



Emergence of the Pedo-Econometric Approach

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SOIL INDICES AND ECONOMETRIC TECHNIQUES

Inter- and transdisciplinary approaches that catapult soil science to the next level in pedometrics are urgently needed to address critical topics in soil health and security. Specifically, the fusion of pedometrics and econometrics is poised to move quantitative soil assessments focused on properties and predictions toward integrative pedo-econometric decision-making instruments. Novel pedo-econometric approaches bear profound potential to revolutionize pedometrics and will facilitate “smart” and strategic soil management. Pedo-econometric approaches view the optimization of soil health to sustain soil quality as salient through simultaneous modeling of input-output interactions between soil and environmental factors. In addition, pedo-econometrics fuses economic-oriented strategies into the soil modeling process that allows land managers, regulators, and decision-makers to guide soil management considering potential efforts (costs and labor) to sustain or improve soil functionality. We present the nuts-and-bolts of pedo-econometrics and a demonstration to assess site-specific efficiency soil carbon scores as well as regional maximum and attainable soil carbon.

Soil scientists conventionally have used metric systems, such as soil quality indices, to assess soil health functions addressed by soil concepts (e.g., soil quality, soil health, and soil security). As a state-of-the-art approach, soil quality indices are generally constructed using multivariate statistics, such as principal component analysis (1, 2). Although these multivariate quantitative approaches are suited for predictive modeling of soil variables they lack to meet axiomatic criteria of index theory (3). Furthermore, Karr and Chu (4) argued that multivariate analyses can be used for the identification of data patterns or structures but not impact assessment. Mizuta et al. (3) argued that soil health index systems based on capabilities or efficiencies, rather than multivariate predictions or the variance of environmental properties, allow to express soil health. The same applies to quantitative modeling of soil quality, security, risk, functionality... etc.

Performance assessments of targeted functions, using econometric techniques are a rapidly growing interdisciplinary field of research (5). Previous studies have produced quantitative methods, such as the data envelopment analysis (DEA), to evaluate capability or efficiency of functions, such as ecological efficiency (6), crop production performance efficiency (7), ecosystem services output efficiency (8). The DEA is used in many different application areas, including engineering, development studies, education, finance, health care studies, natural resource management, public economics, and sports studies (9). Yet, the DEA has been only sparsely used in soil science.

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The DEA, a non-parametric technique, considers aspects of outputs and the relevant inputs; the former is the targeted function to maximize or minimize, and the latter are managerial factors that contribute to produce the function (10). The potential reduction of inputs to achieve the same levels of outputs, or the optimization of outputs based on the same sets and levels of inputs, are examples of the quantitative evaluations that this approach can provide (11, 12). The produced scores are used to evaluate the efficiency of functions for decision-making-units (DMUs). DMUs may include soil pedons, forests, agricultural fields under different managements, and other (3, 13).

A PRACTICAL EXAMPLE—HOW TO ASSESS A SOIL FUNCTION USING ECONOMETRICS

Here, an integrated pedo-econometric approach is demonstrated using an econometric technique, the DEA, to compute the efficiency scores of a specific soil health function—soil organic carbon (SOC) stocks. Our approach of pairing inputs and outputs is grounded in the empirical, longitudinal analysis of non-linear, site-specific effects, and data-driven algorithms. Suppose that the DEA user decides to assess the efficiency of the SOC stock function in Florida U.S., which would be considered as output (*y*-axis in **Figure 1A**). Plant available water capacity (AWC) and/or Normalized Difference Vegetation Index (NDVI) were considered as inputs (*x*-axis). AWC has been shown to regulate the respiration and accumulation of SOC in soils (17, 18), while NDVI is a proxy for the abundance of healthy green vegetation that is a source of carbon input via residues into the soil. These empirical input and output variables drive the frontier (line) that produces a reference system, called in econometrics the frontier or technology line (10). The DMU on the frontier gives the score of one and indicates the maximum efficiency of output operation with a given set of inputs. The further the DMU locates away from the frontier, the closer the score is to zero, and the more inefficient a given site in terms of SOC stocks. In our example DEA-SOC application the option “output orientation” was used undergirding the goal to maximize output levels (in this case SOC stocks) (**Figure 1A**) (19). This setting identifies soils with higher output levels based on the same or less quantities of given inputs. The relationships between the input and output variables may form various shapes of a frontier and consequently produce different scores. **Figures 1B,C** vs. **Figures 1D,E** demonstrate two commonly used Return-to-Scale functions to produce the frontier line: free disposable hull (FDH) and variable returns-to-scale (VRS). See the detail descriptions of the RTS terminology in Bogetoft and Otto (16).

