Published October 4, 2018

New Soil Index Development and Integration with Econometric Theory

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Soil scientists have worked on the conceptualization and contextualization of soil-related notions, such as soil quality, soil health, and soil security, over the past few decades. We reviewed the massive amount of literature regarding those major concepts, and summarized definitions, visions, and constraints. Indicators (In) and indices (Ix) are well suited to aggregate soil and environmental data to assess soil quality, health, and security quantitatively. Our literature review showed that (i) more sophisticated quantification methods are necessary; (ii) often only a single soil property and/or class is modeled rather than more complex soil functions, risks, or services; (iii) there is a lack of harmonization, standardization, and reference frameworks that allow soil comparisons across regions and time; and (iv) methods frequently used to calculate soil In/Ix, such as ordination and factor analysis, do not consider rigorous axiomatic criteria of scientific sound indication systems. In summary, the complex soil concepts stand in sharp contrast to the applied indication methods in the soil science discipline. We investigated the potential to apply econometrical methods to assess soil quality, health, and security that serve as alternatives to more traditional In/Ix in soil science. A case study demonstrated the profound transformative potential of linking econometrics–soil–environmental sciences.

Abbreviations: COLS, corrected ordinary least squares; DEA, data envelopment analysis; DMU, decision-making unit; EC, efficiency change; In/Ix, indicators/indices; OLS, ordinary least squares; PCA, principal component analysis; SCseq, soil carbon sequestration; TPI, Törnqvist Productivity Index.

Core Ideas

- **There is a need for quantitative soil quality, health, and security assessment.**
- **Pros and cons of indication systems used in soil and ecological studies.**
- **Axiomatic criteria advance soil quality, health, and security indices.**
- **There are profound shortcomings of widely used soil indicators and indices.**
- **Linking soil science and econometrics improves soil indicators/indices.**

DISPUTED SOIL CONCEPTS

Soil Quality, Soil Health, and Soil Security

With increased awareness and understanding of the functions that soil resources potentially provide for ecosystems and human kind, known as Ecosystem Services, many researchers have proposed different conceptual schemes related to the recourses of soil, the surface layer of earth (Costanza et al., 1997; Millennium Ecosystem Assessment, 2005). The three major concepts—soil quality, soil health, and soil security—have drawn the attention of the general public, governmental and non-governmental institutions, and researchers (Fig. 1). The Food and Agriculture Organization of the United Nations (1976) viewed land evaluation as a qualitative and empirical expression referring initially to soil quality, defining it as "the process of assessment of land performance when used for specified purposes involving the execution and interpretation of surveys and studies of landforms, soils, vegetation, climate, and other aspects of land to identify and make a comparison of promising kinds of land use in terms applicable to the objectives of the evaluation." According to Wienhold et al. (2004), the term "soil quality" introduced by Warkentin and Fletcher (1977) refers to land quality. The discussions for defining soil quality stretched over decades, with a key definition proposed by the Soil Science Society of America (1987; SSSA) in the "Glossary of Soil

Soil Sci. Soc. Am. J. 82:1017–1032
doi:10.2136/sssaj2017.11.0378
Received 2 Nov. 2017.
Accepted 9 June 2018.
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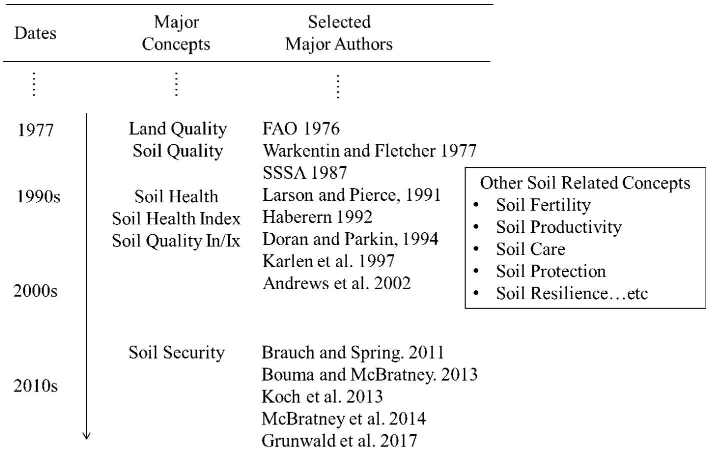

Fig. 1. History of soil-related concepts focusing on soil quality, soil health, and soil security. FAO, Food and Agriculture Organization of the United Nations.

Science Terms". Other definitions, as proposed by various scientists and organizations, such as the United States Department of Agriculture, Natural Resources Conservation Service (USDA-NRCS), are summarized in Supplemental Table S1. The terms "capacity" and "capability" are commonly interchangeable in the definitions. Karlen et al. (2001) reviewed the process of establishing definitions that could gain consensus among scientists with different interests. Both SSSA and USDA-NRCS have adopted the following definition, "the capacity of a specific kind of soil to function, within natural or managed ecosystem boundaries, to sustain plant and animal productivity, maintain or enhance water and air quality, and support human health and habitation". A shortened definition is "the capacity of the soil to function" (Supplemental Table S1) which is inherently vague and often a matter of opinion. Examples of soil functions include (i) biomass production; (ii) storing, filtering, and transforming nutrients, substances and water; (iii) biodiversity pool; (iv) physical and cultural environment for humans and human activities; (v) source of raw materials; (vi) acting as a carbon pool; and (vii) archive of geological and archeological heritage (Commission of the European Communities, 2006). This approach to define the concept of the quality of soil resources could be categorized as a deductive approach.

In contrast, inductive-oriented definitions of soil concepts are often based on the best interests of particular stakeholders. For instance, the concept of soil quality can focus only on the chemical pollutants that degrade soil use (Chen et al., 2005) or on the many ecosystem services involving soil (Cassman, 1999; Fließbach et al., 2007). The concept of soil quality examined from the perspective of soil taxonomy was criticized by Sojka and Upchurch (1999) as a narrow-minded view of soil, suggesting that some soils are better than others. For example, claims have been made that Mollisols and Alfisols are of higher quality than the other soil orders even though the value of soils depends on its purpose. Using soil organic matter (SOM) as a single determining factor for soil quality is another example of over-simplifying the complexity of soil, although soil with relatively low SOM content sustains its own unique habitats, such as SOM-limited soils in arid regions (Gregorich et al., 1994; Franzluebbers, 2002).

These oversimplified approaches allow the assessment of the operational aspects of soil conditions and capabilities, although they are inherently reductionist from a science perspective. The specialized perspectives on soil quality exacerbate the debate by excluding particular stakeholders, regions, or use of soil resources. For a specific soil's function, the quality of soil can be different and so can the evaluations (Karlen et al., 1997). In general, soil functions are difficult to assess and quantify because of the interactions of their functions as well as variability in space and time that are controlled by different soil attributes among geographic regions. Inductive studies have often lacked the integration of various soil concepts. Bouma (2002) assessed the potential impact of soil degradation (erosion and compaction) by developing land quality indicators that did not consider inputs that would help produce yields. The soil quality concept may guide scientists to use and allocate soil resources to sustain them (Wienhold et al., 2004). However, the quantitative assessment still needs further attentions and discussions (El-Ladan et al., 2014).

Soil health is another concept that has emerged. While some scientists suggest the interchangeable use of the terms "soil health" and "soil quality" (Acton and Gregorich, 1995; Warkentin, 1995; Herrick, 2000; Schindelbeck et al., 2008), others, such as Janvier et al. (2007), differentiate between these terms. For example, soil health has been depicted as "an ability to perform or function according to its potential which can change over time due to human use and management or unusual natural events" (Doran and Safley, 1997; van Bruggen and Semenov, 2000; Sojka et al., 2003). One limitation of such a broad definition is that the potential of a soil is often unknown and bound to a specific purpose(s) (e.g., agricultural production, recreation, biodiversity, drainage), thereby constraining its usefulness and ability to generalize among different soilscapes.

Karlen et al. (2008) poignantly discussed the similarity of derivatives from both soil quality and health assessments, such as better public awareness; understanding the importance of soil resources; and the short-, intermediate-, and long-term effects of anthropogenic management and practices. Lima et al. (2011) asserted that soil and agricultural scientists, natural resource management, farmers, policymakers, educators, and economists all have a vested interest in soil quality. Thus, under the umbrella of soil quality and soil health, common goals are shared by multiple stakeholders that target the sustainability of soil resources under diverse natural and anthropogenic threats, among them global climate change, land use shifts, and environmental disasters.

In the twenty-first century, the term "soil security" emerged and is similar in concept to the terms "soil quality" and "soil health" (Bouma and McBratney, 2013; Bouma et al., 2017). Brauch and Spring (2011) proposed a definition of soil security that puts ecosystems and environmental services provided by the land, namely through the interaction between the biota, within and on the soil, and the soil and the atmosphere, in focus

(Supplemental Table S1). The soil scientists of the International Union of Soil Sciences (IUSS) defined soil security as "the maintenance and improvement of the world's soil resources so that they can continue to provide food, fiber, and fresh water; to make major contributions to energy and climate sustainability and help maintain biodiversity and the overall protection of ecosystem goods; and services" (Koch et al., 2013).

Interestingly, this definition explicitly addresses the maintenance of soil resources, and thus, the security of the absolute amount of soils at the global scale that are at risk of being degraded. This enhances the earlier concepts of soil quality and soil health that focused more on the qualitative aspects of soils (e.g., capacity of soils to function). McBratney et al. (2014) argued that soil security is a more integrative concept than soil quality, soil health, or soil protection. They identified five pillars/dimensions undergirding soil security—Capability, Condition, Capital, Connectivity, and Codification—to account for the quantity, quality, and accessibility of soil resources. The pillars/dimensions depict the complexity of the soil securitization process, while the verification of the notation has not yet been discussed sufficiently. A total of 52 different definitions of soil-related concepts are summarized in Supplemental Table S1.

Wander et al. (2002) emphasized the integration of the complex information of soil quality into useful frameworks through interdisciplinary approaches to allow scientists to manage and improve soil quality. Lima et al. (2011) stated that conceptual assessments are valuable only when they are delivered to end-users, such as farmers. Bouma and McBratney (2013) postulated the importance of "knowledge-brokers" for scientists to make scientific findings related to soils visible and indispensable and to be able to communicate with other disciplines.

Some scientists also posited that multiple perspectives integrated into a coherent framework need to be considered to address soil security. Using questions recognizes stakeholders' multiple standpoints, which prevents overlooking conspicuous and inconspicuous roles of soil resources (Grunwald, 2014; Grunwald et al., 2015). Bouma (2005) adopted a communication model adapted from Habermas (1984), which was focused on soil science communication to provide different views on the "real soil" from the perspective of different groups: (i) soil scientists among themselves, (ii) soil scientists and their colleagues, and (iii) citizens at large. Communication among people were assessed using the criteria of "true" when statements can be defined according to an objective standard, "right" when statements comply with the established norms of groups of people, and "real" when statements correspond with personal, individual feelings Habermas (1984). Another more comprehensive multi-dimensional and perspectival soil model was presented by Grunwald et al. (2017). They used Integral Ecology (Esbjörn-Hargens and Zimmerman, 2009) and asserted that cognizance of oneself, communities and soils/soil-ecosystems are key to address soil security. Their approach explicitly integrates subjective (i.e., the "I" perspective of soils as seen, experienced, and perceived by individuals), intersubjective (i.e., the "we" perspective of groups and stakeholder communities), and objective and interobjective (i.e., the "it" perspective disclosed by the assessment of individual chemical, biological, and physical characteristics/processes of soils and the biogeochemical, social, economic, and other systems they are embedded in). The underlying concept to this new integrative thinking is called "integral soil security" (Grunwald et al., 2017). They emphasize that only deeper environmental/ecological awareness evokes the values necessary for the security of the natural world, including soils. The Meta Soil Model was proposed as a new integrative multi-model framework by Grunwald et al. (2016) and Grunwald et al. (2017) as an alternative to the five proposed dimensions of soil security.

