Evaluation of Agricultural Land Suitability: Application of Fuzzy Indicators

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Abstract. The problem of evaluation of agricultural land suitability is considered as a fuzzy modeling task. For assessment of land suitability, it is proposed to use fuzzy indicators. Application of individual fuzzy indicators gives opportunity for assessment of suitability of lands as degree or grade of performance when the lands are used for agricultural purposes. Using composite fuzzy indicator it is possible to obtain weighted average estimation of land suitability. This theoretical technique is illustrated with a simple example.

Keywords: land suitability evaluation, fuzzy set theory, fuzzy indicator.

1 Introduction

Making effective decisions regarding agricultural land suitability problems are vital to achieve optimum land productivity and to ensure environmental sustainability. According to FAO, the term “land suitability evaluation” could be interpreted as the process of assessment of land performance when the land is used for specified purpose.

Baja et al. [3] reported two general kinds of land suitability evaluation approaches: qualitative and quantitative. By qualitative approach [16], it is possible to assess land potential in qualitative terms, such as highly suitable, moderately suitable, or not suitable. In the second approach, quantitative, assessment of land suitability is given by numeric indicators.

Many parameters of soil and plant growth, measurable at various scales of assessment, are used as numeric indicators of agricultural land suitability. For example, weighting factors related to water infiltration (aggregate stability, surface porosity), water absorption (porosity, total C, earthworms), degradation resistance (aggregate stability, microbial processes) and plant growth (parameters affecting rooting depth, water relations, nutrient relations and acidity) could be used [24]. According to Katorgin [26], agricultural lands can be categorized by content of nutritive materials into 6 classes (Table 1).

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Table 1. Soil classification according content of nutritive material

	Available K, %	Available P, %	Humus, %
Very low	<10	< 10	< 2
Low	10,1 - 20	11 - 15	2,1 – 4
Average	20,1 – 30	16 – 30	4,1 – 6
Increased concentration	30,1 – 40	31 – 45	6,1 – 8
High	40,1 – 60	46 – 60	8,1 – 10
Very high	> 60	>60	> 10

Three general types of the qualitative evaluation procedure are distinguished. They are based on deductive, inductive or simulation modeling. Baja et al. [3] indicated that a deductive modeling approach deals mainly with the estimated yield as an index relative to a standard yield, while an inductive technique utilizes land characteristics as evaluation criteria to establish land unit indices [24]. Application of simulation modeling provides an opportunity to analyze non-linear systems characterized by poorly quantified uncertainties. One line of simulation modeling is fuzzy modeling.

Recent development in the handling of applications of fuzzy set theory [1-14, 21-22, 27-43, 47, 56] have created new opportunities for decision of agricultural land suitability problems. In particular, fuzzy indicators have been successfully applied for zoning territory contaminated by heavy metals [33, 36], for the multi-dimensional assessment of urban areas after flooding [27], for the assessment of polluted agricultural fields in order to design a strategy for territorial prophylactic actions [28], for the assessment of burned forest areas with the aim of planning land restoration [29], for land suitability assessment in the process of agricultural experimentation [30], for assessment of agricultural lands to plan site-specific residue management [31], and for the multi-dimensional evaluation of areas on the land market [32, 57].

This paper is devoted to the application of fuzzy indicators for the evaluation of agricultural land suitability. The theoretical consideration is illustrated with a simple example.

2 Concept of Application of Fuzzy Indicators for Evaluation of Agricultural Land Suitability

In general, indicators are a subset of the many possible attributes that could be used to quantify the condition of a particular landscape or ecosystem. They can be derived from biophysical, economic, social, management and institutional attributes, and from a range of measurement types [55].

Indicators are defined as valuable tools for evaluation and decision-making because they synthesize information and can thus help to understand a complex system. Currently indicators are heavily used in the evaluation of land use changes in rural areas [15] and agricultural sustainability [49].

