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Chapter

A Study of the Comparison between Artificial Neural Networks, Logistic Regression and Similarity Weighted Instance-based Learning in Modeling and Predicting Trends in Deforestation

Zeynab Moradi and Ali Reza Mikaeili Tabrizi

Abstract

The change in forest cover plays a vital role in ecosystem services, atmospheric carbon balance, and, thus, climate change. In this study, land use maps for the periods 1984 and 2012, derived from Landsat TM satellite imagery, were used. The goal of this study is comparison of three procedures of artificial neural network, logistic regression, and similarity weighted instance-based learning (SIM Weight) to predict spatial trend of forest cover change. The SimWeight considers the nearest instances in the variable space, which are computed based on past changes and the relative importance of the driving variables. The LogReg approach, on the other hand, is a type of generalized linear model that assumes that the current land use pattern reflects the processes of land use in the past. Artificial Neural Network is a nonparametric algorithm that is capable of fitting complex nonlinear functions to find the relations between past changes and their driving variables. Such approaches are expected to produce better fitting between the change potential and their complex relationships with their driving variables. Artificial neural networks in comparison with logistic regression and SimWeight have higher accuracy and less error in modeling and predicting of forest changes.

Keywords: deforestation, neural networks, logistic regression, similarity-weighted instance-based learning in modeling, Gorganroud watershed

1. Introduction

The change in forest cover plays an essential role in ecosystem services, the carbon balance in the atmosphere, and climate change [1, 2]. The forest ecosystems of Gorganrood watershed play a very important role in controlling surface runoff and

reducing floods, protecting surface soil and reducing soil erosion, adjusting temperature, and reducing the amount of greenhouse gases.

In consideration of the process of forest destruction in recent decades, it is valuable to examine the changes that have occurred in the fields of natural resources and to interpret the cause and extent of these changes and their impact on other sources [3]. Golestan province forests are very important among the forests in the north of Iran, because of their climatic conditions [4]. Golestan province forests have the highest annual destruction rate among the other northern provinces [5].

So far, many studies have used remote sensing (RS) and geographic information system (GIS) methods to effectively monitor forest cover changes [6–10]. Mahiny and Turner [11] modeled vegetation changes in the watershed of the Boorowa river in Australia by using artificial neural network and logistic regression. The results of their study indicated that artificial neural networks generally achieved better outcomes than logistic regression. Mas et al. [12] in a study that modeled deforestation by GIS and artificial neural network, and the results of their study showed that the rate of forest destruction was higher in areas with gentle slopes, high altitudes, and fertile soils. In addition, their outcomes demonstrated that the intensity of deforestation is greatly reduced by maintaining distance from the road and residential areas. Khoi and Murayama [13] modeled deforestation in an area in northern Vietnam using artificial neural networks and Markov chain models. They found that the destruction is intensive in the borders between forests and agricultural lands, fields near water sources, and areas with lower altitudes. Kumar et al. [14] modeled and predicted forest cover changes in forested areas in India. In order to explain the effects of human interventions in the forest, they used three distance variables, as explanatory variables for forest change (the distance from the edge of the forest, the road, and the city, and the map of the slope classes). The highest regression coefficient ($\beta = -26.892$) was related to the distance from the forest, which present that changes in the forest are more significant near the edge of the forest. Bagheri and Shetaei [15] in the research titled modeling the reduction of forest extent using logistic regression in the Chehel Chai watershed of Golestan province during the years 2016 to 2015, determined that the variables of the slope, distance from the village and the road have an inverse relationship with the amount of destruction. In addition, with the increase in height above the sea level in this area, the amount of destruction increased. Hassanzadeh [16] modeled deforestation in Falred forests by using the multivariate methods and artificial neural networks. According to the estimation error of modeling, artificial neural networks are a better method for modeling such variables than multivariate regression. In a study conducted by Arkhi et al. [17], the forests of North Ilam were simulated using logistic regression. According to the modeling results, it was found that the slope variables, the distance from the population centers and the road, have an opposite relationship with the amount of destruction, and the increase of the height above the sea level in this area resulted in decreasing the amount of destruction. Sardarzadeh et al. [18] predicted the destruction of forests in Chehel Chai watershed of Golestan province using artificial neural networks and Markov chain analysis. The obtained results indicate the destruction of 15.8% of dense forests during the years 1988 to 2010. Gholamalifard et al. [19] conducted a study with the aim of comparing logistic regression and artificial neural networks for modeling the transfer potential of coastal land cover change in Mazandaran province. The results showed that logistic regression has higher accuracy.

2. Materials and methods

2.1 Prediction of land cover changes

In recent years, land cover changes have received special attention. Land cover changes are the result of the complex interaction of several factors such as management, economy, culture, human behavior, and environment [20, 21]. Familiarity with how land cover changes is very important because these changes cause major effects on the environment such as hydrological cycles changing [22], the size and order of natural habitats such as forest areas [23], and species diversity [24] and can overshadow the region's economy [25].

Modeling the spatial pattern of land cover changes provides valuable information for a better understanding of the change process, determining the effective factors, and predicting the areas subject to change. Spatial models of land cover change can be divided into three main groups: Empirical Estimation Models, Dynamic Simulation Models, and Rule-base Simulation Models [26]. Empirical estimation methods use statistical techniques to model the relationship between the change based on the user rule and the factors affecting it.

Knowing the effective processes in change is possible by interpreting the output of statistical models. Empirical estimation methods are one of the most widely used methods for simulating the spatial pattern of land cover and its changes over time due to the simplicity of the structure and the ability to analyze multiple variables [27].

2.2 Land change modeler

The land change modeler is a software for creating sustainable ecological development, which was designed to understand and identify land cover changes and environmental and protection requirements caused by these changes. This software exists as a vertical application in the IDRISI software system [28]. This model is also available as Extension for ArcGIS software. In Land Change Modeler (LCM), tools for the assessment and prediction of land cover change and its implications are organized around major task areas: change analysis, change prediction, and planning interventions. Land change prediction in land change modeler is an empirically driven process that moves in a stepwise fashion from 1) change analysis, 2) transition potential modeling, to 3) change prediction. It is based on the historical change from time 1 to time 2 land cover maps to project future scenarios [29].

