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Research Paper

Soil health explains the yield-stabilizing effects of soil organic matter under drought

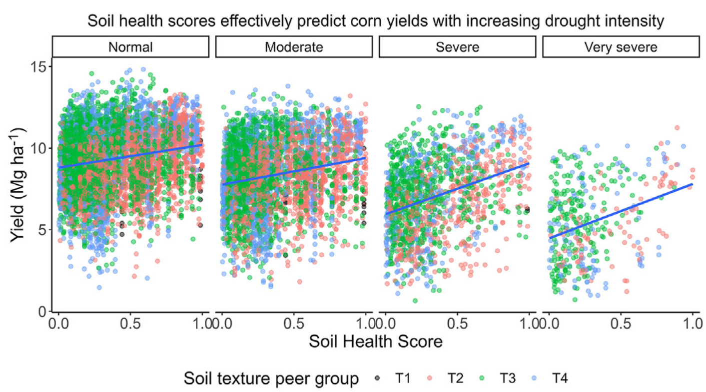
Swarnali Mahmood [a,*], Márcio R. Nunes [a,b], Daniel A. Kane [c], Yang Lin [a,b]

[a] Department of Soil, Water, and Ecosystem Sciences, University of Florida, Gainesville, FL 32611, USA
[b] Global Food Systems Institute, University of Florida, Gainesville, FL 32611, USA
[c] TerraCarbon LLC, Peoria, IL 61614, USA

HIGHLIGHTS

- Soil health score (SHS) is site-specific and based on soil organic matter.
- A 0.5 SHS increase equals ~1.15 Mg ha^{-1} yield boost under severe drought.
- Soil health more effectively predicts yields with increasing drought severity.
- Effects of soil health are largely independent of soil texture and suborders.

GRAPHICAL ABSTRACT



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ABSTRACT

Soil organic matter (SOM) serves as an important indicator of soil health. Soils with high SOM are associated with high crop yield under drought conditions. However, a critical question remains unanswered: is the yield-stabilizing effect of SOM attributable to inherent soil properties, such as soil texture and taxonomy? Or is it driven by dynamic soil properties that reflect the overall health of the soil? Following the Soil Health Assessment Protocol and Evaluation, we derived a soil health score (SHS; range: 0–1) from the SOM concentration by accounting for site-specific variables, including climate, texture, and soil suborder. Using county-level data of rainfed corn across the U.S. from 2000 to 2016, we found that higher SHS were associated with higher yields. During the most severe drought events, an increase of 0.5 in SHS was associated with a 1.15 ± 0.18 Mg ha^{-1} increment in corn yield, suggesting that high SHS helps to stabilize yield in drought. Interestingly, smaller but statistically significant effects of SHS on yield were found during less intensive droughts. The SOM concentration was a slightly better predictor of corn yield than the SHS. We also found similar effects of SHS on corn yield across different soil types, *i.e.*, different textures or soil suborders, under severe drought conditions. Our results suggest that soil health is a main factor in explaining the yield benefits of SOM, while the effects of soil health were not driven by differences in soil texture or suborder. We argue that the resilience of corn yield against drought can be

Abbreviations: SOC, Soil organic carbon; SOM, soil organic matter; SHS, soil health score; AWC, available water capacity; CEC, cation exchange capacity; SHAPE, Soil Health Assessment Protocol and Evaluation; CASH, Comprehensive Assessment of Soil Health; SPEI, standardized precipitation evapotranspiration index.

* Corresponding author.
E-mail address: swarnali.mahmood@ufl.edu (S. Mahmood).

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potentially increased by adopting agronomic practices aimed at augmenting SOM and improving overall soil health across a broad spectrum of geographical locations and site characteristics.

1. Introduction

Healthy soils serve as the cornerstone for achieving food security and promoting environmental sustainability in the agricultural sector. Historically, soil testing mostly concerns itself with soil fertility from the perspective of nutrient management (Chang et al., 2022). In the recent decade, the concept of soil health has gained global recognition to describe the biological, chemical, and physical limitations of soil functions, including their role in sustainable crop production (Lehmann et al., 2020; Wood and Blankinship, 2022). Despite the growing enthusiasm surrounding the soil health concept, the science of quantifying and assessing soil health remains in its early stages. Various indices and scores have been proposed to quantify the extent of soil health (Andrews et al., 2004; Haney et al., 2018; Kibblewhite et al., 2008; Moebius-Clune et al., 2016; Nunes et al., 2021). However, it is unclear how effectively they can capture and predict the key outcomes of healthy soil, such as agricultural productivity and carbon sequestration. For example, establishing the causality between soil health and crop yield continues to be a complex challenge (Crookston et al., 2022; Olayemi et al., 2020; Wade et al., 2020).

Multiple popular approaches for assessing soil health are based on the idea of variance partitioning (Karlen et al., 2019; Nunes et al., 2021; Zuber et al., 2020). For a given soil health indicator (*e.g.*, soil organic matter or aggregate stability), its variance can be explained by two types of factors: inherent site-specific drivers and dynamic drivers. The former include texture, climate, taxonomy, and other edaphic factors that are not easily altered by management practices and do not change drastically over time (Wiesmeier et al., 2019). In contrast, dynamic drivers consist of land use and management practices that can quickly change soil health over time. These soil health assessment methods aim to discern the variance in the given soil health indicator that can be attributed to inherent properties, typically using a peer group approach. After accounting for the variance due to inherent properties, soil health status is reflected in the variance associated with dynamic drivers. For example, soils are categorized into three peer groups based on texture, as in the Comprehensive Assessment of Soil Health (CASH; Moebius-Clune et al., 2016). The variability of soil health indicators, *e.g.*, soil organic carbon (SOC), among these texture groups reflects the effects of texture on soil health. Then, the within-group variability of the soil health indicators is used to quantify soil health conditions. In this instance, high SOC values correspond to healthier soils in each texture group of CASH.

