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OPINION

Initial soil organic carbon stocks govern changes in soil carbon: Reality or artifact?

Eric W. Slessarev[1] | Allegra Mayer[1] | Courtland Kelly[1] | Katerina Georgiou[1] | Jennifer Pett-Ridge[1,2] | Erin E. Nuccio[1]

[1]Physical and Life Sciences Directorate, Lawrence Livermore National Laboratory, Livermore, California, USA

[2]Life and Environmental Sciences Department, University of California Merced, Merced, California, USA

Correspondence
Eric W. Slessarev, Physical and Life Sciences Directorate, Lawrence Livermore National Laboratory, Livermore, CA 94551, USA.
Email: slessarev1@llnl.gov

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Abstract

Changes in soil organic carbon (SOC) storage have the potential to affect global climate; hence identifying environments with a high capacity to gain or lose SOC is of broad interest. Many cross-site studies have found that SOC-poor soils tend to gain or retain carbon more readily than SOC-rich soils. While this pattern may partly reflect reality, here we argue that it can also be created by a pair of statistical artifacts. First, soils that appear SOC-poor purely due to random variation will tend to yield more moderate SOC estimates upon resampling and hence will appear to accrue or retain more SOC than SOC-rich soils. This phenomenon is an example of regression to the mean. Second, normalized metrics of SOC change—such as relative rates and response ratios—will by definition show larger changes in SOC at lower initial SOC levels, even when the absolute change in SOC does not depend on initial SOC. These two artifacts create an exaggerated impression that initial SOC stocks are a major control on SOC dynamics. To address this problem, we recommend applying statistical corrections to eliminate the effect of regression to the mean, and avoiding normalized metrics when testing relationships between SOC change and initial SOC. Careful consideration of these issues in future cross-site studies will support clearer scientific inference that can better inform environmental management.

KEYWORDS
carbon cycle, meta-analysis, regression to the mean, soil, soil organic matter, statistical artifact

1 | INTRODUCTION

Soils hold most of the organic carbon stored in terrestrial ecosystems (Scharlemann et al., 2014), hence relatively small changes in the amount of soil organic carbon (SOC) can have a large influence on future climate (Jones & Falloon, 2009). Furthermore, humans can directly affect SOC at a global scale. For instance, agricultural lands may have lost approximately 8% of their SOC due to cultivation over human history (Sanderman et al., 2017). Restoring a portion of this lost SOC would benefit soil fertility (Tiessen et al., 1994), and has also become a hotly debated strategy for mitigating fossil carbon emissions (Baveye et al., 2018; Paustian et al., 2016; Rumpel et al., 2020). Estimating the potential for active SOC management at global to regional scales is of broad interest to a wide range of environmental stakeholders (Oldfield et al., 2022). Regional or global scale predictions of SOC dynamics should ideally be geographically informed, identifying which underlying soil properties set the potential for SOC sequestration or loss in different environments.

A number of cross-site studies—multi-site experiments and meta-analyses—have identified a major factor that appears to govern accrual and loss of SOC: standing SOC stocks. For instance, improved agricultural management seems to enhance SOC most strongly in SOC-poor soils, while having a weakly positive—or even negative—effect on SOC in SOC-rich soils (Arndt et al., 2022; Berhane et al., 2020; Deng et al., 2016; Hübner et al., 2021; Iwasaki et al., 2017; Lessmann et al., 2022; Li et al., 2018; Minasny et al., 2017). In a different context, a prominent meta-analysis of soil warming experiments found that SOC-rich soils exhibited stronger losses than SOC-poor soils (Crowther et al., 2016, but see van Gestel et al., 2018), and several regional surveys have indicated that SOC-poor soils tend to retain SOC more readily than SOC-rich soils (Capriel, 2013; Hanegraaf et al., 2009; Riley & Bakkegard, 2006). In aggregate, these studies all point to a general pattern: that changes in SOC are often negatively related to initial SOC stocks, with SOC-poor soils gaining or retaining SOC most readily, and SOC-rich soils exhibiting weaker gains or stronger losses. This pattern may emerge because the capacity of soils to store SOC saturates due to biophysical factors, particularly the amount of silt and clay-sized minerals that protect SOC from microbial decomposers. Consequently, after accounting for the quantity and type of minerals, SOC-poor soils may on-average be farther from saturation and more likely to accrue additional SOC than SOC-rich soils (Cotrufo et al., 2019; Georgiou et al., 2022; Stewart et al., 2007).

