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A comparison of soil quality indexing methods for vegetable production systems in Northern California

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Abstract

Consultants, farm advisors, resource conservationists, and other land managers may benefit from decision tools that help identify the most sustainable management practices. Indices of soil quality (SQIs) can provide this service. Various methods were tested for choosing a minimum data set (MDS), transforming the indicators, and calculating indices using data from alternative vegetable production systems being evaluated near Davis, California. The MDS components were chosen using expert opinion (EO) or principal components analysis (PCA) as a data reduction technique. Multiple regressions of the MDS indicators (as independent variables) against indicators representing management goals (as iterative dependent variables) showed no significant differences between the EO and PCA selection techniques in their abilities to explain variability within each sustainable management goal. Linear and non-linear scoring techniques were also compared for MDS indicators. The non-linear scoring method was determined to be more representative of system function than the linear method. Finally, indicator scores were combined using either an additive index, a weighted additive index, or a decision support system. For almost all indexing combinations, the organic system received significantly higher SQI values than the low input or conventional treatments. The efficacy of the indices was tested by comparisons with individual indicators, variables representative of management goals, and another multivariate technique for decision making that used all available data rather than a subset (MDS). Comparison with the comprehensive multivariate technique showed results similar to all of the indexing combinations except the additive and weighted indices using the linearly scored, EO-selected MDS. This suggests that a small number of carefully chosen soil quality indicators, when used in a simple, non-linearly scored index, can adequately provide information needed for selection of best management practices.

Keywords: Soil quality index; Sustainability; Decision support systems; California; Organic agriculture; Eutric Fluvisols

1. Introduction

Sustainable agricultural systems often require increased management inputs (Madden, 1990; Edwards et al., 1993). Instead of filling this need, the myriad of available soil tests and best practice recommendations can actually present management dilemmas in terms of both selection and interpretation. Decision tools that can help organize soil test information as well as interpret how management practices affect soils and ecosystems will improve the reliability and sustainability of management inputs (Beinat and Nijkamp, 1998). Soil quality indices are decision tools that effectively combine a variety of information for multi-objective decision-making (Karlen and Stott, 1994). But there are a variety of possible indexing

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techniques and little research comparing the different methods in complex agroecosystems like vegetable production systems in the Sacramento Valley of California, USA.

Soil quality indices and indicators should be selected according to the soil functions of interest and the defined management goals for the system. Management goals are often individualistic, primarily focused on on-farm effects, but can also be societal, including the broader environmental effects of farm management decisions such as soil erosion, agrochemical contamination of soil and water, or subsidy imbalance (from over-use of fossil fuels or agrochemicals) (Rapport et al., 1997). Larson and Pierce (1991) argue that soil quality should no longer be limited to productivity (a largely individualistic management goal), inferring that emphasizing productivity may have contributed to soil degradation in the past. When management goals focus on sustainability rather than simply crop yield, a soil quality index (SQI) can be viewed as one component within a nested agroecosystem sustainability hierarchy (Fig. 1). The SQI is one factor that contributes to the evaluation of higher level sustainable management goals (both individual and societal). In the Sacramento Valley, where high-input production practices are the norm (Mitchell et al., 2001), some of the applicable soil functions relating to sustainability goals are: (1) promotion of plant growth; (2) partition and regulation of water; and (3) ability to act as an environmental buffer or filter (Costanza et al., 1992; de Kimpe and Warkentin, 1998; Clark et al., 1999a). Decision tools that help land managers identify management choices with the fewest environmental consequences may help reduce environmental degradation (Beinat and Nijkamp, 1998).

Once the system's management goals are identified, soil quality indexing involves three main steps: (1) choosing appropriate indicators for a minimum data set (MDS); (2) transforming indicator scores; and (3) combining the indicator scores into the index (Fig. 2). The concept of the minimum data set of soil quality indicators that reflect sustainable management goals is widely accepted but, up to now, has relied primarily on expert opinion (EO) to select MDS components (e.g. Larson and Pierce, 1991; Doran and Parkin, 1994; Karlen et al., 1996). However, the difficult question of what variables to include in an index of soil quality may be simplified by statistical methods. The physiological rhizosphere studies of Bachmann and Kinzel (1992) used principle component analysis, multiple

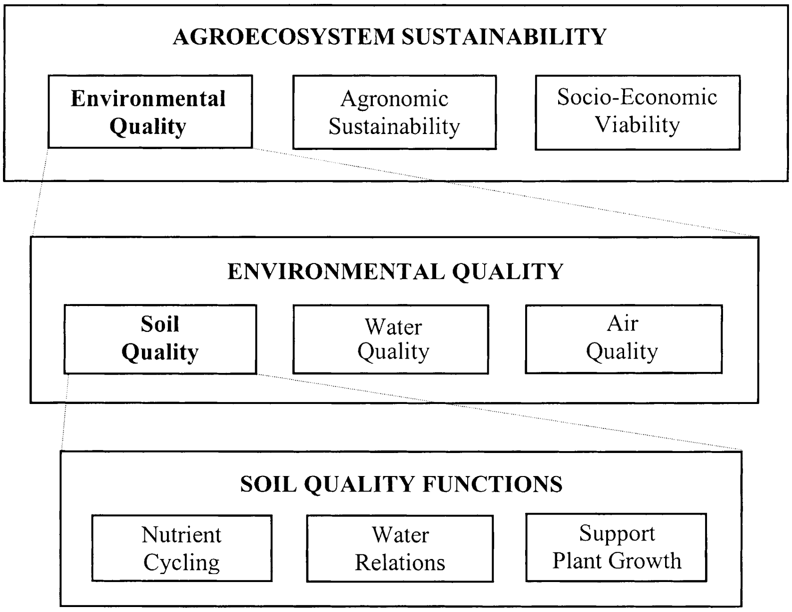

Fig. 1. Nested hierarchy of agroecosystem sustainability showing the relationship of soil quality to the larger agroecosystem.

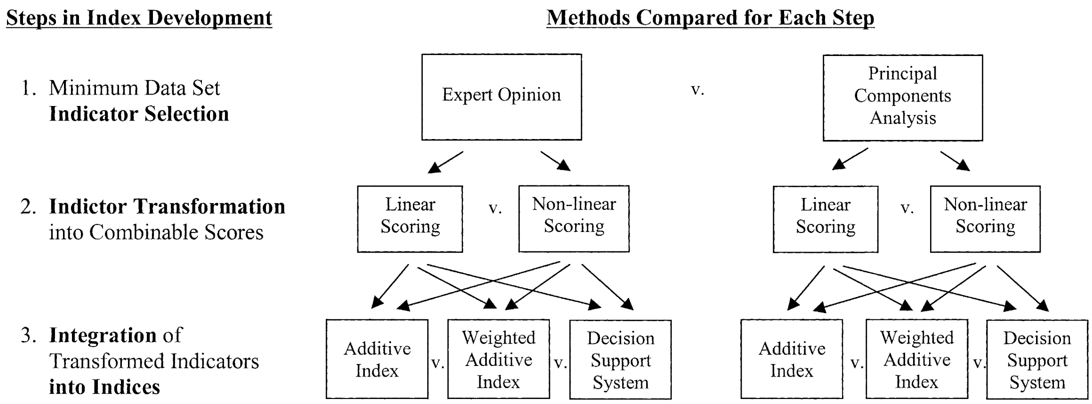

Fig. 2. Flow diagram depicting the three steps of index creation and the alternative methods for each step compared in this study.

correlation, factor analysis, cluster analysis and star plots to select characteristics for their diagnostic index. Bentham et al. (1992) used principal component analysis and other statistical clustering techniques to choose variables best representing the progress of soil restoration efforts. The use of objective mathematical formulas reduces the possibilities for disciplinary biases that inhibit much would-be cross-disciplinary work (Doran and Parkin, 1996; Walter et al., 1997).

Scoring and combining the indicators into indices can also be done in a variety of ways. Liebig et al. (2001) stressed simplicity of design and use by developing a linear scoring technique that relies on the observed data to determine the highest possible score for each indicator and requires little prior knowledge of the system. Non-linear scoring techniques involve the use of curvilinear scoring functions with a y-axis ranging from 0 to 1 and an x-axis representing a range of site- or function-dependent scores for that variable (Karlen and Stott, 1994; Andrews and Carroll, 2001). This type of scoring is used widely under various guises in economics as utility functions (Norgaard, 1994), multi-objective decision making as decision functions (Yakowitz et al., 1993), and systems engineering as a tool for modeling (Wymore, 1993) but does require in depth knowledge of each indicator's behavior and function within the system.