It is well known that the process of evaluating suitability of agricultural fields is characterized by uncertainty. Uncertainty is inherent in this process, which involves data and model uncertainty that range from measurement error, to inherent variability, to instability, to conceptual ambiguity, to over-abstraction, or to simple ignorance of important factors. For dealing with the randomness and uncertainties, fuzzy sets theory and fuzzy logic can be utilized [18, 47, 48]. Fuzzy sets theory is a generalization of conventional set theory, in which the concept of belonging to a set has been modified to include partial degrees of membership, i.e., values along the continuum between 0 and 1, encoded in a fuzzy membership function (MF). The MF is the central concept of the fuzzy sets theory where the MF represents the relationship of an element to a set. The MF of a fuzzy set is expressed on a continuous scale from 1 (full membership) to 0 (full non-membership).

Nowadays, fuzzy set theory is a hot topic and is used in many different fields and technical arenas to address a variety of questions and problems, both mundane and abstract. In framework of fuzzy modeling, it is possible to develop a fuzzy indicator model, which would be useful for decisions regarding problems related with evaluation of agricultural land suitability. In particular, we define two general types of fuzzy indicators (FI): individual fuzzy indicators (IFI) and combined fuzzy indicators (CFI).

The IFI shows degree of accordance of *j* attribute with requests of *i* user group and *k* task of agricultural land suitability evaluation. Examples of possible *j* attributes include: (a) soil characteristics, (b) crop yields, or (c) landscape properties. By the way of examples of *i* user group may include: (a) farmers, (b) governed managers, or (c) market traders. Examples of *k* task of evaluation could include: (a) the use in agricultural activity, (b) application in teaching process, or (c) utilization for land marketing.

The IFI is defined as a number in the range from 0 to 1, which reflected an expert concept and modeled by an appropriate membership function, for which the expert concept has to take into account the specific of *j* attribute, *i* user group and *k* task of resource evaluation. The choice of a membership function is somewhat arbitrary and should mirror the subjective expert concept.

Four main steps are used to realize IFI model as follows:

- *Structuring phase*: perception of problem, identification of task of resource evaluation, definition of user group and identification of criteria;
- *Fuzzy modeling phase*: formulation of expert concept and selection or building of suitable membership functions;
- *Computation phase:* calculation of fuzzy indicators; and
- *Evaluation phase:* perception of results obtained.

The CFI is defined using fuzzy aggregated operations to combine the IFI. Therefore, the CFI provides an integrated estimation of agricultural land suitability.

3 Example of Application

3.1 Study Site

In this example, we used data from an experiment carried out on an agricultural field located in Bell County, TX on the Elm Creek watershed [53]. The soils within the study site consisted of 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 at points designated as bgs 1 – bgs 20 (Fig. 1) at 6 depth increments (0-6, 6-12, 12-24, 24-36, and 36-48 inch).

For each of the soil samples, the soil was analyzed for organic C, inorganic C, Total C, Total N, Total P, extractable P, NO_3 and NH_4. The inorganic C was carbonate ($CaCO_3$) and the Total C was organic C + inorganic C. The extractable P was determined by extracting with a reagent to determine plant available P.

At each of these points, corn yield was also determined for the three years of the study. The corn yield was defined with a yield monitor on the corn harvester, which determined the yield as it harvested the corn on very small increments. The yield at each sampling point was determined by taking an average of the measured corn yield for every point that the yield monitor measured that was within 15 m of the soil sampling point. The yield data is given in bushels/acre.

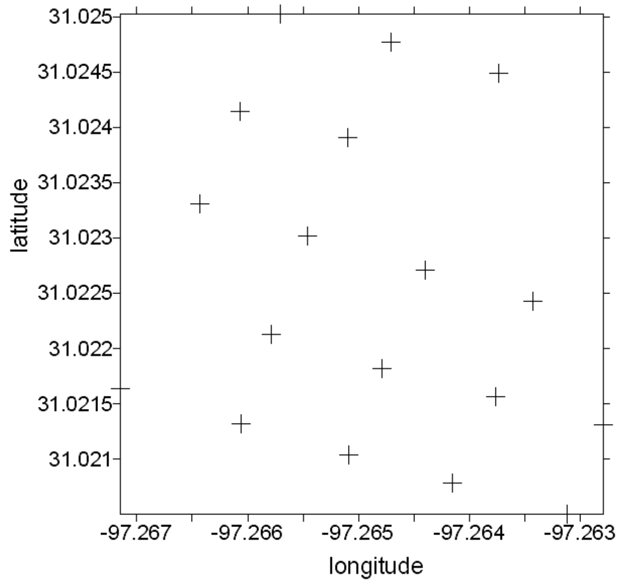


Fig. 1. Sampling on study site

3.2 Definition of IFI for Total C

There is much evidence that the greater soil organic C concentration, the better is soil fertility. At the same time, at the upper boundary of soil organic C concentration, it is not a rule that soil fertility will also increase. Taking into account this information, we formulated an expert concept. In particular, we selected an S-shaped built-in membership function for definition of IFI on organic C concentration (Fig 2).

