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Sustainable rangeland management using fuzzy logic: A case study in Southwest Iran

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ABSTRACT

While there is no consensus on a definition, it is widely recognized that the concept of sustainability has economic, environmental and social dimensions. We used fuzzy logic as a well-suited tool to handle the vague, uncertain, and polymorphous concept of sustainability. For recognizing the major important indicators in defining sustainability in range management, several semi-structured interviews with an open-ended questionnaire in three different areas of the Fars province in Southwest Iran were held. Pastoralists' experts recognized that sustainability in range management is a function of three major components (inputs) which are the *stocking rate* in a pasture, the amount of *plantation density* per hectare, and the *number of pastoralists* who live in a pasture where the output of the model is the *Right Rate of Stocking*. Based on pastoralists' insights we developed a model called Equilibrium Assessment by Fuzzy Logic (EAFL) which provides a mechanism for assessing sustainability in rangeland management. The EAFL model exhibits three important characteristics. First, it permits the combination of various aspects of sustainability with different units of measurement. Second, it overcomes the difficulty of assessing certain attributes or indicators of sustainability without precise quantitative criteria and, third, the methodology is easy to use and interpret. An important outcome of the EAFL model is that all the pastoralists' experts agree with this conclusion that the current, real stocking rates are much higher than the optimal stocking rates.

1. Introduction

A claim is commonly made that the rangelands of the world are overgrazed and hence producing edible forage for feeding livestock has been less than their potential (Wilson and Macleod, 1991). Globally, rangelands are at risk from numerous pressures (Mitchell et al., 1999). Some of these pressures arise from livestock/pasture systems. Livestock have been a key factor in the development of civilization, but their role in the future is not clear as well as how the science of rangeland management should change in order to meet the challenges of the future. Carrying capacity is the most important variable in range management (Walker, 1995). At a time the planet's limited carrying capacity seems increasingly obvious, the rationale and measures of rangelands carrying capacity are increasingly criticized. One of the key elements of rangeland capacity is the stocking rate. If the stocking rate is not near the optimum level of the equilibrium rate, then, regardless of other grazing management practices, employed objectives will not be met (Roe, 1997). This applies to many countries, including Iran. It is a regular topic of books, articles and symposia (Conference on Sustainable Range Management, 2004), and a common justification for further research.

Iran has a total of 90 million hectares of rangeland. These rangelands are divided into three parts according to their qualities. These qualities are known as "good", "fair" and "poor". The "good" quality lands comprise 14 million, the "fair" quality lands comprise 60 million and the "poor" quality lands comprise 16 million hectares. The total number of livestock is estimated at 25 million animal units, which is three times more than the total capacity of rangelands area. Of this number, 45% of livestock are dependent on the current rangelands that exert more pressure on the current resources (Iranian Nomadic Organization, 1992).

The recent literature on rangelands disequilibrium calls in question any specific measures of carrying capacity, whether the

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range is stocked or unstocked, managed or unmanaged. Ideally, such objections can be taken into account for any individual carrying capacity estimated by accepting that it has to be determined on a case-by-case basis in the field. Once one knows the size of the grazing and browsing animals, the biomass production of the area, the pattern of range management, and so on, he/she can – so this argument goes – produce a site specific stocking rate estimated for the range area under consideration. But, it cannot pack livestock into a given rangeland, without at some point deteriorating that range demonstrably. Surely, biomass production is going down on rangelands precisely because stocking rate has been exceeded for so long, even taking into account factors such as drought and climate change (Hardesty et al., 1993).

The rationale and measures of rangeland carrying capacity are increasingly criticized. It seems that even under environmental conditions of great certainty, the notion of rangeland equilibrium would still be ambiguous and confused. Moreover, since environmental conditions are highly uncertain for the dry rangelands of the world such as Iran, current understanding of rangeland equilibrium turns out to be all the more questionable. There is no workable, practical "equation" for rangeland management in general, and carrying capacity in particular (Roe, 1997). Similar problems exist in other field of sustainable development. Here, we have observed a number of publications which used fuzzy logic as a valuable tool (Cornelissen et al., 2001; Phillis and Andriantiatsaholiniania, 2001; Andriantiatsaholiniaina, 2001; Dunn et al., 1995; Marks et al., 1995; Gowing et al., 1996; Sam-Amoah and Gowing, 2001; El-Awad, 1991; de Kok et al., 2000). In these studies, fuzzy logic is used to construct a model for evaluating sustainability in different areas. These models promise to be a valuable tool in evaluating sustainability. Membership functions are at the core of such fuzzy models. They construct based on the experts' knowledge. An expert is a person whose knowledge in a specific domain (e.g., equilibrium in a pasture) is obtained gradually through a period of learning and experience (Bromme, 1992 and Turban, 1995 in Cornelissen, 2003). The purpose of this article is to design a fuzzy model based on the experts' knowledge for solving the mismanagement of the Fars rangelands in Southwest Iran. As far as we know, no other publications are available that discuss this topic.

