Caspian Journal of Environmental Sciences
Online ISSN: 1735-3866
Print ISSN: 1735-3033

Rangelands production modeling using an artificial neural network (ANN) and geographic information system (GIS) in Baladeh rangelands, North Iran

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ABSTRACT
Rangelands production measurement is time-consuming and expensive. Therefore, models are often employed to simulate rangelands conditions as a supplement. Artificial neural network (ANN) is widely used for modeling in environmental studies, yet it cannot preset its results in the form of a map or geo-referenced data. We used ANN to estimate the spatial distribution of rangelands production, then a geographic information system (GIS) was applied as a pre-processing and post-processing framework in rangelands production modeling. The ANN was trained (R_{sqr} = 0.95, MSE = 0.02) and tested using data from the Baladeh rangelands located in the northern part of Iran. Rangelands production was simulated using a multi-layer perceptron (MLP) network. We estimated rangelands production (using many plots and field studies) as the network output, along with the influencing factors in the production (vegetation, climatic, topographic, edaphic and human factors) as the inputs. After modeling and model optimizing in ANN, the model test was performed (R_{sqr}=0.8, MSE=0.3). Furthermore, the studied area was divided with the pixels 100×100 m (raster format) in the GIS medium. Then, the digital layers of the network inputs were combined and a raster layer was prepared including the network inputs values and geographic coordinate. The values of pixels (network inputs) were imported in ANN (NeuroSolutions software). Rangelands production was simulated using the validated optimum network in the sites without production measurements. In the next step, the results of ANN simulation were imported in the GIS medium, then rangelands production map was prepared based on the estimated results of ANN. The results indicated that integrating ANN and GIS exhibits high accuracy and performance in rangelands production estimation. Hence, the prepared rangelands production map can be used for planning and managing the rangelands.

Keywords: Production measurement, MLP network, Rangelands production map, Iran.

INTRODUCTION
Natural ecosystems are considered as a part of the renewable natural resources, including key indicators of sustainable development of each country. The dominant land use in Iran is rangelands with an area of about 90 million hectares (Ramankutty *et al*. 2008; Gavili *et al*. 2011). Rangeland is a type of the land between cropping zones and the deserts predominantly found in the arid and semi-arid regions. In terms of the ecology of natural systems, it is characterized by original vegetation and possessing a natural potential considered as an important source for animal and plant productions (Stoddart *et al*. 1975; Havstad *et al*. 2007).
Unfortunately, lack of proper management of natural resources in the natural areas, particularly rangelands, caused some alterations in the vegetation composition. So that, valuable natural species are replaced by the palatable and toxic species. In the last decades, rangeland productivity has been an important concern (Crush *et al*. 2006; Chapman *et al*. 2008).
However, few studies have been conducted concerning the problem of rangelands production modeling. Hence, some measures should be established and also proper management is adopted to sustain this great resource (Mirjalali 2011; Aeinebeygi & Khaleghi 2016).

DOI: 10.22124/cjes.2020.4139
Received: Sep. 25. 2019 Accepted: Feb. 29. 2020
Article type: Research

Primary productivity in most rangelands depends on the precipitation and soil water availability (Izaurralde *et al*. 2011; Mousel *et al*. 2011; Nyachieo 2016). Rangelands are characterized by many important features limited by water and nutrients (Hooper & Johnson 1999), low and variable long-term average annual precipitation as well as high evaporative demand along with water limitation (Gholami & Mohseni Saravi 2010; Gallardo & Schlesinger 1992), which strongly influence their ability to provide goods and services. Rangelands production is limited through various factors such as the spatiotemporal distribution of climate factors (Picardi 1975; Perez *et al*. 2007; Rutunga *et al.* 2007; Ebrahimi *et al*. 2010), precipitation (Picardi 1975*;* Gholami *et al.* 2015), soil characteristics as well as soil texture, organic matters and management practices, e.g., grazing patterns and stocking rates. Hence, one should be able to integrate them all in a single mathematical model (Hourou & Hoste 1977). Accurate natural resource inventory information such as rangelands inventory information is essential to any public or private land management agency (Blackard & Dean 1999). Therefore, the rangelands evaluation process is essential to determine the production, to optimize utilization of this valuable resource as well as providing practical solutions to prevent overgrazing (Moghadam 2007).

Determining the proper management of the rangelands, make it stable and consequently prevent its degradation, resulting in the stability of desirable plants and their improvement. Most studies for assessing the interactions among locations, developmental actions and environmental elements on rangeland plants are in connection with the reaction of plants to light (Stuefer & Huber 1998; Collins *et al*. 2001; Li *et al*. 2002; Bagheri *et al*. 2013), foodstuffs (De Kroon *et al*. 1996) and salinity (Keshavarzi *et al*. 2015). However, few studies have been conducted about the effects of rangelands grazing capacity and rangelands suitability on the production values. In this context, the allowable use mostly is determined through expert opinions on individual species or according to the sensitivity of soil erosion, status and trends for any vegetation type (Amiri *et al*. 2011).

The amounts of available forage are different, because the most important parameters in determining the number of classes of rangelands suitability for grazing, included: the amount of available forage and given that for the calculation of this parameter, in terms of whether or not production plants with low palatability class (III) dominating vegetation types. It is also mostly because of the grazing pressure, depending on the method determining the allowable use.

