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Modelling and mapping of soil damage caused by harvesting in Caspian forests (Iran) using CART and RF data mining techniques

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Abstract

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Controlling the soil damage caused by forest harvesting has a key role in forest management due to its effect on forest dynamics and productivity, mainly through modifying the physical, mechanical, and hydrological context of soil. This study was conducted to evaluate the soil damage susceptibility in one of the Caspian forests, Iran. For this purpose, two data mining techniques including classification and regression tree (CART) and random forest (RF) were applied. A total of 224 soil damage locations were identified primarily from field surveys. Then, 10 conditioning variables were produced in GIS. For model performance, the outputs of the analyses were compared with the field-verified soil damage locations. Our results show that slope degree, soil type, and slope aspect had the highest weight on soil damage, in the order of their appurtenance. Additionally, according to the relative operating characteristics curve, RF is a more suitable prediction model for soil damage zoning compared to CART. In summary, the findings of this study suggest that soil damage susceptibility mapping is an effective technique for Caspian forests, Iran.

Keywords: forestry operations; hazard zoning; spatial prediction; timber skidding; tree ensemble techniques

Soil damage is among the challenging causes for forestry operations, forest management activities (Brevik et al. 2016; Huang et al. 2017), and especially for the forest areas with ground-based skidding such as Caspian forests in northern Iran. A considerable deal of investigations has addressed the soil damage such as soil compaction, rutting, and displacement during harvesting in these forests (Najafi et al. 2009; Majnounian, Jourgholami 2013). Previous results indicate that soil damage during logging operations has different destructive effects such as modifying soil structural properties (Najafi et al. 2009), increasing soil bulk density (Ezzati et al. 2014), restricting water and air transport into soils (Cambi et al. 2015), decreasing soil porosity (Agherkakli et al. 2014), intensifying soil erosion risk (Ezzati et al. 2014) and reducing soil sustainability (Majnounian, Jourgholami 2013).

Although soil degradation has few benefits in the plant growth, its harmful impacts are much more common (Kozlowski 1999). Most of the studies related to soil damage in Caspian forests deal with soil damage assessment or recovery (Ezzati et al. 2014; Naghdi et al. 2014), however, their findings do not seem to be useful in mitigation of soil damage.

One of the fundamental activities in soil damage prevention is to make soil damage susceptibility maps by prediction models (Pereira et al. 2017). These maps help to divide the forest area into subdivisions according to soil susceptibility levels for harvesting operations (Pourghasemi et al. 2012a). Soil damage susceptibility can be provided using a number of different techniques such as linear regression (Singh, Kushwaha 2011), generalized additive models (Goetz et al. 2011), frequency ratio model (Pourghasemi et al. 2012a), neuro-fuzzy (Manel et al. 1999) and tree-based methods (Cutler et al. 2007). Despite the widespread use of these methods in other sciences, they have been only limited to a linear model which is performed to predict soil damage in forest ecosystems (Sowa, Kulak 2008; Reeves et al. 2012).

Furthermore, in a few soil damage and hazard mappings, however, independent performance of statistical models for soil damage hazard or damage assessment is lacking. Thus, a random-based separation of soil damage, which is also done in the present work, is the most acceptable method of performance (van Westen et al. 2003). The other goals pursued by conducting this work are: (*i*) to employ classification and regression tree (CART) and random forest (RF) modelling as two old and new tree-based method with a bivariate statistical approach to define the physical parameters contributing to the occurrence of soil damage at Lalis forests, Iran, (*ii*) to prepare a soil damage hazard map that possesses high prediction and success rates for the study area.

MATERIAL AND METHODS

Study area. The study area with a coverage area of around 1,500 ha is located in the Caspian forests in northern Iran (Fig. 1). The climate of this mixed hardwood forest is humid and moderate, with temperatures ranging from 3 to 25°C and 1,000 mm of annual precipitation (Administration of Nowshahr Natural Resources 2016). The soil type is classified as clay, silty-loamy and clay-loamy. The dominant tree species are beech (*Fagus orientalis* Lipsky), hornbeam (*Carpinus betulus* Linnaeus), maple (*Acer velutinum* Boissier), and alder (*Alnus subcordata* C.A. von Meyer) (Administration of Nowshahr Natural Resources 2016). In the study area, stands have an uneven-aged structure and 2.5 $m^3 \cdot ha^{-1} \cdot yr^{-1}$ volume increment that is managed under a single selection system.

