Soil Biology and Biochemistry 170 (2022) 108710

Contents lists available at ScienceDirect

Soil Biology and Biochemistry

journal homepage: www.elsevier.com/locate/soilbio

Rigorous, empirical, and quantitative: a proposed pipeline for soil health assessments

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ARTICLE INFO

Keywords:
Soil health indicator
Soil quality
Latent variable analysis
Soil health assessment

ABSTRACT

Soil health is a promising lens through which to approach land management, having the potential to serve as a descriptor of biophysical processes and as an effective communication tool across stakeholders. However, this potential has been largely unrealized due to difficulty in quantitatively assessing soil health and linking those assessments to outcomes. Here we discuss many multiple persistent obstacles to quantitative soil health assessment and outline a suite of analyses to help address those obstacles. Specifically, we propose a quantitative approach to developing and selecting soil health indicators that help connect management-induced changes in soil health to specific outcomes (e.g., yield or water quality). To demonstrate the utility of this approach, we perform a small case study using published data from North Carolina and New York cropping systems. Additionally, we outline how this approach is scalable and flexible enough to integrate future soil health metric development. The proposed approach stands to provide a quantitative, empirical basis for future measurement, assessment, and interpretation of soil health.

1. Introduction

Growing interest in soil health in recent decades from researchers (McDaniel, 2017), farmers (Arbuckle, 2017), and the agricultural industry has garnered legislative support across the globe (Agricultural Tranformation Agency, 2012; EMBRAPA, 2016; Harrigan and Charney, 2019; IWLA, 2019; European Commission, 2020) demonstrating the untapped potential of soil health as both a scientific and communication tool (Janzen et al., 2021; Powlson, 2021). Despite this enthusiasm from stakeholders, researchers have struggled to develop a cohesive, robust, and geographically universal framework for quantitative soil health assessment. This has led some to relegate it as a useful but qualitative metaphor, best suited for communication and not quantitative enough for empirical research (Janzen et al., 2021), while others have implored the soil science community to develop rigorous and robust standards for quantitative evaluation (Baveye, 2021). These discussions are vital, yet not entirely new. Substantive critiques of the concept of soil quality and health were raised in the 1990s (Sojka and Upchurch, 1999; Letey et al., 2003; Sojka et al., 2003), and despite efforts to address them (Karlen et al., 2003), these critiques are largely unresolved.

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https://doi.org/10.1016/j.soilbio.2022.108710
Received 29 October 2021; Received in revised form 25 April 2022; Accepted 9 May 2022
Available online 13 May 2022

Efforts to make soil health more quantitatively robust have largely centered on soil health indicators (Box 1). Ideally, these indicators are inexpensive, high-throughput, and can easily guide land management decisions (Doran and Zeiss, 2000; Stott, 2019). However, many established soil measurements struggle to meet one or more of these criteria, requiring further refinement, optimization, or alteration before they can be successfully implemented within quantitative soil health assessments. In particular, it is less clear how to link management actions to indicator responses. Efforts to standardize testing protocols have largely ignored regional and soil-type biases in quantitative soil health analyses (Kibblewhite et al., 2008; Ross et al., 2009; Biswas et al., 2017; Fine et al., 2017; Santos-Francés et al., 2019). Most importantly, there has been little work explicitly linking quantitative soil health assessments to outcomes of interest, implying that soil health assessment *is* the outcome of interest (Fig. 1a). As a result, the basis for deriving management recommendations from soil health metrics lacks rigor. However, soil health *per* se is not necessarily an outcome of interest across stakeholders (Fig. 1b). Thus there is justifiable skepticism amongst some researchers and extension personnel about the validity of soil health as a scientific enterprise, despite often overlapping goals (Delgado and Cox, 2003). Without comprehensively addressing these shortcomings, the potential of soil health to meet economic and sustainability goals remains largely unrealized (Lehmann et al., 2020).

Here we propose a four-step pipeline for a rigorous, empirically based quantitative soil health assessment (Fig. 2): 1) capture management-induced changes in soil health, 2) develop and refine soil health indicators, 3) select regionally appropriate groupings of indicators and 4) connect indicator(s) to outcomes or soil functions (e.g., productivity and/or water quality outcomes). Our proposed framework helps to resolve several ongoing critiques of the soil health concept while also offering several unique advantages for future soil health assessments. First, this framework allows for soil health to be more than a single value (e.g., a soil health score or index), but rather to derive multiple components of soil health for simultaneous quantitative evaluation. Next, our framework allows us to differentiate between the validity of a measurement across contexts (i.e., the indicator's universality) and the importance of the trait(s) that the measurement is representing in that context (i.e., the saliency of management-induced changes). Lastly, this framework is easily integrated into regression-based techniques that can establish linkages between soil health traits and multiple outcomes. For each step in the pipeline of soil health assessment, we highlight how these quantitative methods can be used to address current shortcomings. Lastly, we analyzed several recently published datasets using a common set of soil health indicators to demonstrate the robustness and flexibility of our framework across differing edaphic contexts. A technical analysis and notes on implementation are provided in the Technical Appendix. While many of the examples are agriculturally oriented, there are many potential parallels with less intensively managed systems.