2.3 Sensitivity analysis of artificial neural network

The artificial neural network option can model multiple transitions at one time. Initially, the dialog for the multilayer perceptron neural network may seem daunting, but most of the parameters presented do not need to be modified (or in fact understood) to make productive use of this very powerful technique.

As launched by LCM, the multilayer perceptron starts training on the samples it has been provided of pixels that have and have not experienced the transitions being modeled. At this point, the MLP is operating in automatic mode whereby it makes its own decisions about the parameters to be used and how they should be changed to

better model the data. Automatic mode monitors and modifies the start and end learning rate of a dynamic learning procedure. The dynamic learning procedure starts with an initial learning rate and reduces it progressively over the iterations until the end learning rate is reached when the maximum number of iterations is reached [29].

Figure 1 illustrates a single hidden layer MLP feed-forward neural network. The back-propagation algorithm [30] is the most widely used learning algorithm for an MLP neural network. The learning process consists of two parts: feed-forward and backward pass. The outputs of the Artificial Neural Network (ANN) are calculated in the feed-forward pass process and the output errors are propagated backward to adjust the weights and biases of the ANN.

In the present research, Skill Measure [28] and Accuracy Rate were used to analyze the sensitivity of the multilayer perceptron artificial neural network model. Skill Measure is a statistic to evaluate the ability of the model based on the validation data and measures the skill of the model to predict future changes based on the training data. In fact, this statistic is used to compare the accuracy of the model based on the validation data and the expected accuracy that is supposed to occur randomly.

This statistic considers the ability of the model for each land cover transfer separately and shows the role of variables in the accuracy of the model for predicting change. This statistic is between -1 and 1 . The closer to 1 , it indicates the high accuracy of the model in predicting changes, and if it is zero, it indicates the random performance of the model. The expected accuracy and Skill Measure statistics are calculated from Eq. (1) and (2) [29].

$$E(A) = 1 + (T + P) \quad (1)$$

$E(A)$, is the expected accuracy rate. T is the number of considered transitions in the transition potential. P is the number of classes that remain constant in transitions.

$$S(\text{Skill Measure}) = (A - E(A)) / (1 - E(A)) \quad (2)$$

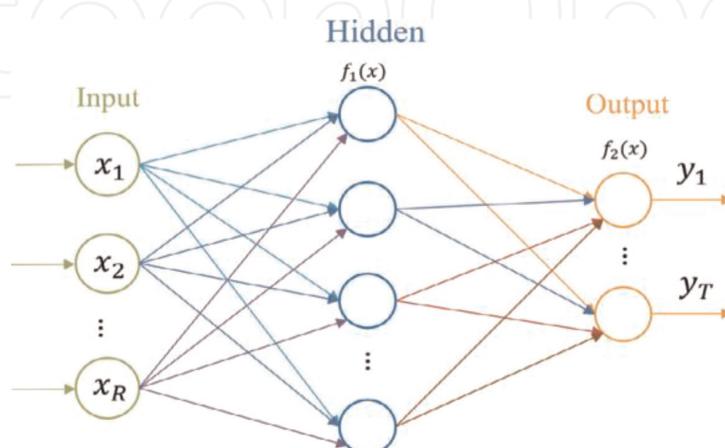


Figure 1.

Example of a single hidden layer MLP feed-forward neural network. x_1, x_2, \dots, x_R are input parameters, y_1, \dots, y_T are output targets, R is the number of input parameters, and T is the number of output targets. $f_1(x)$ is the activation function of the hidden layer, and $f_2(x)$ is the activation function of the output layer.

A is the measured accuracy provided by the model, and $E(A)$ is the expected accuracy.

2.4 Sensitivity analysis of logistic regression

It is one of the experimental models that has been used in many researches in the field of forest area change analysis, urban growth modeling, and agricultural land modeling and has provided very good results [14]. Logistic regression is a probabilistic model that fits between land use change (as a dependent variable) and factors affecting it (as independent variables). Based on this model, the relationship between variables can be explained, the relative importance of index variables can be estimated, and the land cover change probability map can be extracted [31].

In the logistic function, the probability of land use change was defined as a function of explanatory variables, which includes a uniform curve between 0 and 1 [14]. One of the statistical characteristics that are examined in the logistic regression model is Goodness of fit. The goodness of fit is determined based on the difference between the observed values and the predicted values of changes in the value of the dependent variable. The following equation is used to calculate the Goodness of fit (Eq. (3)) [32]:

$$\text{Goodness of fit} = \sum_{i=1}^N (y_i - u_i)/u_i \times (1 - u_i) \quad (3)$$

u_i are the observed values for the dependent variable, and y_i are the predicted values for the dependent variable. The basis of Goodness of fit in logistic regression is the probability ratio, which is determined based on two statistical characteristics $-2\log(L_0)$ and $-2\log(\text{Likelihood})$, where L_0 is the value of the probability function, provided that all coefficients except the intercept are 0 and Likelihood represents the amount of the probability function for the model. The following two statistical characteristics are defined based on the aforementioned two statistical characteristics (Eq. (4) and (5)) [33]:

$$\text{Pseudo R Square} = 1 - (\log(\text{Likelihood}) / \log(L_0)) \quad (4)$$

Therefore, if the value of R (Pseudo R Square) is equal to 1, it indicates a good Goodness of fit; if the value of this characteristic is 0, it means that there is no relationship between the variables, and if its value is greater than 0.2, it indicates a relatively good Goodness of fit:

$$\text{ChiSquare}(K) = -2(\log(\text{Likelihood}) - \log(L_0)) \quad (5)$$

Chi-square is also introduced as a statistical characteristic of the probability ratio, which follows the chi-square distribution when the null hypothesis is correct. This statistical characteristic examines hypotheses in which all coefficients are zero except the intercept. The chi-square degree of freedom (K) is equal to the number of independent variables used in land change modeling.

