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Soil quality assessment using fuzzy modeling

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A b s t r a c t. Maintaining soil productivity is essential if agriculture production systems are to be sustainable, thus soil quality is an essential issue. However, there is a paucity of tools for measurement for the purpose of understanding changes in soil quality. Here the possibility of using fuzzy modeling theory as a means to address the problem of soil quality assessment is considered. For soil quality assessment, two general types of fuzzy soil quality indicators potentially could be defined. The theoretical consideration of this process is illustrated with an example. Results indicate that the fuzzy multi-attributive approach could be effectively utilized as a tool leading to better understanding soil quality.

K e y w o r d s: soil quality, fuzzy indicators, fuzzy modeling

INTRODUCTION

Soil is a fundamental natural resource on which civilization depends. Agricultural production is directly related to quality of soil, and as soil degrades so does crop yield. Maintaining soil quality is essential not only for agricultural sustainability, but also for environmental protection. Mechanisms to measure changes in soil quality are important if soil scientists are to develop better methods (which will provide understanding) to manage the soil/crop system.

One method of monitoring soil quality which is being considered is utilization of soil quality indicators. Currently, evaluation of soil quality using indicators is being strongly debated in the scientific literature. Bremer and Ellert (2004) (in a review) provided examples of the development and use of soil quality indices. They note that the first publication related to soil quality assessment addressed the use of a soil productivity rating system, like the Storie Index Rating. This system aggregates variables controlling yield by the use of multiplication, addition, or a combination of the two. The Storie Index Rating is calculated by multiplying separate ratings for profile morphology, surface soil texture, or soil slope, by modifying factors *eg* soil depth, drainage, or alkalinity. Elaboration of soil productivity ratings is carried out by these steps (Huddleston, 1984):

– assignment of numerical values to soil properties, landscape characteristics, and weather conditions that influence plant growth and yield;
– use of both additive and multiplicative processes to formulate factor ratings and combine factors into final productivity ratings;
– use of available yield data (either directly or indirectly) to develop and validate the ratings;
– precision specification of all criteria used to assign numerical values, derive factor ratings, and combine factors in the model.

In another example, Bremer and Ellert (2004) considered soil assessment with the aim of estimating sufficiency of soil conditions for root growth. In particular, soil productivity index (Pierce *et al*., 1983) is defined as a combination of sufficiency of available water holding capacity, bulk density, and pH. Popp *et al*. (2002) modified this approach, adding a factor representing organic matter sufficiency.

Bremer and Ellert (2004) wrote that since the early 1990s, there has been considerable effort to develop soil ratings based on measured soil properties for the comparison of soil management systems (Karlen *et al*., 2001; Letey *et al*., 2003). In th is approach, soil quality is considered an inherent property of soil that can be determined from ascertainable soil attributes (Larson and Pierce, 1994). When a soil quality parameter declines below an acceptable limit, an appropriate management response is required to increase soil quality. Acceptable limits depend on land use, soil characteristics, landform, and climatic conditions.

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Many potential parameters of soil quality assessed at various scales have been proposed (Karlen *et al*., 2001). For example, a soil quality index was estimated by weighing factors related to water infiltration (aggregate stability, surface porosity), water absorption (porosity, total C, earthworms), degradation resistance (aggregate stability, microbial processes), soil pH, and plant growth (rooting depth, water relations, and nutrient relations) (Karlen *et al*., 1994). However, Karlen *et al*. (2001) stated that there is no ideal or universal index for soil quality.

While evaluation of soil quality has been the objective of many field experiments, the results of these extensive investigations have not reduced the complexity of this subject. These studies have not attempted to quantify soil quality as a degree or grade of perfection. An effective remedy which would account for the complexity and allow for evaluation of soil quality as a degree or grade of perfection is the fuzzy multi-attributive approach. This technique would enable soil scientists to solve soil quality problems in a systematic, consistent, and productive manner.

