A Grazing Capacity Model with Fuzzy Inference System in Semi-steppe Rangelands

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Abstract

This paper explains a fuzzy-rule approach to spatial modeling of grazing capacity in semi-steppe rangelands. Using Mamdani-type of inference of fuzzy approach, we develop a simple model based on data's that could be easily earned as easily as possible such as slope, forage production, water supply distances and soil resistance to erosion in order to determine grazing capacity. A dataset of a rangeland in North-western Iran was used to check the generalization capability of the Mamdani model: the grazing capacity derived from the Mamdani-type inference was compared with traditional grazing capacity measured for these rangelands. Sensitivity analysis showed that slope was the most important factor followed by forage production and soil resistance to erosion and water supply distances respectively. The RMSE and correlation coefficient of Mamdani model were minimized by 0.68 and 0.61, respectively. The results confirm the generalization capability of methods for the modeling of cattle grazing capacity.

Keywords: Semi-steppe Rangeland/ Nazlou Pasture/ Fuzzy Approach/ Mamdani Model/ Grazing Capacity

1. Introduction

Rangeland management in arid and semi-arid regions is regularly faced non-sustainable overgrazing systems which cause vegetation deterioration, soil erosion (Fleischner, 1994; Sansom, 1999) and decline of biodiversity (Sansom, 1999). For sustainable use of rangeland production and restoration of grassland diversity, rangeland managers introduce the optimum animal population mass that a specific area sustain during a long time period (Holechek*et al.*, 2004) which can be defined as grazing capacity. However, to introduce optimum animal population density, rangeland managers should manage many uncertainties, such as subjective evaluation and perception (Azadi*et al.,* 2005; Clark and Gelfand 2006) the interaction of subsystems (Deaton and Winebrake 2000), the lack of exact values (Silvert 1997; 2000), missed data and low available information (Srebotnjak 2007). A number of uncertainty types such as inexactness and obscurity are presented in semi-arid rangeland due to spatio-temporal fluctuations of climate condition, the availability and quality of vegetation within and between years. This strengthens the strategy in management of rangelands to have various flock sizes due to the available and reachable provender features and animal needs (Ebrahimi *et al.,* 2010).

Several models have been generated about the issue of transmitting capacity in semi-arid rangeland (Innis, 1978; Pendleton *et al.*, 1983; Wu *et al.,* 1996). While none of the models considers all of the dimensions, but many of these models are very comprehensive, leading to a high burden of input data (Ebrahimi et al. 2007). Supplying more easily gatherable datasets for spatially explicit model could present reply for questions related to nature conservation and would enable feasible application. Prediction of grazing capacity these datasets gathered on wide-ranging rangelands leads to a high degree of analytical uncertainty (compounded by inexact estimations in the field). Thus, traditional system methods including probability theory and statistics cannot model many of these systems in an acceptable way (Checkland 1990, Wang *et al.,* 1998). Fuzzy set theory (Zadeh, 1965) seems to be a proper technique for correcting the problem of uncertainty in environmental data (Andriantiatsaholiniaina 2001; Cornelissen*et al.,* 2001; Dunn *et al.,* 1995; Marks *et al.,* 1995) such as rangeland management (Azadi 2003; 2005; Azadi*et al.,* 2005; Azadi*et al.,* 2007).The aim of the present article is to design a grazing capacity model according to fuzzy control as an accurate tool for nature conservation as well as sustainable rangeland management and exploitation.

1.2 Study area

Nazlou, has an area of about 1480 km^2. It is partially located in Turkey but mainly is positioned in the west Azerbaijan province, north-western part of Iran (Fig. 1). The region has a semi-arid climate, with a mean maximum temperature about 39°C in July and a mean temperature of -33°C in January. The average annual precipitation is 534 mm. Elevation ranges from 1291 m to a maximum of 3600 m. There are 12 vegetation types in the study area (table 1).

2. Methodology

2.1 Research Method

Different methods of fuzzy inference are available that can be implemented in fuzzy rule based systems. The available descriptive terms in this equation describe fuzzy sets which are featured by proper membership functions.The results of every equation possess a fuzzy set form and are generated by the rule's firing strength (the minimum or outcome of the degrees of the match between the input value and the premise part)

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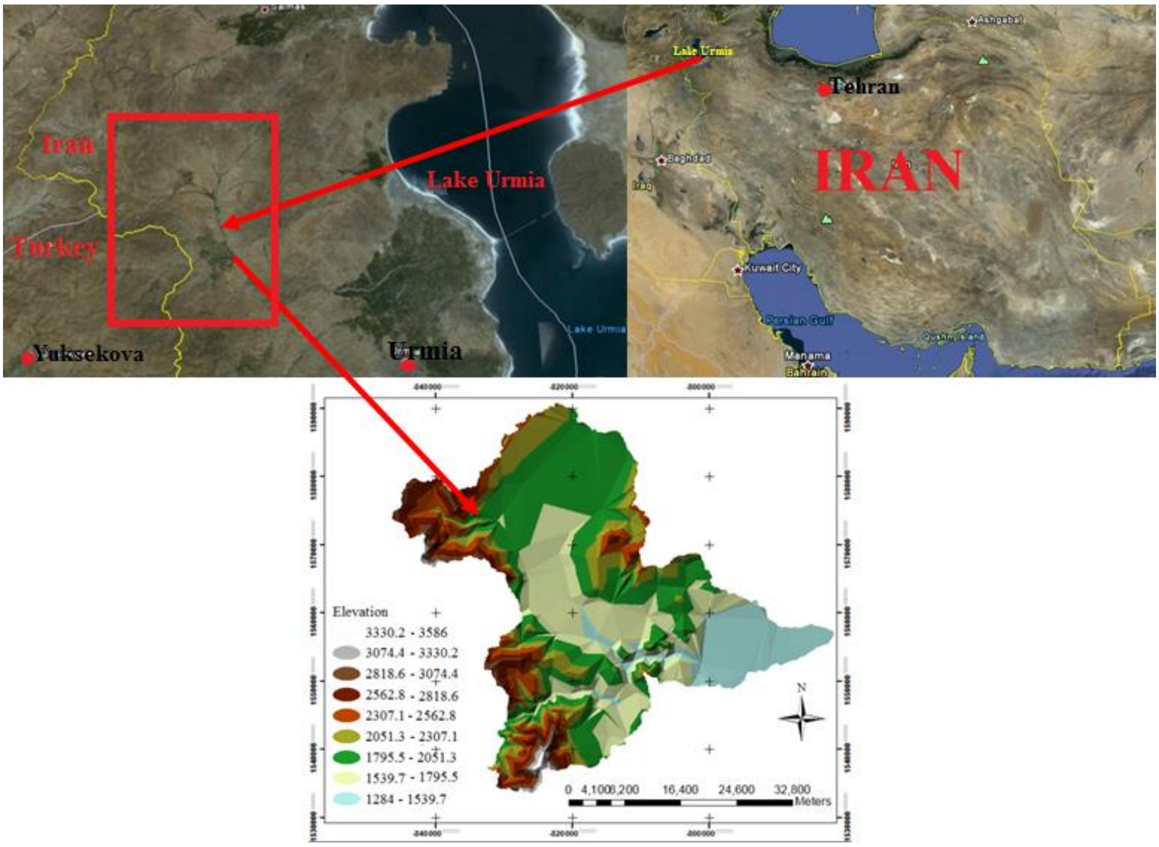