The characteristic of the ROC (Relative Operating Characteristic) is a very suitable statistic for measuring the degree of Goodness of fit in the logistic regression model. The amount of this statistic are between 0 and 1, where 1 indicates proper Goodness of fit and 0.5 indicates random Goodness of fit [14]. Finally, the logistic regression equation is defined as follows (Eq. (6)):

$$\log_e(P) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \dots + \beta_n X_n + errorterm \quad (6)$$

β_0 : intercept,
 $\beta_0, \beta_1, \dots, \beta_n$: regression coefficients,
 X_1, X_2, \dots, X_n : used variables.

2.5 Sensitivity analysis of SimWeight

The similarity-weighted sample-based learning method is a sample-based learning algorithm based on the K-nearest neighbor (KNN) algorithm. This method identifies the relationship between the stimulus variable and the transmission potential prediction for areas that show cases of change. This method is based on the calculation of weighted distances in variable space for known examples of user classes. SimWeight should have two classes (fixed pixel and variable pixel) for each transfer to create transfer potential in the direction of land change modeling.

In this method, the K-nearest neighbor was extracted for each pixel (fixed or variable) and calculates the distance in the variable space from each unknown location to the locations around it (within the range of K) (**Figure 2**). This distance is obtained in the exponential weighting function (e^{1/d_i}) in order to calculate a continuous level of membership of existing land use classes for each pixel from Eq. (7) [34]:

$$Membership\ of\ Class = \frac{\sum_{i=1}^c \left(1.0 - \frac{1}{1+e^{d_i}} \right)}{k} \quad (c \leq k) \quad (7)$$

where K represents the total number of the closest variable and fixed pixels, c represents the number of variable pixels in the nearest neighbor k, and d is the linear distance of the variable pixel i.

This algorithm, like the K-nearest neighbor method, may be influenced by irrelevant variables [35]. Different stimulus variables may have different importance in

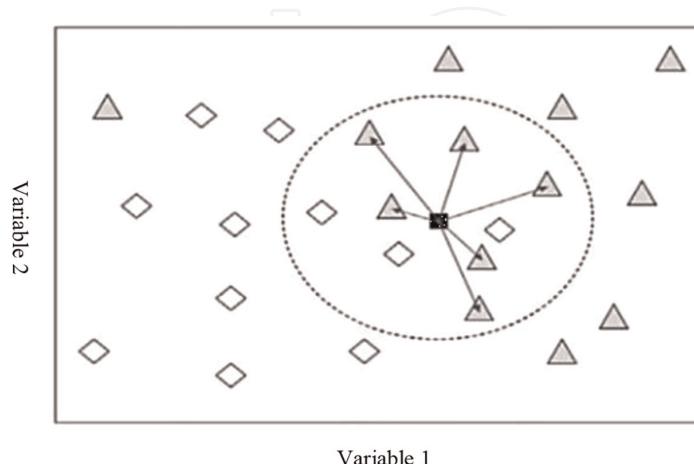


Figure 2.

A representation of the variable space created by two hypothetical variables. In this figure, the triangles represent the variable pixels, and the diamonds represent the fixed pixels. The black square represents the pixel that will be evaluated under the influence of the hypothetical and unknown transmission potential. The dotted circle in the figure represents the range of k ($k = 9$), which is hypothetically 6 pixels for the changing state and 3 pixels for the fixed state, and also the lines showed are the linear distances from the considered pixel in the space is variable [34].

determining transmission potential. This different importance is due to the relative weight by which each variable is multiplied to determine its ability among different classes of land use. In this method, the weight of the importance of each variable is determined by comparing the standard deviation of the variables that have changed within the considered area to the standard deviation of the variables in the study area (Eq. (8)) [34]:

$$\text{The correlation weight of each variable} = \frac{\text{the standard deviation of the variable pixels in the change area}}{\text{the standard deviation of the variables in the study area}} \quad (8)$$

2.6 The location of the study

The Gorganroud river watershed with an area of about 9350 square kilometers with a longitude of 54°2' to 56°22' and a latitude of 36°22' to 37°47' North is in Golestan province (**Figure 3**). The said river is from Golestan National Park originates from Golida Heights, and flows into the Caspian Sea after passing through Gonbadkavous and Aghqala in the west of Khajenafas. This river is located in the southeastern part of the Caspian Sea. Most of its branches are from Alborz mountain and flow from south to north. Among its rivers, we can mention the Madersu, Zaringol, Tilabad, and Chehelchai rivers. The Gorganroud river length is about 300 km, and the direction of the river water flow is from east to west [36].

2.7 Data used

In this study, in order to prepare the forest cover map of 1984 and 2012, the land use maps produced in the Golestan province survey plan have been used. In order to evaluate the accuracy and determine the extent of the forest in 2015, the previous studies [37] by using the TM sensor of the Landsat satellite and also the visual classification of the area through Google Earth images, have been used.

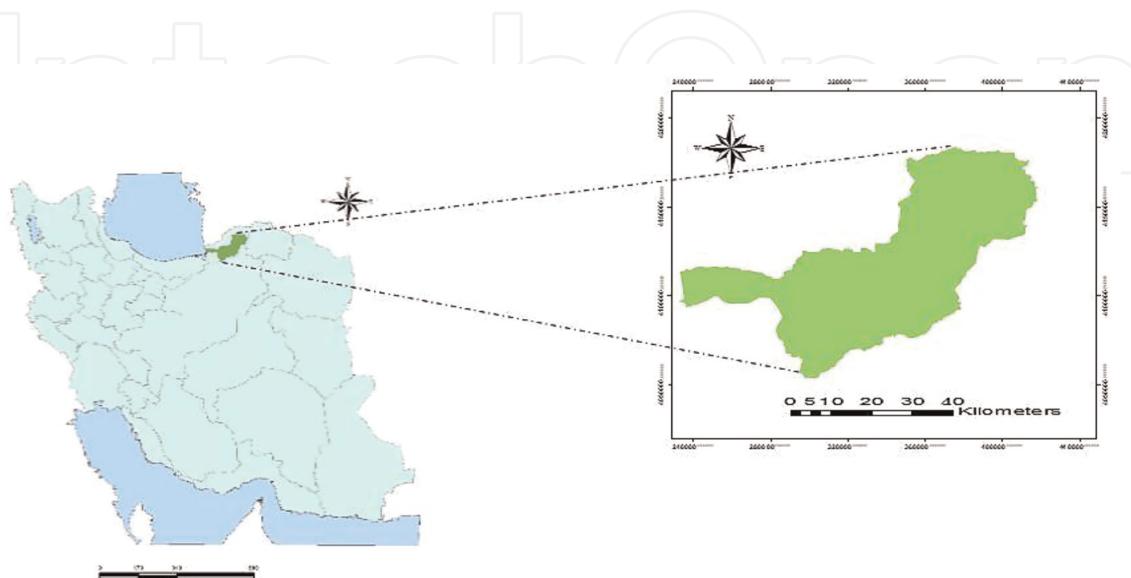


Figure 3.
Location of the study area.