This paper proposes the fuzzy multi-attributive method for assessing soil quality. It is devoted to the explanation of the fuzzy multi-attributive approach and its application to soil quality assessment. The utilization of this approach for soil quality assessment is explained and a theoretical consideration for the process is illustrated.

CONCEPT OF FUZZY SOIL QUALITY INDICATORS

It is well known that soil quality evaluation has not been fully quantified, as evidenced by the ongoing debate in scientific literature. The uncertainty that is inherent in any evaluation process involves both data and model ambiguity; this ambiguity includes measurement error, inherent soil variability, soil instability, conceptual ambiguity, over-abstraction, simple ignorance of key factors that can impact soil quality. Because of the wide range of factors that make up soil quality and its inherent uncertainty, we believe that a unique approach must be taken to address soil quality. We propose that randomness and uncertainty of soil quality be dealt with by using fuzzy sets theory and fuzzy logic (Jager, 1995; Pedrycz and Gomide, 1998; Ross, 1995). This theoretical approach provides the basis for analysis of systems characterized by a high degree of uncertainty, nonlinearly and complexity.

Fuzzy logic has emerged as a more general form of logic that can handle the concept of partial truth. In this context, truth takes intermediate values between ‘completely true’ and ‘completely false’. Fuzzy logic is used as a modeling method that allows an easier transition between humans and computers, and a better way to handle imprecise and uncertain data.

Fuzzy set theory is a generalization of conventional set theory; the concept of belonging to a set has been modified to include partial degrees of membership ie values along the continuum between 0 and 1, encoded as a fuzzy membership function (MF). An MF is the central concept of the fuzzy set theory, where MF represents the relationship of an element to a set. An MF of a fuzzy set is expressed on a continuous scale from 1 (full membership) to 0 (full non-membership).

A major advantage of the fuzzy modeling method is the use of linguistics to represent relationships being modeled, instead of using the quantitative variables of traditional methods. Linguistic or fuzzy variables are those with names that characterize the semantics of the underlying concept under consideration. These fuzzy variables are represented mathematically by fuzzy sets (Corne *et al*., 1999).

Nowadays, fuzzy set theory is a hot topic and is being used successfully to address many scientific and technical in questions and problems, both mundane and abstract. However, to date, fuzzy set theory has not been used as a means of addresing the complexities of soil quality analysis. Recent developments in the application of fuzzy theory for environmental management (Baja, 2002a, 2002b; Burrough, 1989; Burrough *et al*., 1992; Carver, 1991; Joerin *et al*., 2001; Krueger-Shvetsova and Kurtener, 2003; Kurtener and Badenko, 2000a, 2000b, 2002; Kurtener *et al*., 2004; McBratney and Odeh, 1997; Tang and van Ranst, 1992; Xiang *et al*., 1992) has created new opportunities for the utilization of this theory for soil quality assessment. In particular, within the framework of fuzzy modeling, it is possible to develop the concept of a fuzzy soil quality indicator (FSQI). Instead of using the common definitions of soil quality indicators such as ‘physical, chemical, and biological properties, processes, and characteristics of soil’ that can be measured to monitor changes in the soil (http://soils.usda.gov/sqi/assessment.html), FSQI shows the degree of perfection/excellence of soil. In particular, two general types of FSQI are defined: the individual fuzzy soil quality indicator (IFSQI) type and the combined fuzzy soil quality indicator (CFSQI) type.

The IFSQI is considered to be an index of quality for the j soil attribute that takes into account the specifics of the i user group and the k aspect of data quality evaluation. An IFSQI is defined as a number in the range from 0 to 1, which reflects an estimation given by an expert in accordance with soil quality concepts, and modeled by an appropriate membership function.

Within the soil quality concept a selection of the appropriate membership function is the based aspect of fuzzy modeling). We considered many soil attributes and found that the trapezoidal-shaped, built-in membership function to be the most suitable. This function means that there exists an interval for an attribute (and when its value lies within this interval), its utility is optimal.