When either of input, AWC or NDVI, was used in the DEA, our example showed that the efficiency scores of soil with high SOC (orange circle) was equal to 0.85 regardless of assumption or input variables. This indicates that the output level can be further maximized by 15% (SOC stocks up to 34.1 kg m⁻²) with given input quantities. A high SOC status does not always lead to high efficiency because the DEA considers both output and input variables simultaneously. For example, the DEA-FDH

score calculated with NDVI as input for soil with low SOC (blue square) was 0.56, which was 19% greater than the one for soil with medium SOC (green triangle). The site-specific efficiency scores facilitate to assess the potential gains in SOC to meet attainable SOC stocks (i.e., efficiency score of 1). SOC stock gains could be achieved through management (e.g., fertilization, irrigation, amendments) or land use conversions. The “smart” strategic approach of the DEA allows to simultaneously consider site-specific soil-environmental conditions (e.g., soils, vegetation, climate, topography) as well as management and use options to focus on improvement of those inefficient sites that have potential to sequester most carbon (i.e., sites that depart furthest from the frontier line) and provide the most return (SOC stocks) for investment (cost and labor for a management intervention).

The DEA can incorporate multiple inputs and/or outputs to calculate the efficiency scores, which we implemented to compute DEA-FDH scores with both AWC and NDVI as inputs at 1,075 sites across Florida (**Figure 1F**). No obvious spatial trend was observed, however, the high prediction accuracy using an ordinary kriging method ($R^2 = 0.70$) (**Figures 1G,H**) indicates the great potential of integrating DEA scores into digital soil mapping techniques to help decision-makers identify the site-specific location with needs of improvements for local management. The DEA approach allows researchers and stakeholders to identify attainable rates of optimized functions using a data-driven frontier without control sites. Incorporation of new empirical data for inputs and/or outputs may quantify other soil functions. The usefulness of the DEA approach for environmental assessments has been described in the literature (20), though this method has rarely been applied yet for soil functions other than agricultural production except a few studies according to our knowledge [e.g., (21–23)].

RESEARCH OPPORTUNITIES IN PEDO-ECONOMETRICS

Key questions that need to be answered for DEA applications are (1) what drives a standard frontier? and (2) how to construct a frontier function? The main factors that can determine the reference include (1) selection of inputs and/or outputs by discerning relatively stable, dynamic, and/or managerial variables; (2) orientation direction of the DEA; and (3) DEA assumptions (i.e., returns-to-scales).

The proper choice of each factor drives the reference. In the case of carbon credits, Zhai et al. (24) calculated the ecological efficiency of the energy supply chain under carbon credit transactions using multiple inputs (fuel consumption and financial investment) and multiple outputs (fiscal revenue/profit and carbon emission). Liu and Liu (25) used three inputs (energy consumption, capital stock, and labor force) and one output (gross domestic product) to calculate low carbon economy efficiency scores. Other combinations of input(s) and output(s) related to carbon efficiency can be found in the literature review provided by Zhang et al. (26). The data-driven evaluation can identify areas that optimize outputs with