Numerous SQIs, varying widely in complexity and need for expert knowledge, have been developed to compare agroecosystem management practices. Andrews and Carroll (2001) used a simple additive index to compare organic amendments to fescue pastures. Karlen et al. (1998) used weighted indices based on expert opinion to assess land coming out of the Conservation Reserve Program (CRP). Bongers (1990) nematode maturity index, a well-known index of system disturbance, used weighted averages but required detailed knowledge of taxonomy. A decision support system (DSS) that operates as a spreadsheet macro was configured by Yakowitz et al. (1993) to compare system effects of alternative farming systems. This hierarchical DSS allows the decision maker to assign a priority order (ranks) to indicators without having to set specific weights. Some efforts have been made to assess the site-specificity of existing indices by altering the indicator transformation step. For example, Hussian et al. (1999) and Glover et al. (2000) adjusted the index weighting and indicator threshold values of Karlen et al. (1994) to be applicable to their respective systems. Andrews and Carroll (2001) also shifted the expected ranges for indicators between sites. However, no studies that compare different soil quality (SQ) indexing techniques are known to the authors.

The objective of this study was to examine the relative effectiveness of several soil quality indexing methods using assessment of complex vegetable production systems in Northern California as a case study. The alternative indexing methods compared were: expert opinion (EO) and principal components analysis (PCA) methods to select indicators for an MDS; linear and non-linear scoring methods to transform indicators into unitless (and thus, combinable) scores; and additive, weighted additive and hierarchical decision support system indexing methods

(Fig. 2). While many indexing attempts simply choose indicators that differentiate among systems without regard to whether or not there are genuine differences in function (Herrick, 2000), the index outcomes described here are evaluated by comparison with (1) end-point variables representing farm and environmental management goals; and (2) a comprehensive multivariate evaluation method (Wander and Bollero, 1999) that uses all significant data (as opposed to an MDS). A secondary objective was to use the indexing approaches to assess the sustainability of organic, low input and conventional farming system treatments for a long-term vegetable production experiment in the Sacramento Valley of California.

2. Methods

2.1. Data generation

2.1.1. Site description

For this study, data from the sustainable agriculture farming systems (SAFS) Project, initiated in 1988 in the University of California, Davis, Agronomy Farm (38°32′N 121°47′W; 18 m elevation) were used. Soils at the 8.1 ha site in Yolo Co., CA, are classified as Reiff loams (coarse-loamy, mixed, nonacid, thermic Mollic Xerofluvents) and Yolo silt loams (fine-silty, mixed, nonacid, thermic Typic Xerothents). Both soils classify as Eutric Fluvisols in the FAO World Reference Base for Soil Resources. The climate is Mediterranean with average daytime temperatures between 30 and 35 °C during the growing season. Total annual precipitation ranges from 400 to 500 mm with most occurring December through March. Furrow irrigation is widespread in the region and was used for all treatments in this study.

2.1.2. Experimental design

The on-going SAFS project compares agronomic, economic and biological aspects of farming systems in the Sacramento Valley, CA. The randomized split plot design includes four management system treatments that differ by crop rotation and use of external inputs: conventional 2-year (Conv-2), conventional 4-year (Conv-4), low input (LOW), and organic (ORG). The two conventional treatments apply 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 (*Triticum aestivum* L.). The Conv-4 rotation is tomato; corn (*Zea mays* L.); safflower (*Carthamus tinctorius* L.); and wheat and dry beans (*Phaseolus vulgaris* L.) (double crop). The ORG treatment uses composted and aged animal amendments, rotations of winter cover crops and some organic supplements for fertility and pest management. The LOW treatment combines 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 ORG and LOW treatments have identical rotations of cash crops including tomato; safflower; corn; and oats (*Avena sativa* L.) + vetch (*Vicia* spp.) and dry beans (double crop). All possible entry points for the rotations are represented each year as part of the split plot design (with four blocks) to make 56 subplots, each measuring 68 m × 16 m (0.12 ha) (Table 1). All systems use crops representative of the region (California Department of Food and Agriculture, 1996) and “best farmer management practices” as determined by consultation with farmer-cooperators on this project (see Clark et al. (1998) for a more thorough description of the SAFS project).

2.1.3. Soil sampling and laboratory analyses

In September 1996, 30 soil cores were taken from each subplot to a depth of 30 in 15 cm increments. Because 0–15 cm is the most common sampling depth for soil testing, only those data are considered for the indices. Well-mixed, 2 mm sieved, and air-dried samples were analyzed by the University of California’s Division of Agriculture and Natural Resources Analytical Laboratory. Soil organic matter (SOM) was determined using a modified Walkley–Black method (Nelson and Sommers, 1982). Total organic carbon (TOC) and total nitrogen (TN) were determined via dry combustion of dried, ground samples using a gas analyzer (Pella, 1990a,b). Soluble phosphorus (P) was determined by extracting samples with a 0.5N sodium bicarbonate solution, reacting the extracts with *p*-molybdate and determining P concentrations with a spectrophotometer (Olsen et al., 1954). Exchangeable potassium (K) (Knudsen et al., 1982), exchangeable calcium (*x*-Ca), and exchangeable magnesium (*x*-Mg) (Lanyon and Heald, 1982) were determined using a 1N ammonium acetate extraction followed by emission

Table 1
Farming system treatments at the Sustainable Agriculture Farming Systems (SAFS) Project at the University of California, Davis (begun in 1988)[a]

Farming system	Year	Crop rotation	Description
Organic (ORG)	1	Tomato	4-Year, five crop rotation; fertilization from composted and
	2	Safflower	aged animal manures, legume and grass cover crops, and or-
	3	Corn	ganic supplements; cultivation and hand hoeing for weed con-
	4	Oats + vetch; bean	trol; no synthetic pesticides or fertilizers
Low-input (LOW)	1	Tomato	4-Year, five crop rotation; fertilization from legume and grass cover
	2	Safflower	crops and synthetic fertilizer at about one-half recommended rates;
	3	Corn	reduced pesticide use through cultivation and hand hoeing
	4	Oats + vetch; bean	
Conventional, 4-year (Conv-4)	1	Tomato	4-Year, five crop rotation; fertilization from synthetic fertilizer at
	2	Safflower	recommended rates; pesticides at conventionally recommended rates
	3	Corn	
	4	Wheat; bean	
Conventional, 2-year (Conv-2)	1	Tomato	2-Year, two crop rotation; fertilization from synthetic fertilizer at
	2	Wheat	recommended rates; pesticides at conventionally recommended rates

[a] Adapted from Clark et al. (1998).

spectrometry. Total sulfur (S) was determined by microwave digestion of 0.5 g soil samples with subsequent ICP analysis (Sah and Miller, 1992). Zinc (Zn) was determined using the DTPA (diethylenetriaminepentaacetic acid) micronutrient extraction method developed by Lindsay and Norvell (1978). Sodium Absorption Ratio (SAR) was calculated using results from saturated paste extracts of sodium (Na^+), calcium (Ca^{2+}), and magnesium (Mg^{2+}) in milliequivalents per liter (US Salinity Laboratory Staff, 1954). Electrical conductivity (EC) (Rhoades, 1982) and pH of saturated pastes (US Salinity Laboratory Staff, 1954) were measured for each sample using conductivity and pH meters, respectively.

The following analyses were run on soil samples from a subset of plots (tomato and corn only) five times over the 1996 growing season. Gravimetric soil moisture was determined for field moist soils by drying at 105 °C for 24 h (Gardner, 1986). Soil nitrate (NO_3^-–N) and ammonium (NH_4^+–N) were extracted with potassium chloride solution (Keeney and Nelson, 1982). Extracts were analyzed for NH_4^+ by the salicylate–hypochlorite method and for NO_3^-–NO_2^-–N by cadmium reduction via a modified Griess–Ilsovay method, using a diffusion-conductivity analyzer (Carlson, 1978). Potentially mineralizable nitrogen (PMN) was determined from NO_3^-–N present in field moist 35 g soil samples that were equilibrated at −30 kPa soil water potential before and after a 4 week aerobic incubation (Bundy and Meisinger, 1994). The phospholipid fatty acid (PLFA) method for soil microbial community composition analysis was performed on soils from tomato plots only in July, 1996, using the methodology of Bossio et al. (1998).

Ideally, a more balanced data set, including more physical and biological indicators, would be used for soil quality indicator selection. However, in practice, such data sets are relatively rare. Therefore, we used this data set despite its heavy reliance on chemical indicators due to its large number of indicators overall *and* its inclusion of end point data available to represent sustainable management goals (see Section 2.1.4).

