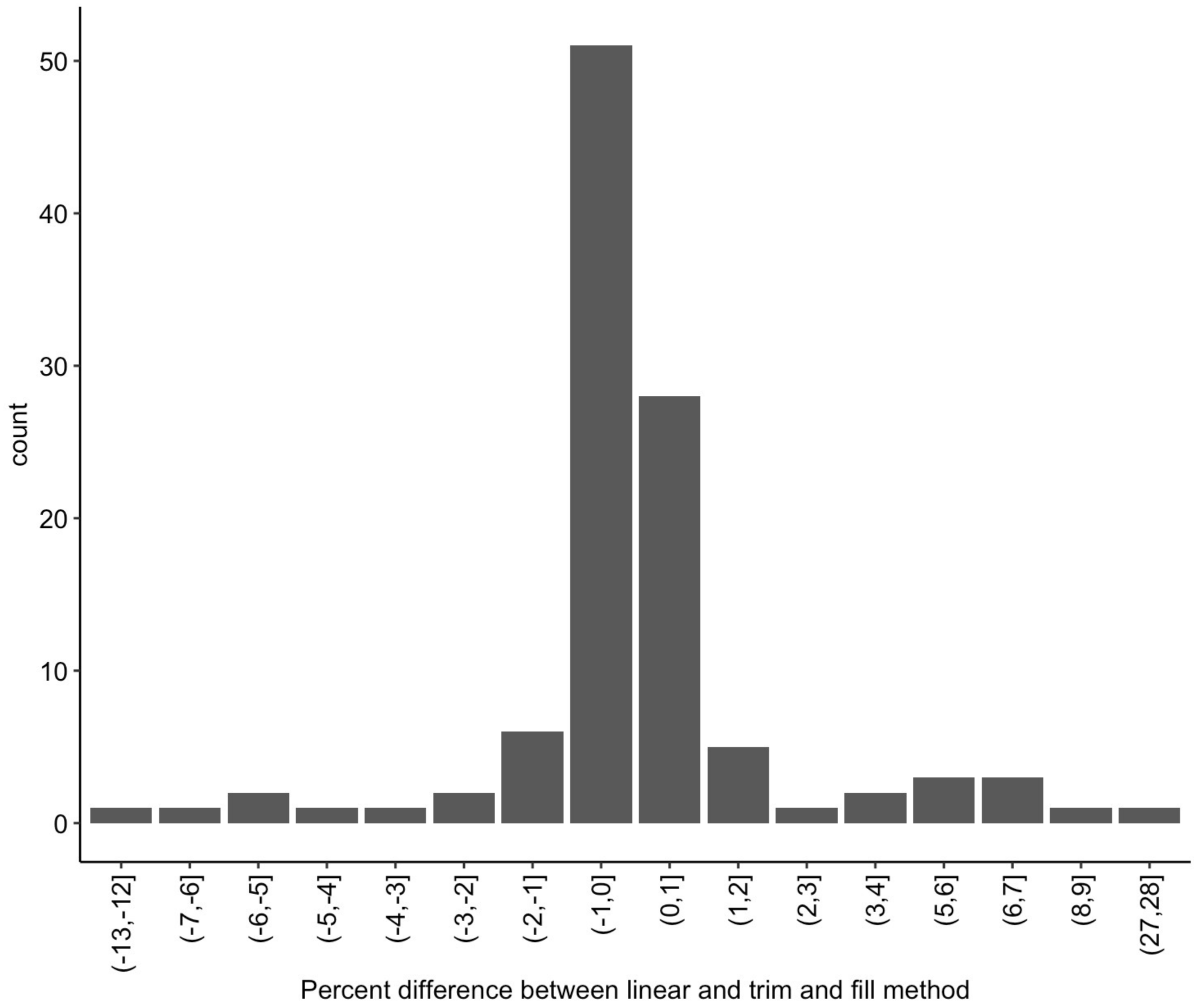
Supplementary 3. Comparisons of the results between the best frequentist mixed model (selected based on their AIC) and fixed effect model. Each point represents a mean calculated effect-size. Colors indicate the difference between the two models.



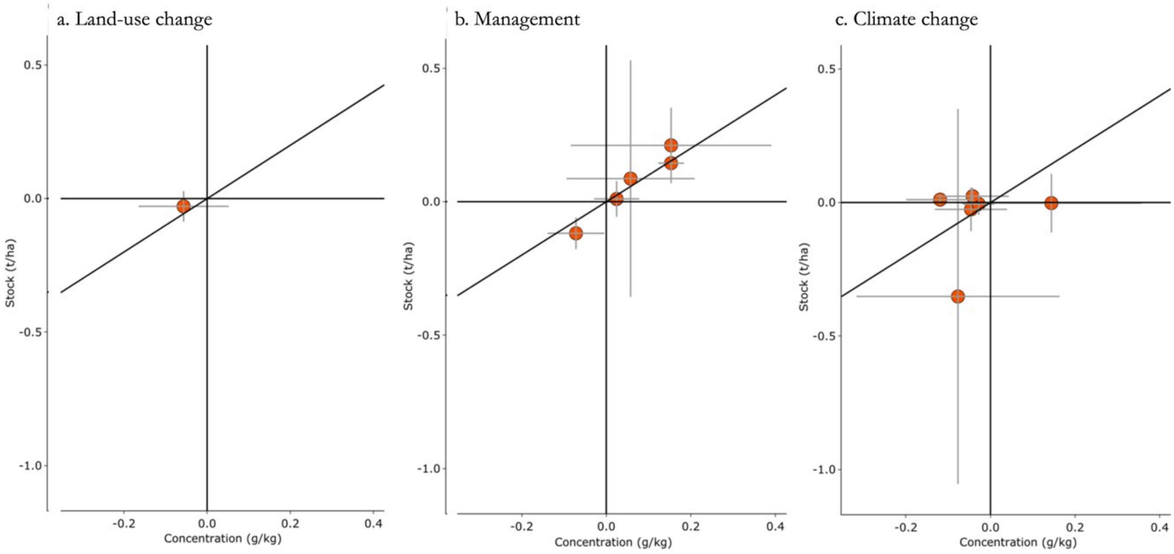
Supplementary 4. Funnel plot: Mean effect size vs. their precision for the whole database. Each point represents an effect-size. The bubble size is proportional to the number of Data. Color represent the various land-use type.



Supplementary 5. Comparison between linear and trim and fill method impact on the mean estimates.



Supplementary 6. Comparison of results (when available) between SOC Stock and SOC concentration. Only few comparisons were available to compare results between SOC stock and SOC concentration.



Supplementary 7. Details effect for various soil depth:

https://rpubs.com/dbeillouin/Supl_soil_depth

Supplementary 8. Other results available non presented in the main paper (warning; these results are obtained with a non-systematic review of the literature)

https://rpubs.com/dbeillouin/Suppl_All_effects

Supplementary 9. Results for combination of practices.
https://rpubs.com/dbeillouin/Combi_practices