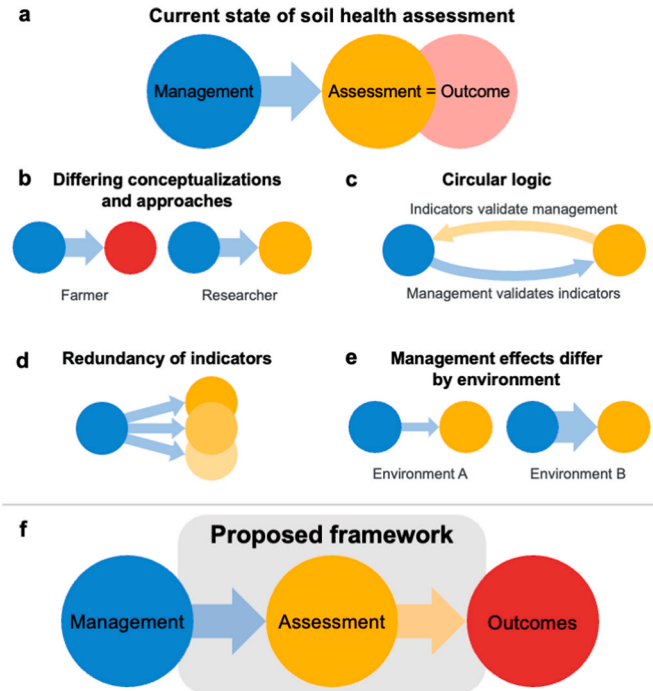

Fig. 1. (a) The current state of quantitative soil health assessments and (b–e) several problems and pitfalls associated with current approaches. These include (b) differing approaches to soil health by key stakeholder groups, (c) a circular logic that is ubiquitous among the soil health literature, (d) current difficulties in addressing the redundancy of soil health indicators, and (e) the differing management effects across environments, while (f) outlines the scope of the currently proposed framework.

2. Analytical pipeline

2.1. Step 1: capture management-induced changes in soil health

A primary goal of soil health assessments is to describe management-induced changes in soil functioning. Land managers are often interested

Box 1
Definitions and terminology

Currently, there are many terms in soil health that may be inconsistently or poorly defined. Therefore, we will use the following operational definitions:

- Soil health: the capacity of a soil to function as a vital living ecosystem that sustains plants, animals, and humans (USDA definition). This definition is similar to the definition of soil quality, although soil health tends to emphasize the dynamic (i.e., management-responsive) traits of soil, which often tend to be biological.
- Soil health indicators: specific measurements that are used to quantify soil health. These often differ from research methods due to the desire for high-throughput analyses in commercial settings. Ex: organic matter via loss on ignition, or permanganate oxidizable carbon (POXC).
- Soil health assessment frameworks: the quantitative and conceptual approach towards integrating and interpreting soil health indicators. Ex: Soil Management Assessment Framework (SMAF), the Comprehensive Assessment of Soil Health (CASH), or the Haney Soil Health Test (HSHT).
- Soil health outcomes: specific, measurable manifestations of one or more of the five soil health functions (https://www.nrcs.usda.gov/wps/portal/nrcs/main/soils/health/). Ex: plant productivity or decreased NO_3^- losses.
- Soil health traits: here, we used this term to refer to the biological interpretation of the underlying conceptual construct (i.e., the latent variable). The Technical Appendix includes additional discussion of terminology for quantitative methods.

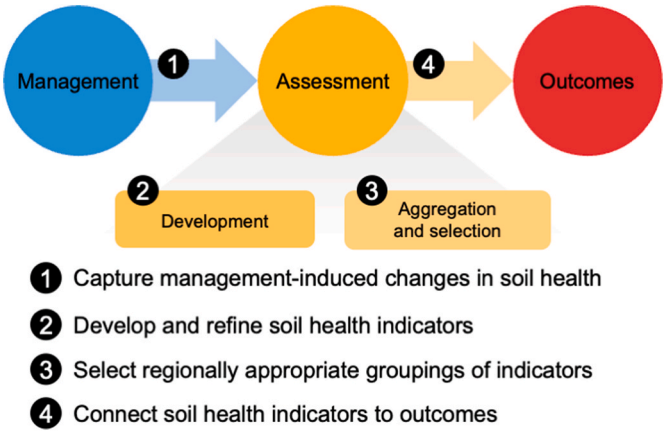

Fig. 2. An overview of the proposed pipeline for quantitative soil health assessments, including Steps 1–4 discussed in-text.

in monitoring changes in soil health to help troubleshoot or monitor progress towards a desired outcome (e.g., yield, profitability, etc.) (Andrews et al., 2003; Lobry de Bruyn and Andrews, 2016; Upadhaya et al., 2021; Wade et al., 2021a). However, the magnitude and direction of management effects tend to be context specific. For example, the effect of specific soil health management practices like no-till or cover crops on yields are often contingent upon immutable characteristics such as soil type or climate (Pittelkow et al., 2015a; Hijbeek et al., 2017; Wortman et al., 2017; Reiss and Drinkwater, 2018; Morugán-Coronado et al., 2020; Peterson et al., 2020). Moreover, on-farm conditions often stack multiple management practices and are adaptive to a changing environment, in contrast to the controlled comparisons of single practices in research trials. To bridge both the context-specificity and the stacking of soil health building practices, soil health researchers have developed indicators and soil health assessments to aid farmer decision making. However, this can lead to differing end-goals: researchers are often focused on soil health assessment, whereas farmers are primarily interested in agroecological outcomes resulting from improved soil health (Fig. 1b).

The use of soil health indicators as outcome or response variables has led to a circular logic in the broader arc of implementation and interpretation. Much of the current soil health literature essentially asks "does management change the values of these soil health indicators?" (Congreves et al., 2015; Chahal and Van Eerd, 2018; Dhakal and Islam, 2018; Diederich et al., 2019; Wade et al., 2019; Agomoh et al., 2020; Williams et al., 2020), and a change in indicators is interpreted as a change in soil health. These studies are valuable for understanding management effects and the sensitivity of indicators across contexts. However, the interpretation of these results takes one of two generalized forms: 1) "when we perform X soil health-building management practices, these indicators respond, therefore these indicators reflect soil health" (e.g., Franzluebbers et al., 2000b; Weil et al., 2003; Acosta-Martínez et al., 2004; 2008; Franzluebbers and Stuedemann, 2008; Lucas and Weil, 2012; Culman et al., 2013), or 2) "these soil health indicators respond with management, therefore this management builds soil health" (e.g., Nunes et al., 2018, 2020; Wood and Bowman, 2021). Thus, 1) management is used to validate the indicators while 2) the indicators are also used to validate the management (Fig. 1c). This circular logic entails soil health indicators becoming the *ends*, rather than the *means*, compromising the ability of soil health assessment to reliably achieve broader on-farm or environmental goals. For soil health research and implementation to advance, this tautology must be addressed by independently verifying soil health indicators.

