The Soil Management Assessment Framework: A Quantitative Soil Quality Evaluation Method

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ABSTRACT

Erosion rates and annual soil loss tolerance (T) values in evaluations of soil management practices have served as focal points for soil quality (SQ) research and assessment programs for decades. Our objective is to enhance and extend current soil assessment efforts by presenting a framework for assessing the impact of soil management practices on soil function. The tool consists of three steps: indicator selection, indicator interpretation, and integration into an index. The tool's framework design allows researchers to continually update and refine the interpretations for many soils, climates, and land use practices. The tool was demonstrated using data from case studies in Georgia, Iowa, California, and the Pacific Northwest (WA, ID, OR). Using an expert system of decision rules as an indicator selection step successfully identified indicators for the minimum data set (MDS) in the case study data sets. In the indicator interpretation step, observed indicator data were transformed into unitless scores based on site-specific algorithmic relationships to soil function. The scored data resulted in scientifically defensible and statistically different treatment means in the four case studies. The efficacy of the indicator interpretation step was evaluated with stepwise regressions using scored and observed indicators as independent variables and endpoint data as iterative dependent variables. Scored indicators usually had coefficients of determination (R^2) that were similar or greater than those of the observed indicator values. In some cases, the R^2 values for indicators and endpoint regressions were higher when examined for individual treatments rather than the entire data set. This study demonstrates significant progress toward development of a SQ assessment framework for adaptive soil resource management or monitoring that is transferable to a variety of climates, soil types, and soil management systems.

High rates of soil erosion, losses of organic matter, reductions in fertility and productivity, chemical and heavy metal contamination, and degradation of air and water quality have sparked interest in the concept of soil quality (SQ) and its assessment (Larson and Pierce, 1991; National Research Council, 1993; Doran and Parkin, 1994; Karlen et al., 2001). Although it has a variety of (sometimes conflicting) definitions in the current literature, SQ is most often defined as "the capacity of the soil to function" (Karlen et al., 1997). Some important soil functions (or ecosystem services) include: water flow and retention, solute transport and retention, physical stability and support; retention and cycling of nutrients; buffering and filtering of potentially toxic materials; and maintenance of biodiversity and habitat (Daily et al., 1997). The term dynamic SQ refers to the effects of human use and management on these soil functions (Seybold et al., 1998). Because improper management can lead to deleterious changes in soil function, a need for tools and methods to assess and monitor SQ was recognized (e.g., Doran and Jones, 1996).

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Published in Soil Sci. Soc. Am. J. 68:1945–1962 (2004).

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Although some misconceptions exist, the recent emphasis on soil function (and dynamic soil quality) is not intended to detract from the importance of soil taxonomy, where inherent soil properties, resulting from the five soil forming factors (Jenny, 1941), and land use suitability are emphasized. Soil quality uses taxonomy as a foundation (Karlen et al., 2003). The specific definition of soil quality for a particular soil is dependent on its inherent capabilities, the intended land use, and the management goals. For instance, optimum levels of organic matter (and other soil properties) will differ depending on the condition under which the soils formed, leading to variation in potential functioning. The use-dependence of the SQ concept can be illustrated simply: the functions, properties, and processes necessary to hold up a physical structure are not the same as those needed to grow a crop. More subtly, the soil qualities (functions or properties) critical for environmentally benign land application of animal waste are not identical to those for maximized production—even within the same field or under the same crop.

As with defining SQ, assessing SQ also requires consideration of taxonomy, land use and management goals. Appropriate SQ assessment measures a soil's changes in function in response to management, within the context of what the soil is being asked to do, its inherent properties, and environmental influences, such a temperature and precipitation. The target or optimum soil quality is not one standard for the USA or the world; instead, it is a series of thresholds defined by limiting factors and user needs.

Indicators of SQ can be defined loosely as those soil properties and processes that have greatest sensitivity to changes in soil function. Doran and Parkin (1996) emphasized that SQ indicators should correlate well with ecosystem processes, integrate soil properties and processes, be accessible to many users, sensitive to management and climate, and, whenever possible, be components of existing databases. Indicator groups or MDSs, used to indirectly measure soil function, must be sufficiently diverse to represent the chemical, biological, and physical properties and processes of complex systems (Gregorich et al., 1994; Doran and Parkin, 1996; Snakin et al.,

Abbreviations: AGG, water-stable aggregates; AWC, plant-available water-holding capacity; D_b, bulk density; EC, electrical conductivity; MBC, microbial biomass C; MDS, minimum data set; NRI, Natural Resources Inventory; PMN, potentially mineralizable N; R^2, coefficient of determination; SMAF, Soil Management Assessment Framework; SOM, soil organic matter; SQ, soil quality; T, soil loss tolerance; SAR, sodium adsorption ratio; TOC, total organic C; WS, watershed.

1996; Karlen et al., 2003). While the concept of indirect measures (indicators) has been widely used to monitor water quality (Karr, 1981), the idea was first applied to soil function through pedotransfer functions (Larson and Pierce, 1991). Because there are so many competing uses and inherent limitations for the world's soils, the components of a MDS are not universal: the appropriate indicators for indirect assessment of soil function are determined by which functions are critical to meet management goals (Harris et al., 1996; Andrews et al., 2002a).

Larson and Pierce (1991) argued that the measure of SQ in agriculture should no longer be limited to productivity goals, inferring that emphasizing productivity may have contributed to soil degradation in the past. The design of any generalized assessment tool for SQ must be flexible enough to capture multiple soil functions in various combinations. This must be accomplished with respect to the broader goals of sustaining plant and animal productivity, maintaining or enhancing water and air quality, and supporting human health and habitation (Karlen et al., 1997). In addition, a SQ assessment tool needs to interpret the indicators of those functions in terms of the inherent abilities of the soil and climate in which the assessment takes place. Such a tool would address most of the misgivings and misconceptions among those who have reservations regarding the SQ concept (e.g., Sojka et al., 2003), by using quantitative laboratory analyses, providing site-specific interpretations, and evaluating and understanding management effects on a specific soil resource with respect to multiple endpoints (which are outcomes driven by management or societal goals, e.g., productivity and environmental quality).

The objectives for this current work were (i) to design a tool to assess the relative effects of management on SQ based on indicator measurement, and (ii) to test the framework for transferability across soils, climate, and management practices.

This paper outlines a three-step framework (without describing details of the computer code), called the Soil Management Assessment Framework (SMAF), and imparts the results of its application to four case studies that vary in climate, management practice, spatial extent, and soil type. The case study demonstration shows how the framework interprets soil indicator data and computes relative SQ indices to compare management practices or monitor change over time. We call on other researchers to continue to test, critique, and refine the SMAF as a tool for sustainable soil management.

MATERIALS AND METHODS

Soil Management Assessment Framework Design

The SMAF is designed to follow three basic steps: indicator selection, indicator interpretation, and integration into a SQ index value (Andrews, 1998) (Fig. 1). An object-oriented Java version of the SMAF is currently under development. An Excel[1] (Microsoft Inc., Redmond, WA) spreadsheet containing

[1]Mention of a trademark, proprietary product, or vendor does not constitute a guarantee or warranty of the product by the USDA and does not imply its approval to the exclusion of other products or vendors that may also be suitable.

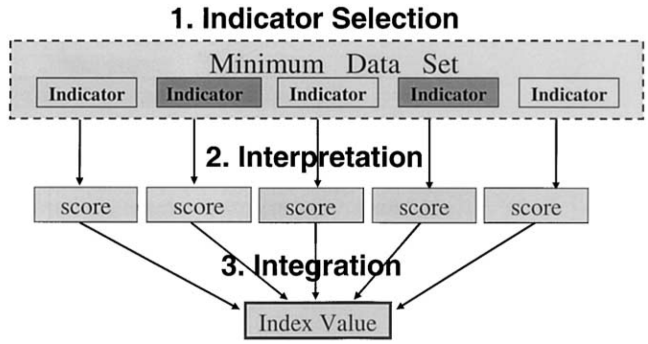

Fig. 1. Conceptual framework for the soil management assessment tool (after Andrews, 1998).

the second and third steps is available on request from the authors. It is not within the scope of this paper to describe the computer code in detail but we do describe the driving logic statements and algorithms used.

Indicator Selection

The SMAF uses a series of decision rules (Bellocchi et al., 2002; Schadt et al., 2002), in a database format, to generate a list of suggested MDS indicators from the more than 80 integrative measurements related to ecosystem processes and function currently residing in the database. The decision rules use the management goals for the site, associated soil functions, as well as other site-specific factors, like region or crop sensitivity, as selection criteria. These rules tables serve as an expert system to select appropriate SQ indicators (Andrews et al., 2002a).

To generate a list of suggested indicators, a user of the tool replies to a number of questions, one of which pertains to the user's primary management goal for the site. A table in the database identifies the critical functions associated with each management goal: maximize productivity, waste recycling, or environmental protection (Table 1). For example, if the user chooses waste recycling as the primary management goal, the program identifies the functions nutrient cycling, water relations, filtering and buffering, and resistance and resilience as important to that goal. There are currently three management goals and six functions identified in the program's database but more can easily be added if additional land uses are targeted.

In a second database table, a list of indicators is associated with each identified soil function. The list is further narrowed using several additional criteria: climate, crop or rotation, tillage practice(s), assessment purpose, and inherent soil properties (such as organic matter class, texture, slope, degree of weathering, or pH). Each indicator has a unique combination of goals, functions, and additional criteria that must be satisfied for it to be suggested as a MDS indicator. Table 2 shows a subset of potential indicators for the soil functions and associated management goals. The entire database includes 81 indicators and 169 selection rules, which are combinations of functions and other criteria for selection, making an average of approximately two selection scenarios per indicator. The database structure of the decision rules program for Step 1 allows for easy updates and refinements: goals, functions, indicators, selection rules, and their associations can all be altered, added or deleted via changes to the database, updating selection rules without altering the program itself.

The resulting suggested indicator list is grouped according to critical soil function. The user is asked to select four to eight indicators with at least one indicator from each function. To maximize flexibility and accessibility, the user has final say as

Table 1. Potential management goals and associated soil functions used to select appropriate soil quality indicators.