2.8 The transmission potential modeling by using the logistic regression and artificial neural network and similarity weighted instance-based learning (SIM weight)

In this study, by using the forest cover maps of 1984 and 2012, the calibration period is considered, and the transfer potential is modeled by using six variables, and by using the driver variables of the digital model, height, slope, distance from the road, distance from agricultural land, the distance from the edge of the forest and the distance from the village in 1984, the relationship between the change of use from forest to nonforest is determined by using cramer's correlation coefficient.

The probability of changing each user to another user is calculated by using the Markov chain [38]. In this study, changes are predicted for the year 2015 using the hard forecasting model and the calibration period of 1984–2012.

2.9 Validation of the model

For evaluating the accuracy of the modeling, the forest cover map of 2015 and statistics such as the relative performance characteristic curve (ROC), figure of merit [39], and ratio Hits/False Alarms [40] are used. From the ROC/AUC statistic, the range is 0–1 based on the percentage of false positives and true positives. It is used to compare a continuous image of merit with a Boolean image, where a value of 1 indicates complete spatial agreement and a value of 0.5 indicates random agreement. The merit number statistic has a value between zero and one hundred, where the value of one hundred indicates the complete agreement of the predicted map with the ground reality, and the value of zero indicates noncompliance [41]. The closer the figure of merit is to 100. It means that the predicted map has higher accuracy [39]. The figure of merit is obtained from Eq. (9):

$$\text{Figure of merit} = \left(\frac{B}{A + B + C} \right) \quad (9)$$

A: The number of pixels that have changed in reality but remained constant in the prediction (Miss).

B: The number of pixels that have changed in the ground reality, and these changes were correctly predicted by the model (Hits).

C: The number of pixels that have remained constant in the ground reality, but these pixels have changed in the model prediction (False Alarm).

If the ratio of success to error warning in the used model is more than 25%, it can be said that the model has good accuracy in predicting the considered changes [29].

At this stage, according to the relevant statistics, for evaluating the accuracy, the best model with the highest accuracy was selected to continue the research process.

3. Results

The investigation of the changes in the land cover of the Gorganroud watershed showed that during the study period (1984–2012), the largest amount of changes occurred in the field of forest cover destruction (77,214 hectares), and the largest amount of increase is related to agricultural use (28,866 hectares) (**Table 1**).

Class	1984	2012	Changed area Between 1984 and 2012
Residential	3258/4	13,577/3	10,319
Forest	353,128/7	275,914/3	-77,214
Rangeland	178,108/3	197,763/3	19,655
Agriculture	386,290/6	415,156/9	28,866
Water bodies	7253/9	9887/5	2634
Rivers	6825/4	19,821/3	12,996

Table 1.
Changes in all classes of land cover in 1984 and 2012 in terms of hectares.

Figure 4 shows the increase and decrease for each user class during the period of 1984 to 2012 based on the percentage of the study area. The largest increase observed during this period is related to agricultural use (with an increase of 1.2%), and the largest decrease occurred in dense forest use (with an increase of 1.54%).

As **Figure 5** presents, forest destruction during the years 1984 to 2012 mostly occurred in the northeastern part of the area. Severe erosion in the loess soils and destructive floods in this region are among the most important reasons for forest degradation in the northeastern part of this area [42].

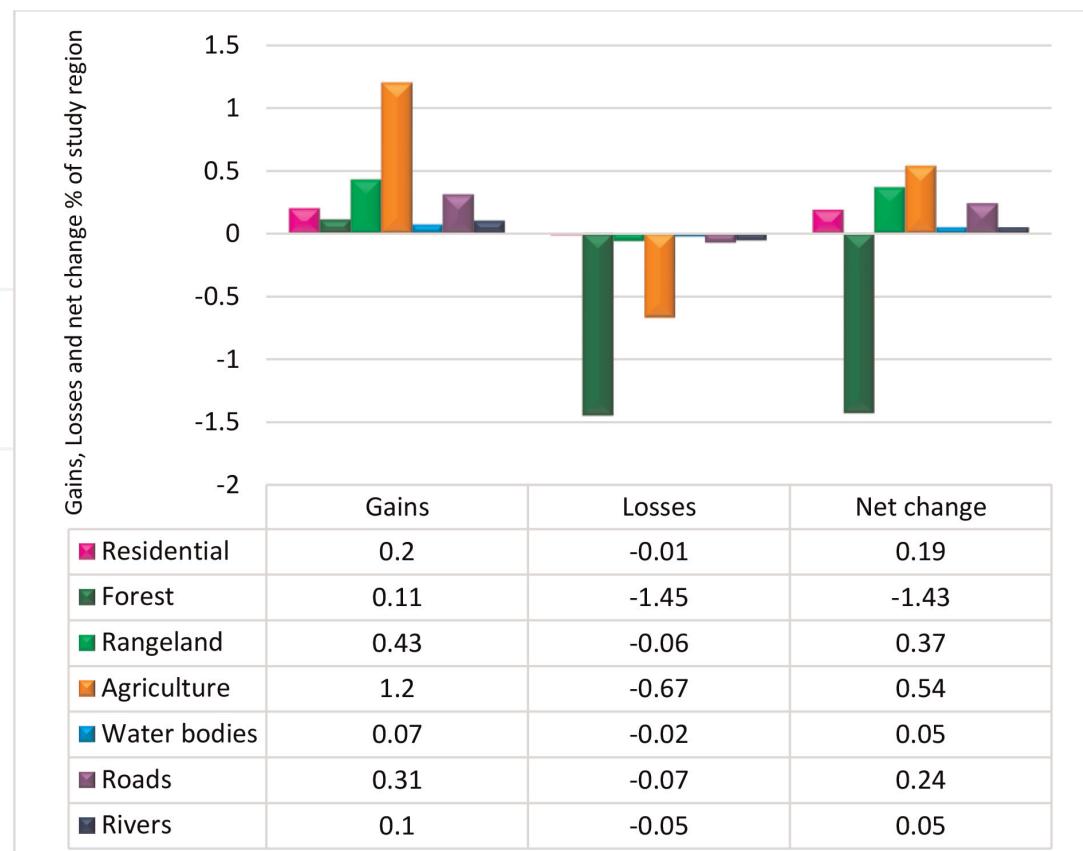


Figure 4.
Gains, losses, and net change for each land cover category between 1987 and 2012 in percentage of the study area.