1.1. Objective

The above-given considerations make clear that rangeland management is a complex and confusing phenomenon. The main purpose of this empirical case study is to analyze an important issue in range management in Iran: "To what extend are Iranian pastoralists allowed to use range and pasture resources for their livestock in the field?".

To derive a good answer to this question, we use fuzzy logic to develop a model for supporting pastoralists in making suitable decisions. In practice, the construction of such a fuzzy model is an engineering task where many choices have to be made (van den Berg, 2004).

2. Application of fuzzy logic in rangeland management

The use of fuzzy systems is one of the fastest growing methodologies in systems engineering (Grint, 1997). In a broad sense, fuzziness is the opposite of precision. Most concepts, such as sustainability, that cannot be defined precisely (that is, according to some broadly accepted criteria or norms of precision) or have no clearly described boundaries in space or time are considered a bearer of fuzziness.

In a narrow sense, fuzzy logic relates to the definition of fuzzy sets as proposed by Zadeh (1965). In his approach, the belongingness to which an element is member of a fuzzy set is measured by means of a membership function whose values are between 1 (full belongingness) and 0 (non-belongingness). In addition, he formulated the *principle of incompatibility* stating that, as the complexity of a system increases, the human ability to make precious and relevant (meaningful) statements about its behavior diminishes until a threshold is reached beyond which the precision and the relevance become mutually exclusive characteristics (Zadeh, 1973). It is now realized that complex real-world problems require intelligent systems that combine knowledge, techniques, and methodologies from various sources (Jang et al., 1997). Ecological studies are known to be complex in nature (Silvert, 1997) and therefore fuzzy logic seems to be an appropriate technique to solve the dichotomy (black and white) that is inherent in sustainability of natural resources (Cornelissen et al., 2001; Phillis and Andriantiatsaholiniania, 2001; Andriantiatsaholiniaina, 2001; Dunn et al., 1995; Marks et al., 1995).

The theory of fuzzy sets provides a more realistic mathematical representation of the perception of truth than traditional, two-valued logic and Boolean algebra. In the transition from crisp sets to fuzzy sets, the key element is membership functions (Zimmerman, 1996). Membership functions give the truth-values of expressions like "natural resources are somehow sustainable and unsustainable" or more complex expression articulated in daily life.

Because of the complexity and ambiguous nature of rangeland management, fuzzy logic can be useful to evaluate sustainability in rangeland management. Fuzzy logic provides a useful tool for:

- selecting rangeland equilibrium indicators;
- assessing the above indicators'values;
- decision-making by policy makers.

3. Fundamentals of fuzzy set and operators

The mathematics of fuzzy sets and fuzzy logic is discussed in detail in many books (e.g., Lee, 1990; Zimmerman, 1996; Jang et al., 1997; Ruspini et al., 1998). Here, we only discuss certain basic aspects concerning the mathematics that underly fuzzy logic. We try to provide the minimal information needed to understand the construction method and the general working of the fuzzy model introduced later on (in Sections 4 and 5, respectively).

3.1. From crisp to fuzzy sets

Let U be a collection of objects u which can be discrete or continuous. U is called the universe of discourse and u represents an element of U. A classical (crisp) subset C in a universe U can be denoted in several ways like, in the discrete case, by enumeration of its elements: $C = \{u_1, u_2, \ldots, u_P\}$ with $\forall i$: $u_i \in U$. Another way to define C (both in the discrete and the continuous case) is by using the characteristic function χ_F: $U \to \{0,1\}$ according to $\chi_F(u) = 1$ if $u \in C$, and $\chi_F(u) = 0$ if $u \notin C$. The latter type of definition can be generalized in order to define fuzzy sets. A fuzzy set F in a universe of discourse U is characterized by a membership function μ_F which takes values in the *interval* [0, 1] namely, μ_F: $U \to [0, 1]$.

3.2. Operators on fuzzy sets

Let A and B be two fuzzy sets in U with membership functions μ_A and μ_B, respectively. The fuzzy set resulting from operations of union, intersection, etc. of fuzzy sets are defined using their membership functions. Generally, several choices are possible:

Union: The membership function $\mu_{A\cup B}$ of the union $A\cup B$ can be defined by $\forall u{:}\mu_{A\cup B} = \max\{\mu_A(u), \mu_B(u)\}$ or by $\forall u{:}\mu_{A\cup B} = \mu_A(u) + \mu_B(u) - \mu_A(u)\mu_B(u)$.