Management goal	Supporting soil function	Reference for soil function
Productivity†	nutrient cycling¶	Doran and Parkin (1994); Seybold et al. (1998)
Waste recycling‡	water relations#	Harris et al. (1996); Seybold et al. (1998)
Environmental protection§	physical stability and support††	Daily et al. (1997); Doran and Parkin (1994); Harris et al. (1996); Seybold et al. (1998)
	filtering and buffering‡‡	Daily et al. (1997); Harris et al. (1996); Seybold et al. (1998)
	resistance and resilience§§	Doran and Parkin (1994); Karlen et al. (1994)
	biodiversity and habitat¶¶	Doran and Parkin (1994); Karlen et al. (1994); Seybold et al. (1998)

† The Productivity Goal is defined as enhancing or maintaining the production quantity, quality, and stability of economically important plants as a primary management concern.
‡ The Animal Waste Recycling Goal involves the reuse of animal (or other) waste to eliminate it from the waste stream, while providing fertilizer and other added values in an environmentally sound manner as a primary management concern.
§ The Environmental Protection Goal is defined as the use of efficient practices that enhance or maintain the quality of the soil, air and water on-farm and in the surrounding ecosystem as a primary management concern.
¶ Nutrient cycling–Soils that are functioning well have a high potential to provide optimal amounts of essential plant available nutrients and tie up excess nutrients that may be toxic to plants or harmful if released to air or water.
# Water and solute flow–Water movement is important to provide water within a plant's root zone and to allow for the movement of nutrients and beneficial soil organisms in solution. Partitioning and storage of water and solutions can maximize deep percolation for ground water recharge and help soils withstand erosive forces.
†† Physical Stability and structural support–Soils that function well have a physical structure that provides a medium for plant root growth and withstands the erosive forces of wind and water. Soil structure is closely related to and often necessary for many other functions.
‡‡ Filtering and Buffering–Soils have a natural capacity to degrade or reduce toxic or hazardous compounds. When functioning properly, soils can make moderate amounts of certain contaminants less toxic to plants and animals, often by degrading the compound or adsorbing it onto a particle surface.
§§ Resistance and resilience–These two related terms refer to the functional stability of the soil ecosystem; that is, they are measures of the stability of the other (listed) functions. Resistance is the ability of a soil to maintain function in the face of disturbance (i.e., to resist change). Resilience is the ability of a soil to bounce back after a disturbance. These disturbances can be human-induced (such as tillage or pesticide application) or natural (like a large storm) (Herrick and Wander, 1998).
¶¶ Biodiversity and habitat–This function refers to the soils' natural ability to provide the necessary conditions to support a variety of unstressed plants and animals. It is agronomically important for integrated pest management, nutrient cycling, and ecotourism (health of the surrounding ecosystem).

to which indicators are selected for the MDS and can elect to ignore the suggested list or use a different number of indicators (i.e., greater than four or less than eight). At this time, although all 80+ indicators can be offered for the suggested list, only 10 are available for use in the next step (because scoring algorithms have yet to be fully developed).

Indicator Interpretation

After selecting (Step 1) and measuring the appropriate indicators for the MDS, indicator interpretation (Step 2) involves transformation of each observed MDS indicator value using nonlinear scoring curves (e.g., Karlen and Stott, 1994; Andrews et al., 2002a, 2002b). It is assumed that indicator measures are performed according to standard methods for the near surface (0–15 cm) and that sampling design is appropriate for the area to be assessed (see the case study section for examples). Measured values are transformed into unitless values so that scores may be combined to form a single value in Step 3. The use of scoring curves for data analysis and synthesis allows interpretations to reflect both ecosystem function and farmer and societal values regarding crop production and environmental protection (Schiller et al., 2001). For example, society currently places a value on the protection of surface water, therefore, the measurements for soil P that are above what is necessary for crop production receive lower scores, particularly on sloping land, to reflect the increased risk of surface water contamination (Fig. 2). Scoring curves are used in a similar manner in a variety of disciplines such as measurement of utility in economics (e.g., Norgaard, 1994), evaluation of decision outcomes in multi-objective decision science (e.g., Yakowitz et al., 1993), and assessment and modeling in systems engineering (e.g., Wymore, 1993).

Each SMAF scoring curve consists of an algorithm or logic statement (e.g., if, then, else) with alternative algorithms (Table 3). The algorithms are quantitative relationships between empirical values of measured indicators and normalized scores, reflecting the performance of ecosystem service(s) or soil function(s). In the framework, each indicator measure is transformed via the scoring algorithm into a unitless score (0 to 1) that represents the associated level of function in that system. An indicator score of 1 represents the highest potential function for that system, that is, the indicator is nonlimiting to pertinent soil functions and processes, within the soil's inherent capability.

We assume the general relationship between a given indicator and the soil function(s) it represents holds relatively constant among systems. This relationship dictates the shape of an indicator's scoring curve (or the algorithm's equation). Some general shapes include more-is-better (upper asymptotic sigmoid curve), less-is-better (lower asymptote), and mid-point optima (Gaussian function) (Karlen and Stott, 1994; Andrews and Carroll, 2001; Andrews et al., 2002a, 2002b). Current scientific knowledge allows us to predict general shapes and the flexibility of the framework will make refinements simple as the knowledge base improves.

The nonlinear scoring algorithms were originally constructed using a curve-fitting program, CurveExpert v. 1.3 shareware (available online at http://curveexpert.webhop.biz/ [verified 22 June 2004]). The curve shapes were determined by literature review and consensus of collaborating researchers. Total organic C (TOC) and water stable aggregation (AGG) are ascending logistic or more-is-better functions based on their roles in soil fertility, water partitioning, and structural stability (Tiessen et al., 1994; Herrick and Wander, 1998). Plant available water holding capacity (AWC) was assigned a more-is-better curve, based on the role of water availability for crop productivity and other biological activity (e.g., Gregory et al., 2000). The more-is-better curve was also used for potentially mineralizable N (PMN) based on nutrient availability and a theorized relationship between microbial activity and plant productivity (e.g., Hendrix et al., 1990; Sparling, 1997). The more-is-better curve was also used for microbial biomass C

Table 2. A subset of potential indicators for each function (with associated management goals in parentheses) including: the additional selection criteria for that indicator; the case study for which each rules set applied (if any); and references for each indicator or selection criteria (when available).

Soil function	Indicator†	Criteria for selection of indicator ‡	Case study	Reference for use as SQ indicator§
Biodiversity and habitat (environmental goal)	MI	large spatial area of interest (Neher et al., 1995)	NRI (as endpoint)	Bongers (1990); Linden et al. (1994); Blair et al. (1996)
	qCO_2	environmental management goal or C change assessment	(not used)	Gregorich et al. (1994); Sparling (1997)
Filtering and buffering (waste managment and environmental goals)	D_b	manure management goal	GA	Larson and Pierce (1991); Doran and Parkin (1994); Arshad et al. (1996)
	test P	environmental goal or manure applied (Sharpley et al., 2003; Sims, 1995)	NRI GA	Harris et al. (1996)
	TOC	always suggested under this function	NRI	Larson and Pierce (1991); Doran and Parkin (1994); Elliot et al. (1994); Sikora and Stott (1996)
Nutrient cycling (all goals)	MBC	C change assessment or alternative to PMN (Sparling, 1997)	NRI, IA GA	Turco et al. (1994); Gregorich et al. (1994); Rice et al. (1996)
	PMN	always suggested under this function	NRI, IA	Doran and Parkin (1994), Needelman et al. (1999)
	soil pH	always suggested under this function	NRI, IA, CA, GA	Doran and Parkin (1994); Smith and Doran (1996); Karlen et al. (1996)
	test P	organic amendment comparison or southern region + productivity goal	CA	listed above
Physical stability and support (environment and productivity goals)	AGG	always suggested under this function	NRI, IA	Harris et al. (1996); Arshad et al. (1996); Karlen et al. (1996)
	D_b	clay texture + practice comparison	(not used)	listed above
	soil pH	arid region	NRI, CA	listed above
Resistance and resilience (all goals)	soil depth	environmental or productivity management goal	(not used)	Arshad et al. (1996); USDA-NRCS (2001); Grossman et al. (2001b)
	TOC	comparisons over time or C change assessment or organic amendment comparison	IA NRI CA, GA	listed above
Water relations (all goals)	AWC	always suggested under this function	GA	Larson and Pierce (1991); Lowery et al. (1996)
	D_b	tillage comparison	IA	listed above
	EC	arid regions or manure management goal	CA	Smith and Doran (1996)
	SAR	selected in arid regions	CA	Andrews et al. (2002a, 2002b)
	soil pH	arid region or manure management or fertilizer comparison + water quality	NRI, CA GA	listed above

† MI, nematode maturity index (used as an endpoint measure instead of a MDS indicator, see text); qCO_2, metabolic quotient (a proportion of soil respiration and microbial biomass); D_b, bulk density; test P, soil test P; TOC, total organic C; MBC, microbial biomass C; PMN, potentially mineralizable nitrogen (aerobic incubation); AGG, macroaggregate stability; AWC, available water capacity; EC, electrical conductivity; SAR, sodium absorption ratio.
‡ When the stated criteria are met under a given function, the corresponding indicator is suggested as a potential minimum data set component.
§ SQ, soil quality.

(MBC) based on its role as a pool of readily available C and N and an association with improved soil structural functioning (Elliott and Coleman, 1988; Hendrix et al., 1990). A lower asymptotic or less-is-better function was used for bulk density (D_b) because of the inhibitory effect that high D_b often has on root growth and soil porosity (Grossman et al., 2001b). Variations of mid-point optimum or Gaussian functions were used for soil pH (Whittaker et al., 1959; Smith and Doran, 1996) and electrical conductivity (EC) (Tanji, 1990) based on crop sensitivity and effects on nutrient availability. Scores for sodium adsorption ratio (SAR) were dependent on potential for soil dispersion, environmental (water quality) risk, and associated EC levels (Oster and Schroer, 1979; Hansen and Grattan, 1992). The mid-point optimum curve for P is based on crop response and environmental risk (Pierzynski et al., 1994; Maynard, 1997).