2.1.4. Collection of end point data representing management goals

One reason why this data set provided an excellent test case for soil quality indexing was the abundance of end point data reflecting sustainable management goals that could be used to evaluate index performance. We assumed that the management goals for all systems were identical. The available agronomic goal indicators included measures of yield quantity and quality: crop yield (in mg ha^{-1}) for within crop comparisons (Clark et al., 1999b); a proportional yield factor (using measured yield in the numerator and county averages for the corresponding crop in the denominator (Yolo County Department of Agriculture, 1996) for between crop comparisons; and leaf nitrogen content (% N), as a measure of plant health. Leaf tissues were sampled at two times during the growing season: at the V5 and V8 stages for corn and at first bloom and first color for tomato. Leaf tissue N was determined by the block digester method of Issac and Johnson (1976) for corn and tomato only. For economic comparisons, net revenues for each system and crop were used, including price premiums for organic produce (Clark et al., 1999b). Available environmental performance measures included SAR (or meq $Na\,l^{-1}$ when SAR was included in the MDS), water use (millimeter per season), weed cover (%), pesticide use (based solely on application rates in pints per hectare without differentiating between chemicals), and the number of tillage operations per year. Because these measures serve here as proxies for the identified management goals at the agroecosystem sustainability level (Fig. 1), these tests are referred to as "sustainability goals" and are used to examine the efficacy of the MDS and index combinations.

2.2. Index comparisons

2.2.1. Indicator selection

We compared the most common method of MDS selection, expert opinion (EO), with the use of a multivariate data reduction technique, standardized principal components analysis (PCA) (Fig. 2). Unless otherwise noted, results are for soils from all crop rotations combined for the 0–15 cm sampling depth. To see if this process required data from all crops in the complex rotation or could use data from just one crop, the PCA process was repeated on data for each crop individually. For tomato and corn, the PCA technique was also repeated using data from the extended number of tests performed on soils planted to these crops. The MDS results were compared using soils data segregated by crop to results using data combined for all crop rotations.

2.2.1.1. Expert opinion. Minimum data set variables were chosen from the available data according to consensus of the project investigators, recommendations in the literature (e.g. Larson and Pierce, 1991; Doran and Parkin, 1994), and common management concerns in the Sacramento Valley.

2.2.1.2. Principal components analysis. Principal components (PCs) for a data set are defined as linear combinations of the variables that account for maximum variance within the set by describing vectors of closest fit to the n observations in p-dimensional space, subject to being orthogonal to one another (Dunteman, 1989). While there are many documented strategies for using PCA to select a subset from a large data set, the one described here is similar to that described by Dunteman (1989). We performed standardized PCA of all (untransformed) data that showed statistically significant differences between management systems via Kruscall–Wallis χ^2 using JMP® version 3 for Windows (SAS Institute, Cary, NC).[1] We assumed that PCs receiving high eigenvalues best represent variation in the systems. Therefore, only the PCs with eigenvalues ≥ 1 (Kaiser, 1960) were examined. Additionally, PCs that explain $\geq 5\%$ of the variability in the soils data (Wander and Bollero, 1999) were included when fewer than three PCs had eigenvalues ≥ 1.

Under a particular PC, each variable is given a weight or factor loading that represents the contribution of that variable to the composition of the PC. Only the highly weighted variables were retained from each PC for the MDS (Table 2). Highly weighted factor loadings were defined as having absolute values within 10% of the highest factor loading or ≥ 0.40 (Wander and Bollero, 1999). When more than one factor was retained under a single PC, multivariate correlation coefficients were employed to determine if the variables could be considered redundant and, therefore, eliminated from the MDS (Andrews et al., 2001). If the highly weighted factors were not correlated (assumed to be a correlation coefficient <0.60) then each was considered important, and thus, retained in the MDS. Among well correlated variables, the variable with the highest factor loading (absolute value) was chosen for the MDS. Once all of the MDS indicators were chosen, a final check for correlations (between PC indicators) led to selecting one replacement indicator (from the originating PC) for an indicator pair with correlation coefficients ≥ 0.70 (in very few instances).

Multiple regressions of both the EO selected and PCA-MDSs were performed using management goal

[1] Reference to trade names and companies is made for information purposes only and does not imply endorsement by the USDA or University of California.

Table 2
Results of principal components analysis of soil quality indicators having significant differences between the four management systems at the SAFS Project, 1996

Principal components	PC1	PC2	PC3	PC4
Eigen value[a]	**5.78**	**1.45**	**1.41**	0.79
Percent	52.50	13.19	12.83	7.19
Cumulative percent	52.50	65.69	78.52	85.72
Eigen vectors[b,c]				
SOM	0.333	0.146	−0.021	−0.357
TOC	**0.382**	0.072	0.037	−0.327
TN	***0.385***	0.122	0.045	−0.300
SAR	0.295	−0.360	0.317	0.376
Na	0.277	***−0.503***	0.169	0.223
pH	0.176	0.303	***0.589***	0.305
P	0.275	0.094	***−0.491***	0.346
K	**0.352**	−0.047	−0.174	0.095
x-Ca	0.120	***0.643***	0.214	0.193
S	**0.357**	−0.169	0.030	−0.302
Zn	0.243	0.176	**−0.449**	0.366

[a] Boldface eigenvalues correspond to the PCs examined for the index.

[b] Boldface factor loadings are considered highly weighted.

[c] Bold-italic factor loadings correspond to the indicators included in the MDS.

variables as the dependent variables. Each management variable, in turn, served as the dependent variable while the MDS comprised the independent variables (Hussian et al., 1999; Andrews and Carroll, 2001). To evaluate difference between MDS method, crop influences, and goal variables, three-way ANOVAs of the multiple regression results (R^2 values) were performed. This step served as a check of how well each MDS represented the selected goals for the management systems by crop and by entire rotation.

2.2.2. Indicator transformation (scoring)

After determining the variables for the MDS, every observation of each MDS indicator was transformed for inclusion in the SQI methods examined. Two techniques were compared: linear scoring or non-linear scoring (Fig. 2).

2.2.2.1. Linear scores. Indicators were ranked in ascending or descending order depending on whether a higher value was considered "good" or "bad" in terms of soil function. For 'more is better' indicators, each observation was divided by the highest observed value such that the highest observed value received a score of 1. For 'less is better' indicators, the lowest observed value (in the numerator) was divided by each observation (in the denominator) such that the lowest observed value receives a score of 1. For many indicators, such as pH, P, and Zn, observations were scored as 'higher is better' up to a threshold value (e.g. pH 6.5) then scored as 'lower is better' above the threshold (Liebig et al., 2001).

2.2.2.2. Non-linear scores. For this method, indicators were transformed using non-linear scoring functions constructed using CurveExpert version 1.3 shareware (http:/www.ebicom.net/∼dhyams/cvxpt.htm). The shape of each decision function, typically some variation of a bell-shaped curve ('mid-point optimum'), a sigmoid curve with an upper asymptote ('more is better'), or a sigmoid curve having a lower asymptote ('less is better'), was determined according to agronomic and environmental function using literature review and consensus of the collaborating researchers. For example, scoring included upper asymptote sigmoid curves or 'more is better' functions for SOM, TOC, and TN (Tiessen et al., 1994); a lower asymptote or 'less is better' function for SAR (dependent on EC) (Oster and Schroer, 1979; Hanson and Grattan, 1992); and variations on 'mid-point optimum' curves for soil pH (Whittaker et al., 1959; Smith and Doran, 1996), P (Maynard, 1997; Pierzynski et al., 1994), EC (Tanji, 1990; Smith and Doran, 1996), *x*-Ca (as a proportion of CEC) (Graham, 1959), and Zn (Maynard, 1997).

2.2.3. Indicator integration into indices

Three soil quality indices were compared: an additive SQI (ADD SQI); a weighted, additive SQI (WTD SQI); and a hierarchical decision support system (DSS SQI) (Fig. 2). For all the indexing methods, SQI scores for the management treatments were compared using a two-way ANOVA for split plot design and Tukey–Kramer means comparison test at $\alpha = 0.05$. Higher index scores were assumed to mean better soil quality.

2.2.3.1. Additive index. The additive index was a summation of the scores from MDS indicators. From these summed scores, the ADD SQI treatment means and standard deviations were calculated.

2.2.3.2. Weighted additive index. Once transformed, the MDS variables for each observation were weighted using the PCA results (Table 2). Each PC explained a certain amount (%) of the variation in the total data set. This percentage, standardized to unity, provided the weight for variables chosen under a given PC. We then summed the weighted MDS variable scores for each observation and calculated the treatment means and standard deviations.