The tendency of SOC-poor soils to gain or retain SOC more readily than SOC-rich soils appears to be widespread and has some basis in the carbon saturation concept. However, we suspect that this pattern is often exaggerated by a pair of statistical artifacts. These are: (1) a phenomenon termed regression to the mean; and (2) artifacts that result from normalizing changes in carbon by baseline carbon levels. Here, we illustrate these artifacts using simulated data and suggest more robust approaches to test the relationship between initial SOC stocks and changes in SOC going forward.

2 | REGRESSION TO THE MEAN

Regression to the mean occurs when random variation affects repeated observations. When initial observations are collected, random variation will tend to produce some extreme low or high values. When follow-up observations are collected on these extreme cases, the second observations will—more likely than not—produce less extreme values, simply because extreme values are by definition unlikely. This tendency, where extreme values tend to be followed by moderate values that "regress" to the population mean, was classically described by Francis Galton in relation to the inheritance of height in human populations (Galton, 1886). Regression to the mean is a general phenomenon that can occur when paired samples are collected sequentially or simultaneously, regardless of the distribution of a random process. For instance, it can be illustrated by simultaneously rolling two dice of different colors and subtracting the value of one die from the other across repeated trials (Figure 1a). We may safely assume that the dice rolls are independent—and yet, regression to the mean will create a negative relationship between the individual dice rolls and the difference between the rolls (Figure 1b).

Regression to the mean emerges in SOC surveys because all SOC stock estimates are affected by randomness to some degree. This is in part because the measurements required for calculating the SOC stock—carbon content, bulk density, and rock fraction—all carry significant levels of uncertainty (Goidts et al., 2009). In addition to measurement error, soil sampling is inherently random because samples

(a)

Red	Blue	Difference
1	13	12
6	13	7
14	19	5
9	15	6
20	5	−15
16	20	4
6	5	−1
6	7	1
3	20	17
6	4	−2
12	18	6
3	10	7
8	3	−5
4	18	14
...	...	...

(b)

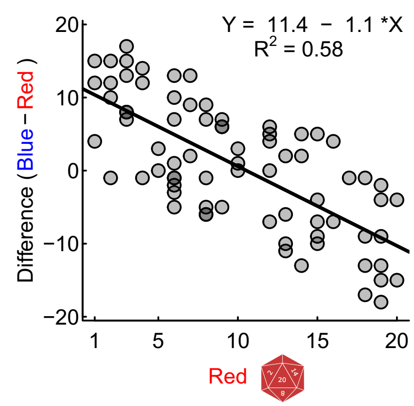

FIGURE 1 Regression to the mean illustrated with 20-sided dice. A red and a blue 20-sided dies were rolled 75 times (panel a). In panel (b), the difference (blue–red) was plotted against the red die roll. When the red die roll is high, it is most likely that the blue die roll will be lower, and so the difference (blue–red) will tend to be negative. When the red die roll is low, it is most likely that the blue die roll will be higher, and so the difference (blue–red) will tend to be positive. Consequently, random chance will generate a negative relationship between blue–red and red die rolls. In this example, the red die is analogous to an initial SOC estimate, and the blue die is analogous to a final SOC estimate. SOC, soil organic carbon.

are collected at the centimeter scale (e.g. by coring), while SOC stocks can vary substantially (10% or more) at the scale of meters (Goidts et al., 2009; Maillard et al., 2017). In combination, measurement and sampling error will inevitably cause the mean SOC stock estimate at a given site to vary randomly from one sampling campaign to the next. Increasing the number of replicate soil samples taken at a site will reduce this variation, but can never eliminate it completely.

Random variation between sampling events can explain apparent negative relationships between the initial SOC stock ($SOC_{initial}$) and change in SOC ($SOC_{final} - SOC_{initial}$; ΔSOC). Estimates of $SOC_{initial}$ that are extremely high due to chance will likely coincide with more moderate follow-up estimates, and these paired measurements will hence tend to generate low or negative values of ΔSOC. Conversely, extremely low $SOC_{initial}$ estimates will likely coincide with more moderate follow-up estimates, and will hence yield high values of ΔSOC. This pattern can develop even when samples are not taken sequentially—for instance, regression to the mean will occur in cases where SOC estimates from control plots are substituted for $SOC_{initial}$, or in cases where $SOC_{initial}$ is approximated using paired "across the fence" or chronosequence sampling designs. The process of extreme baseline values regressing to the mean during repeated sampling will on average produce the appearance that baseline SOC stocks—however, they are defined—are a control on SOC change, regardless of whether any real relationship exists.