In these forests, ground-based extraction systems are commonly used as the primary bunching extraction and transportation system by all logging companies. A steel-tracked skidder Zetor LTT-100A (KEMP company, Russia) equipped with a winch (90,000 MPa pulling force) was used to remove the timber from the study area to the landing (Table 1). Primary skid trails leaving the road were constructed and used only by the skidder.

Extraction was done between June and July (2009–2016). At the time of logging and sampling, weather conditions were dry and warm for more than one month, so that average soil-water content at the time of logging was 29%.

Data collection. The selection of forest site factors for susceptibility prediction depends on the availability of database and resources and terrain attributes (Pourghasemi et al. 2012b). The pre-

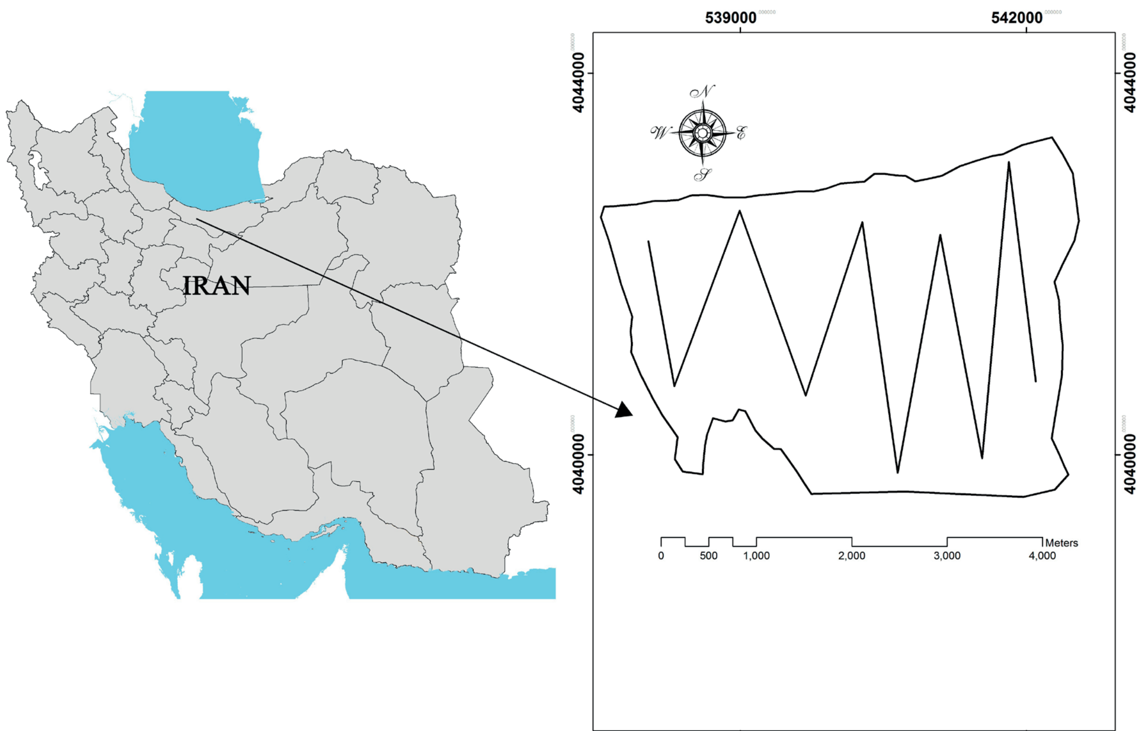

Fig. 1. Study area and traversed transect maps

Table 1. Technical details of the Zetor LTT-100A steel-tracked skidder (KEMP Company, Russia)

Length (m)	6
Width (m)	2.6
Track (m)	3
Operation power (kW)	88.2
Ground unit pressure (MPa)	0.049
Track drive sprockets	cast-steel toothed wheel
Pressure in hydraulic system (MPa)	14
Number of teeth	9
Width of caterpillar (cm)	44
Tractor mass maintenance (kg)	11,200

dictor variables were determined according to field observations and then converted into a vector type spatial database using the GIS. A digital elevation model (DEM) by 10 m interval contours was created from the 1:25,000 scale topographical map.