2.2.3.3. Decision support system SQI. This technique applied the additive value function method to solve hierarchical multi-attribute problems (Yakowitz and Weltz, 1998). To create the importance order hierarchy for the DSS SQI, the results of an informal survey completed by Central Valley farmer collaborators (unpublished data) were used. Like the other SQIs, the DSS used scored indicator values from either the PCA or EO selected MDSs. The DSS used indicator scores for the treatment means and reported a median and range of outcomes that are not statistically comparable. Instead, dominance among alternatives is established (Yakowitz and Weltz, 1997). However, because one objective for this study was to detect statistically significant differences between treatments and compare those outcomes with the results from the other SQIs, the DSS using was also run using scored observations from each plot (i.e. 56 DDS runs for 56 experimental plots). The DSS SQI treatments means and standard deviations were then calculated, allowing statistical means comparisons. All DSS graphs show the results from the scored treatment means in the typical output format while all reported statistics are for the runs of individually scored observations for each plot.

2.2.4. Outcome comparisons

Index outcomes were compared to the original data in two ways, to understand the driving mechanisms and as a validation attempt. First, the relationships between the treatment means for each SQI combination and those of the unscored indicators were examined. A Varimax rotation of the standardized PCA using all significant soil indicators was also performed. An ANOVA was calculated using the rotated scores from Varimax PC1 to compare treatment means (Wander and Bollero, 1999). This result was then compared with the SQI results by using Pearson correlation coefficients.

3. Results and discussion

3.1. Indicator selection

3.1.1. Expert opinion

The indicators chosen by expert opinion from the available data set were SOM, EC, pH, P, and SAR. The first four indicators have been suggested as MDS components for a variety of systems (Larson and Pierce, 1991; Doran and Parkin, 1996; Karlen et al., 1998). The fifth indicator, SAR, was included as an important indicator in irrigated systems (Hanson and Grattan, 1992).

3.1.2. Principal components analysis

The soil variables having significant differences between farming systems treatments, and thus, included for the PCA were: SOM, TOC, TN, SAR, Na, pH, P, K, *x*-Ca, S, and Zn. The first three PCs had eigenvalues >1 (Table 2). The highly weighted variables under PC1 were TOC, TN, K, and S. All four variables were significantly correlated. Total N had the highest factor loading, and thus, was retained for the MDS. Under PC2, Na and *x*-Ca were highly weighted. Both were retained for the MDS because they were not well correlated. Soil pH, P, and Zn were highly weighted under PC3. Soil pH was retained for the MDS because it was uncorrelated to P and Zn. However, P and Zn were well-correlated to each other so only P was retained for the MDS by virtue of its higher factor loading. The final PCA chosen MDS for all crops combined was TN, Na, *x*-Ca, pH, and P (none of which were well-correlated). An on-farm study comprised of similar management treatments in the Central Valley of California using this PCA technique for MDS selection retained several similar indicators including SOM, EC, pH, and Zn (as well as two indicators not measured in the SAFS study, bulk density and water stable aggregates) (Andrews et al., 2001).

This same procedure was followed using soils data from each crop separately and, for tomato and corn, a second time including additional data available only for plots planted to those crops. Using the common data set, the PCA-chosen MDS specific to tomato was Na, pH, and Zn; using the extended data set, the MDS was straight chain:branched chain PLFA groups, TN, and Zn. For corn, the common data set PCA-MDS was SOM, Na, and *x*-Ca; with the extended data set the PCA-MDS was NH_4, *x*-Ca, and S. For safflower, the PCA-chosen MDS included EC, P, TOC, and Zn. The PCA-chosen MDS specific to bean was EC, SAR, and Zn. Zinc was the only indicator chosen for three of the four crops. Although, Zn was highly weighted under PC3 when data for all crop rotations combined were used, it was not included in the MDS (because P received the highly factor loading).

3.1.3. *Indicator representation of management goals*

The ability of both the EO and the PCA selected-MDSs to explain variability in end-point data representing sustainable management goals was examined. When the MDSs (comprising the independent variables) were regressed iteratively using each sustainability end-point (as a dependent variable), several trends emerged (Table 3 shows data for all crops combined and tomato only). The results showed no clear dominance for one MDS selection method over the other (see EO versus PCA in Table 3). Both the EO and the PCA (using data for all crop rotations) selected MDSs seemed to provide stronger explanations of variability in the individual goal indicators (higher R^2) when using data from individual crops than for all crops combined, due to the strong crop influence on the soil indicators (see all crops EO & PCA versus tomato EO & PCA in Table 3). For example, July weed cover is poorly explained by the MDSs using data for all crops but a much better explanation emerges when data for only corn or tomato is used. Fig. 3 illustrates this crop dependent result using the relationship between weed cover and pH (an indicator present in both the EO and the PCA MDS). However, MDSs selected using data specifically for one crop are not representative of all crops combined (see Table 3; all crops spec versus tomato spec). Also the R^2 for regressions using MDSs selected from extended data sets tended to be higher than R^2 values for the MDSs selected from the common data set for the corresponding crop (see spec versus extd; shown only for tomato).

To enumerate these trends in MDS ability to explain variability in sustainability end-points, the resulting R^2 values were treated as observations in three-way ANOVAs using MDS, crop, goal end-points, and their interactions in the model (Table 4). In the first ANOVA, differences between the MDS selection techniques were examined. This ANOVA compared regression results from the expert opinion selected

Table 3
Coefficients of determination (R^2) for multiple regressions of PCA or expert opinion (EO) selected minimum data sets (MDSs) (as independent variables) against end-point variables representing management goals (as iterative dependent variables) using data for all SAFS crop rotations combined or for tomatoes only, 1996

Goal	Data source for regression						
	All crop rotations			Tomato only			
	EO[a]	PCA[b]	spec[c]	EO	PCA	spec	extd[d]
Net revenue (US$/ha)	0.63	0.67	0.06	0.90	0.92	0.69	0.94
Yield[e] (mg/ha)	0.15	0.09	0.06	0.58	0.43	0.39	0.48
SAR or Na (meq/L)	0.98	0.87	0.85	0.99	0.97	0.95	0.79
Water use (mm per year)	0.72	0.68	0.60	0.90	0.93	0.77	0.92
WUE[f]	0.34	0.34	0.29	0.86	0.90	0.75	0.91
July weed cover (%)	0.17	0.23	0.16	0.85	0.88	0.68	0.87
Average weed cover (% per month)[g]	0.18	0.25	0.07	0.76	0.81	0.76	0.81
Pesticide use (kg ha^{-1})	0.62	0.62	0.45	0.87	0.87	0.84	0.80
Tillage (no. operations per year)	0.25	0.18	0.32	0.96	0.97	0.80	0.96

[a] EO: MDS chosen by expert opinion from the available data—EC, P, pH, SAR, SOM.
[b] PCA: MDS determined by PCA of data from all crop rotations—Na, P, pH, TN, *x*-Ca.
[c] spec: Specific PCA-chosen MDS determined using data for tomato only—Na, pH, Zn.
[d] extd: PCA-chosen MDS using extended data set for tomato only—fungal:branched PLFA, TN, Zn.
[e] For all crops combined a proportional yield factor based on Yolo Co. averages was used.
[f] WUE: water use efficiency as a proportion of water applied and crop yield.
[g] Average percent weed cover sampled once per month for 9 months.

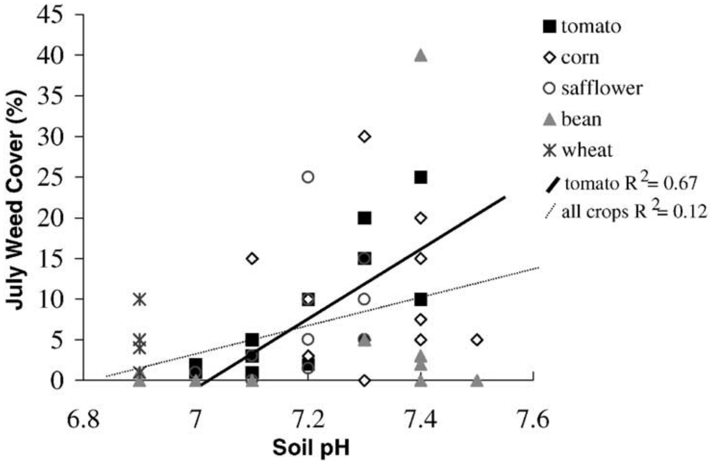

Fig. 3. The relationship between percent weed cover in July and soil pH at SAFS, 1996, highlighting crop specific differences in the ability of MDS components (e.g. pH) to explain variability in management goal variables (e.g. percent of weed cover).

