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A standardized soil quality index for diverse field conditions

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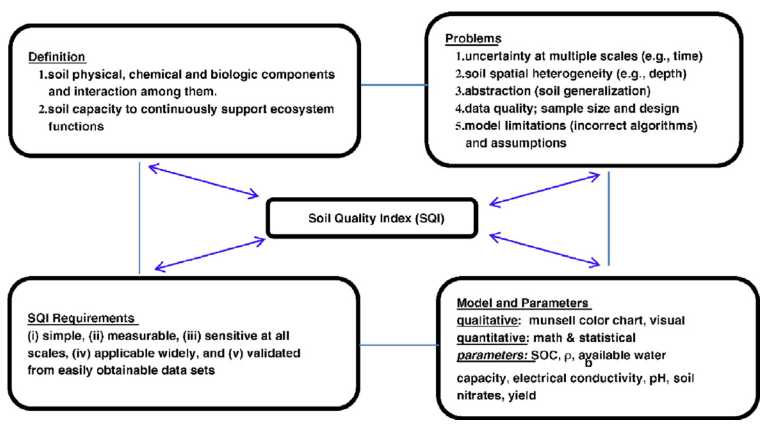
HIGHLIGHTS

- Tested 4 methods for constructing a Soil Quality Index (SQI)
- Partial Least Squares Regression (PLSR) method optimal for constructing SQI
- Identified significant soil attributes influencing site specific soil quality
- New SQI highly correlates with crop yields.

GRAPHICAL ABSTRACT



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ABSTRACT

Understanding the nexus between soil quality and productivity is constrained by data artifacts, compounded by limitations of the existing models. Here, we explore the potential of 4 regression methods (i.e., Reduced Regression (RR), SIMPLS, Principal Component Regression (PCR), and Partial Least Squares Regression (PLSR)), to synthesize 10 soil physical and chemical properties acquired from 3 major management practices and different soil layers, into an unbiased soil quality index (SQI) capable of evaluating soil functions (e.g., biomass production). The data was acquired from privately owned fields within the state of Ohio, USA, at the following land use and management sites: natural vegetation (NV) or woodlands, conventional till (CT), and no-till (NT). The soils were sampled at similar landscape positions (i.e., summit) at depth intervals of 0–10, 10–20, 20–40 and 40–60 cm, and analyzed for bulk density (ρ_b), carbon/nitrogen (C/N) ratio, soil organic C (SOC), total N (TN), available water capacity (AWC), pH and electrical conductivity (EC). Preliminary analyses revealed the PLSR method as the most robust. The PLSR Variable Importance of Projection (VIP) was calculated, transformed into the SQI score and compared with yield data. SOC, $\rho_{b,}$ C/N and EC were identified as the major variables influencing soil quality status. The data shows that the quality of Pewamo silty clay loam (P_w) soil was higher than Crosby Celina loams (CtA), Kibbie fine sandy loam (kbA), Glynwood silt loam (GWA) and Crosby silt loam (CrA), respectively. In 2012, the mean SQI was 42.9%, with corn and soybean yields of 7 and 2 Mg/ha. The R^2 of SQI versus yield was 0.74 for corn (*Zea mays L.*), and 0.89 for soybean (*Glycine max* (*L.*) *Merr.*). Future studies will investigate techniques for mapping this SQI.

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1. Introduction

Sustainable agro-ecosystem management requires tools that provide discernible soil quality status information. The variability in soil quality influences biogeochemical cycling, weather patterns, biodiversity, agricultural productivity, and thus food, energy and water security; socio-economic viability and human-wellbeing (de la Paz Jimenez et al., 2002; Doran et al., 1996; Lal, 2009; Ohlson, 2014). Unlike air and water quality, legislation and policy on soil quality are scantily defined. This deficiency in legislation may be attributed to the fuzzy definition of soil quality, accentuated by the inherent difficulty in quantifying and mapping its spatial variability. Notwithstanding the importance of soil quality information, many models depicting global issues related to climate change or to food, water and energy security embody limited soil expertise (McBratney et al., 2014). Quantifying soil quality changes vis-à-vis soil functions are construed by data artifacts and lack of data, absence of clear reference points or baseline values, model omissions and validation challenges (Andrews and Carroll, 2001; Andrews et al., 2003; McBratney et al., 2014). Moreover, because soil has many functions (e.g., pollution control, biomass production, climate regulation etc.), simply measuring a single or specific soil property to infer soil quality is insufficient. Incoherence in soil quality information can result in disasters such as landslides, disease outbreaks from contaminated water etc., not being detected on time. Accurate, repeatable, systematic, and transparent soil quality measurements can enhance interpretation and comparability between sites (Andrews and Carroll, 2001; de Paul Obade and Lal, 2014).

