Evaluation of Resources of Agricultural Lands
Using Fuzzy Indicators

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Abstract: With ever increasing demands on agriculture, it is essential that we be able to adequately evaluate agriculture land resources. Recently, efforts have been undertaken to develop methods and tools for the purpose of evaluating agricultural land resources. However, to be successful, assessments need to incorporate the state of the art knowledge in agronomy, soil science, and economics into a user-friendly, decision support tool. Also, it is well known that the process of assessment land resources is full of uncertainty. Uncertainty is inherent in this process, which involve 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. This manuscript examines the evaluation of land resources as a fuzzy modeling task. Data collected from a precision agriculture study in central Texas, USA was utilized for the assessment of land resources, and a model of fuzzy indicators and procedures for computer simulations were developed. The theoretical considerations are illustrated within this example.
Key words: land resources, agriculture, fuzzy indicators.

INTRODUCTION and LITERATURE REVIEW

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 land 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 land resources. 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 examples of these efforts. In these efforts, many methods and tools have recently been developed to evaluate agricultural land resources. These tools have incorporated state of the art knowledge in agronomy, animal science, and economics into user-friendly, decision support tools. Crop simulation models, for example, are excellent tools for assessing potential impacts of weather-related production variability associated with natural resources (GPFARM DSS, 2003).

The process of assessing agricultural land 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 and Gomide, 1998; Ross, 1995). 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; 1998; Baja et al., 2002; 2007; Krueger-Shvetsova et al., 2003; Kurtener et al., 2000; 2000a; 2002; Ramli and Baja, 2007; Yakushev, 2002). Undoubtedly, investigations of Burrough (1989; 1992) have pioneered the real world applications of fuzzy technology for land evaluation. This manuscript uses fuzzy modeling for the evaluation of land resources. The manuscript is organized into two parts. The first part addresses the use of fuzzy indicator modeling for the evaluation of agricultural land resource, and the second part contains an example which illustrates this approach.

MATERIAL AND METHODS

Model of fuzzy indicators for evaluation of agricultural land resource

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. These indicators can be developed from a range of measurement types (Walker, 1996; 2002). Indicators can be used as valuable tools for evaluation and decision-making process because they synthesize information and can thus be used to help understand a complex system. Currently, indicators are heavily used in the evaluation of land use changes in rural areas (de la Rosa and van Diepen, 2002) and agricultural sustainability (Rigby et al., 2000).

According to Sombroek (2006), land quality indices in relation to agriculture can be distinguished into several classes as follows: 1.) Land quality indices related to productivity from crops or other plant growth (crop yields, moisture availability, nutrient availability, oxygen availability in the root zone, adequacy of foothold for roots, workability of the land (ease of cultivation), salinity or sodicity, soil toxicity, resistance to soil erosion, pests and diseases related to the land); 2.) Land quality indices related to domestic animal productivity (productivity of grazing land, climatic hardships affecting animals, endemic pests and diseases, nutritive value of grazing land, toxicity of grazing land, resistance to degradation of vegetation, resistance to soil erosion under grazing conditions, availability of drinking water); and 3.) Land quality indices related to management and inputs (terrain

factors affecting mechanization (trafficability), terrain factors affecting construction and maintenance of access-roads (accessibility), size of potential management units (e.g. forest blocks, farms, fields), location in relation to markets and to supplies of inputs). A Special class of the land quality indices is fuzzy indicators. These indicators are based on fuzzy sets theory (Jager, 1995; Pedrycz and Gomide, 1998; Ross, 1995).

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). MF is the central concept of the fuzzy sets theory. MF represents the relationship of an element to a set. MF of a fuzzy set is expressed on a continuous scale from 1 (full membership) to 0 (full non-membership).

Recently, several models of fuzzy indicators have been developed to address a variety of questions and problems related to land evaluation. These models include a model of a fuzzy reliability index intended for assessment of difference between fuzzy resistance of ecosystem and fuzzy antropogeneous load (Bogardi et al., 1996), a concept of management of fuzzy indicators (Krueger-Shvetsova, 2003), and a model of land suitability indices for cropping (Baja 2001, 2001a). Examples where Fuzzy indicators have been successfully applied include uses for zoning territory contaminated by heavy metals (Kurtener et al., 1999; 2002), for the multi-dimensional assessment of urban areas after flooding (Kurtener et al., 1999), for the assessment of polluted agricultural fields in order to design a strategy for territorial prophylactic actions (Kurtener et al., 1999a), for the assessment of burned forest areas with the aim of planning land restoration (Kurtener et al., 2000), for land suitability assessment in the process of agricultural experimentation (Kurtener et al., 2000a), for assessment of agricultural lands to plan site-specific residue management (Kurtener et al., 2000b), and for the multi-dimensional evaluation of areas on the land market (Kurtener et al.,2000c;Yakishev et al., 2000). Likewise, a model of fuzzy indicator has been

developed to address the decision needed for the evaluation of agricultural land resources.