The Soil Health Assessment Protocol and Evaluation (SHAPE) is another example of the peer group approach. However, SHAPE is more robust as compared to CASH, taking into account not only the variation in soil texture but also climate (local precipitation and temperature) and soil taxonomy across the continental U.S. (Nunes et al., 2021). In addition, SHAPE was developed using a large, continental-scale database, making it more representative of U.S. edaphoclimatic conditions. Using SOC as an example, the SHAPE framework categorizes soils into five soil texture classes and five soil suborder classes (Table S1) based on the inherent potential of each soil to accumulate organic carbon. This results in the creation of 25 peer groups, each representing a unique combination of texture and suborder classes (Fig. 1C). Using a Bayesian modeling approach, it also adjusts the scoring function for variations in annual temperature and precipitation (Nunes et al., 2021). Similar to CASH, it produces scores in the range of 0–100% that correspond to the quantile of SOC values within each peer group.

Methods like CASH and SHAPE rely on several assumptions to quantify soil health: (1) the peer group approach effectively accounts for the variance associated with inherent properties, (2) an increase in a soil health indicator within a peer group corresponds to an increase in soil health, and (3) the increase in soil health leads to an increase in ecosystem functions (such as improved nutrient cycling and retention). From the evolution of CASH to SHAPE, these methods have increasingly incorporated inherent drivers to more comprehensively account for their impacts on soil health indicators (1st assumption). While the 2nd assumption is intrinsic to these methods, they enable us to evaluate the 3rd assumption when we compile a dataset with matching records of soil health and ecosystem functions. The outcome of these evaluations will ultimately inform us about the effectiveness of these methods in assessing soil health.

Soil organic matter (SOM) content is a critical indicator of soil health and is fundamental to various ecosystem processes. High SOM concentrations have been shown to benefit crop yields (Kane et al., 2021; Oldfield et al., 2019; Vendig et al., 2023). For instance, using county-level corn yield data from the U.S., Kane et al. (2021) showed that soils with higher SOM were associated with lower mean yield losses under drought conditions. Their results indicate that SOM-rich soils help to stabilize corn yield under drought conditions. However, it is unclear whether these yield benefits are driven by soil health or the inherent site-specific drivers. We obtained predominantly rainfed county-level corn yields in the U.S. from 2000 to 2016 to fill this research gap. Building upon Kane et al. (2021), we used linear mixed effects models to assess the effects of SOM-derived soil health scores (SHS) on corn yields under different drought conditions. We hypothesized that counties with higher SHS, associated with higher SOM levels in the root zone (0–30 cm), would have greater yield stability during drought. In other words, soils with high SHS are associated with high yield under severe drought conditions. To evaluate whether inherent factors (*i.e.*, soil texture, suborder, and climate conditions) were responsible for the positive effects of SOM on crop yield, we followed the peer group approach of SHAPE to categorize soils into different texture and suborder groups (Fig. 1C) as well as compared the effects of SOM on yield between peer groups. If the effects of the SOM are independent of peer groups, then a similar linear relationship between SOM and yield would be observed both within and between peer groups, as illustrated in scenario A (Fig. 1A). In contrast, if the effects of SOM are driven by differences in inherent factors between peer groups, then the SOM-yield relationship between peer groups would drastically differ from those within peer groups, as illustrated in scenario B (Fig. 1B).

2. Materials and methods

2.1. Data collection

County-level soil attributes, corn yields, and Standardized Precipitation Evapotranspiration Index (SPEI) data were obtained from Kane et al. (2021). These data were all derived from publicly available sources, including the USDA's corn-frequency raster, the Gridded Soil Survey Geographic (gSSURGO) database, the National Agricultural Statistics Service's corn yield data (USDA, 2018), and the Centers for Disease Control and Prevention SPEI database (National Environmental Public Health Tracking Network, 2018). Details of data processing can be found in Kane et al. (2021).

2.2. Soil health scoring

We adopted the SHAPE framework to derive SHS from soil organic carbon (SOC) concentrations (Nunes et al., 2021). The SHAPE framework scores soil health based on scoring curves developed from a