This function is characterized by two reference points: x_{low} and x_{opt}. In this study $x_{low} = 0.4\%$ and $x_{opt} = 3\%$.

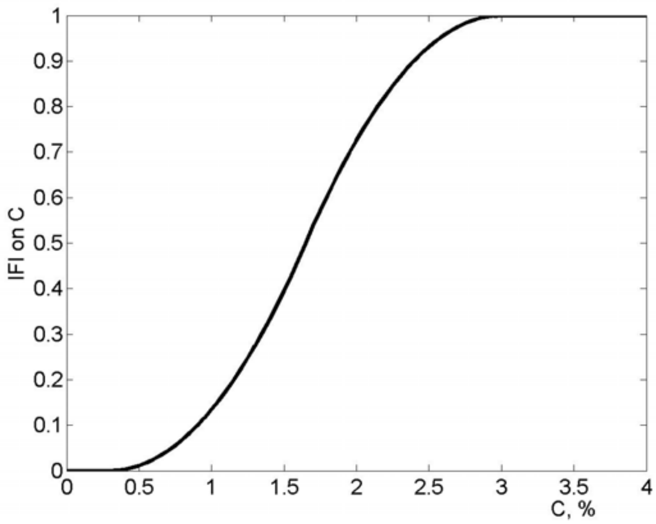


Fig. 2. Sigma-shaped built-in membership function used for definition of IFI on organic C concentration

It should be noted that this model may have considerable shortages in explaining the relationship of organic C, however, it is of no matter, because the aim of this example is to illustrate the suggested approach.

3.3 Definition of IFI for Available P

For definition of the IFI for available P, we selected an expert concept formulated by Kaiumov [25]. Kaimov analyzed suitability of yield-controlled factors for crops and defined the intervals of soil attributes, which are more suitable for crops (Table 2). He emphasizes that very low and very high P values are limiting for agricultural crops.

In other words, according Kaiumov's empirical model, there exist an interval of soil attribute that if the values of this attribute lie within this interval then its utility is the best. For example, in the case of loam, the optimal values of available phosphorus

Table 2. Intervals within which values of soil attributes are more suitable for crops [25]

Soil	pH	SOM, %	P_2O_5, mg kg^{-1}	K_2O, mg kg^{-1}
Very low	<10	< 10		< 2
Low	10,1 - 20	11 - 15		2,1 - 4
Loam	6,5 - 7	1,8 - 2,2	250 - 280	200 -260
Loamy sand	6 - 6,5	2 - 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

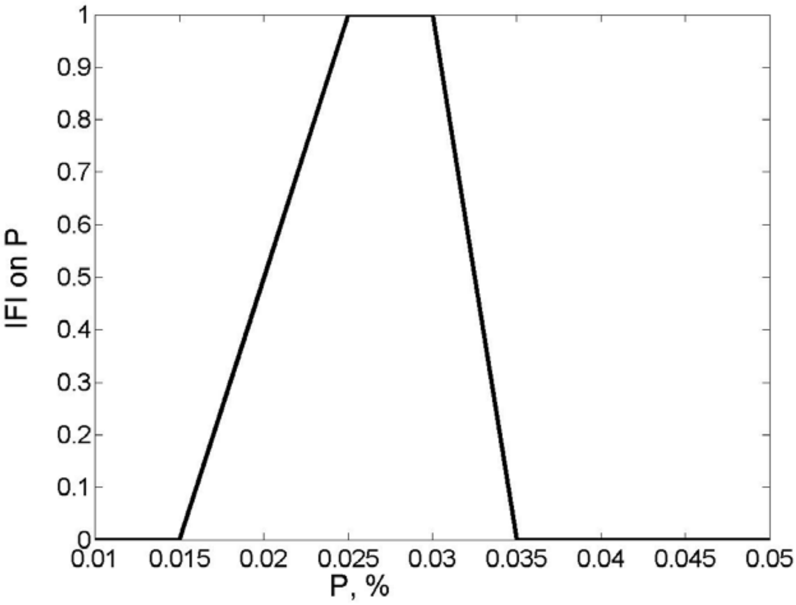


Fig. 3. The trapezoidal-shaped built-in membership function used for definition of IFI on available P