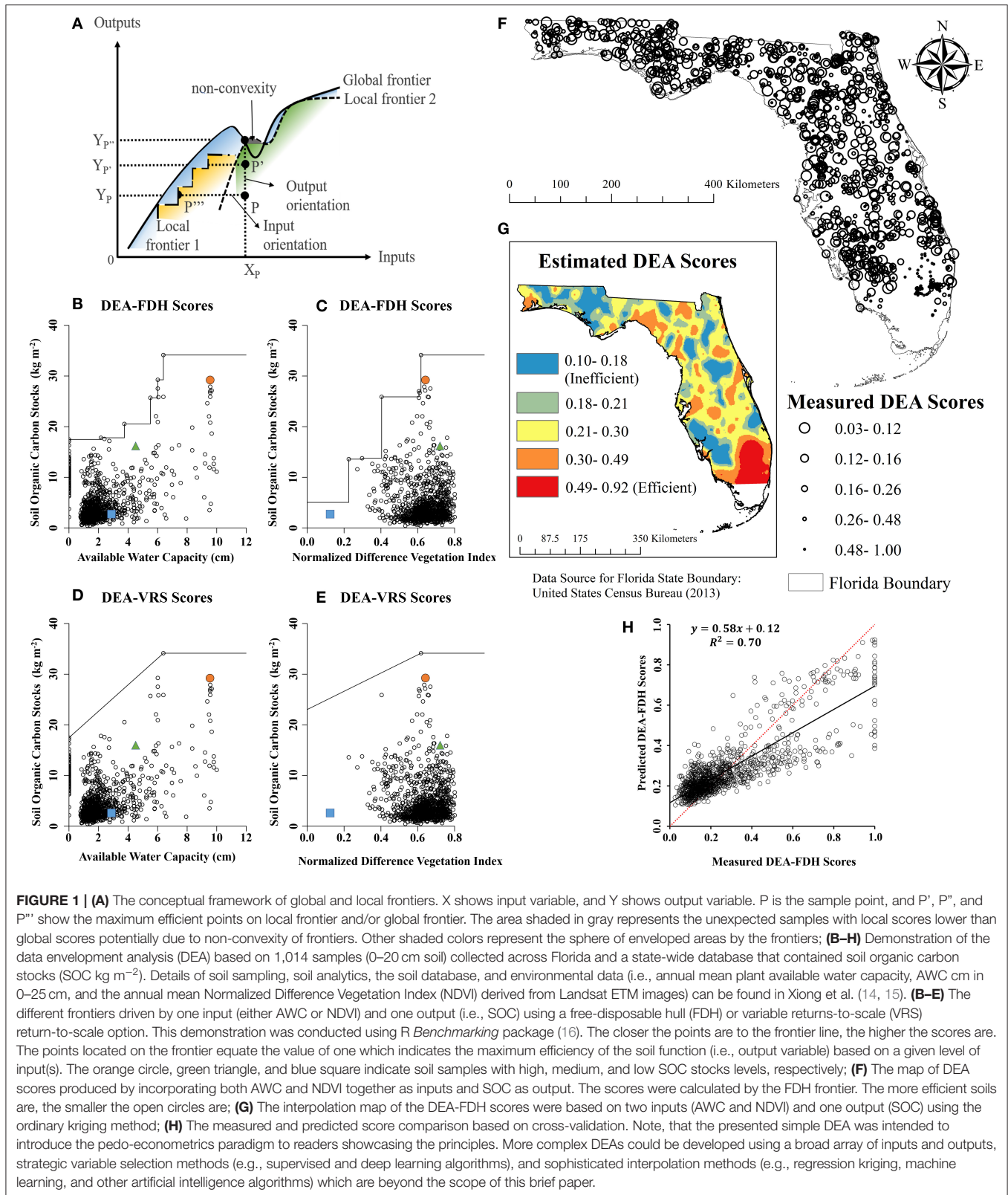


FIGURE 1 | (A) The conceptual framework of global and local frontiers. X shows input variable, and Y shows output variable. P is the sample point, and P', P'', and P''' show the maximum efficient points on local frontier and/or global frontier. The area shaded in gray represents the unexpected samples with local scores lower than global scores potentially due to non-convexity of frontiers. Other shaded colors represent the sphere of enveloped areas by the frontiers; **(B–H)** Demonstration of the data envelopment analysis (DEA) based on 1,014 samples (0–20 cm soil) collected across Florida and a state-wide database that contained soil organic carbon stocks (SOC kg m^{-2}). Details of soil sampling, soil analytics, the soil database, and environmental data (i.e., annual mean plant available water capacity, AWC cm in 0–25 cm, and the annual mean Normalized Difference Vegetation Index (NDVI) derived from Landsat ETM images) can be found in Xiong et al. (14, 15). **(B–E)** The different frontiers driven by one input (either AWC or NDVI) and one output (i.e., SOC) using a free-disposable hull (FDH) or variable returns-to-scale (VRS) return-to-scale option. This demonstration was conducted using R *Benchmarking* package (16). The closer the points are to the frontier line, the higher the scores are. The points located on the frontier equate the value of one which indicates the maximum efficiency of the soil function (i.e., output variable) based on a given level of input(s). The orange circle, green triangle, and blue square indicate soil samples with high, medium, and low SOC stocks levels, respectively; **(F)** The map of DEA scores produced by incorporating both AWC and NDVI together as inputs and SOC as output. The scores were calculated by the FDH frontier. The more efficient soils are, the smaller the open circles are; **(G)** The interpolation map of the DEA-FDH scores were based on two inputs (AWC and NDVI) and one output (SOC) using the ordinary kriging method; **(H)** The measured and predicted score comparison based on cross-validation. Note, that the presented simple DEA was intended to introduce the pedo-econometrics paradigm to readers showcasing the principles. More complex DEAs could be developed using a broad array of inputs and outputs, strategic variable selection methods (e.g., supervised and deep learning algorithms), and sophisticated interpolation methods (e.g., regression kriging, machine learning, and other artificial intelligence algorithms) which are beyond the scope of this brief paper.