We assume that the expected range for each indicator will vary according to site-specific controlling factors, such as climate or inherent soil properties. For instance, in a southeastern U.S. Ultisol, a TOC of 2% would be considered a high value; this soil would receive a high TOC score. In a Midwestern Mollisol, however, a TOC of 2% would be considered a low value, consistent with a degraded soil. It would receive a correspondingly low score. The factors controlling these differences in expected range for TOC include average annual precipitation, average annual temperature, soil texture, and soil taxonomic suborder (as a surrogate for inherent soil organic matter). To model these associations between indicators, function, and controlling factors, one must have knowledge of (or make assumptions about) not only the appropriate curve shape (based on the indicator's relationship to ecosystem function) but also the expected direction of change in curve inflections as major controlling factors change. For instance, as temperature and precipitation increase, expected TOC decreases

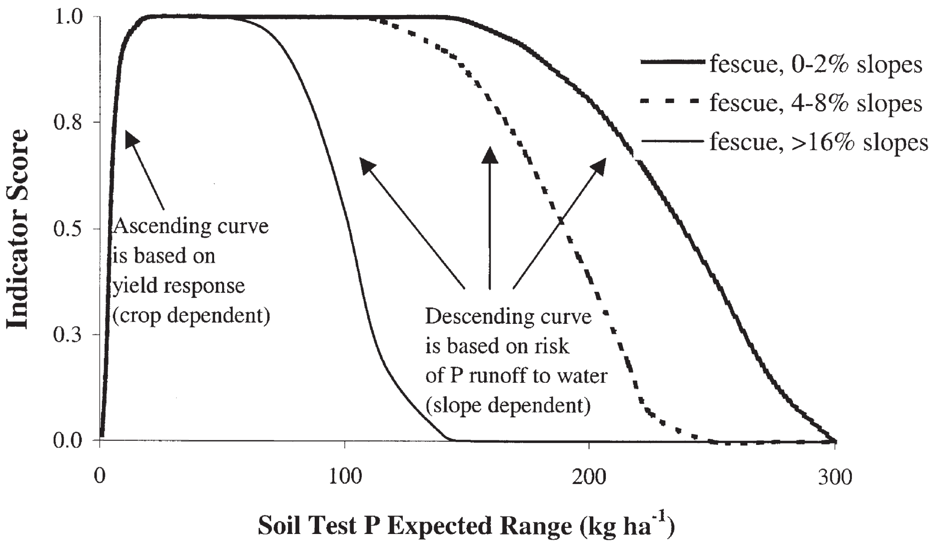

Fig. 2. Scoring functions for soil test P, showing differences based solely on slope: for sites with 0–2% slopes, for 4–8% slopes, and >16% slopes. Other assumptions made to generate this example were: P was determined using Mehlich III, soils were planted to fescue, and inherent soil characteristics include medium high organic matter (approximately 3.5–5% total organic C), silt or silt loam texture, and only slight weathering. In this example, the inflection points for the ascending portion of the curve depend on primarily crop requirements while the descending portion inflection points are largely dictated by slope.

due to increased decomposition rates under these conditions. This results in a shift to the left in the algorithm's inflection points.

We used CurveExpert v. 1.3 shareware to identify which parameters in the scoring curve algorithms needed to change to best represent the relationships between each indicator and soil function(s) in various systems, for example, climate, soil, and crop combinations. We also, by default, identified those parameters in the algorithms that do not change, which are termed fixed parameters. We then determined, via literature review, the most important controlling factors for each MDS indicator. We linked these controllers to the site-specific parameters, using database tables in Java and look-up tables in Excel. For example, the controlling factors for the D_b scoring-algorithm are texture and mineralogy (Table 3). Using a logic statement, the program chooses between two sets of parameters for one algorithm based on soil texture. As texture becomes coarser, Parameters b, c, and d change to reflect a greater tolerance of higher D_b's before root restriction or aeration become a problem. In clayey soils, mineralogy comes into play, such that glassy and smectitic soils have a lower tolerance of high D_b's compared with other mineral classes (Grossman et al., 2001a). Table 3 shows the algorithms, fixed parameters, site-specific parameters, and controlling factors for 10 scoring curves.

For some of the site-specific parameters, there were too many controlling factors to identify exact values for every possible combination. To circumvent this problem, we grouped some factors into classes that behave similarly. For instance, soil texture is grouped into five classes based on the work of Quisenberry et al. (1993). Conversely, a few parameters are modeled as continuous (rather than step) functions. For example, we used observed TOC as a site-specific factor in the test P scoring algorithm. By identifying expected trends in function due to controlling factors, this approach yields site-specific soil indicator interpretations without the need to construct formal thresholds for every possible combination of soil, climate, and crop.

Using these algorithms and their fixed and site-specific parameters, we created scoring curves that shift to provide a site-specific interpretation for each indicator. Figure 2 illustrates a hypothetical example of this phenomenon for the indicator soil test P (test P). The left side of the P scoring curve (ascending to an upper-asymptote) is based primarily on crop requirements (or crop class) and well supported in the literature (e.g., Maynard, 1997). The right side (lower-asymptote) reflects environmental risk (P runoff to surface water) and is based primarily on slope. (Slope is grouped into five classes: 0–2, 2–4, 4–8, 8–16, and >16%.) The right-side portion of the curve is currently less well defined in the literature. Both sides of the curve are influenced by observed TOC (as a continuous function), soil texture class (as a step function), and method of soil P detection (acting as classes to form a step function) as well (Fig. 2 and Table 3).

Integration into an Index

Step 3 of the SMAF, index integration, is optional but offers the potential to integrate all of the indicator scores from the previous interpretation step into a single, additive index value. This value is considered to be an overall assessment of SQ, reflecting management practice effects on soil function. Andrews et al. (2002a) found few differences among various integration techniques including additive (e.g., Andrews and Carroll, 2001), weighted (Harris et al., 1996); and max–min objective functions (e.g., Yakowitz et al., 1993) when used to combine nonlinearly scored indicator values. Therefore, we chose the simplest alternative, the additive index, for the integration step. This step is accomplished by summing the scores for each indicator, dividing by the total number of indicators, and then multiplying by 10 (Eq. [1]):

$$\mathrm{SQI} = \left(\frac{\sum_{i=1}^{n} S_i}{n}\right) \times 10 \qquad [1]$$

where S represents the scored indicator value and n is the number of indicators in the MDS.

Using the number of indicators in the MDS as a divisor corrects for any missing data in the data set. The index value was multiplied by 10 to provide index values in a range (1 to 10 rather than 0 to 1) found to be more amenable for producers and other potential users (Andrews et al., 2003).

Table 3. Algorithms and logic statements used for interpretation of the indicators, macroaggregate stability (AGG) (%), available water capacity (AWC) (g g^{-1}), bulk density (D_b) (g cm^{-3}), electrical conductivity (EC) (dS m^{-1}), microbial biomass C (MBC) (mg kg^{-1}), soil solution pH (pH) ($-$log H$^+$), potentially mineralizable N (PMN) (mg kg^{-1}), sodium absorption ratio (SAR), soil test P (test P) (mg kg^{-1}), and total organic C (TOC) (%), and the case study's minimum data set in which each indicator is found.

Indicator	Scoring Algorithm†	Fixed Parameters‡	Site-specific factors§	Selected site-specific factor references	Case study MDS¶
AGG	IF AGG > 50 AND [$y = a + b \times \cos(c \times \mathrm{AGG} - d) < 1$], THEN $y = 1$	$a = -0.8$, $b = 1.799$, c = 0.0196	$d = f$(iOM#, texture††, Fe_2O_3‡‡)	USDA (1966); Jastrow (1996)	NRI, IA
	ELSE $y = a + b \times \cos(c \times \mathrm{AGG} - d)$				
AWC	IF region = arid, THEN $y = (a \times b + c \times \mathrm{AWC}^d)/(b + \mathrm{AWC}^d)$,	$a = 0.0114$; $c = 1.088$; $d = 2.182$	region§§, $b = f$(texture, iOM);	Seybold et al. (1998); Gregory et al. (2000)	GA
	ELSE $y = a + b \times \cos(c \times \mathrm{AWC} + d)$	$a = 0.477$; $b = 0.527$; $c = 6.878$	$d = f$(texture)		
D_b	IF texture > 35% clay, THEN $y = a - b \times \exp(-c \times D_b^d)$,	$a = 0.994$	$b, c, d = f$(texture, mineralogy¶¶);	Grossman et al. (2001a, 2001b)	IA, GA
	ELSE $y = a - b \times \exp(-c \times D_b^d)$	$a = 0.994$	$b, c, d = f$(texture)		
EC	IF EC ≤ 0.3, THEN y = EC × 3.33,			Smith and Doran (1996); Maas (1990)	CA
	IF 0.3 < EC < T, THEN y = 1		T## = f(method†††, crop‡‡‡, texture); $b = f(T)$		
	IF EC ≥ T, THEN $y = a + b \times$ EC	$a = 1 - bT$			
MBC	$y = a/[1 + b \times \exp(-c \times \mathrm{MBC})]$	$a = 1.0$; $b = 40.478$	$c = f$(iOM, texture, season§§§)	Franzluebbers et al. (1996); Sparling (1997)	NRI, IA, GA
pH	$y = a \times \exp[-(\mathrm{pH} - b)^2/(2 \times c^2)]$	$a = 1.0$	$b, c = f$(crop)	Whittaker (1959)	NRI, IA, CA, GA
PMN	$y = a/[1 + b \times \exp(-c \times \mathrm{PMN})]$	$a = 1$; $b = 50.1$;	$c = f$(iOM, texture, climate¶¶¶)	Franzluebbers (1998); Jones et al. (1982)	NRI, IA
SAR	IF EC ≤ 0.2, THEN $y = 1/[a + b\,(\mathrm{SAR}^c)]$;	$a = 4.06$; $b = 0.79$; $c = 3.05$	EC	Hanson and Grattan (1992)	CA
	IF 0.2 < EC ≤ 0.55, THEN $y = a + b \times \mathrm{SAR} + c \times \mathrm{SAR}^2 + d \times \mathrm{SAR}^3 + e \times \mathrm{SAR}^4 + f \times \mathrm{SAR}^5 + g \times \mathrm{SAR}^6$;	$a = 0.8$; $b = 0.013$; $c = -0.07$; $d = 0.03$; $e = -0.005$; $f = 5.5 \times 10^{-4}$; $g = -2.1 \times 10^{-5}$	EC		
	IF EC > 0.55, THEN $y = a + b \times \mathrm{SAR} + c \times \mathrm{SAR}^2 + d \times \mathrm{SAR}^3 + e \times \mathrm{SAR}^4$	$a = 1.0$; $b = -0.07$; $c = 0.012$; $d = -6.8 \times 10^{-4}$; $e = -2.39 \times 10^{-5}$	EC		
Test P	IF P ≤ max(for crop and method), THEN $y = (a \times b + c \times P^d)/(b + P^d)$;	$a = 9.26 \times 10^6$; $c = 1.0$; $d = 3.06$	$b = f$(crop, TOC, texture, method†††)	Havlin et al. (1999)	NRI, CA, GA
	IF P > max(for slope and method),THEN $y = a - b \exp(-c \times P^d)$, ELSE $y = 1$	$a = 1$; $b = 4.5$; $d = -2$	$c = f$(slope###, TOC, texture, method)	Sharpley et al. (2003)	
TOC	$y = a/[1 + b \times \exp(-c \times \mathrm{TOC})]$	$a = 1$; $b = 50.1$	$c = f$(iOM, texture, climate)	USDA (1966); Needelman et al. (1999)	NRI, IA, CA, GA