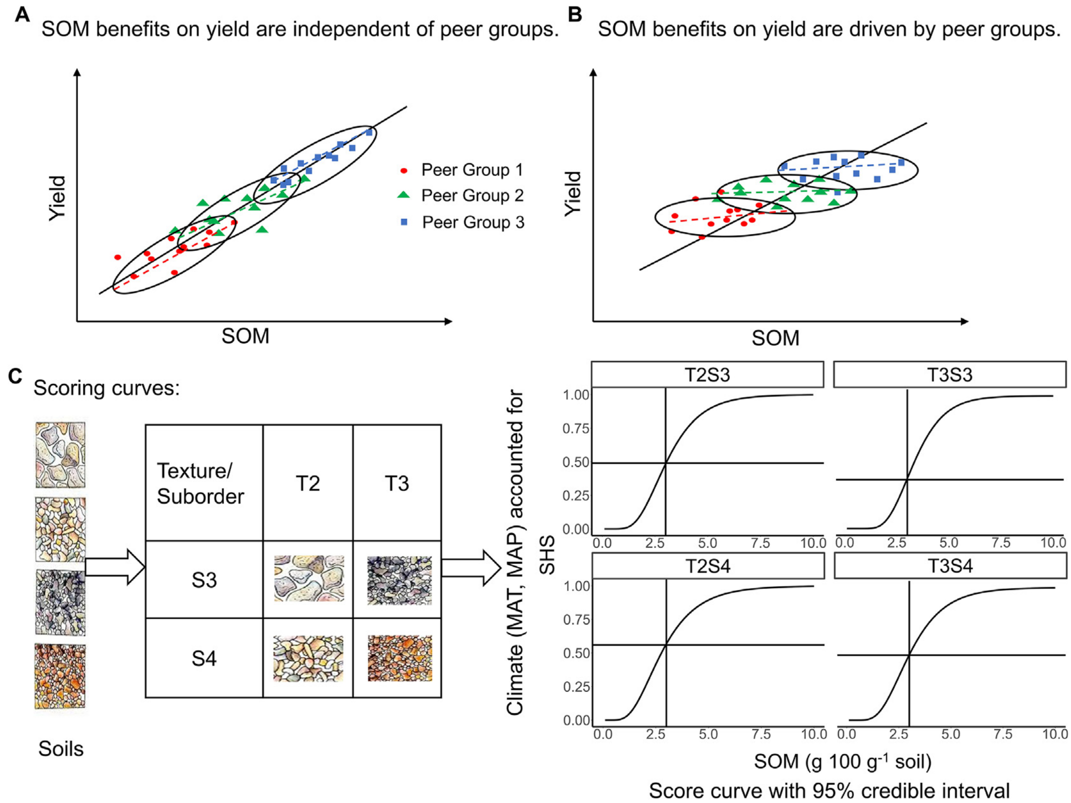

Fig. 1. Schematic diagrams comparing the yield-stabilizing effects of soil organic matter (SOM) across peer groups and how the SHAPE tool works to score soil health. T2 and T3 refer to two texture groups, while S3 and S4 refer to two soil suborder groups (Table S1). Since soils from T2 have coarser texture than those from T3, a T2 soil with 3 g 100 g^{-1} SOM receives a higher soil heath score (SHS) than a T3 soil with the same SOM concentration. As soils from S3 are more SOM-rich than those from S4, a S3 soil with 3 g 100 g^{-1} SOM receives a lower SHS than a S4 soil with the same SOM concentration.

comprehensive national database and Bayesian model-derived conditional cumulative distribution functions. It considers all possible combinations of five soil suborders and five texture classes as peer groups (Table S1) and accounts for variations in temperature and precipitation (*i.e.*, climate variables). The SHS indicates the quantile of a SOM value in relation to other soils with similar inherent and climate conditions, *i.e.*, the SHAPE approach accounts for the inherent factors driving soil health before accounting for the dynamic (management) impact. It is worth noting that a soil from the Midwestern U.S. can have the same SHS as a soil from the Southeastern U.S. This implies that both soils are positioned similarly in their SOM concentrations when compared to soils with similar inherent and climate conditions. However, their SOM concentrations differ because of regional differences in soil-forming factors. Thus, the SHAPE approach controls for the regional variability in SOM values by accounting for their inherent and climate drivers. The mean SOM concentration decreases as the suborder class number increases from S1 to S5, while it increases from texture class T1 (coarse) to T5 (fine) (Table S1). These groupings were chosen to consolidate the large number of suborders ($n = 75$) and texture classes ($n = 12$) available in Soil Taxonomy and to amplify the differences in SOM among groups and the variance explained by them (Nunes et al., 2021).

County-level values of SOM (%), sand, silt, and clay were acquired from the gSSURGO database following Kane et al. (2021). Briefly, the *aqp* package in R (Beaudette et al., 2023) was used to convert the gSSURGO characterization data for each series to the 0–30 cm soil depth, which corresponds to a typical root depth of corn (Feldman, 1994). Then, we estimated the mean value of selected soil properties for each map unit by weighing the coverages of the included soil series and converted the data to a raster format. These raster layers were then masked to remove areas that did not grow corn consistently and used to calculate county-level mean SOM (%, corresponding to g SOM 100 g^{-1} soil) values weighted by the relative proportions of map units. The SOC (g 100 g^{-1} soil) was calculated by dividing the SOM by the van Bemmelen factor (1.724) (Nelson and Sommers, 1996). Soil suborder data were obtained in a similar fashion, where the suborder of each map unit was determined as that of the major component with the largest spatial coverage in the given map unit. County-level suborders were determined as the suborder with the largest spatial coverage. The mean annual temperature (MAT) and the mean annual precipitation (MAP) at the county level were obtained from the NOAA Climate Divisional Database (nClimDiv) (NOAA, 2018). The SHSs were calculated using a customized R script available at https://github.com/paparker/SHAPE. The SHSs vary between 0 and 1 (0–100%), where the higher value represents healthier soil within the peer group. Even though the SHS is derived from only SOM, the SHAPE approach enables us to answer our primary question, *i.e.*, whether the benefits of SOM on yield were driven by soil health or inherent factors.