The effect of regression to the mean on the interpretation of SOC dynamics has gone largely unnoticed to date. In a notable exception, regression to the mean was discussed in 2006 in the context of repeated soil surveys across the United Kingdom (Lark et al., 2006). These surveys initially indicated that SOC-rich soils were losing carbon, while SOC-poor soils were not (Bellamy et al., 2005), but this pattern was later partly attributed to regression to the mean (Lark et al., 2006; Potts et al., 2009). Several studies have followed the suggestion of Lark et al. (2006) by correcting for regression to the mean or at least estimating its effect size (Callesen et al., 2015; Hong et al., 2020; Saby et al., 2008; Senthilkumar et al., 2009). However, a large number of studies published since 2006 have not performed a correction when relating ΔSOC (or ΔSOC/time) to $SOC_{initial}$ or SOC in paired control plots. These studies include analyses focused on agricultural practices and land-use change (Arndt et al., 2022; Berhane et al., 2020; Deng et al., 2016; Fujisaki et al., 2018; Haddaway et al., 2017; Hübner et al., 2021; Iwasaki et al., 2017; Sun et al., 2010) but also purely observational studies (Capriel, 2013; Hanegraaf et al., 2009), and meta-analyses of warming experiments (Crowther et al., 2016; van Gestel et al., 2018). The majority of these studies found that ΔSOC and $SOC_{initial}$ are negatively related. This convergence is striking: If the patterns reported in these studies were caused by actual biological processes, this would imply that SOC-rich soils lose carbon under a wide range of conditions—including high C input scenarios (Arndt et al., 2022; Berhane et al., 2020)—while SOC-poor soils remain unchanged or gain carbon under an equally large range of conditions. However, the extent to which this pattern can be attributed to regression to the mean remains unclear. The dice example that we presented earlier (Figure 1) is an extreme case; in practice, the effect of regression to the mean might be moderated by several of factors, such as the range of initial SOC values included in the analysis, or the variance associated with site-level SOC estimates.

To explore the effect of regression to the mean in a more realistic set of scenarios, we used simulated data to replicate the error structure of a typical cross-site study (Figure 2a). To achieve this, we first created a distribution of "true" $SOC_{initial}$ values, which represented the site level mean SOC stocks across a set of hypothetical sites ($n = 200$). We generated these data by randomly drawing a set of 200 values from a lognormal distribution with a mean value of 30 tC ha^{-1}, which is roughly representative of the distribution of $SOC_{initial}$ values featured in several cross-site studies (Arndt et al., 2022; Berhane et al., 2020; Sun et al., 2010). We varied the width of the distribution

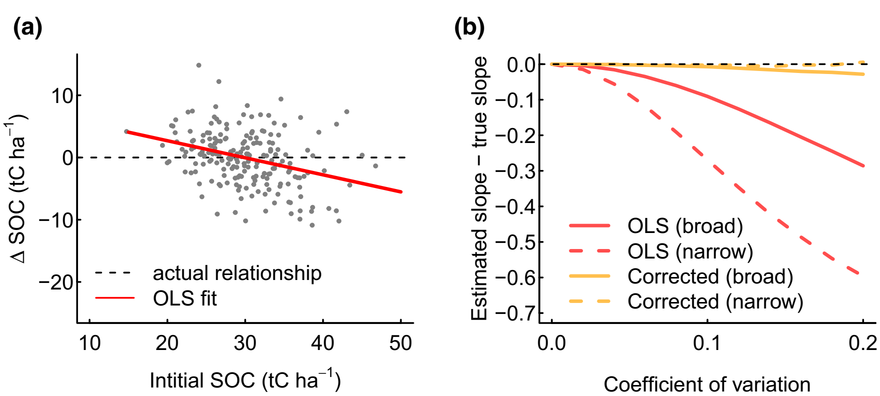

FIGURE 2 Simulated SOC data illustrating regression to the mean. (a) Shows a simulated data set in which the true values of $SOC_{initial}$ and SOC_{final} were defined to be equal, and random error was added to each variable before relating $SOC_{initial}$ to ΔSOC (coefficient of variation = 0.1). (b) Shows bias attributable to regression to the mean as a function of the coefficient of variation. Red lines show mean bias when ordinary least squares (OLS) is used to fit the data. The solid lines show results for a "broad" simulated data set, representing a regional- to global-scale analysis with high population variance. The dashed lines show bias for a "narrow" simulated data set, representing a local analysis with low population variance. The yellow lines show bias after applying the correction from Blomqvist (1977).

