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Soil health assessment: A critical review of current methodologies and a proposed new approach

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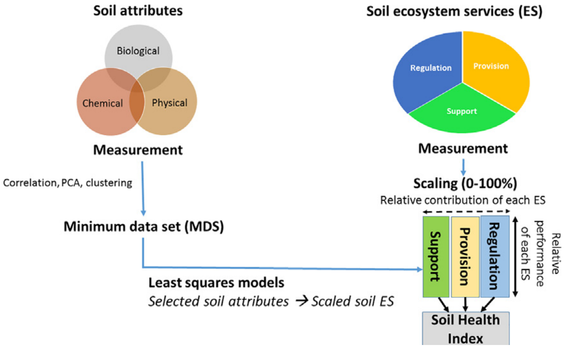
HIGHLIGHTS

- A holistic approach for soil health assessment is crucial to sustain land resources.
- Current approaches and essential steps to assess soil health are briefly reviewed.
- Soil health index should reflect soil ability to provide ecosystem services (ES).
- The relationship between soil attributes and ES should be quantified.

GRAPHICAL ABSTRACT



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ABSTRACT

The wellbeing of soils is crucial for securing food production worldwide. The soil health (SH) concept has been introduced due to an evolving understanding that soil is not just a growing medium for crops but that it provides a foundation for other essential ecosystem services (ES). The SH concept requires development of a holistic index for reliable and quantitative assessment of soil wellbeing related to the effects of different soil management practices and land uses. The *aims* of this paper are to: (1) review current approaches and methods to assess SH, (2) highlight the role of soil ES in characterizing soil function and (3) propose a new approach to assess SH via monitoring of ES provided by soils. We introduce a brief critical review of the following three main steps required for assessment of common SH indices: (1) selection of relevant attributes; (2) quantification and scoring approaches; and (3) integration of the selected attributes to construct the SH index. These steps usually include statistical or expert opinion-based approaches. In addition, we present a new approach that highlights the relevance and importance of soil ES, i.e., provisioning, regulating and supporting services that must be quantified for comprehensive assessment of soil functions and for fitting models that relate selected soil attributes to ES. This will allow practitioners and scholars to identify the most significant and universal attributes, quantify the relative contribution of each attribute to each ES, and subsequently assess the overall health of soils.

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1. Introduction

There is a broad understanding that soils are not just a growing medium for crops but that they also support other essential ecosystem services (ES), such as: water purification, carbon sequestration, nutrient cycling and the provision of habitats for biodiversity (Bünemann et al., 2018). Soils are a critical contributor to the ability of the earth's biosphere to maintain local, regional and global environmental quality. The health of soils is not only affected by soil genesis or soil formation factors, but also by other factors, which are related to soil use and management (Moebius-Clune, 2016).

A better understanding of the main components of the soil system and the synergy between them should lead to a holistic approach to characterizing soil functioning. A holistic approach is not easy to define because soil is a complex system, where physical, chemical and biological characteristics and processes are involved and interact. Such an approach has been recently represented and adopted by the concept of soil quality or soil health (SH). The health of soils is defined as "*the capacity of soil to function as a vital living system*, *within ecosystem and land-use boundaries*, *to sustain plant and animal productivity*, *maintain or enhance water and air quality*, *and promote plant and animal health*" (Doran and Zeiss, 2000). Consequently, sound knowledge of the quantitative effects of different soil management practices and land uses on soil functioning is needed to develop a holistic index. Such an index should portray those complex relations in a reliable manner (Congreves et al., 2015; Doran, 2002; Idowu et al., 2009; Morrow et al., 2016; Velmourougane and Blaise, 2017). A recent review paper discussed the differences between the widely used terms "soil quality" and "soil health", concluding that these terms can be considered equivalent and thus can be used interchangeably (Bünemann et al., 2018). In this review, we opted to use the term soil health.

Many attempts have been made to develop indices to assess SH (e.g. Andrews et al., 2004; Bünemann et al., 2018; Haney, 2012; Lilburne et al., 2004; De Paul Obade and Lal, 2016; etc.). Ewing and Singer (2012) suggested that it is essential to establish a set of biotic and abiotic indicators to develop a feasible SH index and that existing interactions among the various indicators need to be used to provide a holistic overview. A multi-indicator index can subsequently be utilized to classify the full spectrum of soils, including examining the effectiveness of reclamation management regimes for degraded agricultural lands.

