Journal of Agricultural Science; Vol. 6, No. 4; 2014
ISSN 1916-9752 E-ISSN 1916-9760
Published by Canadian Center of Science and Education

Evaluation of Agricultural Soil Resources Using Fuzzy Modeling

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Received: February 24, 2014 Accepted: March 12, 2014 Online Published: March 15, 2014

doi:10.5539/jas.v6n4p199 URL: http://dx.doi.org/10.5539/jas.v6n4p199

Abstract

Assessment of agricultural soil resources is a very difficult because exists knowledge is much fuzzy. Developed fuzzy model is effective tool for dealing with randomness and uncertainties. This model is based on a two-level system of fuzzy indicators. The first level - is individual fuzzy indicators (IFI), reflecting the assessment of individual characteristics. Second level - is combined fuzzy indicators (CFI), reflecting a combination of individual indicators. IFI are developed for the four characteristics of the soil (humus, amount absorbed cations, acidity (pH) and physical clay content). The proposed method is illustrated with a simple example.

Keywords: agricultural soil resources, agriculture, fuzzy indicator model

1. Introduction

The ultimate goal of sustainable agriculture is to develop farming systems that are productive and profitable, conserve the natural resource base, protect the environment, and enhance health and safety over the long term. Assessment of agricultural soil resources is a very important component of understanding agriculture potential and therefore maintaining a sustainable agriculture. Many investigations have been carried out with aims to inventory and protect agricultural soil resources (Behzad, 2009; Dorronsoro, 1998; FAO, 1983, 1984, 1985; Teka & Haftu, 2012; Rossiter, 1994). Research on classification of agricultural soil types based on their ability to sustain agricultural crops (CDC, 2003) and assessment of soil capability for agriculture (Ali et al., 2007) are well known. Recently many methods and tools have been developed to evaluate agricultural soil resources. These tools have incorporated state of the art of knowledge in agronomy, soil science, and economics. Crop simulation models, for example, are excellent tools for assessing potential impacts of weather-related production variability associated with natural resources (Ascough et al., 2005).

The process of assessing agricultural soil resources is full of uncertainty. Uncertainty is inherent in this process because it involves both data and model imprecision. This uncertainty ranges from measurement error, to inherent variability, to instability, to conceptual ambiguity, to over-abstraction, or to simple ignorance of important factors. Current technology utilized in assessment tools do not necessarily deal well with this uncertainty because they depend on the multiplicity of specific relationship of the measured components. In other words, small errors in any measured data or modeled relationship can propagate through the tool, potentially resulting in large errors in interpretation.

For dealing with the uncertainties and randomness that occurs with assessing agricultural land, fuzzy sets theory and fuzzy logic can be utilized (Jager, 1995; Pedrycz & Gomide, 1998). Fuzzy set theory is a mathematical approach that has been used successfully to address many scientific and technical problems dealing with abstract questions.

Recently several tools, based on fuzzy sets theory and fuzzy logic, have been developed for decision support regarding the problems of land evaluation (Burrough, 1986, 1989; Burrough et al., 1992; Baja et al., 2002, 2007; Krueger-Shvetsova & Kurtener, 2003; Kurtener & Badenko, 2000, 2002; Ramli & Baja, 2007).

Application of fuzzy modeling for evaluation of agricultural soil resources was discussed in Torbert et al. (2009, 2010). This article uses fuzzy modeling for the evaluation of agricultural soil resources.

The article is organized into two parts. The first part addresses the use of fuzzy indicator modeling for the evaluation of agricultural soil resource, and the second part contains an example which illustrates this approach.

2. Modelling of Agricultural Soil Resources

2.1 General Description

Fuzzy model for evaluation of agricultural soil resources can be achieved on the basis of a two-level system of fuzzy indicators.

The first level - is individual fuzzy indicators (IFI), reflecting the assessment of individual characteristics. Second level - is combined fuzzy indicators (CFI), reflecting a combination of individual indicators.