† Scoring algorithms transform data according to performance of soil function, where the indicator abbreviation is the observed measure (x) and y is the indicator score. Other variables in these algorithms are defined as either fixed parameters or site-specific factors in adjacent columns.
‡ Variables in the scoring algorithms that do not change.
§ Variables in the scoring algorithms that are site-dependent and, therefore, change as a function of site characteristics, such as soil type or climate.
¶ Listing of case studies that include the designated indicator in their mimimum data set (MDS).
# iOM = inherent organic matter levels grouped by soil suborder (USDA-NRCS, 1998; C. Seybold, personal communication, 2001).
†† Texture = soil texture grouped into five classes (Quisenberry et al., 1993).
‡‡ Fe_2O_3 = class includes ultic subgroup and Ultisols (USDA-NRCS, 1998).
§§ Region = major land resource areas grouped into arid versus non-arid or northern versus southern (USDA-SCS, 1981; Bailey, 1995).
¶¶ Clay mineralogy grouped as smectitic, glassy and other (USDA-NRCS, 1998).
T = crop- and EC method-dependent threshold level for EC beyond which yield reductions are expected to occur (Smith and Doran, 1996).
††† Method = the methodology used for the specified assay (Smith and Doran, 1996 [for EC]; Wolf and Baker, 1985 [for test P]).
‡‡‡ Crop = requirements for the current crop or, for EC, minimum threshold crop among all crops in a rotation (Smith and Doran, 1996; Maynard, 1997).
§§§ Season = expected seasonal changes as affected by climate (USDA-SCS, 1981; Bailey, 1995).
¶¶¶ Climate = major land resource areas classed by average annual precipitation and degree days above freezing (USDA-SCS, 1981; Bailey, 1995).
Slope P = slope classes for assessing P transport factors.

The Case Studies

Site Descriptions and Experimental Designs

We applied the SMAF to four large, existing data sets from studies conducted at different scales and regions within the USA. Site descriptions for each of the studies are presented below; metadata is summarized in Table 4.

The largest scale case study was a 1996 Natural Resources Inventory (NRI) pilot project, for which SQ indicator data were collected from a representative subset of the NRI monitoring sites located in Major Land Resource Area 9. This area comprises the Palouse and Nez Perce Prairies and spans southeastern Washington, northwestern Idaho, and northeastern Oregon. The approximately 23 140-km^2 region includes broad ranges in elevation and average annual precipitation and temperature (Brejda et al., 2000a, 2000b). The agricultural land uses in the region consist of about 50% cropland, most of which is dryfarmed to wheat (*Triticum aestivium* L.), spring pea (*Pisum sativum* L.), and lentils (*Lens culinaris* L.), 40% rangeland, and 10% permanent pasture or vegetable production (USDA-SCS, 1981). Soil samples were collected irrespective of soil series or land use using the NRI sampling design (Brejda et al., 2000a, 2000b).

For the Iowa case study, we used data collected in 1994 and 1995 from two field-scale watersheds (WS) with a 25+ yr tillage system comparison at the Deep Loess Research Station near Treynor, IA. One of the watershed treatments (WS2) was cropped to continuous corn (*Zea mays* L.) on the contour from 1964 to 1995. The other watershed treatment (WS3) was used for cattle grazing from 1964 to 1972, and then converted to continuous corn production using ridge tillage in 1972 (Cambardella et al., 2004). Soils at summit positions are Monona silt loams (fine-silty, mixed, superactive, mesic Typic Hapludolls). Ida or Dow silt loam soils (fine-silty, mixed, calcareous, mesic Typic Udorthents) are found in backslope positions. Footslope soils are generally Napier or Kennebec silt loams (fine-silty, mixed, superactive, mesic, Cumulic Hapludolls) (Karlen et al., 1999). Twelve sampling locations were distributed within each WS based on soil series, slope, and erosion class. Locations were consistent each year.

A third study, the Sustainable Agriculture Farming Systems project, involved 1.2-ha plots managed using different vegetable production systems near Davis, CA (Clark et al., 1998, 1999a, 1999b) in a randomized split plot design. The four management system treatments differed by crop rotation and use of external inputs: conventional 2 yr (Conv-2), conventional 4 yr (Conv-4), low input, and organic. Both conventional treatments received applications of synthetic pesticides and fertilizers at rates recommended for the region by University of California Cooperative Extension Service. The Conv-2 rotation consists of processing tomato (*Lycopersicon esculentum* Mill.) and wheat. The Conv-4 rotation was tomato, corn, safflower (*Carthamus tinctorius* L.), and wheat and dry beans (*Phaseolus vulgaris* L.) (double cropped). The organic treatment used composted and aged animal manures, rotations of winter cover crops, and some organic supplements for fertility and pest management. The low treatment combined both synthetic and organic techniques: synthetic fertilizer was applied at about one half the recommended rate and pesticide use was reduced by cultivation and hand hoeing. The organic and low treatments had identical cash crop rotations of tomato, safflower, corn, oats (*Avena sativa* L.) + vetch (*Vicia* spp.), and dry beans (double cropped) (Clark et al., 1998, 1999a, 1999b; Andrews et al., 2002a). All possible entry points for the rotations were represented each year. The soils were classified as Reiff loams (coarse-loamy, mixed, nonacid, thermic Mollic Xerofluvents) and Yolo silt loams (fine-silty, mixed, nonacid, thermic Typic Xerorthents). We used the 1996 data set.

The smallest scale case study was a plot-scale experiment in Georgia to compare the residual effects of fresh versus composted broiler litter on SQ in tall fescue (*Festuca arundinacea*) pasture, 3 yr after application (Andrews, 1998; Andrews and Carroll, 2001) in May 1995. Four experimental treatments (split application totals) consisted of surface-applied poultry (broiler) litter applied at approximately 1845 kg N ha^{-1}; surface-applied composted broiler litter at approximately 1845 kg N ha^{-1} (representing the high end of litter application rates in the region); surface-applied ammonium nitrate treatment providing 100 kg N ha^{-1}, 13 kg P ha^{-1}, and 33 kg K ha^{-1}; and a no amendment control, applied in a randomized complete block design (Tyson, 1994). The high litter amendment rates were representative of (the high end of) surface applications for waste disposal in the region. The study was conducted at two locations, with four blocks at each site: near Calhoun, GA, on a Conasauga silt loam (fine, mixed, semiactive, thermic, Oxyaquic Hapludalfs) in the Southern Appalachian Ridges and Valleys region; and near Farmington, GA, on a Cecil sandy loam (fine, kaolinitic, thermic, Typic Kanhapludults) in the Piedmont region.

Laboratory Analyses

The SQ indicators were measured for bulked core samples taken from 0 to 10 cm (for NRI), 0 to 15 cm (at IA and CA), and 0 to 5 cm (for GA) of soil at each case study location, using standard methods. The NRI dataset included approximately 20 chemical, biological, and physical indicators (Brejda et al., 2000a, 2000b). The Iowa study included 21 chemical,

Table 4. Selected metadata for the soil management assessment framework (SMAF) case studies: the 1996 Natural Resources Inventory (NRI); Deep Loess Research Station, 1994–1995 (IA); Sustainable Agriculture Farming Systems project, 1996 (CA); two Experiment Stations in northeast and northwest Georgia, 1995 (GA).

	Case study			
Property	NRI	IA	CA	GA
Location	ID, WA, OR	near Treynor, IA	near Davis, CA	Calhoun and Farmington, GA
Scale	regional	30–60 ha watersheds	1.2 ha plot	2.5 m plot
Treatment	multiple land uses	conventional and minimum tillage	vegetable production system	poultry litter amendment
Soil suborders	primarily Xerolls, Albolls, Xeralfs	Udolls, Orthents	Fluvents, Orthents	Udults, Udalfs
Data types	chemical, biological, and physical	chemical, biological, and physical	mostly chemical	chemical, biological, and physical
Source	NRI pilot†	DLRS‡	SAFS§	Andrews¶
Management goal	environmental protection	productivity	productivity	manure (or waste) management

† Natural Resources Inventory pilot study (Brejda et al., 2000a, 2000b).
‡ Deep Loess Research Station (Cambardella et al., 2004).
§ Sustainable Agricultural Farming Systems project (Clark et al., 1998, 1999a, 1999b).
¶ Ph.D. dissertation (Andrews, 1998) and previous SQ assessment publication (Andrews and Carroll, 2001).

biological, and physical indicators SQ indicators (Cambardella et al., 2004). The California dataset was comprised of 19, mostly soil chemical, SQ indicators (Clark et al. (1998).) The Georgia study included 38 chemical, biological, and physical SQ indicators (Andrews and Carroll, 2001). The indicators with methods described below are included in at least one case study MDS.