Recently, Bünemann et al. (2018) reviewed major national soil assessment approaches worldwide, focusing on the selection of relevant indicators, based on conceptual relations between the measured indicator and relevant soil threats, functions or ES. However, these conceptual relations were usually not quantitatively tested or validated. Roper et al. (2017) examined two common SH tests (Cornell and Heaney) in North Carolina and concluded that neither test was able to differentiate between agronomic management systems or demonstrate a correlation between SH score and yields. In addition, focusing on a specific soil threat, function or ES cannot capture the overall status of the soil. For example, many indices focus mainly on soil productivity over limited growing periods and are not validated to reflect the sustainability of the soil system. Moreover, in some cases the scoring approaches used to assign the SH index were not consistent and could easily be manipulated, based on experts opinion or inappropriate statistical methods. There is general agreement that maintaining SH is critical to human sustainability and that soils should be carefully managed to provide for human health and welfare, while minimizing soil and environment degradation. A transparent, repeatable methodology to assess and subsequently manage soils is thus needed, and is the focus of this paper.

The current and projected rapid growth in world population highlights the need for securing food production worldwide. Unfortunately, according to the FAO, this crucial need for food security triggers the "**poverty trap**" spiral that demonstrates a global trend of increased pressure on land resources, resulting in accelerated land degradation coupled with reduced food production (van Beek et al., 2014; Hamdy and Aly, 2014; Kraay and McKenzie, 2014; Rojas et al., 2016). Restoration of currently cultivated lands and expanding land conversion for agricultural purposes coupled with sustainable food production is a global challenge of high priority, which requires a quantitative, comparative tool to evaluate the successes or failures of specific activities. An index tailored to a specific soil type may fail to project SH status, condition, and dynamic changes at different scales (regionally and globally) required to meet the abovementioned global challenges. Therefore, we maintain that a reliable index must bridge the variability among soil types, soil uses, climate regions, etc.

The aims of this review are to (i) review currently used approaches for the assessment of SH, (ii) highlight the role of soil ES in characterizing soil function and, (iii) propose a new approach, which considers soil ES for quantitative assessment of SH.

2. Current approaches for the assessment of soil health

The reliability and generality of a developed SH index mainly depends on (De Paul Obade and Lal, 2016): (1) its ability to account for soil heterogeneity in space and time; assessing SH on a large scale is crucial to reaching constructive decisions for sustainable land management. For this purpose, a spatial sampling design should be determined for selecting strategic sampling points, and interpolation is essential to connect them. High-resolution mapping of certain attributes, such as soil organic matter, may be acquired by remote sensing devices as well as advanced geostatistical methods (Forkuor et al., 2017; Hartemink and Minasny, 2014; Liu et al., 2006; Marchetti et al., 2012; Svoray et al., 2015) (2) use of a standard soil sampling scheme and analysis procedures (Nortcliff, 2002); and (3) model limitations, related to indicator selection, algorithms and assumptions used for its assessment.

Assessment of SH thus comprises three main steps, as illustrated in detail (Fig. 1): (1) selection, measurement and minimization of the set of relevant soil attributes; (2) quantification of the selected soil attributes through direct measurement and assigning an appropriate score; and (3) integration among the scored attributes to construct the final index, by providing criteria for defining the weight of each attribute or group of attributes.

2.1. Selection of soil attributes

Selection of the most relevant attributes to describe SH status and to construct the SH index is a crucial step because they serve as the building blocks for the SH index. Many studies have focused on selecting SH attributes (e.g. Bastida et al., 2008; Bünemann et al., 2018; Ewing and Singer, 2012) based on the following principles (Cardoso et al., 2013; Doran and Parkin, 1996; Idowu et al., 2008; Lima et al., 2013; Morrow et al., 2016; Schloter et al., 2003): (1) measurement of relevant, scientifically-based data, which represent chemical, biological and physical soil properties and processes that occur in the complex soil system; (2) sensitivity analysis to clarify variations in soil functions caused by soil management, land use, climate change, etc.; (3) manageable, available, accurate and cost-effective measurements, which can be conducted at a relevant time scale for decision making; and (4) reflection of the connection between soil functions and management targets, such as agricultural productivity and ES, e.g., prevention of soil erosion, water contamination and air pollution, biodiversity conservation, etc. The target values need to be precisely defined and determined for selection and integration of the measured soil attributes. Furthermore, correlation between indicators should be examined to minimize the number of required measurements, e.g. by using a Minimum Data Set (MDS) (Andrea et al., 2017; Andrews et al., 2004; Erkossa et al., 2007; Govaerts et al., 2006; Raiesi, 2017) (Fig. 1). This may also be achieved by other statistical tools such as analysis of variance (ANOVA), which