because regression to the mean has a stronger effect when the population variance (i.e., the variance of $SOC_{initial}$ across sites, or s_z^2) is small relative to the variance associated with individual estimates (i.e., the variance of $SOC_{initial}$ within sites, s_u^2) (Blomqvist, 1977). We explored two cases with differing types of variance (s_z^2): (1) a "broad" cross-site study representing a regional-scale analysis with a larger (s_z^2) (standard deviation [SD] of $SOC_{initial}$ = 10 tC ha^{-1}), and (2) a "narrow" cross-site study representing a local survey with a smaller (s_z^2) (SD of $SOC_{initial}$ = 5 tC ha^{-1}) (Figure 2b, red lines). SOC distributions were bounded between 10 and 100 tC ha^{-1} to avoid sampling extremely high or negative values. After generating $SOC_{initial}$ values, we defined the "true" value of SOC_{final} to equal $SOC_{initial}$, assuming zero management effect. We then added error to $SOC_{initial}$ and SOC_{final} to represent measurement uncertainty plus natural variability in SOC across the sampled area. We generated errors from a normal distribution by varying the coefficient of variation (CV) of the sampling distribution of the mean SOC value at each site between the values of 0 and 0.2. Importantly, this range of values represented the CV of the *sampling distribution*, that is, the ratio of the standard error to the mean—hence, in practice, larger sample sizes would generate lower CV values. After generating errors, we calculated ΔSOC and modelled its dependence on $SOC_{initial}$ using ordinary least squares regression. We calculated bias by taking the mean difference between the true slope (units of tC tC^{-1}, defined as 0, i.e., no change) and the fitted slope across 10,000 iterations of the simulation for each combination of parameters.

The simulations showed that the effect of regression to the mean increases as the CV increases (Figure 2b). Real-world studies likely fall within the middle of the range of CV values that we explored in our simulations. For instance: a global synthesis of SOC change in perennial cropping systems found within-site population CV values (SD/mean) of 0.05–0.30 (Ledo et al., 2019); a systematic survey of variation in SOC stocks in Belgium reported field scale population CV values of 0.11–0.26 (Goidts et al., 2009); and an extensive survey of SOC change after afforestation in Northern China reported a mean within-site population CV of 0.19 (Hong et al., 2020). Assuming a typical population CV of 0.20 and a typical sample size of four replicates per site, the CV of the sampling distribution would be 0.10, which is approximately in the middle of the range of values that we simulated.

In addition to site-level error, the effect of regression to the mean is sensitive to the overall breadth of $SOC_{initial}$ values across sites. Specifically, our simulations confirmed that bias increases when the distribution of SOC values is narrow, and decreases when the distribution is broad (Figure 2b, solid vs. dashed lines). Assuming a typical CV for the sampling distribution of 0.10, these results indicate that regression to the mean might generate slopes in the range of −0.1 to −0.3 (tC tC^{-1}) when ΔSOC is regressed against $SOC_{initial}$. This result will ultimately depend both on the actual within-site sample errors and overall breadth of SOC stocks included in a cross site study.

The simulations demonstrate that regression to the mean has the potential to generate negative relationships between ΔSOC and $SOC_{initial}$ under conditions typical of cross-site studies. To apply this approach to a real-world example, we downloaded the data from a global soil warming synthesis study (van Gestel et al., 2018). We found that this data set was somewhat broader than the "broad" example explored above (mean SOC stock = 36 tC ha^{-1}, SD = 27 tC ha^{-1}). We simulated the effect of regression to the mean given these parameters and assumed a within-site CV for the sampling distribution of 0.10. Given the assumed error level, the simulation yielded a slope of −0.04 tC tC^{-1}. This slope was similar to the slope of the ΔSOC versus $SOC_{initial}$ regression line that we calculated for the entire data set (−0.05 tC tC^{-1}), and a significant fraction (24%) of the slope obtained when we fit a regression to the subset of the data from an earlier synthesis (Crowther et al., 2016; −0.17 tC tC^{-1}). This result suggests that regression to the mean partly explains the apparent relationship between ΔSOC and $SOC_{initial}$ in this data set (if one exists, see van Gestel et al., 2018). Clearly, future meta-analyses should correct for regression to the mean when testing whether initial carbon stocks mediate changes in SOC.