2.3. Yield and yield deficit modeling

First, we created four different drought categories based on the mean and standard deviation of the SPEI values. The SPEI is a drought index where the differences between cumulative monthly precipitation and potential evapotranspiration are determined from long-term climate data (National Environmental Public Health Tracking Network, 2018). It is a robust measurement of drought severity through time and space across a wide range of climates (Vicente-Serrano et al., 2010). As drought effects are expected to be more distinct on corn growth and yield during summer (Kane et al., 2021), we considered SPEI values for summer months (*i.e.*, May to August). The drought categories were as follows: very severe drought, greater than or equal to two standard deviations (SPEI ≤ -1.02); severe drought, between one and two standard deviations ($-1.02 < \text{SPEI} \leq -0.46$); moderate drought, between one standard deviation and the mean ($-0.46 < \text{SPEI} \leq 0.10$); and normal condition, greater than or equal to the mean ($\text{SPEI} \geq 0.10$). We standardized all relevant data following Gelman (2008) by subtracting the mean from each observation and dividing the resulting value by two standard deviations. We built linear mixed models of yield (Mg ha^{-1}) using SHS, soil clay content (%), soil pH, and available water capacity (AWC; %) as independent variables. We added clay content, pH, and AWC to soils in addition to SHS in the model to account for other potential drivers of yield. We calculated the variance inflation factors (VIF) to identify the variables with high collinearities with others (Table S2). Due to its high VIF (>5), cation exchange capacity was excluded from the models. We also added a random effect of states following Kane et al. (2021) to capture the regional variability of agricultural management and environment in the model results. We acknowledge that the state is only a coarse indicator of this regional variability. Then, a linear mixed model was constructed for each drought category. The *lme4* package in R (Bates et al., 2015) was used to fit and analyze linear mixed effect models, and the *lmerTest* package (Kuznetsova et al., 2017) was used to obtain the *p*-values of model coefficients. The model was coded in *lme4* as follows:

Yield ~ SHS * clay * pH * AWC + (1|State)

We estimated the marginal and conditional coefficient of determination (R^2) of the models with the *MuMIn* package (Barton, 2020). We observed the effects of SHS by plotting SHS against yields, adapted for each drought category. We also estimated the yields for each drought category for a one-unit increase in SHS by dividing the standardized coefficients from the yield models by two standard deviations, as it converted the standardized data back to their raw values (Gelman, 2008).

We calculated yield deficits across all counties for very severe, severe, and moderate drought categories by subtracting the mean yield under normal conditions in the county from the mean yield under each drought category. This approach helps to control for the temporal autocorrelation in yields across different years in the same county. Yield deficit is expressed as negative values, and large absolute values indicate a stronger decline in yield under drought. To evaluate the effect of SHS on the yield deficits, we built similar linear mixed models with yield deficit (Mg ha^{-1}) as the response using SHS, soil clay content (%), soil pH, and available water capacity (AWC; %) as independent variables after standardization of data following Gelman (2008). Similar to yield models, we also added a random effect of states following Kane et al. (2021) to capture the regional variability in the yield deficit model results. The model was coded in *lme4* as follows:

Yield deficit ~ SHS * clay * pH * AWC + (1|State)

To evaluate whether the effects of SHS on yield (and yield deficit) differed between different soil texture classes, we built additional linear models of yields (and yield deficits) at each drought class with independent variables including the SHS, soil texture class, and their interaction. The models were coded in R as follows:

Yield ~ SHS * Texture class

Yield deficit ~ SHS * Texture class

A significant interaction effect ($\alpha = 0.05$) would indicate that the regression coefficients of SHS differed significantly across different texture classes. The significant interaction effect was also followed by pairwise comparisons of the regression coefficients between texture classes using the *emmeans* package in R (Lenth et al., 2022). We repeated this analysis across soil suborder classes. Similarly, the models were coded in R as follows:

Yield ~ SHS * Suborder class

Yield deficit ~ SHS * Suborder class

We omitted the very severe drought class from the suborder models due to their small sample size (less than 100; Table S1). The relatively small sample size also prevented us from conducting similar analyses in each combination of texture and suborder classes. The county-wise extent of mean SHS and yield deficits under different drought categories are shown in Fig. S1.

3. Results and discussions

3.1. Effects of SOM and soil health on corn yield

We found that soil health scores (SHS) significantly affected corn yield in four drought categories (Fig. 2A). During the most severe drought events, an increase of 0.5 (out of 1) in SHS was associated with a 1.15 ± 0.18 Mg ha^{-1} (mean ± standard error unless otherwise noted) increase in corn yield ($p < 0.001$). Smaller, yet statistically significant effects were observed with the decrease in drought intensity (Table S3A; all $p < 0.001$). For instance, an increment of 0.5 in SHS only resulted in a yield increase of 0.40 ± 0.03 Mg ha^{-1} under normal conditions. These results expand upon the prior research conducted by Kane et al. (2021) and align with previous studies that documented positive correlations between SOM and yield under drought conditions in the U.S. (Williams et al., 2016; Zhou et al., 2021). Our results also demonstrate that SHS becomes more effective in predicting corn yield under increasing drought severity, highlighting a yield-stabilizing role of SOM.

