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Key Points:

- Comprehensive global database advances robust estimates of land use change's (LUCs) effect on soil organic carbon (SOC) vital for Earth system modeling
- Higher initial SOC does not solely control rapid SOC loss in carbon-negative LUC as often proposed
- Despite SOC buildup in the past four decades, the amount lost cannot be regained by restoration during similar time frames

Supporting Information:

Supporting Information may be found in the online version of this article.

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Land Use Change Alters Soil Organic Carbon: Constrained Global Patterns and Predictors

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Abstract Land use change (LUC) alters the global carbon (C) stock, but our estimation of the alteration remains uncertain and is a major impediment to predicting the global C cycle. The uncertainty is partly due to the limited number and geographical bias of observations, and limited exploration of its predictors. Here we generated a comprehensive global database of 5,980 observations from 790 articles. The number of sites evaluated is at least seven times larger than in previous meta-analyses. Our constrained estimates of different LUC's effects on soil organic C (SOC) and their variations across global climates reveal underestimation/overestimation in previous estimates. Converting forests and grasslands to croplands reduced SOC by 24.5% ± 1.53% (−11.03 ± 1.06 Mg ha^{-1}) and 22.7% ± 1.22% (−8.09 ± 0.67 Mg ha^{-1}), while 28.0% ± 1.56% (4.46 ± 0.42 Mg ha^{-1}) and 33.5% ± 1.68% (5.8 ± 0.38 Mg ha^{-1}) increases, respectively, were obtained in the reverse processes. Converting forests to grasslands decreased SOC by 2.1% ± 1.22% (−1.13 ± 0.44 Mg ha^{-1}), while the reverse process increased SOC by 18.6% ± 1.73% (3.31 ± 0.51 Mg ha^{-1}). Modeled relative importance of 10 drivers of LUC's impact on SOC revealed that higher initial SOC (iSOC) does not solely determine SOC loss in SOC-negative LUC scenarios as previously proposed. Across four decades, reconverting croplands to forests and grasslands recovered only 49.5% (6.1 ± 0.51 Mg ha^{-1}) and 75.3% (7.0 ± 0.38 Mg ha^{-1}) of the iSOC, respectively, indicating the need for protecting C-rich ecosystems. Our global data set advances information on LUC's effect on SOC and can be valuable to constrain Earth system models to reliably estimate global SOC stocks and plan climate change mitigation strategies.

Plain Language Summary Land use change (LUC) could increase or decrease the global soil organic carbon (SOC) stock and affect carbon cycling and climate change, but estimating its effect size is the most uncertain aspect of the global carbon cycle. Available estimates vary among studies, most of which often use few observations that do not cover most global regions. To provide more accurate estimates of different LUC types' effects on SOC, we compiled a comprehensive database that contains 5,980 observations across all global regions; and revealed that previous studies have underestimated/overestimated these effects. We modeled the predictors of SOC change and found that previous conclusions that higher initial SOC is the main reason for higher organic carbon loss under negative LUC scenarios were inexact. We show that land use practices aimed at restoring SOC could only recover part of the amount lost during similar time frames; hence, it is important to protect carbon-rich ecosystems. Our study provides robust estimates of LUC's effect on SOC and provides data sets that can reliably assess and model the global carbon cycle and plan strategies for controlling global climate change.

1. Introduction

Since the industrial revolution (onset in 1750), land use change (LUC) has induced the loss of about 240 Pg carbon (C), representing over one-third of the total anthropogenic C loss (~685 Pg) (Canadell et al., 2021), and contributes significantly to global warming. LUC practices that promote soil organic carbon (SOC) accumulation are part of the strategies that can contribute to providing potential solutions to alleviate the current global climate change by 25% (Bossio et al., 2020). Thus, accurately estimating the global SOC dynamics across different LUC scenarios will reinforce strategies aimed at increasing/protecting SOC stocks. Comprehensive Earth system models (ESMs) have shown that from 2010 to 2019, LUC systems have induced a loss of 1.6 ± 0.7 (standard

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deviation (SD)) GtC yr^{-1} (Friedlingstein et al., 2020). The uncertainty of these estimates is a major impediment to the robust prediction of the global C balance (Arneth et al., 2017). Besides, the bias in the geographical representation, where many regions are underrepresented among studies, increases the uncertainty of the global estimates of LUC's effect on SOC. While LUC's impact on vegetation C pool can be reliably determined using global satellite-based biomass observations, its effects on SOC remain poorly estimated (Canadell et al., 2021; Sanderman et al., 2017).

Over the past decades, several attempts have been made to examine how LUC affects SOC stocks across terrestrial ecosystems (Beillouin et al., 2022; Deng et al., 2016; Guo & Gifford, 2002; Laganiere et al., 2010). These studies have generally concluded that whenever one of the LUCs decreases SOC, the reverse process usually increases SOC (Deng et al., 2016; Guo & Gifford, 2002). It is also noted that the effect of LUC on SOC varies largely among sites and is regulated by several drivers, such as the type of LUC, climate, soil depth, and soil physical and chemical characteristics (e.g., clay content) (Don et al., 2011; Paul et al., 2008). Despite these essential understandings, the global estimates of the impact of LUC on SOC still suffer from large uncertainties, with the magnitude and direction of the mean effect differing widely among studies (Ding et al., 2020; Guo & Gifford, 2002; Zhou et al., 2018). For example, the estimates of SOC change resulting from converting forests to croplands were between −11.4% and −96.5% in global meta-analyses (Harris et al., 2015; Zhou et al., 2018), and the global estimate of the reverse process ranged from 2.6% to 71.2% (Deng et al., 2016; Shi et al., 2013). Moreover, the mediators of LUC's effect on SOC are still incompletely understood, with inconsistencies in the significance of mediators among studies (Beillouin et al., 2022). For instance, mean annual precipitation (MAP) was found to be a significant predictor of SOC change when forests are converted to plantations in some meta-analyses (Guo & Gifford, 2002) but not in others (Deng et al., 2016).

The uncertainties and inconsistencies in the global estimates of LUC's effect on SOC become more apparent as several regions are underrepresented (Guo & Gifford, 2002; Powers et al., 2011). Geographic bias is common in global meta-analyses of LUC because LUC occurs globally. Still, studies on LUC are disproportionately conducted in countries and locations with more funding or internationally funded field stations (Powers et al., 2011). Despite the increasing research interest in LUC, the number for a specific type of LUC (e.g., conversion of plantation forests to grasslands) is usually too small (less than tens) to reach robust estimates of the global mean effect or detect potentially important mediators (Winkler et al., 2021). Moreover, most existing meta-analyses have estimated the effects of a specific type or group of LUC on SOC at a regional scale (Don et al., 2011; Poeplau et al., 2011), which are not directly comparable to most global estimates (Beillouin et al., 2022; Guo & Gifford, 2002; Powers et al., 2011). Thus, how SOC responds to specific LUC types across different climatic regions and in comparison to the global estimate using a comprehensive data set approach is lacking. Besides, modeling the predictors of SOC changes across different LUC scenarios will be vital for providing a deeper understanding of the regulators of global SOC dynamics. ESMs still struggle to project soil C turnover and stocks accurately (Liu et al., 2024; Todd-Brown et al., 2013), and the uncertainty in SOC stock due to LUC is one of the key aspects contributing to the lack of consensus among these models. Therefore, our data sets and observations will be vital for constraining ESMs relying on published estimates to predict the global C cycle.