The CFSQI is defined using fuzzy aggregated operations. The CFSQI provides an integrated estimation of the soil quality of a given agricultural field. The computation process for IFSQI and CFSQI is illustrated by the flow chart Fig. 1.

Fuzzy indicators of soil quality allow the researcher to take into account the linguistic and conceptual uncertainties of the factors being considered in their analysis. The linguistic uncertainty is conditioned by polysemy (ambiguity of semantics of a term). Uncertainty arises from the incompleteness of the conceptual view, which could include an excessively detailed description or a reductive model with ignorance of key factors. The Fuzzy Modeling Approach (FMA) should allow researchers to develop meaningful interpretations of soil quality. These adjust and filter for uncertainties while providing a rating of the level of soil quality. Further, these ratings can be tracked as the affects of soil management changes are monitored over time. In this study, we used data collected from a precision agriculture experiment as a study site to further develop the theoretical considerations of fuzzy multi attributive decision-making process.

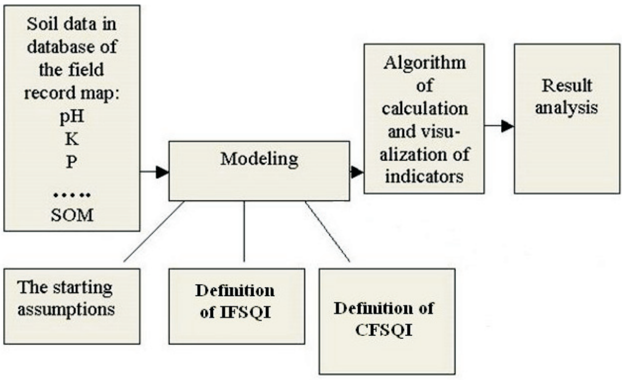

Fig. 1. Flowchart of the process for computing of IFSQI and CFSQI.

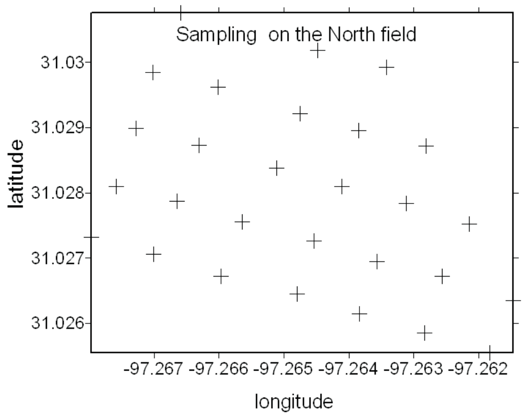

Fig. 2. Study site with points sampled for determination of soil properties.

STUDY AREA AND METHODS

The FMA was applied to the evaluation of soil quality of a crop field located in Bell County, TX, USA, on the Elm Creek Watershed (Fig. 2). The soils within this study site were a Heiden clay (fine, montmorillonitic, thermic Udic Chromusterts), a Houston black clay (fine, montmorillonitic, thermic Udic Pellusterts), and a Ferris clay (fine, montmorillonitic, thermic Udorthertic Chromusterts). Soil samples were collected when the study was initiated. These 15 cm soil cores were taken a one ha grid. Analysis included total nitrogen (N), total phosphorus (P), and organic carbon (C) concentration (Torbert *et al.*, 2000).

The application of FMA is a two step process. The first step requires the selection of the various IFSQIs to be utilized and to define the membership functions for all of these IFSQIs. In the second step, parameters of the membership functions have to be defined with suitable soil quality concepts. In this example, soil total P and soil organic C values taken at the study site were employed.