Aggregate stability was assessed according to methods described by Cambardella and Elliott (1993) and expressed as the percentage of the total soil that was water-stable macroaggregates >250 μm in diameter. Available water capacity was estimated by difference in water retention between soils held at 1.5 and at 0.01 MPa (15 and 0.1 bar) (Klute, 1986). Bulk density was estimated by a modified core method (Blake and Hartge, 1986), in which soil moisture content, determined by drying a subsample of the cored soil at 105°C, was used to convert the total mass of the field-moist soil core to an oven-dry weight. Electrical conductivity (Rhoades, 1982) of saturated pastes (U.S. Salinity Laboratory Staff, 1954) was measured using a conductivity meter. Microbial biomass C was measured by fumigation–extraction method (Sparling and Ross, 1993) for the NRI, Iowa, and Georgia case studies, and by the chloroform-incubation method (Horwath et al., 1996) for the California study. Soil pH was determined in 1:1 soil/water for NRI and Georgia, 2:1 soil/water in Iowa, and saturated paste in California (Thomas, 1996). Potentially mineralizable N was measured using a 28-d aerobic incubation methods described by Drinkwater et al. (1996) (for IA and NRI) or Bundy and Meisinger (1994) (for CA). Sodium Adsorption Ratio was calculated using results from saturated paste extracts of Na^+, Ca^{2+}, and Mg^{2+} in milliequivalents per liter (U.S. Salinity Laboratory Staff, 1954). Soil test P was measured via a different method for the case studies: for NRI and IA studies, the method followed the Mehlich-III extraction procedure (Mehlich, 1984); at the California site it was determined by extracting samples with a 0.5 *M* sodium bicarbonate solution (Olsen et al., 1954); and the GA study used Mehlich-I double acid extraction (Kuo, 1996). Extractions were followed by inductively coupled plasma emission (NRI) or colorimetric detection via molybdate reaction. Total organic C (after removal of carbonates with 1 *M* H_2SO_4) was determined via dry combustion of dried ground samples using a gas analyzer (Pella, 1990).

Endpoint Measures

One reason the case studies were selected to demonstrate the framework was that their large, existing data sets included either direct endpoint measures or other indirect endpoint surrogates, which reflected the management or societal goals at each site. The available endpoint data varied with each case study. Some data were available for each sample point and other data were only available as treatment means (noted below). When only means were available, comparisons were made among treatment means rather than individual sample points. These endpoint measures and surrogates served as proxies for the identified management goals and were used to validate the efficacy of the MDS and indicator scoring.

The NRI case study included multiple land uses. Therefore, we assumed the management goal to be environmental protection. The endpoints were a percentage of C change and a nematode maturity index, which were calculated from the existing data. We defined the percentage of change in TOC to be the percentage of difference in observed TOC and mean soil survey TOC value for each observed soil series, as an indirect measure of C sequestration. We calculated the nematode maturity index based on the method of Bongers (1990). It is a measure of system disturbance based on the relative abundance of nematode functional groups or feeding guilds. The maturity index met the selection criteria in the selection rules database (in Step 1) (Table 2) and thus was a potential MDS indicator for this case study. We chose to use it as a endpoint measure instead, in part because there were few endpoints available for this dataset but also because: (i) increased biodiversity is a legitimate societal goal and (ii) the expertise and time involved in performing this measure makes it an unattractive indicator for future use.

Productivity was assumed to be the management goal for the Iowa case study. The endpoint measures were yield (Mg ha^{-1}), collected from plots at various landscape positions (e.g., hilltop or shoulder/summit, sideslope or backslope, and toeslope) that were adjacent to the soil sampling sites, and sedimentation (Mg ha^{-1}), measured as soil material leaving each WS in stream water collected at a weir. The endpoint surrogates, available as WS means, included pesticide application rates for atrazine and metalochlor (liters applied), as representatives of potential soil and water contamination.

The management goal for the California case study was assumed to be productivity. The endpoint measures used net revenues for each system (treatment means) and net revenues and yield for tomatoes (the main cash crop) (Clark et al., 1999b). The endpoint surrogates used included: water use efficiency (mm water × crop $yield^{-1}$); weed cover (%); and the number of tillage operations per year (treatment means only) (Andrews et al., 2002a), included as an indirect measure of soil disturbance.

The Georgia study's assumed goal was waste recycling. The available endpoint data, from Years 1 and 2, were amount of litter applied (kg dry litter applied ha^{-1}), using a conversion factor adapted from Safley and Safley (1991) to represent compost as an equivalent volume of fresh litter, and fescue yield (kg dried biomass ha^{-1}). Both litter applied and yield were available as treatment means only. From Year 3, when soils were sampled, the endpoint surrogates used were soil extractable As and Cu, determined via Mehlich-I double acid extraction (Amacher, 1996). These metals are common poultry feed fungicidal components and serve as proxies for all metal contaminants.

Statistics

We used JMP v. 3 software for Windows (SAS Institute, Cary, NC) for all statistical analyses. We performed analysis of variance (ANOVA) on the observed and the scored MDS indicators, to compare the statistical differences between treatments in each case study with and without scoring (Step 2). We also examined the overall index values in Step 3 by plotting and analyzing treatment means and standard deviations using ANOVA and Student's *t*. Finally, we performed stepwise regressions of all available indicators (independent variables) and endpoints (as iterative dependent variables) for each case study. The p values for acceptance and rejection in the stepwise models were 0.25 and 0.1, respectively. Examining the incidence of MDS indicators that were not added to the regression models acted as a check of the indicator selection step. We also examined the efficacy of indicator scoring by comparing the R^2 for regressions using scored versus observed data. The indicators available for the regressions were limited to those having scoring curves (see Table 3), to allow the direct comparison of observed and scored regression results. To make the R^2 values comparable among models with different numbers of parameters, we report the adjusted coefficients of determination (R^2) value, which uses the degrees of freedom in its calculation (SAS Institute, 1995).

RESULTS AND DISCUSSION

Beginning with several concept papers (e.g., Doran and Parkin, 1994; Larson and Pierce, 1991; Karlen and Stott, 1994), quantitative SQ assessments have been reported widely in the literature over the past decade (e.g., Karlen et al., 1994, 1996, 1998; Bockstaller et al., 1997; Beare et al., 1999; Hussain et al., 1999; Liebig and Doran, 1999a, 1999b; Wander and Bollero, 1999; Andrews and Carroll, 2001; Liebig et al., 2001; Andrews et al., 2002a, 2002b; Herrick et al., 2002). Andrews et al. (2002a) first documented the three-step process on which the current tool was developed. The tool, SMAF, is called a "framework" because it is intended to be malleable so that it can be applied in a variety of climates, soil types, management practices, and end-user goals.

Currently, SMAF's focus is on agricultural land use but that, too, is flexible. This tool is concerned with the evaluation of change in soil function as a result of management, using SQ indicators (that are dynamic or use-dependent soil properties) interpreted with respect to taxonomy, climate, land use, and goals. The tool, therefore, does not address the question of whether the user's goals are actually appropriate for a particular site. That would be a land capability question that relates to inherent soil properties that do not readily change due to management.

The results from the four case studies, presented below, are organized according to the three steps of the framework.

Indicator Selection

Using the decision rules developed for Step 1 of the SMAF, a set of indicators (MDS) was chosen for each case study. Table 2 illustrates the subset of rules applied to generate the case study MDSs. The NRI MDS was composed of AGG, MBC, pH, PMN, test P, and TOC, following rules for the environmental protection goal in arid systems. The indicators selected for the Iowa MDS were: AGG, BD, MBC, pH, PMN and TOC, applying rules for a productivity goal, tillage comparisons, and assessments over time. The California MDS indicators were: EC, pH, SAR, test P, and TOC, using criteria such as productivity goal, arid region, and organic amendment comparison. For the Georgia study, the selected MDS indicators were: AWC, BD, MBC, pH, test P, and TOC, applying the criteria for manure management. The selected MDSs consisted of biological, chemical, and physical SQ indicators suggested by several authors including Larson and Pierce (1991), Doran and Parkin (1994, 1996), and Seybold et al. (1998). All of these published SQ minimum data sets include TOC and pH, which were selected as indicators for all four studies, because of their importance and influence on so many critical soil functions. However, it is the decision rules *process* of Step 1 that we are trying to convey, not the specific indicators selected. Therefore, these results should not be taken as a recommendation for the indicators named.

To check the efficacy of SMAF Steps 1 and 2, we performed stepwise regressions using the observed and scored indicators as independent variables and endpoints (or endpoint surrogates) as iterative dependent variables for each case study (Table 5) (Results germane to Step 2 are discussed in the next section.). Most of the selected MDS indicators were added to the stepwise regressions models, with the following exceptions: scored AGG was not added to the NRI regressions, PMN was not part of any of the Iowa stepwise regressions; and scored D_b was not selected for the Georgia regressions. Although these indicators were not part of the MDSs, each was suggested for possible MDS inclusion according to the rules table. The authors chose not to include every possible indicator in an effort to keep the MDSs' size small.

The stepwise regressions added indicators in some cases that were not immediately explicable. For instance, test P was not expected to be explanatory of water use efficiency in the California dataset. While the decision rules are quite flexible, it is not possible to capture this type of spurious relationship in an expert system, nor would it be advisable to try.

In a study comparing indexing methods, Andrews et al. (2002a) found that both expert opinion- and multivariate statistic-selected MDS indicators performed equally well in describing the variation in endpoint measures or their surrogates, such as yield, water use efficiency, and weed biomass. In the multivariate selection method, indicator covariance was checked and redundant indicators eliminated from the MDS. Since this added step did not affect the MDS performance, covariance is not considered in the current selection step. (The covariance of indicators acts as a built-in weighting factor for the related indicators in Step 3, when indicator scores are combined.) The decision rules of Step 1 were based on expert opinion of those familiar with each indicator and literature review, similar to the Andrews et al. (2002a) study but formalized into an expert system format.