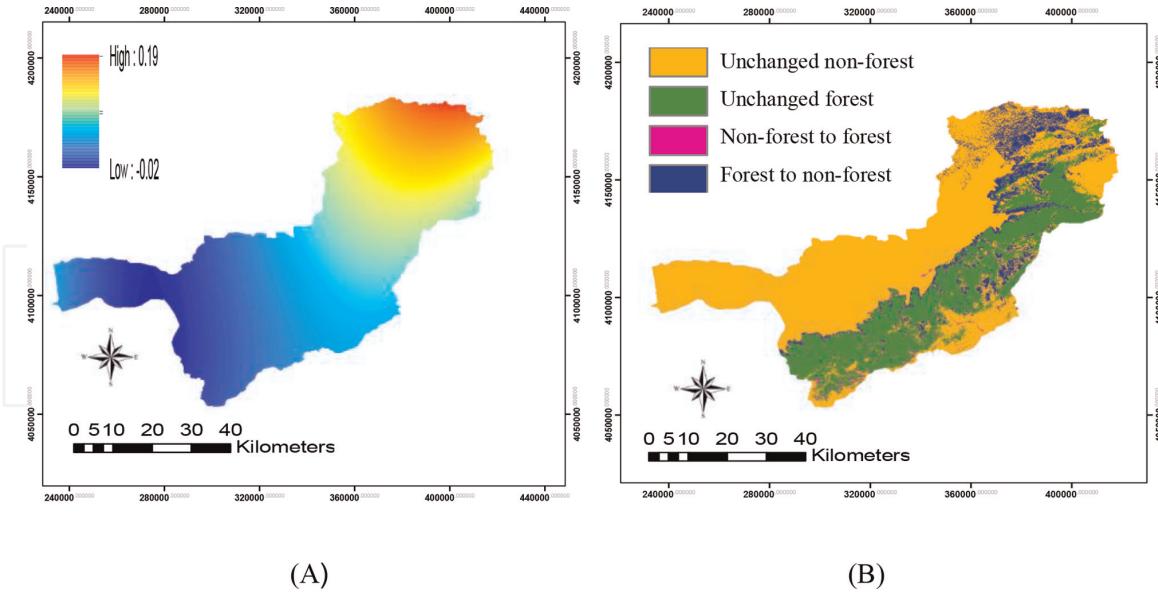


Figure 5.
Spatial distribution of deforestation. A: Transition of forest cover between 1984 and 2012; B: Spatial trend of changes (deforestation) between 1984 and 2012.

3.1 Modeling of transfer potential and predicting changes by using artificial neural network, logistic regression, and SIM weight model and examination of correctness or integrity

With the aim of transfer potential modeling, the connection between motivator factors variants and jungle cover changes by using Crammer coefficient methods has been accomplished for all three modeling (**Table 2**). Cramer's V amounts for the most of variants is upper than 0.15 that demonstrates desirable suitable described power of coefficients that been researched [33]. Highest and lowest cramer's V is related to slope and distance from the village respectively.

3.2 Predicting changes for year 2015 using artificial neural network model

Demanding changes has occurred using Markov chain, and predicting changes for the year 2015 has been accomplished (**Figure 6**). Correction and analyze numbers of Skill Measure for examining term had been 84.52% and 0.6850 ordinarily that is declaring suitable and right prediction. The results of correction examining of this model show that the outcome resulted from model with ROC amount, 0.975 has high

Driver variables	Cramer's V
Slope	0.44
Elevation	0.41
Distance from agriculture	0.41
Distance from forest	0.36
Distance from roads	0.22
Distance from village	0.16

Table 2.
Values of the Cramer coefficient for driver variables.

