Sustainable Rangeland Management Using a Multi-Fuzzy Model:

How to Deal with Heterogeneous Experts' Knowledge

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ABSTRACT AND KEYWORDS	
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Free Keywords	sustainable rangeland management, carrying capacity, multi-fuzzy model, heterogeneous experts' knowledge, voting methods.

Sustainable Rangeland Management Using a Multi-Fuzzy Model:

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Abstract

While fuzzy specialists usually use homogeneous experts' knowledge to construct fuzzy models, it is much more difficult to deal with knowledge elicited from a heterogeneous group of experts. This issue especially holds in the area of the sustainable rangeland management. One way to deal with the diversity of opinions is to develop a fuzzy system for all experts and to combine all these so-called primary systems into one multi-fuzzy model. To derive each of the primary fuzzy systems using the knowledge of a group of administrative experts, several semi-structured interviews were held in three different areas of the Fars province in Southwest Iran. In order to find the final output of the multi-fuzzy model, we applied different 'voting' methods. The first method simply uses the arithmetic average of the primary outputs as the final output of the multi-fuzzy model. This final output represents an estimation of the *Right Rate of Stocking*. We also propose other (un)supervised voting methods. Most importantly, by harmonizing the primary outputs such that outliers get less emphasis, we introduce an *unsupervised voting method* calculating a weighted estimate of the Right Rate of Stocking. This harmonizing method is expected to provide a new useful tool for policymakers in order to deal with heterogenity in experts' opinions: it is especially useful in cases where little field data is available and one is forced to rely on experts' knowledge only. By constructing the three fuzzy models based on the elicitation of heterogeneous experts' knowledge, our study shows the multidimensional vaguenesses that exist in sustainable rangeland management. Finally, by comparing the final Right Rate of Stocking with its medium range, this study proves the existence of overgrazing in pastures of the three regions of the Fars province in Southwest Iran.

Key words: sustainable rangeland management, carrying capacity, multi-fuzzy model, heterogeneous experts' knowledge, voting methods.

1. Introduction

1.1. Sustainable development: A multidimensional vague concept

Since Sustainable Development (SD) is a vague continually evolving concept, it is difficult to define it in an appreciate way (McKeown *et al.*, 2002; Pembleton, 2004). One of the original descriptions of SD is credited to the Brundtland Commission: "Sustainable development is development that meets the needs of the present without compromising the ability of future generations to meet their own needs" (World Commission on Environment and Development, 1987, p 43). SD is generally thought to have three components: environment, society, and economy (Hart, 2000) and recently, is more defined by adding the fourth, which is institutional dimension (Gleam, 2002). While, environmental sustainability identifies energy, fresh water, and reversing land and soil degradations as priorities, especially for developing countries to protect their natural resource base (EC, 2002; Pembleton, 2004), social sustainability seeks to reduce the vulnerability of various segments of the society, particularly the poor, and maintain the health of social and cultural systems. Nevertheless, economic sustainability aims to maximize the flow of income, while maintaining the stock of assets required for these benefits. The institutional dimension reflects the whole set of norms and beliefs on which personal preferences and attitudes as well as private and public organizations are built. Institutional sustainability links to the availability of mechanisms to implement other dimensions of sustainability and the long-term viability of the institutions in them. The earth's capability to withstand shocks (vulnerability and resilience) is an important aspect of sustainability (Gleam, 2002). The environmental dimensions of sustainability refer to the need to maintain (or restore) the physical resource base so that it endures indefinitely to meet the needs of the present without compromising the capacity of future generations to meet their needs. This also highlights the underlying and fundamental *time* component inherent in sustainability. Economic sustainability is equally conditional on the use of resources so as to avoid their overexploitation either in terms of their quality or quantity, or the use of resources which results in the generation of waste in excess capacity of the environment's to absorb it effectively. The balance between environmental and economic sustainability is mediated through the institutional arrangements that shape and condition the management and use of the land, and those social norms that influence community values. Thereby, two major issues in the international dialog on sustainability are population and resource consumption. Increases in population and resource use are thought to jeopardize a sustainable future (McKeown *et al.*, 2002). In effect, the different dimensions of sustainability constitute the key components of the system, and act in concert to either promote or constrain the achievement of sustainability. Land use is the visual expression of the interplay among those different dimensions and as such can be an important indicator of the health of the overall ecosystem. Therefore, SD calls for long-term structural change in our economic and social systems, with the aim of reducing the consumption of the environment and resources to a permanently affordable level, while maintaining economic output potential and social cohesion (ARE, 2005).

1.2. Sustainable rangeland management

Sustainable rangeland management calls for balancing science with social values, economic feasibility, institutional traditions and political muscle. This could be a recipe for sustainable rangeland use, but it has largely been associated with wetlands protection, endangered species, or biological diversity. Rangeland management, in new definitions, is the manipulation of rangeland ecosystems to improve past damage, to provide societal needs from those systems, and to keep options open for future generations. This definition implies that long-term sustainability has priority over short-term commodity extraction. It depends, in part, upon determining the ecological carrying capacity of the land, determining what people want and need from the land, and a political and economic system that matches what people want and need with land capability (Box, 2002).

1.3. Issues and current challenges

1.3.1. Overgrazing

The most contentious and emotional rangeland use issue now and in the foreseeable future is balancing private rights with the public interest. This debate often terminates to overgrazing (private rights) and sustainability (public rights). This issue will surface in such different rangeland use debates as historical preservation, endangered species, location of waste disposal facilities, and public rangeland management. The controversy of overgrazing on public rangelands, therefore, is not just about cows and grass. It is about ownership of the public lands and it is about what rights pastoralists can hold in a common resource (Box, 2002). Whenever pastoralists prefer to focus on their own rights and to neglect the public rights, rangeland degradation will be unavoidable, especially for next generations.

In generally, rangeland degradation falls into two broad categories: that resulting from extended periods of drought, and that resulting from overuse through cultivation or overgrazing (Hiernaux, 1996). With uncontrolled grazing, most rangelands are overgrazed and the vegetation is depleted. Due to overuse of resources, especially overgrazing, and the application of non-suitable management practices such as low recognition of prevalent natural vegetation cycles in grass and thorn bush savannahs without considering long-term degradation processes, the rangeland quality of many rangeland areas has declined (Buss & Nuppenau, 2002). A visible decreasing appearance of natural composition of grass and bush cover, bush encroachment and a decreasing biodiversity indicate lower stocking potentials for domestic livestock on large areas of rangeland, especially in developing countries such as Iran (Azadi *et al.*, 2003). In this case, rangeland degradation becomes an economical threat to falling pastoralists' income, a social threat to the continuation of rural-urban immigration, and an environmental threat to desertification. As a response, on one hand, many pastoralists increase their livestock and overgraze the pastures. On the other hand, economic and political pressures push them to produce red meat for a growing population. Plantation density, therefore, will decrease and degradation will happen. Sometimes, government policies inadvertently provide incentives that encourage overgrazing. Overgrazing occurs, even though analysis demonstrates that maximum net economic returns will occur below the maximum sustainable level of livestock off-take per unit area (Buxton & Stafford Smith, 1996). Financial crisis is another factor tempting graziers to push stocking to the limit. Pastoral businesses facing insolvency are greatly tempted to increase stocking rates in an effort to sustain their operation until commodity prices or climate take a favourable turn. Carrying capacity and the appropriate stocking rate cannot be determined until the decisions relative to so species of livestock, season of use and distribution have been revised (Walker & Hodgkinson, 2000).