(P_2O_5) are changed from 250 to 280 mg kg^{-1} (Table 1) or from 0.025 to 0.028 %. Taking into account this information, we selected the trapezoidal-shaped built-in membership function for definition of the IFI for phosphorus concentration (Fig. 3).

This function is characterized by four reference points: x_{low1} , x_{opt1} , x_{opt2} and x_{low2} . In this study, values of reference points are defined using Kaiumov's model as follows: x_{low1} = 0.015%, x_{opt1} = 0.025%, x_{opt2} = 0.028%, and x_{low2} = 0.034%.

It should be noted that this model may have considerable shortages for defining the relationship for phosphorus. However, it is of no matter, because again the aim of this example is to illustrate the suggested approach.

3.4 Definition of IFI for Yield

In many cases yield is planed as some number, which could be less than highest possible yield. Therefore, in this study we selected S-shaped built-in membership function for definition of IFI for yield (Fig 4). Values of reference points are: x_{low} = 20 Bu/acre and x_{opt} = 120 Bu/acre.

3.5 Definition of CFI

In this study, CFI is defined using fuzzy aggregated operations. The CFI gives an integrated estimation of the suitability of agricultural fields. In this study, the CFI is defined using weighted average operation.

3.6 Calculation and Visualization

Calculation of fuzzy indicators is carried out with author's program including several scripts written on MATLAB [44]. Also, a prototype of software developed by Krueger-Shvetsova and Kurtener [39] was used. Visualization (building contour maps) was accomplished with Surfer® (http://www.goldensoftware.com).

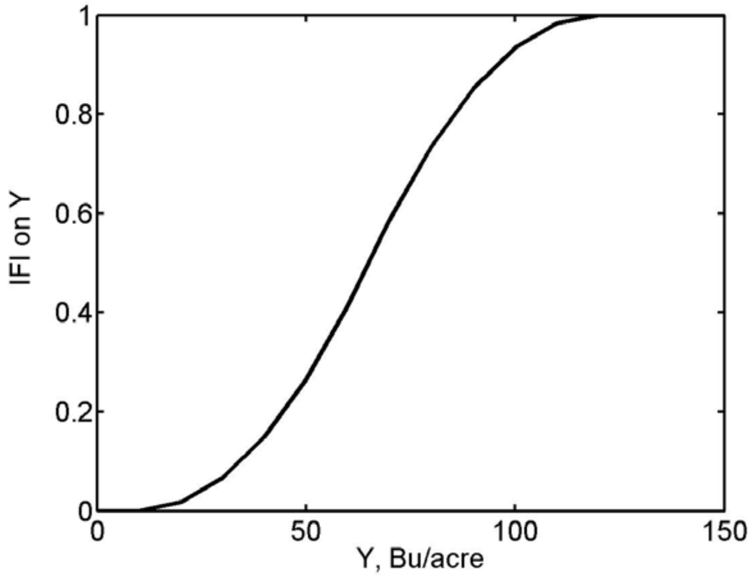


Fig. 4. Sigma-shaped built-in membership function used for definition of IFI on yield

4 Results and Discussion

Figures 5a-8a show spatial distribution of attributes, which are ordinarily considered as numbered indices for the suitability of agricultural lands. However, it is easy to see, that this traditional approach does not provide a means to define the land suitability as a degree or grade of performance when the land is used for cropping systems. Figures 5b-8b present the spatial distribution of individual fuzzy indicators (IFI). Using these figures, it is not difficult to understand that the application of fuzzy indicators provides an opportunity for the assessment of land suitability as a degree or grade of performance when the land is used for agricultural purposes.