Here, we generated a comprehensive global database of 5,980 observations from 2,068 sites, compiled from 790 published papers (Figure S1 in Supporting Information S1). The number of sites evaluated in our study is at least seven times larger than those in the previous meta-analyses (Tables S1 and S2 in Supporting Information S1). We examined the mean, variation, and drivers of LUC's impacts on SOC on a global scale during the last four decades. We further discriminated the variations in SOC across LUCs in the tropical, subtropical, temperate, and boreal ((sub)arctic) regions. Among the 790 published studies, 86.3% and 46.2% were published after 2000 and 2010, respectively.

2. Materials and Methods

2.1. Data Compilation and Extraction

We generated a comprehensive database on the changes in SOC stocks to different LUC scenarios. The experimental sites spread over 84 countries and spanned over 111° in latitude (46.2°S–65.1°N) (Figure 1). We included all major types of LUCs in literature, and searched for data in individual observation studies from online scientific databases and source data in previous global/regional syntheses. We included seven types of LUC: conversions between grasslands, forests, and croplands (a total of six combinations) and forest conversion to

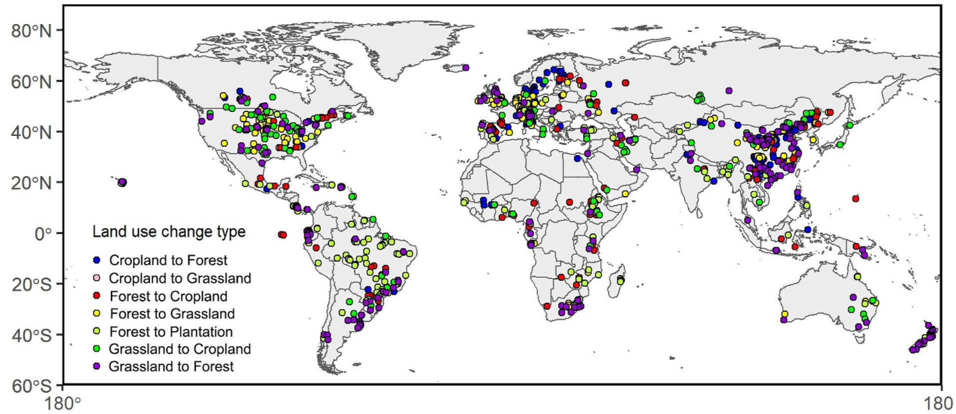

Figure 1. Locations of the experimental sites where studies on the effect of land use change on soil organic carbon stocks were collected.

plantation. We searched data from individual observation studies using keywords combination of ("LUC," "land use conversion," or "land cover change") and ("soil organic C*" or "soil organic matter") in Web of Knowledge (Web of Science), Google Scholar, and China Knowledge Resource Integrated (CNKI) Database. Moreover, we collected source data from 19 global/regional meta-analyses and review papers (Table S2 in Supporting Information S1). A PRISMA flow diagram outlining the data collection process in the year 2020 is given in Figure S1 in Supporting Information S1.

We used the following criteria to select our data. First, we included data in one of the seven LUC types listed above. Second, we included only site-level field observations and excluded regional and remote sensing data. Third, we included observations in paired-site, chronosequence, or repeated sampling studies. Both paired-site and chronosequence studies use a "space for time" method, with the assumption that the original soil states of the sites are the same. Predictions relying on space-for-time substitution have been observed to be about 72% as accurate as "time-for-time" predictions, provided the temporal and spatial variations are minimal (Blois et al., 2013; Damgaard, 2019). We conducted sensitivity analyses to test the 'space for time' hypothesis, in the two groups: paired-sites and chronosequence studies, and compared the effect sizes among the groups (Table S3 in Supporting Information S1). The results showed no significant variation in the effect size among the chronosequence and paired site across the LUC scenarios evaluated, except in the conversion of forest to grassland and its reverse process. Therefore, our assumption of space for time did not confer significant uncertainty on the data collected, except in the conversions between forest and grassland. Finally, we excluded studies that didn't report soil depth because soil depth is a key variable in calculating SOC stock and a key moderator of LUC's effect on SOC stock.

In total, we collected 5,980 observations on the effect of LUC on SOC stock from 790 published papers. The observations were derived from 84 countries covering all continents, ranging from humid tropics along the equator to arid regions such as Saudi Arabia and South Africa. Seven different LUC types were classified and investigated, which cover the most occurring LUC types over the globe (Table S1 in Supporting Information S1). Besides SOC measure and LUC type, our data also included site properties, including geographic coordinates (latitude and longitude), slope, climate variables (MAP and mean annual temperature (MAT)), vegetation type, years after LUC, and soil characteristics before LUC (bulk density (BD), pH, and clay). The search criteria used in the present study included various parameters exempted in other meta-analyses, thus increasing our data sets and reducing the uncertainties of our estimates. For example, we included observations with missing BD (53.6% of all observations), which was excluded in some previous meta-analyses (Laganiere et al., 2010). To obtain missing data in the data sets, we used WorldClim2 to extract missing MAT or MAP data. The NASA shuttle radar topographic mission DEM data was used to fill missing values of site slope with 30 m resolution with the aid of the SAGA-GIS platform (v2.1.4) (Conrad et al., 2015). Also, the SoilGrids database was used to fill in missing values of site sand and clay contents (Poggio et al., 2021). Missing values of other variables were obtained from the mean or median values of the complete data.

2.2. Estimated SOC Stocks

In cases where soil organic matter content was reported in place of SOC, SOC concentration (SOC_C) was calculated based on Guo and Gifford (2002) as follows:

$$SOC_C = SOM * 0.58 \tag{1}$$

where the values of soil BD were not available, BD was predicted from an empirical relationship between BD (g cm^{-3}) and SOC concentration (g kg^{-1}) in our database (Figure S2 in Supporting Information S1), as follows:

$$BD = 0.319 + 1.092 * e^{-0.013 * SOC_C} \tag{2}$$

The relationship between BD and SOC has been frequently used to estimate missing BD values when SOC data is available (Walter et al., 2016). Random forest modeling has shown a significantly high correlation coefficient of greater than 0.5 between soil BD and SOC content (Zihao et al., 2022).

For 76.1% of our data set, SOC concentration was directly available, thus, SOC stock (Mg ha^{-1}) was derived using:

$$SOC\ stock = SOC_C * BD * D \tag{3}$$

where D is soil depth (cm). To adjust SOC stock for an equivalent mass of soil, SOC stock after LUC (SOC $stock_{aft}$, Mg ha^{-1}) was estimated as follows:

$$SOC\ stocks_{aft} = SOC_C * BD * D + \Delta BD * \Delta V * SOC_{aft} \tag{4}$$

where ΔBD is the change in BD, which is calculated by subtracting BD before LUC from BD after LUC, ΔV is the change in soil volume (cm^3 m^{-2}), and SOC_{aft} is SOC concentration after LUC (g kg^{-1}).