1.3.2. Carrying capacity

The science of rangeland management adapted carrying capacity concepts to grazing systems on the rangelands. The logic basis for this concern is the concept of rangeland carrying capacity. Carrying capacity is considered to be the average number of animals that a particular pasture or range can sustain over time. *Stocking Rate* (*SR*) is expressed as the number of animal unit months (aum) supplied by one hectare of land. An animal unit month is the amount of forage required by an animal unit grazing for one month (Kopp, 2004). The responsibility of rangeland managers is to try to balance livestock grazing pressure with the natural regenerative capacity of rangeland plants. The estimations of carrying capacity are usually based on assumptions about the impact of livestock on plants and plant succession. Heavy livestock grazing is thought to lead to a decline in rangeland condition, and reducing or removing grazing pressure assumed plant successional processes would restore the rangeland to its previous condition. By knowing the rangeland condition class, the proper use factor, or the amount of forage to leave to allow plant nutrients to be restored, and taking into account distance to water, slope steepness, and other factors, carrying capacities for a particular rangeland or pasture could be determined (Miller, 2005). These managerial estimations have usually been used in many countries such as Iran.

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 millions 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).

Where there is overstocking, this is environmentally unfriendly since overgrazing and subsequent land degradation would result. Iranian pastoralists have to be educated on limiting their livestock according to the carrying capacity of the land somehow overgrazing and degradation do not occur. In this case, a restocking program for the districts is needed. Therefore, it is a challenge to improve the management of livestock rising by introducing new methods of rangeland management including zero grazing (Azadi *et al.*, Submitted).

1.3.3. Modeling problems

As a consequence of the above-mentioned dilemma, there is a conflict that arises between consumption (economic dimension) and conservation (environmental dimension). Nowadays, social scientists try to reconcile this conflict (social dimension) (Azadi *et al.*, 2003) by creating interdisciplinary experts' teams, which are constructed by cooperation of technical scientists (Shaner *et al.*, 1982). This approach, which started in 1970s, has labelled differently[1]. The interdisciplinary experts' teams usually offer new methods of grazing management for reaching sustainability (Azadi *et al.*, 2003). They try to develop a systematic approach for better understanding the complex situation of pastoralists. But as the interdisciplinary team tries to implement different ideas belonging different experts for the same situation, the members often fail to reach an identical understanding of this complex situation (Shahvali & Azadi, 1999). Thereby,

[1]. FSA: Farming System Analysis, FSAR: Farming System Adaptive Research, FSCR: Farming System Component Research, FSBDA: Farming System Base-line Data Analysis, NFSD: New Farming Systems Development, FSRAD: Farming Systems Research and Agricultural Development FSRE: Farming System Research Extension (Sands, 1986).

when presenting their ideas concerning the sustainability in rangeland management, they usually: (Azadi *et al.,* 2003)

- Select rangeland equilibrium indicators differently;
- Weigh the indicators unequally; and
- Assess them in different ways.

Since fuzzy models usually use the expert knowledge, it is important to identify an expert properly. For example, there are some differences between stakeholders and experts (Cornelissen, 2003) and also differences between experts and those people who select to interview based on a few personal contacts, or on the basis of availability during a short time period (Davis and Wagner, 2003). In this study, we define an expert as 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). We selected the experts based on a 'socio-metric' method. Based on this method, concerned information obtains directly from key informant experts who are nominated by the majority of stakeholders (Ortega, 2002).

While there is almost an agreement among pastoralist experts (Azadi *et al.*, Submitted), administrative experts usually present different indicators, weigh them unequally and use different ways to assess. Thus, it seems that even under stable environmental conditions, the notion of rangeland equilibrium is still ambiguous and confusing. Moreover, since environmental conditions are highly uncertain for the dry rangelands of the world such as in 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 noticed a number of publications which used fuzzy logic as a valuable tool in the sustainability areas to solve these problems (Andriantiatsaholiniaina, 2001, Azadi *et al.*, 2003; Azadi *et al.*, Submitted; Bosma *et al.*, Submitted; Cornelissen *et al.*, 2001; de Kok *et al.*, 2000; Dunn *et al.*, 1995; El-Awad, 1991; Ferraro, *et al.*, 2003; Gowing *et al.*, 1996; Marks *et al.*, 1995; Phillis and Andriantiatsaholiniaina, 2001; Sam Amoah and Gowing, 2001; Sicat *et al.*, 2005). In these studies, fuzzy logic is used to construct a model for evaluating sustainability in different areas. These models usually try to elicit and deal with homogenous experts' knowledge and hardly refer to heterogeneous experts. Experts' knowledge, however, is influenced by individual perspectives and goals (Ford & Sterman, 1998). When constructing a fuzzy model, an important consideration is how to deal with differences in personal experience. The effect of these differences is assumed to be smaller in a homogeneous (e.g. only pastoralists) than in a heterogeneous group (e.g. different experts). As experts have graduated in different disciplines, they may come to a different evaluation of sustainable rangeland management than, for example, pastoralists. Such differences, however, are not necessarily disadvantageous. A heterogeneous group of experts, can be an advantage over a homogeneous group through considering all knowledge and, compensating for dissenting points of view by more liberal ones (Cornelissen, 2003).

The purpose of this article is to design a fuzzy model based on heterogeneous Iranian Natural Resources Administrative experts' knowledge for solving the disequilibrium of the Fars' rangelands in Southwest Iran. As far as we know, no other publications are available that discuss this topic.

1.4. Objectives

The above-mentioned heterogeneity in experts' knowledge makes unclear decisions in rangeland management for reaching sustainability in practice. The main purpose of this paper is to present a holistic approach by developing a multi-fuzzy model in the area of sustainable rangeland management based on heterogeneous experts' knowledge. In order to test its working, a case study was conducted in Southwest Iran.