Figure 9 illustrates result of the evaluation of the suitability of agricultural land using composite fuzzy indicator (CFI) procedure. It is easy to see, that the integrated estimation is dependent on the depth of measurements of land attributes.

As a whole, results of this study show that the application of fuzzy indicators is a promising method for determining effective decisions of agricultural land suitability problems.

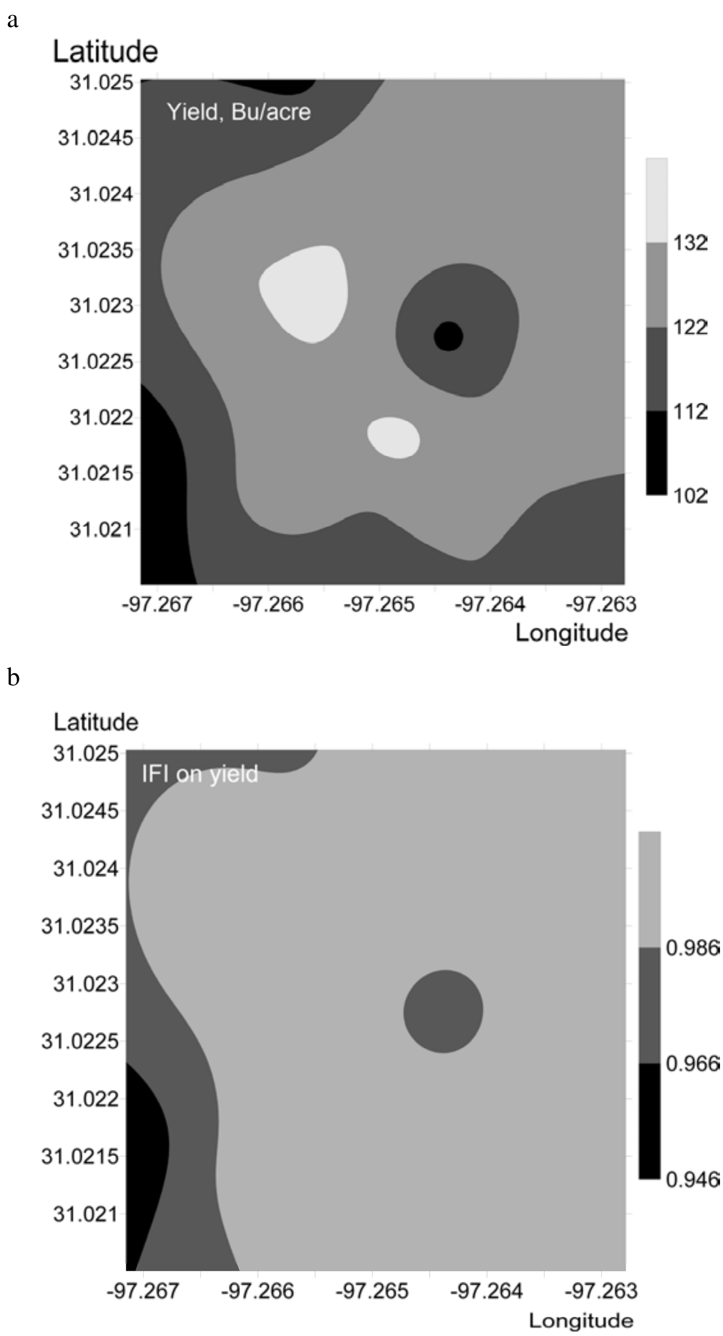


Fig. 5. Spatial distribution of yield, Bu/acre (a), and IFI on yield (b)