An IFI is defined as a number in the range from 0 to 1, which reflected an expert concept and modelled by appropriate membership function. The choice of a membership function is somewhat arbitrary and should mirror the subjective expert concept. Recently methodological basis for definition of membership functions was developed (Burrough, 1986, 1989; Burrough et al., 1992; Baja et al., 2002, 2007; Krueger-Shvetsova & Kurtener, 2003; Kurtener & Badenko, 2000, 2002; Ramli & Baja, 2007; Yakushev, 2002).

It is noted that some soil characteristics are quite stable values over time and can be used as the main (basic) to assess the agricultural soil resources. These include humus, the amount of absorbed cations, acidity (pH), and the content of physical clay.

The combined indicators (CFI) are defined using fuzzy aggregated operations.

2.2 Model of IFI on Variable "Humus"

According to experimental data the content of humus of 5% or more can be equated with 100 points. If the value of humus is less than 5%, then every 0.05%, it is reduced by 1 point. Taking into account this information we built IFI on variable "humus" using the linear built-in membership function (Figure 1).

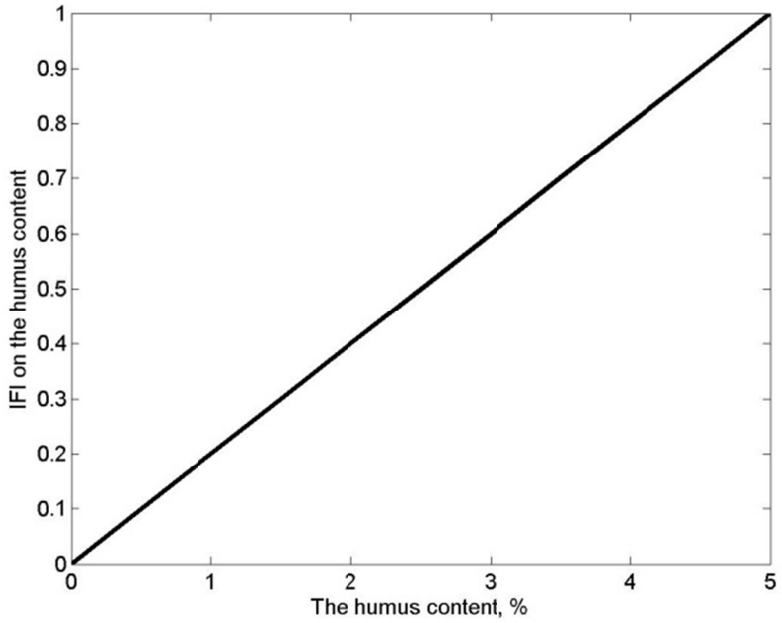

Figure 1. The graphical presentation of individual fuzzy indicators (IFI) on variable "humus"

2.3 Model of IFI on Variable "the Amount of Absorbed Cations"

The scale for measuring the parameter "the amount of absorbed cations" in points (Table 1) was used as the base for development of corresponding IFI. Considering data in Table 1, this IFI was modeled by sigmoidal shaped built-in membership function (Figure 2).

Table 1. The scale for measuring the parameter "the amount of absorbed cations"

The Amount of Absorbed Cations, milligram-equivalent	5	7	9	13	17	21	25	27	30
Score, from 1 to 100	28	38	48	64	78	88	95	97	100