More specifically, it focuses on the following issues:

- Selecting rangeland equilibrium indicators;
- Elicitation of heterogeneous experts' knowledge concerning the indicators
- Dealing with different experts' knowledge;
- Evaluating final model behaviour.

2. Foundations of fuzzy modeling

The mathematics of fuzzy sets and fuzzy logic is discussed in detail in many books (e.g., Lee, 1990; Zimmermann, 1996; Jang, Sun and Mizutani, 1997; Ruspini et al, 1998). Here, we only discuss the most fundamental aspects concerning the fuzzy systems.

2.1. 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: $U \rightarrow \{0, 1\}$

according to χ_F (u) = 1 if $u \in C$, and χ_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: $U \rightarrow [0, 1]$.

2.2. Linguistic variables

Fuzzy logic enables the modeling 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 *stocking rate* (*SR*) in a pasture is interpreted as linguistic variable, then its linguistic values could be one from the so-called term set *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 month (aum) per hectare", *medium* as a "stocking rate close to 2 aum per hectare", and *high* as a "stocking rate of roughly more than 2.5 aum per hectare" where the class boundaries are fuzzy. These linguistic values are characterized by fuzzy sets whose membership functions are shown in Fig. 1.

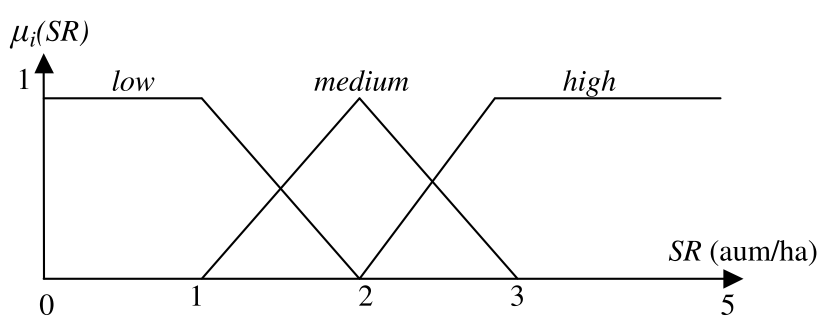

Fig. 1. Diagrammatic representation of the linguistic variable *stocking rate* in a pasture having linguistic values *low, medium,* and *high* defined by a corresponding membership function $\mu_i(SR)$.

2.3. Knowledge representation by fuzzy IF-Then rules

Fuzzy logic is a scientific tool that permits simulation of the dynamics of a system without a detailed mathematical description. In an expert-driven approach, 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 is medium.

2.4. Architecture of fuzzy systems

Fuzzy Inference Systems or, shortly, Fuzzy Systems (FSs) usually implement a crisp input-output (IO) mapping 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).

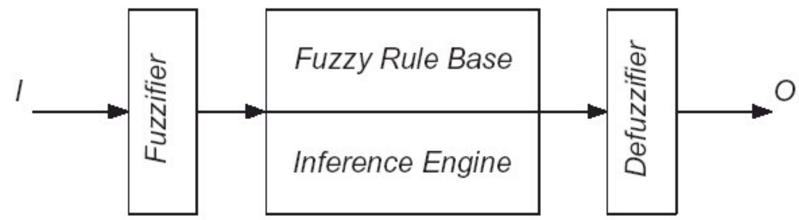

Fig. 2. Building blocks of a Fuzzy Inference System.

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

2.5. 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 fulfil this requirement.

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.

3. Research method

In order to construct a multi-fuzzy model, 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\her experts);
2. in which the interviewer (researcher) initiates and varyingly controls the exchange with the respondents (the experts);
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 the variation of the questions posed to interviewees. This helps to reduce the bias that can occur from having different interviews with different 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). More specifically, the questions were conducting the experts i) to introduce the main indicators of sustainability in range management, ii) to define the labels (linguistic values), iii) to determine the fuzzy ranges of each value label, and iv) to express the fuzzy if-then rules.

Three different regions of the Fars province in Southwest Iran were studied: first, Cheshme-Anjir from Shiraz county which covers 2575 hectares, 3200 livestock and 12 pastoral families; second, Morzion from Sepidan county having 2000 hectares, 1570 livestock and 19 pastoral families; and third, Kheshti from Lamerd county where it is 6900 hectares, 3804 livestock and 20 pastoral families. The regions have different climate and geographical conditions. The main reason to select these three regions was that management activities done by the Natural Resources Administration of the Fars province for making the balance between livestock and pastures take mainly place in these regions. The administration has hired a large number of experts who have graduated in bacholar and master degrees in different diciplines of range management science.

Totally, in this study, three main interviews and six follow-ups during a period of 18 months were conducted for elicitation the administrative experts' knowledge as the main indicators of sustainability in range management in the study regions. Finally, we used the Matlab Fuzzy Toolbar (version 7) for implementing the fuzzy model.

4. Development of the multi-fuzzy model

To deal with heterogeneous experts' knowledge, we have designed a specific multi-fuzzy model (Fig. 3) based on three Mamdani-type of fuzzy models to assess the *Right Rate of Stocking* (*RRS*). The following basic steps were executed to be able to calculate the final crisp output:

1. Constructing the fuzzy models, based on the experts' knowledge resulting from the semi-structured interviews (described in section 3);

2. Computing, for several typical cases, the crisp primary outputs of the models and comparing them; and
3. Combining different outputs using a voting process and calculating the final crisp output.

The architecture of the multi-fuzzy model is visualized in Fig. 3.