Table 4
Significant differences (P-values) for three-way ANOVA of the coefficients of determination for multiple regressions of alternative minimum data set (MDS) indicators against end point variables representing management goals[a]

Source	EO MDS versus PCA MDS[b]	All crop PCA versus single crop PCA[c]	PCA comparison of number of observations[d]	PCA comparison of number of variables[e]
MDS	n.s.d.	0.0001	0.001	0.04
Crop	0.0001	0.0001	0.0002	0.009
Goal variable[f]	0.0001	0.0001	0.0001	0.005
MDS × crop	0.07	n.s.d.	n.s.d.	n.s.d.
MDS × goal	0.02	0.09	n.s.d.	n.s.d.
Crop × goal	0.0001	0.0001	0.008	n.s.d.

[a] Four ANOVAs using different combinations of MDSs and crop data are shown.

[b] This ANOVA compares the expert opinion selected (EO) MDS (EC, P, pH, SAR, SOM) with the MDS selected by PCA of data from all crop rotations PCA (Na, P, pH, TN, x-Ca) using data for each crop individually and for all crop rotations combined.

[c] This ANOVA compares the effectiveness of PCA performed only single crop (corn: Na, SOM, x-Ca; or tomato: Na, pH, Zn) to the use of data from all crop rotations for PCA (Na, P, pH, TN, x-Ca). The MDSs were imposed on data for bean, safflower, and all crop rotations combined.

[d] For this ANOVA, we used the MDS chosen via PCA of data from all crop rotations PCA (Na, P, pH, TN, x-Ca) ($N = 56$) compared with MDSs specific to each crop, chosen by PCA using data from each crop individually ($N = 16$ for tomato or $N = 12$ for others). Only individual crop data was used. The specific PCA-chosen MDSs for each crop were: tomato—Na, pH, Zn; corn—Na, SOM, x-Ca; bean—EC, SAR, Zn; and safflower—EC, P, TOC, Zn.

[e] For this ANOVA, we used the PCA-chosen MDSs specific to tomato or corn only that differed in the number of variables that comprised the original data set. The data set for specific PCA chosen MDS (described above) had 16 variables. The extended data sets for tomato and corn had 40 and 31 variables, respectively. The extended data set PCA MDSs were: tomato—fungal:branched PLFA, TN, Zn; corn—moisture, NH4, S, x-Ca.

[f] Nine goal variables served as iterative independent variables. They included net revenue, yield (or the proportion of observed yield to Co. average yields when all crop rotations were considered together), SAR (or Na if SAR was part of the MDS), water use, water use efficiency, weed cover in July, average weed cover for 9 months, pesticide application rate, and number of tillage operations.

(EO) MDS (EC, P, pH, SAR, SOM) with the MDS selected by PCA of data from all crop rotations PCA (Na, P, pH, TN, x-Ca) using data for each crop individually and for all crop rotations combined. No significant differences were observed in the regression results from EO and PCA selected MDSs, suggesting that the two techniques were equally representative of management goals in these systems. Contrasts showed differences among crops; when MDSs selected from the entire data set were regressed against sustainability goals using data from each crop individually, the tomato and safflower data resulted in significantly higher R^2 values compared with the corn and bean, which in turn were higher than that for all crops combined. This pattern held true for the remaining ANOVAs implying that MDSs may perform better for some crops than for others. There were also significant differences in R^2 values among sustainability goals. The pattern of contrasts was similar for all ANOVAs (across MDS types): SAR or Na, pesticide use, and tillage operations tended to have the highest R^2 values while yield, July weeds, and average weeds had among the lowest R^2 values. Only two pairs of end point variables had correlation coefficients higher than 0.60 (SAR and water use; tillage operations and yield), this autocorrelation did not appear to affect the goal variable response in the ANOVAs. Differences among goal variables suggest that certain management goals will be better represented by the SQIs than will others. Importantly, the MDS-SQI method may not be a good predictor of yield for these systems.

The second ANOVA compared the effectiveness of PCA performed for only a single crop (corn: Na, SOM, x-Ca; or tomato: Na, pH, Zn) to the use of data from all crop rotations for PCA (Na, P, pH, TN, x-Ca) (Table 4). The MDSs selected specifically for corn or tomato and all crop rotations combined were imposed on data for bean, safflower, and all crop rotations combined. The ANOVA showed significant differences among MDSs, crops, and goal variables. The MDS selected using soils data from all crops had significantly higher R^2 values than the MDS for tomato or corn when imposed on data from the other crop rotations. This suggests that data from one crop (or 1 year) is not sufficient to form a PCA selected MDS when complex rotations are used. Crop and goal variable contrast results were similar to those described above.

The third ANOVA explored the effect of data set size on the efficacy of the PCA selected MDS (Table 4). We compared the MDS chosen via PCA of data from all crop rotations (Na, P, pH, TN, x-Ca) ($N = 56$) with MDSs specific to each crop, chosen by PCA using data from each crop individually ($N = 16$ for tomato or $N = 12$ for others). Only individual crop data was used. The specific PCA-chosen MDSs for each crop were: tomato—Na, pH, Zn; corn—Na, SOM, x-Ca; bean—EC, SAR, Zn; and safflower—EC, P, TOC, Zn. The R^2 values for the PCA MDS using all crops ($N = 56$) were significantly higher than for the crop specific PCA MDSs. This result implies that the number observations in the original data set influences the ability of the resultant PCA selected MDS to represent management goals. This is likely because more observations in the original data set tended to generate a greater number of significant PCs under PCA. In turn, the more significant PCs, the more indicators were selected for the MDS. The higher number of indicators in the MDS probably contributed to greater explanation of management goal variability.

To test this possibility, multiple regressions against goal variables were run with randomly assigned indicators as the independent variable MDS using progressively higher numbers of indicators (three to six indicators). In general, the greater the number of variables included in the MDS, the higher the R^2 values ($P < 0.0001$; data not shown). The reasons for these results are largely mathematical and lead to the conclusion that the PCA method works better for larger data sets than smaller ones.

The trend toward better performance for the PCA-MDS method with larger data sets is not limited to number of observations but also includes the number of variables in the original data set. The last ANOVA used only the PCA-chosen MDSs specific to tomato or corn (Table 4). These MDSs differed in the number of variables that comprised the original data set. The data set for specific PCA chosen MDS (described above) had 16 variables. The extended data sets for tomato and corn had 40 and 31 variables, respectively. The extended data set PCA MDSs were: tomato—straight chain:branched chain PLFA groups, TN, Zn; and corn—moisture, NH_4, S, x-Ca. Contrast results showed extended data set PCA MDSs garnered higher R^2 values than the PCA selected MDS using the only the variables common to all crops, even though the MDSs usually had the same number of indicators. In contrast, the extended data MDSs (with three indicators) usually performed as well or better than the PCA-MDS for all crops or the EO MDS (each with five indicators) (see Table 3; extd versus PCA and EO). This suggests that a greater number of indicators in the original data set may offset the problems associated with using a data set with fewer observations.

These potential problems with the PCA method also belie it's largest limitation: the PCA selection method is management and site specific. The first step in the process eliminates indicators that do not have significant differences between the practices to be evaluated. If conditions change this subset will likely change as well. The process most likely needs to be repeated any time a different management practice is to be evaluated. So too if climatic conditions change to the extent that shifts may occur in the factors limiting soil function. Without time series data it is impossible to know how long the MDS chosen by this method is valid. It would be prudent to repeat the process periodically to make sure that the important indicators have not changed. In contrast, the EO method does not rely on treatment differences but knowledge of the system. Changes to the EO MDS would need to follow the same guidelines as for the PCA but this would not entail collecting data, making the EO method the more easily adaptable method (when expert knowledge, including farmer experience, is available).

3.2. Indicator transformation (scoring)

3.2.1. Linear scores

The linear scoring method results were highly dependent on the variance of each indicator because each observation is a proportion of the highest (lowest) observation for "higher (lower) is better" indicators. In addition, if the high (low) score is an outlier, intimate knowledge of the dataset is required to know that it should be thrown out, otherwise all of the subsequent scores become unjustly skewed. In several cases, linear scores did not appear to be justifiable either agronomically or environmentally. For example, the high variability in the observed range for P, from 64 to 9 mg kg^{-1}, led to scores for the treatment means ranging from 0.70 to 0.37, a range which was probably too broad (Table 5). The most obvious problem scores were for SAR and Na, both of which were at very benign levels for all observations. However, after being scored by this technique, the scores for the treatment means ranged from 0.68 to 0.51 for SAR and from 0.47 to 0.66 for Na, all considerably lower than was reasonable (Table 5).