Janssen *et al*. (2000) believed that in commercial rangeland systems, declines in productivity generally are due to changes in investigation structure and soil. Stafford Smith (1996) suggested that a typology of rangeland vegetation according to factors such as climate, principal economic and subsistence activities, mobility and access to outside resources, would lead to greater clarity compared to the results of different studies. It was also pointed out the danger of broadly adopting a paradigm as dogma when even its proponents were explicit about the conditions under which it applies (Vetter 2004). It remains unclear whether modern methods such as artificial neural networks (ANN) and geographic information system (GIS) have enough efficiency in the modeling of rangelands production modeling. Further investigations are needed to evaluate this accurately. GIS is a powerful tool for the arrangement of input, storage and retrieval, manipulation and analysis as well as the output of spatial and attributes data (Bagheri *et al*. 2013; Gholami *et al.* 2016; Alshehri *et al.* 2020; Sahour *et al.* 2020). Therefore, GIS can be used as an efficient tool in data-processing, model running, data analysis, and mapping in environmental modelling. In recent years, ANNs as the current methods of artificial intelligence, are being increasingly used as a modeling tool in a wide range of applications and due to their ability to identify patterns. So that, complex trends have also been employed for elevating our understanding of the ways in which rangelands production change and evolve. The method of integrating ANN and GIS proved to be effective for solving several various problems. Jayasinghe & Yoshida (2009) used neural network technology with a GIS to carry out land suitability analysis for rangelands.

They used the Levenberg-Marquardt (LM) algorithm to perform the ANN modeling. Subsequently, the fuzzy set theory was introduced into GIS to obtain more flexibility and more effective results and capabilities (Gholami *et al*. 2017). Pijanowski *et al*. (2002) combined ANN and GIS, achieving a couple model, i.e. land Transformation Model (LTM) to understand the complex process of land use change. Goharnejad *et al*. (2015) used Mamdani-type of inference of the fuzzy approach, to determine grazing capacity and to develop a simple model. They prepared the maps of land cover using satellite images and then the map was completed by field visits (Sahour *et al.* 2014).

Integration of ANN and GIS has achieved considerable progress in rangelands management (by lowering the analysis cost of the natural resource data and also by reducing the amount of time spent for interpreting data) during the last decade (Skidmore *et al*. 1997; Blackard & Dean 1999; Li & Yeh 2002; Pijanowski *et al*. 2002;

Caspian J. Environ. Sci. Vol. 18 No. 3 pp. 277~290 Received: Sep. 25. 2019 Accepted: Feb. 29. 2020
DOI: 10.22124/cjes.2020.4139 Article type: Research

Malczewski 2004; Mas *et al*. 2004; Dai *et al*. 2005; Pijanowski *et al*. 2005; LotfiAnari *et al*. 2011; Obade & Lal 2013).

Accordingly, in this study, by estimating and modeling available forage, we tried to assess the effects of environmental factors (climatologic, topographic, and edaphic factors) on forage production and eventually rangelands suitability. Therefore, the goal of the present study is to assess the mean rangelands production using field studies and an optimum ANN coupled to a GIS. Further, to map rangelands production in the Baladeh rangelands) for conservation practices.

MATERIALS AND METHODS

Study area

The study area is located at 51º 29' to 51 º 45' E longitudes and 36º 05' to 36º 14' N latitude in North Iran (Fig. 1) the southern Caspian coasts in the Alborz highlands. The area of the studied rangelands is about 200 km^2. The most area of Baladeh watershed was included rangelands. The climate of the studied area is cold semi-humid. The mean annual precipitation and temperature are approximately 580 mm and 5.3 Cº respectively. Precipitation mainly consists of snow. The main part of precipitation falls in the cold season (Gholami *et al*. 2008). Frost and low temperature are the most important limiting factors in the vegetation growth during the cold seasons. Moreover, climatic data are available from the Baladeh meteorological station. The area consists of rangelands with different types of vegetation included *Artemisia fragrans, Amygdalus lycioides, Astragalus* spp., *Achillea* spp., *Onobrychis cornuta, Psatyrostachys fragillis-Leucopoa scrophylla, Artemisia fragrans-Onobrychis cornuta, Astragalus* sp.-*Cousinia multiloba, Astragalus* sp., *Astragalus* sp.- *Bromus tomentellus* and *Amygdalus* sp.-*Astragalus* sp. Different growth forms of rangelands vegetation are observed such as shrub and grass species. Elevation alterations from 2000 to 4200 m and slope changes from flat parts to 70 degrees in the area. The mean slope degree of the area is 24.5. There are nine villages in the studied area and the people jobs are mostly animal husbandry or farming. Human activities are of the main factors resulting in vegetation degradation in North Iran.

Fig. 1. Location of the studied rangelands in the north of Iran.

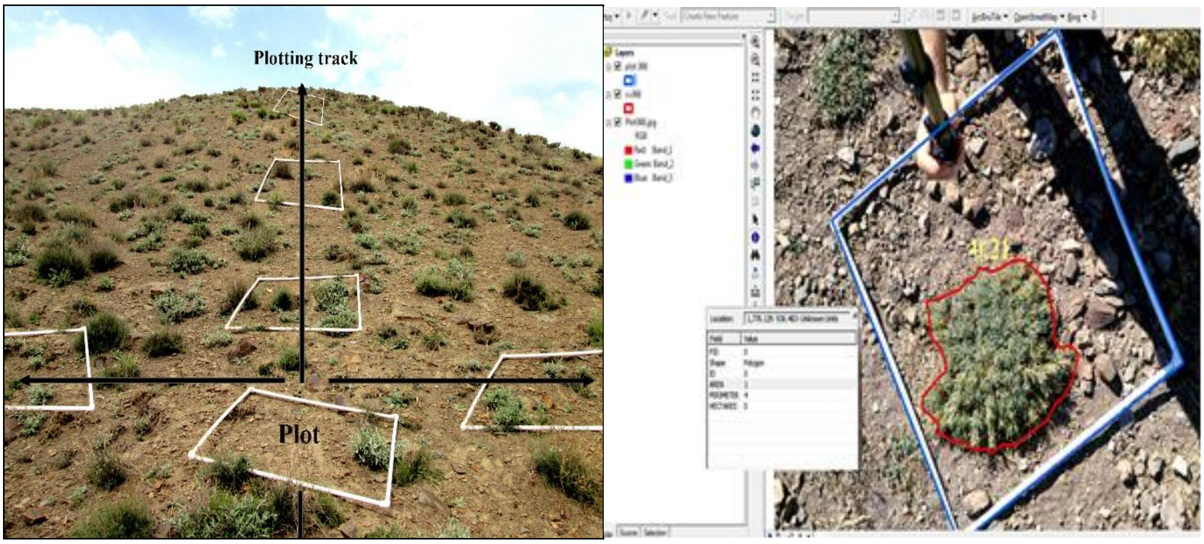
Measurement of rangelands production using plots