2.3. Meta-Analysis

We quantified the variation in SOC stock among plots indicating the control and managed soils. The sample sizes (N) and SD LUC were used to estimate the size effect of LUC before and after conversion. Where the standard error (SE) was stated instead of the SD, we estimated the SD as follows:

$$SD = SE \times \sqrt{N} \tag{5}$$

If cases where the SD or SE were not reported, the omitted SD was derived by multiplying the provided mean by our complete database's average coefficient of variance. If the sample size (N) was not stated, it was assigned using the median of our complete database's sample size. The number of the originally extracted samples from literature, their proportion relative to the entire database, and the proportion of the filled samples are shown in Table S4a in Supporting Information S1. The WorldClim2 was used to extract missing MAT or MAP (Fick & Hijmans, 2017), while soil pH, soil clay, and sand content were filled with values derived from the SoilGrids database (Poggio et al., 2021) based on the temporal and spatial scales reported in the respective studies (Table S4b in Supporting Information S1). Validation of these site properties obtained a good fit for MAT ($R^2 = 0.76$) and MAP ($R^2 = 0.72$), but not for pH ($R^2 = 0.39$), sand ($R^2 = 0.21$), and clay contents ($R^2 = 0.17$) (Figure S3 in Supporting Information S1). Due to the coarse resolution of soil pH, soil clay, and sand contents from the global map, we filled the missing values using the multivariate imputation by the chained equations with random forests method in the "mice" package in R (van Buuren & Groothuis-Oudshoorn, 2011) and obtained improved validations (pH: $R^2 = 0.64$, clay: $R^2 = 0.55$, and sand: $R^2 = 0.57$, Figure S4 in Supporting Information S1). The validation of using the median value to fill the missing N values was done by comparing the effect sizes between three N filling methods: using the median, the mean, and randomly selected N from the complete data set. The results showed insignificant differences among these methods across the LUC scenarios (Tables S5 and S6 in Supporting Information S1).

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The effect size of the seven LUC types was weighed using the natural log-transformed response ratio (Ln(RR)) (Gurevitch et al., 2018). The key reason for log transformation is that the logarithm linearizes the metric, treating deviations in the numerator the same as deviations in the denominator. Also, the sampling distribution of the RR is skewed, and the distribution of the Ln(RR) obtained is much more normal than that of the RR (Hedges et al., 1999). The Ln(RR) was calculated by the relationship:

$$\mathrm{Ln(RR)} = \mathrm{Ln}\frac{\overline{X}_{\mathrm{t}}}{\overline{X}_{\mathrm{c}}} = \mathrm{Ln}\left(\overline{X}_t\right) - \mathrm{Ln}\left(\overline{X}_c\right) \tag{6}$$

Where $\overline{X}_t$ and $\overline{X}_c$ are the mean SOC stock after LUC and the control (before LUC), respectively.

After assigning a weight to each LUC type, the combined effect is denoted by the weighted mean across all studies. We utilized the random-effects model because study weights are more uniform (similar to one another) than under the fixed-effect model. Thus, the weighted mean response ratio ($\mathrm{Ln(RR_+)}$) of individual LUC types was estimated using:

$$\mathrm{Ln(RR_+)} = \frac{\sum_{i=1}^{m} w_i^* \times \mathrm{Ln(RR}_i)}{\sum_{i=1}^{m} w_i^*} \tag{7}$$

where m denotes the number of experiments reported for each LUC type, and w_i^* represents the weighting factor of the ith investigation in each LUC type. More generally, the variance of any study's observed score about the common mean is v_i. Therefore, the weight assigned to each LUC type under the inverse variance scheme w_i^* is:

$$w_i^* = \frac{1}{v_i^*} \tag{8}$$

where v_i^* represents the study's variance (i) across each LUC type.

Under the random-effects model, the weight assigned to each LUC under the inverse variance scheme is derived from the value of v_i^* using the relationship:

$$v_i^* = v_i + T^2 \tag{9}$$

where v_{i} is the within-study variance of study (i), and T^2 is the variance between studies. Note that the within-study error variance, v_i, is unique to each LUC, but the between-study variance T^2 is common to all LUCs. Details on the determination of T^2 can be found in Borenstein et al. (2010). The v_i in Equation 9 was calculated as follows:

$$v_i = \frac{S_t^2}{n_t\overline{X}_t^2} + \frac{S_c^2}{n_c\overline{X}_c^2} \tag{10}$$

Where S_t and S_c denote the SD of the LUC type and control groups, respectively, n_{t} and n_{c} denote the sample sizes of the LUC type and control groups, respectively. $\overline{X}_t$ and $\overline{X}_c$ are the mean SOC stock after LUC and the control (before LUC), respectively.

The SE of the weighted mean response ratio ($\mathrm{Ln(RR_+)}$) was derived using the formula:

$$s_{\mathrm{Ln(RR_+)}} = \pi\sqrt{\frac{1}{\sum_{i=1}^{m} w_i^*}} \tag{11}$$

The confidence interval (CI) for the $\mathrm{Ln(RR_+)}$ at 95% was estimated using:

$$95\%\ \mathrm{CI} = \mathrm{Ln}(\mathrm{RR}_+) + 1.96 s_{\mathrm{Ln}(\mathrm{RR}_+)} \tag{12}$$

The overall effect of each LUC type is significant if the CI at 95% does not overlap with zero (0). The effect size ($\mathrm{Ln}(\mathrm{RR}_+)$) and CI at 95% were stated as a percentage alteration from LUC before each type and were estimated using:

$$\text{Effect size }(\%) = \left(e^{\mathrm{Ln}(\mathrm{RR}_+)} - 1\right) \times 100\% \tag{13}$$

The "metafor" package was used for conducting the meta-analysis (Viechtbauer, 2010).

To estimate the absolute magnitude of SOC change across different LUCs, we converted the SOC stocks to 30 cm depth using the functions below (Jobbágy & Jackson, 2000):

$$Y = 1 - \beta^d \tag{14}$$

$$X_{30} = \frac{1 - \beta^{30}}{1 - \beta^{\mathrm{d}0}} + X_{\mathrm{d}0} \tag{15}$$

where Y denotes the quantity of SOC from the surface of the soil to a depth d (cm); β is the relative rate of reduction in SOC as the depth increases; X_{30} is the SOC stocks in the top 30 cm of the soil; d_0 represents the actual soil depth reported in the observation (cm); and Xd_0 is the actual SOC stocks. Jobbágy and Jackson (2000) showed that SOC has no significant variation ($p > 0.98$) across soil depth in different biomes or between different biomes and the average for 11 biomes globally. Therefore, we utilized the average depth distribution for soil carbon globally to estimate the value of $\beta(0.9598)$ in Equation 14.

To avoid the effect of statistical artifacts on the impact of initial SOC (iSOC) on SOC change, we corrected the regression lines among the change values of SOC and the slope derived from this regression (Slessarev et al., 2022). This approach relies on calculating the regression line between the change value (final − initial) and the initial value, and then correcting the slope derived from this regression (β^{l}) using variance estimates to generate an unbiased estimate (β). To clarify the convergence of effect size ln(RR) on SOC stocks in different LUC types, we used "meta-analyze" to synthesize estimates of the potential variation of effect size with reference to various meta-analyses published over the years. The *R* software (v4.3.2) was used for the convergence analysis and generating the corresponding graphs.