Scientific concepts are generally institutionalized at a certain point, typically after reaching consensus among scientists. However, researchers such as Sojka and Upchurch (1999) are concerned about compromising scientific accuracy in the soil science literature due to the popularization of concepts. They stated that "the more complex a concept, the greater the danger of popularizing or prematurely institutionalizing it." This alludes to finding the middle ground to sustain and secure soil quality without becoming stuck in the complexity of global soil security or the oversimplification of approaches and their operationalization to assess soils. Therefore, we conceptualize the three types of models:

1. Simple: Operationalizing the conceptual frameworks with intuitive simplification (e.g., simple tools, such as field kits and simple field-based ad hoc assessments).
2. Complex: Developing complex models that are scientifically rigorous and research-oriented and demand a large amount of data and scientific expertise to be understood.
3. In-between: Finding the middle ground by striving for parsimonious data collection feeding into soil assessments to optimize knowledge that informs decision-making.

Motivation for Quantification Assessment of Soil Concepts

The conceptual frameworks related to soil resources mentioned above are interrelated, sharing the same goals to sustain and protect the soils, although they take somewhat different vantage points to achieve these goals and have adopted different methodologies. Karlen et al. (1997) stated that many highly tangible scientists have had similar questions using different words, such as soil quality, soil health, soil care, soil resiliency, or sustainable land management. These various soil concepts could be very helpful as a general framework to increase awareness. In addition, other environmental/ecological concepts, such as ecosystem services that emphasize the valuation of soils to the benefit of humans (Millennium Ecosystem Assessment, 2005), are helpful to raise awareness of the importance of limited natural resources.

However, if they are not quantified and formalized coherently as to how to assess soil quality, soil health, and soil security, they remain shallow buzz words. Karlen et al. (2003) argued about the needs to quantify Indicator/Index frameworks assessing trends of soil condition and capability that are strongly influenced by human uses. The approach can be qualitative, semi-quantitative, or quantitative. Farmers, for example, would examine soil condition often by looking at the color, pore sizes, softness, abundance of organic matters, water and soil fauna, and so forth (Romig et al., 1995). These measurements are highly subjective based on expert knowledge and experience, which conflicts with comparable judgments that enable decision makers to evaluate the limiting factors of soil for a given purpose of use (Adeyolanu and Ogunkunle, 2016). Semi-quantitative methods have been developed to overcome these shortcomings by the inclusion of some quantitative aspects. Examples include the Willamette Valley Soil Quality Card (Burket, 1998); Soil Management Assessment Framework, Agroecosystem Performance Assessment Tool (Liebig et al., 2003); Cornell Soil Health Test program (Moebius-Clune et al., 2016); and Visual Evaluation of Soil Structure (Karlen et al., 2008; Guimarães et al., 2011). These applied approaches have the benefit of semi-quantitative assessment of multiple chemical, physical, and biological soil attributes; however, they lack accuracy and precision. These semi-quantitative soil assessment methods often use the additive model, which is very simple yet has limited scientific validity to accurately assess soil condition or capability.

Parr et al. (1992) speculated on ten ways of using soil quality indices, especially for land in the United States and Australia:

- Assess the impact of management practices on soil degradation and soil conservation.
- Assess the accrued benefits of highly erodible lands under the Conservation Reserve Program that was authorized in the 1985 United States Farm Bill.
- Provide a basis for conservation compliance.
- Establish the loan value and price of land.
- Establish a more realistic base for tax assessment and tax credit.
- Assess the impact of management practices on human and animal health.
- Assess the impact of management practices on food safety and quality.
- Assess the impact of management practices on water quality.
- Provide information for simulating and predicting environmental change.
- Provide an improved basis for land capability classification.

Schindelbeck et al. (2008) also encouraged the development of a quantification scheme with five virtues for soil science: (i) improvement of soil inventory assessment, (ii) development of guidelines for good land management by assessing the monetary value of land, (iii) identification of best management practices, (iv) quantification of soil degradation or aggradation from management, and (iv) establishment of educational opportunities.

Thus, we recognize the need for integral, yet feasible and meaningful quantification schemes, such as indicator/index (In/Ix). They are beyond single measurements or predictions of variables because they infer on various different or similar conditions or functions of soils (Granatstein and Bezdicek, 1992; Wu and Wu, 2012). An indication system is expected to play a key role to connect the Simple-Complex aspects and pragmatically strive for solutions to improve and/or sustain the quality and quantity of soils.

All three major soil concepts are broad, lack quantification, and are highly dependent on the dominant land uses and management within a given soilscape exposed to a variety of different natural and anthropogenic forcings. We posit that the degree of departure from the "optimum" state needs to express degradation (loss) or enhancement (gain) of functionality. Because there are multiple and interacting functions of soils, the challenge is to identify observable properties that allow depicting losses/gains of functionality. This is profoundly difficult in soils where functions depend on soil genesis operating over long time frames (hundreds to thousands of years) where "natural" reference conditions of soils are unknown (Vrščaj et al., 2008). In contrast, the health/quality of water and food is tied to shorter response times because of changes in the larger ecosystem compared with soils. Soil quality and health inherently focus on soil characteristics that limit external uses, whereas soil security (to some extent) and integral soil security (to the full extent) consider soils as part of broader interacting biophysical-human-systems that are undergoing change. To maintain/enhance the quality and quantity of soil resources inherently requires contextualization to human preferences (e.g., maximize crop yield, enhance biodiversity, minimize adverse impacts to drinking water resources) and human value (e.g., soils are less important than jobs). A new soil indication system that is universally applicable in different geographic multi-use, multi-function soilscapes undergoing change is urgently needed.

Objectives

The objectives of this study were to (i) review major concepts and identify shortcomings, progress, and future needs of research related to soil index development; (ii) depict axiomatic features of In/Ix in soil and environmental sciences; (iii) assess compliance of widely used In/Ix approaches in soil and environmental science with the identified axiomatic features; and (iv) describe econometric techniques, specifically the Data Envelopment Analysis (DEA) and Malmquist Index (MI), and their potential to assess soils through In/Ix that ideally meet axiomatic index theory assumptions.

INDEX RESEARCH IN CONTEXT OF SOIL QUALITY, HEALTH, AND SECURITY

First, we clarify indication terminologies. Second, we outline the criteria for indicator/index development. Third, we present the pros and cons of different methods used for index formation in the context of soil quality, soil health, soil security, and the broader realm of environmental and ecological studies.

What Are Indicators and Indices?

Gallopin (1997) broadly defined an indicator as an operational representation of an attribute of a system. Similarly, Meadows (1998) described an indicator as a sign, signal, or measurement that indicates the state of the level of something, and are directly calculated from raw data or lab measurements. Wu and Wu (2012) stated that an indicator often refers to a variable or an aggregate of multiple relevant variables whose values can provide information regarding conditions, status, or changes of a system or phenomenon of interest. According to the In/Ix hierarchy system proposed by Braat (1991), the indices are located above the indicators, which means that the indices are derived from a combination of indicators, not directly from raw or processed data (Fig. 2, adopted from Braat [1991] and Shields et al. [2002]). Guo et al. (2015) outlined that the indices are the result of an aggregated set of indicators as a single measure, meaning that the index is an aggregate of two or more indicators (Beck et al., 2010). The integration process for In/Ix delineation can be highly complex, especially when the entities, such as the original measurements or indicators, have different units or meanings (Bauler et al., 2007). At higher condensation levels, indices emerge to support decision-making and provisioning to the general public, whereas direct measurements and processed data are of interest to researchers (Fig. 2). Although there is a consensus on the In/Ix term usage among the majority of ecologists, it seems that many of the other disciplines, including soil science, randomly use the terms without clear definitions or assumptions. After-effects that occur when those terms are used interchangeably can lead to confusion of characteristics or roles of the indication system (Gallopin, 1997). Increasing the level of aggregation is observed when the acquired data are transformed into more inferable knowledge for end-users who often do not possess specialized expert knowledge, yet do have an influence on decision makings (Volk et al., 2009). Thus, the differentiation between indicators and indices may act as a guide to avoid inconsistency in future discussions (Meadows, 1998). Recently, BIGDATA analysis and data mining techniques have been suggested ways to aggregate and synthesize large datasets, including large soil–environmental datasets. These efforts are doomed, resulting in mere data crunching if they lack a coherent indication system. The details of the benefits and risks in terms of index development are further discussed below.

Pros and Cons of Indicator/Index Development as an Integral Assessment Tool

Although the constituents of the In/Ix measures are different as described above, the roles those techniques can play are very similar, such as simplification, quantification, and visualization of capability, condition, phenomenon, system, function, status, and so on. The massive amounts of data increase the likelihood of data redundancy, which can be reduced by transforming sample data into In/Ix scores serving various interests of stakeholders (Meadows, 1998). The environmental sustainability index, ecological health index, and water security index are examples of complex indication systems with condensed information (Xu et al., 2005; Jia et al., 2015). Some soil scientists have attempted to envision the quality of soil holistically based on land use/land cover types or management systems (Andrews et al., 2002; Kinoshita et al., 2012; Paz-Kagan et al., 2014; Askari and Holden, 2015). Numerous indicators for agro-ecosystems as well as non-agricultural soils have been developed (Bastida et al., 2008). Some researchers have visualized the threats to human water security and global biodiversity by using digital mapping techniques (Sullivan et al., 2003; Vörösmarty et al., 2010). Communications techniques illustrating paradigms with numbers or scores help decision makers understand a phenomena or problem. There are also inherent risks in the delineation of In/Ix. Some scientists have warned that a large amount of indicators or indices can lead to chaotic confusion (Shields et al., 2002; Wu and Wu, 2012). In his book, "Indicators and Information Systems for Sustainable Development", Meadows (1998) condensed seven major pitfalls in the choice and use of indicators and indices:

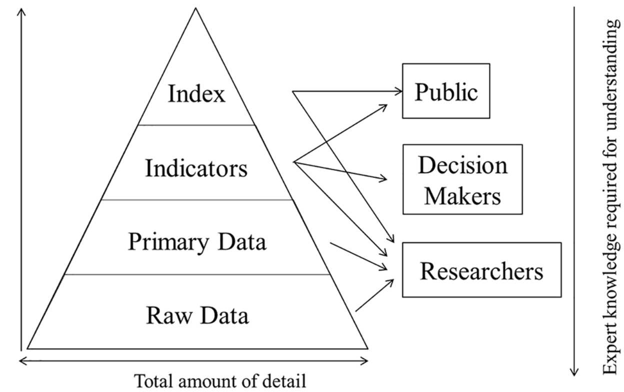

Fig. 2. Indicators/Indices hierarchy system with data condensation and targeted audiences.

1. Overaggregation: If too many things are lumped together, their combined message may be indecipherable.
2. Measuring what is measurable, rather than what is important: Tons of hazardous chemicals rather than toxicities.
3. Dependence on a false model: We may think the price of oil tells us about the underground abundance of oil, when it primarily tells us about the built capacity of oil wells relative to the built capacity of oil-consuming devices.
4. Deliberate falsification: If an index carries bad news, someone may be tempted to alter it, delay it, change the terms or definitions, defund it, lose it, or otherwise suppress it.
5. Diverting attention from direct experience: Indicators may mesmerize people with numbers and blind them to their own perceptions.

6. Overconfidence: Indicators may lead people to think they know what they are doing, or to think what they are doing is working, when in fact the indicators may be faulty.

7. Incompleteness: Indicators are not the real system. They may miss many of the subtleties, beauties, wonders, warnings, diversities, possibilities, or perversities of the real system.