3 | CORRECTING FOR REGRESSION TO THE MEAN

Disentangling the effect of regression to the mean from the true underlying relationship between ΔSOC and $SOC_{initial}$ is possible given the right statistical approach. In fact, several studies have found persistent negative relationships between ΔSOC and $SOC_{initial}$ after applying a statistical correction (Hong et al., 2020; Lark et al., 2006; Senthilkumar et al., 2009). One correction 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 ($\hat{\beta}'$) using variance estimates to generate an unbiased estimate ($\hat{\beta}$) (Blomqvist, 1977):

$$\hat{\beta} = \frac{\hat{\beta}' + \lambda}{1 - \lambda} \tag{1}$$

where λ is the ratio of s_u^2 (the within-site variance of the initial values) to s_z^2 (the across-site population variance of the initial values). This equation shows that if $s_z^2 \gg s_u^2$, (i.e., λ approaches 0) as in in a large cross-site study, then $\hat{\beta}$ approaches $\hat{\beta}'$. This corrected slope value can be calculated manually by estimating s_z^2 and an average value of s_u^2 across the data set, dividing these values to obtain λ, and obtaining $\hat{\beta}'$ from a regression of ΔSOC against $SOC_{initial}$ [e.g., using a standard regression calculator, such as the lm() function in R]. In our simulated example, this approach substantially reduced bias in the relationship between ΔSOC and $SOC_{initial}$ (Figure 2b; yellow lines). The usefulness of this correction is limited in the case of soil survey data because it requires knowledge of the uncertainty at individual sampling sites (Lark et al., 2006). However, in the case of cross-site studies, sampling is often replicated at each site, and so reported SDs and sample sizes can be used to calculate site-level standard errors, and hence the average value of s_u^2 across the data set.

For hypothesis testing, it may also be valuable to estimate the variance associated with $\hat{\beta}$ (var$\left(\hat{\beta}\right)$). This value can be used to construct confidence intervals and determine whether $\hat{\beta}$ differs significantly from zero. We have provided R code for performing these calculations and obtaining confidence intervals (see Supplementary Information; Appendix S1). If $SOC_{initial}$ is normally distributed, this variance can be calculated from $\hat{\beta}$, the variance of $\hat{\beta}'$ (obtained from ordinary least squares regression), the coefficient of variation of s_z^2 (CV(s_z^2)) and the coefficient of variation of s_u^2 (CV[s_u^2]) (Blomqvist, 1977):

$$\mathrm{var}\left(\hat{\beta}\right) = \mathrm{var}\left(\hat{\beta}'\right)\left(\frac{1+\hat{\beta}}{1+\hat{\beta}'}\right)^2 + \left(\frac{\lambda}{1-\lambda}\right)^2\left[\mathrm{CV}\left(s_z^2\right)^2 + \mathrm{CV}\left(s_u^2\right)^2\right]\left(1+\hat{\beta}\right)^2 \quad (2)$$

To parametrize this equation, CV(s_z^2) must be obtained from the SD of $SOC_{initial}$ (s_z) and the overall sample size (total number of sites, n):

$$\mathrm{CV}\left(s_z^2\right) = \frac{1}{s_z^2} \times \sqrt{\frac{1}{n}\left(\mu_4 - \frac{n-3}{n-1} \times s_z^4\right)} \quad (3)$$

In this equation, the term μ_4 represents the fourth central moment of $SOC_{initial}$. The value of CV(s_u^2) can be obtained by estimating the standard error of the error variance across sites and dividing it by s_u^2. It is important to note that in practice, $SOC_{initial}$ may not be normally distributed, and s_u^2 may be correlated with SOC initial (as was the case in our simulated data sets). Consequently, both $\hat{\beta}$ and var$\left(\hat{\beta}\right)$ will remain somewhat biased, albeit to a relatively small degree (Figure 2b, yellow lines). While these corrections reduce the artifact caused by regression to the mean to almost zero, clearly there is a need to develop statistical approaches that are tailored for error structures typical of SOC data sets. In the meanwhile, an imperfect correction (Equations 1–3) is preferable to no correction.