Figure 1: Position of the study area in Iran

Table 1: Species of the studied area

N	Vegetation type	Summary sign
1	*Agropyron ibonaticum _Astragalus parrowianus _Noeae mucronata*	*Agr ibo-Ast par-Noe muc*
2	*Astragalus gummifera _Hordeum fragilis _Prongos uloptera*	*Ast gum-Hor fra- Pro ulo*
3	*Astragalus gummifera_ Atraphaxis spinosa _Agropyron libonaticum*	*Ast gum-Atr spi-Agr lib*
4	*Astragalus gummifera _Eringium billardierii _Stipa barbata*	*Ast gum-Eri bil-Sti bar*
5	*Astragalus gummifera _Festuca ovina _Eringium billardierii*	*Ast gum-Fes ovi- Eri bil*
6	*Astragalus gummifera _Prongos uloptera _Bromus tomentellus*	*Ast gum-Pro ulo-Bro tom*
7	*Astragalus macrostachyis _Noeae mucronata _Stipa barbata*	*Ast mac-Noe muc- Sti bar*
8	*Astragalus parrowianus _Agropyron libonaticum _Noeae mucronata*	*Ast par-Agr lib-Noe muc*
9	*Atraphaxis spinosa _Agropyron libonaticum _Noeae mucronata*	*Atr spi-Agr lib-Noe muc*
10	*Atraphaxis spinosa _Noeae mucrona _Stipa barbata*	*Atr spi-Noe muc-Sti bar*
11	*Onobrychis cornuta _Festuca ovina _Bromus tomentellus*	*Ono cor-Fes ovi-Bro tom*
12	*Onobrychis cournuta _Festuca ovina _Thymus kotschyanus*	*Ono cou-fes ovi-Thy kot*

and an output fuzzy set is appointed to the resulting part. Using union performance to the fuzzy set outputs of all rules creates the final output for an if-then rules set. A specialist can develop the rules for Mamdani models. In this condition, specialist science is the exclusive premise for modeling if we don’t have adequate data or if the uncertainty surrounding the data is remarkably more. In this study, the results of modeling based on a Mamdani -type model appropriate for ecosystem managements (Azadi, 2009) was used.

2.2 Constructing the grazing capacity model

The Flow chart of a fuzzy model to assess the grazing capacity (GC) is portrayed in Fig.2. The following important steps (van den Berg, 2004) were performed to construct the model:

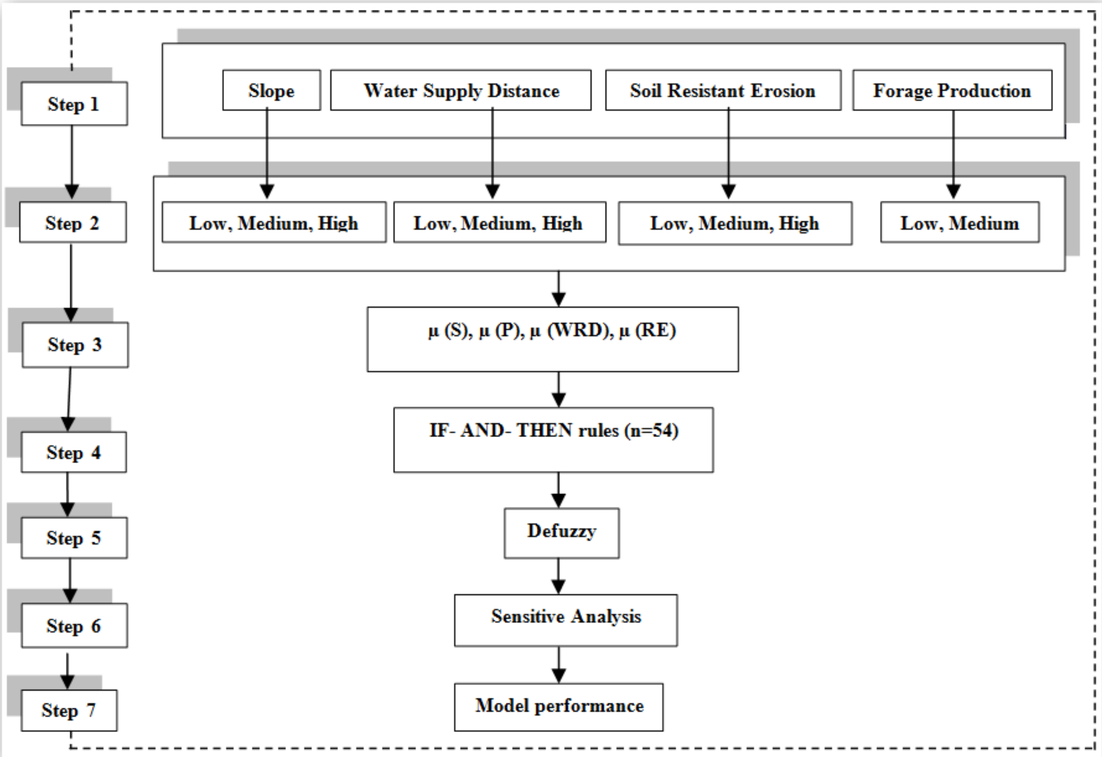

Figure 2: Flow chart of development of the grazing capacity model based on the input values (S, FP, WSD, and SRE) in fis model.