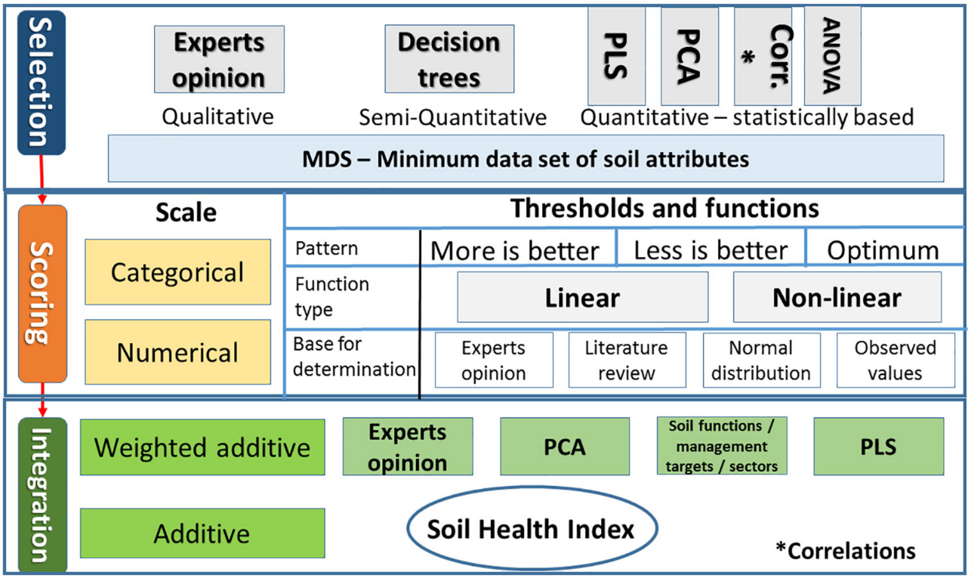

Fig. 1. Main steps and approaches currently used for soil health index assessment.

can exclude attributes that do not change significantly in response to different management regimes or crops (D'Hose et al., 2014) and/or principal component analysis (PCA) (D'Hose et al., 2014; Fine et al., 2017; Mukherjee and Lal, 2014; Sharma et al., 2014). PCA may serve as a flexible tool for identifying the most relevant attributes under different crop and soil conditions (Andrews et al., 2002). This tool highlights the most statistically "sensitive" attributes rather than environmentally or agronomically significant parameters. Other "stable" attributes which are relevant for soil functioning may not be included in the minimum dataset (Bünemann et al., 2018). Testing the relations between soil attributes and soil functions may increase the importance of such attributes (Andrews and Carroll, 2001).

Fine et al. (2017) used PCA to examine the relationships between SH indicators measured in distinctively different regions across the US. They found a relatively high number (6) of significant principal components (PCs), where the dominance of the first PC was relatively low. Consequently, they suggested that each PC tends to represent a relevant process (e.g. physical, biological, or chemical) that is differently expressed in each soil sample. PCA may be followed by clustering techniques, such as best subsets regression (BSR) as a way to define the most significant and relevant attributes for predicting the overall SH index and to enable more simple estimation of the index (Fine et al., 2017). The findings of Fine et al. (2017) support the use of indices based on a large number of indicators rather than indices based on a small number (1–5) of indicators (e.g. Haney, 2012; Mohanty et al., 2007; Puglisi et al., 2006). Indices based on a small number of indicators were proposed and formulated by Haney (2012), who established a SH index, based on three biological attributes (soil respiration, dissolved organic nitrogen, dissolved organic carbon) in addition to the concentration of the most relevant nutrients. Haney's index is intended to represent microbial activity and nutrient availability as the main factors describing SH. A more comprehensive index, developed at Cornell University (Gugino et al., 2009; Idowu et al., 2008), included 39 potential attributes. To make this test more simple and cost-effective, the number of attributes was limited to 12–13 physical (e.g. aggregate stability, penetration resistance, available water capacity) chemical (pH, P, K, micronutrients, organic matter content) and biological (soil proteins, soil respiration, soil pathogens) parameters. Zvomuya et al. (2008) chose attributes such as soil salinity (EC), cation exchange capacity (CEC) and calcium carbonate content as SH indicators which were examined under a field bio-assay in semi-arid regions.