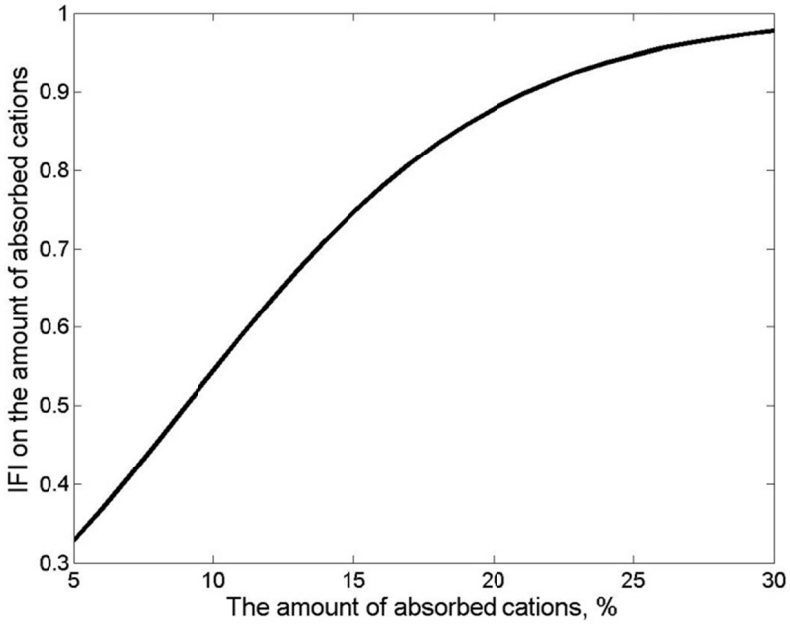

Figure 2. The graphical presentation of individual fuzzy indicators (IFI) on variable "the amount of absorbed cations"

2.4 Model of IFI on Variable "Acidity (pH)"

The scale for measuring the parameter "acidity (pH)" in points (Table 2) was used as the base for development of corresponding IFI. Taking into consideration data in Table 2, this IFI was modeled by S-shaped built-in membership function (Figure 3).

Table 2. The scale for measuring the parameter "acidity (pH)"

pH	4.0	4.2	4.4	4.8	5.0	5.2	5.6	5.8	6.0
Score, from 1 to 100	30	50	56	70	76	82	92	96	100

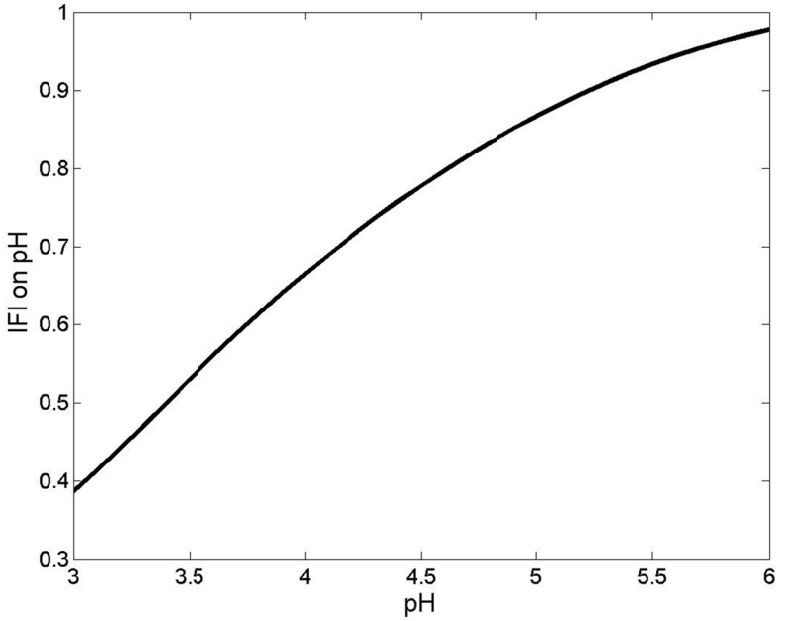

Figure 3. The graphical presentation of individual fuzzy indicators (IFI) on variable "soil acidity (pH)"

2.5 Model of IFI on Variable "the Content of Physical Clay"

The scale for measuring the parameter "the content of physical clay" in points (Table 3) was used as the base for development of corresponding IFI. Taking into account data in Table 3, this IFI was modeled by the generalized bell-shaped built-in membership function (Figure 4).