1. assigning the related input and output datas;
2. clarifying descriptive values;
3. developing membership functions;
4. assigning the fuzzy rules;
5. Combination of the rules (Defuzzy)
6. Computing the sensitivity analysis
7. Assessing the model performance.

2.3 The data's of the model of grazing capacity

In the first step, grazing capacity model requires assembling the essential information such as forage production, slope and distance of water supplies, as well as the soil resistance to erosion (Mesdaghi, 1995). These four parameters were included in the model as the input variables derived from GIS-based maps of Nazlou rangeland, with cells size of 100×100 m in Arc GIS 9.3(Fig.3). Also, The NDVI index was extracted from Landsat ETM 2011 images and forage production maps of the study area were generated. Morover, ground based forage production values were determined using clipping and weighing method (Bonham 1989). Alsoو field data was harvested in the same year. To integrate field data with satellite data, topographic map with 1:50000 scale was used for geo reference. The maps of land cover were prepared by use of satellite images, then the map was completed by field visits. The land cover map and assessment of forage production using remote sensing (NDVI index) and clipping and weighing methods. To do so, 10 plots of $1m^2$ were established in each vegetation type, then available forage was clipped in the plots and grazing capacity was calculated based on animal forage requirements (AUM) (Arzani, 2009):

$$GC\ (AUM) = \frac{Available\ Forage\ \left(\frac{kg}{ha}\right) \times Area\ Grazed\ (ha)}{Average\ Daily\ Intake\ (kg) \times Grazing\ Period\ (months)} \tag{1}$$

Where; GC= grazing capacity in animal unit menths (AUM) per hectare

Finally, the output dataset consisted of five classes of grazing capacity. In the GC, the descriptive values of each parameter are presented in Table 2.

2.4 Slop

Holechek*et al.*, (2004) provided recommendations for adjusting the stocking rate for cattle for account of distance from water. The suggested reductions in grazing capacity with are shown in Table 2. A Slope steepness map was extracted from Digital Elevation Model (DEM) which was interpolated from cartographical map developed by National Cartographic Center (NCC) in scale of 1/25000.

2.5 Forage production

The available forage of a site has a main effect on the GC of a plant type (Ebrahimi 2006, Steenekamp *et al* 1995, Teague *et al* 2011). The land cover map and assessment of primary production using remotely sensed images was done based on the diagram showed in fig. 4. To achieve a reliable, economic, and rapid estimate of forage production at the study area level, direct measurement of forage production (see Bonham 1989) scaled up through synchronous remotely sensed data of Landsat images (see Parueloet *al.*, 1997) using of Vegetation Index (NDVI) (Rouse *et al.* 1974). The geographic position of the in situ data was obtained with Global Positioning System (GPS, Vertex).

2.6 Distance of water supplies

Water is a major determinant of livestock distributions. Animals graze from a water point to a distance that depends on the availability of forage and their on water requirements (Sileshi *et al.*, 2003; Bailey, 2004; Schlecht *et al.*, 2004). Access to water supplies was determined using GIS buffering operation (ESRI 1996). around those rivers with year-round water.

2.7 Soil Resistance to Erosion

A penetrometer was used by Benn (2002) to measure soil density and its effects on grazing animals. Moreover, Ebrahimi et al., (2010) recommended grazing should be reduced or excluded based on the susceptibility of an area to erosion to avoid degradation of rangeland. In this study we used of K factor that is soil erodibility factor to represent the susceptibility of soil to erosion. As, this factors depends on the organic matter and texture of the soil, its permeability and profile structure.

Table 2: Input variables and linguistic values in the GC model

Variable	Range of variable	Linguistic Values	Source
Slope (S)	0-20٪, 20-40٪, 40-60٪	Low, medium , high	Holechek *et al.*, (2004)
Forage Production (FP)	≤ 225, 225-450, 450 ≤ (Kg/ha)	Low, medium , high	Arzani., (2009)
Water Supply Distance (WSD)	0-600, 600-1000 (m)	Low, medium	Holechek *et al.*, (2004)
Soil Resistance to Erosion (SRE)	≤ 0.22, 0.22- 0.3, ≥0.3	Low, medium, high	Refahi., (2006)