We propose an additional peril, over-simplification. The vulnerability of soil ecosystem services or the effects of management systems on soil quality cannot be described based on a single soil property. For example, some scientists have utilized soil organic carbon (SOC) as the sole determining factor for soil quality, thereby oversimplifying the complexity of soil (Zornoza et al., 2007). Grunwald et al. (2016) found that the number of soil carbon publications is exploded, with over 1.76 million publications identified by Google Scholar, often with the sole focus on SOC. This type of simplification implies that SOC is the only and most important indicator for soil health, quality, and security. The scientific debates on soil quality have ignored many other soil biochemical variables, such as phosphorus, nitrogen, micronutrients, microbial biomass, and soil carbon sequestration. Those studies not limited to the eight traps outlined by Meadows (1998) may result in inappropriate interpretation and miscommunication among scientists and decision makers, which might even further aggravate real soil degradation problems.

Criteria for Indicator/Index Development

Clear documentation regarding In/Ix quality, in particular the relationship between the components of calculated In/Ix scores and the aims of the metrics' development, needs to be formalized when quantitative approaches are applied for conceptual notions (Kerans and Karr, 1994; Karr and Chu, 1997). Various scientists have proposed many ideal characteristics of the In/Ix systems as the criteria (Supplemental Table S2). There are some similarities among those propositions. For example, the interpretability of the In/Ix systems and relevance to the calculation components are commonly considered as key characteristics because the aim is to convey to the audience, including decision makers, the current status of a given situation. From the methodological perspective, measurability and methodological soundness, including data accessibility, appear to be important.

Zaiko and Daunys (2015) suggested the following criteria for In/Ix development in the biological community, specifically benthic ecosystems: (1) science-based; (2) ecosystem relevant and biologically important; and (3) other features such as accuracy, responsivity, sensitivity, specificity, and predictability. Other scientists have stressed the reproducibility and validity of the indication system as most salient characteristics (Sullivan, 2002; Sullivan et al., 2003; Rosenberg et al., 2004; Fleischer et al., 2007). Chaves and Alipaz (2007) provided a set of criteria for sustainability indicators and parameters, such as the availability of data to calculate indicators; comprehensibility for non-scientists; credible indicators supported by valid evidence in a scientifically defensible manner; relevant indicators that reflect changes in management or activities; and integration that facilitates indicators to demonstrate connections among the environmental, social, and economic aspects of sustainability. Loomis et al. (2014) summarized 11 unique criteria used for the indicator selection to include measurable variables within each focal ecosystem component, such as relevance to ecosystem services, responsibility, the ability to respond to stress earlier than the rest of the system (i.e., leading indicator), allowing enough time to show a response to possible management actions, and implementation effectivity in a study area (Supplemental Table S2).

Karlen et al. (1997) argued that the indication system applicable to soil quality and health should be (1) influential on assessable soil functions, (2) measurable against definable standards, and (3) sensitive enough to detect changes at the point scale in time and space. Doran (2002) proposed some criteria for soil quality/health indication systems that demonstrate sensitivity to management and climatic variation, and provide accessibility and utility to agricultural specialists, producers, conservationists, and policymakers.

In addition to the criteria presented above, Karlen et al. (1997) suggested that soil quality evaluations should be viewed as relational rather than absolute because of the diverse purposes of use. They argued for the use of relative measurements, such as ratios, rather than absolute values of measurements for the calculation of In/Ix values. In/Ix measures for soil concepts are artificial scores that do not have any true value in nature.

We also propose adaptability as one of the features that is critically important in the In/Ix systems when applied to soil science. This criterion describes how In/Ix systems provide the necessary flexibility applied under varying conditions (e.g., soil-landscape or climatic conditions in different regions). The measure can be adapted to specific purposes/goals. For example, the In/Ix framework could be applied using a small or large set of inputs (e.g., soil-environmental variables) or different inputs aligned with a specific purpose (e.g., soil quality, soil security, soil health, soil fertility, or soil degradation risk). The soil indication system requires adaptability due to the complexity of the critical vadose zone that serves as an integrator in which multiple ecosystem processes concurrently operate. In contrast, water science often focuses only on the purpose of provisioning healthy water for drinking, and thus, the chemical and physical characteristics of water. The idea of purity is applicable for water but not for soil (Karlen et al., 2003). The use of In/Ix systems for soil concepts is associated with a soil's fitness for a specific use, indicating the capacity of soils to function (Doran and Zeiss, 2000) or for a variety of ecosystem services, such as soil carbon sequestration (SCseq), soil nutrient storage, or pedo-diversity.

Meadows (1998) pointed out that it is easy to list the ideal characteristics of In/Ix systems derived from the accumulation of experiments and experiences, whereas it is much more challenging to find ones actually satisfying those standards. Many soil scientists have attempted the development of index systems to evaluate soil quality that meets the criteria mentioned above, but this has been difficult due to the heterogeneous characteristics of soil in space and time (Ross et al., 2013). Some proxy techniques and their fusion techniques, including geospatial modeling/simulations and soil spectroscopy modeling, have been developed and applied to predict soil attributes (Grunwald et al., 2015). However, each technique has limitations that can be costly and laborious over time (Shepherd and Walsh, 2002), or the focus can be too narrow.

Another reason could be that no purification concepts exist for soil science (Warkentin and Fletcher, 1977). As opposed to water quality/health, no "pure" natural soil can be found that could be used as a reference or standard measured by certain chemical concentrations. In order words, especially when conceptual notations are quantified, the condition or status of soil has to be evaluated based on specific uses (e.g., biodiversity) or human needs/benefits (e.g., food production or conservation).

Furthermore, discussions on objective criteria for In/Ix evaluation based on mathematical/statistical (axiomatic) viewpoints in environmental studies have not advanced as much as the conceptual characteristics of In/Ix systems (Table 1). According to Whittaker et al. (2012), the four criteria Fisher (1922) used to evaluate the quality of an indication system are: Homogeneity, Time-reversibility, Transitivity (or Circularity), and Dimensionality (Commensurability). The first axiomatic property, Homogeneity, describes the relationship of changes between inputs and outputs.

We propose three additional In/Ix criteria: (1) Monotonicity, (2) Homology in space, and (3) Time and space sensitivity (Table 1) that are specifically relevant in the soil quality, health, and security context. Monotonicity evaluates an ordinal-directional behavior of an In/Ix measure. When agricultural production does increase with increasing amounts of inputs (e.g., chemical fertilizers applied to soil), the relationship between the input and output is monotonic increasing. For example, Monotonicity can be tested using the Mann-Kendall test (Gilbert, 1987).

Homology in space indicates that the In/Ix behavior is invariant under the same/similar conditions in different geographic regions. For example, Homology in space is met if an index derived under specific soil-environmental conditions in Region A is the same/similar when derived under the same/similar soil-environmental conditions in Region B. 'Homosoil' was adopted for extrapolating soil information from knowledge-rich soil regions to those that lack sampling and knowledge (Mallavan et al., 2010). We believe that Homology in space is important for soil properties/types and for soil In/Ix.

The last criteria we propose for the indication quality is Time and space sensitivity, which ensures that there are significant measurable/observable changes of the In/Ix value in time and space under external (e.g., climate change or crop management) and internal forcings (e.g., pedogenesis). A soil In/Ix value might not change dramatically if the calculation is made based on variables which do not change significantly within a short period or among regions (Smith et al., 2005; Dawson and Smith, 2007). Similarly, the external anthropogenic-environmental and internal pedogenic factors may exhibit sensitivity across space, which make the In/Ix value site-specific. The sensitivity of the In/Ix value to changes of variables (inputs/outputs) in time and space is profoundly important for a soil-specific In/Ix system.

General Pros and Cons of Indication Systems

The benchmarking process can be understood as a systematic comparison of the performance of objects with reference (Bogetoft and Otto, 2011). The In/Ix metrics are often used as a quantitative assessment tool to distinguish the level of performance. Two major steps generally exist in In/Ix development: (1) selection of entities (observed measurements or indicators) and (2) conversion from original values of entities to new In/Ix values (Karlen et al.,

Table 1. Axiomatic features in the Indicators/Indices (In/Ix) system.

Mathematical/Statistical properties for In/Ix quality	Description
Homogeneity (or Scalability)	This criterion implies a proportional response of the In/Ix system when all inputs increase or decrease. The response is expressed with a scaling factor or scaling function.
Time-reversibility	This criterion expresses that the index is reversible in time along a fixed time trajectory.
Transitivity	This criterion captures that if the relation holds between the first and second elements and between the second and third elements, consecutively, it holds between the first and third elements (i.e., equality as in transitive relation).
Dimensionality (Commensurability)	This criterion refers to the robustness of the index to changing units of inputs/outputs. Dimensionality guarantees that the index value does not change under varying inputs/outputs (e.g., change in units of both inputs and outputs).
Monotonicity	This criterion expresses the monotonic trends (i.e., better to worse; lower to higher, and vice versa) in an index value responding to a change in inputs. Monotone behavior describes the successive index as either consistently increasing or decreasing.
Homology in space	This criterion describes the index behavior as invariant under the same/similar conditions in different geographic regions. For example, an index derived under specific soil-environmental conditions in Region A is the same/similar when derived under the same/similar soil-environmental conditions in Region B.
Time and space sensitivity	This criterion expresses an underlying causative relationship between inputs and the index. Sensitivity means that when the inputs change over time or in space there is a statistically significant observable/measurable response in the index value. Or, in other words, the index is not invariant to changes in space-time inputs.

2003; Wienhold et al., 2004; Schindelbeck et al., 2008). The aggregation to combine those scores into a single form may be required to measure and compare types of conditions or qualities in a meaningful way because those characteristics are often viewed multi-dimensionally (Zago, 2009). Thus, the benchmark developers often ask two fundamental questions: (1) "What variables need to be selected for the In/Ix calculation?" and (2) "How can those be converted into In/Ix scores (Meadows, 1998; Whittaker et al., 2015)?" Each question or step in the In/Ix development has been explored using subjective, objective, or a combination of subjective/objective approaches (Bastida et al., 2008). Each approach taken for variable selection and In/Ix conversion can provide the developers with merits and drawbacks.

We regarded the objective approach as reproducible and less biased by beliefs and opinions of the developers. Biases may include knowledge, experience, and perception of particular stakeholders or In/Ix developers. The selection of variables and weights for score conversion are derived from original (raw) data statistically or mathematically, although some subjectivity may occur due to preselection of variables (Xiong et al., 2014) or conversion methods. Importantly, the strategy underlying the objective method is formalized in the form of an algorithm or quantitative selection method based on specific criteria.

Chaves and Alipaz (2007) described the watershed sustainability index calculated by incorporating four so-called HELP (Hydrology, Environment, Life, and Policy) indicators (Supplemental Table S3). The use of those factors was adapted to the framework developed by international organizations, such as the United Nations Educational, Scientific, and Cultural Organization. Those calculated indicators were simply averaged to obtain the overall score of the watershed sustainability index. Another example was provided by Karr (1981) who presented the biological community quality index calculated by categorizing observed communities into several quality classes (very poor to excellent) subjectively and assigning them an index value based on the author's experience. This type of In/Ix system usually does not require any statistical computations or knowledge in calculations to generate scores; hence, end-users would possibly prefer this type of approach. We cannot technically justify the validity of In/Ix values developed in the subjective way due to the incapability of measuring the amount of subjectivity in each process. However, knowing what to measure based on the expert-based approach prior to sampling campaigns is considered valuable.