In practice, Step 1 would occur before data collection. Because the case data was pre-existing, indicator selection was constrained by the indicators available in each data set. Nevertheless, using the assumed management goals and site-specific data for each study resulted in lists of suggested indicators that included a subset of the available data that could be used for MDSs. We envision this step being useful by itself for choosing indicators for adaptive management, monitoring, or assessment. Conversely, it could be skipped entirely when a minimum data set already exists.

Indicator Interpretation

After selecting an appropriate MDS for each study, we evaluated the framework's sensitivity to site-specific differences by examining shifts in scoring algorithms (or expected ranges) for each indicator. Plotting the observed and scored values for each indicator illustrated how the algorithms responded to changes in controlling factors, such as soil type, crop, and climate, within and among the case studies (Fig. 3). The shifting inflection points and expected ranges were based on the best avail-

Table 5. Stepwise regression of observed and scored indicator values with endpoint or endpoint surrogates for each case study. Indicators in italics were added in the regression but not part of the selected MDS.

Endpoint or surrogate	Observed Adjusted R^2†	Observed Indicators added	Scored Adjusted R^2	Scored Indicators added
		NRI		
TOC change, %‡	0.66	TOC, MBC, P, PMN, AGG	0.54	TOC, test P
Nematode MI§	0.00	pH	0.00	
		NRI cropped Xerolls		
TOC change, %	0.65	TOC, test P	0.62	TOC, AGG
Nematode MI	0.04	MBC, TOC	0.04	MBC, PMN
		NRI Xerolls in no-tilled continuous small grains		
TOC change, %	0.62	TOC, MBC	0.62	TOC, P, PMN
Nematode MI	0.10	TOC	0.68	TOC, pH, PMN
		IA		
Sedimentation, Mg ha^{-1}¶	0.56	TOC	0.99	TOC, pH
Yield, Mg ha^{-1}	0.52	BD, pH	0.59	BD, *test P,* AGG
Atrazine (L applied)	0.99	*test P*, TOC	0.76	MBC
Metalochlor (L applied)	0.44	pH	0.99	TOC, pH
		CA		
Water use efficiency#	0.29	SAR, EC, test P	0.17	pH, test P, TOC
Weed biomass, %††	0.73	SAR, TOC, pH	0.55	TOC, pH, test P
Tillage operations‡‡	0.17	EC, pH	0.38	test P, TOC, pH
Net revenue, US$ ha^{-1}	0.72	TOC, P	0.72	TOC
		CA tomatoes		
Water use efficiency	0.83	TOC, pH	0.84	TOC
Weed biomass, %	0.88	TOC, SAR	0.89	TOC, SAR
Tillage operations	0.99	TOC, EC	0.97	TOC
Net revenue, US$ ha^{-1}	0.99	TOC, EC	0.89	pH
Yield, Mg ha^{-1}	0.36	P, PMN	0.25	test P
		GA		
Arsenic, μg kg^{-1}	0.45	pH, test P, AWC	0.41	test P, pH, AWC, MBC
Copper, μg kg^{-1}	0.21	*AGG*, AWC, test P	0.19	test P, pH, AWC, TOC
Yield, Mg ha^{-1}	0.37	AWC, test P	0.82	pH, test P, AWC, TOC
Litter applied, Mg ha^{-1}	0.55	AWC, BD	0.56	MBC, pH

† Adjusted R^2 is the coefficient of determination adjusted by the degrees of freedom in the model to account for differences in the number of variables in each model and allow comparisons among models (SAS Institute, 1995).
‡ Total organic C (TOC) change is the percentage of difference in observed TOC and mean Soil Survey TOC value for the observed soil series.
§ Nematode MI is the Maturity Index (Bongers, 1990), a measure of system disturbance based on the relative abundance of nematode functional group.
¶Sedimentation is estimated from amount of soil collected at a stream weir draining the watershed or field.
Water use efficiency as a proportion of water applied and crop yield.
††Percentage of weed cover sampled once per month, averaged over a 9-mo growing season.
‡‡Number of field passes for tillage operations.

able information but can be refined and altered as the knowledge base improves. Again, it is the mathematical framework allowing for site-specific interpretation that we wish to emphasize, not the specific parameters.

Although we attempted to make the framework and Step 2, in particular, as objective as possible, values and preferences are inherent in any decision-making process (Keeney, 1992). Even within basic science, the choice of what to study is value laden (Kuhn, 1970). Individual and society goals necessarily play a role in all interpretations and assessments. Specifying assumptions, stating goals, and building on other peer-reviewed science are the best ways to clarify and to some extent minimize, the unavoidable role of human values.

When examining the results of the site-specific interpretation step, four main patterns in treatment differences emerged when treatment means for the scored and observed indicators were compared using ANOVAs. These four patterns demonstrated the benefits associated with using scoring based on performance of function to help interpret indicator data for multiple objectives, including productivity and environmental protection.

The first and most commonly occurring pattern was characterized by similar results between case study treatments for an observed and scored indicator (Pattern 1) (Fig. 4a). Pattern 1 was seen for AGG, MBC, pH, PMN, and TOC in the NRI study; MBC at the IA study; EC, test P, and TOC at the California study; and AWC and pH in the Georgia case studies. This seemed to occur whenever the majority of observations fell on the ascending portion of the scoring algorithm, giving a 'more-is-better' result. The second pattern was when the observed and scored indicator values had opposite results (e.g., the highest observed treatment was the lowest after scoring—a 'less is better' effect) (Pattern 2) (Fig. 4b). This pattern was seen for test P in the NRI study; D_b at Iowa; pH at California; and test P in the Georgia case study. This opposite scoring pattern was seen when the majority of observations occurred on the descending portion of a curve. Pattern 2 for NRI was driven by the test P values in woodland, where very high observed test P values resulted in significantly lower scores for test P in this land use (data not shown). This could be due to P applications in managed forests or simply due to inherently high P in relatively undisturbed soils. If the latter, then the low score is unwarranted and would call for an adjustment to the algorithm under this land use. Unfortunately, the authors did not have enough information about the NRI management practices to make a determination. Because the curves were developed primarily

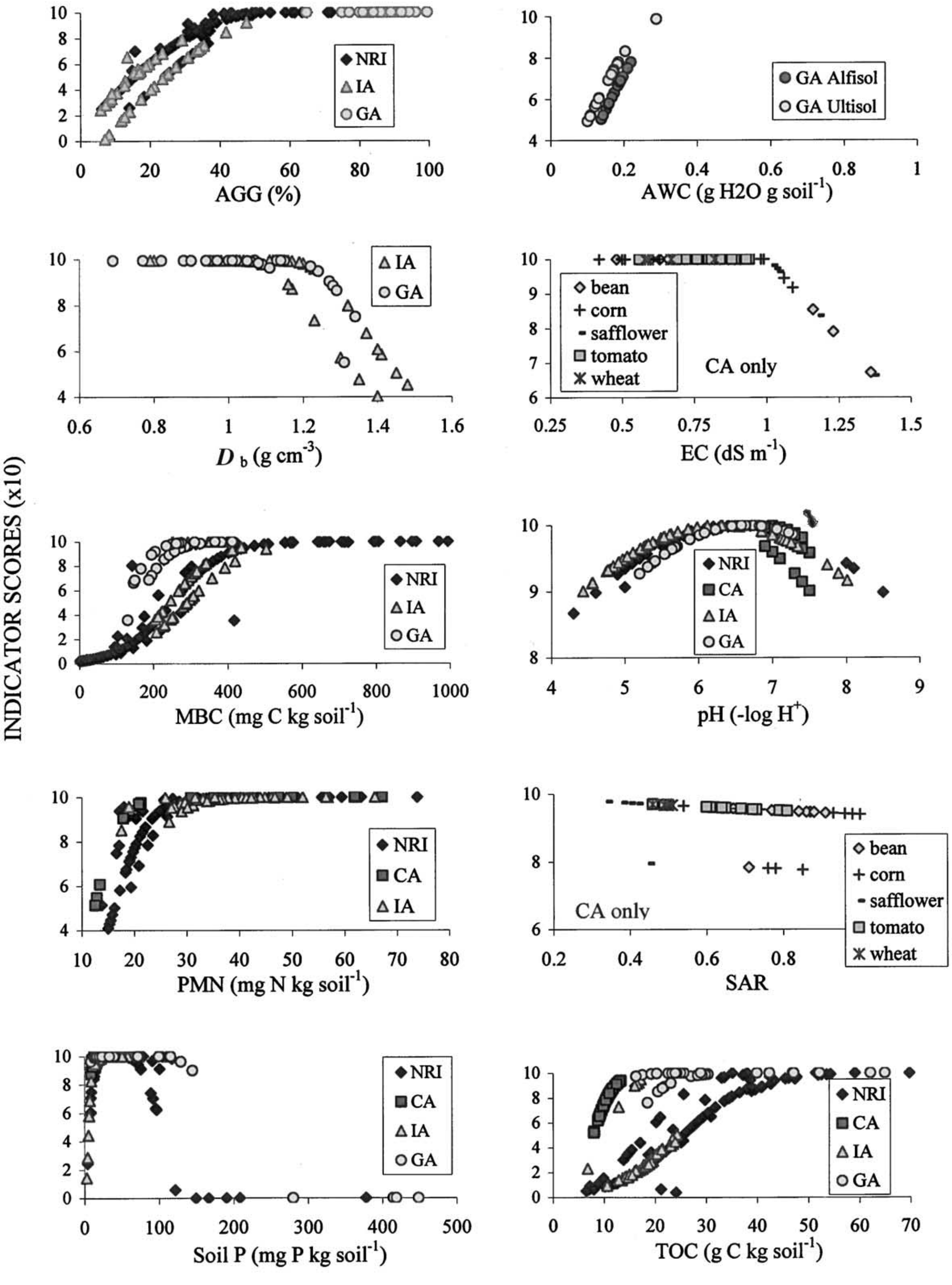

Fig. 3. Scoring algorithms (multiplied by 10) for all indicators and case studies, illustrating the site-specific shifts in scores. AGG, water-stable aggregates; D_b, bulk density; MBC, microbial biomass C; PMN, potentially mineralizable N; AWC, plant-available water-holding capacity; EC, electrical conductivity; SAR, sodium adsorption ratio; TOC, total organic C.

for agricultural land uses, we also looked at treatment differences in a more homogeneous subset of the NRI: cropped Xerolls. In those two-way ANOVAs, by cropping practice (continuous small grains vs. wheat-fallow) and tillage (till v. no-till), all indicators fit under Pattern 1, similar results for observed and scored. (Fig. 4a shows the Pattern 1 seen for PMN in the NRI subset).