One reason for this difficulty in widespread implementation of soil health assessments is the current approach to quantifying soil health. These approaches rely on *a priori* specification of which indicators to include in an assessment and assumptions about how to interpret those indicators. This *a priori* specification can be implicit—variables are simply included at the conception of the integrating framework without empirical justification (Andrews et al., 2004; Moebius-Clune et al., 2017; Haney et al., 2018)—or explicit—expert judgements are included as part of indicator selection process (Rinot et al., 2019; Stott, 2019; Zwetsloot et al., 2022). After selection and measurement of soil health indicators, each indicator's data may be used to calculate a final "score". Scoring is done by one of two approaches: scoring functions or expert opinion. The resulting soil health "scores" can then be used to construct a single value to represent the overall health of a soil (Fig. 3a). The scoring functions approach uses existing databases of soil health indicator values to assign a grade (often as a percent) based on where an observation falls within the cumulative normal distribution.

The use of scoring functions in soil health frameworks presents two main obstacles to widespread implementation. First, systematic sampling biases can influence scoring of underrepresented soils. For example, published values from the Comprehensive Assessment of Soil Health (CASH) database are dominated by the relatively less weathered and higher organic matter soils of the temperate Midwest and northeastern United States (Fine et al., 2017). Thus, comparisons across contrasting soils are biased towards specific sets of soil traits (e.g., organic matter content). This is not unique to the CASH, as scoring functions have long been criticized for their regional biases (Sojka et al., 2003). Further differentiation based on soil taxonomic classification, texture, and climatic properties is possible (Fine et al., 2017; Nunes et al., 2021), although ensuring sufficient sample size within each of these sub-classes requires large databases to fully evaluate the potential range of soil health indicators. Resources required to construct large, representative datasets are a barrier to introducing new soil health indicators, potentially stymying innovation. While consolidation of databases and accompanying scoring functions may be conducive to

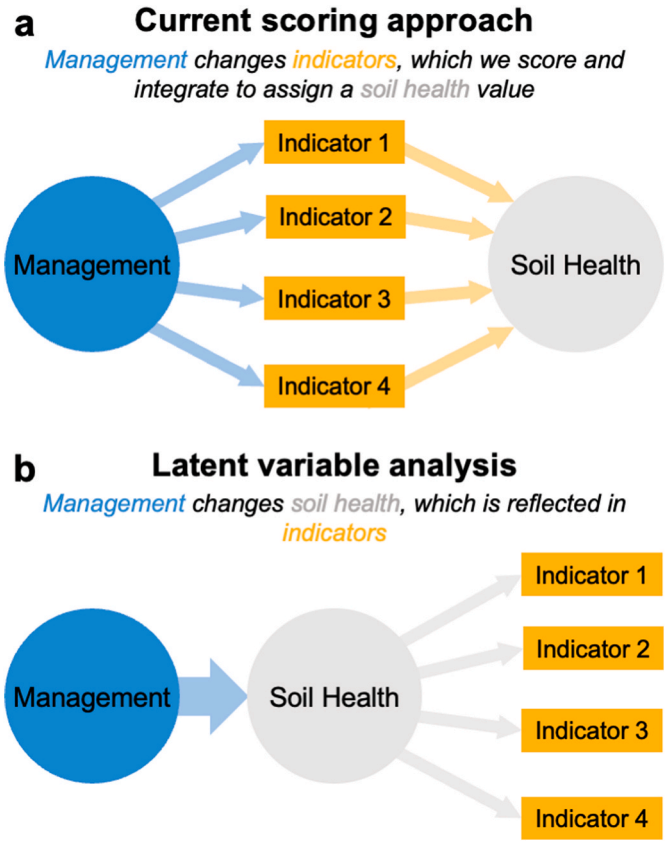

Fig. 3. The difference between (a) current approaches to soil health scoring and (b) a latent variable analysis approach to quantifying soil health.

regional-scale assessments of soil health, these databases (in their entirety or a representative sample) are often not publicly available.

Another approach to integrating multiple soil health indicators to arrive at a final overall soil health value is based solely on expert opinion. While this approach is far less common in the realm of soil health *research*, it is more common in commercial soil health *testing* (e.g., Haney et al., 2018; used by several large labs - wardlabs.com and blinc.com; accessed 11 April 2022). The formula for calculating the overall Haney soil health score has changed several times since its inception (Yost et al., 2018; Singh et al., 2020; Adhikari et al., 2021), which hinders comparability and exposes the weak theoretical basis of the scoring. Other prominent commercial soil health frameworks (e.g., solvita.com, accessed 11 April 2022) also have expert opinion based scoring schema, which are similarly opaque and unvetted in peer review.

Our proposed framework addresses these shortcomings in describing management effects by using latent variable analysis to derive, rather than assume, the traits of a healthy soil and how these traits are represented by indicators. Latent variable analysis uses patterns of covariation in measured variables to describe unobservable underlying *constructs* (Borsboom et al., 2003). For soil health, these relationships imply that management causes changes in underlying soil health traits (i.e., constructs), which are imperfectly reflected in multiple soil health indicators (Fig. 3b). Importantly, this assumes that management-induced changes in the underlying soil health traits *causes* changes in measured variables (i.e., soil health indicators). This quantitative approach reflects the implied logic of soil health indicators as proxies for traits of healthy soils: soil health indicators are imperfect reflections of underlying changes in soil health. The mathematical implication of this is that measurement error associated with soil health indicators (e.g., analytical variability) is attributed entirely to the measured variable, rather than the latent variable, providing an error-free measurement of the underlying soil health trait (Fig. S1).