Subjectivity involved in the In/Ix development process may easily outweigh property selection. Thus, the objective approach which excludes those biases is preferable, especially from a science perspective, although most of the thresholds required for decisions, such as a significance level (p-value) in classical statistics using probability distribution theory (Halsey et al., 2015), are arbitrary and have been disputed (Ponsonby and Dwyer, 2014; Baker, 2016). Variables to be considered for calculation of In/Ix metrics were preselected based on their statistical relevance to a specific property (often carbon-related) using the analysis of variance (ANOVA) (Paz-Kagan et al., 2014; Askari and Holden, 2015). The objective approach generally requires additional efforts for implementation compared with the subjective method yet helps avoid biases of particular stakeholders. The less biased weighting system derived from an actual dataset is preferable to ensure reproducibility. Xiong et al. (2014) demonstrated strategic, objective selection of environmental co-variates (n = 210) using the Boruta algorithm and machine learning methods to infer on SOC as an indicator.

Overall, we identified some of the common pros and cons found in the process of variable selection as well as the score calculation process. There is no evidence that either the subjective or objective approach is better for identifying true benchmark scores in the In/Ix development process. Each approach adopts fundamentally different assumptions along the spectrum from subjective to objective selection methods.

Constraints in Current Indicator/Index Quantification Research in Soil Science

Intensified global environmental crises need solutions to address the impacts on dwindling soil/land resources and the degradation of their quality. This involves quantifying the absolute amounts of soil/land that have been impacted and the quantitative assessment of the gradation of the impacts (i.e., quality). Although the need to quantify soil resources, their quality, capacity, vulnerability, risk for degradation, and potential use are imminent, the transition from conceptual to quantitative systems/models is still primitive.

Soil scientists have employed quantitative analysis tools to assess soil information across different spatial or temporal scales, such as pedo-transfer functions, pedometrics, and Digital Soil Mapping (DSM). These techniques are aimed to help understand soil-landscape distribution patterns. For example, some statistical techniques, such as regression models, regression trees, and neural networks, are often utilized along with geostatistics and spatial data to map/model soil attributes and classes at a given time. The conceptual, factorial model framework for soil assessment, called CLORPT (CL, Climate; O, Organisms, biota; R, Relief; P, Parent material, and T: Time) model, was popularized by Jenny (Jenny, 1941). McBratney et al. (2003) modified the model to include age and space variables formalized in the SCORPAN model (S, Soil; C, Climate; O, Organisms; R, Relief; P, Parent material; A, Age; and N, Space). Grunwald et al. (2011) enhanced these models by incorporating explicitly the human dimension, known as STEP-AWBH model (pronounced "step-up") (with S, Soil; T, Topography; E, Ecology; P, Parent material; A, Atmosphere; W, Water; B, Biota; H, Human). However, those conceptual models have been often used to predict only a single soil variable, which indicates a lack in recognition to predict integrative In/Ix scores. Importantly, SCORPAN and STEP-AWBH models have the potential to infer on soil-related In/Ix. Grunwald et al. (2015) discussed the benefits and constraints of sophisticated/complex and simple/parsimonious quantification techniques, the latter allowing operationalizing soil/land management and protecting these resources.

Earlier works featured the calculation of In/Ix measures based on straightforward conceptual models of soils. For example, Doran and Parkin (1994) advocated a basic framework for soil quality (SQ):

$$SQ = f(SQE1, SQE2, SQE3, SQE4, SQE5, SQE6) \quad [1]$$

where SQE1 is food and fiber production, SQE2 is erosivity, SQE3 is ground water quality, SQE4 is surface water quality, SQE5 is air quality, and SQE6 is food quality. Parr et al. (1994) developed another equation:

$$SQ = f(SP, P, E, H, ER, BD, FQ, MI) \quad [2]$$

where SP is soil properties, P is potential productivity, E is environmental factors, H is human/animal health, ER is erodibility, BD is biological diversity, FQ is food quality/safety, and MI is management inputs. Although the validity of those calculations is clearly knowledge-based, the challenge in populating the variables in the soil quality functions is evident. Karlen et al. (1997) pointed out that no direct-measurable element(s) to assess soil quality exist, rather integrated relationships and functions should be evaluated with various parameters. However, many contemporary scientists have focused only on observations of a single property of soil, especially carbon content, to infer on soil quality and/or health (Carter, 2002; Zornoza et al., 2007; Sharma et al., 2011). This stands in contrast to suggestions that the indices and indicators should be selected according to the soil functions of interest and the defined management goals for a particular ecosystem (Andrews et al. 2002)

Kim et al. (2000) detected two types of problems related to the quantification of soil quality. One major issue is the arbitrary variable selection for In/Ix calculations. Another issue is the difficulty of data collection to calculate the In/Ix values continuously that is restricted by spatial and temporal soil data availability in the existing databases (Grunwald et al., 2011). Karlen et al. (1997) asked: (1) "How does the soil function?" and (2) "What indicators are appropriate for making the evaluations to assess the amelioration/degradation of function?" These questions highlight the different underlying interests or objectives that should be considered when developing individual In/Ix scores. Recently, Grunwald (2014) highlighted that soils can only be quantitatively assessed co-dependent on its valuation. This valuation is aligned with a specific purpose/need which is based on either extrinsic (i.e., focused to fulfill a specific human need, such as food production) or intrinsic (i.e., just for the sake of it; natural/organic) motivational principles.

When In/Ix measures aim at monitoring (e.g., soil quality change), data restrictions become another challenge. Kim et al. (2000) described the issue of data collection in spatial-temporal format. Wienhold et al. (2004) claimed that quantitative tools to assess soil concepts are critically important to identify problematic areas spatially and to evaluate management practices over time. Thus, some authors extended their assessment using indirect approaches, such as soil quality models derived from spectral (proximal) data (Paz-Kagan et al., 2014; Veum et al., 2015; Askari and Holden, 2015). The soil proximal and remote sensing techniques enable scientists to estimate soil attributes cost effectively, thus allowing the collection of temporal soil datasets or spatially denser sets (Grunwald et al., 2015). Although the uncertainty in soil estimates derived from spectral data is typically larger than laboratory measured ones, the former offers the potential for cost-effective monitoring of In/Ix, assuming they are sufficiently accurate to detect soil change.

Another problem can be found in the statistical methodologies applied to In/Ix development. Whittaker et al. (2012) revealed that statistical methods, such as factor analyses and ordination techniques, were prominently found in over 800 publications of their comprehensive literature review to develop environmental In/Ix. However, the most widely used approaches for environmental In/Ix assessment (including PCA, discriminant analysis, fuzzy logic, and cluster analysis) did not meet most of the axiomatic criteria for sound In/Ix development (Whittaker et al., 2015). This critique of inappropriate methodology environmental In/Ix development entails soil-specific In/Ix. For example, variable selection as well as score transformation in the In/Ix development processes have been conducted often using ANOVA and ordination techniques, such as PCA. The In/Ix scores developed through those techniques assert that the variation (variance) in a given dataset allows inference on the indicator of importance. These methods compute weights or loadings to transfer original values into abstract scores, which may lead to the misunderstanding that variables with relatively large variations are important or significant components of an In/Ix expressing soil quality, security, or health. These assertions also ignore the fact that the variability of soil and environmental properties are not scale invariant, nor are they invariant in space and through time. Thus, principal component scores that express the variability in one study (or geographic region, or specific time) have limited meaning to be compared to another region or at another time (e.g., providing inference on soil quality improvement/degradation) due to lack of a formalized In/Ix reference system that allows comparisons. Karr and Chu (1997) stated that an important aspect of multivariate techniques is that they can be used with the purpose of pattern analysis, but not impact assessment or biological monitoring. In particular, PCA, as well as other ordination techniques, aim at identifying the major ecological or environmental gradients of variation among sampling entities (McGarigal et al., 2000). But soil variation does not necessarily imply quality, health, or security of soils as some ecological index studies have suggested (Karr and Chu, 1997; Meadows, 1998).

There are indeed some attractive features in using ordination techniques or other multivariate techniques to calculate In/Ix measures for impact assessment, such as the capability of handling multiple variables and data reduction. Some statistical techniques, such as Mantel tests, can flexibly accept a variety of datasets under different conditions, such as non-normal distributions, multi-collinearity in variables, existing outliers or missing values, or even temporal and spatial auto-correlations (McCune and Grace, 2002). Yet the variance of variables is not directly related to the condition or quality of soils. The application of such widely used multivariate statistical techniques imposes major drawbacks on In/Ix development, including the requirement of local calibration and validation when incorporating new samples collected at different times or spatial locations as well as not considering axiomatic criteria.

We thus invite a critical debate to further discuss soil In/Ix development. Some soil scientists have apparently used these statistical methods in an uninformed manner without any methodological justification. This situation motivated us to explore methods to derive In/Ix scores that are able to overcome the discussed limitations. In particular, DEA and the advanced version of the technique, called Malmquist Index (MI), fulfill the axiomatic criteria for a scientifically sound In/Ix system. They can provide a new direction applicable to environmental issues and soil quality, health, and security assessments (Färe et al., 2004; Thanassoulis et al., 2008). The DEA and the MI have very rarely been applied in soil science. We describe the DEA and the MI briefly in the next section.

ECONOMETRIC APPROACHES FOR INDICES CALCULATION

Some Terminology in Econometric Theories

First, important terms that are commonly used in the economic realm are explained, such as productivity and efficiency, which are uncommon in the soil science literature. Their relevance for soil/environmental In/Ix assessment will be explored. Those terms have been commonly used as a comparison measure in regard to performance levels of a decision-making unit (DMU) which are composed of input(s) and output(s) (Charnes et al., 1978).

Traditional Methods in Econometrics to Identify the Best Performance Level

Benchmarking is part of managerial tool-kits which can improve the quality of goods and services and optimize operations (Berg, 2007). The performance scores derived from the benchmarking process can serve as catalysts for better stewardship of natural resources, such as soil. The ordinary least squares method (OLS) is a basic method to evaluate productivity or performance with a regression line calculated from the combination of input(s) and output(s) (Belbase and Grabowski, 1985). When the observation points or entities of DMUs are closer to the regression line or frontier (technology) line, it suggests that they have better productivity than other points far from the line (McDonald, 2009).

The corrected OLS, called COLS, uses the regression line with the same slope but a new intercept, which enables the line to be crossed through the highest or lowest point in the panel (Table 2). This could depend on whether the analyst wants to maximize the output with the same input or minimize the input but reach the same output (Coelli and Perelman, 1999). Since the frontier line represents the maximum output attainable from each level of input, it reflects the current quality/status or "technology" of the DMUs. The observation point located on the frontier line shows the technical efficiency. Another parametric method to calculate the efficiency scores is the Stochastic Frontier Analysis (SFA) which mainly uses the maximum likeli-

Table 2. Comparison chart on methodological features in productivity theory. Solid circles (●) indicate productivity methods can meet respective indicators/indices features, whereas question marks (?) indicate open sections for further discussion.

	Productivity Methods†				
	Parametric			Non-Parametric	
Indicators/Indices Features	OLS	COLS	SFA	DEA	Malmquist
Multiple inputs/outputs	●	●	●	●	●
Statistical assumptions - Homogeneity of variance - Independence - Normality - Linearity	● (P test)§	● (P test)	● (P test)	NA‡ (NP test)§	NA (NP test)
Conceptual characteristics of ideal indicators/Indices					
Relativity	●	●	●	●	●
Axiomatic and statistical/mathematical characteristics of ideal indicators/Indices					
Homogeneity (or Scalability)	?	?	?	?	?
Time-reversibility	NA	NA	NA	NA	●
Transitivity	?	?	?	?	?
Dimensionality (Commensurability)	●	●	●	●	●
Homology in space	?	?	?	?	?
Time and space sensitivity	?	?	?	?	?
Monotonicity	?	?	?	?	?
Spatial transferability	?	?	?	?	?

† OLS, ordinary least squares; COLS, corrected ordinary least squares; SFA, stochastic frontier analysis; DEA, data envelopment analysis.

‡ NA, not applicable.

§ P test, parametric test; NP test, non-parametric test.

hood or generalized least-squares method to draw the estimated frontier line (Gong and Sickles, 1992).