Study design can also minimize the effect of regression to the mean when relating ΔSOC to $SOC_{initial}$. For instance, in the case of cross-site studies that involve collecting new samples (e.g., locally replicated experiments), ensuring the close proximity of final and initial soil samples will reduce variation between sampling events, limiting the effect of regression to the mean. Similarly, increasing the number of samples collected within experimental strata will result in smaller within-site standard errors, further limiting bias. Granted, these remedies will often not be available in cross-site studies that rely on data that have already been collected (i.e., meta-analyses). In these cases, increasing the breadth of initial SOC values across sites (i.e., increasing the population variance, s_z^2) will dilute the effect of regression to the mean (Equation 1; Figure 2b). Importantly, study design will only incrementally reduce the effect of regression to the mean, and so statistical corrections are essential.

4 | NORMALIZATION ARTIFACTS

The problem of regression to the mean affects studies that relate differences in SOC stocks to initial SOC, but many studies express changes in SOC in terms of ratios rather than differences. Here, we briefly discuss three types of analysis relying on ratios that are prone to statistical artifacts: (1) analyses that normalize changes in SOC by the initial SOC level (e.g., $SOC_{final}/SOC_{initial}$, or change in SOC in % or ‰ year^{-1}; Li et al., 2018; Minasny et al., 2017); (2) analyses that normalize changes in SOC by the time since a treatment was imposed and then regress this average rate against time (Cai et al., 2022; Han et al., 2016; Liu et al., 2014; Minasny et al., 2017; West & Six, 2007; Xu et al., 2019); and (3) analyses that normalize changes in SOC by SOC levels in an experimental control (as opposed to the initial SOC level), and then relate this value to initial SOC level. (Gross & Glaser, 2021; Han et al., 2016; Liu et al., 2014). We expect that all three of these cases are susceptible to artifacts when relating changes in SOC to initial SOC levels.

Analyses that normalize changes in SOC by the initial SOC level are prone to strong statistical artifacts. These artifacts occur because relative changes in SOC—whether positive or negative—will by definition tend to appear larger in SOC-poor soils, simply due to the fact that the denominator is smaller in these soils. For instance, consider a case in which a positive relative change SOC change in % ($100 \times \Delta SOC/SOC_{initial}$) is regressed against $SOC_{initial}$. Quite predictably, if the change in SOC is on-average positive, this calculation will generate a decreasing concave curve (a hyperbola) relating the relative rate of change and $SOC_{initial}$, even when ΔSOC is entirely independent of $SOC_{initial}$ (Figure 3a,b). This pattern is tautological: a fixed increase in carbon will by definition be large relative to a small value of $SOC_{initial}$, or vice versa, will be small relative to a large value of $SOC_{initial}$. Consequently, while it may often be true that relative changes in SOC appear larger at low SOC levels, this fact is in no way diagnostic of the actual relationship between the mass balance of SOC and initial SOC levels.

Similarly, analyses that normalize changes in SOC by the time and then regress this average rate against time can produce normalization artifacts. This type of analysis is common in studies of SOC dynamics in agricultural experiments (Cai et al., 2022; Han et al., 2016; Liu et al., 2014; Minasny et al., 2017; West & Six, 2007; Xu et al., 2019), which often aim to characterize the time it takes for changes in SOC to level off after changes in management. Time-averaged sequestration or loss rates are calculated by dividing ΔSOC (Figure 3c, y axis) by the amount of time that has elapsed since new land management practices were adopted. Because time is used as a denominator in this calculation, the average rate will by definition tend to be related to time by a hyperbolic curve that approaches zero, even when ΔSOC is unrelated to time (Figure 3c,d). Consequently, an apparent decline in the average SOC sequestration or loss rate over time is not necessarily indicative of gradual SOC equilibration or saturation; rather, it may emerge even when ΔSOC and time do not have a clear functional relationship.