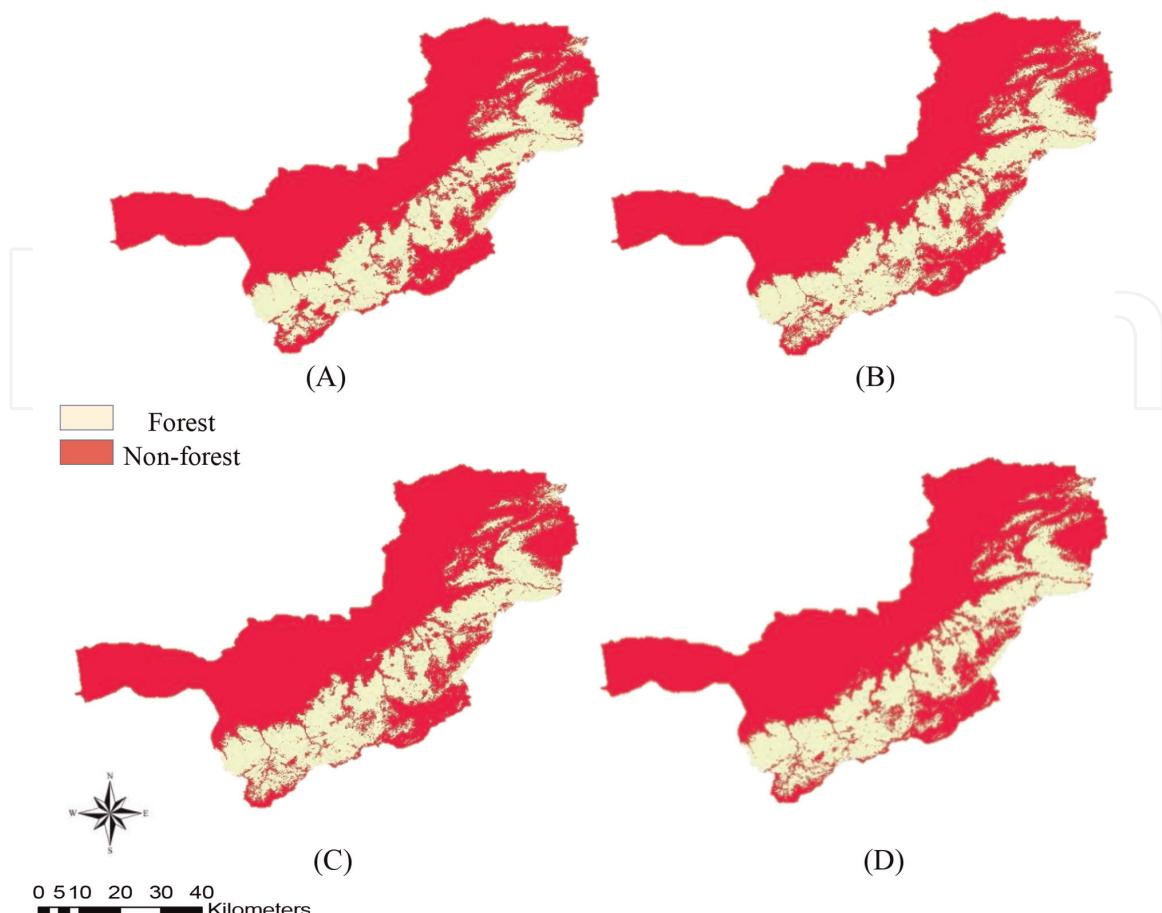


Figure 6.
A: Actual map for 2015; B: Predicted map for 2015 using artificial neural network; C: Predicted map for 2015 using logistic regression; D: Predicted map for 2015 using SIM weight.

harmony with occurred changes. The ratio of Hits/False Alarms for artificial multi-layer perceptron neural network model is 63%, and the ratio of the figure of merit equals 12.

3.3 Predicting changes for year 2015 using logistic regression model

In this case also demanding change has been occurred using Markov chain and changes by prediction for year 2015 has been done (**Figure 6**). Correction examining results logistic regression model shows that outcome resulted from model with ROC amount 0.922 has high harmony with occurred changes. Ratio Hits/False Alarms for logistic regression model is 50% and also amount of figure of merit is 10.

3.4 Predicting changes for year 2015 using SIM weight

In this case, demanding change has also been occurred by using Markov chain and has been done by prediction for year 2015 (**Figure 6**). Correction examining results for SIM Weight Process shows that ROC amount is 0.979. Ratio of Hits/False Alarms for SIM Weight is 52% based on similarity weight model, and also figure of merit is 10.

According to **Table 3**, artificial neural network, in two factors ratio Hits/False Alarms and figure of merit, for examining correction has shown higher quality and, compared to other processes, has more ability and capability for predicting forest

Modeling procedures	Ratio Hits/False Alarms	Figure of merit	ROC
Artificial neural network	63%	12%	0/975
Logistic regression	50%	10%	0/922
SIM Weight	52%	10%	0/979

Table 3.

Comparison between accuracy of the modeling of three approaches was used.

Class	Area (in terms of hectares)						
	1984	2012	2015 (Actual)	2015 (Predicted)	2020 (Predicted)	2025 (Predicted)	2030 (Predicted)
Forest	353,128	275,914	256,659	264,877	253,316	242,169	231,381
Nonforest	585,351	662,565	681,820	673,602	685,163	696,310	707,098
Total	938,479	938,479	938,479	938,479	938,479	938,479	938,479

Table 4.

Areas under forest cover and nonforest during 1984, 2012, 2015, 2020, 2025, and 2030 (actual and predicted).

coverage changes. The amount of ROC has not been observed so much differences between three approaches used. Therefore, artificial neural network model has been chosen as the best model for predicting forest changes prediction.

3.5 Predicting changes of land coverage by using artificial neural network method

Results produced by researching forest cover changes in years 2015 to 2020 shows that in this time 11,561 acres of forest surface (equal to 46 % of region forest surface) been corrupted or ruined. Besides, around 2020 to 2025, approximately 11,147 forest surface (equal to 44 % of the region forest surface) will be declined. Examining forest cover changes between 2025 and 2030 also shows the reduction of 10,788 acres of region forest surface (equal to 42 %'s of region forest surface) (**Table 4**).

4. Discussion

Although many methods are available to model land transition potentials, they are usually not user-friendly and require the specification of many parameters, making the task difficult for decision-makers not familiar with the tools, as well as making the process difficult to interpret. SimWeight is an instance-based learning algorithm based on the logic of the K-nearest neighbor algorithm. The method identifies the relevance of each driver variable and predicts the transition potential of locations given known instances of change. Although computationally simple, the method cannot handle complex nonlinear relations, which is often visible in built-up growth in heterogeneous environments. However, this method can be useful for areas to project infilling or edge-expansion type of built-up growth [43]. SimWeight focused on the distance from the past transitions producing most potential zones near the

change areas, LogReg produced suitable areas considering the linear relationship between driving factors and the built-up change.

While the LogReg approach is straightforward and easy to reproduce, it cannot mimic the complex relationship between the variables and the land use pattern in the changing space. This, therefore, indicates the unsuitability of the method for prediction, especially for dynamic and heterogeneous built-up growth. However, this statement might be applicable for only short-time-scale studies and might not be true for applications that incorporate larger time-scale predictions [44].

The Artificial neural networks, as it iterates multiple times to produce the best fit between the transition and driving variables are able to estimate high change potentials for areas of actual change. Artificial neural networks are a sum of the complex of improving methods that can analyze and calculate nonlinear relations after well training and adjusting weights between income and outcome parameters by high currency. Although the SIM weight model and also logistic regression model are not able to calculate nonlinear relations between variants [40]. Artificial neural networks compared to Logistic Regression Model and SIM weight model, do not need a specific formulation for the statement relation between income and outcome data; otherwise, the relation between income and outcome data has been taken by the learning process [45]. At last, using the artificial neural network method to predict jungle cover changes in the future (years 2020, 2025, and 2030) has been discussed.