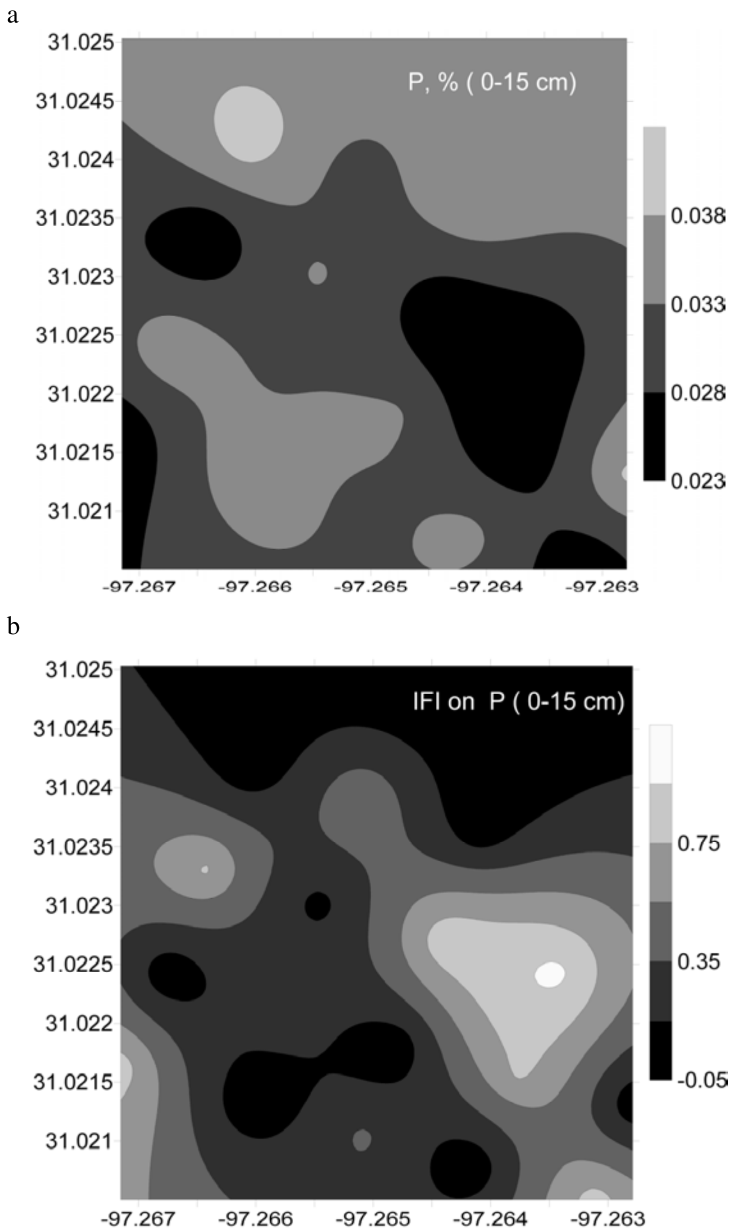


Fig. 6. Spatial distribution of total P, %,, at a depth of 0-15 cm (a), and IFI on total P at a depth of 0-15cm (b)