The fuzzy indicator model for the evaluation of agricultural land resources used two general types of fuzzy indicators (FI). These two general types utilized were the individual fuzzy indicators (IFI) and the combined fuzzy indicators (CFI). The IFI shows the degree of accordance of n category of land resource, j attribute characterized land resource, i user group, and k task of land resource evaluation.

As an example, a j attribute could be: (a) attributes related to yield productivity from crops or other plant growth, (b) attributes related to domestic animal productivity, or (c) attributes related to management and inputs. Examples of i user groups could be (a) farmers, (b) government managers, or (c) market traders. Examples of k task of evaluation could be: (a) use in agricultural activities, (b) application in teaching process, or (c) utilization on land market.

One of the crucial questions for the evaluation process is to determine the categories to be used to describe the land resources. For example, three categories were used in Kaiumov's (1977) data: low, average, and high. In determining land resources, categories Katorgin (2004) gave six categories shown in Table 1.

A IFI is defined as a number in the range from 0 to 1, which reflected an expert concept and modeled by appropriate membership function. The expert concept has to take into account the number of categories of land resources. For example, if the number of categories is equal to five, then the number of the membership functions also has to be five. In this case, for definition of the first category and the fifth category, asymmetric left and asymmetric right membership functions were utilized (Fig. 1). Definition of second, third, and fourth categories is carried out with symmetric membership functions. 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; 1998; Baja et al., 2002; 2007; Krueger-Shvetsova et al., 2003; Kurtener et al., 2000; 2000a; 2002; Ramli and Baja, 2007; Yakushev 2002).

In natural conditions, boundaries between categories of land resource are fuzzy. In other words, between neighboring categories there is a transition zone. In order to take into account this fact in the design of membership functions, it is necessary to allow a transition zone between two neighboring membership functions. In this example (Fig. 1), the transition zone between membership functions one and two is characterized by interval from 0.1 to 0.16, transition zone between the membership functions two and three is characterized by interval from 0.35 to 0.4, etc. It is easy to see that within the boundaries of transition zones, one value of land attribute fit two values of membership functions.

A CFI is defined using fuzzy aggregated operations. A CFI gives an integrated estimation of agricultural land resources. A structure for the model of fuzzy indicator for the evaluation of agricultural land resources is outlined in Figure 2. Four main steps were used to realize this 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.

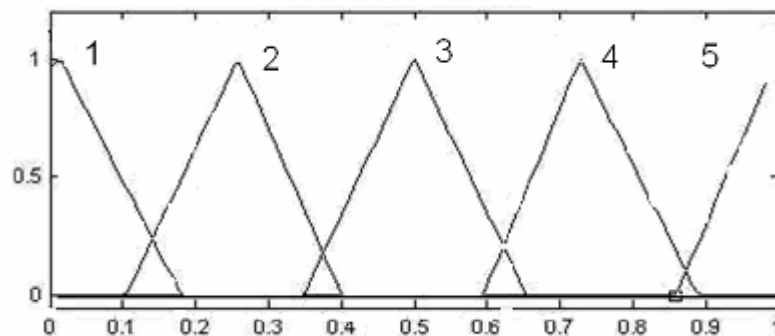| Table 1. Soil classification according nutrient content (Katorgin, 2004)				
	Category	Available K, %	Available P, %	Humus, %
1	Very low	<10	< 10	< 2
2	Low	10.1 - 20	11 - 15	2.1 - 4
3	Average	20.1 - 30	16 - 30	4.1 - 6
4	Increased concentration	30.1 - 40	31 - 45	6.1 - 8
5	High	40.1 - 60	46 - 60	8.1 –-10
6	Very high	> 60	>60	> 10