2.4. MetaForest Analysis

The relative importance of topographical features, climate variables, and soil properties in predicting the Ln(RR) in each LUC type was quantified using the *R* package "*metaforest*" in MetaForest computation. MetaForest analyses were performed following the recommendation of Viechtbauer (Viechtbauer, 2010), which includes checking model convergence, recursive pre-selection of independent variables, tuning parameters, and inspecting the results. The convergence of the original model we utilized was first checked, then moderators were pre-selected. For this purpose, we used the "*glmulti*" and "*rma.mv*" functions of the *R* package "*metafor*" to automate the fitting of all possible models containing the important predictors and their interactions. The model parameters were tuned and the final model was selected and checked for convergence. Moderators were pre-selected using a recursive algorithm with a 100-fold replicate to avoid model overfit. Model parameters were tuned using the *R* "*caret*" package (Kuhn, 2008). The model with the minimum root mean square error was chosen as our final model based on five-fold clustered cross-validation. Finally, the moderators of MAT, MAP, slope, initial SOC, initial pH, soil depth, and years were used to explain the Ln(RR) in each LUC type. For all MetaForest computations, we used the "metaforest" package for the *R* statistical language.

3. Results and Discussion

3.1. Impacts of Land Use Change on SOC

Using larger data sets, our synthesis provides more constrained and convergent estimates with significant variations in the effects of LUC on SOC than previous global meta-analyses (Figure 2, Figures S5–S8 in Supporting

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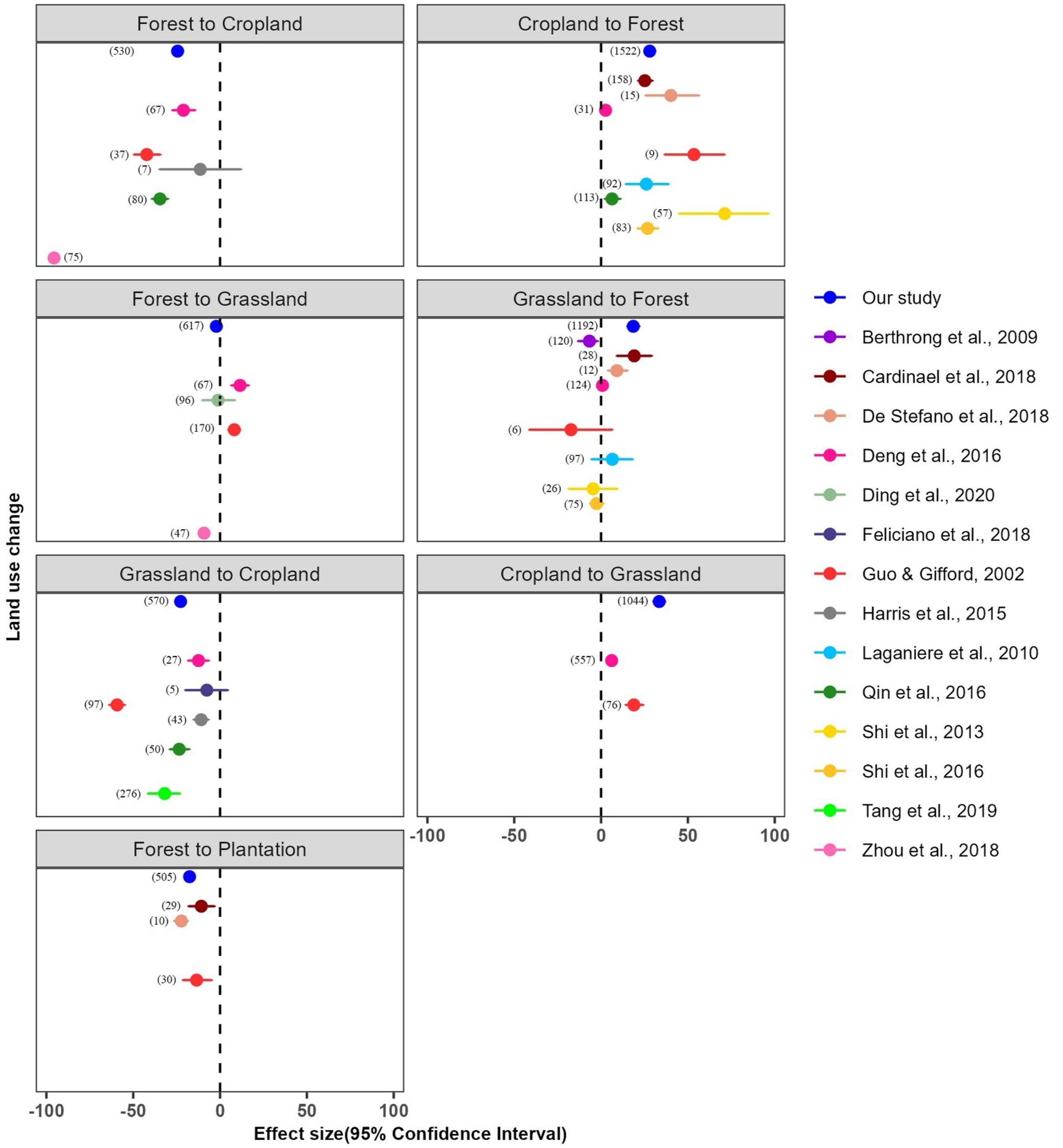

Figure 2. Effect size of land use change in soil organic carbon stocks plotted for different types comprising over 50 years of publication data. Ln(RR) joints indicate the convergence of estimated means at 95% confidence interval, (showing a reduction in uncertainty in our estimates). The numbers beside each mean point represent the sample size evaluated (as presented in Table S2 in Supporting Information S1).

Information S1). The mean estimates of previous meta-analyses (Cardinael et al., 2018; De Stefano & Jacobson, 2018; Deng et al., 2016; Ding et al., 2020; Feliciano et al., 2018; Guo & Gifford, 2002; Harris et al., 2015; Laganiere et al., 2010; Li et al., 2020; Qin et al., 2016; Shi et al., 2013, 2016; Tang et al., 2019) (Table S7 in Supporting Information S1) differed from our estimates. When the sample size is comparable between our study and previous meta-analyses (e.g., the impact of converting forest to cropland on SOC) (Deng et al., 2016; Guo & Gifford, 2002; Harris et al., 2015; Qin et al., 2016), the confidence intervals of our estimates are generally narrower than their estimates. This could be because, previous meta-analyses utilized the fixed-effect modeling approach to estimate the effect size (Qin et al., 2016), we used a random-effect modeling approach, which is theoretically more comprehensive. Also, we filled the missing values with the mean or median values of the complete data, while previous meta-analyses calculated unweighted mean due to missing SD or sample size (Guo & Gifford, 2002).