It is important to measure rangelands production using field plots for modeling. The mean production of rangelands was estimated on the quadrats distributed over the plots using the random method. We used two sizes of plots for measuring rangelands production: a) 1 ×1 m plots for grass species; b) 5×5 m for shrub species with an extensive canopy. Hence, 84 sampling sites were evaluated for plotting and production measurement.

The studied sites were selected based on the spatial changes in vegetation cover, forage production and rangelands conditions. Twenty plots were used for measuring production in each of the studied sites, hence, the mean production of the twenty plots was evaluated as the production of the site. The plotting was performed randomly in two vertical directions (the length and width of hillslope) with an approximate distance of 10 m (Fig. 2). Therefore, a sampling site had an area of about one ha (100×100 m). Then, annual vegetation growth

Caspian J. Environ. Sci. Vol. 18 No. 3 pp. 277~290 Received: Sep. 25. 2019 Accepted: Feb. 29. 2020
DOI: 10.22124/cjes.2020.4139 Article type: Research

was evaluated as rangelands production. Therefore, the method of cutting and weighting was used for estimating rangelands production for grass species. For shrub species, the annual vegetation growth was exactly separated by drying the samples (Fig. 3). The samples were dried in the air. Thereafter, samples were weighed using a digital scale with 0.1 g accuracy. Finally, rangelands production was estimated based on the mean of the twenty plots production for each of the sites and consequently, the measured production values in the sites were defined as ANN output in the modeling process.



(A) **(B)**

Fig. 2. A) Plotting method on the studied sites, B) Picturing method, and estimating vegetation canopy percentage in GIS.

(A) **(B)** **(C)**

Fig. 3. A) Measurement of rangelands production by evaluating the annual vegetation growth, B) Estimation of rangelands production by cut and weighting method for grasses and shrub species, C) Separation of annual growth by drying shrub species.

Estimation of the influencing factors in rangelands production

Influencing factors (the predictors) are the network inputs for modeling rangelands production. Different factors were evaluated for this type of modeling including vegetation, topographic, climatic, edaphic and human factors. Rangelands canopy is an important factor or input in the modeling process. Therefore, vegetation cover percentage was evaluated as an important vegetation factor in the studied area. Spatial changes in a cover rate were evaluated using satellite image (Quickbird, resolution 1 m) and field studies. Canopy estimation was performed by plotting and imaging, then digitizing the obtained images in GIS (Fig. 2). The mean cover percentages of the twenty plots were evaluated to estimate that of the studied site. Furthermore, satellite images were used to evaluate cover percentages outside the accessed areas. The topography is one of the main factors in the climatic and vegetation conditions. Topographic maps (scale 1:25000) were used for evaluating the spatial distribution in site elevation, land slope, and aspect in a GIS framework. At first, the digital elevation model (DEM, 10 m) was prepared using topographic maps. Then, slope and aspect maps of the studied area were prepared using DEM and GIS capabilities. Finally, the spatial distribution in elevation, slope and aspect of

Caspian J. Environ. Sci. Vol. 18 No. 3 pp. 277~290
DOI: 10.22124/cjes.2020.4139

Received: Sep. 25. 2019 Accepted: Feb. 29. 2020
Article type: Research

sampling sites were evaluated in GIS. Climatic parameters are also important factors in vegetation indices such as rangelands production. Precipitation and temperature are the most important climatic factors in vegetation conditions. There are many climatology stations in the region (Baladeh, Polemon, Panjab, Razan, Polemergen, and Valiabad).

The secondary data of climatologic stations were used to evaluate the spatial distribution in precipitation and temperature in the area of studied rangelands. Different methods were evaluated for simulating precipitation and temperature. The used methods including interpolation of secondary data, multivariate regression using elevation and distance from the Caspian Sea along with the gradient method were used to simulate the spatial distribution of the mean annual precipitation and temperature as well as the temperature, and precipitation of the growing season. Comparison between the results and the secondary data obtained from the climatology stations indicated that multivariate regression is the best method for simulating the spatial distribution of precipitation and temperature in the studied area. Moreover, statistical analysis revealed that there is a significant relationship between the results of the multivariate method and rangelands production. Therefore, different linear relations were given using multivariate regression methods (for simulating climatic parameters). Finally, the linear relations were used for simulating climatic parameters in GIS. Spatial distribution of the mean annual temperature and precipitation was evaluated by the prepared raster layers in the sampling sites. Different climatic parameters were evaluated in the sites including: the mean annual precipitation, the mean precipitation of the growing season, the mean annual temperature, the mean temperature of the growing season, the mean maximum annual temperature and the mean minimum annual temperature.

However, soil is one of the most important factors in vegetation growth. So, we evaluated different factors of soil in the sampling sites. At first, soil texture map of the sampling area was provided using profile digging and field studies. Nine soil parameters were evaluated in the sites including soil texture (clay, silt and sand percent) from the depths of 20 cm and total depth, soil depth, soil salinity in the depths of 20 cm and the total soil depth. Also, mankind activities are a determinative factor in vegetation degradation.