These methods can work easily with a single input and output; however, multiple inputs on either side can make the analysis process hard to implement. Considering assumptions of linear regression models, such as homogeneity of variance, independence, normality, and linearity assumptions, non-parametric analyses (e.g., DEA) which can handle non-normal variables or missing data are frequently used (Coelli and Perelman, 1999).

Data Envelopment Analysis and Malmquist Index

One well-known technique in benchmark studies is the DEA which was developed by Charnes et al. (1978). This technique uses the linear programming method that handles multiple inputs/outputs and is adaptable to different scenarios (i.e., returns to scales) (Banker et al., 2011; Cooper et al., 2011). When inputs and outputs are collected over different periods or regions, external factors, such as time, are influential on the productivity levels (Whittaker et al., 2015). Considering these cases, the MI originally proposed by Malmquist (1953), was applied as an extension of DEA method to the productivity analysis (Caves et al., 1982a).

In the early index number theory, Fisher Ideal Index and Törnqvist Productivity Index (TPI) were of particular interest in research among econometricians. These indices are mathematically classified as a second-order approximation technique that is exact for flexible aggregator functions. In other words, the indices can compare input, output, and productivity calculated from two components simultaneously using either time-series, cross-section, or panel data (Caves et al., 1982a). Since the TPI is equal to the geometric mean of two MI (Caves et al., 1982b), the indices encompass the axiomatic characteristics as described in the section on criteria for indices (Whittaker et al., 2015).

In practice, the MI is calculated based on the distance function proposed by Shephard (1977) in the context of consumer index. Two different types of functions, input-oriented or output-oriented, can be utilized depending on the scenarios users select (Grifell-Tatjé and Lovell, 1995). In calculating the MI, there are at least two single periods (t and $t + 1$) and two mixed period distance functions between observation points and frontier lines described as $D_i^t\left(x_i^t\ y_i^t\right)$, where x_i^t and y_i^t are the ith input and output for DMU$_i$ in time period t (Fig. 3). Thus, the MI$_i^t$ can be described as the ratio of $D_o^t\left(x_o^{t+1}, y_o^{t+1}\right)$ to $D_o^t\left(x_o^t,\ y_o^t\right)$. Since the input-oriented or output-oriented MI (MI$_i$) is the geometric mean of the two Malmquist indices developed for each period, the formula can be illustrated as:

$$\begin{aligned}\mathrm{MI}_i &= \left(\mathrm{MI}_i^t \times \mathrm{MI}_i^{t+1}\right)^{1/2} \\ &= \left[\frac{D_i^t\left(X_i^{t+1}, Y_i^{t+1}\right)}{D_i^t\left(X_i^t,\ Y_i^t\right)} \times \frac{D_i^{t+1}\left(X_i^{t+1}, Y_i^{t+1}\right)}{D_i^{t+1}\left(X_i^t,\ Y_i^t\right)}\right]^{1/2}\end{aligned} \qquad [3]$$

where D indicates distances driven from two different frontier lines based on the two periods (Färe et al., 2008).

One of the advantages of the MI calculation is that the geometric mean of two distance functions can be further decomposed to address the (technical) efficiency change (EC) and technology frontier shift (FS) as shown here (Färe and Grosskopf, 1992):

$$\begin{aligned}\mathrm{MI}_i &= \mathrm{EC} \times \mathrm{FS} \\ &= \frac{D_i^{t+1}\left(X_i^{t+1}, Y_i^{t+1}\right)}{D_i^t\left(X_i^t,\ Y_i^t\right)} \times \\ &\quad \left[\frac{D_i^t\left(X_i^{t+1}, Y_i^{t+1}\right)}{D_i^{t+1}\left(X_i^{t+1},\ Y_i^{t+1}\right)} \times \frac{D_i^t\left(X_i^t, Y_i^t\right)}{D_i^{t+1}\left(X_i^t,\ Y_i^t\right)}\right]^{1/2}\end{aligned} \qquad [4]$$

The value of EC (left part of ratio in front of the half-powered blanket in Eq. [4]) reaches above one when DMU$_i$ at time $t + 1$ has a higher efficiency in output(s) given input(s) than the DMU$_i$ at time t because the former is more closely located to the frontier rather than the latter. FS (right part of ratio multiplication within the blanket in Eq. [4]) explains the overall technol-

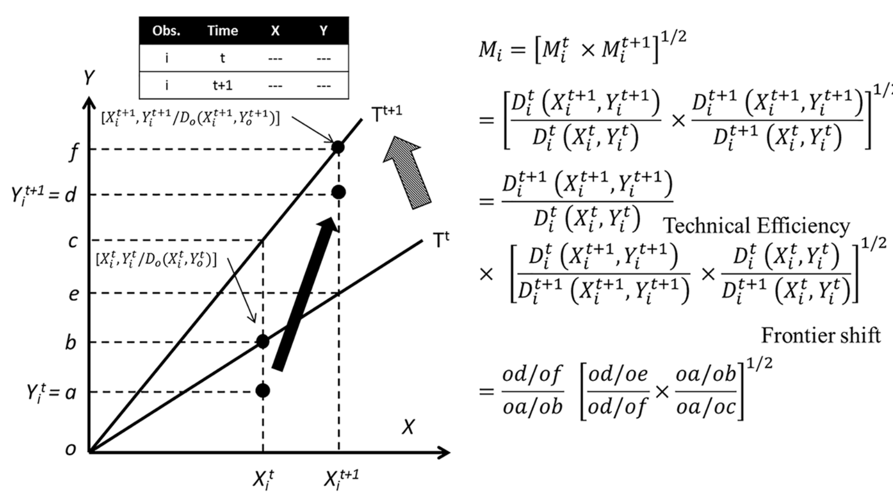

Fig. 3. Graphical illustration of the Malmquist Index (T is the technology line, *X* is input, *Y* is output, *t* or *t* + 1 means time, *i* is each observation/sample). The original point is represented by a zero "0" on the horizontal and vertical axes. The solid black arrow shows the change in efficiency of the sample over time, while the shaded arrow indicates of frontier shift. D_i^t (x_i^t, y_i^t) is the distance function for the sample *i* in the time *t* with input *x* and output *y*. Solid circles are samples.

ogy shift from time t to $t+1$. The positive technology progress is observed when FS is above the value of one, while FS below the value of one indicates a technology decline.

In another graphical illustration to explain calculations of the MI, EC, and FS, the following equation is helpful (Fig. 3; Coelli et al., 2005; Färe et al., 2008):

$$\mathrm{MI}_i = \left(\frac{od/oe}{oa/ob} \times \frac{od/of}{oa/oc} \right)^{1/2} \qquad [5]$$

where

$$\mathrm{EC} = \frac{od/of}{oa/ob} \qquad [6]$$

$$\mathrm{FS} = \left(\frac{od/oe}{od/of} \times \frac{od/ob}{oa/oc} \right)^{1/2} \qquad [7]$$

and the conditions of technology T should be satisfied with $D_i\left(x, y\right) = \min\left\{\theta : \left(x, y\right)/\theta \in T\right\}$.

Chen and Ali (2004) even attempted to decompose further the above equation, which implies that MI is useful when evaluating the trends for the total technology level and each DMU's productivity with multiple inputs/outputs is collected at different times.

When this technique is applied to soil quality research, improvements or declines of soil quality over time can be identified based on the Malmquist In/Ix measures. For example, assume we have a dataset of SOC collected at three or more times to calculate the gain or loss of soil carbon through time. Then we can use the carbon sequestration rate as output and relevant environmental- and human variables as inputs to calculate the scores. This allows identifying the most efficient geographical areas or land use/land cover types with the highest sequestration rate based on the input levels. We may also calculate the distance from the DMU point locations to the technical frontier line so that we can identify the attainable capability of SCseq in each region or time. Other soil functions and conceptual frameworks, besides soil carbon sequestration, such as nutrient efficiency, erodibility, vulnerability to human impacts, and so forth, could be evaluated. Importantly, these efficiency metrics represent an Ix that considers simultaneously and explicitly inputs and outputs relative to the optimum (the frontier). For example, the SCseq Ix in an arid soilscape is constrained by physical, biological, and chemical processes compared to wetland soils (Histosols) even if the same amount of carbon residue serves as input into the soil.

Jaenicke and Lengnick (1999) used the DEA and MI approaches to assess soil productivity to optimize agricultural management. In this study, the crop yield was set as output, while soil chemical, physical, and biological properties were set as inputs. Consequently, seven variables in total were chosen: available phosphorus and potassium as well as acidity and available magnesium as chemical indicators, bulk density and water-holding capacity as physical indicators, and carbon-nitrogen ratio as biological indicator. The calculated MI scores were used to create contour maps throughout the study area. This pioneering study demonstrated that soil quality In/Ix across space and time can be assessed through the DEA and MI.

The econometric methods are not necessarily constrained to use for agricultural production capability or efficiency. Other functions/capability of soil such as soil carbon sequestration (SCseq) can also be assessed. A case study using two basic econometric methods, DEA and SFA, was developed (see Appendix). Environmental/soil information and SCseq rate were incorporated into models as inputs and outputs for calculating a capability index of the function, respectively (Supplemental Table S4). The data for two different land use types, improved pasture and upland forests, were simulated from values originally found in the literature. The DEA scores showed the statistical significance found in the capability of the soil carbon sequestration function among two different land use types compared to the SFA (Supplemental Figure S1). The case study indicated that the nonparametric approach, DEA method, is more sensitive than the SFA when incorporating multiple inputs, although results from DEA and SFA can be highly correlated (Ghorbani et al., 2010). More importantly, both methods produced scores indicating the capability level of the function as well as the attainable level beyond measuring or estimating outputs (SCseq rate) alone. Thus, we believe the soil science community would benefit by applying such underexplored innovative methods from econometrics for quantifying various kinds of soil functions and soil concepts. Details of the case study can be found in the Appendix. The actual case study using the SCseq rate derived from measured soil carbon to calculate the SCseq capability index is also available in a previous publication (Mizuta et al. 2016).

FUTURE RESEARCH OPPORTUNITIES

The incorporation of the knowledge and skills developed in the economy field, particularly econometric theory, could be used to address integral issues in soil science and environmental science. Many different complex soil function models can be developed with more integrated combinations of inputs and/or outputs using econometric methods such as DEA and MI. The authors imagine that the calculated soil In/Ix measures could be predicted using visible-near-infrared/mid-infrared spectroscopy. However, such spectral-derived soil In/Ix need to be verified and validated carefully.

The In/Ix measure can also be spatially mapped out to view the In/Ix measure distribution throughout geographical space. This may allow shifting from soil property maps/models to more integrative spatially-explicit assessment of soil quality and soil security.

FINAL REMARKS

We demonstrated that soil paradigms, such as soil quality, health, and security share commonalities, namely to sustain and protect soils. However, the quantification of these critically important soil concepts have been often limited to single soil properties/classes and have shown a lack to meet the criteria of axiomatic indication systems.

We provided a comprehensive review of In/Ix in soil and environmental sciences and their constraints. We identified several econometrical methods with the potential to be applied to assess the quality and quantity of soils. These methods, such as the DEA and MI, are in line with the axiomatic criteria of In/Ix systems and provide a reference framework that can be applied to assess diverse soil function, quality, risk, degradation, and security at various spatial and temporal scales. The benefit of econometrical methods is their ease of use and adaptability. They allow comparing efficiency and capability scores in different soilscapes that has not been possible with conventional DSM and pedometric approaches. The transformative potential to take the leap for more integrative soil quality, health, and security assessments by interfacing econometrics and soil/environmental sciences is profound. This will enable scientists to bring interdisciplinary research grounded in soil science- econometrics, "Pedo-Econometrics", to decision makers and the general public.

