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# New Indication Method Using Pedo-Econometric Approach

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ABSTRACT

Conventional multivariate statistics that have been used to create indication systems to assess soil functions raise theoretical and practical issues. The Data Envelopment Analysis (DEA) that can overcome such issues is a well-known management tool in other fields than soil science. This study is the first to use the DEA for a soil-related phenomenon across a large region. Soil carbon sequestration (SCseq) capability index scores in Florida, USA, were computed using the DEA with two settings (free disposability hull, FDH and variable returns-to-scale, VRS) to assess the soil carbon sequestration function. Findings suggest that sites with high annual temperature, precipitation,

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and Normalized Difference Vegetation Index as inputs were most efficient to sequester carbon in soils. The novel pedo-econometric approach enables to optimize the SCseq and guides future management to enhance soil carbon, and thus, soil health.

*Keywords:* Soil; ecology; environmental health; soil health/quality; climate change

## Abbreviations

AWC, available water capacity; BD, bulk density; DEA, Data Envelopment Analysis; FDH, free disposability hull with no convexity; In/Ix, indicators/index; K–W test, Kruskal–Wallis; LOI, loss-on-ignition method; LULC, land use/land cover; NDVI, Normalized Difference Vegetation Index; PCA, principal components analysis; SCI, SCseq capability In/Ix; SCseq, soil carbon sequestration; SOC, soil organic carbon; SOM, soil organic matter; VRS, variable returns-to-scale with convexity and free disposability; WB, Walkley–Black method.

## 1 Introduction

### *1.1 Index Studies in Soil Science*

Conceptual notions related to soil resources, such as soil and environmental quality, soil health, and soil security, may help improve awareness of scarce land resources and, in turn, satisfy increasing human needs for nutritious food (Kattumuri, 2018). However, these soil concepts are complex and cannot be easily measured in the field or laboratory (Diack and Stott, 2001; Ludwig *et al.*, 2018). Integration and indication approaches that go beyond individual soil attribute measurements are necessary to address the health and security of soils (Granatstein and Bezdicek, 1992; Karlen *et al.*, 2001; Wander *et al.*, 2002). Indication schemes can quantitatively represent attributes or internal characteristics of processes or systems that are onerous to measure/represent (Joint Research Centre–European Commission, 2008). This approach has been used to evaluate and/or monitor the effects of management practices (Gentile *et al.*, 2001). An indication method is also practical for scientists who present their findings to the public (Ceddia *et al.*, 2017; Karlen *et al.*, 2001; Mukherjee and Lal, 2014; Sharma *et al.*, 2011). Multidisciplinary information can be integrated into a single score or fewer data in the scheme so that decision makers can apply scientific findings to guide their decisions as knowledge brokers (Bouma and McBratney, 2013).

Two steps are generally required in indication development (Karr and Chu, 1997): (1) Variable selection (observed measurements or indicators) and (2) conversion to index scores (e.g., Karlen *et al.*, 2003; Schindelbeck *et al.*, 2008; Wienhold *et al.*, 2004). Aggregation to combine scores into a single form may require that types of conditions or qualities be measured and compared in a meaningful way, because those characteristics are often viewed multidimensionally (Meadows, 1998; Whittaker *et al.*, 2015; Zago, 2009).

Whittaker *et al.*'s (2012) comprehensive review found that statistical methods such as factor analysis and ordination techniques were used in more than 800 publications to develop environmental indicators/indices (In/Ix). Many soil scientists have also calculated In/Ix metrics using principal component analysis (PCA) to benchmark soil quality (e.g., Mukhopadhyay *et al.*, 2016; Paz-Kagan *et al.*, 2014; Zobeck *et al.*, 2014). Andrews *et al.* (2002), who were pioneers in the use of PCA to produce a soil quality index, employed criteria for selecting a number of eigenvectors and eigenvalues to determine variables for index calculations. The value of each attribute was weighted by eigenvalues to produce the soil quality index. In this study, soil attributes with high variability were considered to provide important information for score calculation, assuming that the variability of attributes rather than observed soil measures express soil quality. Using the same ordination approach, Askari and Holden (2015) examined the human effect of management systems on soil quality. However, the notion that soil variability computed through an ordination approach, such as PCA, infers on soil quality stands in opposition to other approaches that consider continuous or ordinal soil metrics to characterize soil fertility or soil quality, which determine crop yield or ecosystem health.

Other issues with the conventional use of multivariate statistical methods for In/Ix implementation have been reported in the literature.

For example, Karr and Chu (1997) argued that multivariate analyses aim to identify patterns or structures of data rather than to assess impacts. Some requirements for performing PCA — including, but not limited to, assumptions regarding multivariate normal distribution and the linearity of variables — were also characterized as shortcomings for In/Ix development (Shlens, 2014). Such assumptions can often be overcome by data transformation, but the process may obscure ecological/environmental patterns and relationships. Analytical shortcuts to produce In/Ix scores using multivariate statistics can easily misguide decision makers and scientists who may reach wrong or inappropriate conclusions (Karr and Chu, 1997).

The Data Envelopment Analysis (DEA) is a popular management tool for developing In/Ix scores in order to assess the performance levels of functions/systems (Emrouznejad and Yang, 2017). It has been used in diverse disciplines, such as agriculture, banking, engineering, ecology, public policy, education (Emrouznejad, 2014; Fried *et al.*, 2008), and economics, but rarely in soil applications to assess the capability of soil–environmental functions (Mizuta *et al.*, 2018).

### *1.2 Data Envelopment Analysis*

The DEA was used in an agronomic study to assess agricultural productivity and to optimize agricultural management (Jaenicke and Lengnick, 1999). Crop yield was used as the output, and soil chemical, physical, and biological properties were used as inputs. Seven variables were chosen, as follows: (1) Chemical indicators: Available phosphorus and potassium, acidity, and available magnesium, (2) Physical indicators: Bulk density and water-holding capacity, and (3) Biological indicator: Carbon–nitrogen ratio. Contour maps of the calculated scores were also developed for the study area. This pioneering study demonstrated the benefits of using DEA applications in soil science to assess the crop yield function.

The DEA has also been shown to be useful for creating environmental indices for units such as firms, farms, farmers, and countries (Bellenger and Herlihy, 2009). Soil pedons, soil map units, or soil pixels (grid cells) are examples of units used in soil science (Mizuta *et al.*, 2018). In DEA studies, performance is measured by efficiency (capability), which is composed of inputs and outputs (Banker *et al.*, 1984; Charnes *et al.*, 1978; Thanassoulis *et al.*, 1996). Efficiency in general refers to the total factor efficiency that is considered to be an optimum level or status, with the possibly largest/highest output(s) based on a given set of input(s) (Farrell, 1957). Note that we use "efficiency" and "capability" interchangeably throughout this study to facilitate communication between economists and soil scientists.

Capability is calculated by optimizing the quantitative relationship between inputs and outputs in two ways: (1) Maximization of outputs with a given quantity of inputs or (2) Minimization of inputs with a given quantity of outputs (Bogetoft and Otto, 2011b). Either calculation requires two steps: (1) Calculation of a frontier based on all sample points and (2) Calculation of the distance between the frontier and the observation points or entities of units. The reference system (i.e., the frontier) represents the best performance level, with the points of units located on the line assigned the value of one as the capability score. The achievable level of capability can be represented as a comparison between observed units and the optimum goal units that can be achieved (Fried *et al.*, 2008). A short distance between the frontier and observation points suggests that the units are more efficient than points far from the frontier (McDonald, 2009).