The role of human factors was evaluated in the studied area and sampling sites. The distance from settlement areas and roads were evaluated using digital layers in GIS as human factors in vegetation degradation. Moreover, water is a key factor in vegetation life. Rangelands production is significantly affected by water access. Hence, water access parameter was evaluated by estimating the precipitation values and distances from streams in GIS.

Estimation of rangelands production using ANN

At first, the performances of the SPSS program and the ANN in rangelands production were compared. Ultimately, the ANN was selected because of its higher efficiency. Thereafter, the Pearson coefficient correlations between rangelands production and the influencing factors or the predictors were evaluated using SPSS. A multilayer perceptron (MLP) was used to estimate the rangelands production. MLP is a neural network architecture widely employed to simulate environmental parameters in the literature (Gholami *et al*. 2017). A feed-forward neural network was employed to estimate production in Baladeh rangelands.

The production was selected as output, while the vegetation (vegetation percentage), topographic (elevation, slope and aspect), climatic (precipitation, and temperature), edaphic (soil texture, soil depth, and soil salinity), human (distance from roads and settlement areas) and hydrologic (distance from streams) factors were the inputs. In order words, 21 input parameters were evaluated as network inputs for modeling rangelands production. At first, all data were normalized and divided into two classes: training (70% of all data) and testing (30% of all data). An ANN was used for simulating by NeuroSolutions software. In the training stage, different transfer functions and learning techniques were evaluated. A trial-and-error approach was used to determine the optimum structure, learning rate and momentum parameter (Li *et al*. 2002).

To find the optimum number of hidden neurons, their number was changed from 1 to 10. The results of the trial-and-error method indicated that the MLP network with a tangent hyperbolic transfer function and a step training technique is the best network architectures for estimating rangelands production. The appropriate input variables were selected by the trial-and-error method and statistical analysis (Pearson's correlation). Different input patterns were evaluated, then their performances were evaluated and compared. The mean squared error (MSE) and the coefficient of determination (R_{sqr}) were used for evaluating the different structures (inputs) in rangelands production. The MSE and R_{sqr} are defined in Eqs. 1 and 2:

Caspian J. Environ. Sci. Vol. 18 No. 3 pp. 277~290 Received: Sep. 25. 2019 Accepted: Feb. 29. 2020
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$$MSE = \frac{\sum (Pi - \hat{Pi})}{n} \qquad \textbf{(1)}$$

$$Rsqr = [\frac{\sum_{i=1}^{n}(Pi - \overline{Pi}).(\hat{\text{P}}\text{i} - \tilde{\text{P}}\text{i})}{\sqrt{\sum_{i=1}^{n}(Pi - \overline{Pi})^2 . \sum_{i=1}^{n}(\hat{\text{P}}\text{i} - \tilde{\text{P}}\text{i})^2}}]^2 \qquad \textbf{(2)}$$

where Pi is the measured value of rangelands production, $\hat{Pi}$ is the estimated production value, $\overline{Pi}$ is the mean of the measured production values, $\tilde{Pi}$ is the mean of the estimated production values, and ni is the number of data points. An optimum network has three main components: the optimum transfer function, the optimum network architecture, and the optimum learning technique. The optimum network was determined by the trial-and-error method. We start with one neuron in one hidden layer and then progress (with increasing size) until the performance of the test is satisfactory (Nestor 2006). After optimizing the network, its validation or test stage was performed. Finally, the estimated results were compared with the measured values of rangelands production to evaluate network performance.

Integrating ANN and GIS in the modeling rangelands production

In this study, an integrating ANN and GIS were employed to estimate rangelands production. ANN was used for estimating rangelands production, while GIS for simulating the spatial distribution of the ANN inputs and also for mapping the ANN results (as a pre- and post-processing system). GIS was applied as an effective tool to provide base maps and to estimate network input parameters.

Different digital-base raster maps were prepared in GIS including vegetation percentage, DEM, slope, aspect, the mean annual precipitation, the mean precipitation of the growing season, the mean annual temperature, the mean temperature of the growing season, soil texture (clay, silt, sand), soil salinity (EC), soil depth, distance from streams as well as the distance from roads and settlements. Eighty-four sampling sites were studied to simulate rangelands production in the studied area. Then, the estimated data of these parameters were incorporated in ANN for modeling, followed by performing MLP network training.

The network was optimized using the trial-and-error method. Furthermore, the optimized network was evaluated by testing data. After network validation or test, the tested optimum network was used for estimating rangelands production in the sites without production measurement. GIS had a pre-processor role in the simulation process. The goal of the study was to employ ANN for estimating rangeland production in a manner of geo-referenced graphic for the sites without production measurements.

The modeling results exhibited that the optimized network needs to have eight inputs such as: rangelands cover percentage, ground slope, annual precipitation, precipitation of growing season, percentages of silt and clay, soil depth, and distance from the stream. So, in the GIS pre-processing stage, raster layers of these eight input factors were provided and combined using overlay analysis with a pixel size of 100 ×100 m, followed by separating the surface of the sampling area to about 20000 geo-referenced pixels. The pixels indicated values of the tested network inputs or eight factors influencing rangelands production. Then, the pixels coordinate were inserted automatically in the GIS framework, followed by exporting the pixels data from GIS, and importing to NeuroSolutions software.

In ANN, the tested network was used to estimate rangelands production in all of the 20000 pixels or sites (the entire studied surface area). Thereafter, the estimated rangelands production was imported from ANN to GIS with geographic location data, where GIS played a post-processing role in rangelands production modeling.