Intersection: The membership function $\mu_{A\cap B}$ of the union for all $A\cap B$ can be defined by $\forall u:\mu_{A\cap B} = \min\{\mu_A(u),\ \mu_B(u)\}$ or by $\forall u:\mu_{A\cap B} = \mu_A(u)\mu_B(u)$

Complement: The membership function of the complementary fuzzy set A^c of A is usually defined by $\forall u : \mu_{A^c}(u) = 1 - \mu_A(u)$.

3.3. Linguistic variables

Fuzzy logic enables the modelling of expert knowledge. The key notion to do so is that of a *linguistic variable* (instead of a quantitative variable) which takes *linguistic values* (instead of numerical ones). For example, if the *stocking rate* (*SR*) in a pasture is a linguistic variable, then its linguistic values could be one from the so-called termset $T(SR)$ = {*low*, *medium*, *high*} where each term in $T(SR)$ is characterized by a fuzzy set in the universe of discourse, here, e.g., U = [0, 5]. We might interpret *low* as a ''stocking rate of less than approximately 1.5 animal unit (au) per hectare'', *medium* as a ''stocking rate close to 2 au/ha'', and *high* as a ''stocking rate of roughly more than 2.5 au/ha'' *where the class boundaries are fuzzy*. Therefore, these linguistic values are characterized by fuzzy sets described by a membership function as shown in Fig. 1.

3.4. Knowledge representation by fuzzy IF-THEN rules

Fuzzy logic enables the formulation of prototypical linguistic rules of a fuzzy model that can easily be understood by experts where, at the same time, all kinds of mathematical details are hidden. To do so, knowledge is represented by fuzzy IF-THEN linguistic rules having the general form:

$$[\text{If } x_1 \text{ is } A_1 \text{ AND } x_2 \text{ is } A_2 \cdots \text{AND } x_m \text{ is } A_m \text{ THEN } y \text{ is } B,]$$

where $x_1, \ldots, x_m$ are linguistic input variables with linguistic values $A_1, \ldots, A_m$, respectively and where y is the linguistic output variable with linguistic value B.

To illuminate we consider *animal units* and *plantation density* as the principal factors for having *equilibrium*. Then the relevant fuzzy rules could be:

- IF *amount of animal units* is *high* AND *plantation density* is poor THEN *equilibrium is very weak*,
- IF *amount of animal units* is *low* AND *plantation density* is *poor* THEN *equilibrium* is *medium*.

3.5. Architecture of fuzzy systems

Fuzzy inference systems or, shortly, fuzzy systems (FSs) usually implement a crisp input–output (*I*–*O*) mapping (actually, a *smooth function* $O = f(I)$) consisting of basically four units, namely:

- a *Fuzzifier* transforming crisp inputs into the fuzzy domain,
- a *rule base* of fuzzy IF-THEN rules,
- an *inference engine* implementing fuzzy reasoning by combining the fuzzified input with the rules of the rule base,
- a *Defuzzifier* transforming the fuzzy output of the inference engine to a crisp value (Fig. 2).

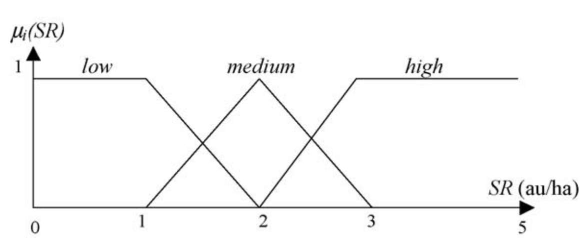

Fig. 1. Diagrammatic representation of the linguistic variable *stocking rate* in a pasture having linguistic values *low*, *medium*, and *high* defined by a corresponding membership function.

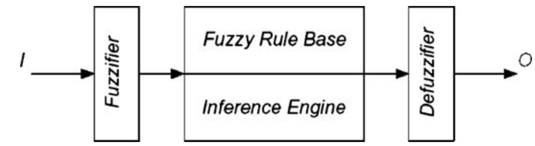

Fig. 2. Building blocks of a Fuzzy Inference System.

In some practical systems, the Fuzzifier or the Defuzzifier may be absent.

3.6. Fuzzy reasoning

Probably the hardest part to understand is the precise way fuzzy reasoning can be implemented. An extensive discussion of this topic is outside the scope of this paper so we limit ourselves here to present just the basic idea. Classical logic is our starting point using the classical reasoning pattern 'modus ponens':

> Given fact ''x is A'' and rule ''IF x is A, THEN y is B'', we conclude that ''y is B''.