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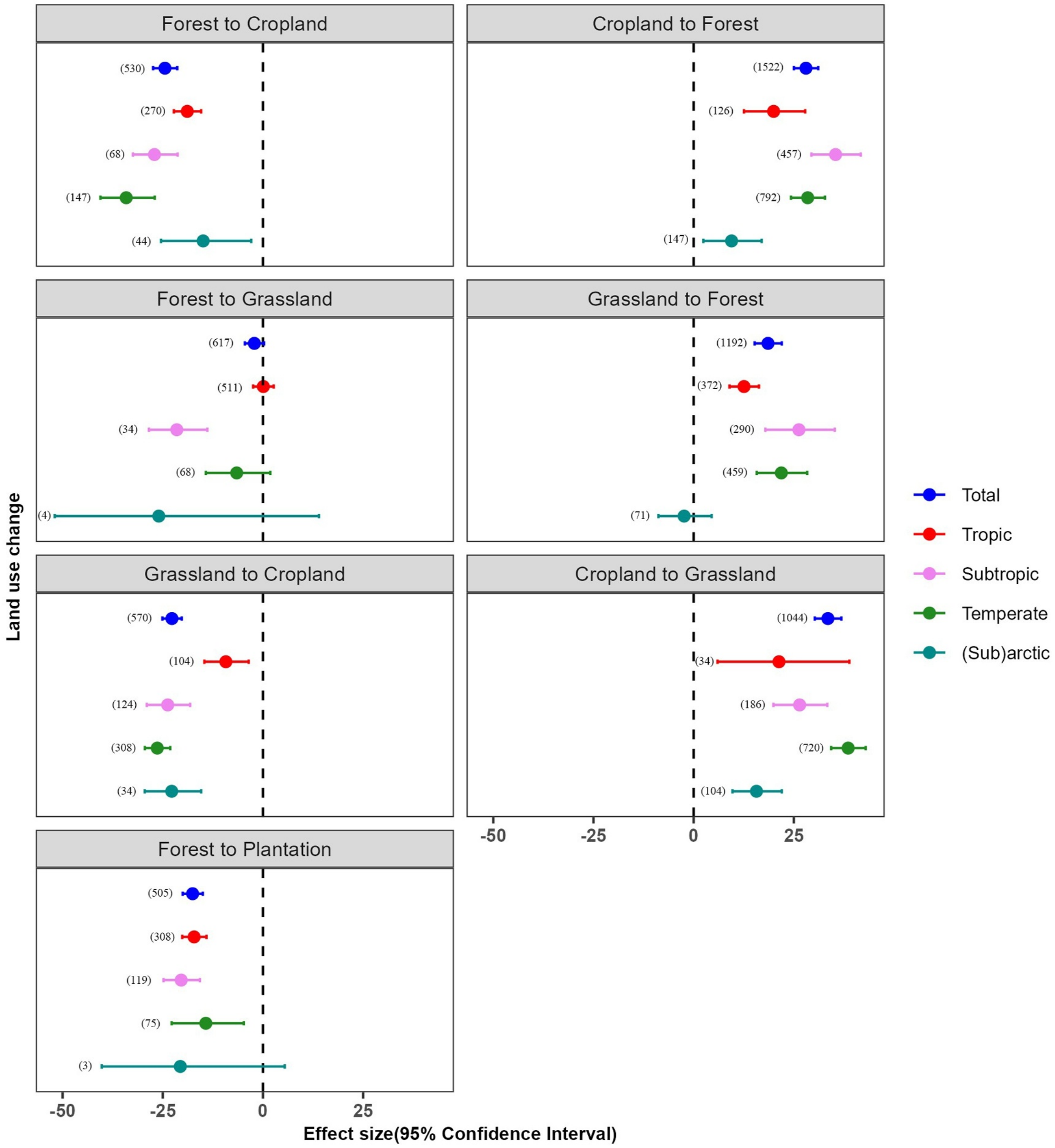

Figure 3. Relative influence and relationships of multiple variables-Ln RR (response ratio) with each land use change type across different global climatic regions. Values represent effect sizes ±95% confidence intervals. The numbers beside each mean point represent the sample size evaluated (as presented in Table S4 in Supporting Information S1 (source data)).

Globally, previous studies have indicated that the mean effects of forest lands conversion to croplands and its reverse process on SOC varied from −11.4 ± 11.96% to −95.6 ± 0.64% and from 2.6 ± 1.38% to 53.5 ± 8.78%, respectively (Deng et al., 2016; Guo & Gifford, 2002; Harris et al., 2015; Zhou et al., 2018). While our estimates (−24.5 ± 1.54% (−11.03 ± 1.06 Mg ha^{-1}) and 28.0 ± 1.55% (4.46 ± 0.42 Mg ha^{-1}), respectively) are within these ranges (Figure 3, Tables S8 and S9 in Supporting Information S1), they provide constrained estimates. We further give insights into these estimates using the variations across global climatic regions. The effect of converting forest to cropland on SOC had mean effects of −18.9% ± 1.73% (−7.4 ± 1.44 Mg ha^{-1}), −27.1% ± 2.84% (−8.44 ± 2.84 Mg ha^{-1}), −34.1% ± 3.46% (−21.51 ± 1.95 Mg ha^{-1}), and −14.9% ± 5.74% (−2.47 ± 3.56 Mg ha^{-1}) for the tropical, subtropical, temperate, and boreal regions, respectively. On the other hand, converting croplands to forests increased SOC by 20.0% ± 3.89% (4.50 ± 1.51 Mg ha^{-1}), 35.4% ± 3.14% (6.13 ± 0.77 Mg ha^{-1}), 28.5% ± 2.16% (3.97 ± 0.58 Mg ha^{-1}), and 9.5% ± 3.71% (1.81 ± 1.36 Mg ha^{-1}) in the tropical, subtropical, temperate, and boreal regions, respectively (Figure 3, Tables S4 and S5 in Supporting Information S1). The significantly higher SOC buildup in the subtropical areas after converting cropland to forest than in other regions is due to favorable climatic conditions for microbial degradation of accumulated litter (Zheng et al., 2022). In the boreal regions, SOC buildup is slow due to the limitation of microbial decomposition of litter during prolonged cold winters with low precipitation (Adamczyk, 2021) than in other regions. Our results do not only support the conclusion that conversions of grasslands and forests to croplands reduce SOC, and the reverse process increases SOC (Guo & Gifford, 2002) but also provide constrained estimates and regional variations for these changes.

Significantly positive effects of converting forest to grassland (or pasture) on SOC have been documented in previous global meta-analyses (11.5 ± 2.55%, 8.2 ± 1.71%) (Deng et al., 2016; Guo & Gifford, 2002). In contrast, a significantly negative effect (−9.2% ± 0.64%) has also been reported.However, we show that this effect is slightly negative (−2.2 ± 1.22% [−1.13 ± 0.44 Mg ha^{-1}]) and statistically non-significant. We further show that across global climatic regions, converting forests to grasslands significantly reduced SOC in the subtropical regions (−21.5% ± 3.72% [−7.69 ± 1.83 Mg ha^{-1}]), compared to 0.1% ± 1.31% (−0.43 ± 0.48 Mg ha^{-1}) and −6.6% ± 4.11% (−2.45 ± 1.31 Mg ha^{-1}) in the tropical and temperate regions. These effects remain largely uncertain in the boreal regions (Figure 3), which could be mainly attributed to the limited number of studies in this ecosystem. The high temperature, humidity, and climatic conditions in the subtropical region contribute significantly to the degradation of organic matter, hence, a more rapid reduction in SOC compared to other climatic regions (Zheng et al., 2022).

