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ORIGINAL RESEARCH

Ecological Modelling as a Tool for Damages Reduction in Forest Ecosystems during Skidding

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ABSTRACT:

Stand ecology can be affected during forest harvesting. The aim of the present study was to determine potential area extent of stand damages on the forests based on stand monitoring data collected from 351 circle plots with the surface area of 314 m^2 before the beginning of logging operations. Slope percent, land form, roughness, forest type, stand density, extracted volume and extraction system were collected as predictor variables. Residual tree and regeneration damage as response variables were measured during postharvest assessments too. In this context a geospatially explicit predictive model of stand damage was developed using LR and FR as an interface and collection of functions in R. Geospatially, stand damages in terms of residual tree and regeneration map were depicted by GIS package, separately. According to success and prediction rates, LR had the best performance model compared with FR in residual tree and regeneration damage modelling. Based on the LR results slope, forest type, stand density, harvested volume and extraction system were the most effective variables controlling stand damages. These models by local calibration are decision support tools to predict stand damages during ground-based harvest operations on other forest lands.

Keywords:
AIC, Forest Ecosystems, Logging, Predictor Variables

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INTRODUCTION

In all of the hyrcanian forests in the north of Iran, selection silviculture is a common forest management system and it is progressively becoming a more common forest management practice globally (Marvie Mohadjer, 2004). In single-tree selection logging, 1-2 percent of standing volume is removed from the stand and residual trees are retained across a full range of size classes approximating a target tree diameter distribution, intended to ensure recruitment of trees into successively larger size classes.

Uncontrolled selection logging causes vast soil disturbances (Najafi *et al*., 2009), reduced floral and faunal diversity (MacDonald *et al.,* 2014), extensive canopy cover removal (Rockwell, 2007), residual tree damages, regeneration loss and long-term changes in tree species composition and forest types (Saga and Selas, 2012).

The guiding idea of sustainability orders that a commercial forest should be managed to decrease as much undesirable damage as possible to the residual stand and all over forest ecosystem. This is an essential purpose for both ecological and economic reasons (Muller, 1998). Reduced Impacts on Logging (RIL) is one of the harvests methods that minimize residual stand damages via directional felling, pre-harvest inventory, precise planning of forest roads and skid trails, finding an optimal log landing location, and mapping.

Mapping of stands susceptibility to damages during skidding is performed by modelling; whereas it is assumed which conditions that lead to stand damages in the past are likely to them in the future as well (Vorpahl *et al.,* 2012). Modelling predict damages by a set of predictor variables in any location in a landscape over a period of time without the necessity of mathematically describing the underlying processes in a physical way. Few studies have reported the prediction of stand damages in forest operations (Sowa and Kulak, 2008; Reeves *et al.,* 2012). Logistic Regression (LR) with a logit link function, is one of the most frequently used techniques in damages susceptibility modelling. LR consists of an additive combination of single parametric terms, each representing a linear function of a single predictor. Due to their simplicity LR allow for a broad variety of statistical analyses. Nonlinearities as well as predictor interactions can be regarded by explicit definition of additional predictor variables (Vorpahl *et al.,* 2012).

Besides LR, Frequency Ratio (FR) is such a models that have not been used for prediction of forest stand damages despite of extensive application in other natural resource sciences. FR as a bivariate statistical method can be applied as a suitable geospatial assessment tool to determine the hypothetical relationship between response and predictor variables, consist of multi-classified maps (Pourghasemi *et al.,* 2012).

The objectives of this study was to apply LR and FR ecological modelling techniques to model the relationships between stand damages (consisting residual tree and regeneration) and predictor variables and evaluate the performance of above models using Area Under the Curve (AUC).

MATERIALS AND METHODS

Study Area

The study area is located in the western part of Mazandaran province, Iran (Figure 1). The application forest lies between the latitudes 36° 30′ to 36° 35′ N, and the longitudes 51° 27′ to 51° 33′ E, that covers an area of 108 ha. Altitude in the study area varies between 1400 and 2000 m above sea level. The slope percent of the area range from 18 to as much as 120. Based on Iranian Meteorological Department, the temperature of region area ranges between 0 °C and 32 °C. The mean annual rainfall is around 800 mm, most of which falls during the month of September and December. The study area is covered by two soil textures clay and clay – loamy according to laboratory results. The dominant species are beech (*Fagus orientalis* Lipsky), with other species consisting maple (*Acer velutinum* Boiss), horn (*Carpinusbetulus* L.), alder (*Alnus subcordata* C. A. Mey), and oak (*Quercus castaneifolia* C. A. Mey).