Compared to SOM concentration, SHS had a slightly less pronounced effect on yields, as it had a smaller standardized coefficient and a slope less steep than SOM in each drought category (Table S3A). The SOM being slightly better in predicting yields than SHS could be due to the added effect of inherent soil and climate drivers with SOM, indicating the significance of regional variability. The SHS models also had slightly lower marginal R^2 values than the SOM models but higher conditional R^2 values. For instance, under very severe drought, the fixed effects of the SOM model explained 21.5% of the variability in yield (*i.e.*, marginal $R^2 = 0.215$), while those of SHS explained 18.0% of the variability. Under severe drought, the marginal R^2 was higher in the SOM model than in the SHS model (0.239 vs. 0.188, respectively). After accounting for the inherent drivers of SOM, SHS models still retained most of the variation in yields. These results suggest that soil health is the main factor in explaining the yield stabilizing effect of SOM. Other factors, including inherent ones, likely explained the rest of the yield stabilizing effect of SOM. Since the difference between conditional R^2 and marginal R^2 corresponds to the effects of the random factor (*i.e.*, state), it is worth noting that the state explained more yield variability than SOM (or SHS). The state reflects regional variability in inherent soil-forming factors and management practices, such as fertilization application, highlighting their roles in regulating corn yield at the continental scale (Kane et al., 2021).

The SHS also significantly affected yield deficits under severe droughts (Fig. 2B; Table S3B). With increasing SHS, the yield deficit decreased in all drought categories ($p < 0.001$, and $p < 0.05$). During a very severe drought, an increase of 0.5 in SHS resulted in a 0.5 ± 0.15 Mg ha^{-1} decrease in yield deficit. Smaller changes were observed as the drought severity decreased. For example, under moderate drought, a 0.5 increase in SHS only decreased the yield deficit by 0.12 ± 0.05 Mg ha^{-1}. The impact of SHS on yield deficits was consistent with their effects on yields, indicative of the robustness of these yield stabilizing effects. Interestingly, yield deficits under very severe drought exhibited substantial variability in instances of low SHSs, with some of these less healthy soils registering near-zero yield deficits. In contrast, soils with high SHS displayed a decrease in yield deficit values approaching zero. Although these patterns could have been influenced by the uneven distribution of samples across the full range of SHS, these results could also suggest that corn yield was more stable against intensive drought when SOM levels were high.

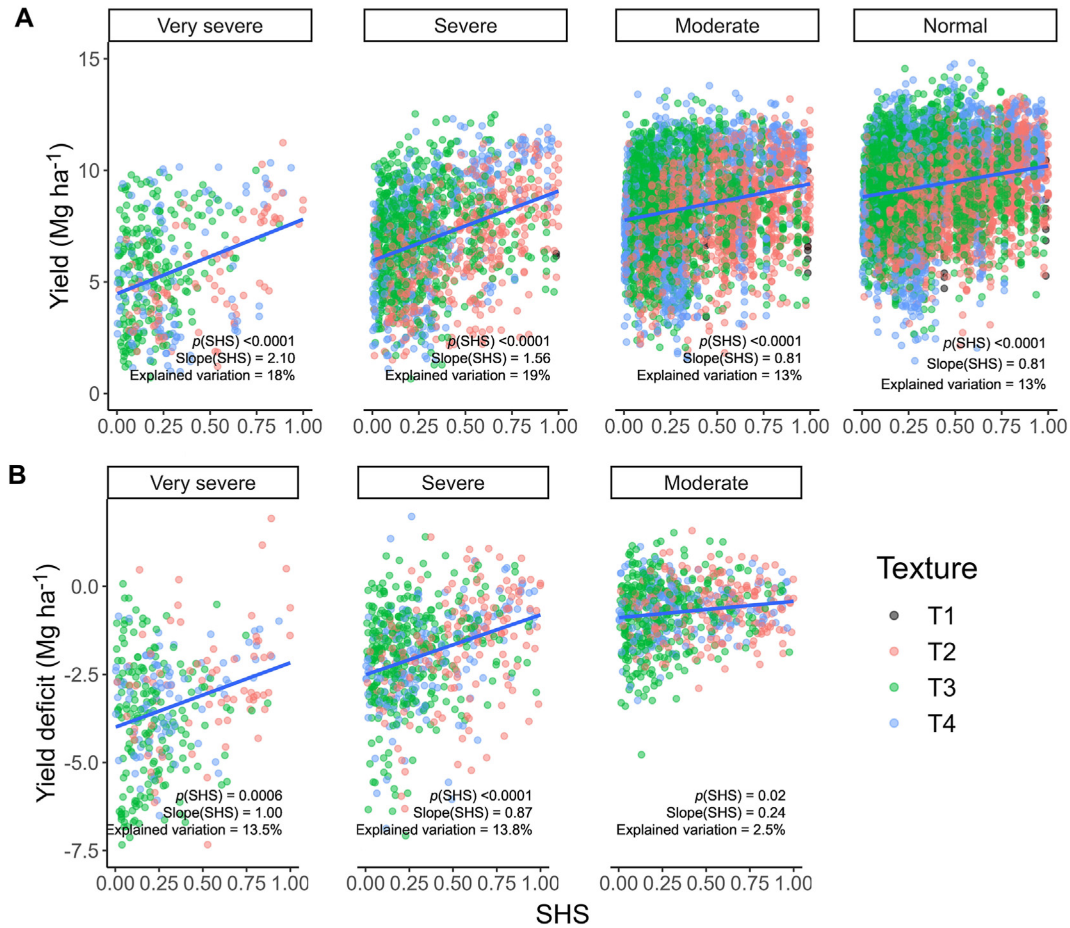

Fig. 2. (A) Yield stability increases with soil health scores (SHS) throughout county years and different texture peer groups, with effects becoming more pronounced with increasing drought severity. (B) Yield deficit decreases with increasing SHS with the effects becoming stronger with increasing drought severity. Trend lines represent predicted yields (or yield deficits) based on the marginal effect. The *p* values indicate the significance of the effect of SHS. The standardized coefficients (or slopes) represent the yield (or yield deficit) prediction in response to the marginal effect of SHS. Explained variation indicates marginal R^2 of the model.