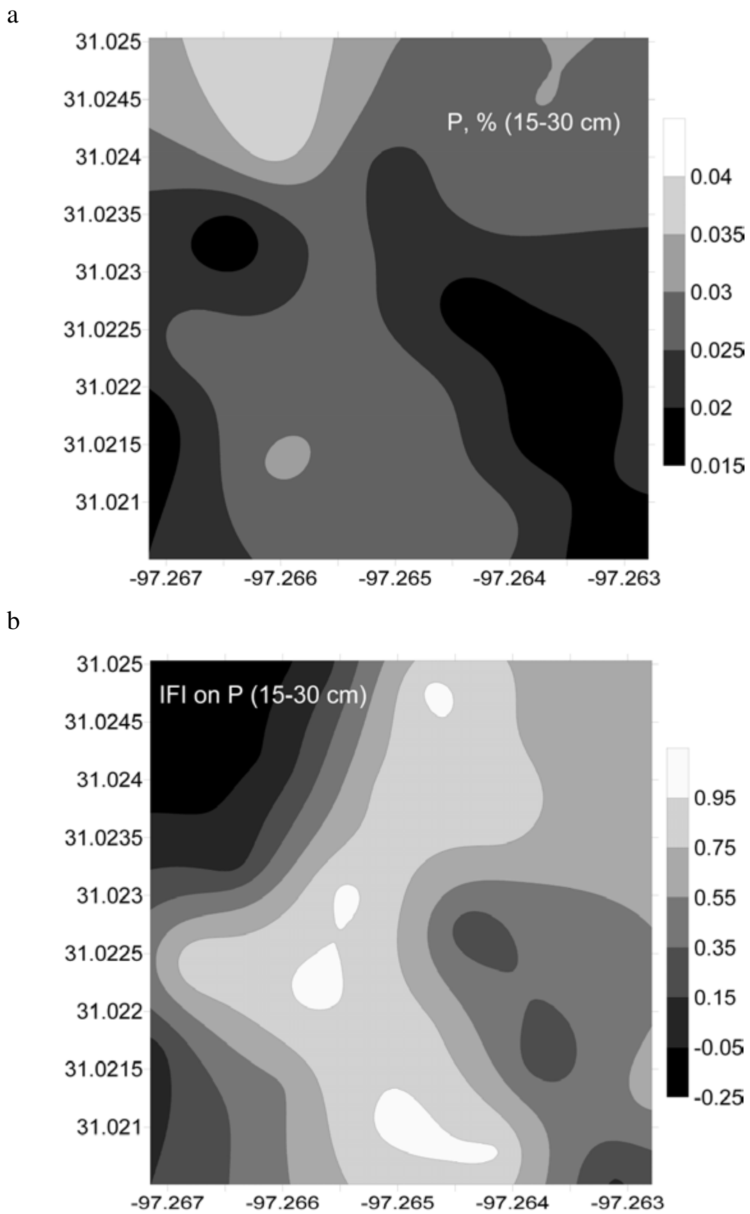
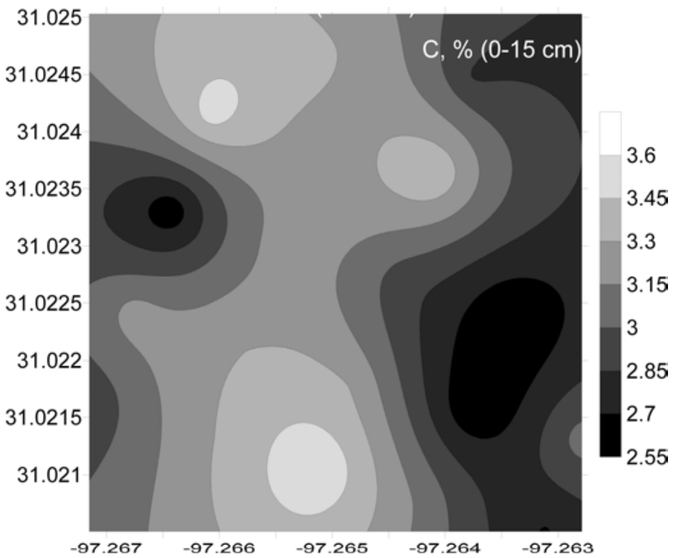


Fig. 7. Spatial distribution of total P, %, at a depth of 15-30 cm (a), and IFI on total P at a depth of 15-30 cm (b)

a



b

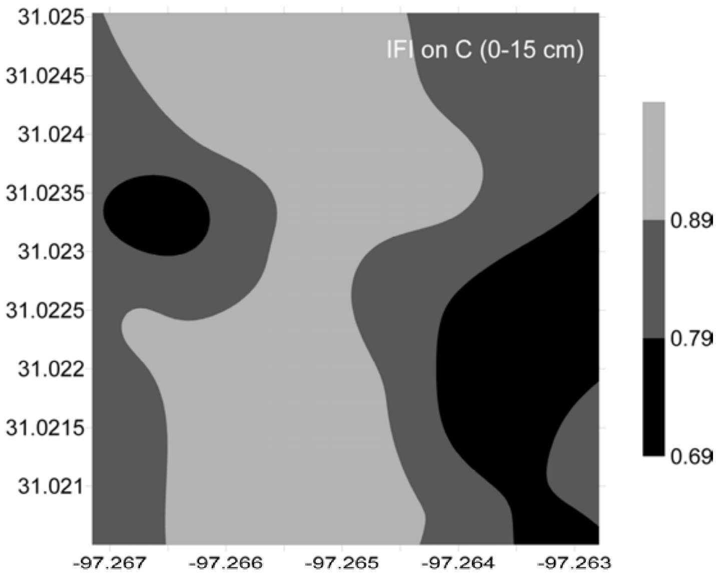


Fig. 8. Spatial distribution of total C, %, at a depth of 0-15 cm (a), and IFI on total C at a depth of 0-15cm (b)