Moncada et al. (2014) used decision trees, which are based on predetermined thresholds of relevant explanatory variables that should explain SH as the response variable. They assessed SH by morphological classification using Visual Soil Assessment (VSA). Andrews et al. (2004) established a set of decision rules to select the relevant indicators. This set was based on the management goals for each site, associated soil functions and other selection criteria such as regional or crop tolerance, sensitivity and other inherent properties such as climate conditions, soil taxonomy etc. "Each indicator has a unique combination of goals, functions, and additional criteria that must be satisfied for it to be suggested as a MDS indicator" (Andrews et al., 2004). These rules can serve as a framework for an expert opinion-based system to select the most relevant attributes for each site. However, this flexible framework tends to be too complex and thus can be easily manipulated. Such expert opinion-based frameworks contain simple and robust decision rules which may increase the number of degrees of freedom for the model, and consequently weaken the relations between soil properties and soil functions. The question of which attributes should comprise the soil health index may be simplified by the aforementioned statistical methods, which may reduce the possibilities for disciplinary biases (Andrews et al., 2002). Another tool for exploring the role of each component is the expert-based system which may be based on the accumulated knowledge of scholars and practitioners and not on a specific database (Malczewski, 1999). Both statistical methods and expert-based systems have been found to be valid for establishment of a soil quality index in vegetable production systems (Andrews et al., 2002) and rice management systems (Lima et al., 2013) to represent different management goals or soil functions. In addition, Ritz et al. (2009) utilized an expert-based framework to select the most relevant biological attributes for monitoring soil health on a national scale. They claimed that attributes selected by experts and stakeholders must also be capable of addressing national soil/environmental protection policy requirements. On the other hand, Svoray et al. (2012) studied land degradation due to soil loss and found that statistical models (based on various data mining techniques) provided better predictive abilities than expert-based models. In addition, such complex, expert-based frameworks, may lack methodological transparency and simplicity, which is imperative to allowing wide application of minimum dataset selection (Bünemann et al., 2018), especially in different environments and cropping systems and across a wide range of soil attributes.

2.2. Quantification

Lilburne et al. (2004) argued that: "There seems little point in proposing any soil property as a soil quality measure if we cannot provide for its interpretation." The selected soil attributes can be divided into quantitative, numerical attributes (Moebius-Clune, 2016) or qualitative, usually categorical attributes (Amacher et al., 2007, Moncada et al., 2014), which may also be evaluated in the field based on visual assessment (FAO, 2008). The measured value of a specific attribute can be converted into a numerical or categorical, unitless grade, representing the relative status of the attribute in question. This conversion can be achieved by calibration curves. These curves should be based on a broad range of data, where threshold (e.g. maximum, minimum, optimum) values must be defined to provide appropriate scoring functions. The general shapes of the scoring functions are "more is better", "less is better" and "optimum", according to the specific attribute. The threshold definitions may be achieved by: 1) expert opinion or thresholds taken from the literature (taking into account local conditions and relevant soil functions) (e.g. Fernandes et al., 2011), 2) statistical methods, usually based on normal distribution patterns (e.g. Fine et al., 2017) or 3) considering observed values (Andrews et al., 2000, Sharma et al., 2014). For linear scoring functions, where the measured value is divided by the minimum/maximum/optimum value (Sharma et al., 2014), the scores may be highly dependent on the variance of the specific attribute. Thus, extreme outlier values, measured for a specific attribute, may cause bias in the calculated scores. In addition, linear scoring may not represent the current agronomic or environmental status of some attributes (Andrews et al., 2002). Non-linear scoring functions usually assume normal distribution of the measured attributes and depend on non-linear patterns of response (Andrews et al., 2002, Fernandes et al., 2011, Svoray et al., 2015). Andrews et al. (2002) found that non-linear functions better represent the soil system attributes and are thus more suitable as scoring functions. Lilburne et al. (2004) established non-linear scoring functions for selected SH attributes, measured over a wide range of soils, land uses and crops in New Zealand, in order to obtain a sufficiently flexible framework for coping with natural differences between soils and different land uses. The target ranges and response curves were based on expert workshops and characterized to be able to meet both environmental and production goals, which may be in conflict in some cases. Different transformation functions for the same attribute can be applied for different soils, ecosystems, climate zones and regimes (soil use), taking into account soil texture or other soil attributes and functions (Andrews et al., 2004; Fine et al., 2017; Lilburne et al., 2004). Consequently, scoring functions developed at a specific location can hardly be adopted in other regions; hence threshold values as well as calibration curves should be applied at each site. Soil attributes may be also quantified categorically by discrete grading according to predetermined thresholds, based on a literature review or other external knowledge. To enable reliable discrete grading, the number of degrees of freedom should be limited to provide sensitive evaluation of changes in soil attributes (Amacher et al., 2007).