Factor analysis is a specific form of latent variable analysis where a set of continuous measured variables are used to construct new, continuous, normally distributed latent variables. One benefit of applying factor analysis to soil health is that exploratory factor analysis (EFA) makes no *a priori* assumptions about the relationships between measured variables or the number of latent constructs they describe (Fig. 4a). Therefore, the latent constructs and the variables describing them are empirically derived, rather than constructed. This characteristic of deriving functionality (rather than assuming) is especially important given the prevailing uncertainty in interpreting soil biological measurements (Fierer et al., 2020) and in the tenuous linkages between gene abundance for proteins and the functions they are presumed to represent (Rocca et al., 2015). Confirmatory factor analysis (CFA) can then be used to test the robustness of the latent soil health constructs and the soil health indicators describing them (Fig. 4b).

2.2. Step 2: develop and refine soil health indicators

The development of soil health indicators serves as the basis of quantitative soil health assessments. These indicators are often classified *a priori* as representing physical, chemical, or biological aspects of soil health (Andrews et al., 2004; Moebius-Clune et al., 2017; Rinot et al., 2019; Xue et al., 2019). Despite the emergence of several new indicators over the past two decades, there is little convergence in the literature on which indicators should be used to assess soil health (Bünemann et al.,

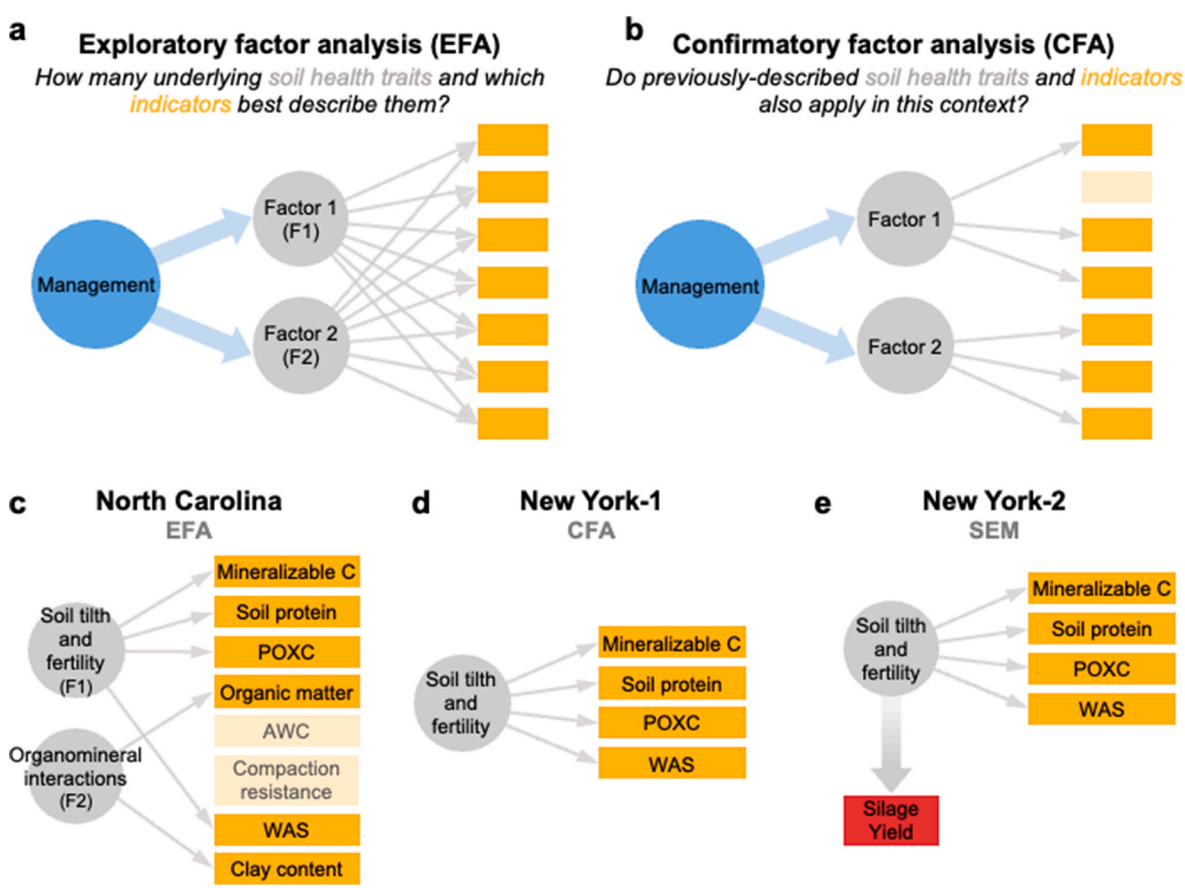

Fig. 4. The conceptual differentiation between exploratory (a) and confirmatory (b) factor analysis. Results of the case studies using (c) exploratory factor analysis for the case study North Carolina datasets, (d) confirmatory factor analysis on the New York-1 dataset, and (e) a structural equation model on the New York-2 dataset relating the factor to corn yield (silage) are also shown. Factor loading scores for (c) can be found in Table 1. Factor loading scores and regression coefficients for (d) and (e) can be found in Table 2.

2018; Stewart et al., 2018). This is partially, if not mostly, attributable to difficulty in defining meaningful criteria for deciding which indicators to measure (or not measure) and subsequently selecting the preferred analytical methods for the included indicators.

New soil health indicators should not be redundant with existing, well-established methods, but rather should provide novel information that reflects novel ecological functions (Fig. 1d). As with many complex biological processes, soil health indicators are often highly correlated with one another (Fine et al., 2017; Caudle et al., 2020), complicating the process of indicator selection, analysis, and interpretation.

As efforts are made to streamline and adapt previous soil measurements to the high-throughput requirements of soil health indicators, it is often unclear which methodological compromises are acceptable and which are not. This has resulted in extensive debate within the literature on soil health indicator methods (Franzluebbers and Haney, 2018; Wade et al., 2018, 2020b, 2021b; Franzluebbers and Veum, 2020; Pulleman et al., 2020; Culman et al., 2021). This is not unique to soil health indicators, as even characterization of fundamental and relatively static soil characteristics such as texture (Faé et al., 2019) or total soil organic matter (Pribyl, 2010; Hoogsteen et al., 2015; Roper et al., 2019) have proven difficult to generalize across soil types. Though differing methods are often "closely related" to one another—as indicated by a high correlation coefficient or R^2—this does not necessarily provide insight into which method is preferable or providing novel information (Fig. 1d). For example, total C and N are often highly related ($R^2 > 0.90$), but clearly provide differing information and describe different characteristics of a soil. Similarly, methodological permutations for soil health indicators could be describing differing, but as yet unrecognized, soil health traits. The ability to distinguish the merit of specific methodological alterations is further complicated by the paucity of studies reporting relationships between indicators and agronomic or ecological outcomes. Our proposed framework addresses these shortcomings by determining 1) if a given indicator provides unique or meaningful information and 2) what combination(s) of indicator variables best describe underlying soil health processes.