The trees were felled using manual chain saw and logs transported from stump to forest road side by *mule* and *Zetor* (LTT-100A) fuel woods and timbers, respectively. Extraction was done between mid-June to July 2013.

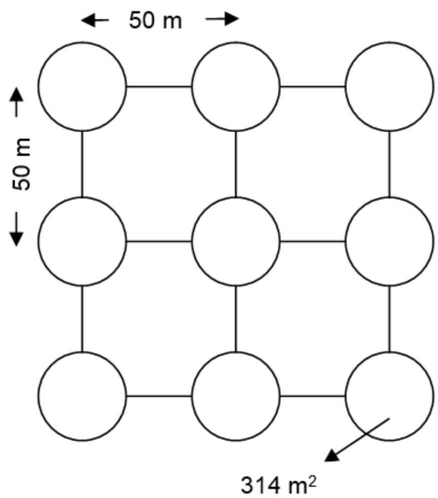

Figure 1. Study design for single plot

Sampling Methods

From mid-June to July in 2013 we used random-systematically methods to determine response and predictor variables for forest. We established 50 * 50 network to set up 351 sampling plots of 314 m^2 (radius 10 m) in network crossing. Prior to skidding were recorded; predictor variables consisting of slope percent (<30, 30-60, >60), land form (ridge, hillside, canyon), roughness (even, uneven, rough) (Owende *et al.,* 2002) forest type (pure beech, beech-maple, mixed: alder-oak-hornbeam), stand density per ha (<150, 150-200, >200), extraction system (*Mule* or *Zetor*), and were carried out extracted volume m^3/ha (<10, 10-13, >13) during skidding.

Post-harvest stand damages data (response variables) had been assigned 0 for absent of damages (non-occurrence) or 1 for present of damages (occurrence) for each plot. Taking into account studies concerning ecological damages to stands by other studies (Iskandar *et al.,* 2006) the following classification was assumed:

Residual tree damage: bark-wood damage > 25 cm^2;

Regeneration Damage: breaking and regeneration destruction (DBH < 7.5 cm^2)

Geospatial-Ecological Modelling

Logistic Regression Model

In general, to predict ecological damage, it is necessary to assume that damages occurrence is determined by damage-related variables, and that future damages will occur under the same situations as previous damages. In the present study, was fitted a third order polynomial was fitted for each predictor and additionally performed a backwards stepwise variable selection based on the Akaike Information Criterion (AIC) and displayed prediction values in GIS. The purpose of using AIC is to find an optimal trade-off between an unbiased approximation of the underlying model and the loss of accuracy caused by estimating a number of parameters, and the number of data points used in its calibration (Dawson *et al.,* 2006). The standard logistic model equation can be expressed in its simplest form as (Eq. 1):

(Eq. 1):

$$\mathrm{Y} = \frac{Exp^{\alpha + \beta 1\mathrm{X}1 + \beta 2\mathrm{X}2 + ... + \beta \,\mathrm{i}\mathrm{Xi}}}{1 + Exp^{\alpha + \beta 1\mathrm{X}1 + \beta 2\mathrm{X}2 + ... + \beta \,\mathrm{i}\mathrm{Xi}}}$$

Where:

Y: varies from 0 to 1,

a: intercept of the model,

βi (i=1, 2, 3, …, n): slope coefficient of the model

i: number of independent variables

Xi (i= 1, 2, 3, …, n) is the independent variable.

Frequency Ratio Model

To quantitatively construct the damage susceptibility map, the FR model should be in a GIS environment. The FR is the ratio of the area where damages occurred in the total study area, and is also the ratio of the damage occurrence to non-occurrence for the given attribute. At first, the FR was calculated for each range or type of variable; the FR were then summed to calculate the Damage Susceptibility Index (DSI) (Eq. 2) (Pourghasemi *et al.,* 2012):

(Eq. 2):

$$DSI = \sum_{i=1}^{n} FR$$

Where DSI is damage susceptibility index and n is the number of variables. The FR method is very easy to apply, and results reported by many authors (Yilmaz, 2009) are readily intelligible.