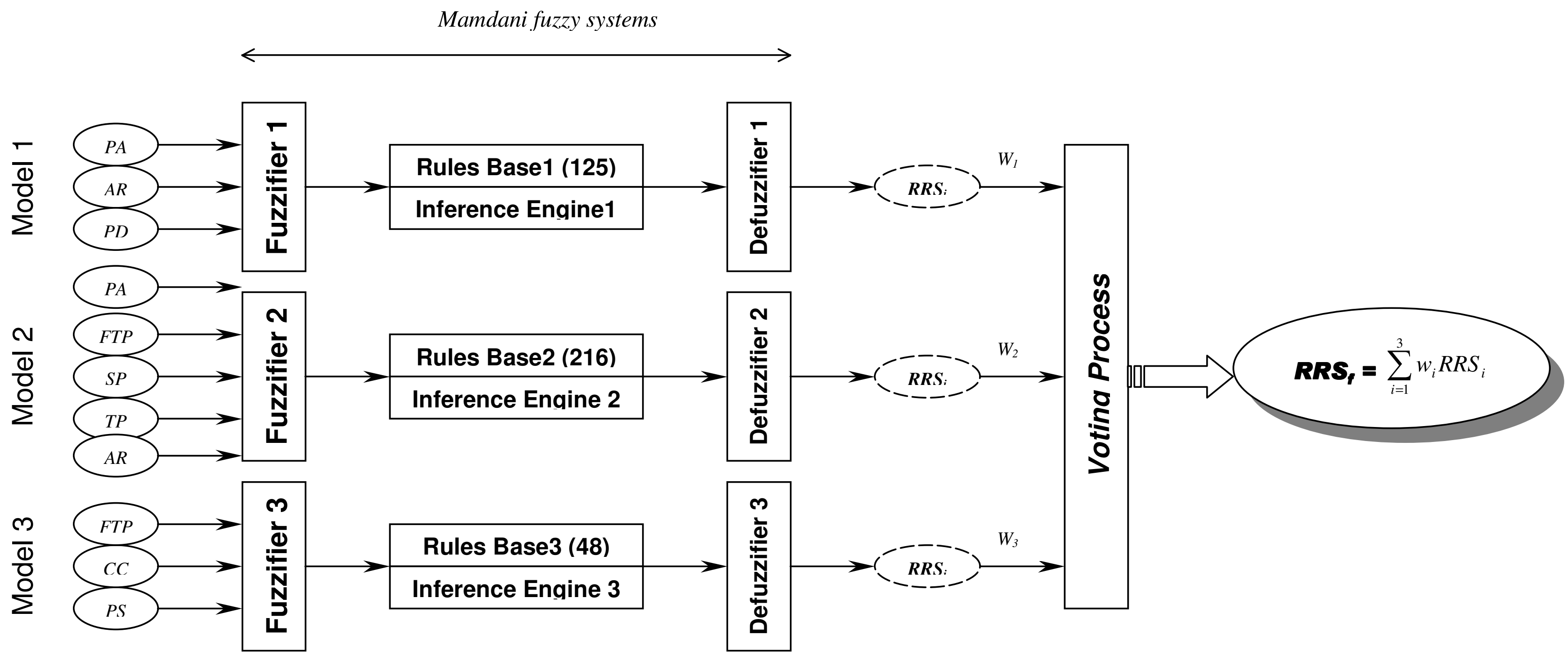

Fig. 3. Architecture of the multi-fuzzy model to deal with different experts' knowledge: The Primary outputs RRS_i (i = 1,2,3) of three Mamdani fuzzy systems having different input variables and different number of rules base (125, 216, and 48 respectively), are combined into one output value RRS_f using a weighted voting process (Abbreviations: *PA: Pature Area*, *AR: Annual Rainfall*, *PD: Plantation Density*, *FTP: Future Trend of a Pasture*, *SP: Slope of Pasture, TP: Topography of Pasture, CC: Carrying Capacity, PS: Pastoralists Situation* and *RRS: Right Rate of Stocking*).

4.1. Constructing the fuzzy models

Due to heterogeneous experts' knowledge as collected in the semi-structured interviews, we have constructed three different Mamdani-types of fuzzy models. Each model has its own specific inputs, linguistic values, fuzzy range and if-then rules (Table 1).

Table 1. Inputs, linguistic values and fuzzy range of each experts.

Expert	His discipline	Inputs (I_i)	Linguistic values	Fuzzy range	Unit
1	Desert Management	*PA*	*Verylow,Low,Medium,High,Veryhigh*	500,2500,5000,10000,20000	ha
		AR	*Verylow,Low,Medium,High,Veryhigh*	100,200,350,600,800	mm
		PD	*Verylow,Low,Medium,High,Veryhigh*	10,25,35,55,70	%
2	Rural Development	*PA*	*Low,Medium,High*	500,1000,2000	ha
		FTP	*Negative,Stable,Positive*	20,50,70	%
		SP	*Deserts,Mountains*	5,12	%
		TP	*Low,Medium,High*	100,450,1700	m^2
		AR	*Verylow,Low,Medium,High*	50,100,250,500	mm
3	Husbandry	*FTP*	*Negative,Stable,Positive*	0,50,100	%
		CC	*Low,Medium,High,Veryhigh*	0.5,2,5,6	aum
		PS	*Poor,Normal,Good,Rich*	25,50,75,100	%

Abbreviations: *PA: Pature Area, AR: Annual Rainfall, PD: Plantation Density, FTP: Future Trend of a Pasture, SP: Slope of Pasture, TP: Topography of Pasture, CC: Carrying Capacity, PS: Pastoralists Situation.*

Considering the second column with the third of Table 1 makes clear that the different administrative experts, graduated in different disciplines, have different knowledge concerning the indicators influencing the balance between consumption and conservation in sustainable rangeland management. They usually introduce those indicators which are most related to their own discipline. Thereby, based on the experts' knowledge, we constructed three fuzzy models. The inputs of the first model are *Pature Area*, *Annual Rainfall*, and *Plantation Density*, where the second model holds *Pature Area*, *Future Trend of a Pasture*, *Slope of Pasture, Topography of a Pasture, and Annual Rainfall* and the third model includes *Future Trend of a Pasture*, *Carrying Capacity* and *Pastoralists Situation* as the inputs (Table 1).

The administrative experts introduced different linguistic values for their inputs. The first expert, for example, considered five levels (*Very low, Low, Medium, High, Very high*) for all three his own inputs, while, the second expert considered two, three and four levels for his own indicators. The third expert deemed three and four levels for his own inputs. Table 1 also shows for the same input (e.g. variable *AR* and *FTP*), experts may have different ideas regarding the linguistic values to be used.

We also asked the experts to define the fuzzy ranges of the linguistic values, i.e., the membership functions that define the linguistic values selected. All experts considered the trapezoidal shape for the smallest and the largest linguistic values and the triangular for the rest. In this way, we defined both triangular and trapezoidal membership functions based on administrative experts' knowledge.

The experts were also asked to express their knowledge in a set of 'fuzzy IF-THEN rules' while offering all possibilities. We prepared all combinations of the inputs and asked the experts to fill out the output column. Thereby, the number of if-then rules was determined based on the number of inputs variables and their linguistic values:

The number of if-then rules $_{\text{(Model 1)}}$ = 5 * 5 * 5 = 125

The number of if-then rules $_{\text{(Model 2)}}$ = 3 * 3 * 2 * 3 * 4 = 216

The number of if-then rules $_{\text{(Model 3)}}$ = 3 * 4 * 4 = 48.

Although the inputs of the three fuzzy models are different due to quantity and linguistic values, the *Right Rate of Stocking* (*RRS*) is chosen as the only output of the model (Table 2).

Table 2. Characteristics of the output (*RRS*) for three fuzzy models.