ACKNOWLEDGMENTS

This work was supported by the Japan Association Student Service Organization, Soil and Water Sciences Department, Univ. of Florida as well as Public Utility Research Center at Warrington College of Business, Univ. of Florida. We would also like to appreciate Dr. Sanford V. Berg, Dr. Theodore J. Kury, Dr. Gustavo M. Vasques, Dr. Wonsuk Lee, and Dr. Wendell P. Cropper for their critical feedbacks on our research.

SUPPLEMENTAL MATERIAL

A supplemental file is available with the online version of this article. The supplemental material includes one figure and four tables. Supplement Fig. S1 shows simulated scores calculated by the DEA and the SFA for improved pasture and upland forests. Supplemental Table S1 shows the list of 52 different definitions of soil-related concepts. Supplemental Table S2 summarizes proposed criteria on roles/characteristics for ideal indicators/indices. Supplemental Table S3 explains selected examples of indicators/indices calculated in ecological and environmental sciences. Supplemental Table S4 shows the summary of descriptive statistics for simulated data of variables used for index calculation.

APPENDIX

The purpose of this case study is to demonstrate the applicability of econometric techniques suggested for soil science studies. A parametric method, Data Envelopment Analysis (DEA), and non-parametric method, Stochastic Frontier Analysis (SFA) were used (Table 2). The soil carbon sequestration function was chosen as a target output function to be maximized. Soil/environmental inputs that contribute to the function, including Normalized Difference Vegetation Index (NDVI), pH, and fertilizers (nitrogen, phosphorus, and potassium), were incorporated into the models. Randomly generated values (n = 1000) were simulated from the normal distribution for each variable based on values with specific ranges and means found in the literature (Supplemental Table S4). Index scores from both DEA and SFA range between zero and one (Supplemental Figure S1). Scores close to one represent high capability of the function. The parametric method, DEA, found statistically significant differences in the scores using non-repeated measures of the ANOVA (Tukey comparison tests) among land use types (F value = 186.2, $p < 0.05$), whereas SFA scores did not (F value = 0.037, $p > 0.1$). DEA and SFA results are not directly comparable because both models are built based on different assumptions and trade-offs (Hjalmarsson et al., 1996; Johannes, 2007). However, the DEA approach indicated that soils in improved pasture are more capable than soils in upland forests to sequester soil carbon. Although the SFA showed insignificant results, both methods evaluate the capability of this selected soil function, which is beyond measuring or estimating the SCseq rate itself. The level of capability was calculated considering the output and input aspects despite incorporating multiple variables with different units. An additional benefit of using such analysis is its transferability to other geographic regions, providing a standardized indication system to quantify specific soil functions (Table 1). This econometric approach also provides a reference value to calculate the attainable level of capability, which would not be possible by using conventional multivariate statistics methods in the literature. Innovative methods entail great potential to advance research of quantifying various soil functions and concepts, but more investigations are necessary to adopt these underexplored approaches for soil science as suggested in the manuscript.

REFERENCES

Acton, D.F., and L.J. Gregorich. 1995. The health of our soils: Toward sustainable agriculture in Canada. Centre for Land and Biological Resources Research, Agriculture and Agri-Food Canada, Ottawa, Ontario.

Adeyolanu, O.D., and A.O. Ogunkunle. 2016. Comparison of qualitative and quantitative approaches to soil quality assessment for agricultural purposes in South-western Nigeria. Cogent Food Agric. 2:1149914. doi:10.1080/23311932.2016.1149914

Andrews, S.S., J.P. Mitchell, R. Mancinelli, D.L. Karlen, T.K. Hartz, W.R. Horwath, G.S. Pettygrove, K.M. Scow, and D.S. Munk. 2002. On-farm assessment of soil quality in California's Central Valley. Agron. J. 94:12–23. doi:10.2134/agronj2002.0012

Askari, M.S., and N.M. Holden. 2015. Quantitative soil quality indexing of temperate arable management systems. Soil Tillage Res. 150:57–67. doi:10.1016/j.still.2015.01.010

Baker, M. 2016. Statisticians issue warning over misuse of P values. NATNEWS 531:151. doi:10.1038/nature.2016.19503

Banker, R.D., W.W. Cooper, L.M. Seiford, and J. Zhu. 2011. Returns to Scale in DEA. In: W.W. Cooper, L.M. Seiford, and J. Zhu, editors, Handbook on data envelopment analysis. International Series in Operations Research and Management Science. Springer, New York. p. 41–70. doi:10.1007/978-1-4419-6151-8_2

Bastida, F., A. Zsolnay, T. Hernández, and C. García. 2008. Past, present and future of soil quality indices: A biological perspective. Geoderma 147:159–171. doi:10.1016/j.geoderma.2008.08.007

Bauler, T., I. Douglas, P. Daniels, V. Demkine, N. Eisenmenger, J. Grosskurth, T. Hak, L. Knippenberg, J. Martin, P. Mederly, R. Prescott-Allen, R. Scholes, and J. van Woerden. 2007. Identifying methodological challenges. In: T. Hak, B. Moldan, and A.L. Dahl, editors, Sustainability indicators-A scientific assessment. The Scientific Committee on Problems of the Environment, of the International Council for Science (SCOPE). Island Press, Washington, DC. p. 49–64.

Beck, H., K. Morgan, Y. Jung, S. Grunwald, H. Kwon, and J. Wu. 2010. Ontology-based simulation in agricultural systems modeling. Agric. Syst. 103:463–477. doi:10.1016/j.agsy.2010.04.004

Belbase, K., and R. Grabowski. 1985. Technical efficiency in Nepalese Agriculture. J. Dev. Areas 19:515–526.

Berg, S.V. 2007. Conflict resolution: Benchmarking water utility performance. Public Adm. Dev. 27:1–11. doi:10.1002/pad.437

Bogetoft, P., and L. Otto. 2011. Introduction to benchmarking. In: Benchmarking with DEA, SFA, and R. International Series in Operations Research and Management Science. Springer, New York. p. 1–22.

Bouma, J. 2002. Land quality indicators of sustainable land management across scales. Agric. Ecosyst. Environ. 88:129–136. doi:10.1016/S0167-8809(01)00248-1

Bouma, J. 2005. Soil scientists in a changing world. In: D. Sparks, editor, Advances in agronomy. Academic Press, New York. p. 67–96.

Bouma, J., M.K. van Ittersum, J.J. Stoorvogel, N.H. Batjes, P. Droogers, and M.M. Pulleman. 2017. Soil capability: Exploring the functional potentials of soils. In: D. Field, C.L. Morgan, and A.B. McBratney, editors, Global soil security, Progress in soil science. Springer, Cham. p. 27–44. doi:10.1007/978-3-319-43394-3_3

Bouma, J., and A. McBratney. 2013. Framing soils as an actor when dealing with wicked environmental problems. Geoderma 200–201:130–139. doi:10.1016/j.geoderma.2013.02.011

Braat, L. 1991. The predictive meaning of sustainability indicators. In: O.J. Kuik, H. Verabruggen, editors, In search of indicators of sustainable development. Environment and management. Springer, the Netherlands. p. 57–70.

Brauch, H.G., and Ú.O. Spring. 2011. Securitizing land degradation and desertification: A proactive soil security concept. In: H.G. Brauch, Ú.O. Spring, C. Mesjasz, J. Grin, P. Kameri-Mbote, B. Chourou, P. Dunay, and J. Birkmann, editors, Coping with global environmental change, disasters and security. Hexagon Series on Human and Environmental Security and Peace. Springer, Berlin. p. 803–833. doi:10.1007/978-3-642-17776-7_47

Burket, J. 1998. Willamette Valley soil quality card. Oregon State Univ. Ext. Service, Corvallis, OR.

Carter, M.R. 2002. Soil quality for sustainable land management. Agron. J. 94:38–47. doi:10.2134/agronj2002.0038

Cassman, K.G. 1999. Ecological intensification of cereal production systems: Yield potential, soil quality, and precision agriculture. Proc. Natl. Acad. Sci. USA 96:5952–5959. doi:10.1073/pnas.96.11.5952

Caves, D.W., L.R. Christensen, and W.E. Diewert. 1982a. Multilateral comparisons of output, input, and productivity using superlative index numbers. Econ. J. 92:73–86. doi:10.2307/2232257

Caves, D.W., L.R. Christensen, and W.E. Diewert. 1982b. The economic theory of index numbers and the measurement of input, output, and productivity. Econometrica 50:1393–1414. doi:10.2307/1913388

Charnes, A., W.W. Cooper, and E. Rhodes. 1978. Measuring the efficiency of decision making units. Eur. J. Oper. Res. 2:429–444. doi:10.1016/0377-2217(78)90138-8

Chaves, H.M.L., and S. Alipaz. 2007. An integrated indicator based on basin hydrology, environment, life, and policy: The watershed sustainability index. Water Resour. Manage. 21:883–895. doi:10.1007/s11269-006-9107-2

Chen, Y., and A.I. Ali. 2004. DEA Malmquist productivity measure: New insights with an application to computer industry. Eur. J. Oper. Res. 159:239–249. doi:10.1016/S0377-2217(03)00406-5

Chen, T.-B., Y.-M. Zheng, M. Lei, Z.-C. Huang, H.-T. Wu, H. Chen, K.-K. Fan, K. Yu, X. Wu, and Q.-Z. Tian. 2005. Assessment of heavy metal pollution in surface soils of urban parks in Beijing, China. Chemosphere 60:542–551. doi:10.1016/j.chemosphere.2004.12.072

Coelli, T., and S. Perelman. 1999. A comparison of parametric and non-parametric distance functions: With application to European railways. Eur. J. Oper. Res. 117:326–339. doi:10.1016/S0377-2217(98)00271-9

Coelli, T.J., D.S.P. Rao, C.J. O'Donnell, and G.E. Battese. 2005. Productivity and efficiency measurement concepts. In: D.P. Rao, G.E. Battese, and T. Coelli, An introduction to efficiency and productivity analysis. Springer, New York. p. 41–83.

Commission of the European Communities. 2006. Proposal for a directive of the European Parliament and of the Council establishing a framework for the protection of soil and amending Directive 2004/35/EC. Commission of the European Communities, Brussels, Belgium.

Cooper, W.W., L.M. Seiford, and J. Zhu. 2011. Data envelopment analysis: History, models, and interpretations. Springer, New York.

Costanza, R., R. d'Arge, R. de Groot, S. Farber, M. Grasso, B. Hannon, K. Limburg, S. Naeem, R.V. O'Neill, J. Paruelo, R.G. Raskin, P. Sutton, and M. van den Belt. 1997. The value of the world's ecosystem services and natural capital. Nature 387:253–260. doi:10.1038/387253a0

Dawson, J.J.C., and P. Smith. 2007. Carbon losses from soil and its consequences for land-use management. Sci. Total Environ. 382:165–190. doi:10.1016/j.scitotenv.2007.03.023

Doran, J.W. 2002. Soil health and global sustainability: Translating science into practice. Agric. Ecosyst. Environ. 88:119–127. doi:10.1016/S0167-8809(01)00246-8

Doran, J.W., and T.B. Parkin. 1994. Defining and assessing soil quality. In: J.W. Doran, D.C. Coleman, D.F. Bezdicek, and B.A. Stewart, editors, Defining soil quality for a sustainable environment. Proceedings of a symposium sponsored by Divisions S-3, S-6, and S-2 of the Soil Science Society of America, Division A-5 of the American Society of Agronomy, and the north Central Region Committee on Soil Organic Matter (NCR-59) in Minneapolis, MN. SSSA, ASA, Madison, WI. p. 3–22.

Doran, J.W., and M. Safley. 1997. Defining and assessing soil health and sustainable productivity. In: C. Pankhurst, B. Doube, and V.V.S.R. Gupta, editors, Biological indicators of soil health. CAB International, New York. p. 1–28.