The third pattern (Pattern 3) was characterized by observed indicator results that had significant differences but scored results that had no difference between

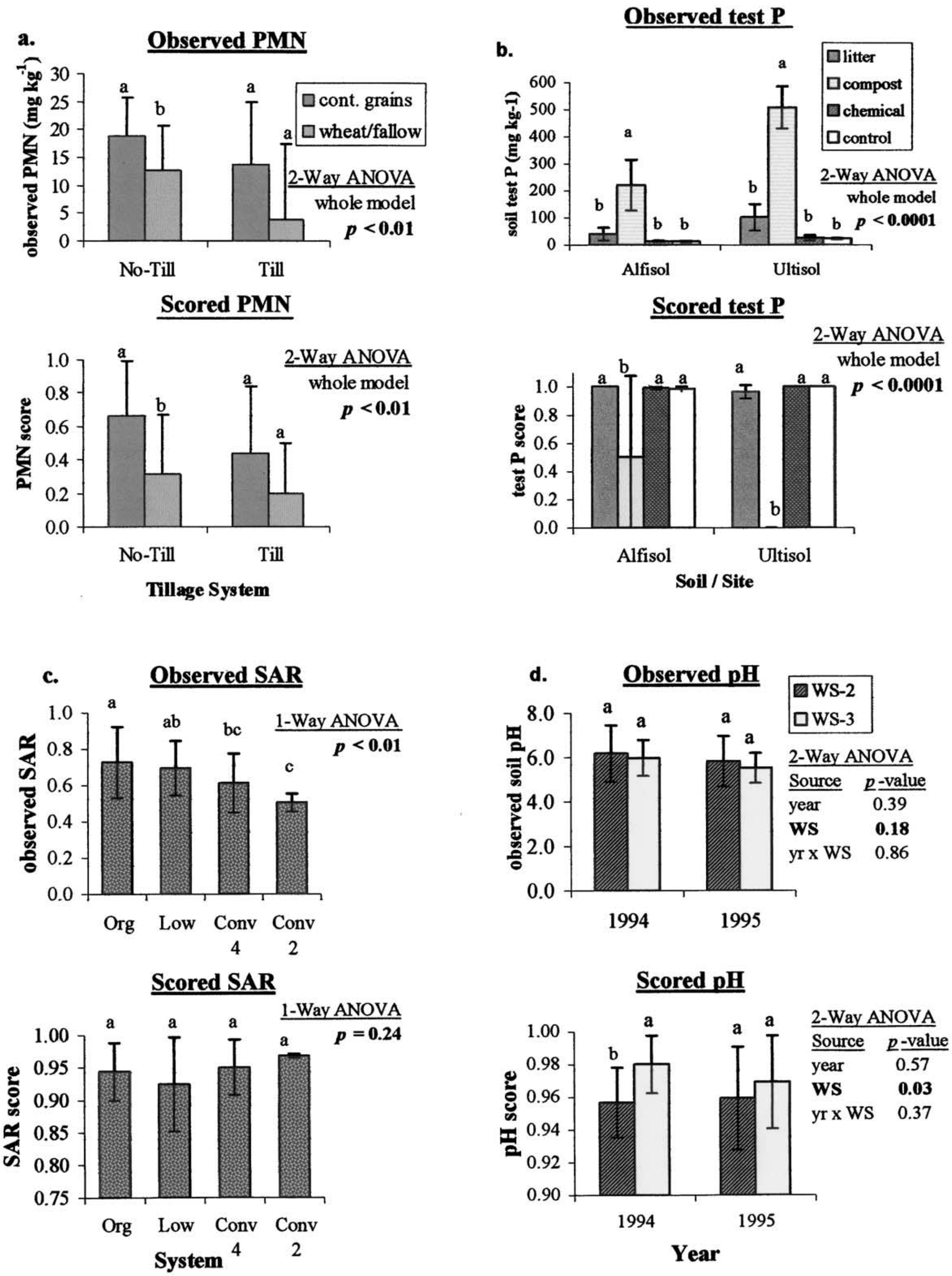

Fig. 4. Examples of observed and scored indicator results, illustrating the four general relationships that occurred: (a) observed and scored results were equivalent (example is potentially mineralizable N from Natural Resource Inventory [NRI] cropped Xerolls data), (b) observed and scored results were opposite (example is soil test P from GA data), (c) observed results had significant differences but scored results did not (example is sodium adsorption ratio [SAR] from California data (org = organic; low = low input; conv 4 = 4-yr conventional rotation; conv 2 = 2-yr conventional rotation), and (d) observed results showed no significant differences among treatments but scored results were significantly different (example is soil pH from IA data). Treatments labeled with different letters are significantly different at α = 0.05. Error bars represent one standard deviation from the mean. WS represents watershed.

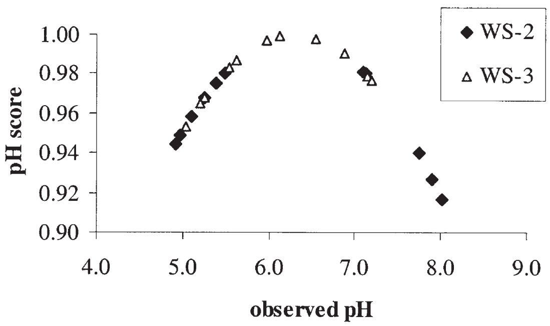

Fig. 5. Detailed example of observed and scored indicator results for soil pH in 1994 from the IA case study data. WS represents watershed.

case study treatments (Fig. 4c). Pattern 3 occurred when most points fell on an asymptote or plateau in the scoring algorithm, as was observed for PMN and TOC at Iowa; SAR at California (Fig. 4c); and D_b, MBC, and TOC in the Georgia case study. For instance, although there were significant differences among the observed treatment means for SAR in the California study (Fig. 4c), none of the observed values was in a range that would be considered detrimental to plant health, water quality, or soil aggregation. Therefore, all of the treatments received equally high scores (with no significant difference) for SAR on the basis of soil function. Although differences among treatments may have statistical significance, functional differences within the observed range are not always a given. The ability to discern this subtlety highlights an important strength of the tool.

The fourth, least common, and unexpected pattern (Pattern 4) occurred when the observed results for an MDS indicator showed no significant differences among treatments but scored results were significantly different (Fig. 4d). This was only seen for two indicators, pH and AGG, at the Iowa study. In a two-way ANOVA, pH at Iowa was only significant for the scored indicator among watersheds (Fig. 4d). The AGG scores were significantly different among years but observed AGG data were not (data not shown). This unexpected pattern occurred when the observed data had scores in the ascending and descending portions of a Gaussian curve with few, if any, points in the optimum range (e.g., top of the curve), such as for soil pH in WS2 in 1994 of the Iowa case study (Fig. 5). These WS2 pH data resulted in a lower score compared with the WS3 data, which fell largely in the optimum range of the curve, even though the means for observed pH were not significantly different. This suggests that important information can be captured by scoring that might otherwise go undetected when examining observed means alone.

The stepwise regressions were used to examine the ability of the MDSs to explain variation in endpoints or their surrogates. Table 5 shows regression results (adjusted R^2s) for scored indicators were 0.54 or greater for TOC change in the NRI study, 0.59 or greater in the Iowa study, 0.55 or greater for two of four endpoints in the California study, and >0.41 in three of four endpoints in the Georgia study. In addition, the regressions were most informative for Step 2 because scored and observed indicators were directly compared. The scored indicators usually had R^2s that were similar or greater than those of the observed indicator values (shown below in parenthesis). For example, indicator-endpoint regressions at the Iowa site had adjusted R^2 results of 0.99 (0.56), 0.59 (0.52), and 0.76 (0.99), for sedimentation in surface water, crop yield, and atrazine applied, respectively. The R^2s between indicators and endpoints were higher when examined for subsets of data, such as one treatment or one crop, rather than the entire data set. For instance, when using all NRI data, there was no relationship with nematode diversity. When data for no-tilled Xerolls, cropped to continuous small grains were examined alone, the adjusted R^2 was 0.68. Similarly, all R^2 results increased for the California data set when data collected under tomatoes were examined alone. This regression test seemed to confirm that the scored indicators were capturing intended information about system performance. But the need to minimize the amount of data used in the regression, which reduced spatial extent, land uses represented and/or environmental differences, to adequately explain the variation in endpoints probably reflects a need to use different indicators as scale increases (Karlen et al., 1997; Bouma, 2002) or land use changes. This need can easily be filled as indicators, selection rules, and scoring algorithms are added to the framework.

While using existing data and surrogate endpoint measures is a good beginning, an ideal test of SMAF efficacy has yet to be performed. The ideal would be a study explicitly designed for this purpose that included endpoint measures specific to each management goal and soil function of interest.

Index Integration

Step 3, integration of indicator scores into an index, is probably the most controversial. Concerns most often expressed are about the use of an index as a regulatory tool. Yet, in focus groups with farmers, an integrative index was very attractive as a monitoring tool, as long as they could also access individual indicator information from which to make specific management decisions (Andrews et al., 2003). If desired, however, Steps 1 and 2 could stand alone: one could use the SMAF only to select the most appropriate indicators to measure or only to interpret existing data. Step 3, on the other hand, relies on the scored indicators from Step 2, because the indicator measurements must be transformed into unitless values before they can be meaningfully combined. While the first two steps are the most critical, Step 3 allows one to see the overall health of the soil, without the distraction of (potentially) conflicting individual indicator results.