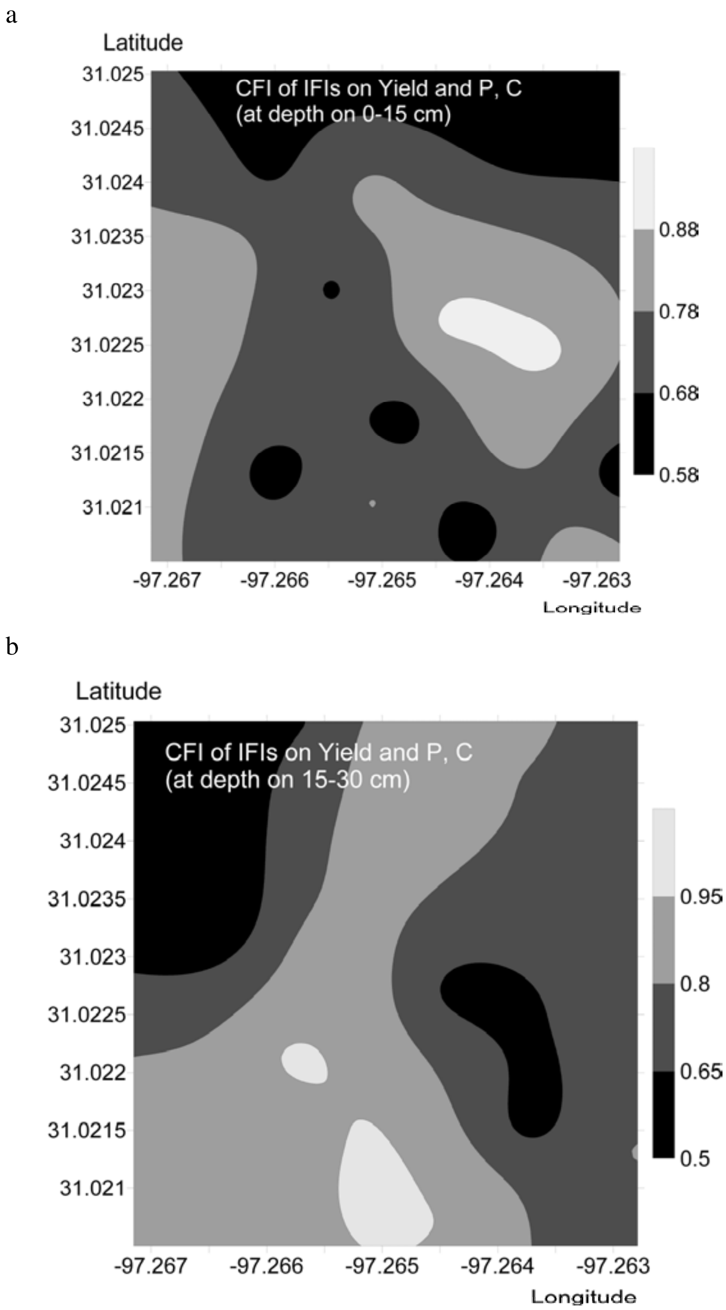


Fig. 9. Spatial distribution of CFI at a depth of 0-15 cm (a), and a depth of 15-30 cm (b)

5 Conclusions

Recently, there has been an increased interest in studying the methods for evaluation of agricultural land suitability, because of the potential for improvements in soil water conservation, fuel energy savings, erosion control, government erosion compliance regulations, to achieve optimum productivity of the land and to ensure environmental sustainability. Application of the agricultural land suitability fuzzy indicators method is a promising way to accomplish these tasks. It provides an opportunity for assessment of the suitability of lands as a degree or grade of performance when the lands are used for agricultural purposes. By individual fuzzy indicators, it is possible to assess the suitability of lands as a degree or grade of performance for each attribute when the lands are used for agricultural purposes. Composite fuzzy indicator gives the opportunity to obtain a weighted average estimation of land suitability across all of the attributes. It was found that the further development of this fuzzy indicator tool would be advantageous for application in future studies for elaboration of problem-oriented research.

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