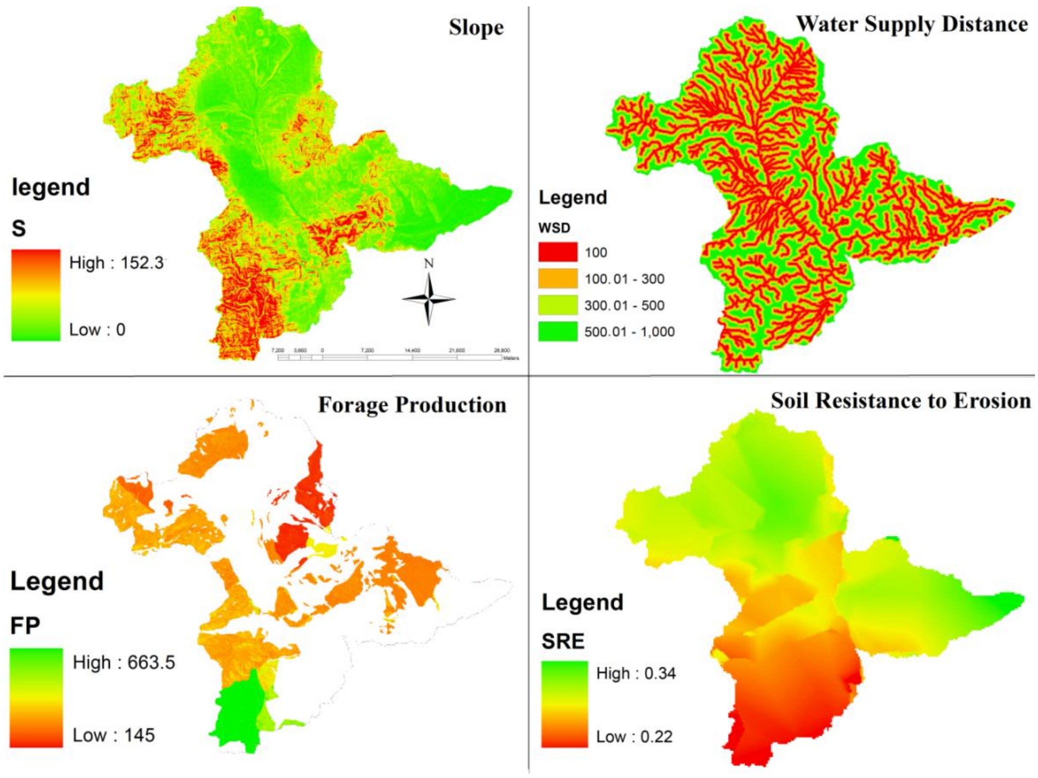

Figure 3: Maps of input variables the model, i.e., slope(S), water Supply Distance (WSD), Forage Production (FP) and Soil Resistance to Erosion (SRE)

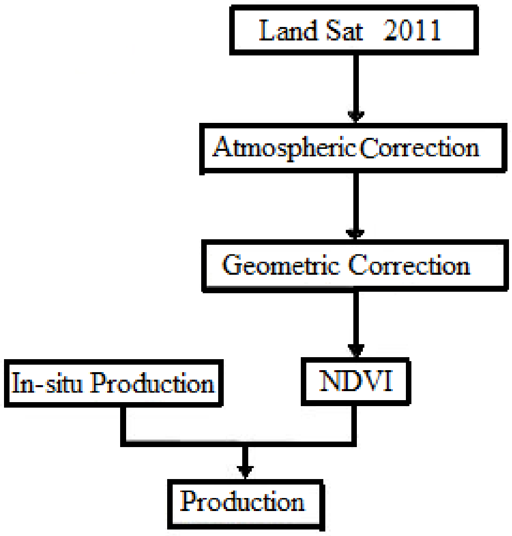

Figure 4: The Flowchart of mapping forage production using remotely sensed images.

2.8 The grazing capacity (output variable)

Rhe grazing capacity was calculated by summing up the rates from the different field mappings of each grid cell. Areas are not capable for determining grazing capacity:

(1)Areas with greater than 60% slope. Some parts of an area which has potential comestible phytomass may not be accessible for herbivores due to some natural obstacles such as steep slopes (Holechek, 1988).

(2).Areas producing less than or having the potential to produce an average of 50 kg of forage/ha.

(3).Areas more than 2 miles (3.2 km) from water. (Holechek *et al.,* 2001).

2.9 Membership Functions

More studies have included other methods for earning membership functions. Turksen (1991) reviewed the various methods and research into the acquisition of membership functions and expressed 4 different methods to earn membership functions: direct values, set rated statistics, polling and reverse values. (Park *et al.*, 1994).

The membership function of slope, forage production, water supply distances and soil resistance to erosion allocated an area to one of five grazing capacity five classes; very low, low, medium, good, and very good as presented in Figure 5

2.10 The knowledge base of the model

The major view of the Mamdani method is to explain the steps modes by descriptive parameters and to apply these parameters as inputs in order to control equations. In fuzzy inference system model, fuzzifier operates a mapping which conveys the input data into linguistic variables and the fuzzy sets will be formed by the range of these data.Its an interaction between the real world parameters and fuzzy system and change the output set to crisp (non-fuzzy). The determined rules had been used by the fuzzy inference engine and fuzzy outputs were developed from the outputs. The applied descriptive steps in these equation are unclear and inexact, but they can be determined in the form of fuzzy sets (Zadeh, 1965).The science of Mamdani model will be formed by these fuzzy sets which had been defined for all results parameters and the set of equations. Fuzzy logic prepares the mediums for processing this science and determines the results values for given input data. It is not worthy that all input criterion are related with AND function.

The 54 descriptive if–then equations, e.g.:If production is ‘good’ And the slope is ‘medium’And the distance of water resource is ‘medium.’ And the soil resistance to erosion is ‘good’Then the capacity of grazing is ‘good’.The complete set of linguistic rules are showed in Table 3.

In this research grazing capacity evaluates and classify by FIS. Four inputs and one output FIS. Four inputs and one output FIS were consider to evaluated and determine the classification grazing capacity in the Nazluo area, Iran. Based on considered membership function for input, the FIS has 3×3×3×2=54 rules.