Comparisons of index outcomes using the NRI data showed that SQ was significantly greater in forage, range, and woodland soils than for soils under CRP, continuous grain or wheat-fallow, with the latter being the lowest (Fig. 6a) for all land uses. Since the CRP data were grouped together without respect to length of time in CRP, this land use probably included some

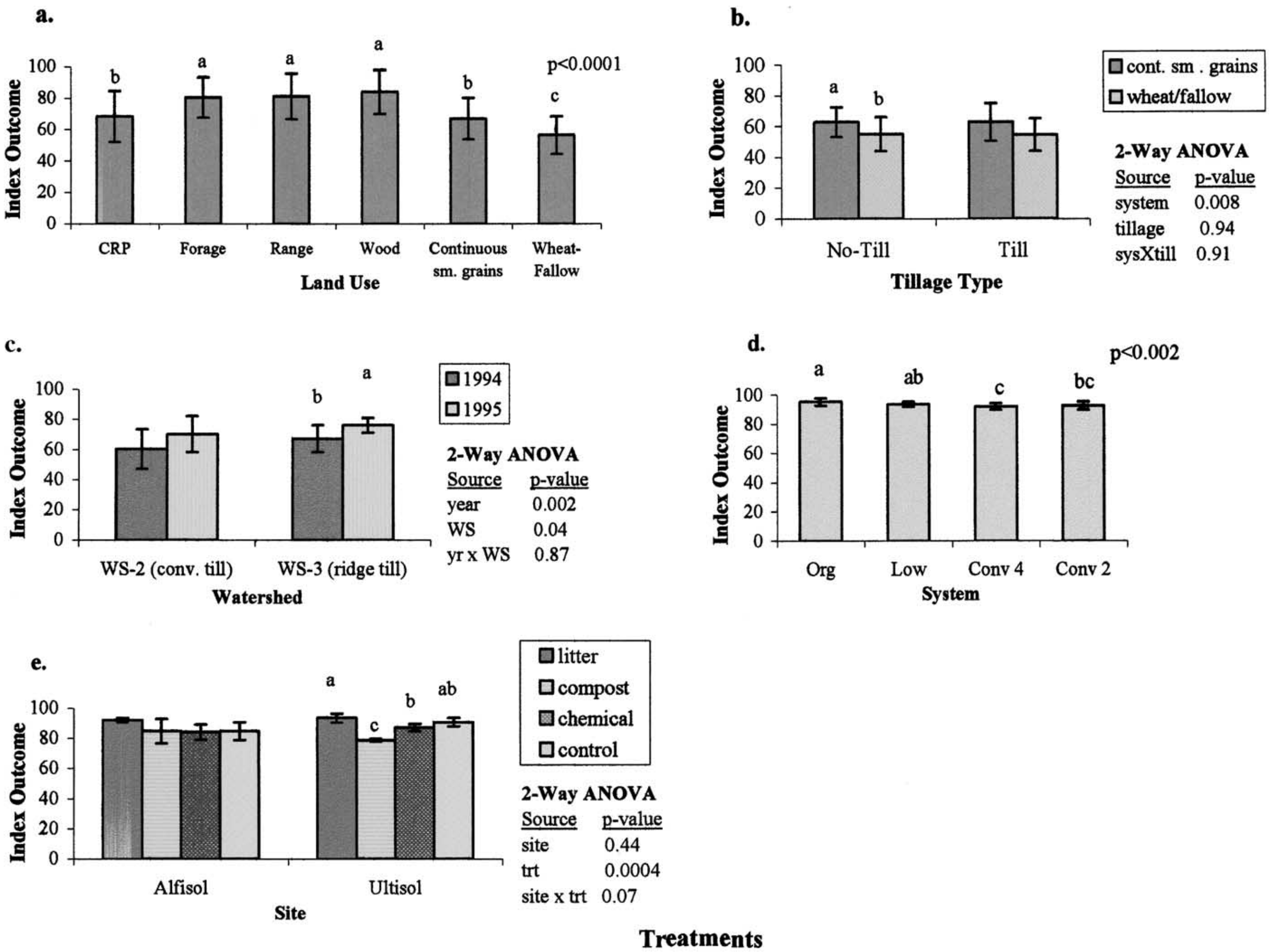

Fig. 6. Soil management assessment framework (SMAF) outcomes for the four case studies including ANOVA and Student's *t* results: (a) Natural Resources Inventory (NRI) data for all land uses and soil types; (b) NRI cropped Xerolls only, grouped by tillage type and cropping system; (c) Iowa (IA) data grouped by watershed (WS) or tillage type and sampling year; (d) California (CA) data grouped by vegetable production system (org = organic; low = low input; conv 4 = 4-yr conventional rotation; conv 2 = 2-yr conventional rotation); and (e) Georgia (GA) data grouped by site (or soil order) and amendment treatment (trt). Treatments or land uses labeled with different letters are significantly different at $\alpha = 0.05$. Error bars represent one standard deviation from the mean.

of the most degraded soils along with soils that had a recovery period. This supposition also explains the higher variance observed for CRP compared with all other land uses. When we examined the homogeneous subset of NRI data, cropped Xerolls, differences between cropping systems were only significant under no-tillage (Fig. 6b). A similar result was also observed using individual SQ indicator data for a long-term cropping systems study in the Northern Great Plains (B. Wienhold, personal communication, 2003.)

The Iowa field-scale watershed data showed that long-term use of ridge tillage resulted in a higher index rating than for the conventionally tilled watershed. The results also showed that both watersheds had significantly higher index outcomes in 1995 than 1994 (Fig. 6c) even though soil management practices for the 2 yr were essentially the same (Karlen et al., 1999). We attribute the time differences to sample variation, stressing the response to management was consistent each year.

The Framework showed that soils used for organic vegetable production in California had significantly higher SQ index ratings than for the two conventional rotations (Fig. 6d). This result using the SMAF is comparable with that of Andrews et al. (2002a), where scoring curves were created specifically for the California data set (as opposed to using the site-specific factors to shift parameters in the scoring algorithms). This suggests that the site-specific scoring of the current framework is working as well as individually tailored SQ assessments.

Using data from the Georgia case study, the SMAF showed significant differences in SQ index results only for the Ultisol site (Fig. 6e). None of the MDS indicator scores were significantly different among the management treatments at the Conasauga site. At the Ultisol site, individual scores for pH, AWC, and test P differed among treatments. The score for pH was significantly greater for compost compared with the chemical and control. Scored AWC was higher in compost and litter compared with chemical. However, it was the soil P score, which was significantly lower for compost compared with the other treatments (the converse of observed P—a Pattern 2) that drove the index outcome. For this reason, the compost treatment had a significantly lower index outcome than the other treatments at the Ultisol site.

The ability to assess relative system function, whether as an integrative index or individual indicator scores, may have strong implications for both natural resources management and policy. We anticipate that this framework, when fully developed, could have such diverse uses as: evaluating the effects of bioenergy crop production (or residue harvest) on soil resources at the field scale; assessing management intensities at the farm scale for Conservation Security Program Enhancement Payments; and interpreting watershed scale data (both measured and modeled) as part of the Conservation Efforts Assessment Program. The framework's flexibility, leading to site-specific interpretations, is its biggest strength.

CONCLUSIONS

A relatively user-friendly version of a SQ assessment tool for evaluating the integrated effects of various soil management practices was developed. The tool was demonstrated and tested using data from four SQ assessment studies, representing different scales of evaluation, management goals, and regions of the USA. The SMAF has the flexibility to accommodate site-specific differences due to soil, crop, climate, and other factors within the scoring curves. Based on these initial evaluations, the framework can help select appropriate SQ indicators, interpret their measurement outcomes, and integrate the interpretations to accurately assess the effects of management practices on overall soil function. The analyses in some cases (Patterns 3 and 4), can give more information than observed data alone. This interpretative function of SMAF may allow users without extensive soils training to utilize soil test data more effectively than currently possible. The integration portion of the tool may also be useful to scientists interpreting complex data sets with conflicting or contradictory trends. The efficacy check revealed some weaknesses in the ability of scored indicators to explain variation in endpoints at the largest spatial scale, pointing to a need for additional indicators for this type of assessment. Nevertheless, the flexibility of the framework allows for SQ assessments at various spatial and temporal scales as well as use in various regions and management systems.

Currently the framework is being further evaluated and improved as part of the USDA-ARS Soil Resource Management National Program but a prototype is also available to other interested users. We fully acknowledge and anticipate that the current version will undergo significant improvement as the capacity for additional SQ indicators is added and as knowledge improves regarding soil function in various ecosystems. We will continue to work with experts that are familiar with each of the biological, chemical and physical indicators under a variety of management practices and ecosystems to improve selection rules and interpretation algorithms relative to management goals and site-specific factors. In addition, we fully expect that the integration step will be improved in the future by the inclusion of rules for weighting indicators' scores in some situations. Due to its flexible, database-driven design, many aspects of the SMAF can be changed and updated simply. In addition, efforts to improve the user interface have begun. When fully operational, we expect an advanced version to be even more flexible, user-friendly, and useful for relating the effects of soil management on various soil functions in a broad range of settings. We conclude that SMAF is a useful assessment tool that, with further standardization and validation, may help move soil conservation and resource management beyond assessments of soil erosion and changes in productivity toward stewardship (Wander and Drinkwater, 2000), with such diverse applications as model output interpretation, conservation program assessment, soil test interpretation, green payments and conservation credits.

ACKNOWLEDGMENTS

We gratefully acknowledge the following individuals for contributions of data for the case studies: Cathy Seybold, Elaine Ingham, John Brejda (NRI); Tom Steinhiemer, and Tom Moorman (IA); and Jeff Mitchell, Stu Pettygrove, Tim Hartz, Will Horwath, Kate Scow and Dan Munk (CA). For the Georgia data, we thank Sarah Tyson-Pierson for Year 1 data and Miguel Cabrera, Ronald Carroll, and Paul Hendrix for lab space, and useful ideas and discussions. Thanks to Christien Ettema and Deborah Neher for help converting species data to a nematode Maturity Index. We also thank Stu Pettygrove, Tim Hartz, Dennis Corwin, Joe Pikul for useful feedback about shapes and shifts of scoring curves. We also thank Mark Liebig, Jeff Herrick, and Mike Jawson for encouragement and many helpful discussions about the philosophy and logistics of multiple aspects of the framework. Finally, thanks to Brian Wienhold, Phil Bauer, and the anonymous reviewers for useful comments on the manuscript.

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