In relation to the better performance of the artificial neural network, we can mention the following: high processing speed, the ability to learn the pattern, the ability to generalize the pattern after learning, flexibility against unwanted errors, and not causing significant disruption in case of problems in part of the connections due to the distribution of network weights. This discussion declares that artificial neural network has higher power capability for predicting forest changes.

The results of this part demonstrate forest cover changes in the Gorganroud watershed as well and declare that continuing of the current process in recent 30 years, what kind of problems and huge big enormous obtains, and obstacles to the forest of this region will occur. Putting an obvious clear picture of the future in front of Managers and program makers, scheduling Personals can be efficient and effective capable in scheduling for saving and cohabitating forest regions.

5. Conclusion

According to high valued importance of Golestan province forest study and researching and modeling of corruption amount of these forest seems to be urgent and important. In this research of Land Changer Modeler by using Markov chain utilizing three approach logistic regression, artificial neural network, and learning based on similarity weight sample, researching, and examination of forest cover changes has been done. Produced results from evaluating of model showed higher capability and power of land change modeler for predicting forest cover changes that after investigating and comparing dignity correctness of three modeling approaches based on three factors, ratio of Hits/False Alarms and figure of merit and ROC amount, results show a high level of efficiency and potential for artificial neural network and lower errors obtain from this method compared to other two approaches. In fact, the result shows artificial neural networks could correctly predict changes in pixels that have been changed in ground reality (Hit). On the other hand, models mistake pixels that have been changed in ground reality but stayed constant in prediction for artificial

neural network model compared to Logistic Regression Model and SIM weight model was lower (Miss). Also, mistakes and bugs resulted from the prediction of pixels that have stayed unchanged but changed in predicting model was also lower in the artificial neural network model compared to the other two approaches (false alarm).

This research's results have coordination with those of Mahiny and Turner who compared artificial neural networks to logistic regression. Also, Bayati et al. [46] compared two models of artificial neural networks and logistic regression in forest surveys. In their study, the artificial neural network model produced better results; In justifying this phenomenon, they stated that the reason for the difference between the better performance of artificial neural networks compared to statistical methods could be found in the ability to estimate and predict artificial neural networks with a small amount of data. This is despite the fact that the performance and accuracy of regression methods depend on the sample size strongly, and the small sample size can be a limitation of statistical models. Therefore, in the designed models of the artificial neural network, the small number of samples has not created a significant limitation.

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References

- [1] Le Quéré C, Raupach MR, Canadell JG, Marland G, Bopp L, Ciais P, et al. Trends in the sources and sinks of carbon dioxide. *Nature Geoscience*. 2009;2:831-836
- [2] Van der Werf GR, Morton DC, DeFries RS, Olivier JGJ, Kasibhatla PS, Jackson RB, et al. CO₂ emissions from forest loss. *Nature Geoscience*. 2009;2: 737-738
- [3] Darvishsefat A, Namiranian M. The Study of Spatial Distribution of Changes in the Northern Forests of Iran. 2004. <http://www.GISDevelopment.net/application/nrm/overview>. pp. 1-2
- [4] Naad Ali A, Mahini E, Feghhi J, mathematics B. Classification of forest areas of Golestan province with maximum possibility method by using satellite pictures+ETM. 2012 Autumn. *Environmental Technology and Science Quarterly*. 2001; **Fourteenth Period**(number 3):47-56. (In Persian)
- [5] Mirakhoorloo KH, Akhavan, R. Study the changes of upper border of north forests by using satellite data. *Forest Study and Iran's Senobar*. 2008; **Sixteenth Period**(number 1):139-148. (In Persian)
- [6] Kushwaha SPS. Forest type mapping and change detection from satellite imagery. *ISPRS Journal of Photogrammetry Remote Sensors*. 1990; **45**:175-181
- [7] FSI. India State of Forest Report 2011. Dehradun: Forest Survey of India, Ministry of Environment and Forests; 2011
- [8] Srivastava S, Singh TP, Singh H, Kushwaha SPS, Roy PS. Mapping of large-scale deforestation in Sonitpur district. *Assam Current Science*. 2002; **82**(12):1479-1484
- [9] Nandy S, Kushwaha SPS, Mukhopadhyay S. Monitoring Chilla-Motichurcorridor using geospatial tools. *Journal for Nature Conservation*. 2007; **15**(4):237-244
- [10] Kushwaha SPS, Hazarika R. Assessment of habitat loss in Kameng and Sonitpur elephant reserves. *Current Science*. 2004; **87**(10):1447-1453
- [11] Mahiny AS, Turner BJ. Modeling Past Vegetation Change Through Remote Sensing and GIS: a comparison of neural networks and logistic regression methods. In: Proceedings of the 7th international conference on geocomputation. UK: University of Southampton; 2003. pp. 1-24
- [12] Mas JF, Puig H, Palacio JL, Lopez AS. Modeling deforestation using GIS and artificial neural networks. *Environmental Model Software*. 2004; **19**:461-471
- [13] Khoi D, Murayama Y. Modeling deforestation using a neural network-Maarkov model. *Spatial Analysis and Modeling in Geographical Transformation Process*. 2011; **100**: 169-190
- [14] Kumar R, Nandy S, Agarwal R, Kushwaha SPS. Forest cover dynamics analysis and prediction modeling using logistic regression model. *Ecological Indicators*. 2014; **45**:444-455
- [15] Bagheri R, Shetayi SH. Modeling the reduction of forest area by using logistic regression. *Iran's forest journal*. 2010; **3**: 243-252 (In Persian)