We obtained a positive effect of converting grassland to forest on SOC (18.6% ± 1.73% [3.31 ± 0.51 Mg ha^{-1}]). Such positive effects have been documented in previous global meta-analyses (9.1% ± 2.86%, 19.1 ± 5.13%) (Cardinael et al., 2018; De Stefano & Jacobson, 2018). However, a negative or statistically non-significant effect was recorded in some global meta-analyses (−17.3 ± 12.19%, 6.5 ± 6.07%) (Guo & Gifford, 2002; Laganiere et al., 2010). These unprecedented variations are attributed to regional bias and the fewer studies utilized in these reported studies. We further reveal positive mean effects of 12.6% ± 1.88% (4.86 ± 0.91 Mg ha^{-1}), 26.3% ± 4.42% (3.08 ± 1.01 Mg ha^{-1}), and 21.9% ± 3.21% (2.62 ± 0.81 Mg ha^{-1}) for tropical, subtropical, and temperate regions, respectively. However, a slightly negative and insignificant mean effect (−2.4% ± 3.39%) was obtained in the boreal regions. This could be attributed to the fact that even though the conversion of grassland to forest could increase litter fall, its decomposition into SOC in boreal forests is slow due to the freezing temperatures (Wickland & Neff, 2008).

The conversion of grassland to cropland and its reverse process on SOC (−22.7% ± 1.23% [−8.09 ± 0.67 Mg ha^{-1}] and 33.5 ± 1.69% [5.8 ± 0.38 Mg ha^{-1}], respectively) (Figure 3, Tables S8 and S9 in Supporting Information S1) provides constrained estimates than previous estimates (−7.6 ± 6.25% to −59.3 ± 2.30% and 6.1 ± 1.07% to 18.9 ± 2.58%, respectively) (Deng et al., 2016; Feliciano et al., 2018; Guo & Gifford, 2002). We further show that converting cropland to grassland has positive mean effects of 21.3% ± 8.39% (3.88 ± 2.11 Mg ha^{-1}), 26.4% ± 3.44% (6.06 ± 0.91 Mg ha^{-1}), 38.6% ± 2.19% (6.09 ± 0.46 Mg ha^{-1}), and 15.7% ± 3.14% (3.96 ± 1.21 Mg ha^{-1}) on SOC, while the reverse process reduced SOC by −9.3% ± 2.82% (−2.52 ± 1.54 Mg ha^{-1}), −23.8% ± 2.76% (−8.7 ± 1.41 Mg ha^{-1}), −26.6% ± 1.61% (−9.74 ± 0.90 Mg ha^{-1}), and −22.8% ± 3.59% (−7.82 ± 2.70 Mg ha^{-1}) in the tropical, subtropical, and temperate regions, respectively (Figure 3). In addition, we provide a more constrained estimate of the effect of converting forests to plantations on SOC (−17.5% ± 1.3%) than previous studies (−10.8% ± 3.7, −13.5% ± 4.1, −22.3% ± 7.2, respectively) (Cardinael et al., 2018; De Stefano & Jacobson, 2018; Guo & Gifford, 2002). The effect of forest conversion to plantations on SOC showed no significant variation across global regions, even as higher uncertainties exist in the (sub)arctic regions (Figure 3). Generally, the higher number of observations, narrower confidence intervals, and low standard deviations of our estimates make them robust and more reliable for estimating the global effect of different LUC scenarios on SOC stocks.

3.2. Predictors of LUC's Effect on SOC Across Four Decades

Spatio-temporal variations on how LUC affects SOC have been long recognized but still poorly understood. These variations are usually because of limited sample sizes, hence, low statistical powers to identify and compare potentially significant moderators (Powers et al., 2011). The degree of SOC loss/gain is influenced by the initial site condition, known as the "baseline effect" (Anderson et al., 2017; Badgley et al., 2022). The baseline effect has

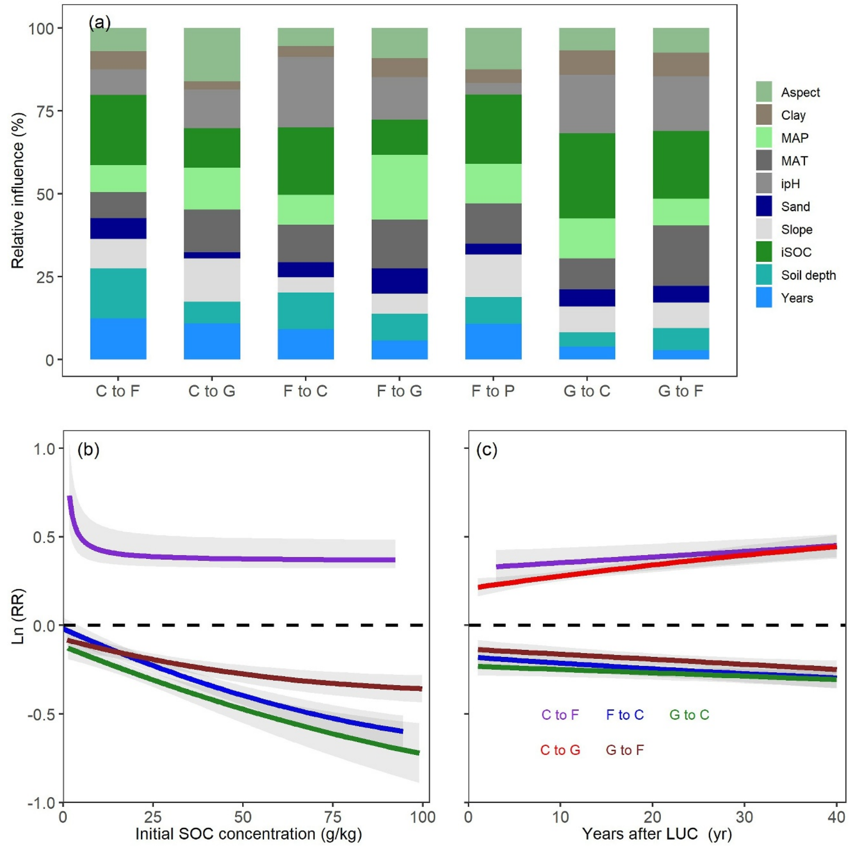

Figure 4. Relative influence and relationships of multiple variables-Ln RR (response ratio) and time with each land use change (LUC) type (a) soil and climatic properties, (b) effect of initial SOC concentration (c) years after LUC. Capital letters "C," "G," "P," and "F" indicate cropland, grassland, plantation, and forest, respectively. SOC: soil organic carbon, MAP: mean annual precipitation, MAT: mean annual temperature, ipH: initial pH, iSOC: initial SOC.

important implications for land use and management, for example, prioritizing protecting soils rich in organic C and restoring organic C-depleted soils.