The rangelands production map was prepared using the estimated production and GIS capabilities for the studied area. Besides, the measured values of 84 sampling sites were overlain on the prepared map in GIS and results accuracy were evaluated through a comparison between the estimated and measured values of rangelands production in GIS. Finally, the raster layer of rangelands production was prepared after classifying as the map of annual rangelands production.

Caspian J. Environ. Sci. Vol. 18 No. 3 pp. 277~290 Received: Sep. 25. 2019 Accepted: Feb. 29. 2020
DOI: 10.22124/cjes.2020.4139 Article type: Research

RESULTS

Rangelands production was measured in the 84 studied sites based on plotting, cut and weighting methods. Then, the influencing factors in the rangelands production were estimated including cover percentage, climatic, topographic, edaphic, hydrologic, and anthropogenic factors. Afterward, digital maps of the influencing factors in rangelands production were prepared in GIS, followed by estimating the aforementioned factors in the 84 sites. Statistical analyses were performed using SPSS software to evaluate the relationships between rangelands production and influencing factors. Pearson correlation coefficients between rangelands production and the influencing factors are presented in Table 1. These inputs and output data were imported in ANN for modeling the rangelands production. In the training process, alterations in the input data pattern revealed that eight factors are the best inputs for estimating rangelands production. These factors include canopy percentage, precipitation of the growing season, annual precipitation, soil depth, soil texture (percentages of silt and clay), aspect and distance from roads and residential areas or anthropogenic factors. According to the results of the trail-error method in network training and also Pearson correlations, the canopy percentage and precipitation of growing season are the best factors or inputs for modeling rangelands production. The training process is the first and the most important stage in the modeling process. In this process, the optimal network structure was defined. The training process for rangelands production revealed suitable results (R_{sqr} = 0.95) which presented in Table 2. Table 3 indicates error values in the training stage. Based on these results, acceptable results were obtained in the training stage. Then, an optimum structure in the rangelands production estimation was obtained that included the MLP with eight inputs, tangent hyperbolic transfer function, step training technique and four neurons. After network training and optimization, validation (test) stage was performed. We evaluated ANN performance in the modeling process, through a comparison between the estimated and measured values of rangelands production. The results of the test stage are illustrated in Fig. 2. According to the results, the optimized network can estimate rangelands production with high accuracy (R_{sqr}=0.8). Previous studies reported ANN capability in similar environmental modeling (Mas *et al*. 2004; Lotfi Anari *et al*. 2011). Table 4 and Figs. 4-5 present the evaluation of ANN performance in the rangelands production estimation during the test stage. The objective of this study was to estimate rangelands production in the sites without rangelands production measurement and also to present the results in a graphical geo-referenced manner available for all users. Therefore, raster layers of the validated network inputs were combined using overlay analysis in GIS. Rangelands production was estimated using the validated network and the obtained input data from GIS in all of the studied area. Finally, the map was provided by integrating the validated network and GIS. The rangelands production map is illustrated in Fig. 6. As shown in this Fig., the measured values of the rangelands production were overlain on the prepared rangelands production map in GIS. So, the accuracy of the results can be evaluated by overlaying the measured values on the prepared map (estimated values). Evaluation of the map revealed that the applied methodology has a suitable accuracy in the modeling and especially results can be used to classify rangelands. According to Fig. 6, the existing error values in the estimated rangelands production do not defect the accuracy of rangelands classification in the area of the studied area or watershed.

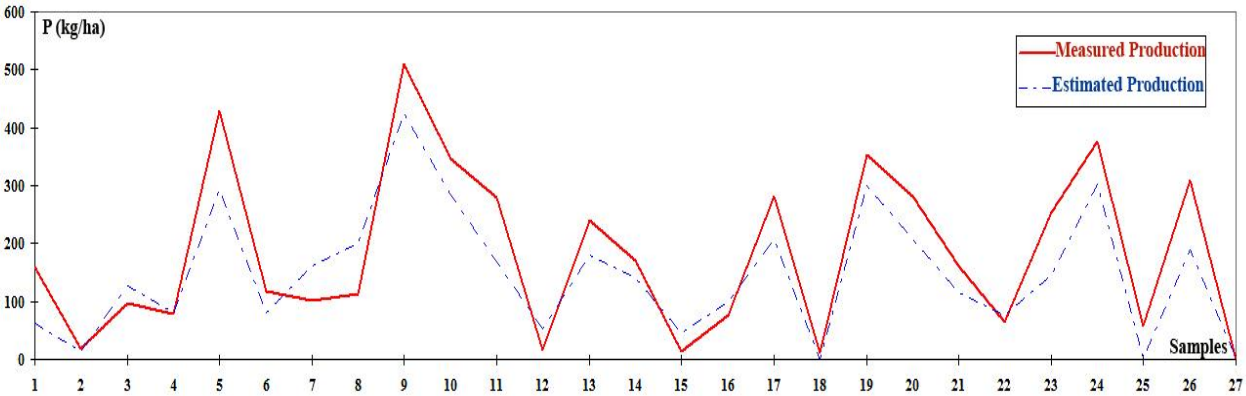

Fig. 4. Evaluation of ANN performance for rangelands production estimation during the test stage throughout the comparison between the estimated and measured production values.

Caspian J. Environ. Sci. Vol. 18 No. 3 pp. 277~290
DOI: 10.22124/cjes.2020.4139

Received: Sep. 25. 2019 Accepted: Feb. 29. 2020
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Table 1. The network optimal inputs (influencing factors) and outputs (the measured rangelands production) for estimating rangelands production in some of the sampling sites.