- [16] Hassanzadehpoohsari M. Deforestation Modeling by Using Multivariate Statistical Methods and Artificial Neural Network in Felard Forests. MA Thesis of Natural Resources of Shahrekord Collage. 2011. pp. 180 (In Persian)
- [17] Arkhi S, Jafarzade EA, Yousefi S. Deforestation modeling by using logistic regression, GIS and remote evaluation. Item: North of Ilam forests. Gography and investment journal. 2012;29:31-42 (In Persian)
- [18] Sardarzade M, Metkan EA, Sadatinezhad SJ, Ashourloo D. Destruction of forests prediction by using GIS and RS technics and combination of artificial neural networks Markov chain(Chehelchaigolestan province watershed). In: 20th Geomatic National Show. Tehran: Iran mapping organization; 2012 (In Persian)
- [19] Gholamalifard M, Jorabianshooshtari SH, Abkar, EA, Naimi B. Logistic regression algorithms and artificial neural network comparison in practical modeling of the change transfer potential in Mazandarn's coastal areas. Environmental Researches. 2014;Year 5 (number 1393):167-176. (In Persian)
- [20] Wu X, Shen ZY. Analysis of the changes of land use/cover and landscape pattern in the upper reaches of the Yangtze River. Transactions of the CSAE. 2007;23(10):86-92
- [21] Huang L, Ni L. Object-oriented classification of high resolution satellite image for better accuracy. Spatial Accuracy Assessment in Natural Resources and Environmental Sciences. 2008. pp. 25-27
- [22] Sun H, Li YM, Wang XZ, Ni SX. Method and application of landscape ecological evaluation in the typical small watershed's land use. Geomatics and Information Science of Wuhan University. 2003;28(2):177-181
- [23] Flintrop C, Hohlmann B, Jasper T, Korte C, Podlaha O, Scheele S, et al. Anatomy of pollution: Streams of North Rhine-Wesphalia, Germany. American Journal of Science. 1996;296:58-98
- [24] Davidson C. Issues in measuring landscape fragmentation. Wildlife Society Bulletin. 1998;26:32-37
- [25] Burchell RW. Economic and fiscal impacts of alternative land-use patterns. In: The Land Use Decision Making Process: Its Role in a Sustainable Future for Michigan. January 9–10, 1996. Michigan: East Lansing; 1996
- [26] He Z, Lo C. Modeling urban growth in Atlanta using logistic regression. Computers, Environment and Urban Systems. 2007;31(6):667-688
- [27] Zeng YN, Wu GP, Zhan FB, Zhang HH. Modeling Spatial Land Use Pattern Using Auto Logistic Regression. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Science. 2008. pp. 115-119
- [28] Eastman J, Luis Solorzano R, Megan F, V. Transition potential Modeling for land-cover change. In: Maguire DJ, Batty M, Goodchild MF, editors. GIS, Spatial Analysis and Modeling. Redlands, CA: ESRI Press; 2005. pp. 357-385
- [29] Eastman JR. IDRISI Andes, Guide to GIS and Image Processing. Worcester, MA: Clark Labs, Clark University; 2006
- [30] Li S, Yang B, Qi F. Accelerate global sensitivity analysis using artificial neural network algorithm: Case studies for

- combustion kinetic model. *Combustion and Flame*. 2016;168:53-64
- [31] ZareGarizi A, Sheikh VB, Saadoddin A, Salman Mahini A. The application of logistic regression method in modeling the spatial pattern of the probability of vegetation change (a case study of Chehel chai watershed in Golestan province). *Geographical Space Scientific-Research Quarterly*. 2011; 12(37):55-68 (In Persian)
- [32] Eastman JR. IDRISI Taiga, Guide to GIS and Remote Processing. Worcester: Clark University; 2009
- [33] DiBari JN. Evaluation of five landscape-level metrics for measuring the effects of urbanization on landscape structure: The case of Tucson, Arizona, USA. *Landscape and Urban Planning*. 2006;79:308-313
- [34] Sangermano F, Eastman JR, Zhu H. Similarity weighted instance-based learning for the generation of transition potentials in land use change Modeling. *Transactions in GIS*. 2010; 14(5):569-580
- [35] Tahir TA, Bouridane A, Kurugollu F. Simultaneous feature selection and feature weighting using hybrid Tabu search/k-nearest neighbor classifier. *Pattern Recognition Letters*. 2007;218: 438-446
- [36] Khakpour A, Mehrdadi N, Noori RA, Soroush M. Evaluation of the quality of the Gorganroud River based on field studies. In: Third Environmental Engineering Conference. Tehran: University of Tehran; 2009 (In Persian)
- [37] Management and planning organization of Golestan province. Executive document of Golestan province. Tehran: National Program and Budget Organization; 2012
- [38] Haibo Y, Longjiang D, Hengliang G, Jie Z. Tai'an land use analysis and prediction based on RS and Markov model. *Procedia Environmental Sciences*. 2011;10(C):2625-2630
- [39] Kim OS. An assessment of deforestation models for reducing emissions from deforestation and forest degradation (REDD). *Transactions in GIS*. 2010;14(5):631-654
- [40] Eastman JR. IDRISI Help System. Accessed in IDRISI Selva 17.02. Worcester, MA: Clark Labs, Clark University; 2012
- [41] Pontius RG, Schneider LC. Land-cover change model validation by an ROC method for the Ipswich watershed, Massachusetts, USA. *Agriculture, Ecosystems & Environment*. 2001;85(1): 239-248
- [42] Ajami M, Khormali F. Pedogenic and micro-morphological evidence of degradation of Losi forestland in eastern Golestan province. *Journal of Agricultural Science and Technology, Water and Watersheds Science*. 2012; 16(61):153-141 (In Persian)
- [43] Mas JF, Kolb M, Paegelow M, Olmedo MTC, Houet T. Inductive pattern-based land use/cover change models: A comparison of four software packages. *Environmental Modelling & Software*. 2014;51:94-111
- [44] Overmars KP, Verburg PH, Veldkamp TA. Comparison of a deductive and an inductive approach to specify land suitability in a spatially explicit land use model. *Land Use Policy*. 2007;24:584-599
- [45] Schaap MG, Bouting W. Modeling water retention curves of sandy soils using neural networks. *Water Resources Research*. 1996;32:3033-3040

- [46] Bayati H, Najafi A, Abdulmaleki P. Comparison between artificial neural network (ANN) and regression analysis in tree felling time estimation. Iranian Forest and Spruce Research Quarterly. 2012;20(4):559-607 (in persian)

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