Across global ecosystems, SOC loss was more accelerated in sites with higher initial SOC (iSOC) but with different magnitudes across different LUCs (Figure 4a, Figures S9–15, Tables S10 and S11 in Supporting Information S1). Thus, iSOC was observed to mainly impact the significant reduction in SOC after converting grassland and forest to cropland, as well as from grassland to forest (Figure 4b, Table S10 in Supporting Information S1). The impact of iSOC on SOC loss after converting forest and grassland to cropland supports the baseline effect of iSOC in the reduction of SOC more significantly in soils with higher SOC quantity (Goidts et al., 2009; Saby et al., 2008), and under warming conditions (Crowther et al., 2016), but not the reverse processes. Thus, less saturated SOC-poor soils have higher capacities to accumulate more SOC compared to SOC-rich soils, while soils with higher iSOC tend to lose SOC more rapidly (Cotrufo et al., 2019; Georgiou et al., 2022). However, our observation that SOC loss was high after the conversion of grassland to forest (Figure 4b) does not strictly follow the baseline effect of iSOC on SOC loss as stated above. Thus, our observations indicated that other predictors, such as environmental and soil variables, would influence the impact of iSOC and provide better explanatory powers (van Gestel et al., 2018) under such conditions.

The initial soil pH (ipH) is an important predictor of SOC change and was correlated with SOC response after the conversion of forests to croplands (Figure 4a, Figure S9, Table S11 in Supporting Information S1). Also, we observed a decrease in SOC accumulation after forests with high ipH were converted to grasslands or croplands (Figures S9 and S10, Table S11 in Supporting Information S1), but not the reverse process. Higher ipH supports the activities of more diverse microorganisms involved in utilizing organic C and CO_2 emissions (Ibrahim et al., 2022), thus reducing SOC. Besides, our results also indicate that higher ipH significantly enhances the accumulation of SOC when changing LUCs toward increasing SOC, such as from cropland to grassland (Figure S10 in Supporting Information S1) or grassland to forest (Figure S12 in Supporting Information S1). This is attributed to the increasing decomposition of abundant organic matter that builds up from litter accumulation, hence increased SOC. Soil depth significantly impacted LUC's effect on SOC in scenarios where forests were converted to cropland and the reverse process (Figure 4a). Our regression analysis indicated the potential of more SOC storage in the lower soil depths after forests or grassland were converted to cropland (Figures S9 and S13 in Supporting Information S1) but not in the reverse process (Figures S11 and S12 in Supporting Information S1). The plowing and deep burial of organic matter during land preparation would result in the integration of higher amounts of organic matter into the lower soil depths during the conversion of forests or grassland to cropland. While we show an insignificant impact of soil depth on SOC accumulation after the conversion of forest to grassland, a previous study estimated that 48% of SOC stock changes occurred below 20 cm depth after LUC from forests to grasslands (Don et al., 2011). Thus, geographical factors and the interaction of other variables could also determine the extent of SOC change, particularly after converting forests to grasslands.

Increasing MAT and MAP showed similar effects on the direction of SOC change under different LUC types (Figure S9–15 in Supporting Information S1). Temperature and precipitation often correlate similarly with changes in soil properties (Zhang et al., 2019). SOC accumulation after cropland conversion to grassland was positively correlated with MAT and MAP (Figure S12 in Supporting Information S1). These climate variables had an insignificant effect on SOC change after croplands were converted to forests (Figure S11 in Supporting Information S1). The change in SOC after the conversions between grasslands and croplands is generally more responsive to climate than between forests and croplands, probably because grasslands are more sensitive to variations in MAT and MAP than forests (Don et al., 2011; Powers et al., 2011). The reduction in SOC under SOC-negative LUC scenarios was associated with higher MAP and MAT, particularly in the tropics and the arctic regions (Figure 3). Hence, the significant global increase in SOC response ratio with increasing MAT (Figure S10 in Supporting Information S1) and MAP (Figure S9 in Supporting Information S1) after forests were converted to grassland and cropland, and the conversion of grassland to cropland, respectively was mainly associated with the tropical and arctic regions (Figure 3). Compared to other climatic regions, these two regions are often extremely affected by global change (Estrada et al., 2021; Zeng et al., 2021). We further reveal that despite the increase in SOC under SOC-positive LUC scenarios (converting cropland to grassland and forest, and grassland to forest), there was a higher SOC decomposition, hence a slower accumulation, particularly in the tropics and arctic regions compared to the subtropics and temperate regions (Figure 3). Previous studies have indicated that higher MAT is expected to accelerate SOC decomposition rates (Alvaro-Fuentes et al., 2012), while higher MAP could increase SOC mineralization and respiration by 30% (Wu et al., 2011). A major implication of our observation is that the increase in MAP and MAT in the tropics and arctic regions contributes to higher SOC decomposition than in the subtropic and temperate regions under SOC-negative LUC scenarios, while the reverse process occurs under SOC-positive LUC scenarios. An increase in MAP can lead to higher SOC losses if it coincides with higher MAT, as this combination can enhance microbial decomposition rates (Poeplau & Dechow, 2023). This phenomenon is more prominent in regions with high initial SOC levels and where increases in MAT are pronounced (Ziegler et al., 2017). An increase in MAT could also enhance evaporation, thus reducing productivity and a decrease in SOC input, while increasing SOC decomposition. On the other hand, higher MAP can be correlated with higher SOC loss rates, and the direction of its effect depends on the corresponding increase/reduction in MAT. Even though MAP has been reported to be a significant predictor of SOC change after forests were converted to plantations (Guo & Gifford, 2002), the insignificant effect obtained globally in our study (Figure 3 and Figure S15 in Supporting Information S1) and across different climatic regions is in line previous observation (Deng et al., 2016). These variations could be linked to different MATs across the reported studies. Disentangling the individual impact of precipitation from temperature has remained a challenge for ecosystem-based studies.

Soil clay content is a key moderator of LUC's effect on SOC because its mineralogy has been proposed as the key factor that explains the differences in SOC among soil types (Powers et al., 2011), likely due to its physical shield of SOC (Torn et al., 1997). Globally, we show that SOC significantly increased with clay when croplands were converted to forest (Figure S11 in Supporting Information S1) and from grassland to cropland (Figure S13 in Supporting Information S1). Aside from these, increasing soil clay content was associated with a reduction in SOC across the other LUCs evaluated (Figures S9–15 in Supporting Information S1). Although high soil clay is essential for SOC protection, its impact on SOC dynamics could be through differential chemical complexation, aggregation, or physical protection by clay (Sollins et al., 1996). Thus, our observed negative impact of increasing