Model	Linguistic values	Fuzzy ranges	Unit
1	*Verylow,Low,Medium,High,Veryhigh*	0.5,1.0,2.5,4.0,6.0	aum/ha
2	*Low,Medium,High*	0.5,0.6,1.0	aum/ha
3	*Low,Medium,High*	1.0,2.0,3.0	aum/ha

4.2. Computing the crisp primary outputs

Before being able to compute a final crisp output value of the multi-fuzzy model, we must first calculate the primary outputs, i.e., the output of each fuzzy model. To do so, we need a representative set of data. We have been able to collect the inputs data of five prototypical cases for each region of our study. Next, we computed the primary output values RRS_i of each the three fuzzy models developed. The results of this procedure are summarized in Tables 3, 4 and 5.

Table 3. Computing the outputs of the first model with 5 cases for each region.

Model: 1					
Region: Morzion					
Case	Real Inputs			Active	Output
	PA (ha)	*AR* (mm)	*PD* (%)	Rules	RRS_1 (aum/ha)
1	100	750	12	16,17,21,22	0.68
2	100	750	11	16,17,21,22	0.56
3	200	750	12	16,17,21,22	0.68
4	50	750	13	16,17,21,22	0.77
5	250	750	12	16,17,21,22	0.68
Region: Cheshme-Anjir					
Case	Real Inputs			Active	Output
	PA (ha)	*AR* (mm)	*PD* (%)	Rules	RRS_1 (aum/ha)
6	100	315	18	6,7,11,12	1.07
7	200	315	19	6,7,11,12	1.11
8	300	315	17	6,7,11,12	1.02
9	250	315	18	6,7,11,12	1.07
10	300	315	16	6,7,11,12	0.97
Region: Kheshti					
Case	Real Inputs			Active	Output
	PA (ha)	*AR* (mm)	*PD* (%)	Rules	RRS_1 (aum/ha)
11	200	240	20	6,7,11,12	1.15
12	500	240	22	6,7,11,12	1.23
13	200	240	19	6,7,11,12	1.11
14	300	240	20	6,7,11,12	1.15
15	700	240	20	6,7,11,12	1.15

Table 4. Computing the outputs of the second model with 5 cases for each region.

Model: 2							
Region: Morzion							
Case	Real Inputs					Active Rules	Output
	PA (ha)	*FTP* (%)	*SP* (%)	*TP* (m^2)	*AR* (mm)		RRS_2 (aum/ha)
1	100	50	15.7	100	750	40	0.70
2	100	50	15.7	120	750	40,44	0.85
3	200	50	15.7	115	750	40,44	0.82
4	50	50	15.7	130	750	40,44	0.91
5	250	50	15.7	145	750	40,44	0.98
Region: Cheshme-Anjir							
Case	Real Inputs					Active Rules	Output
	PA (ha)	*FTP* (degree)	*SP* (%)	*TP* (m^2)	*AR* (mm)		RRS_2 (aum/ha)
6	100	55	13.4	180	315	39,40,43,44,63,64,67,68	1.12
7	200	55	13.4	160	315	39,40,43,44,63,64,67,68	1.12
8	300	55	13.4	200	315	39,40,43,44,63,64,67,68	1.13
9	250	55	13.4	185	315	39,40,43,44,63,64,67,68	1.12
10	300	55	13.4	170	315	39,40,43,44,63,64,67,68	1.12
Region: Kheshti							
Case	Real Inputs					Active Rules	Output
	PA (ha)	*FTP* (degree)	*SP* (%)	*TP* (m^2)	*AR* (mm)		RRS_2 (aum/ha)
11	200	20	8.6	30	240	2,3,14,15	0.45
12	500	20	8.6	20	240	2,3,14,15	0.45
13	200	20	8.6	35	240	2,3,14,15	0.45
14	300	20	8.6	40	240	2,3,14,15	0.45
15	700	20	8.6	25	240	2,3,14,15,74,75,86,87	0.45

Table 5. Computing the outputs of the third model with 5 cases for each region.

Model: 3					
Region: Morzion					
Case	Real Inputs			Active Rules	Output
	FTP (%)	*CC* (aum)	*PS* (%)		RRS_3 (aum/ha)
1	50	0.27	60	18,19	0.84
2	50	0.25	65	18,19	0.84
3	50	0.22	60	18,19	0.84
4	50	0.26	55	18,19	0.80
5	50	0.28	65	18,19	0.84
Region: Cheshme-Anjir					
Case	Real Inputs			Active Rules	Output
	FTP (%)	*CC* (aum)	*PS* (%)		RRS_3 (aum/ha)
6	50	0.36	65	18,19	0.84
7	50	0.34	50	18	0.76
8	50	0.36	70	18,19	0.80
9	50	0.38	60	18,19	0.84
10	50	0.35	60	18,19	0.84
Region: Kheshti					
Case	Real Inputs			Active Rules	Output
	FTP (%)	*CC* (aum)	*PS* (%)		RRS_3 (aum/ha)
11	20	0.42	30	1,2,17,18	0.84
12	20	0.40	35	1,2,17,18	0.84
13	20	0.43	40	1,2,17,18	0.84
14	20	0.44	30	1,2,17,18	0.84
15	20	0.41	35	1,17	0.84

Table 3, 4 and 5 show that, for equal cases, the primary outputs RRS_i (i = 1, 2, 3) are usually different. It clarifies that our decisions to select the best final output as an estimation of the *RRS* is not a trivial task. Actually, we need to find a solution for dealing with the differences among the primary outputs. More formally, we should find an 'optimal' way to combine the primary outputs $RRS_i(I)$, based on a given input vector I, in order to calculate one final crisp output value $RRS_f(I)$ of our multi-fuzzy model. This combining process is sometimes, especially in environments of supervised learning, termed 'voting'[1] (Hastie *et al.*, 2001).

[1]. Voting and rating activities require the gathering of participants' opinions from large distances, and therefore, they are closely connected to network issues and distributed processing (Kovács and Micsik, 2005).

4.3. Implementing voting

In the next sections, we introduce and discuss several ways to implement voting, i.e., to calculate the weights for combining the primary outputs.

4.3. Voting process

4.3.1. Method 1: Calculating the mean of outputs

Table 6 shows the primary outputs of models 1, 2 and 3, and the final output RRS_f of 15 cases (c = 1,2,…,15) in three different study regions. In this approach, all final crisp outputs simple equal the arithmetic *mean* of the primary outputs of the three models, i.e., $RRS_f(I_c) = \text{Mean} = \frac{1}{3}\sum_{i=1}^{3} RRS_i(I_c)$, where I_c represents the input vector for the c^{th} case.

Table 6. Finding the final outputs by calculating the mean of primary outputs.