Slope degree, slope aspect, altitude, slope length (LS), topographic position index, and topographic wetness index were produced by the mentioned DEM. The soil type map was obtained from a 1:100,000 scale geological map. The forest type and density were classified using a Landsat Thematic Mapper and were verified by a field survey. In addition, the buffers of road and skid trails were provided at 50 m intervals.

During the field survey in the study area, a total of 224 soil damage spots were mapped. The modes of failure for the soil damage identified in the study area were divided into four classes (low, medium, high and very high) in accordance with the soil damage classification system proposed by Page-Dumroese et al. (2009).

Using this method, 19,350 m traversing transects were randomly located (Fig. 1) in such a way that 387 monitoring points were set at 50 m intervals on transects. A monitoring point is defined as a 15 cm diameter circular area around. In this work, 224 (56 monitoring points for each soil damage class) monitoring points out of 387 were determined randomly.

Soil damage modelling

CART. CART is an efficient prediction tool since it provides intuitive results that are easy to visualize (Cosman et al. 1993). CART is capable of dealing with any type of predictor variables such as numeric, binomial, ordinal categorical as well as providing a simple predictor preparation method (Steinberg 2009). Furthermore, a difference in measurement scales between predictor variables and monotonic variations cannot affect model outcomes.

CART includes a non-parametric regression method that grows a decision tree ensemble on a binomial partitioning algorithm that iteratively splits the predictors as long as the groups are homogeneous or contain not fewer observations than a user-defined threshold. The mean of the response values in each node presents the terminal node predicted value (Breiman et al. 1984).

Regression trees can cover missing data by surrogates, thus providing an advantage for dealing with outlier data (Huang et al. 2004). In addition to the regression modelling, the hierarchical structure of classification allows model interaction between predictor variables (Provost, Domingos 2002).

In the current study CART was made by the rpart package, as a function of R software (Version 3.2.5, 2016). In order to prune the decision tree, Gini coefficient via complexity parameter ratio was used to determine the most important predictors.

The Gini coefficient (G) measure of impurity of a node t was calculated using Eq. 1, where the target is a binary value (Steinberg 2009):

$$G(t)=1-p(t)^2-(1-p(t))^2 \qquad (1)$$

where:

$p(t)$ – (possibly weighted) relative frequency of class 1 in the node.

RF. RF includes an ensemble of classification and regression trees (Breiman 2001; Liaw, Wiener 2002). In this new technique, random feature selection incorporates with bagging method. Firstly, training data are divided into subsamples and each tree is grown on a bootstrap subsample. In the next step, best split for a random subset of predictor variables is selected at each node. The number of trees and the number of required predictor variables for splitting at each node have a key role in RF model. The number of required predictor variables for splitting at each node is the square root of the number of predictor variables. Like in the CART method, the Gini coefficient is calculated to select the most important variables. For the k^{th} class classification problem the Gini index is defined according to Eq. 2 (Genuer et al. 2010):

$$G=\sum_k P_k(1-P_k) \qquad (2)$$

where:

P_k – proportion of observations at the node in the k^{th} class.

The index is minimized when one of the P_k takes the value 1 and all the others have the value 0

(Cutler et al. 2007). This model was performed by randomForest package in R software.

Models performance. Out of the 224 identified soil damage cases, 157 (70%) locations were assigned randomly for the soil damage susceptibility maps as training, while the remaining 67 (30%) cases were used for the model verification. To apply validation, we used success and prediction rates and relative operating characteristics (ROC) curve, Akaike information criterion (AIC) value (Eq. 3), log likelihood (LL) ratio test (Eq. 4) and pseudo R^2 (Eq. 5) by comparing the existing soil damage locations:

$$\mathrm{AIC} = n\ln\left(\mathrm{RMSE}\right) + 2P \tag{3}$$

where:
n – number of observations,
RMSE – root mean squared error,
P – number of model parameters.