Other methods do not require the conversion step and use the raw values to construct the whole index. For instance, in Haney's test, which is based on only 3–5 attributes, constructive functions are used to develop the SH index. In addition, partial least squares (PLS) methods use the raw measured values of the selected attributes to find the best solution by linear combination of attributes; this approach provides maximum covariance with predetermined target values as well as maximum explained variability of the model. De Paul Obade and Lal (2016) demonstrated the great potential of PLS for predicting crop yields by selected soil attributes (mainly bulk density, electrical conductivity, soil organic C, C/N ratio) taking into account the different soil types and soil management practices for different soil layers. According to this approach, both qualitative and quantitative data can be utilized to construct the PLS model. When using this approach to construct the SH index, no "conversion" step is required. However, this approach may be very challenging since reliable definition and measurement of target values is essential.

2.3. Integration

The next step required is to determine the relative contribution of each attribute to the overall "score". The most common approach is "additive", assigning equal weight to each selected attribute (Fine et al., 2017; Svoray et al., 2015). This approach may be oversimplified and may not reflect the complex contribution of different attributes to the soil system and soil functions. Gradual relative contribution (weighted additive) can be based on literature or expert opinion, where the relative importance of each parameter can be determined according to specific targets, such as productivity (yield or outcome), weed cover, pesticide use, water use efficiency, etc. (Andrews et al., 2002; Krueger et al., 2012; Moncada et al., 2014; Mukherjee and Lal, 2014; Wienhold et al., 2004). In addition, attributes may be divided into several soil functions, for example: root development capacity, water storage capacity, water supply to plants, soil degradation resistance, supporting plant growth and nutrient supply power (Fernandes et al., 2011; Karlen et al., 1994; Mukherjee and Lal, 2014). The relative weight of each soil function may be equal or it may be differential. Differential relative weights could be determined according to the number of attributes in each soil function, or according to the relative importance of each soil function. Higher relative importance may be assigned to field measurements, which provide more relevant, realistic data on the actual state of the soil. Another option is dividing the measured attributes to "sectors" (physical, biological and chemical), where the relative weight of each sector is usually equal (i.e., 0.33) (e.g., Cherubin et al., 2016). Kang et al. (2005) evaluated three different indices by measuring soil attributes (microbial index, nutrient status index and crop yields index) and used the triangle method to integrate them to quantify a unified soil sustainability index. However, the relationship between specific soil attributes or soil categories and certain soil functions is subjective and lacks quantitative tools for validation. In addition, focusing on specific soil functions may be insufficient for such a complex system and thus a more holistic quantitative approach is required. Other methods for integrating the measured attributes and their relative contributions into a SH index are based on statistical analysis that describes the relative variability explained by each parameter, such as PCA (Mukherjee and Lal, 2014; Yu et al., 2018). Attributes included in the MDS for each soil sample can be weighed using the PCA results. Each PC explains a certain proportion (%) of the variation in the entire data set. This proportion should be divided by the total proportion of the variation explained by all the relevant PCs (usually defined by Eigenvalue > 1.0). This can provide the relative weight of the attributes under a given PC (D'Hose et al., 2014). Using this method would assign a higher contribution to the most sensitive components, which are not necessarily identical to the most significant ones in terms of soil functioning. If the scores of the different attributes are not normalized to a common denominator, then maximum-minimum objective functions should be applied to quantify a reliable and comparable index.