Table 5
Comparison of treatments means and standard deviations (in parentheses) of measured indicator values with linear and non-linear transformed scores used for the expert opinion and PCA-chosen minimum data sets (MDSs) selected for all crops combined

System[a]	SOM	TN	EC	*x*-Ca	SAR	Na	pH	P
	($g\,kg^{-1}$)		($dS\,m^{-2}$)	(meq 100 g^{-1})	($meq\,l^{-1}$)		($-\log H^+$)	($mg\,kg^{-1}$)
Organic	18.3 (1.4)	1.4 (0.1)	0.83 (0.23)	8.12 (0.39)	0.7 (0.20)	1.38 (0.42)	7.3 (0.1)	30.06 (12.36)
Low input	17.0 (1.1)	1.3 (0.1)	0.81 (0.22)	7.96 (0.31)	0.7 (0.15)	1.29 (0.25)	7.3 (0.1)	15.13 (2.63)
Conv-4	15.4 (1.3)	1.1 (0.1)	0.81 (0.25)	7.43 (0.23)	0.6 (0.16)	1.23 (0.49)	7.1 (0.1)	14.81 (2.88)
Conv-2	15.3 (3.8)	1.1 (0.1)	0.72 (0.14)	7.44 (0.27)	0.5 (0.05)	0.93 (0.17)	7.0 (0.1)	20.38 (8.33)
Linear scoring results								
Organic	0.75 (0.06)	0.88 (0.06)	0.55 (0.16)	0.90 (0.04)	0.51 (0.17)	0.47 (0.13)	0.89 (0.01)	0.70 (0.18)
Low input	0.70 (0.05)	0.81 (0.04)	0.56 (0.18)	0.88 (0.03)	0.52 (0.13)	0.48 (0.09)	0.89 (0.01)	0.38 (0.07)
Conv-4	0.63 (0.05)	0.72 (0.06)	0.56 (0.16)	0.83 (0.03)	0.60 (0.18)	0.57 (0.22)	0.91 (0.02)	0.37 (0.07)
Conv-2	0.63 (0.16)	0.71 (0.06)	0.60 (0.12)	0.83 (0.03)	0.68 (0.06)	0.66 (0.10)	0.93 (0.01)	0.51 (0.21)
Non-linear scoring results								
Organic	0.96 (0.03)	0.94 (0.04)	0.98 (0.05)	0.84 (0.04)	0.94 (0.04)	1.00 (0.00)	0.95 (0.01)	0.93 (0.06)
Low input	0.93 (0.04)	0.90 (0.03)	0.99 (0.02)	0.83 (0.03)	0.92 (0.07)	0.99 (0.00)	0.95 (0.01)	0.72 (0.07)
Conv-4	0.87 (0.05)	0.82 (0.06)	0.98 (0.05)	0.77 (0.03)	0.95 (0.04)	0.99 (0.00)	0.96 (0.01)	0.71 (0.08)
Conv-2	0.83 (0.10)	0.80 (0.07)	1.00 (0.01)	0.77 (0.04)	0.97 (0.00)	0.99 (0.00)	0.97 (0.00)	0.81 (0.17)

[a] See Table 1 for details on management treatments.

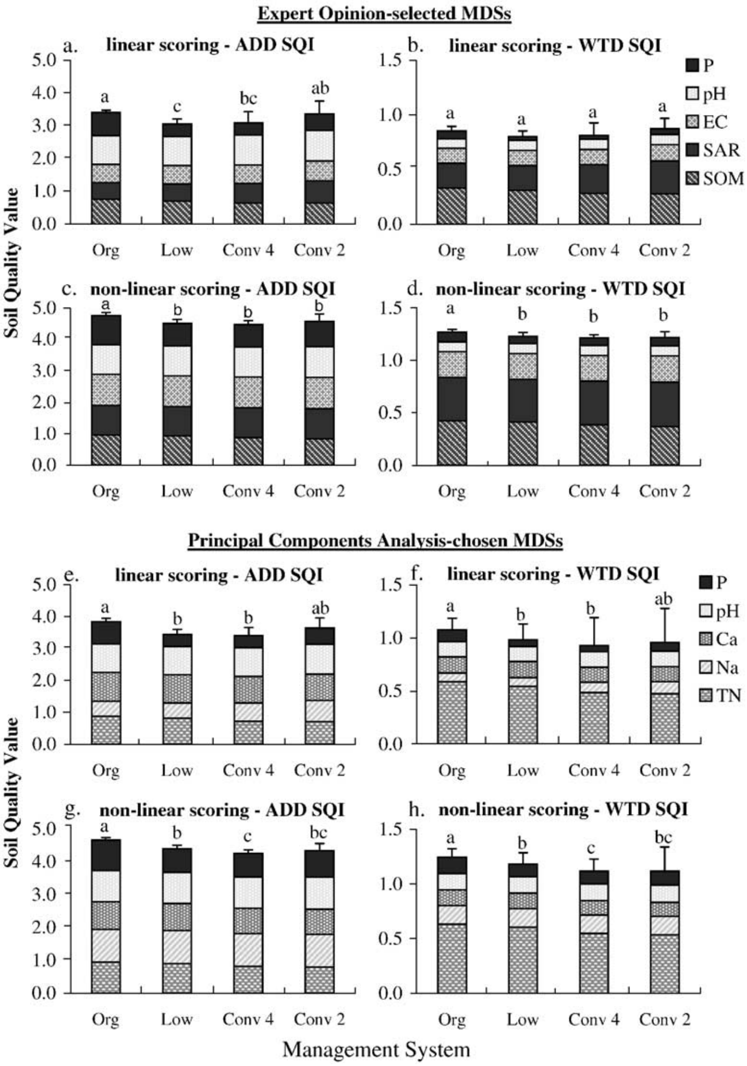

Fig. 4. Additive (ADD SQI) and weighted soil quality indices (WTD SQI) using linear or non-linear scored indicators chosen by expert opinion or principal components analysis minimum data set (MDS) selection techniques for alternative farming management systems in 1996 (error bars represent ±1 S.D. from the mean SQI value for each treatment. Different letters denote significant differences between management treatments at $\alpha = 0.05$).

3.2.2. Non-linear scores

The non-linear scores, although more difficult to determine, seemed to represent system function better than the linear scores. Again the salinity (and sodicity) indicators best illustrate this point. The non-linearly scored treatment means for SAR, Na, and EC reflect the fact that the observed values are all well within the optimum range for crop growth and environmental quality (Table 5). These non-linearly scored indicators have a much lower differences (%) between treatment means than their linearly scored counterparts. For other indicators, like SOM, TN, Ca and pH, both scoring methods appear to perform equally well. Fig. 4 illustrates the relative indicator scores using the linear and non-linear techniques for the PCS MDS in both the additive and the weighted indices (comparing Fig. 4a and c, b and d, e and g, f and h).

Table 6
Comparison of outcomes for alternative soil quality index (SQI) calculations method using a two-way ANOVA (*P*-values for split plot design) of management systems at SAFS, 1996

Model	Additive SQI				Weighted SQI				Decision support system SQI			
	Linear scoring		Non-linear scoring		Linear scoring		Non-linear scoring		Linear scoring		Non-linear scoring	
	EO[a]	PCA[b]	EO	PCA	EO	PCA	EO	PCA	EO	PCA	EO	PCA
System	0.22	0.06	0.06	0.005	0.69	0.06	0.11	0.005	0.02	0.03	0.02	0.01
Crop (system)[c]	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001

[a] EO denotes minimum data set selected by expert opinion.
[b] PCA denotes minimum data set using principal components analyses for data reduction.
[c] This dependent variable indicates the difference between crops within each management system.

3.3. Indicator integration into indices

Once the scored indicators from the two MDSs were combined into the different index alternatives, the SQI outcomes via two-way ANOVA were analyzed for management system effects and crop effects within each management system (Table 6). This analysis revealed several further trends with regard to MDS method and scoring type. Within the additive and weighted indices, the PCA-chosen MDS resulted in better differentiation among management systems. Also for these indices, the non-linear scoring yielded more significant differences among systems than did linear scoring of indicators. The DSS SQI showed significant differences between systems for all MDS and scoring methods but these statistical differences (*P*-values) were probably not meaningfully different from one another. Apparently, the influence of the DSSs hierarchical structure superseded differences in MDS and scoring techniques. All indexing combinations showed very significant differences in SQI values between crops within system. These crop-specific differences appear to have more impact on SQI outcomes than differences among indexing methods.

3.3.1. Additive index

For all MDS-scoring combinations of the additive index, the organic treatment received significantly higher SQI values compared to the LOW and Conv-4 treatments (Fig. 4a, c, e, and g). The Conv-2 treatment was not significantly different from any other treatments when either MDS was scored linearly. There were some minor differences among MDS and scoring methods as to which treatment received the lowest SQI values.

3.3.2. Weighted additive index

Weighting the EO MDS using PCA weights is somewhat artificial because one of the advantages of the EO method is that preliminary statistics are unnecessary. A different weighting scheme (probably also based on EO) would be more pragmatic in practice but for the purposes of this study using the same weights among SQIs allowed for better comparisons.