The accuracy of the final outcome of the Mamdani-type model was control by root mean squared error (RMSE). Totally, there are different indices for determination of prediction models function. In this research, the root mean squared error, correlation coefficient(R) were used, it can be calculated by:

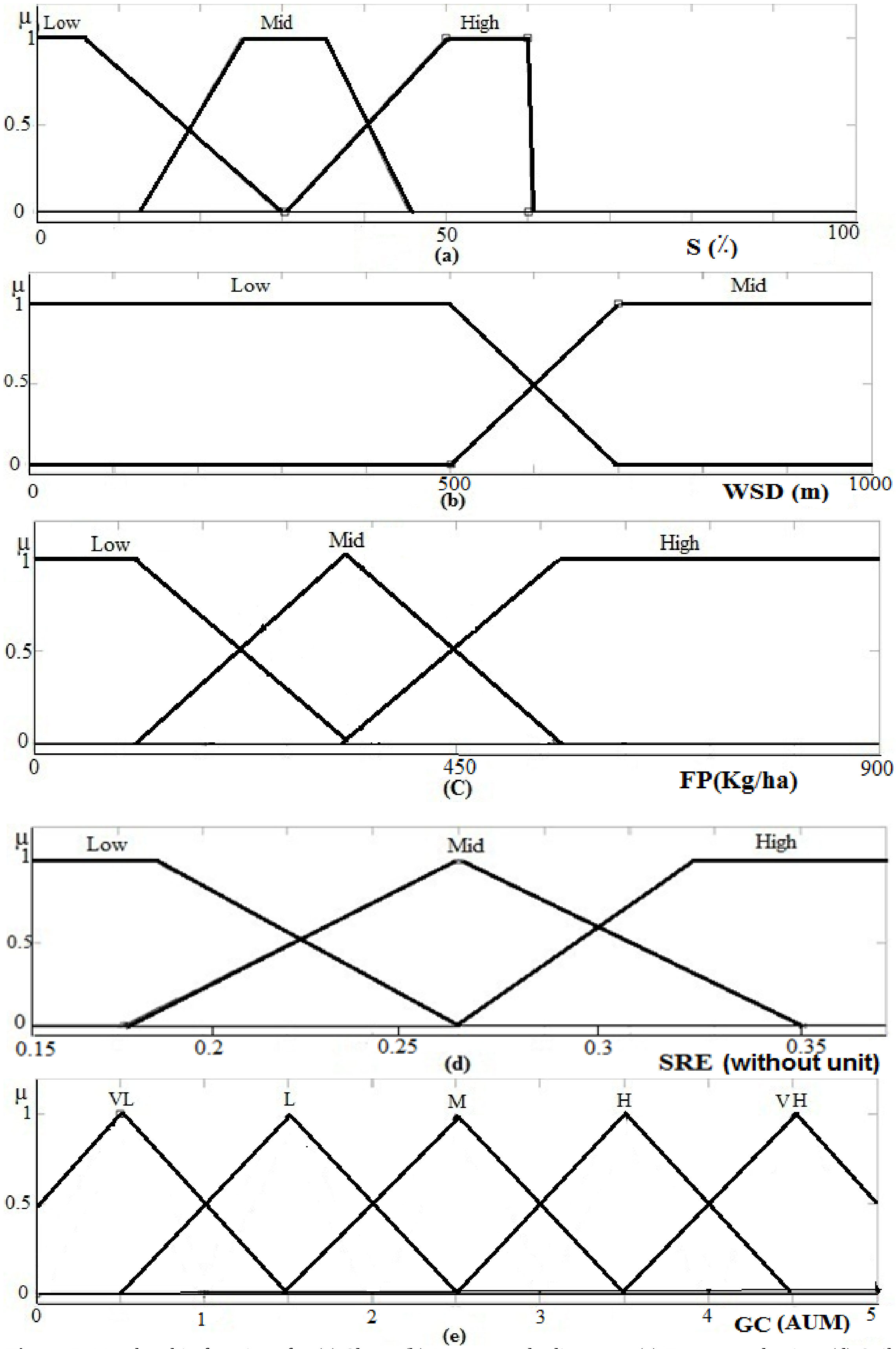

Figure 5: Membership functions for (a) Slope, (b) Water supply distances, (c) Forage production, (d) Soil resistance to erosion. (e) Grazing capacity

Table 3: A fuzzy rule viewer for predicting grazing capacity

N	S	FP	WSD	SRE	GC	N	S	FP	WSD	SRE	GC
1	High	Low	Low	High	Medium	**28**	Medium	Medium	Medium	High	High
2	High	Low	Low	Low	Low	**29**	Medium	Medium	Medium	Low	Medium
3	High	Low	Low	Medium	Medium	**30**	Medium	Medium	Medium	Medium	Medium
4	High	Low	Medium	High	Medium	**31**	Medium	High	Low	High	Very High
5	High	Low	Medium	Low	Low	**32**	Medium	High	Low	Low	High
6	High	Low	Medium	Medium	Low	**33**	Medium	High	Low	Medium	High
7	High	Medium	Low	High	High	**34**	Medium	High	Medium	High	High
8	High	Medium	Low	Low	Medium	**35**	Medium	High	Medium	Low	Medium
9	High	Medium	Low	Medium	Medium	**36**	Medium	High	Medium	Medium	High
10	High	Medium	Medium	High	Medium	**37**	Low	Low	Low	High	High
11	High	Medium	Medium	Low	Low	**38**	Low	Low	Low	Low	Medium
12	High	Medium	Medium	Medium	Medium	**39**	Low	Low	Low	Medium	High
13	High	High	Low	High	High	**40**	Low	Low	Medium	High	High
14	High	High	Low	Low	Medium	**41**	Low	Low	Medium	Low	Medium
15	High	High	Low	Medium	High	**42**	Low	Low	Medium	Medium	Medium
16	High	High	Medium	High	High	**43**	Low	Medium	Low	High	Very High
17	High	High	Medium	Low	Medium	**44**	Low	Medium	Low	Low	High
18	High	High	Medium	Medium	Medium	**45**	Low	Medium	Low	Medium	High
19	Medium	Low	Low	High	High	**46**	Low	Medium	Medium	High	High
20	Medium	Low	Low	Low	Medium	**47**	Low	Medium	Medium	Low	Medium
21	Medium	Low	Low	Medium	Medium	**48**	Low	Medium	Medium	Medium	High
22	Medium	Low	Medium	High	Medium	**49**	Low	High	Low	High	Very High
23	Medium	Low	Medium	Low	Low	**50**	Low	High	Low	Low	High
24	Medium	Low	Medium	Medium	Medium	**51**	Low	High	Low	Medium	Very High
25	Medium	Medium	Low	High	High	**52**	Low	High	Medium	High	Very High
26	Medium	Medium	Low	Low	Medium	**53**	Low	High	Medium	Low	High
27	Medium	Medium	Low	Medium	High	**54**	Low	High	Medium	Medium	High