Doran, J.W., and M.R. Zeiss. 2000. Soil health and sustainability: Managing the biotic component of soil quality. Appl. Soil Ecol. 15:3–11. doi:10.1016/S0929-1393(00)00067-6

El-Ladan, I.Y., N.A. Maiwada, and A.A. Rumah. 2014. Factors affecting soil quality maintenance in northern Katsina Stte, Nigeria. Sci. World J. 9:39–45.

Esbjörn-Hargens, S., and M.E. Zimmerman. 2009. Integral ecology: Uniting multiple perspectives on the natural world. Integral Books Publ., Boston, MA.

Färe, R., and S. Grosskopf. 1992. Malmquist productivity indexes and fisher ideal indexes. Econ. J. 102:158–160. doi:10.2307/2234861

Färe, R., S. Grosskopf, and F. Hernandez-Sancho. 2004. Environmental performance: An index number approach. Resour. Energy Econ. 26:343–352. doi:10.1016/j.reseneeco.2003.10.003

Färe, R., S. Grosskopf, and D. Margaritis. 2008. Efficiency and productivity: Malmquist and more. In: H.O. Fried, C.A.K. Lovell, and S.S. Schmidt, editors, The measurement of productive efficiency and productivity change. Oxford Univ. Press, UK. p. 522–622. doi:10.1093/acprof:oso/9780195183528.003.0005

Fisher, I. 1922. The making of index numbers; a study of their varieties, tests, and reliability. Houghton Mifflin Company, Boston, MA.

Fleischer, D., A. Grémare, C. Labrune, H. Rumohr, E.V. Berghe, and M.L. Zettler. 2007. Performance comparison of two biotic indices measuring the ecological status of water bodies in the Southern Baltic and Gulf of Lions. Mar. Pollut. Bull. 54:1598–1606. doi:10.1016/j.marpolbul.2007.06.011

Fließbach, A., H.-R. Oberholzer, L. Gunst, and P. Mäder. 2007. Soil organic matter and biological soil quality indicators after 21 years of organic and conventional farming. Agric. Ecosyst. Environ. 118:273–284. doi:10.1016/j.agee.2006.05.022

Food and Agriculture Organization of the United Nations. 1976. A framework for land evaluation. Food and Agriculture Organization of the United Nations, Rome, Italy.

Franzluebbers, A.J. 2002. Soil organic matter stratification ratio as an indicator of soil quality. Soil Tillage Res. 66:95–106. doi:10.1016/S0167-1987(02)00018-1

Gallopin, G.C. 1997. Indicators and their use: Information for decision-making. In: B. Moldan and S. Billharz, editors, Sustainability Indicators. John Wiley and Sons, New York, NY. p. 13–28.

Ghorbani, A., A. Amirteimoori, and H. Dehghanzadeh. 2010. A comparison of DEA, DFA and SFA methods using data from caspian cattle feedlot farms. J. Appl. Sci. 10:1455–1460. doi:10.3923/jas.2010.1455.1460

Gilbert, R.O. 1987. Statistical methods for environmental monitoring. Van Nostrand Reinhold Company Inc., New York.

Gong, B.-H., and R.C. Sickles. 1992. Finite sample evidence on the performance of stochastic frontiers and data envelopment analysis using panel data. J. Econom. 51:259–284. doi:10.1016/0304-4076(92)90038-S

Granatstein, D., and D.F. Bezdicek. 1992. The need for a soil quality index: Local and regional perspectives. Am. J. Altern. Agric. 7:12–16. doi:10.1017/S0889189300004380

Gregorich, E.G., C.M. Monreal, M.R. Carter, D.A. Angers, and B.H. Ellert. 1994. Towards a minimum data set to assess soil organic matter quality in agricultural soils. Can. J. Soil Sci. 74:367–385. doi:10.4141/cjss94-051

Grifell-Tatjé, E., and C.A.K. Lovell. 1995. A note on the Malmquist productivity index. Econ. Lett. 47:169–175. doi:10.1016/0165-1765(94)00497-P

Grunwald, S. 2014. Part I: Conceptualization of a meta soil model. In: D. Arrouays, N. McKenzie, J. Hempel, A.C. Richer de Forges, and A. McBratney, editors, Global soil map. CRC Press, the Netherlands. p. 233–238. doi:10.1201/b16500-45

Grunwald, S., P. Chaikaew, B. Cao, X. Xiong, G.M. Vasques, J. Kim, C.W. Ross, C.M. Clingensmith, Y. Xu, and C. Gavilan. 2016. The meta soil model– An integrative framework to model soil carbon across various ecosystems and scales. In: G.L. Zhang, D.J. Brus, F. Liu, S. Xiao-Dong, and P. Lagacherie, editors, Digital soil mapping across paradigms, scales and boundaries. Springer Environmental Science and Engineering, Singapore. p. 165–179. doi:10.1007/978-981-10-0415-5_14

Grunwald, S., C.M. Clingensmith, C.P. Gavilan, K. Mizuta, R.K.K. Wilcox, É.F.M. Pinheiro, M.B. Ceddia, and C.W. Ross. 2017. Integrating new perspectives to address global soil security: Ideas from integral ecology. In: D.J. Field, C.L.S. Morgan, and A.B. McBratney, editors, Global soil security. Progress in soil science. Springer International Publishing, New York. p. 319–329. doi:10.1007/978-3-319-43394-3_28

Grunwald, S., K. Mizuta, M.B. Ceddia, É.F.M. Pinheiro, R.K.K. Wilcox, C.P. Gavilan, C.W. Ross, and C.M. Clingensmith. 2017. The Meta Soil Model: An integrative multi-model framework for soil security. In: D.J. Field, C.L.S. Morgan, and A.B. McBratney, editors, Global soil security. Progress in soil science. Springer International Publishing, New York. p. 305–317.

Grunwald, S., J.A. Thompson, and J.L. Boettinger. 2011. Digital soil mapping and modeling at continental scales: Finding solutions for global issues. Soil Sci. Soc. Am. J. 75:1201. doi:10.2136/sssaj2011.0025

Grunwald, S., G.M. Vasques, and R.G. Rivero. 2015. Fusion of soil and remote sensing data to model soil properties. Adv. Agron. 131:1–109.

Guimarães, R.M.L., B.C. Ball, and C.A. Tormena. 2011. Improvements in the visual evaluation of soil structure. Soil Use Manage. 27:395–403. doi:10.1111/j.1475-2743.2011.00354.x

Guo, D., K. DeFrancia, M. Chen, B. Filiatraut, and C. Zhang. 2015. Assessing sustainability: Frameworks and indices (White Paper No. 3). Columbia Univ. Acad. Commons:1–9.

Haberern, J. 1992. Viewpoint: A soil health index. J. Soil Water Conserv. 47:6.

Habermas, J. 1984. The theory of communicative action. 1. Reason and the rationalisation of society. Heinemann, London.

Halsey, L.G., D. Curran-Everett, S.L. Vowler, and G.B. Drummond. 2015. The fickle P value generates irreproducible results. Nat. Methods 12:179–185. doi:10.1038/nmeth.3288

Herrick, J.E. 2000. Soil quality: An indicator of sustainable land management? Appl. Soil Ecol. 15:75–83. doi:10.1016/S0929-1393(00)00073-1

Hjalmarsson, L., S.C. Kumbhakar, and A. Heshmati. 1996. DEA, DFA and SFA: A comparison. J. Prod. Anal. 7:303–327.

Jaenicke, E.C., and L.L. Lengnick. 1999. A soil-quality index and its relationship to efficiency and productivity growth measures: Two decompositions. Am. J. Agric. Econ. 81:881–893. doi:10.2307/1244331

Janvier, C., F. Villeneuve, C. Alabouvette, V. Edel-Hermann, T. Mateille, and C. Steinberg. 2007. Soil health through soil disease suppression: Which strategy from descriptors to indicators? Soil Biol. Biochem. 39:1–23. doi:10.1016/j.soilbio.2006.07.001

Jenny, H. 1941. Factors of soil formation- A system of quantitative pedology. Dover Publications, New York.

Jia, X., C. Li, Y. Cai, X. Wang, and L. Sun. 2015. An improved method for integrated water security assessment in the Yellow River basin, China. Stoch. Environ. Res. Risk Assess.:1–15. doi:10.1007/s00477-014-1012-2

Johannes, V.B. 2007. Robustness of productivity estimates. J. Ind. Econ. 55:529–569. doi:10.1111/j.1467-6451.2007.00322.x

Karlen, D.L., S.S. Andrews, and J.W. Doran. 2001. Soil quality: Current concepts and applications. Adv. Agron. 74:1–40.

Karlen, D.L., S.S. Andrews, B.J. Wienhold, and T.M. Zobeck. 2008. Soil quality assessment: Past, present and future. http://digitalcommons.unl.edu/usdaarsfacpub/1203 (accessed 12 Oct. 2015).

Karlen, D.L., C.A. Ditzler, and S.S. Andrews. 2003. Soil quality: Why and how? Geoderma 114:145–156. doi:10.1016/S0016-7061(03)00039-9

Karlen, D.L., M.J. Mausbach, J.W. Doran, R.G. Cline, R.F. Harris, and G.E. Schuman. 1997. Soil quality: A concept, definition, and framework for evaluation (A guest editorial). Soil Sci. Soc. Am. J. 61:4. doi:10.2136/sssaj1997.03615995006100010001x

Karr, J.R. 1981. Assessment of biotic integrity using fish communities. Fisheries 6:21–27. doi:10.1577/1548-8446(1981)006<0021:AOBIUF>2.0.CO;2

Karr, J.R., and E.W. Chu. 1997. Biological monitoring and assessment: Using multimetric indexes effectively. Univ. of Washington, Seattle, WA.

Kerans, B.L., and J.R. Karr. 1994. A benthic index of biotic integrity (B-IBI) for rivers of the Tennessee Valley. Ecol. Appl. 4:768–785. doi:10.2307/1942007

Kim, K., B.L. Barham, and I. Coxhead. 2000. Measuring soil quality dynamics: A role for economists, and implications for economic analysis. Agric. Econ. 25:13–26. doi:10.1111/j.1574-0862.2001.tb00232.x

Kinoshita, R., B.N. Moebius-Clune, H.M. van Es, W.D. Hively, and A.V. Bilgilis. 2012. Strategies for soil quality assessment using visible and near-infrared reflectance spectroscopy in a Western Kenya Chronosequence. Soil Sci. Soc. Am. J. 76:1776. doi:10.2136/sssaj2011.0307

Koch, A., A. McBratney, M. Adams, D. Field, R. Hill, J. Crawford, B. Minasny, R. Lal, L. Abbott, A. O'Donnell, D. Angers, J. Baldock, E. Barbier, D. Binkley, W. Parton, D.H. Wall, M. Bird, J. Bouma, C. Chenu, C.B. Flora, K. Goulding, S. Grunwald, J. Hempel, J. Jastrow, J. Lehmann, K. Lorenz, C.L. Morgan, C.W. Rice, D. Whitehead, I. Young, and M. Zimmermann. 2013. Soil security: Solving the global soil crisis. Glob. Policy 4:434–441. doi: 10.1111/1758-5899.12096

Larson, W.E., and F.J. Pierce. 1991. Conservation and enhancement of soil quality. In: Evaluation for sustainable land management in the developing world: proceedings of the International Workshop on Evaluation for Sustainable Land Management in the Developing World. International Board for Soil Resilience and Management, Bangkik, Thailand. p. 15–21.

Liebig, M., M. Miller, G. Varvel, J. Doran, and J. Hanson. 2003. AEPAT: Software for assessing agronomic and environmental performance of management practices in long-term agroecosystem experiments. Publ. USDA-ARS UNL Fac., Univ. of Nebraska, Lincoln. https://digitalcommons.unl.edu/usdaarsfacpub/311.