Soil pH, clay content, and AWC all had meaningful effects on corn yield, as their main effects were significant in most of the models studied (Table S3A). These factors have been well-documented to influence corn productivity. For example, most corn cultivars prefer a soil pH range of 5–6.2 (Heiniger, 2018), and high acidity reduces corn yield during drought (Caires et al., 2008). Soil AWC plays a critical role in buffering plant water stress for rainfed corn (Benjamin et al., 2015; de Araujo Rufino et al., 2018), while clay content is a key factor influencing SOM and AWC (Georgiou et al., 2022; Minasny and McBratney, 2018). Despite their significant main effects, many of the interaction effects between these factors and the SHS (or SOM) were not statistically significant. Only one three-way interaction between SHS, clay, and AWC was consistently significant in all models. These results suggest that the effect of SHS on yield was largely independent of clay, pH, and AWC.

3.2. *Effects of soil texture and suborder on yield and yield deficit prediction curves*

To evaluate whether soil texture influenced the effects of SHS on yield, we built a linear model using SHS, texture classes, and their interaction as the main factors. Under very severe drought, SHS was a significant predictor of yield ($p < 0.001$), and the full model explained 13.5% of the variability in yield (Table S4; Fig. 3). The interaction effect between SHS and texture classes on yield was not statistically significant (Table S4A). When yield was plotted against SHS, the slopes of different texture classes were indistinguishable from each other. Similarly, the interaction between SOM and texture classes did not affect corn yield, and the slopes of SOM models were largely comparable across different texture classes (Fig. S2; Table S4). We then repeated this analysis for county-level yield deficit and found the same patterns where SHS was a significant predictor of yield deficit ($p < 0.001$; Fig. 3). However, the interaction between SHS and texture class did not influence yield deficit (Table S4B). Together, these results suggest that the effect of soil health on yield is independent of soil texture under very severe drought. In other words, inherent variability in soil texture cannot explain the yield benefits of SOM during extreme drought events (Kane et al., 2021; Williams et al., 2016). Our study thus indicates that SOM can contribute to corn yield stability under extreme conditions across a wide range of soil textures.

We also observed that the intercepts of the SHS models differed among texture classes under very severe drought. The intercept here represents the estimated yield when the SHS is zero. Therefore, the differences in the intercepts reflect the effect of texture on corn yield when the SOM has been taken into account. Texture class T2 had a lower intercept than the other two classes, as it contained more coarse-textured soils and, therefore, had a lower capacity to retain SOM. Although the soils in texture class T4 contained more clay particles than those in T3, T4 had a lower intercept than T3. Previous studies have reported a bimodal relationship between clay content and yield (Katerji and Mastrorilli, 2009; Zipper et al., 2015). Clay-rich soils with a low level of SOM are particularly vulnerable to compaction, which subsequently limits root growth and crop productivity (Parent et al., 2008).

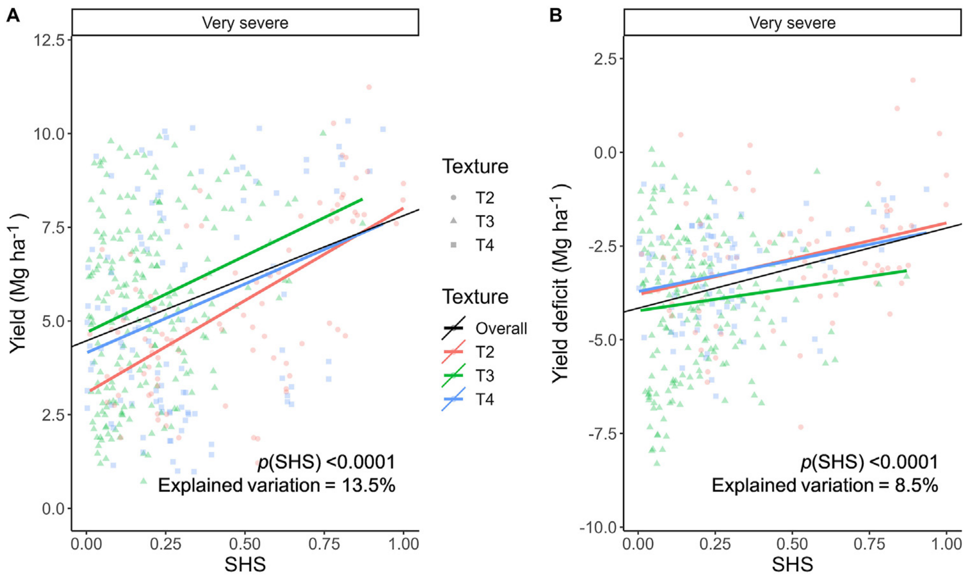

Fig. 3. The effects of SHS on yields (A) and on yield deficits (B) by soil texture classes under very severe droughts. The p values indicate the significance of the effect of SHS. Explained variations indicate the R^2 of the full model, including the SHS, texture classes, and their interaction.