Figure 1. Membership functions, which are used for delineation of resources of agricultural land into five categories.
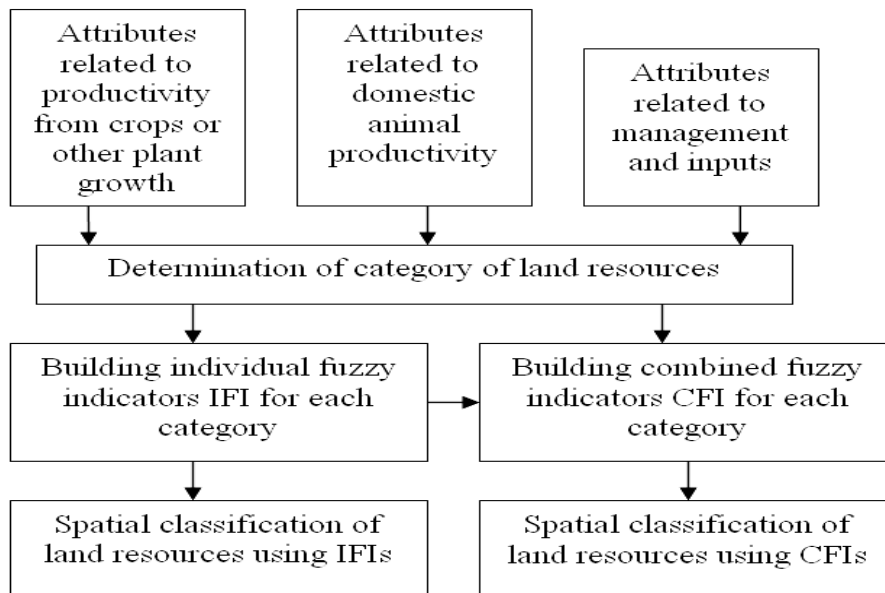

Figure 2. Structure of model of fuzzy indicator for evaluation of agricultural land resources.

Example of application
Study site
In this example, we used data of an experiment carried out on a agricultural field located on the Elm Creek watershed in Bell County, TX (Torbert et al., 2000). 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 multiple points designated as: bgs 1 - bgs 20 (Fig. 3) at 6 depth increments (0-6, 6-12, 12-24, 24-36, 36-48 inches). For each of the soil samples, the soil was analyzed for organic C, inorganic C, Total C, Total N, Total P, extractable P, NO3 and NH4. The inorganic C was carbonate (CaCO3) and the Total C was organic C + inorganic C. The extractable P was soil extracted 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 determined with a yield monitor on a corn

harvester, which continuously 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 was measured in bushels/acre.

Figure 3. Study site, with the soil sampling locations (points bgs 1 - bgs 20).

Definition of individual fuzzy indicator

For definition of each individual fuzzy indicator (IFI) we used a combination of five membership functions shown previously in Figure 1. In particular, an asymmetric left membership function called a "Z-shaped built-in membership function" was used for taking into account the specificity of the first category. A symmetric membership function called a "trapezoidal-shaped built-in membership function" was applied for classes 2, 3, and 4. An asymmetric right membership functions called a "S-shaped built-in membership function" was used for taking into account specificity of the fifth category.

The Z-shaped built-in membership function is characterized by two reference points: xlow and xopt. These points are defined as follows:

$If\ x < x_{low},\ then\ IFI = 1$, and
$If\ x > x_{opt}\ then\ IFI = 0.$

For example, reference points in the case of IFI on organic C concentration (for class one) are: xlow =

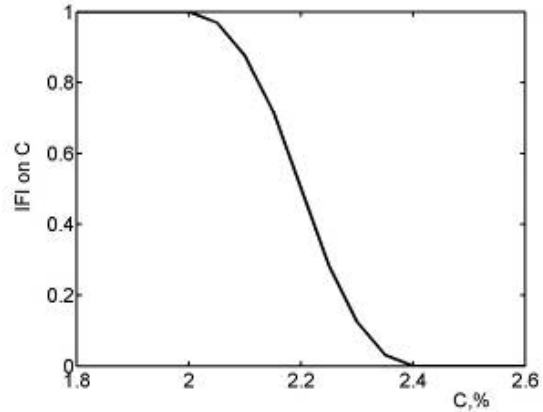2% and xopt = 2.4%. Figure 4 shows graphically the Z-shaped built-in membership function.

Figure 4. IFI on organic C (class one) using the Z-shaped built-in membership function.

Trapezoidal-shaped built-in membership function is characterized by four reference points: xlow1 , xopt1 , xopt2 and xlow2 . These points are defined as follows:

$If\ x < x_{low1},\ then\ IFI = 0,$
$If\ x_{opt1} < x < x_{opt2},\ then\ IFI = 1,$
$If\ x > x_{low2},\ then\ IFI = 0.$

For example, reference points in the case of IFI on total P (for class three) are: xlow1 = 0.015%, xopt1 = 0.025%, xopt2 = 0.028%, and xlow2 = 0.034%. Figure 5 shows graphically the trapezoidal-shaped built-in membership function.