There are significant advantages of using the DEA compared to PCA or other ordination methods to assess soil quality capability. First, capability scores are comparable over different periods, as long as the same types of inputs and outputs are chosen based on the reference system. The DEA can produce the system, even when samples are collected in different locations or periods (Whittaker *et al.*, 2015). If capability scores are calculated based on future sampling campaigns by selecting the same attributes as inputs and outputs, the trend of improvements or deteriorations in soil and ecosystem functions/services could be monitored quantitatively. Second, the DEA yields capability scores that can be compared spatially within and across other regions. Third, identifying site-specific capability via DEA based on selected inputs and outputs has tremendous power. If stakeholders aim to achieve specific outputs, such as sequestering carbon in soils, they can adapt and select specific inputs to achieve specific outputs. For example, selected inputs may include conservation management and/or amendments to enhance the available water capacity (AWC) or land use/land cover (LULC) conversions that enhance the accretion of carbon in soils. Potential improvements can be also evaluated by using DEA in a quantitative manner, because the score value of one serves as a reference value (i.e., an "ideal" or "optimal" value). Another advantage of DEA scores is their ability to assess combinations of site-specific environmental conditions that inform best management practices to optimize/maximize a specific soil function or ecosystem service (e.g., soil carbon sequestration or nutrient holding capacity). Some of these environmental conditions are adaptable (e.g., change in LULC and management), while others depend on global cycles and change (e.g., biogeochemical cycles or climatic cycles with temperature and precipitation as key variables). Other factors, such as soil type, may not be manipulated through management as easily, since soil genesis extends over long periods of time.

This study is the first to apply the DEA to a soil-related phenomenon, soil carbon sequestration (SCseq), across a large region. SCseq capability In/Ix (SCI) scores are expected to help decision makers identify which areas would benefit from changed management from an efficiency/capability point of view. In addition, the scores provide information on how much the target function can be maximized with a given set of inputs.

### *1.3 Objectives*

The main goal of this study was to construct a DEA prototype model to assess the capability of a critical important soil function. The specific objective was to develop SCI scores and evaluate the applicability of the method in soil and environmental sciences. We also aimed to identify areas in the State of Florida that show the largest potential to maximize the SCseq function. Note that the terms "indicators" and "indices" are used interchangeably, because the capability scores computed by the DEA are derived from inputs of multiple environmental variables and the SCseq rate.

## 2 Materials and Methods

### *2.1 Study Area*

This study was conducted in the State of Florida in the southeastern United States, which covers about 150,000 km2 (Figure 1). Previous studies conducted by Ross *et al.* (2013), Xiong *et al.* (2014a), and

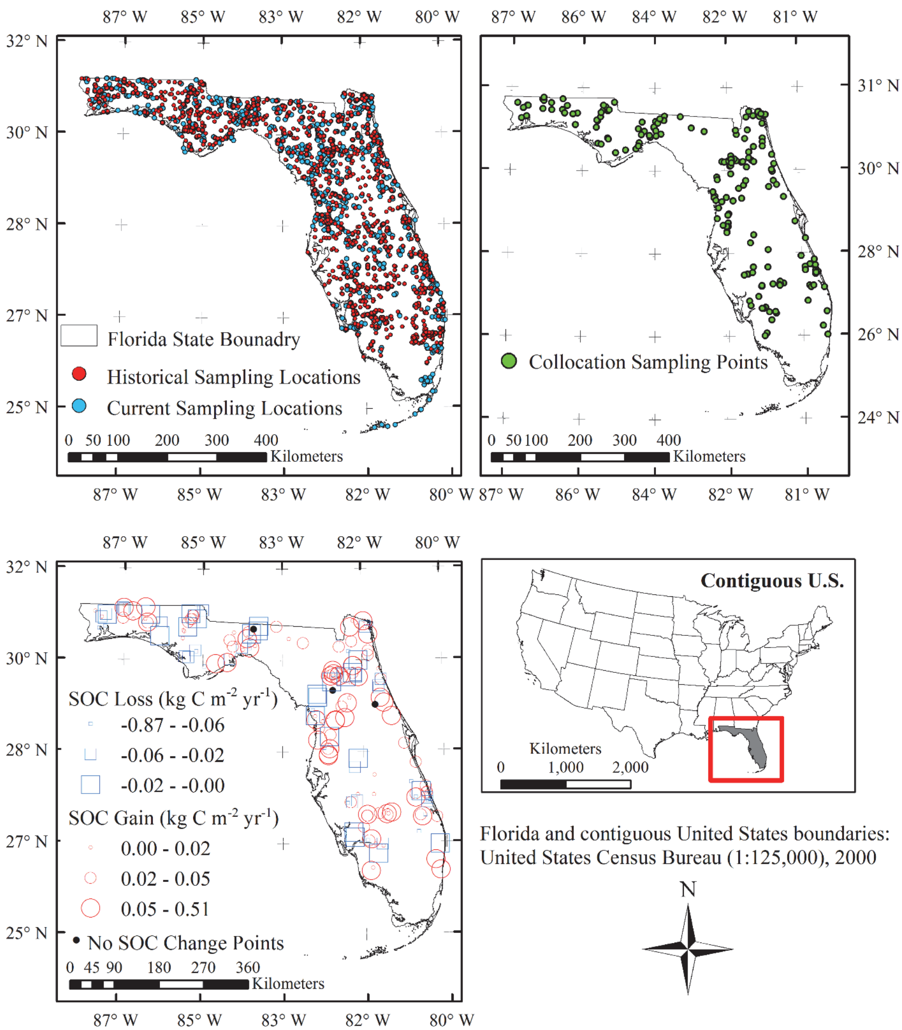


Figure 1: Maps of historic and current sampling, collocated sites, and soil organic carbon (SOC) change between 1965–1996 and 2008–2009. Samples with positive SCseq values are the areas where soil carbon stocks increased (sequestration), while the negative values represent carbon losses over the time period.

Vasques *et al.* (2010b) derived the spatial distribution of soil orders in Florida from the Natural Resources Conservation Service (NRCS) database; this database mainly consists of Spodosols (32%), Entisols (22%), Utisols (19%), Alfisols (13%), and Histosols (11%) (Natural

Resources Conservation Service, NRCS, U.S. Department of Agriculture, 2006). The main LULC types found in Florida are wetlands (28%), pinelands (18%), urban and barren lands (15%), agricultural lands (9%), rangelands (9%), improved pasturelands (8%), and 13% other LULC type (Florida Fish and Wildlife Conservation Commission, 2003). The annual mean temperature in Florida was 22.3°C, and annual mean precipitation was 1,373 mm based on data from the National Climatic Data Center (2008). Slopes vary between 0% and 5% (United States Geological Survey, 1999).