Table 3. The scale for measuring the parameter "The content of physical clay fraction"

Particles < 0.01mm, %	5	10	15	20	25	30	35	40	45	50	55	60	65	70
Score, from 1 to 100	28	54	74	88	96	100	98	92	80	62	42	32	22	12

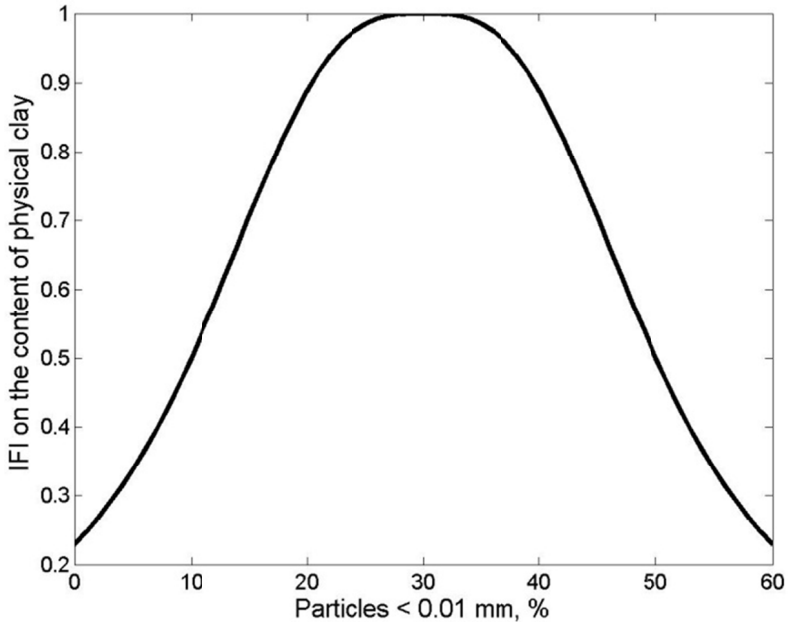

Figure 4. The graphical presentation of individual fuzzy indicators (IFI) on variable "the content of physical clay"

3. Example Illustrating Suggested Approach

The developed approach illustrates with the following example. In particular, several hypothetical combinations of soil characteristics (Table 4) were used as input data for calculations. Also it assumed that all components of soil resources were equal.

The calculation of fuzzy indicators was carried out utilizing MATLAB (http://www.mathworks.com/).

The results of calculations (Table 5) show that variant of calculations 3 (is the best (Combined Fuzzy Indicator (CFI) is equal to 0.7802). The second position has variant of calculations 5 (CFI = 0.77055). Variant of calculations 1 is the worst (CFI = 0.60481).

Table 4. Soil characteristics

Variant of Calculations	Humus, %	The Amount of Absorbed Cations, milligram-equivalent	Soil Acidity (pH)	The Content of Physical Clay, %
1	2.2	6.6	5.5	12.5
2	2.4	8.2	5.2	15.3
3	4.6	15.3	5.8	49.0
4	4.6	11.7	4.7	45.0
5	2.8	12.8	5.8	31.6
6	2.3	7.2	5.3	23.0
7	6.0	13.0	5.1	28.0
8	4.2	9.3	5.0	14.2

4. Conclusions

Assessment of agricultural soil resources is a very difficult because exists knowledge is much fuzzy. Developed fuzzy model is effective tool for dealing with randomness and uncertainties. This model is supplied by computer program. To illustrate the proposed method, a series of calculations were made.

Table 5. Results of complete assessment of soil resources

Variant of calculations	IFI on variable "Humus"	IFI on variable "The amount of absorbed cations"	IFI on variable "Soil acidity (pH)"	IFI on variable "The content of physical clay"	Combined Fuzzy Indicator (CFI)
1	0.44	0.51799	0.8624	0.59883	0.60481
2	0.46	0.53594	0.84467	0.68656	0.63179
3	0.92	0.75325	0.90916	0.53839	0.7802
4	0.92	0.66463	0.69041	0.7033	0.74459
5	0.62	0.61206	0.87906	0.97107	0.77055
6	0.46	0.53594	0.82585	0.95889	0.69517
7	0	0.69847	0.785	0.999	0.62062
8	0.84	0.59773	0.76297	0.66977	0.71762

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