Applying fuzzy reasoning, classical modus ponens can be generalized to an 'approximate reasoning' scheme of type:

> Given fact ''x is A''' and rule ''IF x is A, THEN y is B'', we conclude that ''y is B'''.

Here, the assumption made is that the closer A' to A, the closer will B' be to B. It turns out that especial combinations of operations on fuzzy sets like 'max–min' and 'max-product' composition can fulfill this requirement. The complete fuzzy reasoning in a FS can be set up as follows:

1. The fuzzification module calculates the so-called 'firing rate' (or degree of fulfillment) of each rule by taking into account the similarity between the actual input A' defined by membership function $\mu_{A'}(x)$ and in case of a crisp input x_p defined by the value $\mu_A(x_p)$ and the input A of each rule defined by membership function $\mu_A(x)$.
2. Using the firing-rates calculation, the inference engine determines the fuzzy output B' for each rule, defined by membership function $\mu_{B'}(y)$.
3. The inference engine combines all fuzzy outputs B' into one overall fuzzy output defined by membership function $\mu(y)$.
4. The defuzzification module calculates the crisp output y_p using a defuzzification operation like 'centroïd of gravity (area)'.

For a treatment in depth on FSs, its construction and corresponding reasoning schemes (including the most popular systems like Mamdani (Mamdani and Gaines, 1981) and Tagaki-Sugeno fuzzy models (Tagaki and Sugeno, 1985)), we refer to the above-mentioned textbooks.

4. Research method

In order to construct a fuzzy rule-based assessment for the range management of this study, several semi-structured interviews were held. As Jones (1985) described, a semi-structured interview is:

1. a social interaction between two people (the researcher and one of his experts);
2. in which the interviewer (researcher) initiates and varyingly controls the exchange with the respondent (the expert);

3. for the purpose of obtaining quantifiable and comparable information (defining sustainability indicators); and
4. relevant to an emerging or stated hypothesis (IF-THEN rules for making the balance between the different levels of the indicators).

The entire script was written ahead of time, with an eye to an almost total standardization of the interview from one expert to the next. The standardized, open-ended interview was used when it was important to minimize variation in the questions posed to interviewees. This reduces the bias that can occur from having different interviews with experts (Patton, 1987). The open-ended questionnaire was used to conduct interviews included a set of questions which were carefully worded and arranged for the purpose of taking each expert through the same sequence and asking him the same questions with essentially the same words (Gamble, 1989). In other words, the questions persuaded the experts: (i) to introduce the main indicators of sustainability in range management, (ii) to define value labels, and (iii) to determine the range of each value label.

Three different areas of the Fars province in Southwest Iran were studied, first, Cheshme-Anjir from Shiraz county which covers 2575 ha, 3200 livestock and 12 pastoral families, second, Morzion from Sepidan county having 2000 ha, 1570 livestock and 19 pastoral families, and third, Kheshti from Lamerd county where it is 6900 ha, 3804 livestock and 20 pastoral families. The areas have different weather and geographical conditions. The main reason to select these three areas was the management activities which had been done by the Natural Resources Administration of the Fars province for making the balance between livestock and pastures. Each area has an agent, a local pastoralists who was selected as an expert for the interview. Totally, in this study, three main interviews and three follow-ups were conducted for elicitating the experts knowledge as the main indicators of sustainability in range management. Finally, we used the Matlab Fuzzy Toolbar (version 7) for implementing the fuzzy model.

5. Constructing the EAFL model

The scheme of a fuzzy model applying approximate reasoning to assess the Right Rate of Stocking (*RRS*) is in Fig. 3. The following basic steps (van den Berg, 2004) were done to costruct the model called Equilibrium Assessment by Fuzzy Logic (EAFL):

1. determining the relevant input and output variables;
2. defining linguistic values;
3. constructing membership function;
4. determining the fuzzy rules;
5. computing degree of membership of crisp inputs;
6. determining approximate reasoning;
7. computing crisp output (defuzzify); and
8. assessing the model performance.

5.1. Determining the relevant input and output variables

Equilibrium between stocking rate and plantation density is difficult to define but many experts recognize that it is a function of three major components (inputs) which are:

1. stocking rate in a pasture (*SR*),
2. the amount of plantation density per hectare (*PD*), and
3. the number of pastoralists who live in a pasture (*NP*).