Production (Kg ha^{-1})	Canopy (%)	Precipitation growing season (mm)	Annual precipitation (mm)	Slope (degree)	Clay (%)	Silt (%)	Soil depth (cm)	Distance from road and settlement (m)
82	10	213	580	24.62	25	21	75	139
65	20	234	515	24.15	28	34.67	100	617
71	25	244	526	37.55	29	34	140	621
220	20	223	508	35.14	23	33	40	1120
268	25	242	514	30.83	23.3	42.67	130	1570
183	30	247	509	25.07	23.3	42.67	130	1821
16	3	210	506	14.36	26.5	33.5	110	67
276	28	238	512	35.86	23.33	42.67	130	799
227	20	231	512	20.22	28	38	100	890
48	10	226	513	17.07	28	34.67	100	790
284	30	213	504	17.37	25.3	31.33	80	40
11	12	221	583	23.92	23.3	42.67	130	178
18	5	209	578	43.89	25	21	75	28
67	20	237	516	30.99	28	34.67	100	742
78	30	235	513	14.79	28	34.67	100	1207
76	30	247	527	12.74	26	30	50	1247
75	25	225	508	21.79	23.3	42.67	130	465
0	0	222	489	12.85	0	0	0	1854
5	5	210	503	39.67	25	21	75	475
141	28	229	512	27.18	23.3	42.67	130	584
61	20	237	515	26.48	28	34.67	100	1148
286	50	224	504	26.31	28	38	100	465
16	10	207	506	41.45	25.3	31.33	80	220
73	20	235	514	25.37	26	30	50	998
204	43	238	509	30.37	29	34	140	910
136	7	219	511	35.6	23	33	40	600
13	15	215	556	18.95	25.3	31.33	80	70
80	12	205	509	39.72	23	33	40	150
10	15	227	611	36.81	25	21	75	748
188	23	229	508	18.89	26	30	50	147
117	17	203	504	31.65	23	33	40	250
290	40	218	557	40.11	23.3	42.67	130	30
167	24	231	508	20.61	26	30	50	123
47	15	208	578	20.23	23.3	42.67	130	610
81	23	234	526	25.09	29	34	140	481
14	15	218	586	20.97	23.3	42.67	130	98
13	15	213	542	33.06	25	21	75	273
16	13	220	583	6.82	25	21	20	1225
207	30	233	508	31.54	26	30	50	433
312	30	243	515	30.14	23.3	42.67	130	2256
10	25	230	504	16.07	15	21	30	2233
16	10	218	609	16.46	25	21	75	10
13	10	224	611	32.04	25	21	75	170
37	5	208	505	27.43	23	33	40	332
430	40	245	518	37.46	23.3	42.67	130	3618
107	40	247	517	20.9	23.3	42.67	130	2702
430	40	245	518	37.46	23.3	42.67	130	3618

Caspian J. Environ. Sci. Vol. 18 No. 3 pp. 277~290
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Table 2. The Pearson correlation between rangelands production and the factors influencing rangelands production.

Factor	Pearson correlation	Factor	Pearson correlation
Annual Precipitation	0.25	Soil depth	0.2
Precipitation of the growing season	0.45 *	Soil salinity	-0.15
Vegetation cover percentage	0.77 *	Site elevation	0.06
The mean annual temperature	0.1	Slope	-0.19
The temperature of the growing season	0.1	Aspect	-0.15
Clay	0.34 *	Human factors	0.41 *
Silt	0.48 *	Distance from stream	-0.1
Sand	-0.48 *		

* Significant relation

Table 3. Results of network training for estimating the annual rangelands production.

All Runs	Training Minimum	Training Standard Deviation
Average of Minimum MSEs	0.04	0.0002
Average of Final MSEs	0.04	0.0002
Epoch	1000	
Minimum MSE	0.028	
Final MSE	0.028	
R_{sqr}	0.95	

Table 4. Comparison between the simulated rangelands production and the measured rangelands production in the test stage.

Performance	Production (Kg ha^{-1})
MSE	6496.7
NMSE	0.32
Min Abs Error	2.48
Max Abs Error	179
R_{sqr}	0.8

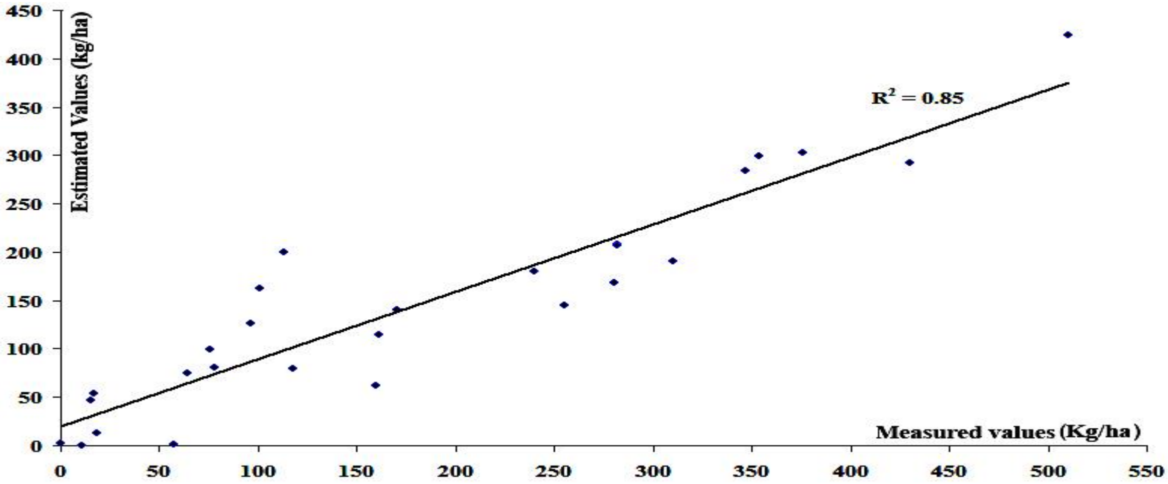

Fig. 5. Evaluation of ANN performance for the rangelands production estimation during the test stage throughout comparison between the estimated and the measured rangelands production values.