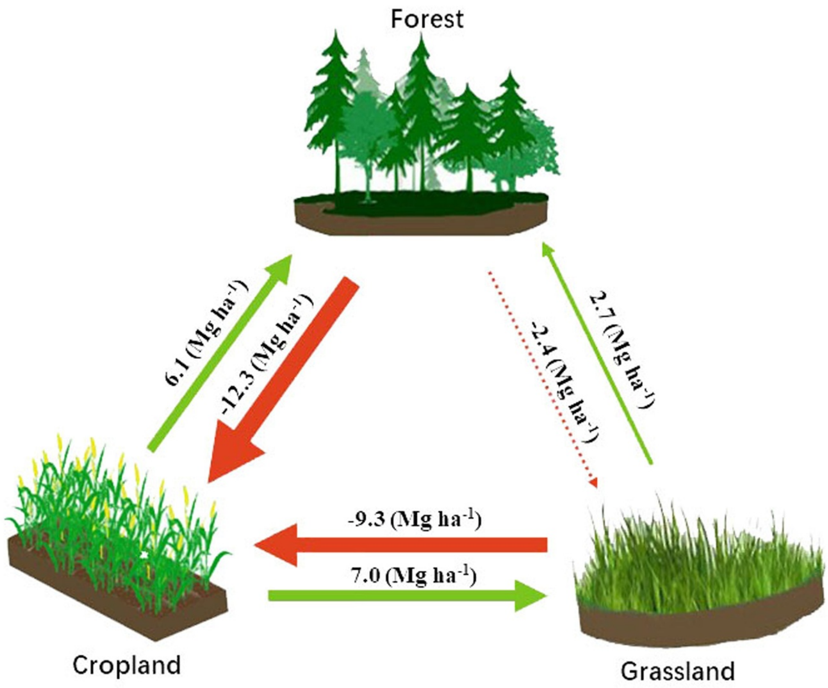

Figure 5. The absolute change of the land use changes (LUCs) on soil organic carbon (SOC) stocks in topsoil (0–30 cm) across four decades. The size of the red and green arrows indicate the magnitude of SOC loss and gain, respectively. Dotted lines indicate no significant difference ($p > 0.05$) in SOC turnover among the LUC types.

clay on SOC stock in most LUCs evaluated indicates that clay mineralogy's role in SOC protection under different LUC scenarios depends on other site-specific attributes, thus requiring more mechanistic understanding.

We show higher SOC accumulation as the slope increases in LUCs that are associated with increased SOC stock (such as converting cropland to forest and grassland) (Figures S11 and S12 in Supporting Information S1), unlike the insignificant or negative effects of the reverse process (Figures S9, S10, and S13 in Supporting Information S1). It has been well documented that steep slopes encourage rapid soil loss by erosion, which is aggravated under LUCs that remove higher soil cover (e.g., converting grassland or forest to cropland) (Bonnesoeur et al., 2019; Khormali et al., 2009). The increase in SOC at higher elevations arising from cropland conversion to grassland and forest could be attributed to a higher protection of SOC by soil covers (grassland, forest/litter) that reduce erosion and SOC loss along the slope. Our results suggest that slope can be viewed as a "diagnostic indicator" and that forest lands and grasslands at steep slopes should be protected as high priorities (Harden et al., 2018). This was the idea behind implementing projects like "the Grain for Green project" in China that required croplands having slopes of more than 25° to be converted into forest lands or grasslands (Chang et al., 2011). Based on the increasing trend of SOC in SOC restoration-based LUC scenarios in the past 4 decades (Figure 4c), the positive impact of increasing SOC to mitigate climate change seems feasible. Therefore, the positive effect size (Ln(RR)) may eventually attain a steady state when a peak C stock is reached. However, the time taken to achieve a steady SOC state will vary depending on pre-existing SOC and climatic conditions, which could take decades (Luo & Weng, 2011). Aside from increasing SOC stock under SOC-positive LUCs, the need for increasing SOC stocks in agricultural soils has also been emphasized and is the focus of the "4 per 1,000" initiative, which sets a global target of increasing annual SOC gain by 0.4% up to 0.3–0.4 m depth; even though this target has been criticized (Beillouin et al., 2022; Poulton et al., 2018).

During the past four (4) decades of LUC evaluated in our study, the positive impact of cropland conversion to grassland and forest on SOC stock maintained an increasing trend (Figure 4c). This pattern supports the dynamic disequilibrium theory that proposes the evolution of soils toward SOC accumulation at a steady state after disturbance (e.g., LUC) and global change (e.g., climate warming) (Luo & Weng, 2011). The evolution rate (i.e., SOC change rate) is proportional to the difference between SOC at steady state and actual SOC stock (Luo et al., 2017). SOC accumulation rate across 4 decades was slower than its loss along similar time scales (Figure 5).

Because of the "fast out, slow in" phenomenon, SOC restoration only recovered part of the SOC lost under the same time frame (Figure 5). SOC restoration strategies recovered only 49.5% and 75.3% of the initial SOC in topsoil (0–30 cm) after croplands were re-converted to forests and grassland, respectively (Figure 5 and Table S12 in Supporting Information S1). This indicates that twice as much C was lost from the soil through deforestation (-12.3 ± 1.10 Mg ha^{-1}, from forest to cropland) as restored by afforestation (6.1 ± 0.51 Mg ha^{-1}, from cropland to forest). Therefore, the protection of forest lands and grasslands is important not only because they store larger SOC pools, but because SOC is lost at a higher rate than it is accumulated. In many scenarios, restoring SOC to its initial levels based on climate-relevant periods is impossible (Bossio et al., 2020; Sanderman et al., 2017).

3.3. Limitations and Uncertainty of Predictions

While our data set is comprehensive and extensive, some limitations could still result in variations in LUC's effect on SOC. First, there would be the need to incorporate more drivers (e.g., soil microbial composition) to provide a more robust estimate. For example, the catalytic efficiency of microbes increases during pasture establishment, thus altering SOC content compared to long-term pastures (Tischer et al., 2015). Therefore, including microbial indicators infrequently reported in literature may improve the estimation of LUC's effect on SOC. Second, our study did not separate forest (natural forest, plantation forest, or secondary forest), grassland (e.g., natural grassland vs. pasture), and cropland into subgroups, Therefore, there is a limitation to the adequate exploration of land management effects (e.g., grazing on grassland) on SOC. Further separation of LUC types will provide additional insights into the impact of LUC on SOC. Although we searched for publications without imposing any geographic restrictions, our data sets had limited observations from some global regions such as the Tibetan Plateau, the western United States, Canada, Australia, Northern Africa, and Siberia. Thus, the certainty of our conclusions may be affected by the paucity of data sets from these regions. This indicates one of the major challenges in accurately predicting the effect of LUC on SOC on a global scale and reinforces the need for more studies in these regions. The use of a "space for time" method which assumes that the original soil states in our observations in the paired-site and chronosequence are similar was associated with significant uncertainties after forest conversion to grassland and its reverse process. This limitation could also influence the certainty of our estimates regarding this land use type. Despite these limitations, we have been able to compile a comprehensive data set that would be useful to further enhance our knowledge about the global C cycle.

4. Conclusion

By constructing a comprehensive global database, we quantified the global extent of how different LUC scenarios impact SOC stock. We further quantified the relative importance and magnitude of the key drivers of SOC under different LUC scenarios. Our results revealed a significant underestimation/overestimation of the previously reported global change in SOC after LUC. We show that higher initial SOC does not solely regulate SOC loss in SOC-negative LUC scenarios as previously proposed. Instead, a combination of predictors is needed to reliably predict SOC change, especially under SOC-negative LUC scenarios. The dynamic impact of soil properties on SOC during LUC indicated that site factors should be considered in future land use designs to better protect SOC. Due to the significant variation in the holistic global impact of LUC on SOC as compared to inter-climatic region variations observed, we propose region-specific strategies for combating SOC loss due to LUC. We further show that while the amount of SOC lost cannot be regained during the same time scale, the increasing trend of SOC accumulation under restoration scenarios could help mitigate the negative impact of climate change. Our improved data sets and constrained estimates will be an important resource for assessments and ESMs utilized to understand the global C cycle and predict future C sinks.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

The data on which this article is based are available in Huang et al. (2023).

Acknowledgments

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