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Towards a standard technique for soil quality assessment

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ABSTRACT

A soil quality index (SQI) that integrates key soil attribute information would be beneficial in minimizing spill-over effects of indiscriminate soil management such as shortages in food, water, energy and abate adverse repercussions of climate change. In this study, a new SQI that synthesizes soil attributes is developed using partial least squares regression (PLSR), and compared with crop yields. The field data were acquired in the year 2013 from 5 different *on-farm* sites within Ohio, USA that were under Natural Vegetation (NV), No-Till (NT), and Conventional Till (CT) management. The data shows that P_w (Pewamo silty clay loam) soil under NV land use had a higher quality, than GWA (Glynwood silt loam), kbA (Kibbie fine sandy loam), CrA (Crosby silt loam), and CtA (Crosby Celina silt loams) soil; whereas CT managed soil had P_w > CrA > kbA > CtA > GWA. The soil bulk density (ρ_b), electrical conductivity (EC), available water capacity (AWC) and soil organic carbon (SOC) greatly influenced the SQI especially at the soil surface. The SQI and yield were highly correlated, with that for corn (*Zea mays* L.) being 64%; whereas soybean (*Glycine max* (L.) Merr.) was 100%. This finding is of special relevance because it explicates the interconnection between *on-farm* soil quality vis-à-vis crop yields by objectively blending soil attributes from different management scenarios and soil layers. Future research will investigate techniques for integrating this SQI with socio-economic indicators of agro-ecosystem sustainability.

1. Introduction

Indiscriminate land use and management, for example, through the inappropriate use of technology may degrade soils and ecosystems, thus adversely affecting the socio-economic fabric of present and future generations (Arshad and Martin, 2002; Bouma, 2015; Lal, 2013; McBratney et al., 2014). Approximately 800 million people are food insecure globally (Lal, 2013), and an estimated 2 billion people still lack access to safe and affordable water (de Paul Obade et al., 2014; World Health Organization and UNICEF, 2015). Unfortunately, tackling such issues remains challenging, because soil which is a critical carrier of information is poorly represented in many ecosystem models (Bonfante and Bouma, 2015; McBratney et al., 2014). In comparison to air and water quality, legislation and policy on soil quality are ambiguous, partly due to conflicting information from existing metrics, and the fact that major policies focus on food, water, biodiversity, health, and energy (Armenise et al., 2013; Bonfante and Bouma, 2015). A universal model that quantifies soil quality remains elusive (Bouma, 2002; de Paul Obade and Lal, 2013). Oversimplification of soil quality information can result to incoherent and spurious conclusions which can result to disasters such as pollution, poverty and malnutrition not being effectively managed. For instance, simply relating crop yields with specific soil attributes (e.g., bulk density (ρ_b)) is insufficient and subjective, because soil is a complex “living” medium consisting of solid, liquid, and gaseous phases, and plants conceptually uptake different nutrients simultaneously (de Paul Obade and Lal, 2016; Ohlson, 2014). Uncertainties in soil information are attributable to data artifacts, vague benchmarks, and validation challenges (Andrews and Carroll, 2001; de Paul Obade and Lal, 2014; Finzi et al., 2011; Karlen et al., 1997; Mota et al., 2014).

Soil quality encompasses the capacity of a specific kind of soil to effectively function through supporting plant and animal survival without jeopardizing environmental quality (Andrews et al., 2004; Doran and Zeiss, 2000; NRCS, 2012). Soil functions include biomass production, climate regulation, heritage, hydrologic storage and pollution control (Bouma, 2015; Bouma and McBratney, 2013; de La Paz Jimenez et al., 2002; Doran et al., 1996; Lal, 2009). Soil quality cannot be directly measured, but is inferable through measuring soil physical, chemical and biological properties. However, documenting biological properties (e.g., earthworms, termite population, or microbial metabolic activity) is practically challenging because this requires substantial taxonomy knowledge (Askari and Holden, 2014; Nortcliff, 2002; Zornoza et al., 2015).

Soil quality indices (SQIs) synthesize measured soil attributes into a simplified format that can support informed decision making on sustainable agro-ecosystem practices (Arshad and Martin, 2002). Soil attributes include organic matter, respiration, texture, bulk density (ρ_b), pH, infiltration, electrical conductivity (EC), aggregate stability, depth and available water capacity (AWC) (Kladivko et al., 2014). A robust SQI should: (i) be sensitive to soil management, (ii) be sensitive to changes in soil function(s), and (iii) be easily measurable (Armenise et al., 2013). An example of a SQI is the Soil Management Assessment Framework

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(SMAF) which is "score-based" and operates in two synergistic steps, namely: (i) indicator selection and interpretation which entails the transformation of measured data (e.g., soil nutrients) into unitless scores, and (ii) aggregation which combines individual scores into a single value (Andrews et al., 2002a, 2002b; Karlen et al., 1994a, 1994b, 2008; Wienhold et al., 2004). The "scoring functions" can be subjective because the approach is based on perceived graphical relationships that may follow a normal distribution, with an upper asymptote, or a lower asymptote, determined through consensus or from literature review values (de Paul Obade and Lal, 2014). Central to the determination of soil quality in crop lands is the identification of management practices that enhance crop yields without adverse effects on ecosystem health (Arshad and Martin, 2002; Lal, 2013). The major challenge in soil quality determination is not missing soil property values, which can be estimated from other measured soil survey data using pedo-transfer functions (PTFs) (Bonfante and Bouma, 2015), but how to objectively blend quantitative and qualitative data to generate holistic SQIs?