## 2.2 Data Sources

### 2.2.1 Historical Dataset

The legacy (historical) data and current data were compiled to assess SCseq standardized on an annual basis in units of $\mathrm{g\,C\,m^{-2}\,yr^{-1}}$ (Vasques *et al.*, 2010a,b,c). The two datasets together covered an approximately 40-year period from 1965 to 2009 (Table 1). The historical data (HD) resemble the "Florida Soil Characterization Database" and contain 1,251 site-specific soil profiles collected between 1965 and 1996. The dataset was described in detail by Grunwald *et al.* (2004). Sampling locations were selected by relying on the tacit expert knowledge of field soil scientists for the purpose of soil surveying.

Both soil organic carbon (SOC) and bulk density (BD) were measured in the laboratory. The soil organic matter (SOM; g soil $\mathrm{g^{-1}}$ C)

Table 1: Description of the historical and current soil observation datasets.

| Datasets | Sampling period | Sampling size | Sampling design | Measurements |
|---|---|---|---|---|
| Historical (HD) | 1965–1996 | 1,251 | Expert knowledge based | BD (g soil $\mathrm{cm^{-3}}$)<br>SOM (%) |
| Current (CD) | 2008–2009 | 1,014 | Stratified random[a] | BD (g soil $\mathrm{cm^{-3}}$)<br>IC (%)<br>TC (%) |

Abbreviations: BD = bulk density; IC = inorganic carbon; SOM = soil organic matter; TC = total carbon.

[a]Two strata including soil suborder and land use/cover types were applied to capture the broad range of soil carbon variability across the Florida State.

was analyzed by the Walkley–Black modified acid-dichromate method ($SOM_{WB}$) for the A, B, C, and E mineral soil horizons, while loss-on-ignition ($SOM_{LOI}$) was employed for O horizon and organic soils (Histosols) (Ross *et al.*, 2013). Two different pedotransfer functions were employed, which were derived by Ross *et al.* (2013). Linear regressions were used for organic soils to convert both historical $SOM_{WB}$ for mineral soils and historical $SOM_{LOI}$ into SOC, the latter representing SOC measured by dry combustion with a Shimadzu SSM-5000A as described below. The calculations from the functions showed an $R^2$ of 0.90 (Equation (1)) and 0.99 (Equation (2)) (Ross *et al.*, 2013). The equations for the conversions are described below.

$$\text{SOC in mass unit}(\%) = 0.08 + (0.85 \times \text{SOM}_{\text{WB}}) \tag{1}$$

$$\text{SOC in mass unit}(\%) = 0.5 \times \text{SOM}_{\text{LOI}} \tag{2}$$

SOC measurements in stocks ($\text{kg C m}^{-2}$) were calculated with SOC measurements in mass units and measured BD (g soil $\text{cm}^{-3}$).

#### *2.2.2 Current Dataset*

The current soil data (CD) were collected between 2008 and 2009 during a reconnaissance soil-sampling campaign in topsoil (0–20 cm depth) across Florida (Table 1). A total of 1,014 samples were collected with a stratified-random sampling design based on soil orders-LULC classes. Inorganic (IC) and total carbon (TC) were measured with 50–500 mg of ball-milled soil samples combusted at 900°C by the catalytic oxidation method (Shimadzu SSM-5000A) and with 20–250 mg of ball-milled soil samples treated with phosphoric acid in the gas analyzer at 200°C, respectively. The SOC was derived by the subtraction of minuscule amounts of IC from TC ($\text{TC} - \text{IC} = \text{SOC}$). SOC measurements in mass units (%) were converted to stock units ($\text{g m}^{-2}$) using the measured BD and soil depth (20 cm).

### *2.3 Data Harmonization and Calculation of Soil Carbon Sequestration Rates*

The HD and CD were harmonized in order to calculate the SCseq rate. The overall protocol developed by Ross *et al.* (2013) was adopted in this study. The HD, which used a horizon-based sampling scheme, had to be further reconstructed to SOC with a fixed-depth profile (0–20 cm) to harmonize it with the CD. Thus, a depth-weighted averaging technique was employed using the statistical software *R*'s (3.2.4) packages "plyr" and "RODBC" to convert horizon-based SOC to fixed depth (0–20 cm). The standardized SOC in mass units (%) in 0–20 cm soil depth was then converted to stock units using the following equation with observed BD measurements:

$$\text{SOC stocks}(\mathrm{kg\,C\,m^{-2}}) = \frac{\text{SOC in mass unit (\%)} \times \text{BD}\,(\mathrm{g\ soil\ cm^{-3}})20\ (\mathrm{cm}) \times 1000(\mathrm{m^{-2}\,cm^{-2}})}{1000\,(\mathrm{g/kg})} \tag{3}$$

Samples that were spatially collocated within a buffered zone (with 30 m diameter) and showed the same soil order in both HD and CD were selected for further analysis (Figure 2). This procedure was conducted in ArcGIS v10.4 (Environmental System Research Institute, Redlands, CA, USA). Soil carbon stock changes were calculated by subtracting SOC stocks of the HD from the CD at the collocated sites. The changes were then divided by the difference in the sampling years between the HD and CD to obtain the SCseq ($\mathrm{kg\,C\,m^{-2}\,yr^{-1}}$). The changes in SOC stocks are described as SCseq in this research, because almost all carbon for topsoils in Florida is stored in organic form, with only miniscule amounts of inorganic carbon (Knox *et al.*, 2015). Samples with positive SCseq values are the areas in which soil carbon was gained (sequestration), while the negative values represent carbon losses over the study period. All calculated SCseq values were positively shifted by the minimum value of SCseq ($-0.87\,\mathrm{kg\,C\,m^{-2}\,yr^{-1}}$) to ensure that SCseq values were equal to or above zero, because the DEA requires nonnegative values for processing.

### *2.4 Environmental Dataset for the DEA*

The SCI scores were calculated based on the inputs of pedogenic, climatic, biotic, and hydrologic factors relevant to the target function of soil carbon sequestration to optimize its capability. Vasques *et al.* (2012a,b) found that AWC plays a significant role in determining the

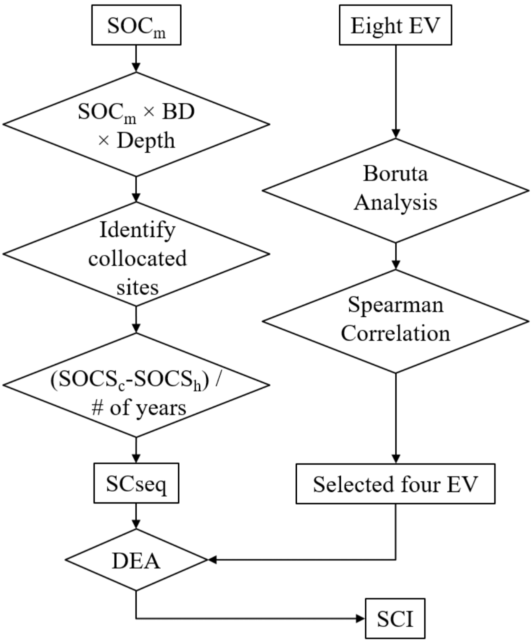


Figure 2: Schematic workflow for indicator calculation using the Data Envelopment Analysis. The selected ED contained AWC, PPT and annual mean Temp, and annual mean NDVI (please see details of environmental data in Table 1). Abbreviations: BD = bulk density ($\mathrm{g\,cm^{-3}}$); c = current dataset; DEA = Data Envelopment Analysis; EV = environment variables; h = historical dataset; SCI = SCseq capability Indicator/Index; SOC = soil organic carbon concentration (%); SOCS = soil organic carbon stocks ($\mathrm{kg\,C\,m^{-2}}$); SCseq = soil carbon sequestration rate ($\mathrm{kg\,C\,m^{-2}\,yr^{-1}}$).