Soil quality entails the capacity of a specific kind of soil to function and sustain plant and animal survival within natural or managed boundaries, without jeopardizing the environmental quality (Andrews et al., 2004; Doran and Zeiss, 2000; NRCS, 2012). Soil quality cannot be directly determined, but can be inferred by measuring soil physical, chemical and biological properties. Practically, soil quality information is gauged by either: (i) the soil test kit and laboratory-based analyses (Wienhold et al., 2004), or (ii) the Munsell soil color chart (Gobin et al., 2000; Staff, 1951), or (iii) remote sensing (Cohen et al., 2007; Minasny and Hartemink, 2011). However, the soil test kit, is not only cumbersome, but also relies on extracting powders which may dissolve poorly with the soil leading to inaccurate results. Furthermore, the soil test kit does not determine the conjoined assessment of soil properties, but measures only specific soil constituents, such as nitrate-N, P_2O_5, K_2O and pH etc. Utilizing specific soil properties to gauge soil quality vis-à-vis biomass production, is non-comprehensive and subjective because of the concept that plants intake different nutrients simultaneously at varying environmental gradients (Ohlson, 2014). Besides, laboratory-based methods disturb the soil; can be expensive and time-consuming especially for analyses done over large spatial extents, which require substantial data inputs. Antithetically, the Munsell color chart is subjective, and depends on the human visual perception. With the Munsell color chart, darker soils are assumed to have a higher soil organic matter, therefore perceived to be of a higher quality (McBratney et al., 2002; Shepherd and Walsh, 2002). Although remote sensing is a non-destructive technique that continuously acquires field data even at inaccessible locations, its flaws include: (a) spectral ambiguity which lower the signal-to-noise ratio (SNR) attributed to signal attenuation, adjacency effects, and atmospheric scattering, (b) rigorous data processing and calibration, (c) mismatches between spatial, spectral and temporal resolution, (d) absence of long-term data (e.g., Landsat data archived from 1972) (de Paul Obade et al., 2013). Soil properties (e.g., SOC, moisture) have been predicted by field remote sensors scanning within the visible and Near Infra-Red (NIR) spectrum (Gogé et al., 2014; Kinoshita et al., 2012; Marín-González et al., 2013).

Soil organic Carbon (SOC) concentration is considered a proxy of soil quality because it optimally typifies soil biota dynamics and plays a key role in fertility, soil water availability and aggregate stability in croplands (de Moraes Sá et al., 2013; McBratney et al., 2014; Stockmann et al., 2013). SOC can be predicted and mapped using regression models, geostatistics, or by pedotransfer functions (PTFs). PTFs translate measured soil attributes into estimates of unmeasured variables, whereas geostatistics predicts unsampled points based on the distance and degree of variation between sample pairs of adjacent measured points using a variogram. Accuracy in geostatistics depends on sampling density of field data. Researchers postulate that soil property information can be gleaned from environmental covariates, abbreviated as *scorpan* factors, comprising (1) *s*: soil, other or previously measured attributes of the soil at a point location; (2) *c*: climate, climatic properties of the environment at the location; (3) *o*: organisms, including land cover and natural vegetation; (4) *r*: topography, including terrain classes; (5) *p*: parent material, including lithology; (6) *a*: age, the time factor; (7) *n*: geographic position (Grinand et al., 2008; Lacoste et al., 2014; McBratney et al., 2002). Thus, the challenge remains how to construct indicators of soil quality that incorporates both qualitative and quantitative information?

Soil Quality Indices (SQIs) synthesize soil attributes into a format that enhances the understanding of soil processes to inform on appropriate management or policy interventions (Boote et al., 1996; Wienhold et al., 2004; Wienhold et al., 2009). Examples of soil attributes include the organic matter (OM) content and stock, bulk density (ρ), respiration rate, soil depth, electrical conductivity (EC), pH etc. Fig. 1 depicts a typical SQI paradigm, encompassing emerging issues on soil quality assessment, tenets for a robust SQI and inherent limitations (Andrews and Carroll, 2001; Karlen et al., 1997; Nortcliff, 2002). The “scoring function” concept is applied in SQIs to decipher the interconnection between soil properties, soil processes (e.g., mineralization), management systems and social perspectives (Andrews et al., 2002a; b; Andrews et al., 2002b; Karlen et al., 1994a; Karlen et al., 1994b; Wienhold et al., 2004). The Soil Management Assessment Framework (SMAF) is an example of a score-based indicator that operates in two synergistic steps: (i) indicator selection and interpretation, and (ii) aggregation (Andrews et al., 2004). The indicator selection and interpretation process entails the transformation of measured, or observed data such as soil nutrients or contaminant concentration, into unitless indicator scores; whereas “aggregation” step combines the individual indicator scores into a single value (Karlen et al., 2008). Despite its prominence as an emerging research domain, quantifying soil biota is not a practical undertaking due to challenges such as: (i) inaccuracies in earthworm counts (i.e., by hand), (ii) difficulty in accounting microbial species diversity, and (iii) difficulty in interpreting the soil respiration tests (Arshad and Martin, 2002; de Paul Obade and Lal, 2014; McBratney et al., 2014). The question then is how to synthesize and transform soil property information sampled from diverse landscapes into a versatile SQI?

To enhance the fidelity of SQIs requires credible information acquired through baseline data and accurate models. Besides, science based techniques are required for establishing a minimum data set (MDS) consisting of critical soil variables (Andrews and Carroll, 2001; Yemefack et al., 2006). Although all models can be considered deficient, some can be useful (Box George and Draper, 1987). The critical question in constructing models is whether: (i) new knowledge can be garnered, or (ii) this knowledge can improve human wellbeing and the overall environmental quality. In essence, statistical models for evaluating trends in complex data are either parametric or non-parametric. Unlike parametric, non- parametric statistical methods being parsimonious, do not require the following assumptions to hold true: (i) independence of observation, (ii) homoscedasticity, and (iii) normally distributed errors (Chong and Jun, 2005; Mehmood et al., 2012). Thus, this study explores the potential of 4 non-parametric methods to develop a new SQI computed by aggregating soil attributes under different management and soil layers that: (i) objectively identifies the minimum data set (MDS) consisting of key soil variables, (ii) investigates the contribution of land use/management on soil quality, and (iii) rates soil quality vis-à-vis crop yields.