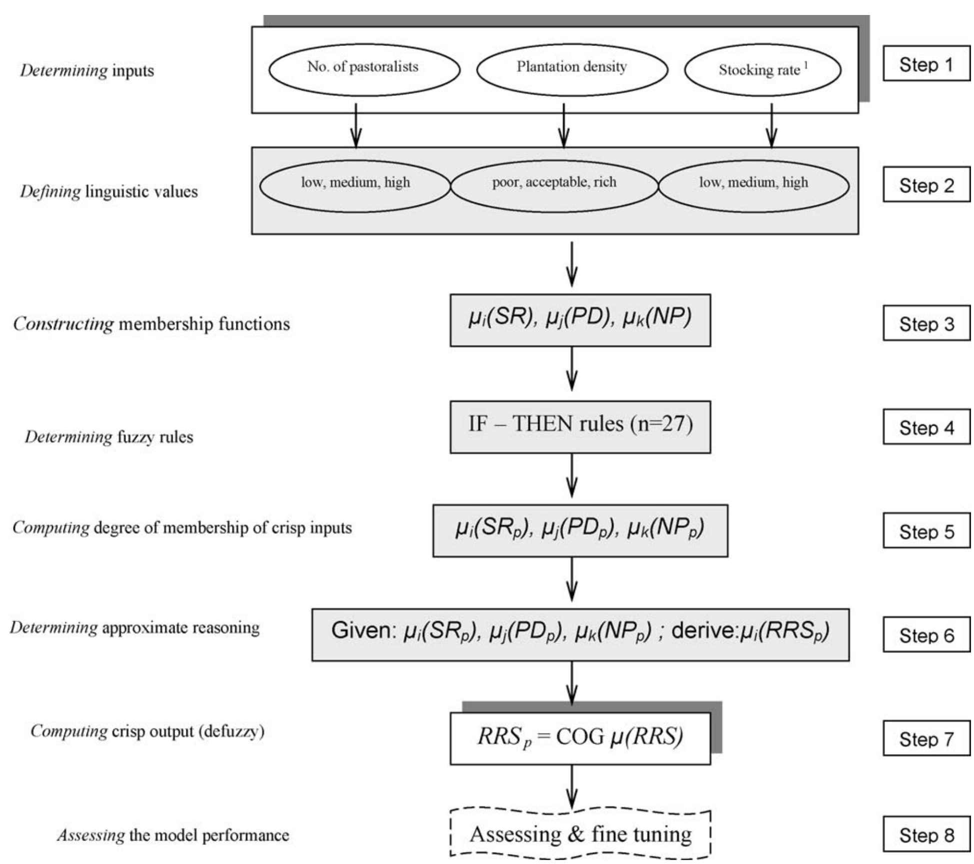

Fig. 3. Scheme of development of the EAFL model applying approximate reasoning to assess the *Right Rate of Stocking* (RRS_p) based on the inputs values (SR_p, PD_p, and NP_p) (The grey color notifies the fuzzy parts of the model) (adapted from Cornelissen, 2003, p. 51). *Note*: the *Stocking Rate* (*SR*) is an input variable of the model and the *Right Rate of Stocking* (*RRS*) the output variable (both having the same linguistic values).

Table 1
Linguistic values used in the EAFL model.

Variable	Linguistic values
Stocking rate (*SR*)	*low*, *medium*, *high*
Plantation density (*PD*)	*poor*, *acceptable*, *rich*
Number of pastoralists (*NP*)	*low*, *medium*, *high*

5.2. Defining linguistic values

In the EAFL model, the linguistic values of each variable are shown in Table 1.

5.3. Constructing membership function

Both triangular and trapezoidal membership functions are selected. The selection was based on special range of values which are stated by the experts for each linguistic value (Fig. 4).

5.4. Determining the fuzzy rules

Therefore, in this study, the rules are expressions of the role of interdependencies among factors of equilibrium which were elicited from pastoralists' experts by interviews. They state different dimensions of sustainability in range management. To determine the overall equilibrium, the rule base needs $3^3 = 27$ rules since we have three linguistic values and three linguistic variables (*SR*, *PD* and *NP*) which are stated by pastoralists' experts. The complete rules base used to construct the overall experts' knowledge base are summarized in Table 2 for different linguistic values. All rules base were elicited by interviews and all pastoralists' experts were agreed at the end with several follow-ups.