As indicated by the similar ANOVA outcomes for additive and weighted indices within MDS and scoring techniques (*P*-values for system in Table 5), there were no differences in the relative ranks of the treatments due to weighting (Fig. 4: comparing a with b and c with d and so on). The one exception was the EO MDS scored linearly (Fig. 4b), where the additive SQI showed significant differences between treatments while its weighted counterpart did not.

The remainder of the discussion is limited to comparisons with the additive index and uses only the non-linearly scored indicators because in most cases the extra step of weighting does not change the SQI outcome and the linear scoring often leads to artificial differences between treatments.

3.3.3. Decision support system SQI

The decision support system is designed to calculate the range of possible SQI outcomes using scored treatment means for each MDS variable, given the user-dictated importance order in the hierarchy. The macro calculates all possible weights for the indicators that maintain that importance order. The graphical DSS output reports a range (median, maximum, and minimum values) of SQI outcomes based on this importance order. Alternatives receiving a smaller range from best to worst SQI value have less sensitivity to the ranking system and are less "risky" (Yakowitz and Weltz, 1998). Alternative treatments with no overlap between outcomes, i.e. the minimum of one is higher than the maximum of the other, are said to display complete dominance; that is to say, the higher one has SQI values in all cases under the given importance order. Therefore, outcomes with high medians and narrow ranges are the most desirable (from a soil quality standpoint). To provide a reference to this unusual graphical format, the DSS was also calculated for each observation separately to allow for Tukey–Kramer means comparisons, not usually possible for the normal use of the DSS. While the DSS median (calculated using treatment means) and the DSS mean (calculated using each observation) were not identical for each treatment, the relative treatment outcomes remained consistent between the two ways to calculate the DDS.

The DSS SQI using the EO MDS resulted in a SQI value for the organic treatment that was completely dominant over all other treatments, where (by the criteria outlined above) the SQI outcomes by system were ORG $\gg$ Conv-2 $>$ LOW $\approx$ Conv-4 (Fig. 5a), a pattern very similar to the outcomes of the other indexing methods. The PCA MDS resulted in incomplete dominance for the organic system with the overall ranking being ORG $>$ Conv-2 $>$ LOW $\approx$ Conv-4 (Fig. 5b). The organic system DSS SQI outcomes were also much less sensitive to the importance order ranks than the other systems as evidenced by the very small range of SQ values. In contrast, when the DSS was run using individually scored observances for the indicators rather than scored treatment means (so that statistical comparisons could be made), the DSS SQI using the PCA MDS showed slightly more significant differences between treatment means than when the EO MDS was used (Table 5). However, the DSS SQI outcomes for management systems received relative ranks identical to those for the ADD SQI using non-linear scoring for the EO MDS (ORG $>$ all others).

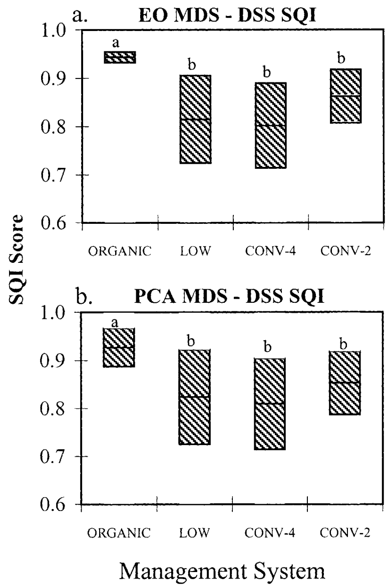

Fig. 5. Outcomes for the hierarchical decision support system soil quality index (DSS-SQI) using non-linearly scored minimum data sets (MDSs) chosen by principal components analyses (PCA) or expert opinion (EO) (the mid-point, high, and low bars represent the median, maximum, and minimum of SQI values, respectively, calculated using the scored treatment means. Different letters denote significant differences between management treatments at $\alpha = 0.05$ calculated using individually scored observations).

3.4. Outcome comparisons

For most indexing method combinations, the organic system received higher SQI values than the other treatments. This is consistent with many of the findings of Poudel et al. (2001), who report on SAFS results from 1994 to 1998. For example, Poudel et al. (2001) found that potentially mineralizable N, an index of N availability, was significantly higher in the organic and low-input systems. At the same time, they found that actual N turnover rates in the conventional system was 100% greater than in the organic and 28% greater than in the low-input system. They relate this finding to reduce risk for N leaching and groundwater pollution in the latter systems. To formalize these intuitive index results, understand the driving mechanisms of the indices' performance, and to test the efficacy of the results, several additional analyses were performed.

First, the multiple regressions of MDS indicators against various goal variables tested the ability of the MDS to represent the management goals for the system (described above). Then, several comparisons of the index outcomes were performed.

We examined the differences between management systems for the individual indicators compared to the index outcomes. This examination highlighted the complexity of trying to evaluate many indicators individually. Fig. 6 shows the means differences for

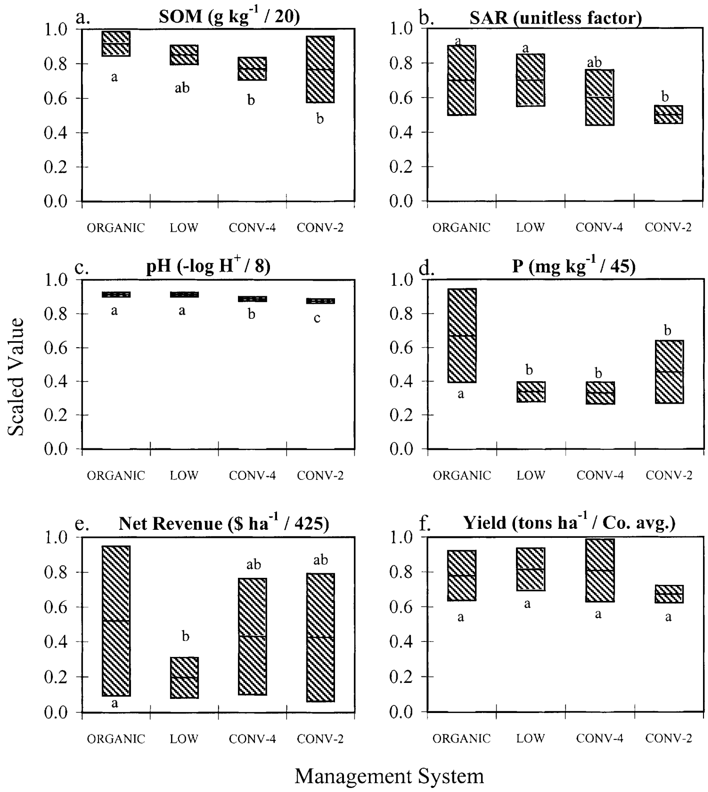

Fig. 6. Individual indicators and management goal variables for SAFS management systems in 1996. For comparison purposes, each is scaled to fit the DSS output format. Scaling factors are reported at the top of each graph. (the mid-point, high and low bars represent the scaled mean and ±1 S.D. from that mean, respectively. Different letters denote significant differences between management treatments at $\alpha = 0.05$).

selected indicators scaled to fit the DSS format. Only three individual soil indicators, P, K and Zn, exhibited the same pattern of significant differences between treatment means as the SQI using the EO MDS and both DSS SQIs: organic treatment means significantly higher than the other three treatment means. Similarly, the treatment means for the management goals exhibited different patterns from the SQI outcomes (not all data shown). This comparison was more useful to illustrate the need for an index (due to the complexity of finding a single interpretation for the sometimes conflicting individual indicator results) than for actually validating the index outcomes.