Caspian J. Environ. Sci. Vol. 18 No. 3 pp. 277~290
DOI: 10.22124/cjes.2020.4139

Received: Sep. 25. 2019 Accepted: Feb. 29. 2020
Article type: Research

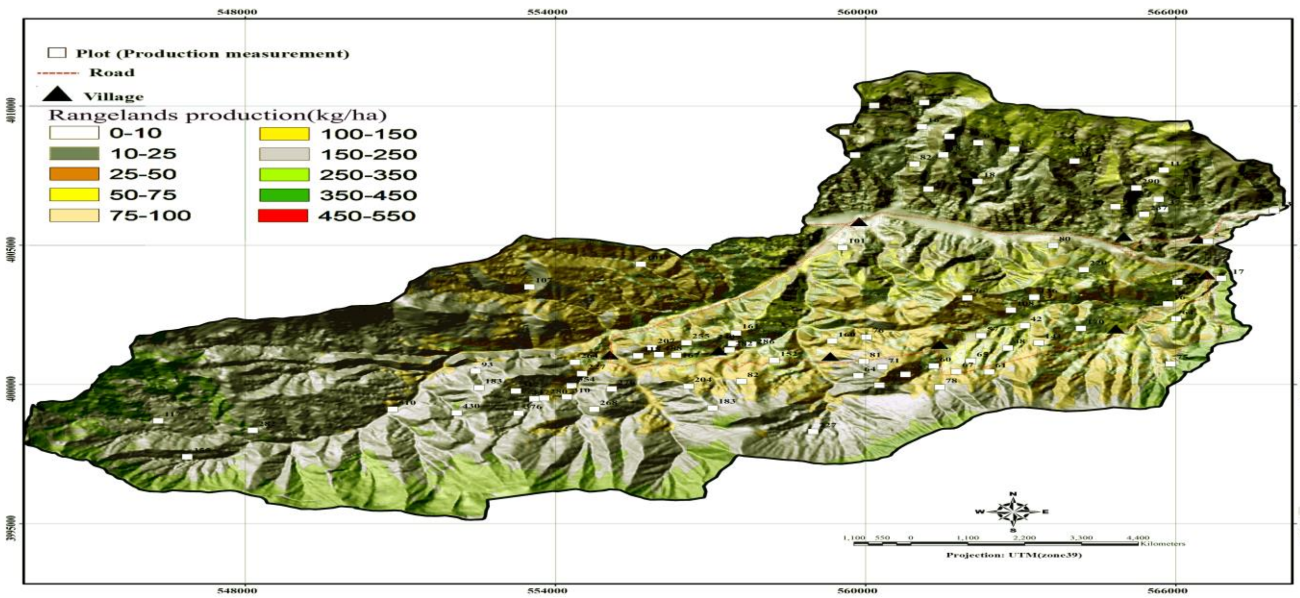

Fig. 6. The map of rangelands production has resulted from the integrating ANN inference system and GIS capabilities. In this map, the accuracy of the results was evaluated using a comparison between the estimated and measured production values.

DISCUSSION

Different network structures were developed to evaluate the probability impacts of enabling/disabling vegetation, topographic, climatic, edaphic, hydrologic, and human factors as inputs. In the present study, the rangelands production varies from 0 on the rock outcrops to about 500 kg ha^{-1} (rich rangelands) in the studied areas. Moreover, canopy percentage alters from 0 to 70% in the studied rangelands. The precipitation of the growing season is between 205 and 245 mm. The maximum soil depth is 140 cm. The values of the other factors influencing rangelands production are presented in Table 1. According to the results, eight factors including the rangelands canopy percentage, precipitation of the growing season, annual precipitation, slope, soil depth, soil texture (percentages of silt and clay) and distance from the road or residual areas (anthropogenic factors) are the most important inputs for rangelands production simulation, respectively. Statistical analysis results revealed that canopy percentage and precipitation of the growing season are the most important factors exhibiting a significant positive relationship with rangelands production. Baladeh is a mountain area covered by snow in the cold season. Therefore, precipitation of the growing season is the more important factor than annual precipitation. Furthermore, soil depth and also the percentages of clay and silt (soil texture) exhibit a significant positive relationship with rangelands production. Therefore, soil evolution is a key factor in vegetation growth or rangelands production. The same relationship was found between the slope and the production. Rangelands vegetation is significantly affected by anthropogenic activities. However, these activities are stronger around the roads and residual areas. According to the statistical analysis results (Pearson coefficient), the human display an inverse relationship with rangelands production. Rangelands exhibit better conditions in the areas away from roads and especially residual areas or livestock tracks. In the training stage, mean square error (MSE) and coefficient of determination (Rsqr) were estimated 0.02 and 0.9 respectively. In the test (validation) stage, mean MSE and R_{sqr} were 0.016 and 0.8 respectively. Using ANN for rangelands production modeling leads to good results, and there was high correlation between estimated and measured productions. Training and test results revealed that ANN can be used for estimating rangelands production in the area without production measurement. ANN can estimate rangelands production in a short time and with a high accuracy if we employ a suitable network and exact inputs. In the modeling process, ANN was applied to estimate rangelands production followed by GIS as a pre- and post-processor tool in estimating the rangelands production monitoring and mapping. Besides, GIS resulted in increased velocity. The optimal network structure in the rangelands production estimation was the MLP network with the tangent hyperbolic transfer function, step training technique and four neurons. Previous studies suggested that an ANN framework combined with the LM technique form an efficient structure in the environmental parameters simulation (Gholami *et al.* 2017). The base of this study is the automatic relationship between ANN and GIS in modeling and mapping rangelands