$$RMSE = \left[\frac{\sum_{i=1}^{N}(s_i - o_i)^2}{N}\right]^{0.5} \qquad (2)$$

$$R = \frac{N\sum_{i=1}^{N} s_i o_i - \sum_{i=1}^{N} s_i \sum_{i=1}^{N} o_i}{\left\{\left[N\sum_{i=1}^{N} s_i^2 - \left(\sum_{i=1}^{N} s_i\right)^2\right]\left[N\sum_{i=1}^{N} o_i^2 - \left(\sum_{i=1}^{N} o_i\right)^2\right]\right\}^{0.5}} \qquad (3)$$

That, O_i is observed value (GC) in time step of i, S_i predicted value (GC) in time step of i, N is number of time step, O_t is mean of observed (GC). Finally a sensitivity analysis was done to determine relative effect of each parameter on the final results of the GC model (frey, 2002, Ebrahimi et al., 2010 , Kousari et al., 2010).

3. Results

The fuzzy logic toolbox facilitates the users with a rule viewer. The rule viewer shows the fifty four rules used for the construction of the system. It also shows the input and the output variable numerical ranges. The following numerical example illustrating how the GC model calculate the membership degree of crisp inputs, as follows: S=8.33, WSD=762, FP=511, SRE=0.28 fuzzification inputs yields are as follows:

Input 1: S is low membership grade μ_l (S) = μ_l (8.33) = 0.85

Input 2: WSD is medium with membership grade μ_m (WSD) = μ_m (762) =1

Input 3: FP is high with membership grade μ_h (FP) = μ_h (511) =0.75

Input 4: SRE is medium with membership grade μ_m (SRE) = μ_m (0.28) = 0.8

Now, applicable degree of each rule to the input were calculated, which S is low, WSD is medium ,FP is high, and SRE is either High or low. That they are determined in table 3 as a rules 52, 53, and 54. The descriptions of these rules are as follows:

Then with consider to membership degree of inputs value, were computed the fuzzy outputs μ (GC) of each rule. Finally, the Center Of Gravity method was used for defuzzification. A crisp output y_q^{crisp} is given by:

And the distance of water resource is 'medium.'

And the soil resistance to erosion is 'good'

Then the capacity of grazing is 'good'.

The complete set of linguistic rules are showed in Table 3.

$$y_q^{crisp} = \frac{\sum_{i=1}^{R} B_i^q \int_{yq} \mu_{\hat{B}_q^i}(y_q)dy_q}{\sum_{i=1}^{R} \int_{yq} \mu_{\hat{B}_q^i}(y_q)dy_q} \quad (4)$$

Where R is the number of equations, B_i^q is the center of area of the membership function of B_q^y associated with the implied fuzzy set $\hat{B}_q^i$ for the ith rule (j,k,…,l;p,q)_i, and $\int_{yq}$? ?$_{\hat{B}_q^i}(y_q)dy_q$ denotes the area under ? ?$_{\hat{B}_q^i}(y_q)$.

In this research grazing capacity evaluates and classify by FIS. Four inputs and one output FIS. Four inputs and one output FIS were consider to evaluated and determine the classification grazing capacity in the Nazluo area, Iran. Based on considered membership function for input, the FIS has 3×3×3×2=54 rules.

The accuracy of the final outcome of the Mamdani-type model was control by root mean squared error (RMSE). Totally, there are different indices for determination of prediction models function. In this research, the root mean squared error, correlation coefficient(R) were used, it can be calculated by:

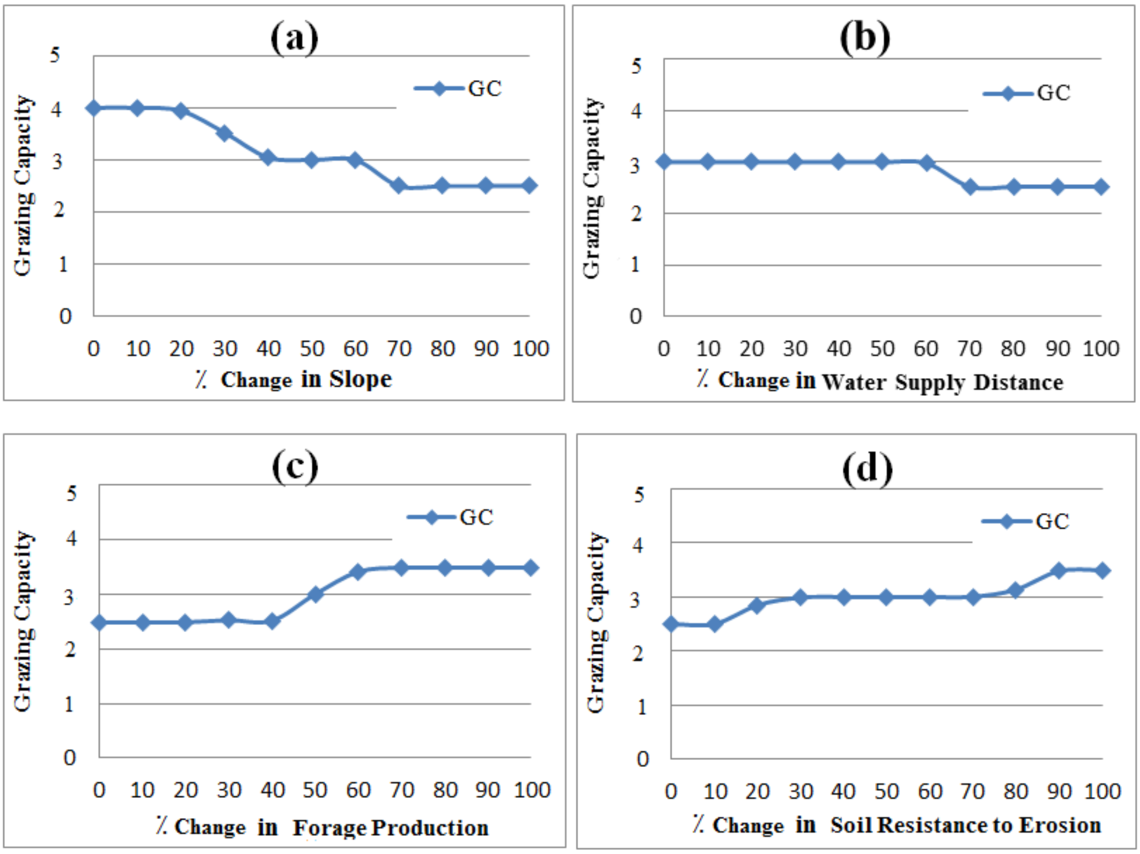

Chart 1: Sensitivity analysis of each parameter

In the example, the GC was estimated by using the Fuzzy Toolbar in Matlab software (version 7) yielding GC = 3.75. The rule viewer provides a platform for the modelers where one can enter the crisp input values and obtain a crisp output value. To estimate the prediction error and the importance of parameters, validation set and Sensitivity analysis were done with 25 percentage of all final outcome. In decreasing order of importance slope, forage production, soil resistance to erosion and distance of water supplies influence grazing capacity. So that, Sensitivity analysis showed that slope was the most important factor followed by forage production and soil resistance to erosion and water supply distances respectively. Also, forage production and soil resistance to erosion have equal effect on GC (Chart.1). The sensitivity analysis was done to earn the value effect of each input parameters on model output on the base on variation in input (frey, 2002, Ebrahimi et al., 2010 , Kousari et al., 2010).

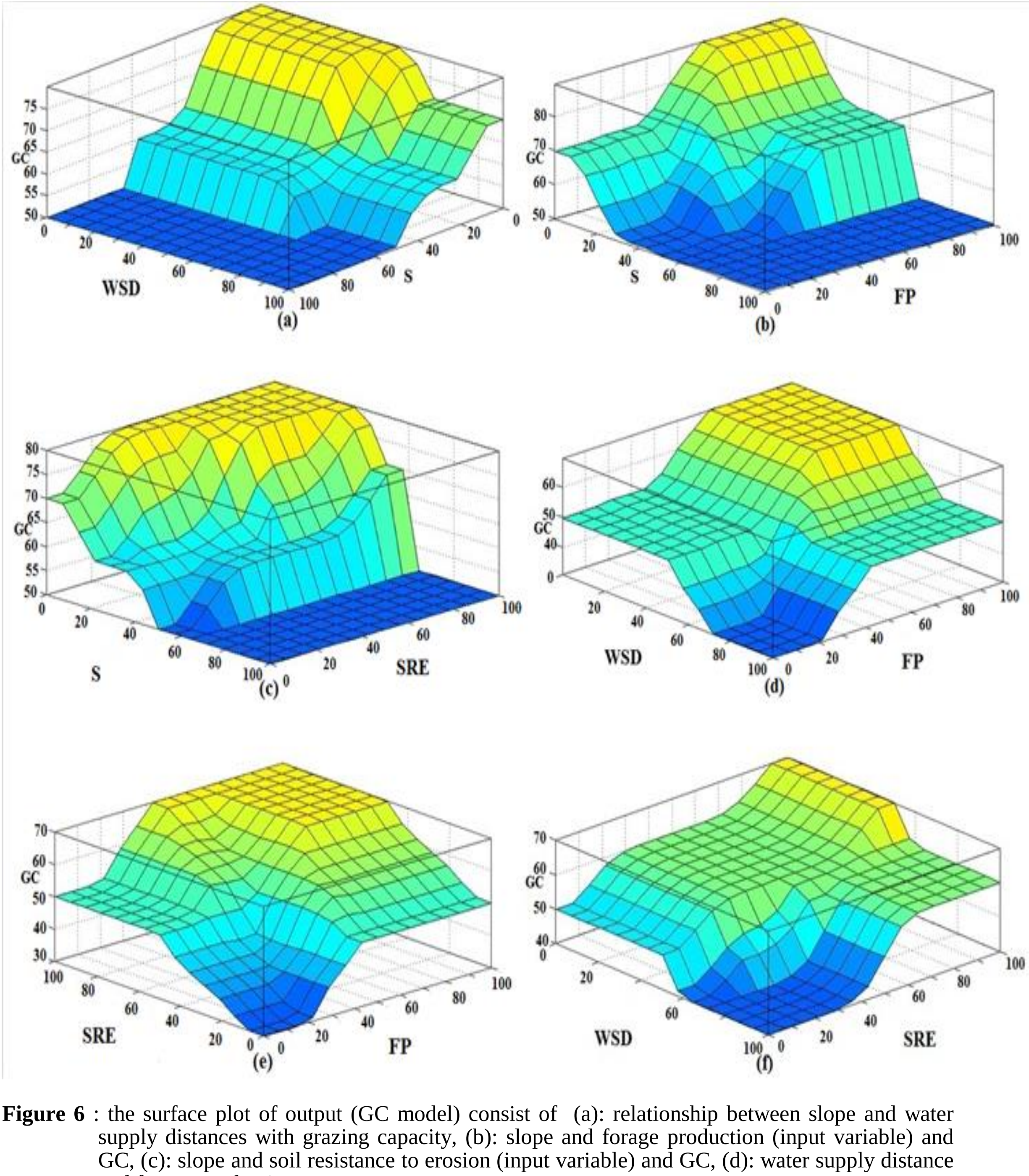

Figure 6 : the surface plot of output (GC model) consist of (a): relationship between slope and water supply distances with grazing capacity, (b): slope and forage production (input variable) and GC, (c): slope and soil resistance to erosion (input variable) and GC, (d): water supply distance and forage production