One distinct advantage of factor analysis for soil health indicator development is the ability to determine *if* the indicator provides novel information. Currently, many minimum data set determinations are based on principal components analysis (PCA). The goal of PCA is to describe the maximum amount of variance which—given the high interrelatedness of total soil organic matter with many other soil properties—explains the prevalence of organic matter in PCA-based minimum data sets (Bünemann et al., 2018). However, this does not allow us to determine which indicator(s) provide unique information about soil health traits. Thus, the latent variable approach of factor analysis allows us to differentiate which indicator(s) correspond to each of the many roles of soil organic matter. For example, this may allow for differentiation between soil health indicators that reflect structural organic matter and soil health indicators that reflect biologically active organic matter.

Another advantage of a factor analysis-based development of soil health indicators is its utility in guiding methodological decisions. Instead of determining if two methods are closely related, a comparison of CFA model fits can help determine if these differing methods describe the same underlying trait/construct. For example, cumulative C mineralization 1 day after rewetting is closely related to cumulative mineralization at 3 or even 24 days (Franzluebbers et al., 2000a), but the mechanistic processes driving 1-day C mineralization differs sharply from the processes driving 3-day or 24-day mineralization (Brangarí et al., 2020; Slessarev and Schimel, 2020). CFA could be used to differentiate between these processes and guide methodological decisions, e.g. incubation duration in mineralizable C (Wade et al., 2018) or enzyme assay conditions (Daughtridge et al., 2021; Li et al., 2021). Importantly, CFA does this without requiring a comparison with an outcome variable (see: Martin et al., 2022). For example, differentiating between mineralizable C incubation intervals can be performed without any of the common response variables N mineralization or plant productivity (Schomberg et al., 2009; Wade et al., 2016, 2020a; Franzluebbers, 2018, 2020; McDaniel et al., 2020). Thus, CFA provides a quantitative basis for establishing conceptual comparability among methods and the soil health traits those methods are measuring.

2.3. Step 3: select regionally appropriate groupings of indicators

There are dozens of existing soil health indicators, yet relatively few are widely used in soil health assessment (Bünemann et al., 2018; Stewart et al., 2018). While this can be attributed to investigator familiarity with specific measurements, it also points to a lack of effective selection criteria in current frameworks. Although some frameworks explicitly include indicator selection (Rinot et al., 2019), most do not, instead implicitly relying on expert opinion and assumptions about the functionality of soil health indicators. The potential biases inherent in this opaque and unvetted process can lead to indicators that are inconsistent or unresponsive to management (Roper et al., 2017; Singh et al., 2020), ultimately resulting in the exclusion of these indicators from future assessments.

Implicit in the rationale that indicators insensitive to management should be excluded is the assumption that these indicators are insensitive because they are ineffective in a specific edaphic context. However, this assumption overlooks the expansive body of meta-analyses showing that the effects of soil health-building management on beneficial soil traits vary widely by climate, soil order/group, and/or texture (McDaniel et al., 2013; Pittelkow et al., 2015b; a; Bowles et al., 2017; Byrnes et al., 2018; Jian et al., 2020; Kim et al., 2020). Thus, attributing a lack of measurable change in a soil health indicator to the inefficacy of the indicator itself neglects the possibility that the management itself may provide limited or negligible improvements in soil health. In other words, this does not consider that the change in the trait described by the indicator may not be salient within that context. This distinction is fundamentally a question of where to attribute uncertainty: is the soil health indicator insensitive to changes in management in that context, or is the management not producing any changes in soil health?

In our proposed framework, factor analysis (or more generally, latent variable analysis) enables us to better differentiate between the insensitivity of the indicator and the ineffectiveness of management to alter soil health. To better distinguish between these sources of uncertainty, factor analysis gives a quantitative basis for establishing conceptual reproducibility (as opposed to direct reproducibility). Conceptual reproducibility emphasizes the interchangeable nature of measurements and measurement methods, whereas direct reproducibility emphasizes the precise replication of results (Nosek and Errington, 2017). This distinction facilitates differentiation between the universality of the indicator (i.e., its ability to describe similar traits across contexts) and the saliency of the trait being described (i.e., the magnitude of the management-induced change across contexts). This shifts the research question from "does a change in management alter X indicator in Y context?" to "does X indicator describe the same trait in Y context?" This distinction provides a grounded, empirical basis for determining which soil or climatic characteristics are influencing results. This can then be coupled with other statistical methods to determine if differing soil orders or sets of inherent soil characteristics (Seaton et al., 2020; Devine et al., 2021) are best analyzed together or separately.

2.4. Step 4: connect soil health indicators to outcomes

One of the primary challenges for quantitative soil health assessments is to causally link soil health indicators and resulting soil health scores to functions or outcomes that are of interest to land managers (e.g., water quality, nutrient use efficiency, decreased erosion). While many studies have linked total soil organic matter content to productivity data (Lal et al., 2004; Congreves et al., 2015; Oldfield et al., 2019), other soil health indicators—many of which are presumed to represent

smaller and more biologically active pools of soil organic matter (Wander, 2004)—have had less success. Overall, individual soil health indicators are moderately correlated with productivity (Culman et al., 2013; Chahal and Van Eerd, 2018; van Es and Karlen, 2019), providing inconsistent, yet often better information about productivity than total organic matter measurements. For example, a direct comparison showed that soil health indicators related more strongly to productivity than SOC in 12 out of 14 comparisons, although the specific preferred indicator varied by context (Hurisso et al., 2016). These linkages to productivity have largely neglected other potentially beneficial outcomes from soil health, such as improvements in water or air quality, improved nutrient use efficiency, resilience to drought, or other ecosystem services (Zwetsloot et al., 2021). This is likely the most important step for widespread adoption and to meet sustainability goals (Lehmann et al., 2020).