Models Comparison

After training, both models will be grouped of one type that were trained on the same functional part of stand damages and calculated quality measures from a tenfold internal cross-validation to determine success and prediction rates.

RESULTS

(Eq. 3):

$$Y = \frac{e^{-5.11 - 22.34\,\text{extractionsystem(mule)} + 0.01\,\text{extractedvolume} + 0.1\,\text{stand density} + 0.04\,\text{slope}}}{1 + e^{-5.11 - 22.34\,\text{extractionsystem(mule)} + 0.01\,\text{extractedvolume} + 0.1\,\text{stand density} + 0.04\,\text{slope}}}$$

According to success and prediction rates, LR had the best performance model compared to FR in residual tree damage modelling (Figure 2, 3).

The results of spatial relationship between residual tree damage and predictor variables using frequency ratio model is shown in Table 1. In the mentioned table, slope<30% and mule extraction system indicated low probability of residual tree damage occurrence (FR: 0). Also zetor extraction system had the highest residual tree damage (FR: 2.434).

Significant predictor variables on residual tree damage based on LR model is shown in table 2. Additionally, the resultant beta coefficients and test statistics for each independent variable in the logistic regression equation are given in Eq. 3. Based on the analysis of logistic regression coefficients, the results showed that slope, stand density and extracted volume have positive effect on residual tree damage occurrence. It also showed that stand density has the highest beta coefficient (0.1), followed by slope (0.04) and extracted volume (0.01). In contrast, mule extraction system has negative effect on residual tree damage (Beta coefficient: -22.34).

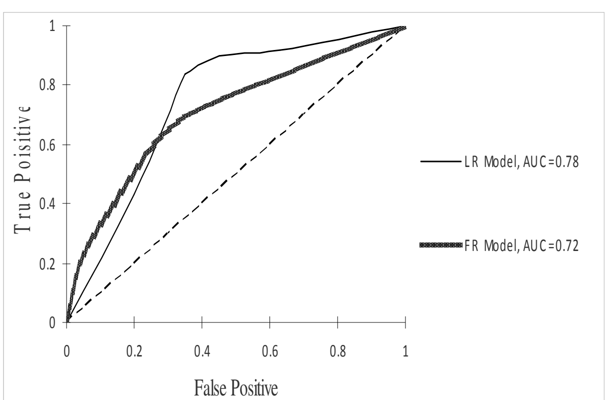

Figure 2. Success rate curves for the residual trees susceptibility maps produced in this study

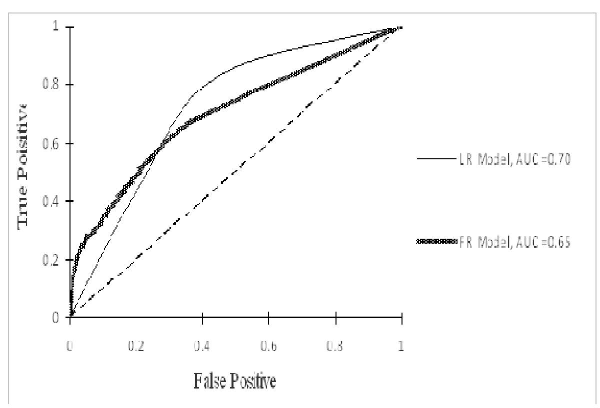

Figure 3. Prediction rate curves for the residual trees susceptibility maps produced in this study

Table 1. Spatial relationship between residual tree damage and predictor variables by FR model

Predictor Variables		No. of pixels in domain	Percentage of domain	No. of Damage	Percentage Of Damage	FR
Slope (%)	<30	200	1.871	0	0.000	0.000
	30-60	6575	61.518	52	46.847	0.762
	>60	3913	36.611	59	53.153	1.452
Land Form	canyon	3733	34.927	36	32.432	0.929
	hillside	2170	20.303	20	18.018	0.887
	ridge	4785	44.770	55	49.550	1.107
Roughness	even	4504	42.141	49	44.144	1.048
	uneven	2971	27.798	30	27.027	0.972
	rough	3213	30.062	32	28.829	0.959
Forest Type	pure beech	2646	24.757	23	20.721	0.837
	beech-maple	5430	50.805	71	63.964	1.259
	mixed	2612	24.439	17	15.315	0.627
Stand Density (ha)	<150	4138	38.716	23	20.721	0.535
	150-200	3631	33.973	43	38.739	1.140
	>200	2919	27.311	45	40.541	1.484
Extracted Volume (m^3/ha)	<10	3190	29.847	10	9.009	0.302
	10-13	1831	17.131	29	26.126	1.525
	>13	5667	53.022	72	64.865	1.223
Extraction System	mule	6297	58.917	0	0.000	0.000
	zetor	4391	41.083	111	100.000	2.434