$$\mathrm{LL} = 2\sum Oi\ \ln\left(\frac{Oi}{Ei}\right) \tag{4}$$

where:
Oi – observed value,
Ei – expected value.

$$\text{Pseudo } R^2 = \left(\frac{\text{null deviance} - \text{residual deviance}}{\text{null deviance}}\right) \times 100 \tag{5}$$

Spatial predictions. Spatial predictions were built in ArcGIS (Version 9.3, 2009). Models were exported from R software as a text file and interpreted in ArcGIS by an avenue script prepared using rpart and randomForest packages. Lookup tables describe each response curve point by point. The obtained pixel values were then classified based on class 0 (low), class 1 (moderate), class 2 (high) and class 3 (very high).

Table 2. Descriptive statistic results of predictor variables (mean ± standard deviation)

Slope (°)	29.04 ± 2.17
Aspect	E, W, NW
Altitude (m)	1,499.47 ± 211.55
Slope length (m)	6.99 ± 5.01
Topographic position index	canyons, slopes, ridges
Topographic wetness index	5.75 ± 1.74
Soil type	silty-loamy, clayey-loamy, clayey
Forest type	pure beech, beech-hornbeam, mixed stand (hornbeam-beech-maple-alder)
Forest density (ha)	147.37 ± 6.60
Road (m·ha^{-1})	16.47
Skid trail (m·ha^{-1})	14.13

RESULTS

Descriptive statistic results of topographic factors and the other site conditions are presented in Table 2.

ROC curve is frequently used for assessing the model performance. The success-rate results were obtained using the soil damage grid cells in the training dataset. Fig. 2a shows the success-rate curves of the two soil damage susceptibility maps (obtained from the CART and RF models) in this study. It could be observed that the RF model has a higher area under the curve values (0.972) than the CART model (0.873). The results of the prediction rates are illustrated in Fig. 2b. These curves indicate that the RF model (0.957) has a relatively higher prediction performance than the CART model (0.861). Table 3 presents AIC and log likelihood index, and pseudo R^2 for the performance of models. The comparison of model performance between

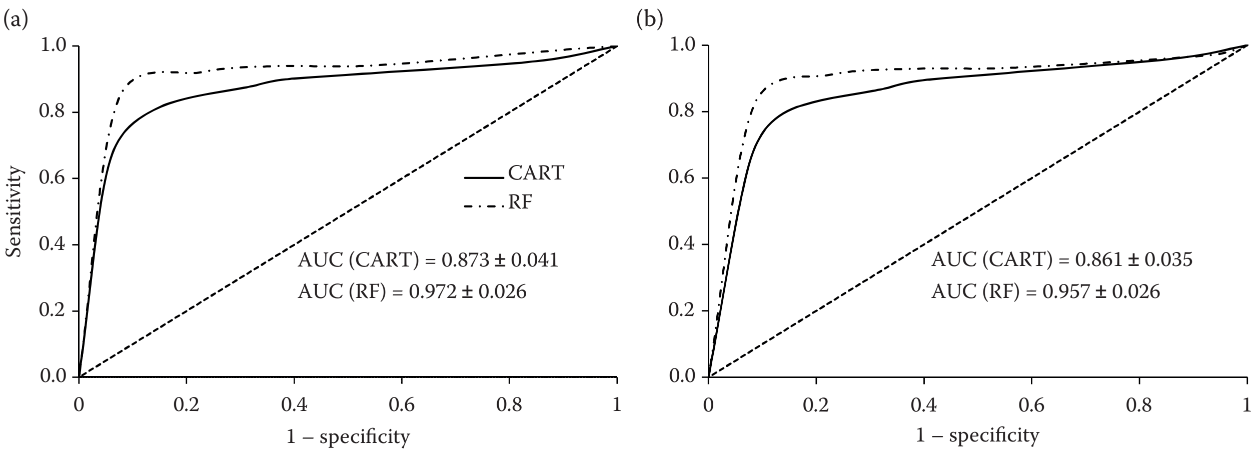

Fig. 2. Success (a), prediction (b) rate curve for the susceptibility maps produced in this study

AUC – area under the curve, CART – classification and regression tree, RF – random forest

Table 3. Performance results of classification and regression trees (CARTs) and random forests (RFs)

		AIC	Log likelihood	Pseudo R^2
CART	training	−134.35	−69.42	0.68
	validation	−84.16	−11.37	0.59
RF	training	−292.08	−203.09	0.95
	validation	−206.17	−113.26	0.92

AIC – Akaike information criterion

Table 4. Importance of variables based on classification and regression tree prior to pruning

	Importance
Slope	23
Soil type	18
Slope aspect	16
Slope length	16
Forest density	15
Altitude	12

CART and RF shows that differences between the models are maximal (Table 3), as RF had a better performance than CART.