spatial variability of soil carbon in Florida. Climatic, biotic, and pedogenic data — such as temperature, precipitation, Normalized Difference Vegetation Index (NDVI), soil order, and LULC types — were also identified as influential contributors to SCseq in other studies (e.g., Guo *et al.*, 2006; Xiong *et al.*, 2012, 2014a). Frank *et al.* (2015) and Guo and Gifford (2002) found that climatic factors, as well as hydrological conditions, affect soil carbon significantly. Xiong *et al.* (2014a) also identified those selected variables among 210 potential environmental–human variables relevant to soil carbon sequestration in Florida (Grunwald *et al.*, 2011). Eight numerical variables that may have an influence on SCseq were identified based on such previous studies (Table 2).

Table 2: Summary of environmental data used as inputs in the Data Envelopment Analysis.

| Variable | Unit | Source | Original scale/ resolution (m) | Date |
|---|---|---|---|---|
| Soil available water capacity (soil depth 0–25 cm)[a] | $cm\,cm^{-1}$ | SSURGO | 1:24,000 | 2009 |
| Annual min, max, and mean NDVI[b] | | MODIS4-NACP | 250 | 2005 |
| Annual min, mean, and max temperature[c] | °C | PRISM | 800 | 1971–2010 |
| Annual mean precipitation[c] | mm | PRISM | 800 | 1971–2010 |

Abbreviations: max = maximum value; min = minimum value; MODIS = Moderate Resolution Imaging Spectroradiometer; MODIS4NACP = MODIS for North American Carbon Project; NDVI = normalized difference vegetation index; PRISM = Parameter-elevation Regressions on Independent Slopes Model; SSURGO = the Soil Survey Geographic Database.

[a]The available water capacity expressed as a volume fraction was estimated as the difference in the water contents of soil at field capacity and at the permanent wilting point (Bliss and Sharon, 2014). [b]The annual mean NDVI were the long-term average on a monthly basis in 2005, while the annual averages of 12 monthly data of min/max NDVI were also obtained.

[c]The annual mean temperatures/precipitations were the long-term average on a monthly basis over 1971–2010, while the averages of 12 monthly data of daily max and min temperatures/precipitations were also obtained.

The NDVI data were derived from the Moderate Resolution Imaging Spectroradiometer (MODIS), which characterizes live green standing vegetation. These data may also serve as a biotic proxy and allow discernment between barren soil areas and vegetated areas (Tucker, 1979). The index is calculated as a normalized ratio of the red (RED) and near-infrared (NIR) spectral wavelengths (Gaughan *et al.*, 2012):

$$NDVI = \frac{NIR - Red}{NIR + Red} \tag{4}$$

Note that overall annual mean and means of maximum and minimum NDVI collected for each month throughout the year 2005 were calculated (Xiong *et al.*, 2014a). Another environmental variable, AWC ($\mathrm{cm\,cm^{-1}}$), expressed as a volume fraction, was estimated as the difference in the water contents of soil at field capacity and at the permanent wilting point (Bliss and Sharon, 2014). In addition, atmospheric properties (i.e., temperature and precipitation) collected from the PRISM Climate Group, Oregon State University (http://prism.oregonstate.edu), were averaged for 1971–2010 overall (Table 2). The means of maximum and minimum temperatures collected for each month throughout the 30-year period were also calculated. The categorical data (i.e., LULC and soil order) were only used for the purposes of interpretation. The spatial extraction function in ArcGIS was used to extract data from geospatial data layers for each collocated sampling site ($n = 170$). Broad LULC groups were generated by combining specific categories to avoid insufficient sample size for statistical procedures. For example, agricultural crop and citrus field were reclassified as the crop group. The grassland group contained freshwater marsh and wet prairie types. Xeric upland forest and mesic upland forest were categorized as the forest group. Lastly, the wetland group contained shrub swamps, hardwood swamps, mixed wetland forests, and cypress swamps.

Of the eight pre-selected variables (Table 2), relevant factors for the DEA were selected. First, the Boruta all-relevant variable selection method was carried out using the Boruta package in *R* (Figure 3). In brief, the Boruta algorithm finds features relevant to SOC variation linearly and non-linearly by comparing the importance of the original attribute(s) with the importance of the shadow variables randomly based on the random forests' classification algorithm (Kursa and Rudnicki, 2010). Attributes that are significantly better than shadows are

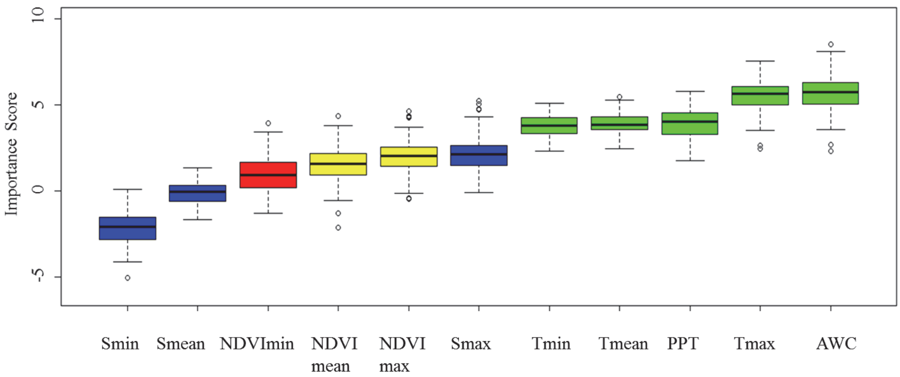


Figure 3: Importance ($Z$-score) of the all-relevant variables to infer the soil carbon sequestration rate ($\mathrm{kg\,C\,m^{-2}\,yr^{-1}}$) identified by the Boruta variable selection method. The 1st to 5$^{\mathrm{th}}$ boxes from right indicate variables of significant importance, while the 7th and 8th boxes identify tentative variables through rough fixation, which require further investigation. Shadow variables as shown on the 6th, 10th, and 11th boxes were created by each iteration of the Boruta algorithm to discern the only relevant variables. The 9th box identifies the variables that are not relevant. Consequently, all variables except NDVmin were selected by the Boruta selection method. Abbreviations: AWC = available water capacity (cm); Max = maximum value, Min = minimum value; NDVI = Normalized Difference Vegetation Index; PPT = annual mean precipitation (mm); S = shadow variable; T = temperature (°C).

accepted for further calculation, while non-significant ones are removed from the iteration (Figure 3). The Boruta test identified the important variables for SCseq rate, which exceeded the importance value of the shadow variables. These included AWC, annual maximum, minimum, and mean temperature, annual mean precipitation, and maximum, minimum, and mean NDVI. Spearman correlation metrics (coefficients) were used to identify redundancy among the relevant variables selected by Boruta (Figure 4). We set the threshold for the $p$ value to over 0.80, according to recommendations provided by Andrews *et al.* (2002). The four variables selected by the Boruta selection method and Spearman correlation metrics were considered as inputs in the DEA (i.e., precipitation, temperature, NDVI, and AWC). The first two input variables as well as soil orders and LULC types were considered to be the fixed factors, and the NDVI and AWC to be managerial (Bauer and Black, 1992; Buma, 2012).