Region: Morzion					
Case	Primary outputs: RRS_i			SD	Mean (RRS_f)
	Model 1	Model 2	Model 3		
1	0.68	0.70	0.84	0.08	0.74
2	0.56	0.85	0.84	0.16	0.75
3	0.68	0.82	0.84	0.08	0.78
4	0.77	0.91	0.80	0.07	0.82
5	0.68	0.98	0.84	0.15	0.83
Region: Cheshme-Anjir					
Case	Primary outputs: RRS_i			SD	Mean (RRS_f)
	Model 1	Model 2	Model 3		
6	1.07	1.12	0.84	0.14	1.01
7	1.11	1.12	0.76	0.20	0.99
8	1.02	1.13	0.80	0.16	0.98
9	1.07	1.12	0.84	0.14	1.01
10	0.97	1.12	0.84	0.14	0.97
Region: Kheshti					
Case	Primary outputs: RRS_i			SD	Mean (RRS_f)
	Model 1	Model 2	Model 3		
11	1.15	0.45	0.84	0.35	0.81
12	1.23	0.45	0.84	0.39	0.84
13	1.11	0.45	0.84	0.33	0.80
14	1.15	0.45	0.84	0.35	0.81
15	1.15	0.45	0.84	0.35	0.81

As table 6 shows, different regions have different RRS_f as the means of the primary outputs. Since, the second region (Cheshme-Anjir) gains the highest and the first region (Morzion) has lowest means, the third region (Kheshti) stands between them. Therefore, according to these estimations, the second region can hold the most animal unit per hectare (aum), while the capacity of the first region is the least. The standard deviations of RRS_i in the three regions have also been calculated. Table 6 shows that the highest deviations of the primary RRS_i are found in the third and the lowest in the first region. The method of calculating the mean of the primary inputs has some strengths and weaknesses. It has some strengths because it concerns a simple calculation and it covers all three outputs. It has some weaknesses, as it uses all data in our calculations with equal weights. By doing so, outliers are equally important as points close to the expected value of the output. Therefore, we think it would be better to look for voting methods where the primary outputs are calculated as a *weighted mean*, i.e.,

$$RRS_f(I_c) = \sum_{i=1}^{N} w_i RRS_i(I_c) \qquad (1)$$

Here, in a more general setting, N equals the number of primary models, where the weights w_i are subject to the following constraints: $\sum_{i=1}^{N} w_i = 1$ and $\forall i : w_i \geq 0$. The underlying assumption of this weighted approach is that ‘each expert has something to say’ and, in addition, that ‘certain experts have something more to say than other ones’. We now discuss a few methods for calculating ‘optimal’ weight values w_i.

4.3.2. Method 2: Minimizing the sum of squared errors

In cases a training set of C input-output cases (I_c,RRS_c), (c = 1, 2, …, C) is available, we can calculate optimal weights w_i by choosing the weights w_i such that the following sum of squared errors SSE is minimized:

$$SSE = \sum_{c=1}^{C} (RRS_f(I_c) - RRS_c)^2 = \sum_{c=1}^{C} (\sum_{i=1}^{N} w_i RRS_i(I_c) - RRS_c)^2 . \qquad (2)$$

This approach of supervised learning can be considered as a regression method where the final outputs $RRS_f(I_c)$ of the multi-fuzzy model are as much as possible equated to the correct output values RRS_c. If desired and needed, even more sophisticated supervised methods from predictive data mining like 'bagging' and 'boosting' (Hastie *et al.*, 2001; Ishibuchi *et al.*, 1999) can be considered for implementing optimal voting schemes.

Unfortunately, like in our case, the above-given methods of supervised learning are not applicable in cases a set of correct input-output values is not available. Therefore, we will not further discuss method 2 in this article. Instead, we are challenged to come up with an *unsupervised* method for implementing voting, i.e., a method where we try to optimize the 'consistency' of the final output values of the system by harmonizing the values of the primary outputs.

4.3.3. Method 3: Minimizing an approximation of the sum of squared errors

One might wonder whether we can approximate the approach of method 2 by using an approximation RRS'_c of the correct ouput values RRS_c**.** Knowing the primary outputs RRS_i, we can use as an approximation $RRS'_c = \text{Mean} = \frac{1}{N}\sum_{i=1}^{N} RRS_i(I_c)$ and next try to minimize the approximation of the sum of squared errors SSE' defined as

$$SSE' = \sum_{c=1}^{C} (RRS_f(I_c) - RRS'_c)^2 = \sum_{c=1}^{C} (\sum_{i=1}^{N} w_i RRS_i(I_c) - \frac{1}{N} \sum_{i=1}^{N} RRS_i(I_c))^2 \,, \qquad (3)$$

where the above-given contraints $\forall i : w_i \geq 0$ and $\sum_{i=1}^{N} w_i = 1$ still hold. Unfortunately, this method does not work since equation (3) has a trivial minimum equal to zero, namely, in case $\forall i : w_i = 1/N$ resulting into Method 1 from section 4.3.1, therefore, we should look for another approach.

Below we shall look for 'harmonizing methods' where the *dissimilarities* between *the primary outputs* RRS_i are minimized.

4.3.4. Method 4: Harmonizing the primary outputs

A natural approach for harmonizing existing differences in the primary outputs is to put less emphasis on outliers. By doing so, we hope to find a more unbiased estimation RRS_f of the right rate of stocking. In addition, a smaller standard deviation *SD* of the weighted primary outputs $w_i RRS_i$ is expected to be found simply because the primary output values close to the mean get more weight in the voting process.

The above-given idea can be formalized as follows. Given input vector I_c, let $\Delta_{i,j}(I_c) = | RRS_i(I_c) - RRS_j(I_c) |$ represent the absolute value of the difference between the primary outputs of model *i* and *j*. Using all input vectors I_c available, we can calculate the sum Δ_i of the absolute differences between primary ouput RRS_i and all other primary outputs RRS_j, $j \neq i$, defined by

$$\Delta_i = \sum_{c=1}^{C} \sum_{j \neq i} \Delta_{i,j}(I_c) = \sum_{c=1}^{C} (\Delta_{i,1}(I_c) + \Delta_{i,2}(I_c) + \cdots + \Delta_{i,i-1}(I_c) + \Delta_{i,i+1}(I_c) + \cdots) \,. \qquad (4)$$

If $\Delta_i > \Delta_j$, this means that model *i* generates, on average, more outlying output values than model *j* and therefore, in our approach, should get a lower weight. This can be implemented by giving model i a weight which equals the *normalized inverse* of Δ_i or, more precisely,

$$w_i = \frac{1/\Delta_i}{\sum_j 1/\Delta_j} = \frac{1/\Delta_i}{1/\Delta_1 + 1/\Delta_2 + 1/\Delta_3 + \cdots}. \tag{5}$$

It should be clear that by providing the primary outputs RRS_i the weights w_i as defined by equation (5), the above-mentioned constraints $\forall i : w_i \geq 0$ and $\sum_{i=1} w_i = 1$ are automatically fulfilled.