However, the current indices for SH are usually based on selected, representative soil attributes that reflect only specific soil ES or soil functions. Some of the indices have been tested to reflect changes in soil functioning, while others have been validated against provisioning services and productivity. The abovementioned indices were found to neglect essential soil ES (supporting and regulating) that are known to be vital for ensuring sustainable soil functioning for the next generation. The present global status of provisioning and regulating services indicates that there has been a major decline in the main regulating services, such as soil erosion, water availability etc. (MEA, 2005), although in recent years there has been a substantial increase in food production from crops and livestock. Here we suggest that we require an imperative shift to a holistic paradigm that considers all the pillars of soil ES, so that in addition to provisioning services, regulating and supporting services must be quantitatively included.

3. Soil ecosystem services

Soil serves as a multifunctional, dynamic and complex ecosystem. The main soil functions can be attributed to ES (Adhikari and Hartemink, 2016; Andrea et al., 2017; Calzolari et al., 2016; Dominati et al., 2010; Jónsson and DavíÐsdóttir, 2016), which are generally classified as provisioning, regulating, supporting and cultural services (Fisher et al., 2009; MEA, 2005; Power, 2010; Swinton et al., 2007; Zhang et al., 2007). According to Dominati et al. (2010) regulating and provisioning services directly affect people while supporting services are there to maintain the other services. Each service may reflect different soil functions, which can be quantified by specific measurements (Table 1). Cultural services, however, are not expected to be affected by soil chemical, physical and biological soil attributes and thus cannot be modelled on the basis of these measurements.

According to Dominati et al. (2010), soil ES may be linked to both manageable and inherent soil attributes. Moreover, FAO (2015) states that: "*Healthy soils are a basic prerequisite to meeting varied needs for food, bioenergy, fiber, fodder, and other products, and to ensuring the provision of multiple ES in all regions of the world*". Soil management, land use, climate change and agricultural intensification have substantial impacts on soil ES (Birgé et al., 2016; de Vries et al., 2013; Orwin et al., 2015; Power, 2010). Calzolari et al. (2016) proposed a conceptual link between soil attributes and specific ES by identifying the most appropriate indicators and input data for evaluating soil functions in relation to the relevant ES.

The selected attributes for these indices were identified according to the main soil functions derived from soil ES and were able to quantify differences in SH between agricultural management regimes (e.g. organic vs. conventional) (Andrea et al., 2017). However, the compatibility between the obtained indices and soil ES was not quantitatively tested. This compatibility should be based on accurate and reliable measurements of the major soil functions that represent soil ES.

Griffiths et al. (2016) selected bio-indicators for European monitoring of soil biodiversity and ecosystem functions such as water regulation, C sequestration and nutrient provision. The selection of indicators was mainly based on their sensitivity to changes, induced by different land uses and management regimes. However, the selected indicators were intended to reflect only specific soil functions, and were not intended to represent all soil ES.

4. A new approach for SH assessment

This review of current methods for SH assessment leads to the conclusion that the time is ripe for a paradigm shift in the evaluation process of SH. The ocean health index, developed by Halpern et al. (2012) for the assessment of the health and benefits of the global oceans, provided the conceptual basis for the new approach to SH assessment via monitoring soil ES. This new index is designed to reflect the combined relative weights of provisioning, regulating and supporting services, according to their relevance in a specific location.

We propose, therefore, a multivariate-complex **SH approach**. Our approach comprises three steps (Fig. 2). It calls quantifying the relationships between soil attributes and ES to allow the transition from point measurements to a broader scale analysis that may consider different land uses, soil types, climatic regions and a more precise definition of the effect of SH on human activities.