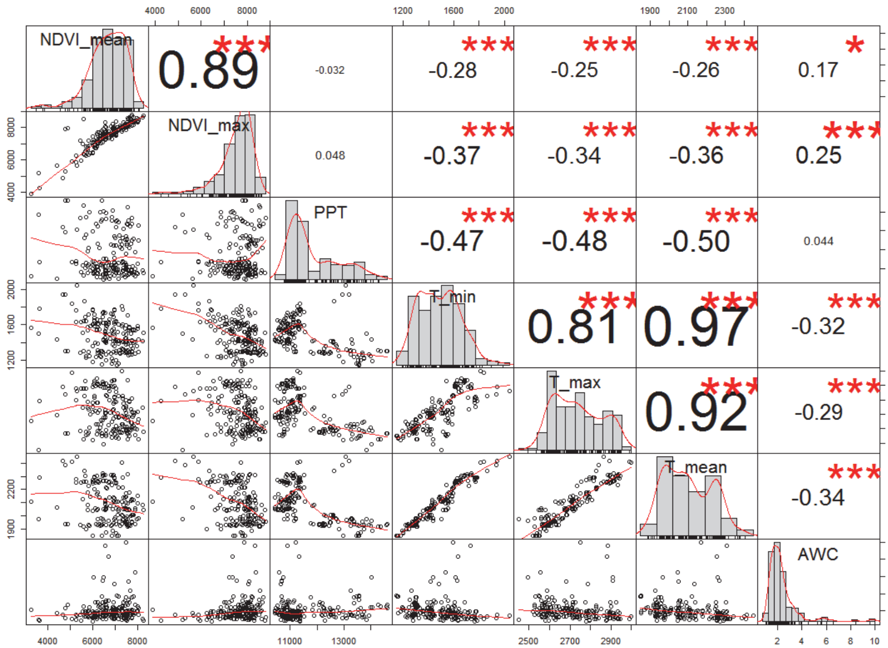


Figure 4: Probability density distribution and Spearman correlation matrix plots of selected environmental variables identified by Boruta: AWC = available water capacity (cm); NDVI = Normalized Difference Vegetation Index; PPT = annual mean precipitation (mm); T = annual mean temperature (°C). Display of the Spearman correlation matrix with data histogram and xy plot between variables ($^{*}p$ value $< 0.1$, $^{**}p$ value $< 0.05$, $^{***}p$ value $< 0.01$). The selected variables based on the Boruta algorithm were analyzed by the Spearman Correlation matrix to reduce data redundancy. Abbreviations: Max = maximum value; Mean = mean; Min = minimum value.

The selected soil and environmental attributes were grouped, based on quartile systems, into four categories: Low, Low–Median, Median–High, and High (Table 3). This allowed to evaluate SCI scores depending on the different levels of the four inputs. For example, annual mean temperature, which ranged from the minimum value (18.5°C) to the first quartile (19.7°C), was classified as Low. The Low–Median, Median–High, and High categories consisted of temperatures from the first quartile to the median (Low–Median), from the median to the third quartile (Median–High), and the third quartile to the maximum value (High).

Table 3: Basic statistics summary of the selected environmental data.

| | Temperature[a] (°C) | Precipitation[a] (mm) | Normalized difference vegetation index[b] (NA) | Available water capacity[c] (cm soil $cm^{-1}$) |
|---|---|---|---|---|
| Minimum | 18.5 | 104.2 | 0.3 | 0.8 |
| 1st Quartile | 19.7 | 108.7 | 0.6 | 1.4 |
| Median | 20.8 | 111.9 | 0.7 | 1.8 |
| Mean | 21.0 | 116.5 | 0.7 | 2.1 |
| 3rd Quartile | 22.5 | 123.0 | 0.7 | 2.3 |
| Maximum | 24.5 | 146.2 | 0.8 | 9.6 |

[a]The annual mean temperatures/precipitations over 1971–2010.
[b]The annual mean Normalized Difference Vegetation Index collected in 2005.
[c]The available water capacity data collected in 2009.

### *2.5 DEA-SCI Calculations and Assumptions*

The hyperdimensional frontier "sheet" was calculated based on sample points with four inputs (i.e., the four environmental input variables selected: annual mean precipitation, annual mean temperature, annual mean NDVI, and AWC) and one output (SCseq). Several options in terms of returns-to-scale assumptions are available when running the DEA. Here the free disposability hull with no convexity (FDH) assumption and the variable returns-to-scale with convexity and free disposability (VRS) assumption were selected as standard scale assumptions underlying the DEA (Banker *et al.*, 1984; Daraio and Simar, 2007). The FDH assumption allows a certain quantity of outputs to be generated by more inputs; in other words, surplus inputs can be freely disposed of. Likewise, a given quantity of inputs can also produce fewer outputs (i.e., free disposability of outputs). The shape of the frontier resembles an isotonic regression. On the other hand, the VRS-DEA accepts not only the features the FDH assumption provides in index development, but also more flexibility for the relationship between inputs and outputs. This approach can create a concave line and, as expected, restricts the efficiency scores to be lower than the FDH scores. Yet both settings are useful, because they enable to capture complex functions or systems. Illustrative examples of different lines created by different assumptions are available in Bogetoft and Otto (2011a).

The output-oriented DEA-SCI was calculated using the Benchmarking package in R, because this study aimed to maximize output capability — that is, the SCseq rate — based on a combination of the selected soil/environmental data inputs. The calculated FDH-SCI and VRS-SCI scores were mapped out in the study area within the State of Florida using ArcGIS software (Environmental Systems Research Institute, Redlands, CA) for spatial interpretation.

### *2.6 Other Statistical Tests*

The Kruskal–Wallis (K–W) rank sum test — which is a nonparametric variance test suited for nonnormally distributed data with uneven sample size for each class — was employed to evaluate whether capability scores differ significantly by soil order and LULC (Holland and Wolfe, 1973; Ross *et al.*, 2016). Pairwise comparisons using the Tukey and Kramer (Nemenyi) test with Tukey-distance approximation were performed to discern any statistical differences among the groups of soil/environmental factors (Pohlert, 2014).

## 3 Results

### *3.1 Selection of Relevant Environmental Variables*

The environmental variables, which were selected by the Boruta and Spearman methods, were not statistically significant for variation of the SCseq rate ($p > 0.05$), according to the K–W test (Figure 5). In addition, any statistical differences in the means of SCseq rates among the categorical groups, including the environmental covariates and LULC and soil orders, were not observed based on the post hoc Tukey and Kramer (Nemenyi) test (Figure 5).