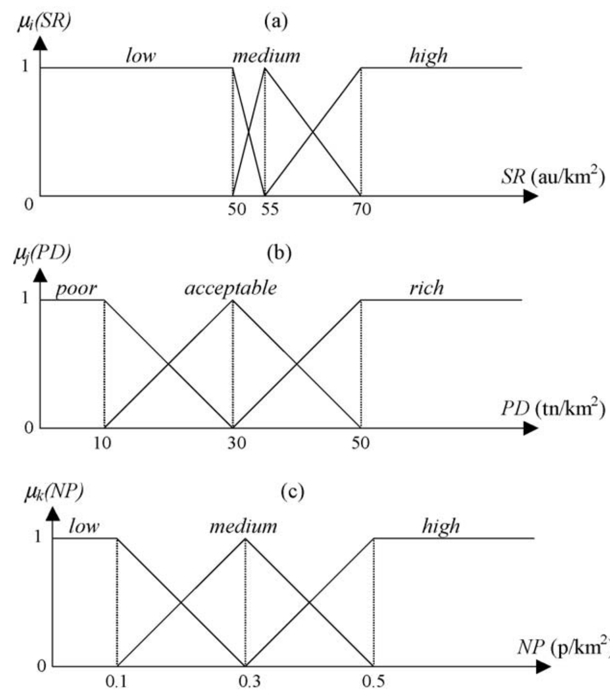

Fig. 4. Membership functions for (a) stocking rate, (b) plantation density, and (c) number of pastoralists (while most of the ranges were elicitated by interview, the rest were calculated by means).

5.5. Computing degree of membership of crisp inputs

We present a numerical example illustrating how the EAFL model can compute degree of membership of crisp inputs. Suppose that information concerning the input variables is expressed numerically as follows: *SR* = 75 (Fig. 5a), *PD* = 35 (Fig. 5b), and *NP* = 0.4 (Fig. 5c).

Table 2
The complete rules base ($3^3 = 27$) used to construct the overall experts' knowledge base.

Rule *r*	if *Stocking Rate* is	and *Plantation Density* is	and *Number of Pastoralists* is	then *Stocking Rate* must be
1	*low*	*poor*	*low*	*low*
2	*low*	*poor*	*medium*	*low*
3	*low*	*poor*	*high*	*low*
4	*low*	*acceptable*	*low*	*low*
5	*low*	*acceptable*	*medium*	*low*
6	*low*	*acceptable*	*high*	*low*
7	*low*	*rich*	*low*	*medium*
8	*low*	*rich*	*medium*	*medium*
9	*low*	*rich*	*high*	*medium*
10	*medium*	*poor*	*low*	*low*
11	*medium*	*poor*	*medium*	*low*
12	*medium*	*poor*	*high*	*low*
13	*medium*	*acceptable*	*low*	*medium*
14	*medium*	*acceptable*	*medium*	*low*
15	*medium*	*acceptable*	*high*	*low*
16	*medium*	*rich*	*low*	*medium*
17	*medium*	*rich*	*medium*	*medium*
18	*medium*	*rich*	*high*	*medium*
19	*high*	*poor*	*low*	*low*
20	*high*	*poor*	*medium*	*low*
21	*high*	*poor*	*high*	*low*
22	*high*	*acceptable*	*low*	*medium*
23	*high*	*acceptable*	*medium*	*medium*
24	*high*	*acceptable*	*high*	*low*
25	*high*	*rich*	*low*	*medium*
26	*high*	*rich*	*medium*	*medium*
27	*high*	*rich*	*high*	*medium*

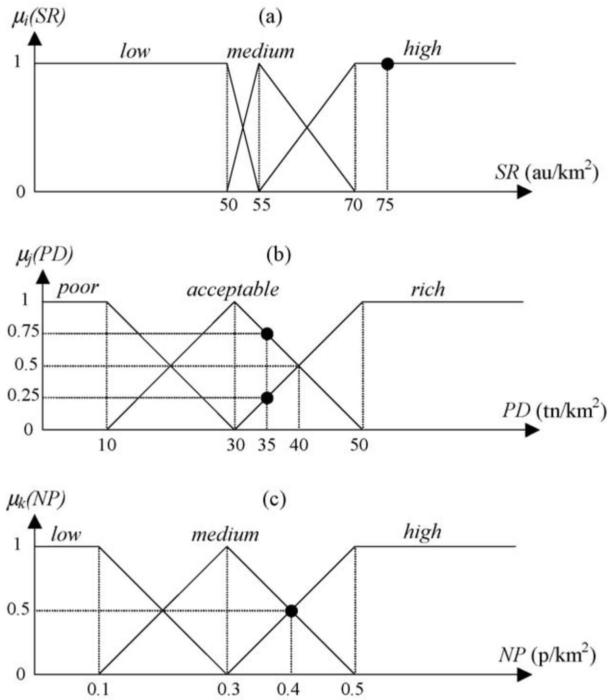

Fig. 5. Linguistic values and fuzzification of crisp inputs.