Under less severe drought and normal conditions, soil texture regulated the effects of SHS on yield, as indicated by a significant interaction effect between texture and SHS (Table S4A). Pairwise comparisons further show that the regression slope of the T3 texture class was lower than those of the other classes in each drought class, while there was no difference in the slope between T2 and T4 (Table S5A; Figs. S2-5). The T3 is made of soils in the texture classes of silt and loamy silt, many of which are from Midwestern U.S., including Illinois, Wisconsin, Indiana, Ohio, and Kentucky. Noticeably, all T3 soils had SHS less than 0.5. Since SHAPE was constructed using data from both natural and agricultural soils, our results suggest that SOM is depleted in agricultural T3 soils compared to their counterparts in natural systems. Given the prevalence of T3 soils in the U.S., further examination is warranted to explain why these SOM depletions were predominantly observed in T3 soils. We speculate that this pattern reflects the degradation of surface soil and SOM in the Corn Belt, which has been well documented (Rhoton et al., 2002; Thaler et al., 2021). Nonetheless, the effects of SHS on yield remained positive and statistically significant in each texture class (all $p < 0.001$; Table S4A), regardless of drought categories, indicative of the beneficial effects of SOM on corn yield.

Under severe drought, the effect of SHS on yield differed between soil suborder classes, as indicated by a significant interaction between suborder and SHS (Table S6A). The slope of the yield model was lower in suborder class S5 than in S4, while other pairwise comparisons of slopes were not statistically significant (Fig. 4; Table S7A). Similar results were also found in the SOM model of yield, such that the regression slope of S5 was lower than that of S4 (Tables S6A and S7A). However, the interaction between the suborder and SHS was not detected in the model of yield deficit. The S5 consisted of soils with the lowest mean SOM of all suborder classes, implying that these soils had the lowest capacity to retain the SOM. Most of the S5 soils in this assessment are Udults (111 out of 115 soils) from states including Alabama, Kentucky, North Carolina, Tennessee, and Virginia. As Udults tend to be heavily weathered, corn productivity is likely limited by other soil properties, such as base saturation and nutrient supply capacity. Their low SOM level also helps to explain why S5 had the lowest regression intercept of the three suborder classes (Tables S7A). Nevertheless, SHS consistently positively affected yield in each suborder class (all $p < 0.001$; Table S6A). Overall, our results point to a moderate effect of suborder on the yield benefits of soil health under severe drought.

The suborder also regulated the effect of soil health on yield under moderate and normal conditions. In both drought categories, the regression slope of S5 was lower than those of S3 and S4 (Table S7A; Fig. S7-8). In fact, both slopes of S5 were indistinguishable from 0 under moderate drought and normal conditions (Fig. S8). Consistent with those under severe drought, these results further illustrate that SOM has a relatively small impact on corn yield in Udults at regional scales. We did not conduct similar analyses under very severe drought due to the limited sample size. These results suggest that the role of suborders in regulating the soil health-yield relationships became stronger under less severe drought.

Our calculation of SHS was influenced by the conversion coefficient between SOC and SOM. While SHAPE was initially formulated using SOC, SSURGO provided data in terms of SOM. Pribyl (2010) suggested that a factor of 2 (*i.e.*, SOM $= 2 \times$ SOC) could be more accurate in most soils. Using a conversion factor of 2, the SHS values decreased compared to those derived from the van Bemmelen factor (Fig. S9); however, our main findings hold, as SHS remains more effective in predicting corn yield with increasing drought severity. These results indicate that our findings are robust against the conversion coefficient between SOC and SOM.

3.3. Implications for soil management

Overall, the results support our hypothesis that healthy soils stabilize corn yield during droughts, and the effect is particularly strong when the drought is severe. Our work builds upon past research (Kane et al., 2021; Williams et al., 2016; Zhou et al., 2021) and identifies soil health, rather than inherent soil properties, as the main driver explaining the yield-stabilizing effects of SOM during drought. Thus, building SOM and soil health has the potential to protect corn yield in a variety of soils with distinct textures and taxonomy. Although the benefits of soil health appear to be weaker in certain regions, *e.g.*, those with Udults, our work supports the notion that the benefits of restoring SOM can be scaled down to the farm scale. Since conservation practices, such as cover cropping and crop rotations, have been shown to be effective in restoring SOM (Joshi et al., 2023; Vendig et al., 2023), they could potentially increase yield stability, especially when extreme weather events are becoming more frequent. Our work also provides evidence supporting the current efforts of large-scale soil health initiatives that seek to promote agricultural resilience by increasing SOM (Lehmann et al., 2020).