Having determined the weights of the primary outputs, the standard deviation of the weighted primary outputs can be calculated. Since for Method 4 outliers have received less weight, these standard deviations are expected to be smaller than in case of using Method 1 where the primary outputs have equal weights. Furthermore, the final output of the multi-fuzzy model can be calculated using equation (1). We have done these calculations using the available field data from each of the different regions of study. The results found are summarized in Table 7.

Table 7. Estimating the final output RRS_f by calculating the sum of weighted outputs for separated regions according to Method 4.

Region: Morzion

Case	Primary outputs (RRS_i)			Delta's			Sum of Deltas				Weighted outputs			SD	(RRS_f)
	Model 1	Model 2	Model 3	$\Delta_{1\text{-}2}$	$\Delta_{2\text{-}3}$	$\Delta_{1\text{-}3}$	Δ_1	Δ_2	Δ_3		w_1RRS_1	w_2RRS_2	w_3RRS_3		Summation
1	0.68	0.70	0.84	0.02	0.14	0.16	0.18	0.16	0.3		0.18	0.24	0.31	0.06	0.74
2	0.56	0.85	0.84	0.29	0.01	0.28	0.57	0.3	0.29		0.15	0.29	0.31	0.09	0.76
3	0.68	0.82	0.84	0.14	0.02	0.16	0.3	0.16	0.18		0.18	0.28	0.31	0.06	0.78
4	0.77	0.91	0.80	0.14	0.11	0.03	0.17	0.25	0.14		0.21	0.31	0.30	0.05	0.83
5	0.68	0.98	0.84	0.3	0.14	0.16	0.46	0.44	0.3	Sum	0.18	0.34	0.31	0.08	0.84
						Sum	1.68	1.31	1.21	4.2					
						Inverse	0.59	0.76	0.82	2.18					
						Weights(w_i)	0.27	0.34	0.37	1.00					

Region: Cheshme-Anjir

Case	Primary outputs (RRS_i)			Delta's			Sum of Deltas				Weighted outputs			SD	(RRS_f)
	Model 1	Model 2	Model 3	$\Delta_{1\text{-}2}$	$\Delta_{2\text{-}3}$	$\Delta_{1\text{-}3}$	Δ_1	Δ_2	Δ_3		w_1RRS_1	w_2RRS_2	w_3RRS_3		Summation
6	1.07	1.12	0.84	0.05	0.28	0.23	0.28	0.33	0.51		0.45	0.38	0.20	0.12	1.03
7	1.11	1.12	0.76	0.01	0.36	0.35	0.36	0.37	0.71		0.46	0.38	0.18	0.14	1.02
8	1.02	1.13	0.80	0.11	0.33	0.22	0.33	0.44	0.55		0.43	0.383	0.19	0.12	1.00
9	1.07	1.12	0.84	0.05	0.28	0.23	0.28	0.33	0.51		0.45	0.38	0.20	0.12	1.03
10	0.97	1.12	0.84	0.15	0.28	0.13	0.28	0.43	0.41	Sum	0.40	0.38	0.20	0.11	0.98
						Sum	1.53	1.9	2.69	6.12					
						Inverse	0.65	0.52	0.37	1.55					
						Weights(w_i)	0.42	0.33	0.23	1.00					

Region: Kheshti

Case	Primary outputs (RRS_i)			Delta's			Sum of Deltas				Weighted outputs			SD	(RRS_f)
	Model 1	Model 2	Model 3	$\Delta_{1\text{-}2}$	$\Delta_{2\text{-}3}$	$\Delta_{1\text{-}3}$	Δ_1	Δ_2	Δ_3		w_1RRS_1	w_2RRS_2	w_3RRS_3		Summation
11	1.15	0.45	0.84	0.7	0.39	0.31	1.01	1.09	0.7		0.34	0.124	0.36	0.13	0.82
12	1.23	0.45	0.84	0.78	0.39	0.39	1.17	1.17	0.78		0.36	0.124	0.36	0.13	0.84
13	1.11	0.45	0.84	0.66	0.39	0.27	0.93	1.05	0.66		0.32	0.124	0.36	0.12	0.81
14	1.15	0.45	0.84	0.7	0.39	0.31	1.01	1.09	0.7		0.34	0.124	0.36	0.13	0.82
15	1.15	0.45	0.84	0.7	0.39	0.31	1.01	1.09	0.7	Sum	0.34	0.124	0.36	0.13	0.82
						Sum	5.13	5.49	3.54	14.16					
						Inverse	0.19	0.18	0.28	0.65					
						Weights(w_i)	0.29	0.27	0.42	1.00					

As Table 7 shows, there are different weights for each region. While the weights of the model 1, 2 and 3 for the first region are 0.27, 0.34, and 0.37, the weights for these models for the second region are 0.42, 0.33 and 0.23 and for the third region are 0.29, 0.27 and 0.42 respectively. In other words, when the first model gets the highest weight in Cheshme-Anjir (w_1 = 0.42), the second model gives the highest weight in Morzion and Cheshme-Anjir (w_2 = 0.34 and 0.33) respectively, and the third model gains the highest weight in Kheshti (w_3 = 0.42). So, we have different weights in different regions showing that the expertize of the expert in the various regions seems to be different.

Now, by calculating the sum of weighted outputs, we can easily estimate the final outputs:

$$RRS_f = \sum_{i=1}^{3} w_i RRS_i \tag{5}$$

Based on equation (5), again, we estimated the final output RRS_f for separated regions. As Table 7 shows, the estimations for various regions are different. While the highest amount of RRS_f (more than 1) is estimated for the second region and the lowest for the first (less than 0.8), the third region has got more than 0.8. On the other hand, although the estimations are different for the 'between groups', they are approximately similar for the 'within groups'. Comparing Table 6 and 7, the standard deviation has indeed been reduced, as expected.

5. Discussion

Based on the two applied methods (*Mean* and *Harmonized*), we estimated the final *Right Rate of Stocking* (RRS_f). In the first method (Table 6), we estimated RRS_f by calculating the average of the primary outputs. The method consideres the same weights for all outputs of the three models and therefore, it treats outliers and 'normal' data equally. This approach may introduce some bias in our calculations. To decrease this weakness, we introduced other voting methods. As discussed, a good voting method is provided by a 'supervised learning' algorithm where optimal weights are calculated by minimizing the sum of squared errors of the output values. A necessary precondition for applying this method is the availability of a representative data set. Otherwise, we can use a voting precedure based on 'unsupervised learning'. Using this method (the harmonized method) and the first method (the mean method), we are able to compare the assessments of the RRS_f for all three regions of our study (Fig. 4).