In this study, data collected includes four attributes: organic C, total N, available P, and yield. Therefore, number of attributes used for characterization of land resources was limited by four attributes. Also we assume that the allocation of these attributes could be presented by five classes. Then we set the lower and upper limits of values for these attributes within each class (Table 2).

However, the actual data only in certain portions of these limits and therefore the values of these attributes were variously allocated among the classes (Table 3). For example, organic C is present in categories 1 and 2, total N is located in category 2 only, available P occurred in categories 3 and 4, and yield was present in categories 2 and 3.

Table 2. The classification of land resources.				
	Category	Organic C, %	Total N, %	Available P, %	Yield, Bu/acre
1	Very low	< 2.3	> 0.1	0.008	> 60
2	Low	2.31 - 4	0.11 - 0.25	0.0081 - 0.02	61 - 120
3	Average	4.1 - 7	0.251 - 0.35	0.021 - 0.04	121 -160
4	High	7.1 -10	0.351 - 0.5	0.041 - 0.06	161 - 220
5	Very high	> 10	> 0.5	> 0.06	> 220

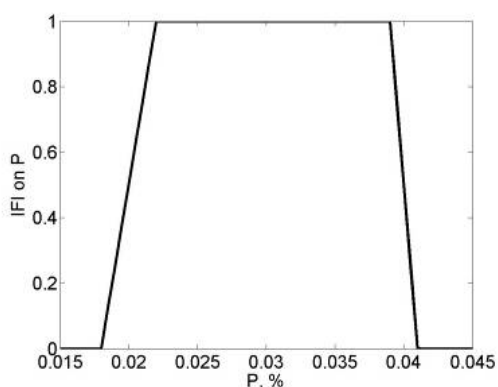| Table 3. Allocation of values of attributes used for characterization of land resources				
	Category	Organic C	Total N	Available P	Yield
1	Very low	+	-	-	-
2	Low	+	+	-	+
3	Average	-	-	+	+
4	High	-	-	+	-
5	Very high	-	-	-	-

Figure 5. IFI on P (class three) using the trapezoidal-shaped built-in membership function

Definition of the combined fuzzy indicators (CFI) for particular case

In this example, CFI was defined using weighted average operation as follows (Baja et al., 2002; 2007; Kurtener et al., 2000; 2000a; 2002):

$$CFI = \Sigma w_i \, IFI(x_i),$$

where w_i is a weighting factor for the i land property x, $\Sigma \, w_i = 1$, and $0 < w_i < 1$; and $IFI(x_i)$ denotes a individual fuzzy indicator for the i land property x. In this study, we assumed that the importance of all IFIs was the same.

Calculation and visualization

The calculation of fuzzy indicators was carried out utilizing the author's program, which included several scripts written on MATLAB (The Mathworks Inc, 2004). Also, a software prototype developed by Krueger-Shvetsova and Kurtener (2003) was utilized. Visualization (building contour maps) was accomplished with Surfer®

(http://www.goldensoftware.com).

RESULTS AND DISCUSION

Using the developed programs, the IFI was calculated and mapped for all categories indicated in Tables 2 and 3. Figures 6 -7 illustrate the maps of IFI (built for each category) which holds the greatest promise for making particular estimations of land resources.   For example, Figure 6 shows the classification of land resources by IFI on N (category two), while Figure 7 shows the IFI on Yield (category three).