Table 2. Significant predictor variables on residual tree damage according to LR model

Variables	DF	AIC	pr (>Chi)
Slope	1	258.38	0.00000
Stand Density	1	226.37	0.00174
Extracted Volume	1	224.17	0.00581
Extraction System	1	429.39	0.00000

Finally based on the best model (LR) was mapped area susceptibility was mapped to residual tree damage. The map reclassified it in two categories of susceptibility: 0-0.25 (low) (41.05%) and 0.50-0.75 (high) (58.95%) (Figure 4), because there wasn't any pixel in two classes' 0.25-0.50 (medium) and 0.75-1 (very high).

In the regeneration damage modelling, LR model had the best success and prediction rate compared to FR model (Figure 5, 6).

It was found that regeneration damage in stand density<150 has a lower frequency ratio (0), but in stand

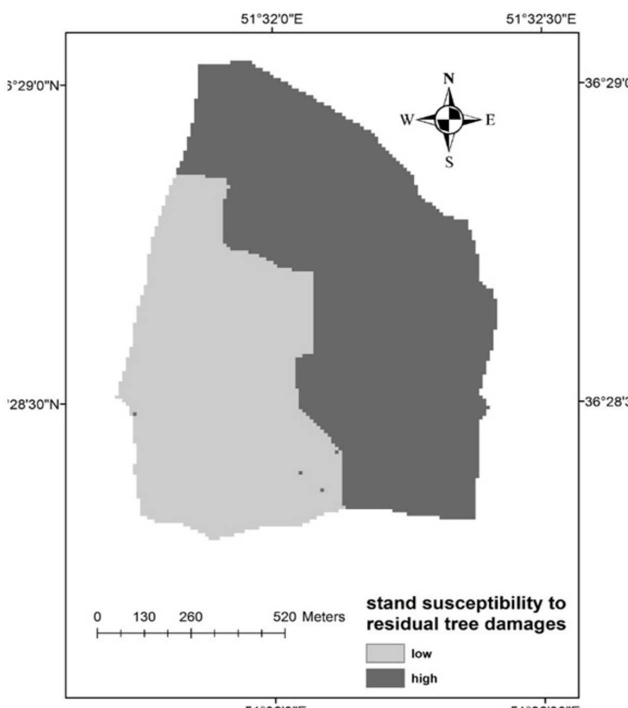

Figure 4. Residual tree susceptibility map produced by LR model

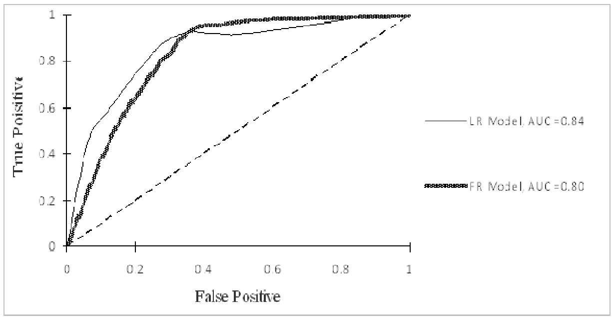

Figure 5. Success rate curves for the regeneration susceptibility maps produced in this study

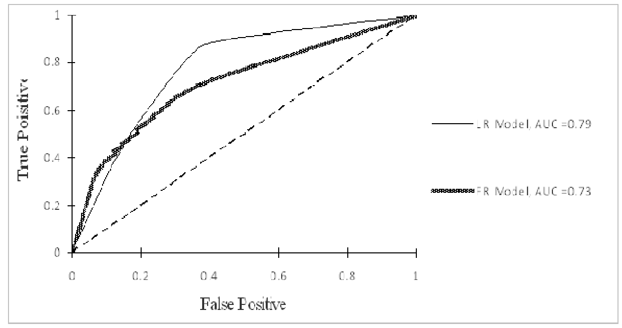

Figure 6. Prediction rate curves for the regeneration susceptibility maps produced in this study

density>200 there was a higher probability of a regeneration damage occurrence (FR: 2.34) (Table 3).