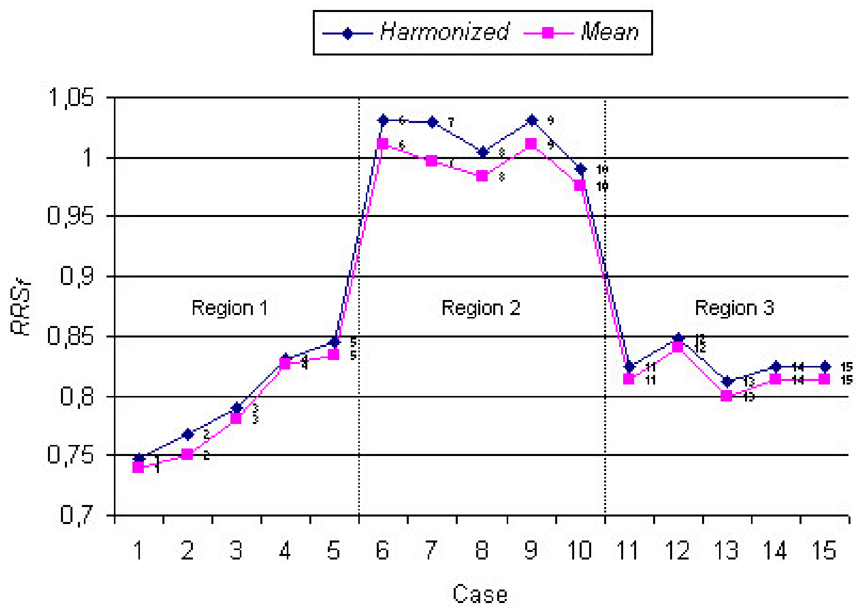

Fig. 4. Comparison of the RRS_f for the harmonized method and mean method.

As Fig. 4 demonstrates both methods estimate the highest RRS_f for the second region and the least for the first where the third region stands between them. Also, while the RRS_f for the second region is considerably different from the two other regions, the RRS_f for the first and third region are quite close. We observe here that differences, even small ones, between the values of the *Right Rate of Stocking* have serious consequences: since the total area of each region is very large (e.g. 2000 hectares in Morzion, 2575 hectares in Cheshme-Anjir and 6900 hectares in Kheshti), small differences become big ones if we multiply the estimated values of the RRS_f by the amount of pasture area.

A first validation shows that all experts confirm the above-mentioned outcomes. They believe that the second region (Cheshme-Anjir) has the best conditions to reach sustainability. These conditions include social, geographical and environmental circumstances and are supposed to be strongly related to the values of the input variables (indicators) of the fuzzy models discussed above. The social problems are supped to be less in Cheshme-Anjir because the region benefits by a good manager who solves many of their problems, especially those related to the usual bureaucratic problems in the different Iranian administrations. The area also benefits by his higher education level. In addition, the administrative experts believe that the second region has better strategic conditions as Cheshme-Anjir stands between the two main roads which are near to Shiraz, the capital of the Fars province. Finally, as the weather in this region is not very cold (like the first region in Morzion) and not very warm (like the third region in Kheshti), the temperate weather makes better environmental conditions in Cheshme-Anjir. Thus, these conditions make the second region the best prototypical case in comparison to the two other regions and can explain the high differences between outcomes for the second area and the rest.

The administrative experts also agree upon estimations of the RRS_f for the two other regions. As the plantation period in the third region (Kheshti) is longer than the first region (Morzion), they expect a less and a higher RRS_f for the first and third region respectively. They also believe the warm weather of Kheshti creates a longer time period of grazing. In contrast, the cold weather of Morzion declines its capacity to hold livestock to graze. The experts believe however that if we neglect the time period of grazing, the capacity of the third region for holding the *RRS* should decrease (as we have seen for the second model). This can be again a good evidence to show that the experts were more expertized in the various regions.

In addition, since the experts consider 2-3 aum/ha as the medium range of *RRS* (see section 4.1), they believe that currently the three regions of our study have a much smaller grazing capacity than might be possible. This outcome confirms the general believe that many pastoral regions in Iran are currently facing overgrazing and are exacerbating by the unsustainable situation. By taking appropriate measures, circumstances for sustainable development may be improve in the future. Consequently, the experts' knowledge will change according to new conditions and higher estimates are likely to be found

As has been shown in Table 1 and 2, domain experts in Iran choose different indicators to estimate the *Right Rate of Stocking*, even in the cases where the same social, environmetal, and geographical conditions hold. They come up with sustainability in rangeland management by different environmental (i.e. *SP*) and soci-economic indicators (i.e. *PS*). Therefore, our study supports the reality that sustainability in range management is a *multi-dimensional vague* concept. We also wish to emphasize here that the supervised voting process (Method 2) should be tried out in future research, after we have collected a set of real input-output data from the field. The collection of this data is, however, a time consuming process which may take several years.

6. Conclusions

While fuzzy specialists usually use homogeneous experts' knowledge to construct fuzzy models, it is generally much more difficult to deal with knowledge elicited from a heterogeneous group of experts, especially in the area of the sustainable rangeland management. In this paper, we proposed a multi-fuzzy model to cope with the muti-dimensional vagueness of sustainability in the field of range management. To deal with the heterogenity of administrative experts' knowledge, we introduced several voting methods for estimating the right rate of stocking as the final output of several fuzzy models. The first method simply uses the average of the primary outputs as the final right rate of stocking. We also introduced a supervised voting method which is applicable in cases a real-world data set is available. In the absence of such a set, like in our study, an unsupervised voting method can be applied which estimates the weights of the primary right rate of stocking using a harmonizing approach. Since this method puts less emphasis on outliers, the harmonizing approach is supposed to result into a more unbiased estimate. In addition, it turns out that the standard deviation of the harmonized weighted primary outputs is smaller that the standard deviation of equally weighted primary outputs.

The harmonized method is expected to provide a new useful tool for policymakers in order to deal with heterogeneous experts' knowledge. By constructing the three fuzzy models based on the elicitation of the heterogeneous knowledge offered by a group of pastoral experts, our study showed the multi-dimensional vaguenesses concerning sustainable rangeland management in Iran. Finally, by comparing the estimated right rate of stocking with its medium range, this study proved overgrazing in the Iranian pastures, specially, in the three regions of the Fars province in Southwest Iran.

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