Our proposed framework to develop robust assessments of soil health is easily integrated into other regression techniques for testing causal linkages between indicators and outcomes. There are several potential quantitative analyses that allow for testing these potential linkages. Factor score regression—where scores for each observation are extracted from latent variables and used as a unique variable in multivariate regression (DiStefano et al., 2009)—allows for multiple predictor variables to estimate effects on a single response variable. However, as a form of multiple linear regression, factor score regression is less robust to potential collinearity and causal links between predictor variables, which are common in soil and ecological sciences (Grace and Irvine, 2020). Structural equation models are another viable analysis, with the added benefit of multi-cause, multi-outcome inference (Grace, 2006). Although structural equation models are increasingly used in soil science (Eisenhauer et al., 2015), they have yet to be widely implemented for soil health analyses. Recently, Bongiorno et al. (2019) used structural equation modeling to loosely link soil health indicators to soil suppressiveness of the plant pathogen *Pythium ultimum*. While not integrating the factor-analytic approach for defining soil health traits, this study demonstrated the potential usefulness of structural equation modeling to integrate theory with empiricism. Using a latent variable approach to integrate multiple soil health indicators into a single "soil health" variable, Wade et al. (2020a) recently demonstrated that increases in soil health substantially increased corn grain yields, independent of N fertilization effects, further extending the potential for integrating theory with empiricism in soil health. While both studies used structural equation models to connect to a singular outcome of interest, these are limitations of those datasets and not of the capabilities of the quantitative methods. Structural equation models are well suited to simultaneously examine multiple outcomes, though this approach has yet to be widely applied.

The evaluation of multiple outcomes is essential in addressing a shortcoming of the current strategy of calculating a single overall value for soil health: the desirability of a process is contingent upon the management goals for a specific system. Current soil health assessments assume that most soil health indicators and the resulting soil health scores should be interpreted using a "more is better" approach (Andrews et al., 2004; Moebius-Clune et al., 2017; Haney et al., 2018). However, this may not always be the case (Oldfield et al., 2019, 2020) and the desirability of a trait varies from system to system. For example, the ability of a soil to supply plant available N is a desirable quality in row crop systems (Osterholz et al., 2017), but produces negative effects in wine grape vineyards (Lazcano et al., 2020). Thus, the simplification of soil health scoring to "more is better" imposes a rigidity to soil health assessments that may not be appropriate and could preclude their widespread utility in land management. Our proposed approach of connecting sets of indicators to specific traits is value-neutral and therefore flexible across contexts, ultimately broadening the applicability of quantitative soil health assessments.

3. Case study of soil health indicator robustness using differing contexts

To demonstrate how our framework can be used to describe underlying soil health constructs from contrasting environmental contexts, we use results from two published studies (3 datasets total) that use the CASH assessment and where the analyses were run in the Cornell Soil Health Lab. The first dataset is from North Carolina (Roper et al., 2017). The soils in this dataset are from NRCS-designated land resource regions N, P, and T, developed on colluvial and alluvial parent materials and are largely classified as Ultisols within the USDA system (Roper et al., 2017). The Köppen climate zones are humid subtropical (Cfa) and oceanic (Cfb). The second and third datasets are from a single study in New York state (Nunes et al., 2018). These two datasets are from land resource region R, where the dominant depositional environments are glacial deposits (till or outwash) (NRCS, 2006). The Köppen climate zones are continental (Dfa, Dfb) and the soils are primarily classified as Alfisols or Entisols. Thus, the North Carolina dataset and the New York datasets differ in depositional environment, climate, and subsequently in the soil classification.

Here, we demonstrate how factor analytic approaches can be used to determine the universality of soil health indicators. Our analysis focuses on selecting indicators (Step 2), using those indicators to describe underlying construct(s) or trait(s) (Step 3), and connecting those trait(s) to some sort of outcome of interest (i.e., yield) (Step 4). This is intended as an example of how to implement and interpret these analyses and not a rigorous testing of the actual indicators themselves. Our datasets were chosen based on data availability and sharply differing edaphic contexts. We provide a brief overview of the results, but more information on the quantitative analyses can be found in the Technical Appendix and reproducible R code can be found online (https://github.com/jordonwade/Quantitative-Soil-Health).

Using factor analysis to determine underlying soil health processes can be split into two separate steps. These steps answer two distinct, yet related questions: 1) how many underlying traits are there and which indicators describe them? And 2) are these traits described by the same set(s) of indicators across regions? These questions directly relate to the quantitative analyses of EFA and CFA, which are analogous to a calibration and validation set (respectively). While it is possible to perform EFA and CFA on the same dataset using resampling or partitioning, here we used two independent, geographically and edaphically diverse studies to demonstrate how to address these questions. We used a total of 8 of the measurements from the CASH as candidate indicators in our factor analysis: compaction resistance at 0–15 cm depth, available water holding capacity (AWC), mineralizable C, soil protein, POXC, total organic matter, wet aggregate stability (WAS), and clay content. These 8 indicators are the most commonly used soil health measurements from the CASH, excluding the modified Morgan nutrient extraction that was developed specifically for soils in Northeastern US. Subsurface compaction resistance (15–45 cm) was also excluded because the other laboratory measurements are conducted on soil from the surface (0–15 cm). While none of these indicators may be considered "true" biological indicators (e.g., gene expression or enzyme activity), they have been loosely linked to 16S rRNA gene expression (Wilhelm et al., 2022).