A robust SQI should accurately relate important facets influencing biomass production with soil quality and management thus providing information required to support proactive decision making (Andrews and Carroll, 2001; Armenise et al., 2013; Yemefack et al., 2006). Table 1 is a synopsis of common multivariate methods that can be used to construct models to enhance the understanding of soil processes. Because of soil complexity, parametric methods may not be optimal for merging soil attributes into a SQI. This study investigates the interrelationship between crop-yields and soil quality using a new SQI computed by partial least squares regression (PLSR) which is a non parametric method, and thus does not require the following assumptions to hold true: (i) independence of observation, (ii) linearity, (iii) homoscedasticity, and (iv) normally distributed errors (Chong and Jun, 2005; Mehmood et al., 2012). Unlike the Principal Component Analyses (PCA) which is based on variance of the predictors, and screens information using the eigen-value >1 criterion, the PLSR evaluates the covariance between response and predictor variables, and objectively interprets all information. (Mehmood et al., 2011, 2012). This study test 2 hypotheses: (i) the crop land soils i.e., under CT (Conventional Till) or NT (No Till) is significantly distinct from soils under Natural Vegetation (NV) land use, and (ii) the SQI highly correlates with crop yields.

2. Materials and methods

2.1. Study site

Data was collected from the following field sites located in Ohio, USA: Miami (40° 10′ 12″ N, 84 °07′ 41.7″ W), Seneca site 1 (41° 00′ 25″ N, 85° 16′ 21″ W), Seneca site 2 (41° 12′ 43″ N, 82° 54′ 39″ W), Preble (39° 46′ 09″ N, 84° 36′ 52″ W and 39° 41′ 45″ N, 84° 40′ 36″ W), and Auglaize (40° 27′ 34.5″ N, 84° 26′ 14.8″ W); which have the soil types: CrA (Crosby silt loam), kbA(Kibbie fine sandy loam), GWA (Glynwood silt loam), CtA (Crosby Celina silt loams), and P_w (Pewamo silty clay loam), respectively. Because these were privately owned fields, prior permission was sought and granted from the farmers before the data could be acquired. The total annual precipitation in Ohio averages between 90 to 120 cm, and the mean temperature varies between 8.1 and 10.7 °C (DeForest et al., 2012). The field management practices were NT with or without manure (M) and cover crops (cc), NV, and CT. The surface residue cover in CT managed fields was low (i.e., <30%). The CT fields at Miami, Seneca, and Preble sites were chisel plowed to approximately 20–25 cm depth, except for the Auglaize site which was disked.

2.2. Sampling procedure

A total of 204 soils were sampled from the different field sites between April and May, 2013. For each site, the soil maps were downloaded from web soil survey (http://websoilsurvey.sc.egov.usda.gov/App/WebSoilSurvey.aspx) and used for reconnaissance, identification of soil series, and selection of the sampling zone. Within each management entity (i.e., NT, CT and NV), 3 points located at the tips of an arbitrary 10 m × 10 m × 10 m *equilateral* triangle were marked on the ground; and the soils sampled at the same topographic slope (i.e., summit). Each sampling point was geo-located using a global positioning system (GPS). Core and bulk soil samples were then obtained from each point at 0–10, 10–20, 20–40, and 40–60 cm depths; totaling 12 samples per management category.

The yield data was determined from crops harvested between August and September, 2013 at the same GPS location where soils were sampled. Although this research targeted corn (*Zea mays* L.) fields, it was realized during harvesting that some locations had soybean (*Glycine max* (L.) Merr.), and therefore soybean yields within these locations were also included. The yield was measured as follows: (i) for corn, the ears from a dimension of 2 rows and 2 m long were hand harvested and weighed in the field; however, the soybeans weights were measured from 1 m^2 dimension, (ii) the corn, and soybean were air dried, shelled, after which the dry weight of the cobs, kennels, beans, and remaining above ground vegetative biomass measured. The plant water content was determined after oven drying subsamples of kernel, cob and beans at 60 °C for 96 h, and the grain yields computed by adjusting the respective weights to 15.5% moisture for corn, and 13.5% for soybean. The Harvest Index (HI) was computed as the ratio of the harvested grains, or beans to the total above ground vegetative biomass.

2.3. Data analyses

The field measurements and laboratory analyses followed the USDA–NIFA project guidelines (project web site: sustainablecorn.org) (Kladivko et al., 2014). Soil texture was assumed to be a fixed soil property that is not significantly altered by management or even climate (Askari and Holden, 2014; Bonfante and Bouma, 2015). Soil ρ_b which rudimentarily explains soil quality, water flow and root development was measured by the core method without stones. Soil moisture content was determined gravimetrically by oven drying a fraction of the soil at 105 °C (Topp and Ferre, 2002), and the water retention determined by a combination of a tension table (Blanco-Canqui and Lal, 2007; Clement, 1996), and the pressure plate extractors (Klute, 1986; Klute and Dirksen, 1986). The available water capacity (AWC) was computed from the difference in volumetric water content at field capacity (FC) (−33 kPa), and permanent wilting point (PWP) (−1500 kPa) (Dane and Hopmans, 2002; Jemai et al., 2013). Alternately, the chemical

Table 1
Synopsis of multivariate parametric and non-parametric statistical methods.

Analyses	Approach	Data description	Limitations
Multiple Linear Regression	Stepwise, forward, backward	Quantitative	Parametric (require transformations); multi-collinearity
Principle Component Analyses (PCA)	Variance of x	Quantitative, non-parametric	2 (or first few components)
Partial Least Squares (PLS)	Covariance ~(x) and (y)	Quantitative and qualitative; non-parametric	

x: predictor variables.
y: response variables.