### *3.2 Relations of Soil/Environmental Factors to SCseq Rate and SCI Scores*

SCI scores were calculated via the DEA, with SCseq as outputs and the four environmental variables as inputs at the collocated sites. Two DEA assumptions (FDH and VRS) produced different results. FDH-SCI and VRS-SCI scores ranged from 1.00 to 1.09 and from 1.00 to 1.15, respectively. The results of the K–W test showed that SCI scores were significantly influenced by annual mean precipitation (Chi-squared = 11.8, degrees of freedom = 3); AWC (Chi-squared = 8.0, degrees of freedom = 3); and NDVI (Chi-squared = 9.5, degrees of freedom = 3) at the 95% confidence level (Figure 6). However, only the precipitation classes had statistically distinct differences in the means of the FDH-SCI scores among the groups. The mean score for the High class was statistically lower and closer to the value of one than was the mean score for the Low class.

The variation in SCI scores calculated under the VRS assumption was statistically influenced by all of the soil/environmental factors, with the exception of AWC (LULC: Chi-squared = 24.6, degrees of freedom = 8; Soil orders: Chi-squared = 13.9, degrees of freedom = 6; Temperature: Chi-squared = 12.5, degrees of freedom = 3; Precipitation: Chi-squared = 18.9, degrees of freedom = 3; NDVI: Chi-squared =

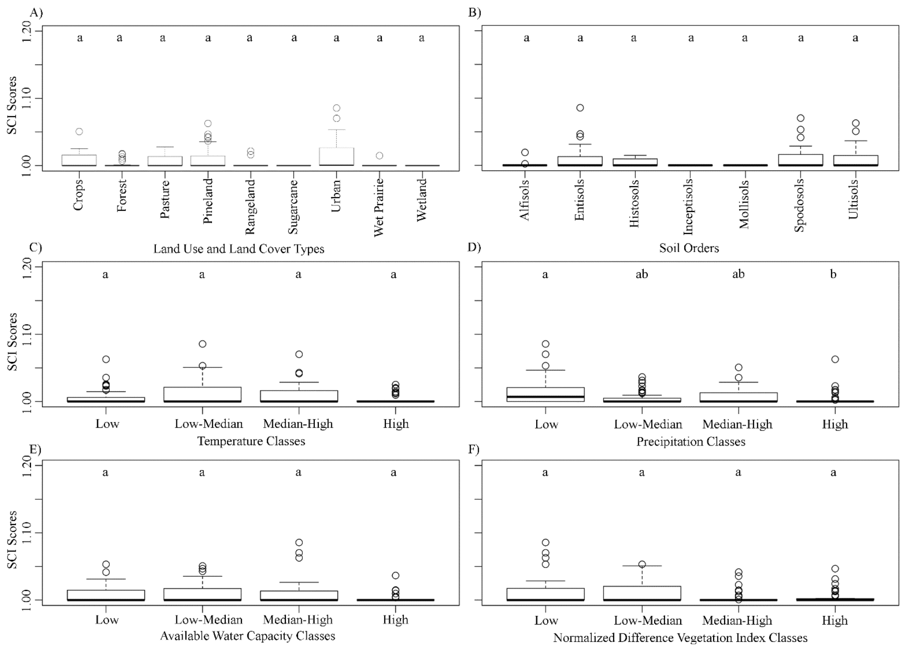


Figure 5: Soil carbon sequestration rates by A) land-use/land-cover types observed during sampling period for current dataset (2008–2009), B) soil orders, C) annual mean temperature (1971-2010), D) annual mean precipitation (1971-2010), E) available water capacity, and F) mean Normalized Difference Vegetation Index (2005) classes. The alphabetic letters designate the significant differences in means between the variables based on the Tukey and Kramer (Nemenyi) test with the Tukey distance approximation at the 95% confidence level.

18.3, degrees of freedom = 3) at the 95% confidence level (Figure 7). VRS-SCI scores for the forest group were significantly lower than the scores for the urban class. Only one sample in sugarcane was observed, thus allowing for no firm conclusions to be drawn. The wet prairie group, rangeland group, and wetland group contained 5, 10, and 7 samples, respectively, while the other groups contained more than 20 samples, providing for a more robust interpretation. SCI scores with high temperature, precipitation, and NDVI were considerably lower than the other groups. Note that each of the soil/environmental factors, except for LULC and soil orders, had a relatively even sampling size of 42 or more.

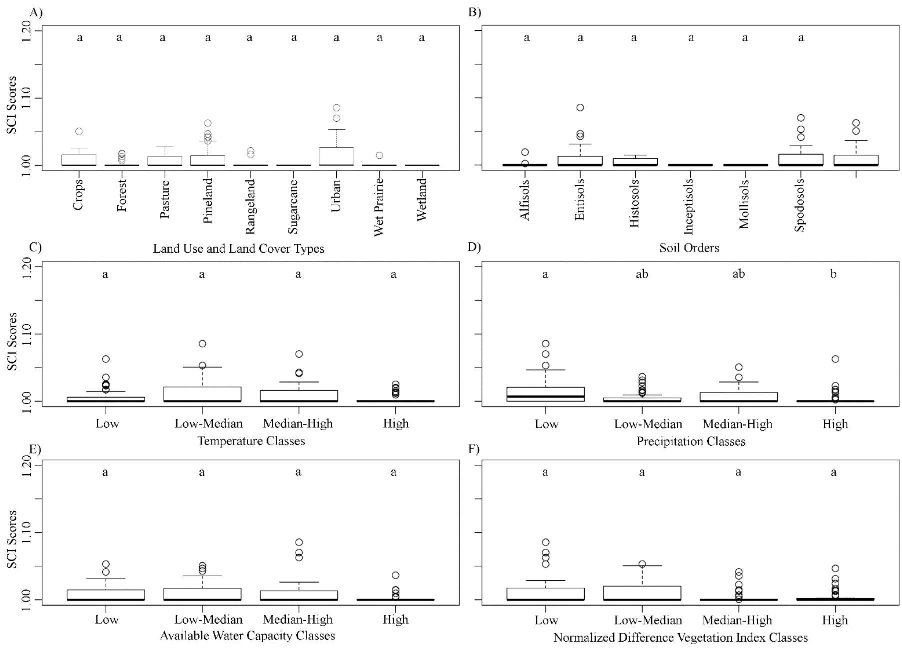


Figure 6: Soil carbon sequestration indicators/indices (SCI) scores under an assumption of free disposability hull without convexity. Each scores is classified by A) land-use/land-cover types observed during sampling period for current dataset (2008–2009), B) soil orders, C) annual mean temperature (1971–2010), D) annual mean precipitation (1971–2010), E) available water capacity, and F) mean Normalized Difference Vegetation Index (2005) classes. The alphabetic letters designate the significant differences in means between the variables based on the Tukey and Kramer (Nemenyi) test with the Tukey distance approximation at the 95% confidence level.

Spatial maps of the SCI scores under FDH and VRS were created. The smaller circle (the larger SCI scores) represents the higher capability of the soil carbon sequestration function. It appears that sampling points located in the south and central regions had the low SCI scores under both assumptions, while VRS-SCI scores emphasized the inefficiency in sequestration capability across the State of Florida. The variation in VRS-SCI scores was spatially larger than that of the FDH-SCI scores.