Calculation of fuzzy indicators was carried out with the use of the author's program, including several scripts written on MATLAB (The Mathworks Inc, 2004). Also, a software prototype developed by Krueger-Shvetsova and Kurtener (2003) was run. Visualization (building contour maps) was performed [Surfer® program (http://www.goldensoftware.com)]. Specifics of the IFSQIs and their membership functions used in this study and the results of the analysis are discussed below.

RESULTS AND DISCUSSION

Example of application of fuzzy modeling approach

Utilization of the concept to evaluate soil quality of crop land in Bell County, TX, USA, demonstrated that of the fuzzy modeling approach could have distinct advantages compared to traditional methods of analyzing soil for soil quality. In this example, total phosphorus and total organic carbon were used because they are soil chemical analysis that are commonly collected for soil fertility assessment and are also common parameters used in soil quality assessment. The specifics of how these parameters are used in the fuzzy modeling approach are described below. Both the traditional method of analysis and this new concept are illustrated.

Total phosphorus

In this FMA example for the definition of total P, IFSQI is a trapezoidal-shaped, built-in membership function and is shown in Fig. 3. This function means that there exists an interval for the soil P attribute such that when its value lies within this interval, its utility is optimal (Fig. 3). The specific definition of the parameters for this total *P* membership function was developed from the empirical model formu-

T a b l e 1. Soil attribute intervals within which values of are more suitable for crop production (Kaiumov, 1977)

Soil	pH	SOM (%)	P_2O_5 (mg kg^{-1})	K_2O (mg kg^{-1})
Loam	6.5-7	1.8 -2.2	250-280	200-260
Loamy sand	6-6.5	2.0-2.4	200-250	180-200
Sandy	5.5-6	2.2-2.6	180-200	140-160
Turf	5-5.5	-	500-600	600-800

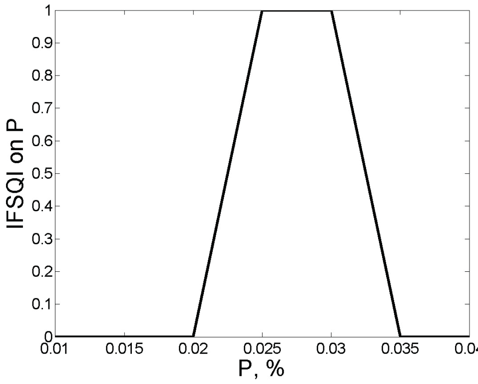

Fig. 3. The trapezoidal-shaped, built-in membership function to define IFSQI of total P.

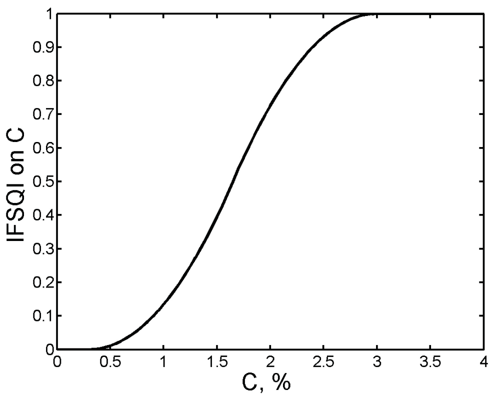

Fig. 4. Sigma-shaped, built-in membership function to define IFSQI of organic C concentration.

lated by Kaiumov (1977). Kaimov analyzed the suitability of yield-controlling factors for crops and defined intervals of the soil attributes which are more suitable for crops. These attributes are given in Table 1.

In other words, according to the Kaiumov empirical model, there exists an interval of the soil attribute, and if values of this attribute lie within this interval, then its utility is optimal. For example, in the specific case of a loam soil, the best values of total P are changed from 250 to 280 mg kg^{-1} (0.025 to 0.028 %) (Table 1). While it may be argued that this model of total P may be inadequate, it serves well as an illustrative example of the suggested approach to soil quality analysis.