Caspian J. Environ. Sci. Vol. 18 No. 3 pp. 277~290
DOI: 10.22124/cjes.2020.4139

Received: Sep. 25. 2019 Accepted: Feb. 29. 2020
Article type: Research

production. It is important that the estimated results by ANN must be capable of overlaying analyses with other digital data. A high volume of input data can be provided using GIS, and also rangelands production can be estimated by ANN both in a short time for the sites without rangelands production measurement. Therefore, the integrated ANN and GIS presents the modeling results in a manner of digital maps. So, in the present study, the rangelands production map was prepared by integrating ANN and GIS capabilities. This map can be used for rangelands classification and can be used as a tool for rangelands planning and management. Fortunately, the quantitative data of network inputs are available in the rangelands area. Therefore, the present methodology can be used for modeling in the area of the extensive watershed or rangelands. In this study, rangelands production was estimated using the ANN and GIS capabilities with high accuracy, followed by presenting the results in the form of a map.

CONCLUSIONS

According to the results, vegetation canopy percentage and precipitation are the most important factor influencing the rangelands production modeling. However, production measurement is costly and time-consuming. Therefore, vegetation canopy percentage can be used as an important input or index for estimating rangelands production. Integrating ANN and GIS obviously can be used for simulating and mapping rangelands production or other vegetation parameters. However, the accuracy of input and output data are the most important determining factors for accurate and efficient modeling. GIS helps us to estimate the special distribution of the input factors. This system has different techniques and capabilities for providing different raster layers of the network inputs. In addition, there is no limitation at the extent of the sampling area or in selecting the pixel sizes. However, the pixel size should be selected based on the study conditions (the inputs and output data accuracy). GIS is also an efficient system in data processing and mapping. Therefore, integrated ANN and GIS can be employed for zoning rangelands production and as a tool for planning and managing rangelands. These capabilities can provide practitioners with an easily interpretable rangelands production map once managing these resources (especially for grass species). For further studies, we suggest using a combination of field measurements and artificial intelligence-based models for modelling other rangeland vegetation indices (e.g., canopy, typology, and special distribution of species).

ACKNOWLEDMENT

We would like to thank the Natural Resources Organization and Watershed Management of Mazandaran for providing the soil and topographic secondary data and for helping us with data preprocessing.

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DOI: 10.22124/cjes.2020.4139

Received: Sep. 25. 2019 Accepted: Feb. 29. 2020
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Received: Sep. 25. 2019 Accepted: Feb. 29. 2020
Article type: Research

مدلسازی تولید مراتع با به‌کارگیری شبکه عصبی و سیستم اطلاعات جغرافیایی در مراتع بلده، شمال ایران

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(تاریخ دریافت: ۹۸/۰۷/۰۳ تاریخ پذیرش: ۹۸/۱۲/۱۰)

چکیده

اندازه‌گیری تولید مراتع، فرآیندی زمان بر و هزینه‌بر است. بنابراین، مدل‌ها به عنوان ابزاری مکمل برای برآورد تولید مراتع به‌کار گرفته شدند. امروزه، شبکه عصبی به‌طور گسترده‌ای در مدلسازی‌های محیطی به‌کار گرفته شده است، اما توانایی ارائه نتایج به صورت نقشه زمین مرجع را ندارد. در تحقیق حاضر، شبکه عصبی برای برآورد تولید مراتع و سیستم اطلاعات جغرافیایی (GIS) به عنوان یک پیش پردازنده و پس پردازنده در برآورد تولید مراتع به کار گرفته شدند. در فرآیند مدلسازی، آموزش شبکه (Rsqr = 0.95, MSE = 0.02) و سپس تست یا آزمون (Rsqr = 0.8, MSE = 0.3) با به کارگیری داده‌های مراتع بلده واقع در شمال ایران انجام شد. در فرآیند مدلسازی، تولید مراتع با به‌کارگیری شبکه MLP (پرسپترون چند لایه) شبیه‌سازی شد. در این راستا مقادیر تولید مراتع به عنوان خروجی شبکه و عوامل مؤثر در تولید شامل درصد تاج پوشش گیاهی، پارامترهای اقلیمی، توپوگرافی، عوامل خاک و عوامل انسانی به عنوان ورودی‌های شبکه در نظر گرفته شدند. سپس، لایه‌های رقومی رستری ورودی‌های شبکه در محیط GIS با فرمت رستری با اندازه سلولی ۱۰۰ در ۱۰۰ متر تهیه و با یکدیگر تلفیق شده و مختصات جغرافیایی هر سلول به آن افزوده شد. داده‌های مذکور به محیط شبکه عصبی (نرم افزار نروسولوشن) وارد شد و تولید مراتع با به‌کارگیری شبکه عصبی بهینه اعتباریابی شده برای هر سلول (مکان‌های بدون رقوم تولید) برآورد شد. سپس، نقشه تولید مراتع با به‌کارگیری نتایج شبکه عصبی (مقادیر تولید شبیه‌سازی شده) در محیط GIS تولید شد. نتایج تحقیق نشان داد که تلفیق شبکه عصبی و GIS ، کارایی بالایی در برآورد تولید مراتع داشت و نقشه رستری تولید شده را می‌توان برای برنامه‌ریزی و مدیریت مراتع به‌کار گرفت.

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Bibliographic information of this paper for citing:

Dianati Tilaki, G.A, Ahmadi Jolandan, M, Gholami, V 2020, Rangelands production modeling using an artificial neural network (ANN) and geographic information system (GIS) in Baladeh rangelands, North IranCaspian Journal of Environmental Sciences, 18: 277-290

Caspian J. Environ. Sci. Vol. 18 No. 3 pp. 277~290
DOI: 10.22124/cjes.2020.4139

Received: Sep. 25. 2019 Accepted: Feb. 29. 2020
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