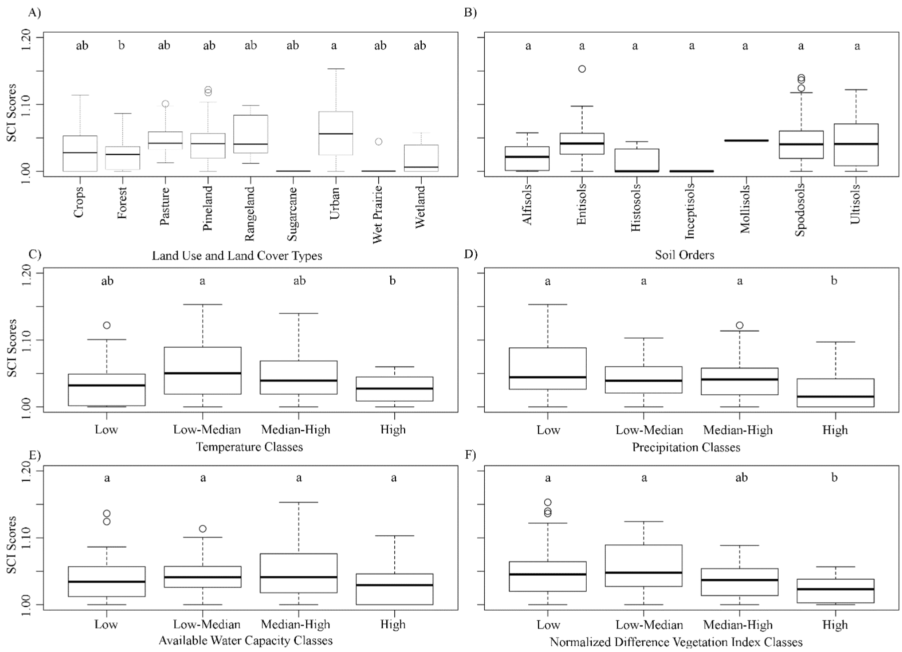


Figure 7: Soil carbon sequestration indicators/indices (SCI) scores under an assumption of variable returns to scale with convexity and free disposability. Each scores are classified by A) land-use/land-cover types observed during sampling period for current dataset (2008–2009), B) soil orders, C) annual mean temperature (1971–2010), D) annual mean precipitation (1971–2010), E) available water capacity, and F) mean Normalized Difference Vegetation Index (2005) classes. The alphabetic letters designate the significant differences in means between the variables based on the Tukey and Kramer (Nemenyi) test with the Tukey distance approximation at the 95% confidence level.

## 4 Discussion

### *4.1 Interactions between Soil Carbon Sequestration Rate, Capability Scores, and Fixed Input Variables*

Four environmental and biotic variables were selected for the DEA calculation based on the Boruta analysis and Spearman correlation metrics: annual mean temperature and precipitation, AWC, and mean NDVI (Figures 3, 4). Statistical differences in the means of VRS-SCI scores for each environmental category (fixed variables include

LULC, soil types, temperature, and precipitations) were identified and compared with FDH-SCI scores (Figures 6, 7). There are several reasons for the environmental factors' lack of significant influence on the SCseq rate, as well as on SCI scores calculated with the FDH. The first reason is the weak power of statistics to detect significant differences among the groups. A nonparametric test (Kruskal–Wallis rank sum test) and Nemenvi pairwise comparison were used because of the unequal sample sizes of nonnormally distributed data for each LULC group. The second reason is the different sample sizes of data, which led to use of the nonparametric test. The third reason is the sample size for each class, which in some cases was small. Lastly, the calculation for the frontier under FDH and VRS assumptions yielded greatly varied results. FDH produced a stair-like frontier, while the one for VRS was somewhat curved, depending on samples or units (Bogetoft and Otto, 2011a). This explains why VRS produced more statistically sensitive scores than FDH.

Significant differences in the SCI scores under the VRS assumption were observed between forested and urban areas among all LULC types (Figure 7). Scores in the urbanized areas were higher than those in the forested areas, meaning that the capacity to sequester carbon was higher in forests than in urban areas. The risk of carbon loss by converting forested areas has been supported by other studies (Bonan, 2008; Dawson and Smith, 2007; Pouyat *et al.*, 2002). Other SOC sequestration studies conducted in Florida have shown that soils in forests did not accrete substantial amounts of carbon over the 40-year period, although conversions of pineland and rangeland sites into wetlands led to profound increases in SOC stocks (Xiong *et al.*, 2014b). Ross *et al.* (2016) demonstrated that wetland sites in northeastern Florida tended to gain SOC, but the results from this study found no statistical differences in SCI scores of wetlands compared with other LULC groups. The differences found in SCI scores, but not in SCseq rates, among some LULC indicate that the capability function can be quantified not by simply measuring/estimating the SCseq rates, but by considering the relationship between the output function and the relevant input factors that produce the function. This interpretation differentiates most of the past studies conducted to quantify soil functions by only measuring soil properties. Thus, further investigations are required to elucidate not only the mechanism of the carbon sequestration function but also its capacity using relevant inputs for various LULC types.

Soil orders did not have much influence on variances in SCseq rate or SCI scores. Histosols, diagnosed by considerable amounts of organic matter (at least 20 to 30% SOM in more than 40-cm thick layers), showed a negative mean SCseq rate (Natural Resources Conservation Service, NRCS, U.S. Department of Agriculture, 1999; Figures 5, 6). This might be due to the erroneous taxonomic classification of sites, the unequal sample size ($n = 5$) and/or nonnormal SCseq rates found in Histosols. Although there is ample literature showing soil carbon accretion of 0.25 to 0.45 cm/year, the few Histosol sites may have been impacted by temperature-induced oxidation (dryness) in these organic soils (Anderson, 1964). Xiong *et al.* (2014a) also found that Histosols in Florida cultivated with sugarcane (Everglades Agricultural Area) have lost substantial soil carbon due to subsurface drainage management in this area. The carbon loss was caused by dramatic oxidation of the organic soils (Histosols) due to changes in land use cover over the last four decades.

### *4.2 Interactions between Soil Carbon Sequestration Rate, Capability Scores, and Managerial Input Variables*

Two managerial input variables (i.e., AWC and NDVI) that were important variables relevant to SCseq were incorporated into SCI calculations. Surprisingly, the AWC did not statistically differentiate the FDH-SCI and VRS-SCI scores in the classification scheme. This may offer valuable insights for future studies, because it infers the mask effect from the input/fixed variables that differentiated the SCI scores statistically by the classification schemes. SCI scores might need to be calculated globally by using all fixed and managerial variables as DEA input variables, as presented in this study, or by calculating the scores locally by having multiple frontiers under certain fixed factors. The reason is that each area may use a different frontier to calculate the capacity/efficiency of the function. O'Donnell *et al.* (2008) also pointed out that using the same frontiers is only meaningful when the frontiers for different groups of units are identical. Thus, a meta-frontier that envelops group frontiers may also be used in future studies of DEA applications in soil science.

VRS-SCI scores by NDVI classes showed that areas with high NDVI tend to have scores closer to the reference value of one. An approximately 2% increase in SCseq capability under high NDVI was observed compared with sites with low NDVI (Figure 7). The NDVI indicates that high ecosystem productivity and biomass production are positively correlated with SOC (Tieszen *et al.*, 1997). Thus, it makes sense to observe a decrease in SCI scores as long-term average precipitation and NDVI (i.e., green dense vegetation) increase (Jobbágy and Jackson, 2000). In other words, areas with lower NDVI might need additional attention in terms of management to improve the output function (i.e., to sequester carbon in soils).