Fuzzification yields the following inputs for the inference engine:

Input 1: *SR* is *high* with membership grade $\mu_h(SR) = \mu_h(75) = 1$;

Input 2: *PD* is *acceptable* with membership grade $\mu_a(PD) = \mu_a(35) = 0.75$ and *rich* with membership grade $\mu_r(PD) = \mu_r(35) = 0.25$;

Input 3: *NP* is *medium* with membership grade $\mu_m(NP) = \mu_m(0.4) = 0.5$ and *high* with membership grade $\mu_h(NP) = \mu_h(0.4) = 0.5$.

5.6. Determining approximate reasoning

Now, we compute the degree to which each rule is applicable to the input. The only consistent rules are those in which *SR* is *high*, *PD* is either *acceptable* or *rich*, and *NP* is either *medium* or *high*. These are rules 23, 24, 26, and 27 of Table 2. The conclusions of these rules are expressed as follows:

Rule 23: If *SR* is *high* with membership grade 1 and *PD* is *acceptable* with membership grade 0.75 and *NP* is *medium* with membership grade 0.5, then *RRS* must be *low* with membership grade:

$\mu_{PREMISE_{23}} = \min(\{1, 0.75, 0.5\}) = 0.5$

$\mu_{PREMISE_{24}} = \min(\{1, 0.75, 0.5\}) = 0.5$

With the same calculation: $\mu_{PREMISE_{26}} = \min(\{1, 0.25, 0.5\}) = 0.25$

$\mu_{PREMISE_{27}} = \min(\{1, 0.25, 0.5\}) = 0.25$

For the remaining rules of the rule base, we have $\mu_{PREMISE_r} = 0$. We observe that rules 23, 24 and 27 assign the same linguistic value *low* to *SR* with membership degree 0.5, 0.5 and 0.25, respectively. Now, based on degree of membership of inputs value, the fuzzy outputs $\mu_{B'}(RRS)$ of each rule are calculated and combined into one fuzzy output $\mu(RRS)$ (Fig. 6).

5.7. Computing crisp output (defuzzify)

Finally, we use the "Center Of Gravity" (COG) method for defuzzification (Zimmerman, 1996; Jang et al., 1997) yielding the *RRS*. In the example, the *RRS* was assessed by using the Matlab Fuzzy Toolbar (version 7) yielding *RRS* = 32.9 (au/km^2) (Fig. 6).

5.8. Assessing the model performance

Having available a large set of input–output data, the performance of the system can be evaluated and parameters of the system can be fine-tuned in order to achieve a low 'generalization error'. In such a data-rich situation, a training set is used to fit the models, a validation set is used to estimate the prediction error for model selection and a test set is used for assessing the generalization error of the final model chosen (Hastie et al., 2001). If, like in our case, no large data sets are available, the best way to assess model performance and fine-tune the system is based on experts' judgements (Davis and Wagner, 2003). By using different *real* inputs and observing crisp outputs, judgement is possible by experts. They can assess several scenarios and conclude whether the performance of the model is (not) reasonable.

In our case, a small set of real input–output data appeared to be available. This data set was used to describe the behavior of the EAFL model (Table 3).

Table 3 shows three different outputs (*RRS*s) corresponding to three real input data. By comparing the *Right Rate of Stocking* (*RRS*) with the current *stocking rate* (*SR*) for each area, it becomes clear

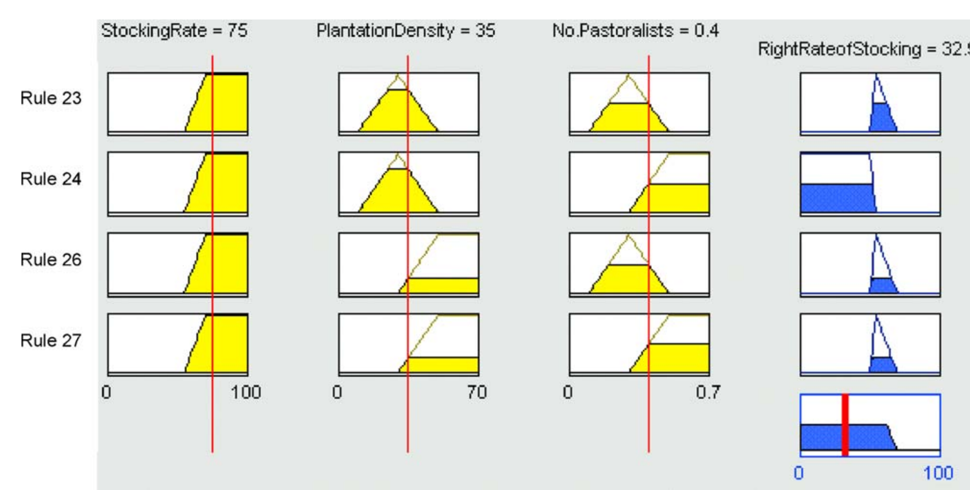

Fig. 6. Graphical illustration of the EAFL model for approximate reasoning and defuzzification. Approximate reasoning starts with a two-step process comprising the implication process and the aggregation process yielding the overal fuzzy output $\mu_i(RRS_p)$ based on the fuzzy conclusions of the inputs (SR_p, PD_p and NP_p) for each rule. Finally, the center of gravity method divides the area under curve into two equal subareas hereby determining the crisp output value: RRS_p = 32.9 (Fuzzytoolbar in Matlab 7).