The third—and most subtle—case that we consider includes analyses that divide SOC values in treatment plots (SOC_{treat}) or treatment effects ($SOC_{treat} - SOC_{control}$) by values in control plots ($SOC_{control}$), and then relate this ratio or its logarithm to $SOC_{initial}$

(Han et al., 2016; Li et al., 2018; Liu et al., 2014). Response ratios of this type are invaluable for synthesizing data that are reported on different measurement scales, and it would seem that they are less prone to artifacts, given that $SOC_{initial}$ is not used in calculating the ratio. However, closer consideration indicates that response ratios will often be related to $SOC_{initial}$ when the absolute treatment effect (SOC_{treat} – $SOC_{control}$) is unrelated to $SOC_{initial}$. This possibility emerges because changes in SOC are typically small relative to SOC stocks; consequently, the denominator in the response ratio will tend to be highly correlated with $SOC_{initial}$. For instance, we can imagine a simplified example in which SOC_{treat} and $SOC_{control}$ always differ by a fixed value, and diverge symmetrically from $SOC_{initial}$ across a range of sites (Figure 4a). In this simplified case, $SOC_{treat} - SOC_{control}$ will be unrelated to $SOC_{initial}$ (Figure 4b), whereas $SOC_{treat}/SOC_{control}$ will tend to be higher at SOC-poor sites and lower at SOC-rich sites (Figure 4c). Similar (but potentially inverted) patterns will emerge if the pattern of gains and losses across the treatment or control values are changed, provided that $SOC_{treat} - SOC_{control}$ is non-zero and constant across sites. While this example is highly simplified in that it assumes a fixed management effect without error, it shows that a

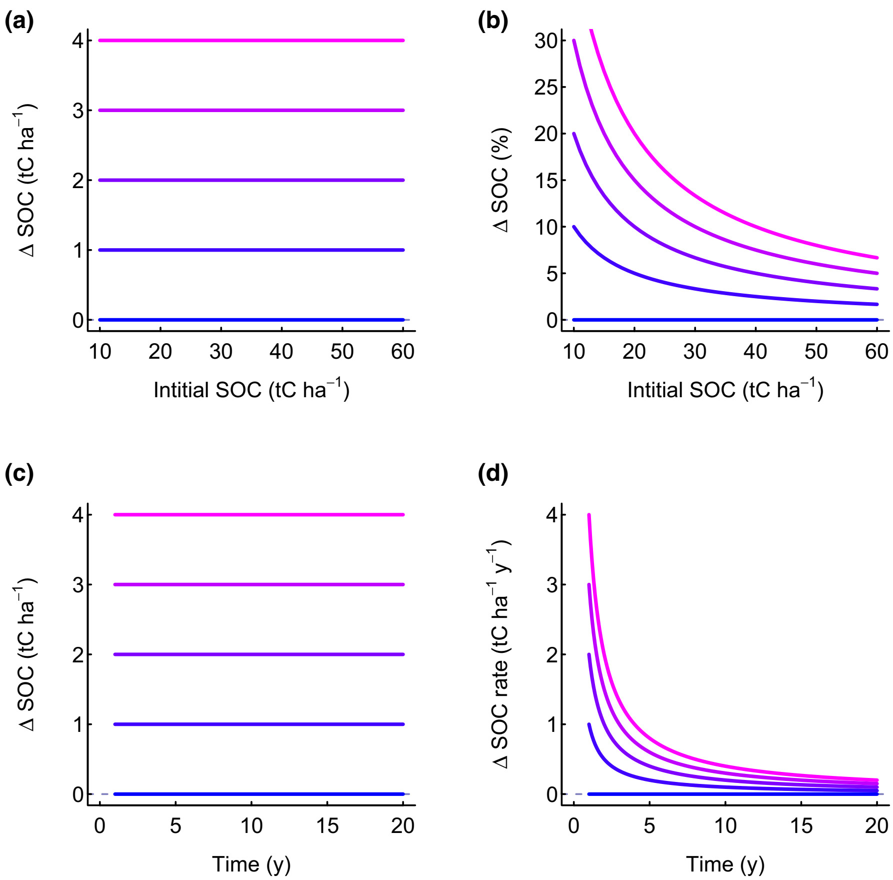

FIGURE 3 Normalization artifacts. (a) Shows constant values of ΔSOC as a function of $SOC_{initial}$. When these constant values are normalized by $SOC_{initial}$ (e.g., as a percentage value), the relationship between the normalized value and $SOC_{initial}$ will by definition be negative (b). Similarly, even if ΔSOC is unrelated to time (c), the average rate of change of SOC will decline as a function of time (d). SOC, soil organic carbon.