We first performed an EFA on the North Carolina dataset to determine the number of soil health constructs. We used four different, yet complementary quantitative analyses which generally agreed that these indicators describe two underlying traits (i.e., two factors was the best fit to the data). One of the four tests (the Kaiser criterion) suggested three constructs, while the other three tests suggested two constructs. Thus, while we did not see full agreement across the four test methods, these discrepancies were consistent with known tendency for the Kaiser criterion to overestimate the number of factors (see Technical Appendix for more details). However, agreement across three of the four tests gives us a high level of confidence (>90%) in the result that our indicators describe two underlying constructs (Ruscio et al., 2010; Ruscio and

Roche, 2012).

Indicators clearly grouped onto two factors. The ability of indicators to describe each construct/soil health trait is reflected in the factor loading, where higher absolute values indicate a greater ability to describe a given construct/soil health trait. While there is no strict cutoff for a "good enough" factor loading, it is generally assumed to be somewhere between the lenient threshold of 0.40 and conservative cutoff of 0.60 (Matsunaga, 2010). Due to the clear delineation of the constructs, all factor loadings met the stricter criteria of >0.60. Mineralizable C, soil protein, POXC, and WAS were retained on the first factor (Table 1), which we will tentatively classify as representing "soil tilth and fertility". The second factor was described by clay content and organic matter content, which we would classify as representing "organomineral interactions". Compaction resistance and AWC did not have strong factor loadings and therefore were eliminated from further factor analysis (e.g., CFA or SEM) (Fig. 4c). This exclusion of AWC and compaction resistance should not be interpreted as a deficiency of these measurements, but rather that they provide little additional information about the two soil health traits described by the other indicators.

Next, we used an existing dataset to validate the robustness of the first factor (soil tilth and fertility) in a contrasting edaphic context (Fig. 4d). Specifically, we used published data on rotation and tillage study (New York-1), which was conducted on a loamy fine sand in New York state (Nunes et al., 2018). We used a CFA to determine if the indicators associated with the soil tilth and fertility construct in North Carolina represented a similar construct in New York (Step 3; Fig. 2). Despite the coarser soil texture, cooler climate, differing soil classification, and sharply differing depositional environment, the CFA showed that the soil health indicators associated with the soil tilth and fertility construct in the North Carolina dataset described a similar construct in this smaller New York-1 dataset (n = 16). The model fit indices most suitable for small datasets (i.e., the SRMR and the CFI) showed a good model fit (Table 2 and Technical Appendix). Therefore, we have reason to believe that 1) these indicators are valid across contexts (i.e., have some degree of universality) and 2) will describe the same trait across contexts. Thus, we have quantitative evidence that this set of indicators—mineralizable C, POXC, soil protein, and WAS—describe a similar trait across these two disparate contexts and is conceptually reproducible. While this allows for us to determine that the indicators are robust across contexts, it does not give us information about whether the trait those indicators describe (i.e., soil tilth and fertility) directly influences productivity (i.e., is agronomically salient).

Table 1
Soil health indicator loadings and communality estimates from exploratory factor analysis (EFA) in the North Carolina dataset. Bolded values indicate that the loading is sufficiently high to be retained in the confirmatory factor analysis. Communality (h^2) is the proportion of the variance for each measured variable that is represented by the factors. Uniqueness (u^2) is the proportion of variance that is not represented by the factors, where $u^2 = 1 - h^2$.

Type of Indicator	Indicator	North Carolina			
		Factor loading		Communality (h^2)	Uniqueness (u^2)
		F1	F2		
Biological	Mineralizable C	**0.69**	0.22	0.51	0.49
	Soil protein	**0.82**	−0.36	0.82	0.18
	POXC	**0.86**	0.09	0.74	0.26
	Organic matter	0.41	**0.84**	0.87	0.13
Soil trait	Clay	−0.27	**0.96**	1.00	0.00
Physical	AWC	0.41	0.35	0.28	0.72
	Compaction resistance	−0.10	−0.04	0.01	0.99
	WAS	**0.63**	0.02	0.40	0.60
	Variance explained (%)	*33.8*	*24.1*		

POXC = permanganate oxidizable carbon; AWC = available water capacity; WAS = wet aggregate stability.

Table 2
Case study results for the New York-1 and New York-2 datasets. Factor loadings scores, regression coefficients (italicized), and model fit are shown for both datasets. Note that New York-1 does not include a regression coefficient since it is a confirmatory factor analysis, which lacks a structural regression component. "Factor 1" is interpreted as representing soil tilth and fertility.

Variable	Parameter Estimates	
	New York-1	New York-2
WAS[a]	0.81	0.88
Soil protein	0.99	0.96
Mineralizable C	0.81	0.81
POXC[b]	0.88	0.93
Factor 1 → Yield	–	0.87 ($p < 0.001$)
Model fit indices		
SRMR[c]	0.042	0.055
CFI[d]	0.982	0.886

[a] WAS = wet aggregate stability.
[b] POXC = permanganate oxidizable carbon.
[c] SRMR = standardized root mean square residual.
[d] CFI = comparative fit index.

The next and final step in our pipeline (Step 4, Fig. 2) is to connect this soil health trait (i.e., soil tilth and fertility) to an outcome of interest. Specifically, we used data from a full factorial cover crop and tillage study (New York-2) on a silt loam in New York state, which included corn silage yield data as our desired outcome of interest (Nunes et al., 2018). To test how and if this trait influenced productivity, we used the soil tilth and fertility factor—developed in the North Carolina dataset (Step 2) and validated in the New York-1 dataset (Step 3)—as a predictor of corn silage yield in a structural equation model (Fig. 4e). We found that while there was a strong, positive relationship between soil tilth and fertility and yield ($\beta = 0.87$, $p < 0.001$; Table 2), the model was only a mediocre fit to the data. While the SRMR showed a good fit, the low CFI (0.89) suggested that the improvements over the null hypothesis (i.e., no relationship) were limited. Therefore, while soil tilth and fertility may have positive influences on yield, there are other traits that are also influencing corn silage yield at this site. In the interest of brevity and not overinterpreting a small dataset (n = 16), we will not explore what other traits are influencing yield at this site. However, it is possible that after accounting for those traits, the effect of soil tilth and fertility on silage yield could become clearer.