Figures 8-11 present the classification of land resources by CFI. Theses maps illustrate spatial allocation of weighted average estimations of land resource. For example, Figure 10 illustrates spatial allocation of land resources for category three. It is easy to see that for category three the greatest estimations are located in eastern part of study site.
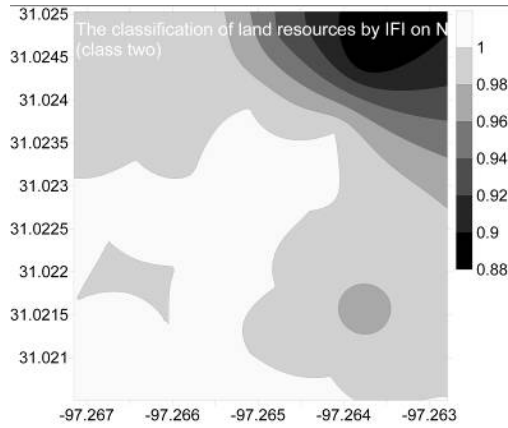
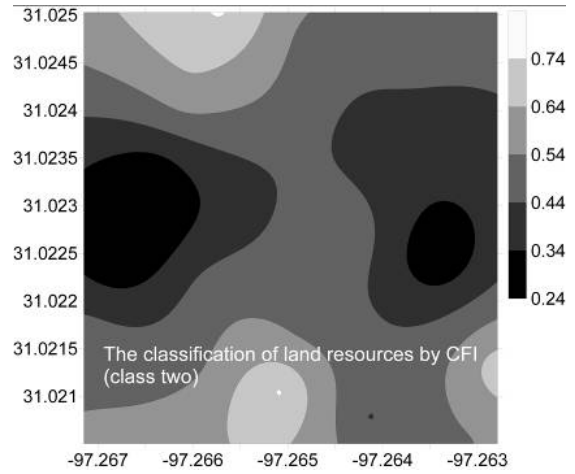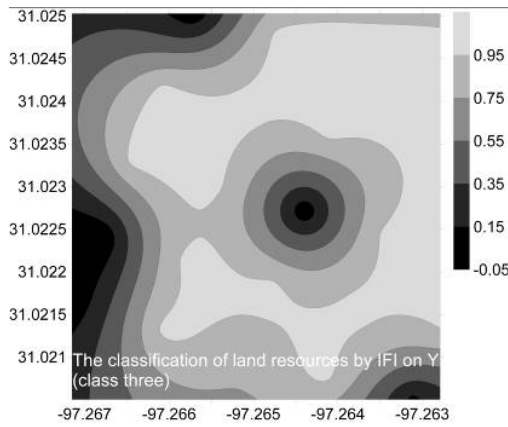**Figure 6. The classification of land resources by IFI on N (category two).**

Figure 7. The classification of land resources by IFI on Yield (category three).

Figure 8. The classification of land resources by CFI (category one).

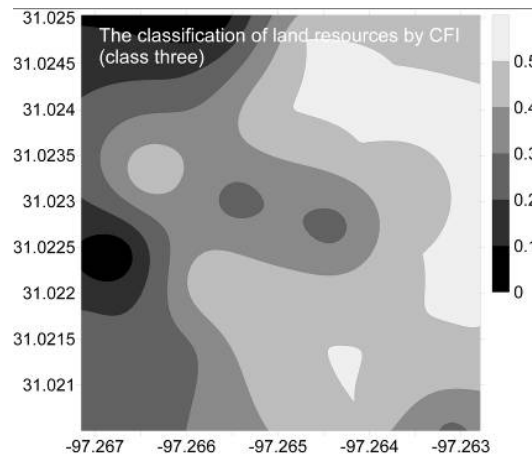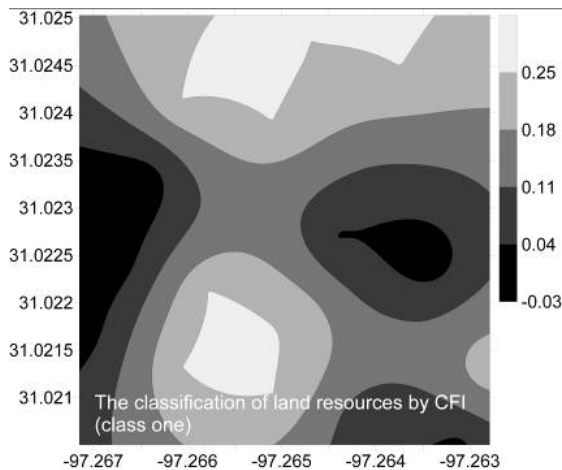**Figure 9. The classification of land resources by I CFI (category two).**

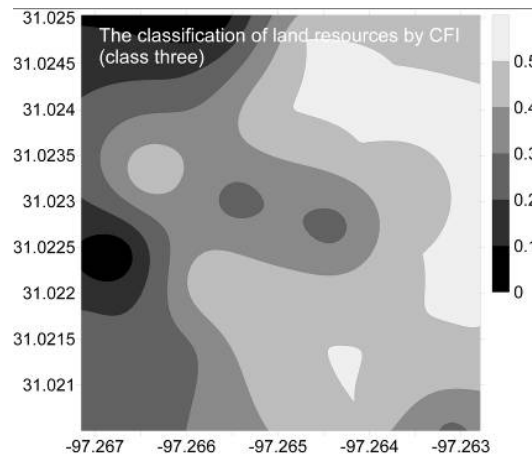**Figure 10. The classification of land resources by CFI (category three).**

Figure 11. The classification of land resources by CFI (category four

The area-average values of CFI are given in Table 4. It is easy to see that categories two and three have the greatest estimations. In other words, in the study site the land recourses would predominately be classified as poor (low to average).

Table 4. The area-average values of CFI

	Category	The area-average values of CFI
1	Very low	0.15
2	Low	0.45
3	Average	0.35
4	High	0.05
5	Very high	0

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