Table 3
Assessing the performance of the EAFL model by using real data.

Area	Real inputs			Active rules	Output: *RRS* (au/km^2)	ΔSR: (*RRS*–*SR*) (au/km^2)
	SR (au/km^2)	*PD* (tn/km^2)	*NP* (p/km^2)			
1. Cheshme-Anjir	124	18	0.4	20, 21, 23, 24	32.1	−91.9
2. Morzion	94	12	0.9	20, 23	26.1	−67.9
3. Kheshti	55	28	0.3	11, 14	26.1	−28.9

that the current *SR* values are considerably higher than the *RRS* values: *RRS* = 32.1, 26.1 and 26.1 when *SR* = 124, 94 and 55, respectively. The negative ΔSRs (−91.9,−67.9 and −28.9 repectively) exhibit the exceeding rate of *SR* compared to that of *RRS* and therefore suggest general *overgrazing* in the three prototypical areas in Sowthwest of Iran.

All pastoralists' experts, on one hand, agree with this result. They believe that the most important issue they are challenging, is overgrazing and this is actually the reason why they did not consider the "*high*" value for *RRS* as the output of the model (Table 2). They are afraid that, by choosing this value, even in the favorite conditions (e.g., rules 8 and 16), overgrazing will continue to happen and further be encouraged in the future.

By comparing the current *SR* to the *RRS*, on the other hand, the correct decision can easily be made by pastoralists. In all three areas, to return to an equilibrium state, pastoralists should decrease the following amounts of their livestock per square kilometer:

$$\Delta SR_1 = RRS - SR = 32.1 - 124 = -91.9\,\text{au/km}^2$$
$$\Delta SR_2 = RRS - SR = 26.1 - 94 = -67.9\,\text{au/km}^2$$
$$\Delta SR_3 = RRS - SR = 26.1 - 55 = -28.9\,\text{au/km}^2$$

Such a decision has a lot of consequenses. In this case, for example, as they would lose a part of their major income, they usually do not consider this option (decrease). Consequently, pastoralists will experience unbalance and unavoidable degradation in their pastures. For making money to return to balance (without any overgrazing), the Natural Resourse Administrations in Iran have started to offer them the other jobs since 2000. These are included handcrafts, horticulture, agronomy, husbandry and other jobs related to agriculture. These jobs can be various due to different weather conditions, geographical areas and pastoralists' experiences.

The current state of the majority of the Iranian pastures, namely overgrazing, of course, may change in the future. In fact, a pastoral system is a dynamic system, where socio-economic conditions change over the time. Therefore, it may be needed to change or add input variables to the model or to redefine the membership functions, yielding in different output rates. If so, "overgrazing" may change to "normal grazing" or even, "undergrazing" based on different and dynamic conditions in the future.

6. Conclusion

Evaluating the EAFL model presented in this paper, we conclude that it exhibits four important characteristics which can be considered by rangeland management interventionists to deal with both ambiguity and diversity of sustanability in rangeland manegement. First, it permits the combination of various aspects of sustainability with different units of measurement. Second, it overcomes the difficulty of assessing certain attributes or indicators of sustainability without precise quantitative criteria. Third, the methodology is easy to use and interpret. The model, therefore, has the potential to become a practical tool to policymakers and scientists (e.g., if, after strong validation, the model still assesses a right stocking rate that is much lower that the actual ones, policy makers make take appropriate measures in order to reach a more sustainable state). Finally, the model is open for improvement, based on our better understanding of realities in the future. For example, one can construct different fuzzy rules. Also, the number of indicators used to evaluate each linguistic variable of sustainability may be changed according to need or the membership functions of certain linguistic values can be redefined. This may also be part of future research where the model can be improved based on data-driven approaches (van den Berg, 2004): this also invites for systematic data collection in the near future with respect to all kinds of features and sustaibable range management, in all pastoral regions of Iran.

At last, it is important to note that we are aware that the EAFL model is just the first step. The flexibility of the model is one of its advantages over existing static methods. The EAFL model is expected to provide a new useful tool for policymakers in order to manage and to predict the overall sustainability in rangelands.

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