The resultant beta (β) coefficients and test statistics for each independent variable in the logistic regression equation are shown in table 4 and Eq. 4. Based on the analysis of logistic regression coefficients, the results showed that slope, forest type, stand density and extracted volume have positive effect on regeneration damage occurrence. It was also observed that mixed forest had type has the highest beta coefficient (3.21), and then, beech-maple forest type, extracted volume, stand density and slope have most effect by coefficients of 2.18, 0.4, and 0.1, respectively. In contrast, the extraction system has negative effect on regeneration damage of study area, having beta coefficient of (β) -1.96.

Finally based on the best model (LR) area susceptibility was mapped to regeneration damage. The map reclassified it in four category of susceptibility: low (60.09%), moderate (10.09%), high (8.70%) and very high (21.12%) (Figure 7).

DISCUSSION

According to the results, presence of extensive ecological damages to stands is due to activities such as skidding operations and site susceptibility degrees. Slope, forest type, stand density, harvested volume, and extraction system had significant effect on modelling of stand damages based on the LR model.

Skidding perform unstable in steep slopes, therefore timbers move around that leads to residual tree and regeneration damages. Sist *et al.,* (2003) and Naghdi et al., (2009) reported that skidding on steep train increase stand damages compared to gentle train.

Site susceptibility to damages is different as for forest types. Sowa and kulak (2008) showed variation among forest types could ascend stand damages occurrence probability from 0.5 to .97 odds ratio.

Stand density is one of the most important effective variables on stand damage during forest skidding. Timber transport is difficult with increasing in tree and regeneration density per ha, because should be kept trees and regeneration groups should be kept against harvesting operators. This condition increases the collision chance of timbers and residual stands. Sist *et al.,* (2003) and Iskandar et al., (2006) showed that stand

(Eq. 4):

$$Y = \frac{e^{\begin{array}{l}-17.85 + 2.18\ \text{forest type (beech - maple)} + 3.21\ \text{forest type (mixed)} - 1.96\ \text{extraction} \\ \text{system (mule)} + 0.40\ \text{extracted volume} + 0.1\ \text{stand density} + 0.08\ \text{slope}\end{array}}}{1 + e^{\begin{array}{l}-17.85 + 2.18\ \text{forest type (beech - maple)} + 3.21\ \text{forest type (mixed)} - 1.96\ \text{extraction} \\ \text{system (mule)} + 0.40\ \text{extracted volume} + 0.1\ \text{stand density} + 0.08\ \text{slope}\end{array}}}$$

Table 3. Spatial relationship between regeneration damage and predictor variables by FR model

Predictor Variables		No. of pixels in domain	Percentage of domain	No. of Damage	Percentage Of Damage	FR
Slope (%)	<30	200	1.871	2	1.639	0.876
	30-60	6575	61.518	74	60.656	0.986
	>60	3913	36.611	46	37.705	1.030
Land Form	canyon	3733	34.927	45	36.885	1.056
	hillside	2170	20.303	16	13.115	0.646
	ridge	4785	44.770	61	50.000	1.117
Roughness	even	4504	42.141	42	34.426	0.817
	uneven	2971	27.798	43	35.246	1.268
	rough	3213	30.062	37	30.328	1.009
Forest Type	pure beech	2646	24.757	14	11.475	0.464
	beech-maple	5430	50.805	63	51.639	1.016
	mixed	2612	24.439	45	36.885	1.509
Stand Density (ha)	<150	4138	38.716	0	0.000	0.000
	150-200	3631	33.973	44	36.066	1.062
	>200	2919	27.311	78	63.934	2.341
Extracted Volume (m^3/ha)	<10	3190	29.847	20	16.393	0.549
	10-13	1831	17.131	29	23.770	1.388
	>13	5667	53.022	73	59.836	1.129
Extraction System	mule	6297	58.917	48	39.344	0.668
	zetor	4391	41.083	74	60.656	1.476