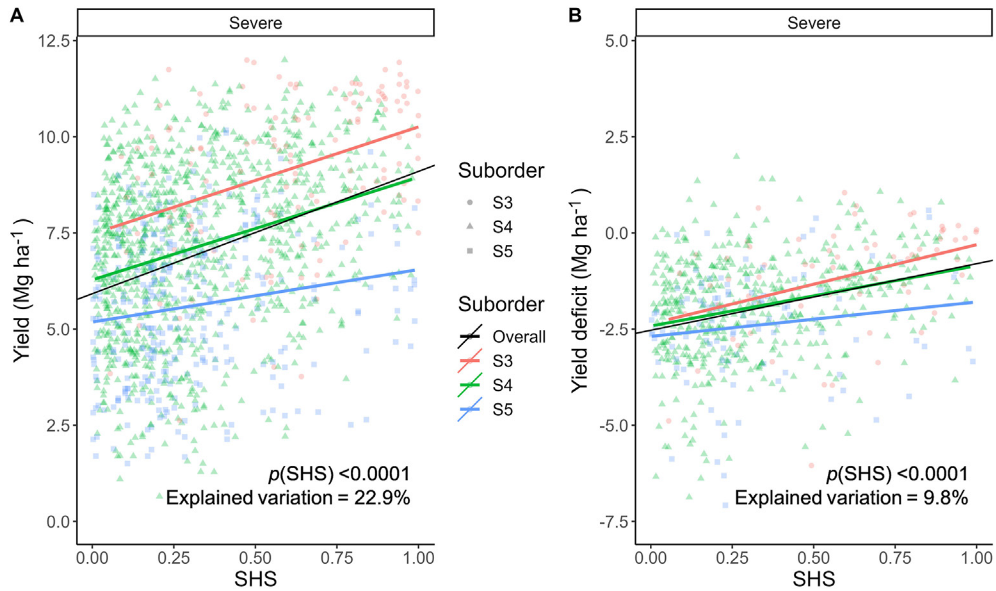

Fig. 4. The effects of SHS on yields (A) and on yield deficits (B) by soil suborder classes under severe droughts. The *p* values indicate the significance of the effect of SHS. Explained variations indicate the R^2 of the full model, including the SHS, texture classes, and their interaction.

Our findings also directly link SHS to yield, an important ecosystem function of soil, affirming the SHAPE's approach to assessing soil health. Following the peer-group approach, SHAPE offers exciting opportunities to quantify the role of soil health in regulating other soil functions. We also recognize that SHS remains a somewhat ambiguous value that acts as a catch-all for potential mechanisms. For example, multiple physicochemical mechanisms have been proposed to explain the benefits of SOM on yield, including enhanced water holding capacity, better aggregation, and improved nutrient cycling and retention (Lal, 2016; Oldfield et al., 2019; Zhang et al., 2007). Our results cannot be used to discern the importance of these mechanisms directly. Instead, we primarily focused on comparing the effectiveness of inherent vs. dynamic factors in regulating the relationships between SOM and corn yield. Nonetheless, the physiochemical mechanisms underpinning the yield benefits of SOM warrant further research.

Even though SOM is a major soil health indicator, this assessment showed that SOM is not the most important predictor of corn yield across the U.S. Our models have shown that the random factor (*i.e.*, state) could explain similar, if not greater, variation in yield compared to the combined effects of SOM, pH, clay, and AWC (Table S3), highlighting the importance of regional variation in soil characteristics and management in regulating yield. Yield was also extremely sensitive to drought (Fig. 2), and SHS or SOM alone only explained 8–15% of the variation in yield in each drought category (Fig. 2; Table S3). These results are consistent with other modeling studies of corn yield in the U.S. (Li et al., 2019; Xu et al., 2021). Our unique contribution is to identify that soil health, rather than inherent properties, is responsible for the yield-stabilizing effects of SOM.

Within this assessment, we took into consideration and discussed several aspects of soil health, including inherent and dynamic soil health indicators (*e.g.*, clay and silt content, AWC, pH, SOM, SOC), with the potential to impact crop yield responses to drought across the U.S. Nevertheless, only SOC was scored and interpreted using the SHAPE approach (Nunes et al., 2021). Incorporating other soil health indicators would have advanced the current understanding of the correlation and causality between crop yield and soil health. Yet, the current approach is adequate to answer our primary question, *i.e.*, whether the yield-stabilizing benefits of SOM could be attributed to soil health or inherent drivers. In addition, we lack large-scale data on other soil health indicators to conduct similar county-level analyses. The SOM remains the most widely adopted soil health indicator, given its close associations with many soil physical, chemical, and biological processes (Karlen et al., 2008). Other indicators beyond SOC (or SOM) are currently being included in SHAPE (personal communication; MR Nunes). It is also worth noting that our SOM and other soil characteristics are derived from a mapping product and are expected to carry relatively high uncertainty (Libohova et al., 2019). The utilization of high-resolution soil characteristics and yield maps would have improved the statistical power of our analyses. Additionally, we lacked reliable county-level fertilization data, a crucial factor contributing to the variability in yield. Future large-scale fertilization data can improve the understanding of soil health and crop yield. Finally, we studied rainfed corn, a drought-sensitive crop, for which the results for other crops in different agroecological settings might not show similar drought resilience with improved soil health as our findings showed.

4. Conclusions

Our results demonstrate that the soil health score explained a majority of the effects of SOM on county-level corn yields in the U.S. The effects of the soil health score on yield were largely consistent across different soil textures and soil suborder groups. Thus, our results demonstrate that soil health, rather than inherent properties, is largely responsible for the yield-stabilizing effects of SOM. Therefore, it is potentially feasible to increase the resilience of corn yield against drought by adopting agronomic practices that build SOM and soil health. The benefits of soil health are largely independent of texture and soil suborder, so building up soil health has the potential to improve crop productivity across a wide range of geographical locations and site characteristics.

Data availability

Data required for reproducing the statistical analyses and figures are available at https://doi.org/10.5281/zenodo.10047650.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.seh.2023.100048.

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