Organic carbon concentration

As with total P, the FMA for soil organic C IFSQI was defined for the objective of this study. While it is commonly understood that increasing soil organic C will improve soil fertility, it is not necessarily a linear relationship for increasing soil organic C to improve soil quality. In other words, the potential incremental improvement to soil quality benefit with increasing levels of soil organic C will be reduced at the upper limits of C concentration in soil. Therefore, in this study we selected an S-shaped, built-in membership function for definition of IFSQI for soil organic C concentration which is shown in Fig. 4. It should be noted that this model may have considerable short comings for defining the contribution of soil organic C to soil quality. However, as with the total soil P function, this function serves as an illustrative example of the suggested approach.

Soil features for total phosphorus and organic carbon levels

Figures 5a and 6a show soil features for soil total P and soil organic C levels, which can be considered as soil quality indices (from the traditional point of view). While these figures provide useful information regarding the soil chemistry and its allocation of plant nutrients across the field, it has limited utility for interpretation as to the potential impact of these chemical components on soil quality. In other words, this traditional approach does not allow soil quality to be defined as a 'degree or grade of perfection' across the field. In most soil quality approaches, analysis such as are shown in Figs 5a and 6a are collected into layers and then an assessment is attempted. However, since no degree of perfection has been assigned, there is often no clear definition of the potential impact to soil quality that each individual attribute contributes.

Figures 5b and 6b present results obtained from the application of the fuzzy soil quality indicators method to the same soil total P and soil organic C data. These figures show the IFSQIs for soil organic C and soil total P concentration as calculated from the IFSQI functions. In this way, not only can the information be displayed regarding specific soil chemical attributes as they are distribution across the field, but specific information regarding how this distribution will

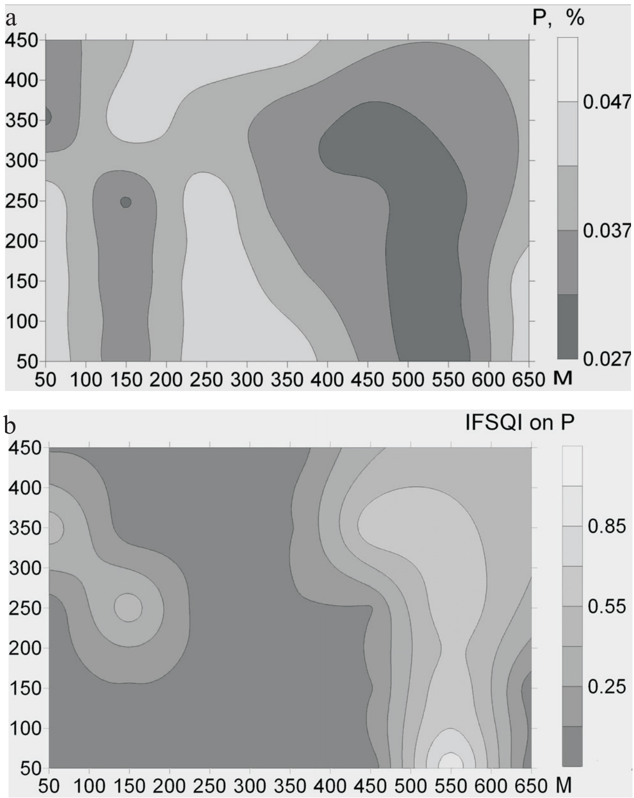

Fig. 5. a – total P and b – IFSQI for total P.