The *first* step in the proposed new approach requires taking soil samples from a wide range of soil types, land uses, climatic regions, etc. The samples should then be subjected to measurements of a large number of chemical, biological and physical attributes. The obtained broad database then serves as the platform for the minimizing dataset step (Fig. 2) aimed at selection of relevant soil attributes, which may portray the ability of soils to provide, support and regulate essential ES. For this purpose, we recommend the use of quantitative statistical models rather than expert-based models. Statistical models require an initial broad dataset. However, once the MDS is established there may be no need for testing a broad array of other indicators to assess soil quality over time (Andrews et al., 2002; Bastida et al., 2008). The expert-based approach assumes that a given expert understands the complexity of the mechanisms studied and that his knowledge can be translated accurately into the model. Thus, expert-based systems, at this selection stage, may differ when interpreting data gathered from different regions, land uses and points of view of the relevant experts. Therefore, minimizing the number of attributes that need to be measured will be done using autocorrelation and principal component analyses (PCA), followed by appropriate clustering techniques to identify the most representative attributes in each group of statistically analogous attributes. Despite the abovementioned limitations, expert opinion can be used to facilitate selection of the relevant attributes when combined with simple additive methods. Thus, the statistical methods should not be handled as a "black box", and measurement costs as well as other considerations (e.g. availability, accuracy, etc.) must be taken into account.

The *second* step includes the conversion of raw data into normalized scores. Current approaches include a conversion of absolute values of the measured attributes to values on a relative scale (termed scoring

Table 1
Soil ecosystem services, characterized by main soil functions and quantified by relevant measurements.

Ecosystem service	Main soil functions	Relevant measurements	References
Regulating	Climate and gas regulation	Temperature, gaseous emissions, surface energy balance	Jasinski and Crago (1999); Argaman et al. (2012);
	Water regulation	Runoff	Hudson (1993); Vacca et al. (2000)
	Erosion and flood control	Erosion	
	Pest and disease regulation	Soil biota and food web structure	Barrios (2007)
	Carbon sequestration	Carbon balance	Jandl et al. (2007)
	Water purification/ contamination	Water quality	Turner and Rabalais (2003); Lin et al. (2004); Essandoh et al. (2013);
Provisioning	Food, fuel and fiber	Yield, energy	Johnson et al. (2002); Somerville et al. (2010);
	Raw materials	Weight, energy	
	Gene pool	Genetic and functional diversity – molecular sequencing, enzyme activities	Rondon et al. (2000); Wallenstein and Weintraub (2008);
	Fresh water/water retention	Water content – field capacity	
	Weathering and soil formation	Mineral content, physical properties, OM content	Wakatsuki and Rasyidin (1992); Mavris et al. (2010);
Supporting	Nutrient cycling	Aboveground Annual Net Primary Production, NPK balance	Bindraban et al. (2000); Stohlgren (2007); Helman et al. (2015)
	Provision of habitat	Aboveground Annual Net Primary Production; soil biota and food web structure	Bindraban et al. (2000); Stohlgren (2007); Barrios (2007); Helman et al. (2015)