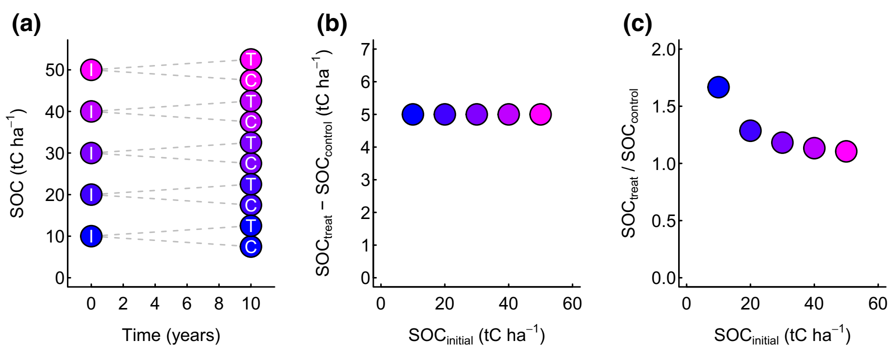

FIGURE 4 Response ratio artifact. (a) Shows a simplified scenario in which five sites have different initial SOC values (I). At each site, SOC in treatment plots (T) increases by 2.5 tC ha^{-1} and SOC in control plots (C) decreases by 2.5 tC ha^{-1}. (b) Shows that the difference between SOC in treatment plots and SOC in control plots is constant (5 tC ha^{-1}) and does not vary as a function of initial SOC. (c) Shows that the ratio $SOC_{treat}/SOC_{control}$ nonetheless declines as a function of initial SOC. Similar (but potentially inverted) patterns will emerge if the pattern of gains and losses across the treatment or control values is changed, provide that (T)–(C) is non-zero and similar in magnitude across sites.

relationship between $SOC_{treat}/SOC_{control}$ and $SOC_{initial}$ does not necessarily indicate dependence of SOC sequestration or loss on initial SOC levels.

5 | CORRECTING FOR NORMALIZATION ARTIFACTS

The best way to avoid normalization artifacts is to avoid normalizing response variables in cases when the independent variable of interest is the same as (or strongly correlated with) the normalizing factor. Absolute metrics like $SOC_{treat} - SOC_{control}$ or ΔSOC are thus likely to be more informative than response ratios in specific cases when $SOC_{control}$ or $SOC_{initial}$ is being used as an independent variable. If ΔSOC is used as a response variable in this context, applying a correction for regression to the mean (Equations 1–3) would be appropriate. In cases where the effect of time on SOC accrual is of interest, the best solution is to treat ΔSOC as a response variable and time as a predictor without first dividing ΔSOC by time (Luo et al., 2010; Poeplau & Don, 2015). If visualizing the instantaneous rate of change in SOC over time is of interest, the modeled relationship between ΔSOC and time can then be differentiated to visualize SOC dynamics without generating normalization artifacts.

6 | CONCLUSIONS

We used simulated data to illustrate that changes in SOC will tend to be negatively correlated with initial SOC due to random chance alone. Furthermore, simple calculations indicate that normalized metrics of SOC change will tend to show larger responses at low initial SOC levels, even when the soil carbon balance is insensitive to initial SOC. These statistical artifacts exaggerate the appearance that initial SOC levels are a major control on SOC change, regardless of whether there is a strong underlying relationship.

This is far from a purely academic issue. Carbon sequestration in agricultural soils is the object of major policy initiatives, and the basis for contentious new carbon crediting schemes (Oldfield et al., 2022). Cross-site studies are an important source of information informing these policy debates; hence statistical artifacts in these studies might skew regional estimates of SOC sequestration potential, adversely affecting environmental management and actual climate change mitigation. The scientific community can play a constructive role in environmental management debates not only by synthesizing data but also by adopting existing countermeasures against statistical bias like those outlined here, and developing new statistical approaches that can be applied to cross site studies going forward.

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CONFLICT OF INTEREST

The authors declare no competing interests.

DATA AVAILABILITY STATEMENT

R code supporting the findings of this study is available in Supplementary Information, and at https://zenodo.org/ at the URL https://doi.org/10.5281/zenodo.7195077.

ORCID

Eric W. Slessarev https://orcid.org/0000-0002-4076-1950
Allegra Mayer https://orcid.org/0000-0003-3408-5906
Courtland Kelly https://orcid.org/0000-0003-2161-8750
Katerina Georgiou https://orcid.org/0000-0002-2819-3292
Jennifer Pett-Ridge https://orcid.org/0000-0002-4439-2398
Erin E. Nuccio https://orcid.org/0000-0003-0189-183X

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