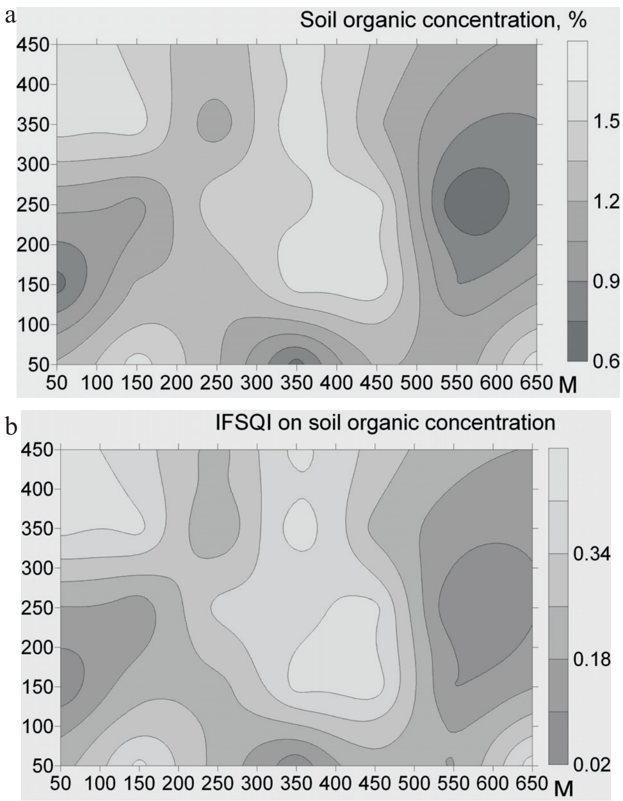

Fig. 6. a – soil organic C concentration and b – IFSQI for soil organic C concentration.

impact soil quality. It is apparent from this example that the suggested concept allows soil quality to be assessed as a 'degree or grade of perfection' for each individual soil attribute.

At this point, the development of the IFSQI's for each soil attribute provides a distinct advantage to the traditional methods because each attribute layer can be examined for its potential impact and overall contribution to soil quality. While this advantage is very important, the fuzzy multi-attributive approach provides an even more important contribution to soil quality assessment by allowing a mechanism for combining these soil layers from any number of soil attributes into one quality assessment across the field.

Utilizing the IFSQIs from this example, the CFSQI was defined using fuzzy aggregated operations. The CFSQI provided an integrated estimation of the soil quality of the study site; from this a soil quality evaluation map was drawn using the composite fuzzy indicator.

Figure 7 provides the CFSQI for the study area as developed in this study. In this case, the CFSQI is based on the combination of IFSQI on total P and IFSQI on soil organic C level. This figure demonstrates how soil quality measurements can be combined through the fuzzy indicator method to assess a 'degree or grade of perfection' for soil quality across the field. Utilizing maps that are generated in this way could then potentially be used to develop management applications either on an individual field or across a landscape setting depending on the individual application.

CONCLUSIONS

1. Application of the concept of the fuzzy multi-attributive approach to soil quality offers a means to assess soil quality as 'a degree or grade of perfection'. This accounts for the specifics of user groups and different aspects of data quality evaluation.

2. Utilization of this concept to evaluate soil quality of crop land in Bell County, TX, USA, demonstrated the advantage of the fuzzy modeling approach.

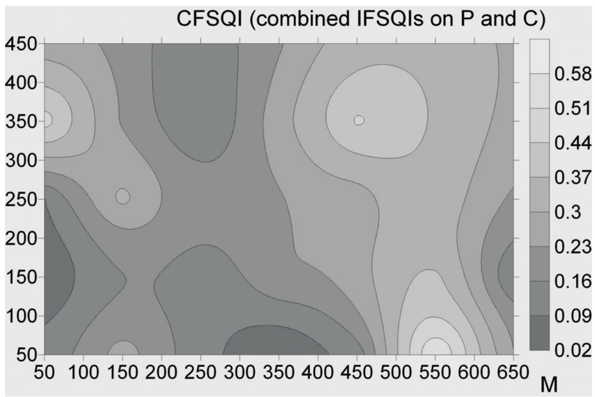

Fig. 7. Composite fuzzy indicator based on two IFSQIs that for total P and soil organic C concentration.

3. It was found that the concept developed (fuzzy indicators) and the author's program could be employed as the basis for the development of a new generation of soil quality tools *ie* software.

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