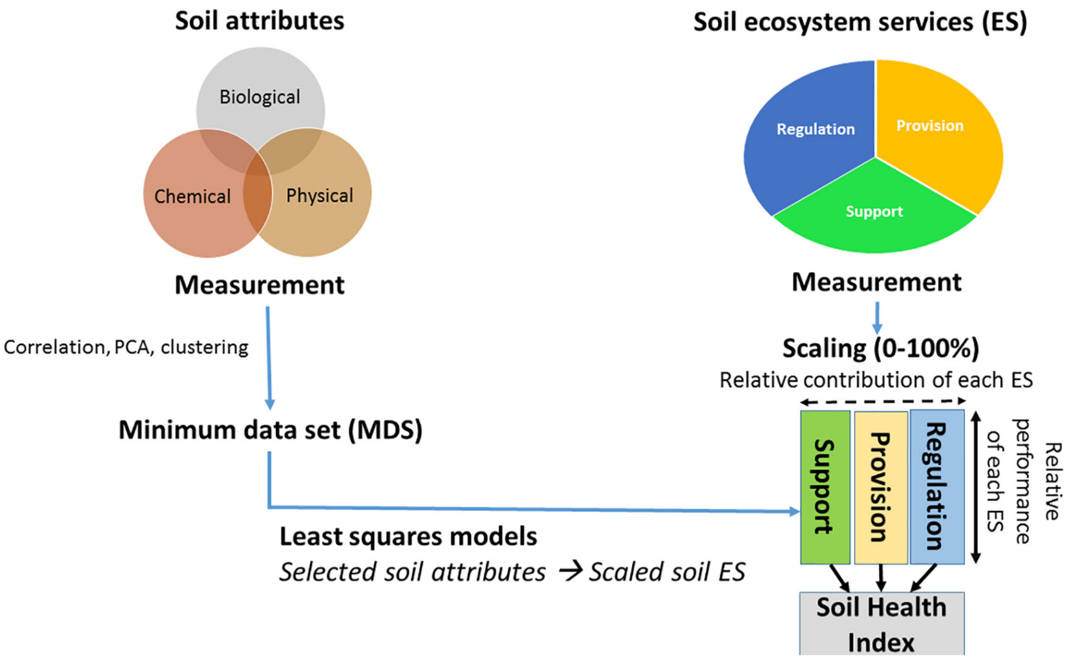

Fig. 2. The proposed approach for assessing soil health by measurement and selection of relevant soil attributes via monitoring and scaling of soil ecosystem services.

functions, usually expressed in percent 0–100%). The type of scale and its magnitude are mainly determined based on soil provisioning services of a specific field, rather than on the entire soil ES. Consequently, these scoring functions may not be valid for different fields, crops, land uses and regions. In addition, when the entire soil ES are considered, the functions may be more complex than linear or non-linear (usually based on normal distribution) and interactions between different attributes can co-exist. Namely, the scoring functions for the measured attributes are over-simplified, do not represent the entire status of soil functions, and may lead to incorrect assessment of soil ES and SH. Therefore, we suggest that soil ES (rather than soil attributes) should serve as the target value for the assessment of soil functioning. For this purpose, soil ES should be defined and quantified (Table 1, Fig. 2). These quantified endpoints of soil ES should be normalized to a uniform scale (0–1 or 0–100) representing the relative performance of each ES (the difference between maximum and minimum value) (Schipanski et al., 2014). This step may be very challenging and a detailed framework (rather than the conceptual model described here), including methods for setting reference points for each soil function, should be constructed to provide a reliable assessment and comparison. This scoring approach, based on the relative performance of the soil ecosystem and represented by soil ES, can be much more reliable than the current scoring approach based on soil attributes since it allows evaluation of the quality of the services and benefits that are provided by the soil and overcomes the problem of comparing soil attributes that are naturally diverse in space and time. In addition, soil attributes may have differential or even contrasting effects on soil ES, particularly when comparing between different crops, soil types, climate conditions etc. For example, high phosphorous (P) content can be related on one hand to enhanced provisioning services (high yields), while on the other hand it may be related to reduced regulating services due to water contamination. The normalization of the widely accepted ES according to their relative performance for a specific site/region should enable establishment of a comparative SH index on larger scales. Least squares models should be utilized to correlate between the selected measured soil attributes, which should serve as the input values for the model, and the normalized target values of ES.

The *third* step focuses on integration and it would be acquired by the obtained least squares models. These models will provide a certain coefficient for each attribute, which expresses its contribution to each ES and to the whole model. Thus, attributes with relatively low contributions may be eliminated. Different least squares models can be applied for each ES. Finally, a holistic model, combining all relevant ES can be constructed. This may be achieved by determination of the relative contribution of each soil ES at a specific site by widely based agreement between experts from different disciplines, as was proposed for the ocean health index (Halpern et al., 2012). Such models must be based on a wide range of soils, land uses and agroecosystems. This will enable identification of the most significant and universal attributes for quantifying the relative contribution of each attribute to each ES and to assess the health of soils.

5. Concluding comments

The "poverty trap" spiral demonstrates the global trend of increased pressure on land resources, which subsequently results in accelerated land degradation coupled with reduced food production. The spiral highlights the urgent need to protect and maintain SH. Soil serves as a multifunctional dynamic and complex ecosystem supporting three main ES: provisioning, regulating and supporting services. We suggest a multivariate-complex SH approach whereby all three pillars of soil ES are quantitatively included in the assessment process of soil functioning. This approach will lead to the development of a new SH index based on quantifying the relationship between soil attributes and ES. Such an index would make a major contribution towards facilitating our understanding of the connection between the need for securing food for the world's growing population and the threat of expanding land degradation.

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