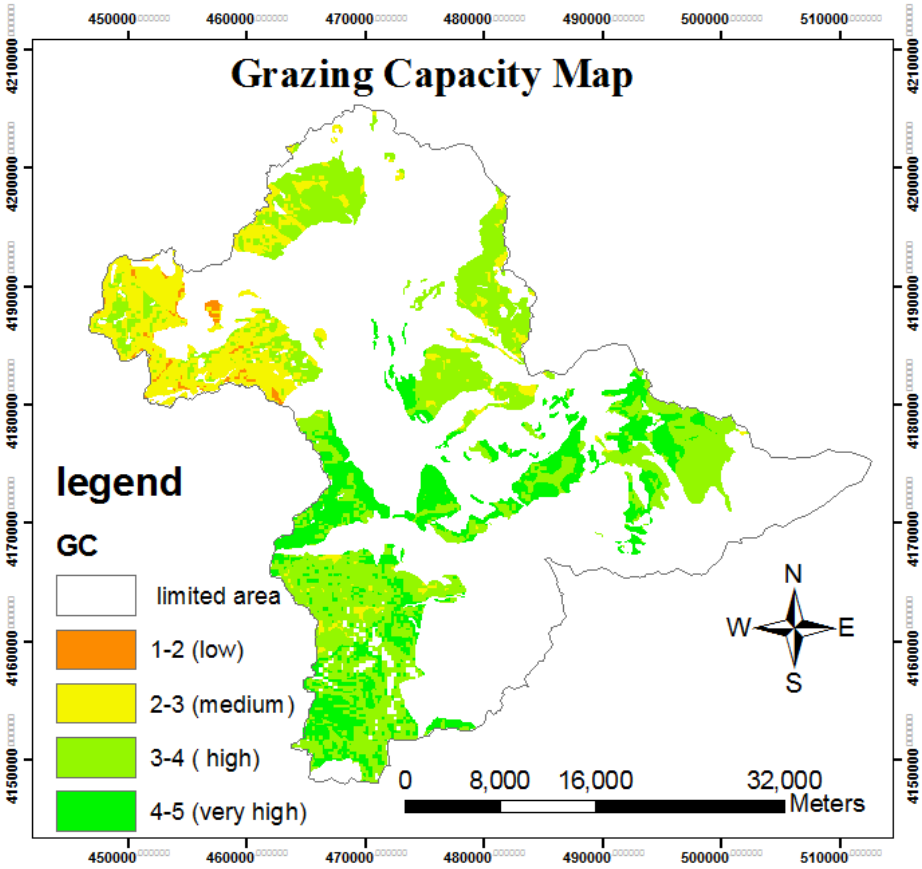

Figure 7: GIS map of grazing capacity classification of study area

Figure 6 shows the surface plot of output (grazing capacity) with respect to the input variables. So the relation between two input variables with output variable (grazing capacity) was showed in above 3D figures, we can observe a direct relationship between each variable with grazing capacity such as increasing of forage production and decreasing of slope lead to increasing GC value (part (b) of fig 6).

The RMSE and correlation coefficient of Mamdani model were 0.68 and 0.61, respectively. Fig. 7 presents the results of grazing capacity classification for the pasture Nazlou. So that, In this Fig.7 limited area are including garden and farmlands, stony and areas with greater than 60% slope which was omitted from calculation.

4. Discussion

Using fuzzy modeling techniques for datasets of high uncertainty has shown to have significantly better results when compared with a statistical model based on the field data. The fuzzy approach differ in their sensitivity to the heterogeneity of data. Relatively high accuracy and good applicability confirm high suitability of fuzzy knowledge-based models of grazing intensity, particularly when data of high quality is unavailable or data is limited.

In this research grazing capacity of Nazlou area evaluated taking into account slope, forage production, distance of water supplies and soil resistance to erosion by a fuzzy logic method. Relatively high accuracy (RMSE=0.68 and R=0.61) show that grazing capacity models on the base on fuzzy logic have high performance, particularly when there is a lack of high quality data.

New models for other pastures with different environmental condition such as different grazing capacity is recommended to improve the ability of this modeling approach. As a generally accepted fact, many of affecting factors of GC estimation boundaries are usually gradual rather than abrupt and crisp, therefore, results showed that the fuzzy representation of boundaries of affecting factors of GC leads to a more accurate and precise estimation of GC than the conventional methods. This method covers more precisely diffusion of boundaries and results a more accurate estimation of GC and consequently guarantees sustainable rangeland exploitation.
Relatively high R coefficient (0.61) between observed and predicted values of GC in this study can be vindicated by incorporating a few of affecting factors of GC estimation (i.e., Slope, FP, WSD and SRE) (refer to Ebrahimi, 2010), to meet parsimony rule of modeling. Integrating these factors in a fuzzy method of GC estimation might increase correlation of observed and predicted values of GC.

This study showed that fuzzy method of Mamdani is a good alternative for GC estimation of traditional crisp and abrupt methods due to continuously changing variables of GC estimation. Considering the high unceprtainty in environmental data and according to obtained results it can concluded that applying fuzzy logic method can be highly effective to eliminate uncertainties. The results confirm the generalization capability of methods for the modeling of cattle grazing capacity.

5. Conclusions

Increasing our understanding of the processes of grazing intensity is best undertaken using other datasets gathered on our investigated pastures by Schrautzer et al. (2004)

The modeling results can be used for the identification of potential conflicts in nature conservation. Grazing capacity should not be calculated without knowledge of social and economic field, even down to the household units. Although quite a number of the researches deal with on bio-physical conditions and the problems of measuring grazing capacity, it must be emphasized that we need still more detailed knowledge on socioeconomic background of land use included into -fuzzy modeling of grazing capacity in order to come to a comprehensive evaluation of grazing capacity.

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