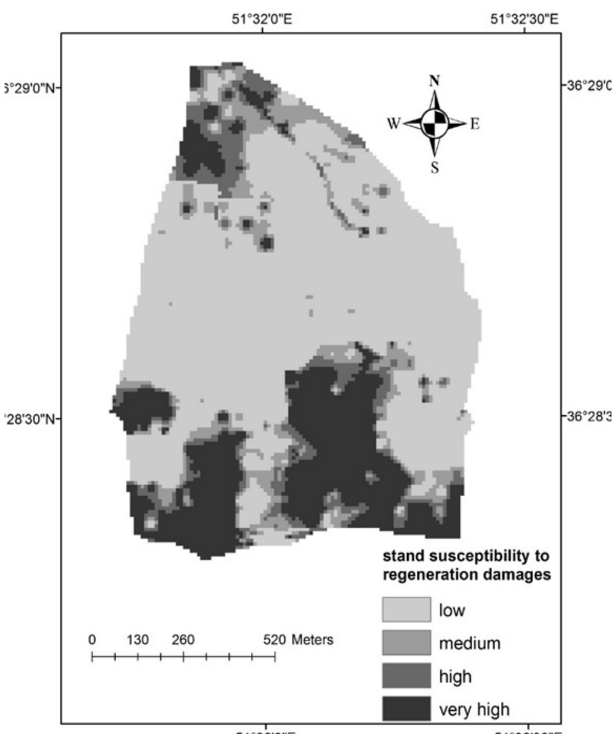

Figure 7. Regeneration susceptibility map produced by LR mode

density has the most effect on stand damages in short and long term, spatially about selective logging method.

In the present study it is shown in relation to variables influenced by harvesting intensity such as stand damages, number of harvested trees per hectare etc.; plays a key role. According to results there have a linear relation between harvested volume and both stand damages, however Panfil and Gullison (1998) reported that the relationship between variables is unlikely such as percent ground area damaged and harvested volume are

Table 4. Significant predictor variables on regeneration damage according to LR model

Variables	DF	AIC	pr (>Chi)
Slope	1	203.86	0.00000
Forest Type	2	162	0.00147
Stand Density	1	354.58	0.00000
Extracted Volume	1	213.90	0.00000
Extraction System	1	160.72	0.00179

linear (Jackson *et al.,* 2002). Additionally they mentioned this relationship affected by other variables of spatial forest types.

This greater damages is primarily due to the extremely large area disturbed by skidder relative to mule logging especially in residual tree damages (Jackson *et al.,* 2002). The much larger area damaged by skidder was the resulting of greater size of transported timbers by it. Also, skidders need large spaces for relocation compared to animals therefore increased neighbor stand damages. Skidder impact on residual trees was more than regeneration compared to mule logging. This can be observed in the residual trees map (Figure 4), the area was divided into two categories low and high susceptibility. Because all of the residual tree damages created by skidder and its role was more than those of others variables. Thus residual tree susceptibility map largely constructed is similar to the extraction system map.

The critical strategy in ecological prediction modelling is the validation of predicted results so that the results can provide a meaningful interpretation with respect to future stand damages. However, the success rate curve can help to determine the resulting of stand damages as well. The susceptibility maps have been classified in the areas of existing damages, but the prediction rate just can just explain how well the model and predictor variables predict the damages.

AUC analysis was used to validate the best model (LR) for stand damages mapping. This curve is a standard methodology to evaluate the model precision (Pourghasemi et al., 2012). The AUC curve can display imagination of the trade-off between the false-negative and false-positive rates for every possible cutoff value. The AUC curve shows the false-positive rate on the X axis and the true positive rate on the Y axis. The AUC plots the accuracy of a prediction model system by describing the system's ability to expect the correct occurrence or non-occurrence of pre-defined "events". According to Pourghasemi *et al.,* (2012) qualitative relationship between AUC and prediction accuracy can be classified into the following categories: 0.9–1 (excellent); 0.8–0.9 (very good); 0.7–0.8 (good); 0.6–0.7 (average); and 0.5–0.6 (poor). According to prediction rate of the best model (LR), it is showed that the model used during this study had a reasonably good precision in predicting the sand damages occurrence mapping in the mapping of study area.

The results of current study also showed that the FR model can be used as an easy tool in the evaluation of stand damages susceptibility when a enough number of data are available.

CONCLUSION

Damage to forest ecosystems consisting residual trees and regeneration may have important negative implications for future harvests in the forests of Iran. The present study suggests that via modelling and prediction of susceptibility forest sites can decrease the number and extent of logging-induced damages on residual trees and regeneration. These approaches are the part of controlled selective logging and reduced impact logging that lead to reduced stand damages. These results are the most appropriate tools for managers to manage forests more accurately.

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