Lima, A.C.R., W.B. Hoogmoed, L. Brussaard, and F. Sacco dos Anjos. 2011. Farmers' assessment of soil quality in rice production systems. NJAS Wagening. J. Life Sci. 58:31–38. doi:10.1016/j.njas.2010.08.002

Loomis, D.K., P.B. Ortner, C.R. Kelble, and S.K. Paterson. 2014. Developing integrated ecosystem indices. Ecol. Indic. 44:57–62. doi:10.1016/j.ecolind.2014.02.032

Mallavan, B.P., B. Minasny, and A.B. McBratney. 2010. Homosoil, a Methodology for Quantitative Extrapolation of Soil Information Across the Globe. In: D.J.L. Boettinger, D.W. Howell, A.C. Moore, P.D.A.E. Hartemink, and S. Kienast-Brown, editors, Digital soil mapping. Progress in soil science series. Springer, the Netherlands. p. 137–150. doi:10.1007/978-90-481-8863-5_12

Malmquist, S. 1953. Index numbers and indifference surfaces. Trab. Estad. 4:209–242. doi:10.1007/BF03006863

McBratney, A., D.J. Field, and A. Koch. 2014. The dimensions of soil security. Geoderma 213:203–213. doi:10.1016/j.geoderma.2013.08.013

McBratney, A.B., M.L. Mendonça Santos, and B. Minasny. 2003. On digital soil mapping. Geoderma 117:3–52. doi:10.1016/S0016-7061(03)00223-4

McCune, B., and J.B. Grace. 2002. Chapter 27 Mantel test. In: Analysis of ecological communities. MjM software design, Gleneden Beach, OR. p. 211–218.

McDonald, J. 2009. Using least squares and tobit in second stage DEA efficiency analyses. Eur. J. Oper. Res. 197:792–798. doi:10.1016/j.ejor.2008.07.039

McGarigal, K., S. Cushman, and S. Stafford. 2000. Summary and comparison In: Multivariate statistics for wildlife and ecology research. Chap 6. Springer, New York. p. 233–248. doi:10.1007/978-1-4612-1288-1_6

Meadows, D. 1998. Indicators and information systems for sustainable development. The Sustainability Institute, Hartland, VT.

Millennium Ecosystem Assessment. 2005. Ecosystems and human well-being: Synthesis. Island Press, Washington, DC.

Mizuta, K., S. Grunwald, W.P. Cropper Jr., W.S. Lee, G.M. Vasques, and M.A. Phillips. 2016. New soil index development and integration with econometric theory. Thesis. Univ. of Florida, Gainesville, FL.

Moebius-Clune, B.N., D.J. Moebius-Clune, B.K. Gugino, O.J. Idowi, R.R. Schindelbeek, A.J. Ristow, H.M. van Es, J.E. Thies, H.A. Shayler, M.B. McBride, D.W. Wolfe, and G.S. Abawi. 2016. Comprehensive assessment of soil health- The Cornell framework manual. 3.1. Cornell Univ., Geneva, NY.

Parr, J.F., S.B. Hornick, and R.I. Papendick. 1994. Soil quality: The foundation of a sustainable agriculture. USDA, Washington, DC.

Parr, J.F., R.I. Papendick, S.B. Hornick, and R.E. Meyer. 1992. Soil quality: Attributes and relationship to alternative and sustainable agriculture. Am. J. Altern. Agric. 7:5–11. doi:10.1017/S0889189300004367

Paz-Kagan, T., M. Shachak, E. Zaady, and A. Karnieli. 2014. A spectral soil quality index (SSQI) for characterizing soil function in areas of changed land use. Geoderma 230–231:171–184. doi:10.1016/j.geoderma.2014.04.003

Ponsonby, A.-L., and T. Dwyer. 2014. Statistics: Biomedicine must look beyond P values. Nature 507:169. doi:10.1038/507169b

Romig, D.E., M.J. Garlynd, R.F. Harris, and K. McSweeney. 1995. How farmers assess soil health and quality. J. Soil Water Conserv. 50:229.

Rosenberg, R., M. Blomqvist, H.C. Nilsson, H. Cederwall, and A. Dimming. 2004. Marine quality assessment by use of benthic species-abundance distributions: A proposed new protocol within the European Union Water Framework Directive. Mar. Pollut. Bull. 49:728–739. doi:10.1016/j.

marpolbul.2004.05.013
Ross, C.W., S. Grunwald, and D.B. Myers. 2013. Spatiotemporal modeling of soil organic carbon stocks across a subtropical region. Sci. Total Environ. 461–462:149–157. doi:10.1016/j.scitotenv.2013.04.070
Schindelbeck, R.R., H.M. van Es, G.S. Abawi, D.W. Wolfe, T.L. Whitlow, B.K. Gugino, O.J. Idowu, and B.N. Moebius-Clune. 2008. Comprehensive assessment of soil quality for landscape and urban management. Landsc. Urban Plan. 88:73–80. doi:10.1016/j.landurbplan.2008.08.006
Sharma, K.L., J.K. Grace, P.K. Mishra, B. Venkateswarlu, M.B. Nagdeve, V.V. Gabhane, G.M. Sankar, G.R. Korwar, G.R. Chary, C.S. Rao, P.N. Gajbhiye, M. Madhavi, U.K. Mandal, K. Srinivas, and K. Ramachandran. 2011. Effect of soil and nutrient-management treatments on soil quality indices under cotton-based production system in rainfed semi-arid tropical vertisol. Commun. Soil Sci. Plant Anal. 42:1298–1315. doi:10.1080/00103624.2011.571735
Shephard, R.W. 1977. Cost and production functions. Univ. Microfilms Intl., Ann Arbor, MI.
Shepherd, K.D., and M.G. Walsh. 2002. Development of reflectance spectral libraries for characterization of soil properties. Soil Sci. Soc. Am. J. 66:988. doi:10.2136/sssaj2002.9880
Shields, D.J., S.V. Šolar, and W.E. Martin. 2002. The role of values and objectives in communicating indicators of sustainability. Ecol. Indic. 2:149–160. doi:10.1016/S1470-160X(02)00042-0
Smith, J., P. Smith, M. Wattenbach, S. Zaehle, R. Hiederer, R.J. Jones, L. Montanarella, M.D. Rounsevell, I. Reginster, and F. Ewert. 2005. Projected changes in mineral soil carbon of European croplands and grasslands, 1990–2080. Glob. Change Biol. 11:2141–2152. doi:10.1111/j.1365-2486.2005.001075.x
Soil Science Society of America. 1987. Glossary of soil science terms. SSSA, Madison, WI.
Sojka, R.E., and D.R. Upchurch. 1999. Reservations regarding the soil quality concept. Soil Sci. Soc. Am. J. 63:1039–1054. doi:10.2136/sssaj1999.6351039x
Sojka, R.E., D.R. Upchurch, and N.E. Borlaug. 2003. Quality soil management or soil quality management: Performance versus semantics. Adv. Agron. 79:1–68. doi:10.1016/S0065-2113(02)79001-9
Sullivan, C. 2002. Calculating a water poverty index. World Dev. 30:1195–1210. doi:10.1016/S0305-750X(02)00035-9
Sullivan, C.A., J.R. Meigh, and A.M. Giacomello. 2003. The water poverty index: Development and application at the community scale. Nat. Resour. Forum 27:189–199. doi:10.1111/1477-8947.00054
Thanassoulis, E., M.C.S. Portela, and O. Despić. 2008. Data envelopment analysis: The mathematical programming approach to efficiency analysis. In: H.O. Fried, C.A.K. Lovell, and S.S. Schmidt, editors, The measurement of productive efficiency and productivity change. Oxford Univ. Press, UK. p. 251–420. doi:10.1093/acprof:oso/9780195183528.003.0003
van Bruggen, A.H.C., and A.M. Semenov. 2000. In search of biological indicators for soil health and disease suppression. Appl. Soil Ecol. 15:13–24. doi:10.1016/S0929-1393(00)00068-8
Veum, K.S., K.A. Sudduth, R.J. Kremer, and N.R. Kitchen. 2015. Estimating a soil quality index with VNIR reflectance spectroscopy. Soil Sci. Soc. Am. J. doi:10.2136/sssaj2014.09.0390
Volk, M., S. Lautenbach, H. van Delden, L.T.H. Newham, and R. Seppelt. 2009. How can we make progress with decision support systems in landscape and river basin management? Lessons learned from a comparative analysis of four different decision support systems. Environ. Manage. 46:834–849. doi:10.1007/s00267-009-9417-2
Vörösmarty, C.J., P.B. McIntyre, M.O. Gessner, D. Dudgeon, A. Prusevich, P. Green, S. Glidden, S.E. Bunn, C.A. Sullivan, C.R. Liermann, and P.M. Davies. 2010. Global threats to human water security and river biodiversity. Nature 467:555–561. doi:10.1038/nature09440
Vrščaj, B., L. Poggio, and F.A. Marsan. 2008. A method for soil environmental quality evaluation for management and planning in urban areas. Landsc. Urban Plan. 88:81–94. doi:10.1016/j.landurbplan.2008.08.005
Wander, M.M., G.L. Walter, T.M. Nissen, G.A. Bollero, S.S. Andrews, and D.A. Cavanaugh-Grant. 2002. Soil quality: Science and process. Agron. J. 94:23–32. doi:10.2134/agronj2002.0023
Warkentin, B.P. 1995. The changing concept of soil quality. J. Soil Water Conserv. 50:226–228.
Warkentin, B.P., and H.F. Fletcher. 1977. Soil quality for intensive agriculture. Society of Science of Soil and Manure, Tokyo, Japan. p. 594–598.
Whittaker, G., B. Barnhart, R. Färe, and S. Grosskopf. 2015. Application of index number theory to the construction of a water quality index: Aggregated nutrient loadings related to the areal extent of hypoxia in the northern Gulf of Mexico. Ecol. Indic. 49:162–168. doi:10.1016/j.ecolind.2014.10.003
Whittaker, G., S. Lautenbach, and M. Volk. 2012. What is a good index? Problems with statistically based indicators and the Malmquist index as alternative. International Environmental Modelling and Software Society, Leipzig, Germany.
Wienhold, B.J., S.S. Andrews, and D.L. Karlen. 2004. Soil quality: A review of the science and experiences in the USA. Environ. Geochem. Health 26:89–95. doi:10.1023/B:EGAH.0000039571.59640.3c
Wu, J., and T. Wu. 2012. Sustainability indicators and indices: An overview. In: Handbook of sustainable management. Imperial College Press, London. p. 65–86. doi:10.1142/9789814354820_0004
Xiong, X., S. Grunwald, D.B. Myers, J. Kim, W.G. Harris, and N.B. Comerford. 2014. Holistic environmental soil-landscape modeling of soil organic carbon. Environ. Model. Softw. 57:202–215. doi:10.1016/j.envsoft.2014.03.004
Xu, F.-L., Z.-Y. Zhao, W. Zhan, S.-S. Zhao, R.W. Dawson, and S. Tao. 2005. An ecosystem health index methodology (EHIM) for lake ecosystem health assessment. Ecol. Modell. 188:327–339. doi:10.1016/j.ecolmodel.2005.01.058
Zago, A. 2009. A nonparametric analysis of production models with multidimensional quality. Am. J. Agric. Econ. 91:751–764. doi:10.1111/j.1467-8276.2009.01268.x
Zaiko, A., and D. Daunys. 2015. Invasive ecosystem engineers and biotic indices: Giving a wrong impression of water quality improvement? Ecol. Indic. 52:292–299. doi:10.1016/j.ecolind.2014.12.023
Zornoza, R., J. Mataix-Solera, C. Guerrero, V. Arcenegui, F. García-Orenes, J. Mataix-Beneyto, and A. Morugán. 2007. Evaluation of soil quality using multiple lineal regression based on physical, chemical and biochemical properties. Sci. Total Environ. 378:233–237. doi:10.1016/j.scitotenv.2007.01.052