The grouping of biologically designated indicators (e.g., mineralizable C, soil protein, and POXC) with physical indicators (e.g., WAS) in all three datasets suggests that delineations of biological, chemical, or physical components of soil health may be less clear than often implied. This demonstrates the potential for factor analytic approaches to address criticisms of biological reductionism in soil health research (Coyne et al., 2022), integrating across these three components, regardless of differences in soil order, texture, or climate. Arguably, both POXC and soil protein are chemical indicators meant to approximate more complex biological processes (Loginow et al., 1987; Rosier et al., 2006; Hurisso et al., 2018), which further underscores the potential of factor analytic approaches to cut across the current conceptualizations used in soil health assessments.

This three-step process—EFA, followed by CFA, and SEM—demonstrates how to differentiate between the universality of indicators (i.e., their robustness in describing soil health traits across contexts) and the saliency of those traits for representing an outcome of interest. Our results show that while the soil health trait is conceptually reproducible across all three datasets, the trait being described (i.e., soil tilth and fertility) does not have a substantial effect on corn silage productivity in the New York-2 dataset. Conventionally the lack of relationship to crop productivity is interpreted as demonstrating the ineffectiveness or

uncertainty of the indicator (Hurisso et al., 2016; Chahal and Van Eerd, 2018; Gannett et al., 2019; Agomoh et al., 2020, 2021; Adhikari et al., 2021), whereas our approach allows for better attribution of uncertainty. Specifically, we show that the indicators associated with our soil tilth and fertility trait—POXC, mineralizable C, soil protein, and WAS—represent a similar trait across all three contexts, though that trait does not have a consistent effect on corn silage yield in the New York-2 dataset. Follow up work could take many forms depending on the theorized cause, but potential options include: 1) if the indicators are considered inherently flawed, then future work could focus on developing new indicators (Step 2) or 2) if the lack of a result is considered to be a regional bias, then future work could focus on replicating the soil health trait of interest (Step 3) and then determining if it affects yield (Step 4). It is important to note that this set of analyses is only intended as a brief proof-of-concept and not a thorough hypothesis test. The New York datasets we used here are relatively small and therefore could be a biased sample. Additionally, we limited our discussion to only one of two potential traits from the North Carolina dataset and only one outcome variable. Nevertheless, it shows the possibility for this approach to integrate soil health measurement and assessment across studies and contexts in a cohesive, empirically based and quantitative manner.

4. Implementation and scalability

As indicator-based soil health assessments become more commonplace in land management decision making and new indicators are developed, the feasibility of these assessments at a commercial scale must also be considered. Importantly, factor analytic approaches are robust to unstructured sampling designs, making them highly amenable to applied on-farm research or survey-based designs. Farmers preference for soil tests over web-based calculators (Tao et al., 2012) suggests that they are more likely to use information from soil health testing, which is further supported by farmer reports that soil health tests are informative and useful (Andrews et al., 2003; Wade et al., 2021a). Thus, as soil health indicators become more actionable and offered by more commercial soil test labs, farmers may increase their overall usage of these indicators. Moreover, as research finds sets of indicators that describe similar soil health traits (Fig. 2, Step 3) and consistently connect those sets of indicators to outcomes (Fig. 2, Step 4), commercial labs could offer "packages" or bundles of indicators to help land managers optimize for specific outcomes. For example, if a land manager wanted to optimize nitrogen efficiency, they could select one set of tests, whereas if they wanted to optimize for increasing C storage, they could select for another (possibly overlapping) set of tests. However, the interpretation and implementation of these results would be specific to the land manager's goals. To return to a previous example: greater soil N supply could be desirable in row crops, but undesirable in wine grape production.

Current suites of soil health indicators are far from exhaustive and therefore the ability to incorporate new measurements is of paramount importance. While this is discussed in NRCS soil health sampling recommendations (Stott, 2019), the path to integration is less clear. Our proposed pipeline for developing and operationalizing new soil health measurements is robust to the introduction and integration of new indicators and outlines a systematic procedure for vetting. While new indicators would need to be understood within the context of existing indicators, this can reasonably be achieved with datasets as small as 50 observations (de Winter et al., 2009). We have outlined a quantitative process for how a new indicator might be vetted and incorporated into soil health assessments. Specifically, future soil health indicators will likely integrate our growing understanding of soil biological processes. Therefore, as our understanding of the soil microbiome and soil food webs improves (Fierer et al., 2020), we can incorporate additional "true" biological metrics such as microbial or nematode richness/abundance data, the presence of keystone taxa, or the prevalence of functional genes. For example, recent work has used factor analytic approaches to integrate conventional soil health indicators with nematode community assessments, establishing linkages across trophic levels and approaches (Martin et al., 2022). Though much of our analysis is primarily oriented towards intensive agricultural management, the framework may also be transferrable to less intensively managed soils. Nevertheless, the soil health pipeline proposed herein thus offers a flexible approach anticipated to respond to likely changes in soil health measurement and assessment.

5. Conclusion

The quantitative assessment of soil health that is universally relevant has thus far proved difficult. Current approaches are highly subjective and lack the ability to integrate multiple soil health indicators into a coherent, interpretable framework. Here we have outlined a quantitative approach to assessing soil health that 1) empirically derives the traits of a healthy soil, rather than simply constructing indices, 2) can quantitatively test the appropriateness of soil health indicators across geographic contexts, and 3) clearly outlines how to connect soil health indicators with outcomes. This approach is reproducible, scalable, and is flexible enough to test and integrate new soil health indicators as they are developed. Therefore, this pipeline addresses many of the current shortcomings in soil health assessment and ultimately provides a way forward for soil health research and implementation.

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.

Acknowledgements

We would like to thank Alan Franzluebbers, Deanna Osmond, Giulia Bongiorno, and Harold van Es for comments on previous versions of this manuscript. Additionally, we would like to thank Jessica Logan for consultations on statistical specifics of factor analysis.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.soilbio.2022.108710.

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