The second avenue of comparison for the index outcomes was to compute the Pearson correlation coefficients between the outcomes, individual soil indicators, and end-point variables (Table 7). This information gave us not only the level of correspondence between the soil quality indices and the individual indicators but also the direction of the change (i.e. does SQI value go up or down when yield goes up?). In almost all cases, the SQIs were significantly correlated with organic matter indicators (SOM, TOC, and TN). This could be expected because these soils are low in organic matter (Clark et al., 1998) and SOM influences most soil functions (Gregorich et al., 1994). Clark et al. (1999a, and 1999b) found that the SAFS organic and low-input systems (with their increased SOM resulting from manure and cover cropping (Table 1)) actually altered the yield-limiting factors compared with the conventional systems. Other significantly correlated soil factors included fertility indicators: P, K,

Table 7
A comparison of Pearson correlation coefficients for soil quality index (SQI) methods with selected, individual soil indicators and management goal variables at SAFS, 1996

Variable	Additive SQI				Weighted SQI				Decision support system			
	Linear scoring		Non-linear scoring		Linear scoring		Non-linear scoring		Linear scoring		Non-linear scoring	
	EO[a]	PCA[b]	EO	PCA	EO	PCA	EO	PCA	EO	PCA	EO	PCA
SOM ($g\,kg^{-1}$)	0.39**	0.43***	0.64***	0.66***	0.25	0.43***	0.74***	0.66***	0.56***	0.51***	0.56***	0.54***
Total N ($g\,kg^{-1}$)	0.23	0.45***	0.65***	0.79***	0.01	0.45***	0.72***	0.79***	0.56***	0.55***	0.60***	0.61***
SAR	−0.33**	−0.23	0.07	0.19	−0.62***	−0.23	0.16	0.19	0.10	0.01	0.07	0.07
Na ($meq\,l^{-1}$)	−0.47***	−0.25	0.12	0.22	−0.73***	−0.25	0.23	0.22	0.11	0.06	0.11	0.12
EC ($dS\,m^{-2}$)	−0.39**	−0.10	0.10	0.20	−0.43***	−0.10	0.17	0.20	0.06	0.10	0.11	0.17
pH ($-\log H^{+}$)	−0.10	−0.05	0.01	0.19	−0.17	−0.05	0.11	0.19	−0.03	−0.04	−0.00	0.04
P ($mg\,kg^{-1}$)	0.56***	0.74***	0.76***	0.76***	0.21	0.74***	0.60***	0.77***	0.91***	0.87***	0.82***	0.80***
x-Ca (meq/100 g)	0.19	0.37**	0.29*	0.54***	0.16	0.37**	0.28*	0.54***	0.26	0.33**	0.32*	0.42***
Zn ($mg\,kg^{-1}$)	0.55***	0.63***	0.62***	0.63***	0.28*	0.63***	0.50***	0.63***	0.71***	0.67***	0.67***	0.63***
Yield[c]	0.32*	0.31*	0.13	0.16	0.41**	0.31*	0.11	0.16	0.15	0.19	0.15	0.16
Net revenues[d]	0.02	0.03	−0.04	−0.05	0.05	0.03	−0.13	−0.05	−0.04	−0.02	0.01	0.00
Pesticide use[e]	−0.41**	−0.45***	−0.27*	−0.35**	−0.37**	−0.45***	−0.23	−0.35**	−0.31*	−0.32*	−0.29*	−0.31*

[a] EO denotes minimum data set selected by expert opinion.
[b] PCA denotes minimum data set selected using PCA as a data reduction technique.
[c] Yield was calculated as a proportion, using measured yield in the numerator and Yolo Co. averages for the corresponding crop in the denominator.
[d] Net revenues (US$ ha^{-1}) included price premiums for organic produce.
[e] Pesticide use was determined by application rates only ($kg\,ha^{-1}$), no differentiation was made for chemical type.
* Significant at the 0.05 probability level.
** Significant at the 0.01 probability level.
*** Significant at the 0.001 probability level.

x-Ca, and Zn. Brejda et al. (2000) also found organic matter and fertility factors to be dominant in their regional scale index of National Resource Inventory data using another statistical technique, discriminant analysis.

Improvements in soil quality must be taken within the context of the system. In a subsequent study of the SAFS project conducted in 1997 and 1998, Colla et al. (2000) found that the higher infiltration rates and soil water content (often considered to be positive soil traits) in the organic and low-input systems, actually led to an increased irrigation water demand and lower tomato yield quality (but not quantity). These consequences, believed to be caused by an increase in surface macroporosity, were attributed largely to the type of irrigation management (furrow) and timing in these systems. The apparent disparity between organic matter indicators and outcomes in irrigated systems was a concern also expressed by Sojka and Upchurch (1999). It is likely, however, that the problem lies not in the indicator but rather in the chosen management practice; an alternate irrigation system, like drip irrigation, would be more compatible with the observed improvements in soil quality indicators. In short, what is considered to be good soil quality in most situations may not always lead to desired outcomes depending on management practices and goals, thus highlighting the need for flexibility in scoring indicators.

The index combinations that were not well-correlated with the organic matter and fertility indicators were the additive and weighted indices using the linearly scored EO MDS. Instead, these two indices were highly negatively correlated with SAR, Na and EC. While an inverse relationship with the salinity indicators would be appropriate, none of these indicators were found to be at deleterious levels in any of the management system treatments. The problems associated with linear scoring (discussed above) seemed to dominate these index outcomes.

The management goals showed fewer significant correlations with the indices. Although yield was also significantly correlated with the linearly scored additive and weighted indices, in general, the indices do not appear to be predictive of yield. Net revenues had no correlation with the indices. Net revenues could be more indicative of market forces than soil quality, and thus, may not be an appropriate measure of SQI efficacy. Pesticide application rates were significantly inversely related to all indices except the weighted index using the non-linearly scored EO MDS. Because pesticides can have a direct effect on soil quality as well as an off-farm environment (Pierzynski et al., 1994), this relationship supports the SQI outcomes.

Finally, the index outcomes were compared with a multivariate approach to analyze systems that uses all significant data (Wander and Bollero, 1999) as opposed to using an MDS. Using the Varimax rotated scores of PC1 as the response variable, a one-way ANOVA of the management systems showed the ORG system to have a significantly higher score than the Conv-4 and Conv-2 systems ($P < 0.0005$), an outcome similar to that for the SQIs. Pearson correlation coefficients comparing the SQI outcomes with the results from the rotated PC method of Wander and Bollero (1999) revealed the most significant correlations for non-linear scoring of either MDS for all index calculation methods (Table 8). There was no correlation between the rotated PC result and the linearly scored EO MDS in the additive and weighted indices, once again suggesting that this combination is less suited for evaluating soil quality in these systems than the other indexing combinations. Among the remaining indexing combinations, outcome comparisons and correlations point to the additive index using the non-linearly scored PCA-MDS as being slightly more representative of overall soil quality in these vegetable production systems.

Table 8
A comparison of correlation coefficients for selected integrative soil quality index (SQI) and decision support system methods with Varimax rotated scores from PC1 using all indicators available for all crops at SAFS, 1996

Variable	SQI correlation coefficients			
	Linear scoring		Non-linear scoring	
	EO[a]	PCA[b]	EO	PCA
Additive SQI	0.24	0.36**	0.56***	0.63***
Weighted SQI	0.16	0.36**	0.69***	0.63***
DSS SQI	0.41**	0.41**	0.48***	0.48***

[a] EO denotes minimum data set selected by expert opinion.
[b] PCA denotes minimum data set selected using PCA as a data reduction technique.
** Significant at the 0.01 probability level.
*** Significant at the 0.001 probability level.

4. Conclusions

Both the PCA and EO methods resulted in MDS that were equally representative of variability in end-point measures of farm and environmental management goals for the vegetable production systems. However, the PCA method requires a large existing data set including all crop rotations. It may not work as well for all data if the number of indicators or observations is low. Conversely, once the MDS is established there may be no need for testing a broad array of other indicators to assess soil quality over time (for some undefined period). But lack of information about the exact applications of a PCA selected data set, i.e. how long it is meaningful, what systems it can be applied to, etc. may pose a significant barrier to adoption. On the other hand, the EO method requires expert knowledge of the system and may be subject to disciplinary biases. A recommendation of one method over the other must be carefully considered and will vary by site and use.

The results of the scoring comparison varied by indicator. Some indicator scores were equally justifiable by either method. For the linear scoring technique, results were highly dependent on observed range. Overall, the functionality of many indicators seemed to be better represented by the non-linear scoring technique. While the non-linear technique is more work intensive and requires better knowledge of the system, this method may be more transferable to other data sets and systems.

For most indexing method combinations, the organic system received higher SQI values than the other treatments. Weighting the additive SQI did not change the relative SQI rankings for the treatments. This extra step was unnecessary for analyzing vegetable production or other systems. The DSS SQI outcomes were comparable to the ADD SQI but requires ranking of indicators within a user defined hierarchy, and thus, may be less user-friendly than the simple additive index.

Examination of the correlation coefficients showed the SQIs to be integrating the indicator results but they were heavily influenced by the indicators of organic matter. In fact, the majority of the SQ indexing combinations found the organic system to have greater soil quality than the other management systems. The comparison of the SQ indexing methods with the rotated PCA approach of Wander and Bollero (1999) showed that a subset of indicators combined into an index can generate similar information to performing a multivariate analysis of all of the available data. This suggests that a fewer number of carefully chosen indicators, when scored non-linearly and used in a simple index, can adequately provide the information needed for decision making. Assessment tools that reliably reflect environmental end-points, such as the ones evaluated here, may significantly improve the sustainability of agricultural management decisions.

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