Overall VRS-SCI scores emphasized the inefficiency in the SCseq function across Florida. The soils may increase the output function by about 15% $\left(= \frac{1-\left(\frac{1}{1.15}\right)}{\left(\frac{1}{1.15}\right)}\right)$ using the same level of inputs. The spatial map (Figure 8) depicts the areas in which attention to management and efforts are needed to optimize the potential capability of the SCseq function. This need was especially notable in the northern part of Florida. In this prototype study the successful differentiation ability of the soil function capability among samples suggests use of the VRS over the FDH.

The seasonal variability of precipitation was not considered due to the use of long-term averaged climatic data in this study, even though this influence has been reported to be one of the driving factors in alternate land cover patterns, the carbon cycle, and the carbon sequestration function (Guo and Gifford, 2002; Knapp *et al.*, 2002). According to Ingram *et al.* (2013), during the past 100 years no long-term trends were revealed in the time series of annual or summer seasonal precipitation across the southeastern U.S. except along the northern Gulf Coast, where precipitation has increased. During the last several decades, inter-annual variability in precipitation has increased, with more exceptionally wet and dry summers. Future projections using multi-model methods suggest that precipitation will increase across most of the southeastern U.S. in all seasons except summer, where a decrease of as much as 15% is noted in South Florida. It is also projected that inter-annual precipitation variability will increase through the first half of the 21st century in the southeastern U.S., with the greatest variability projected during the summer season. The annual number

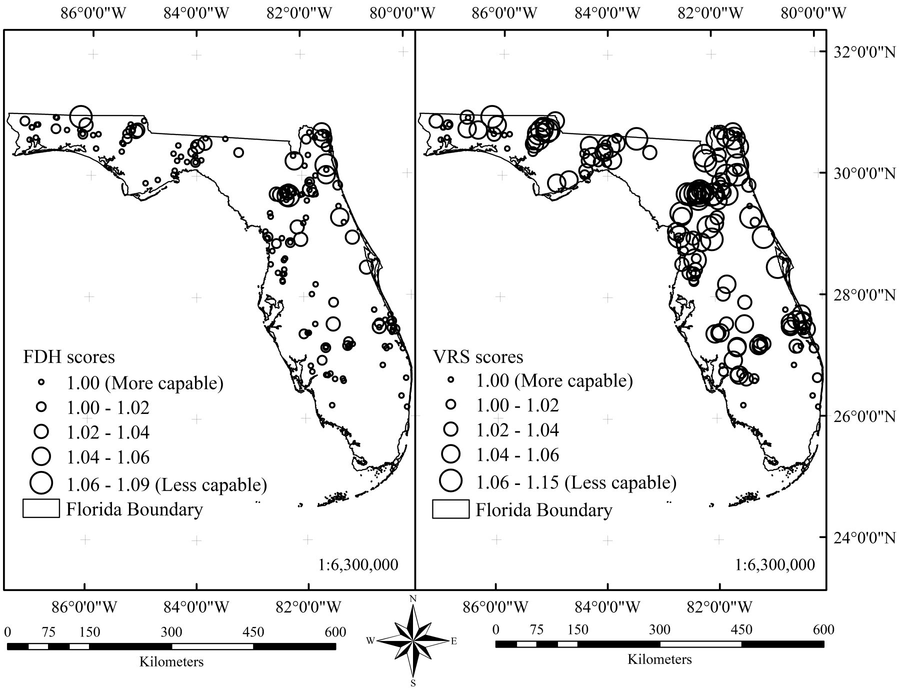


Figure 8: Soil carbon sequestration indicators/indices (SCI) scores under an assumption of variable returns to scale with convexity and free disposability (VRS) and free disposability hull, no convexity (FHD) in the State of Florida. (Florida boundaries: United States Census Bureau, 2000, 1:125,000)

of days with extreme precipitation is expected to increase across more of the southeastern U.S. by the mid-21st century (Ingram *et al.*, 2013). Considering these changes in future precipitation levels in Florida, it is likely that SCI scores will also be impacted by higher precipitation.

According to Ingram *et al.* (2013), mean annual temperatures are projected to increase across the southeastern U.S. throughout the 21st century, with the largest increases (3°F to 5°F) projected over the interior region and the smallest increases over South Florida. The greatest warming trend is projected to take place during the summer months, with the maximum number of temperatures exceeding 95°F to increase by the mid-21st century and with the greatest increase (35 additional days annually) in South Florida (Ingram *et al.*, 2013). Temperature changes may also affect SCI scores, as climatic variables play a role in the computation of SCI scores. Thus, future climate change may impact SCI scores.

In this study covering the past few decades, precipitation showed more significant effects on SCI than temperature. However, the profound increase in climatic warming projected for Florida, which may stimulate increases in soil respiration and SOC losses, may or may not be compensated for by a wetter climate, which in general tends to increase SCseq. It is unknown what the combined effects of changes in temperature and precipitation are on terrestrial ecosystems that differ by geographical region, soil-landscape setting, management, and land use (Cox *et al.*, 2000). Wu *et al.* (2011), in a meta-analysis, found that a warming climate and increased precipitation generally stimulate plant growth and ecosystem carbon fluxes. Their synthesis suggests that warming significantly stimulates total net primary productivity and increases both ecosystem photosynthesis and ecosystem respiration. This is just a first step in understanding the effects of combined climate–soil–yield–nutrient interactions, as presented by Folberth *et al.* (2016). Their global study revealed that soils have the capacity to either buffer or amplify the impact of climate change on yield (productivity) that is modulated by fertilizer application (nutrient status).

## 5 Conclusions

We demonstrated the applicability of the DEA technique to assess SCI scores in Florida. The SCI scores were computed through synthesis of multiple pedogenic, hydrologic, biotic, and climatic inputs. Largest capabilities of the function were identified at sites where more precipitation, higher temperature, and higher NDVI were observed. The SCI scores were highly site-specific, suggesting that future In/Ix assessment requires fine-scale data to capture pedogenic, hydrologic, biotic, and climatic conditions. In light of emergent digital agriculture and fine-scale sensor technology the presented soil-DEA approach has much to offer for future applications. In particular, the VRS successfully enabled clear interpretation of the SCI scores among various fixed/managerial inputs, compared with the FDH.

The DEA offers a soil indication system to assess capability along a continuous spectrum from low to high (soil reference system). The soil indication system presented here encompassed multiple soil-related properties with different units. This input–output pairing yields the reference system, which allows to calculate the achievable rate of output efficiency/capability. It also allows to compare output scores across different space and time scales (e.g., different soilscapes and at multiple time periods). Thus, the integration of econometric and pedometric methods holds the potential for scientists to move beyond the mapping of soil properties to assess soil functions, ecosystem services, risks, quality, and security. These methods may also help propel soil science into a new era that allows the assessment of complex soil–environmental phenomena and their monitoring through time and in space. It is envisioned that the DEA and similar econometric methods are useful to assess nutrient availability and the capacity of soil, water, and other ecosystems under varying stressors, such as changes in land use, climate, or management.

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