a given set of inputs, and thereby, offers profound potential for agricultural, forest, conservation, and land management in general.

Establishing local or global/meta-frontier systems would also be an important research topic (see **Figure 1A**). Such systems are constructed in form of a multiple-layered structure

in which the global frontier envelops local frontiers (27). The metafrontier approach discerns inefficient sites that need management improvements from efficient sites and facilitates to assess the suitability of a targeted function under given environmental conditions. There are two kinds of efficiency metrics produced in this approach. One metric type measures different efficiency levels for each DMU to provide performance assessments of soil functions for the users. The other metric type may derive interpretations from external factors that govern overall performance of soil functions, which are often hardly manageable. For example, climatic factors such as precipitation and temperature may influence some soil functions directly and indirectly (e.g., biodiversity protection function, energy production functions for ecosystems). Relatively stable environmental factors, such as topography, ecological factors, and parent material can be used to classify different soils and then the DEA can be implemented for each class separately to construct a metafrontier framework. Grunwald et al. (28) discerned soil-environmental factors along the stability-dynamic spectrum in an ecosystem that regulate a given target variable (e.g., efficiency of SOC stocks). Such soil-environmental factorial approach combined with the DEA analysis provides profound opportunities to transform state-of-the-art pedometric applications that are focused on digital soil mapping asking “what soil is there?” toward smart pedo-econometric applications asking “how efficient is a site to attain a soil function?” The former traditional pedometrics approach is descriptive while the interdisciplinary pedo-econometric approach focuses on optimization considering simultaneously site-specific soil-environmental inputs and one or multiple soil outputs.

The potential of the metafrontier DEA framework is to address the ambiguities of soil health, soil quality, and soil security assessments bound to mapping of soil properties. The emergence of the pedo-econometrics approach facilitates to move traditional assessments of soil measurements that lack economic considerations, such as non-convexity, into interdisciplinary realms considering explicitly soil-environments and economics (29). Soil functionality within an economic framework can be quantified through DEA efficiency scoring and the meta-frontier or local frontier approaches. The advantages of the metafrontier approach can reveal not only suitability of various soil health functions concomitantly that have not been

quantified but also the efficiencies of the function performance that may be improved by local management.

The quantitative metrics of soil functions can visualize the inconspicuous contribution of soil to environmental and economic systems (30). The more capabilities of soil functions that can be quantified by this pedo-econometric approach, the clearer the value of each function may become, and the more accurate soil function evaluation in economic models would be (31). The new paradigm using this approach would reveal the relationship between output functions of soil and inputs and catalyze prioritization of soil functions over more traditional soil assessments. Measuring the features of soil concepts and soil functioning is essential for sustainable food production and environmental conservation. Thus, the modern paradigm contributes to our understanding of the potential efficiency of soils to sequester carbon, which is an important and understudied element about which knowledge is needed to adapt to global climate change. The DEA and similar econometric methods are envisioned to assess not only carbon related soil function but also other complex functions of soil (e.g., biodiversity function using the Shannon index and soil carbon stocks for input/output) under varying conditions.

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KM, SG, MP, AB, WC, and CM: conceptualization. KM and SG: funding acquisition and writing—original draft. KM, SG, MP, and CM: methodology. SG: supervision. SG, AB, and WC: writing—review and editing. All authors: contributed to the article and approved the submitted version.

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