The slope aspect was the only effective predictor of soil susceptibility in the final model of CART, prior to pruning, where the main variables were soil type, aspect, LS, forest density, and altitude, in the order their appearance (Table 4). Slope aspect was the most important variable in the RF model, whereas slope degree greater than 30° (Fig. 3a) had a higher impact on soil susceptibility maps. Furthermore, clay soil type (Fig. 3b) and eastern aspect (Fig. 3c) were significant contributors to the soil damage occurrence. Table 5 displays the mean decrease in the Gini coefficient for variables prior to pruning in the RF model.

Table 5. Relative importance of variables based on random forest prior to pruning

	Mean decrease Gini
Slope length	8.86
Topographic wetness index	2.15
Altitude	6.20
Slope aspect	14.45
Slope degree	44.68
Topographic position index	0.84
Forest density	6.55
Forest type	1.99
Distance to road and skid trail	1.50
Soil type	23.52

There were only two susceptibility classes (i.e., low and very high) in CART (Fig. 4a, Table 6). In comparison, the forest areas were divided into four classes by RF, with very high and low zones holding their maximum areal area (Fig. 4b, Table 6).

DISCUSSION

Over the past several decades, forest managers have been determined to mitigate harvesting damage. The proper implementation of a prediction model by forest managers or regulatory staff would definitely enable to predict environmental impacts for a wide range of forest operations. Forest management demands must be based on highly developed models; otherwise, irreparable damage would be inevitable. Although soil damage modelling and prediction has attracted more attention recently, it is still a serious challenge. The present study provided an application of two different soil susceptibility predictive models. The results suggested that RF has a better predictive performance than CART. The map produced via CART was more problematic compared to RF due to lacking the medium and high sub-classes. There are fundamental differences between two algorithms; however, they are an extension of the classification and regression tree

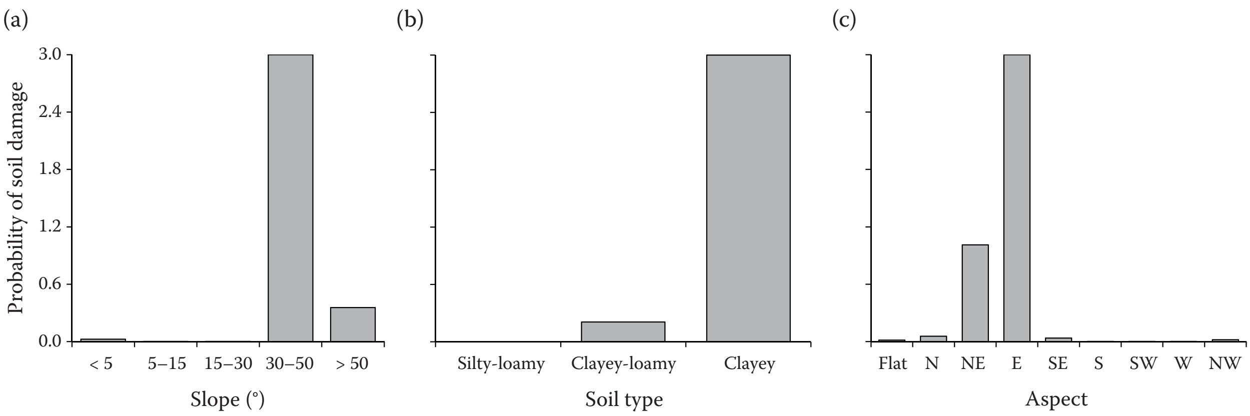

Fig. 3. Partial dependence plot according to random forest model: slope (a), soil type (b), slope aspect (c)

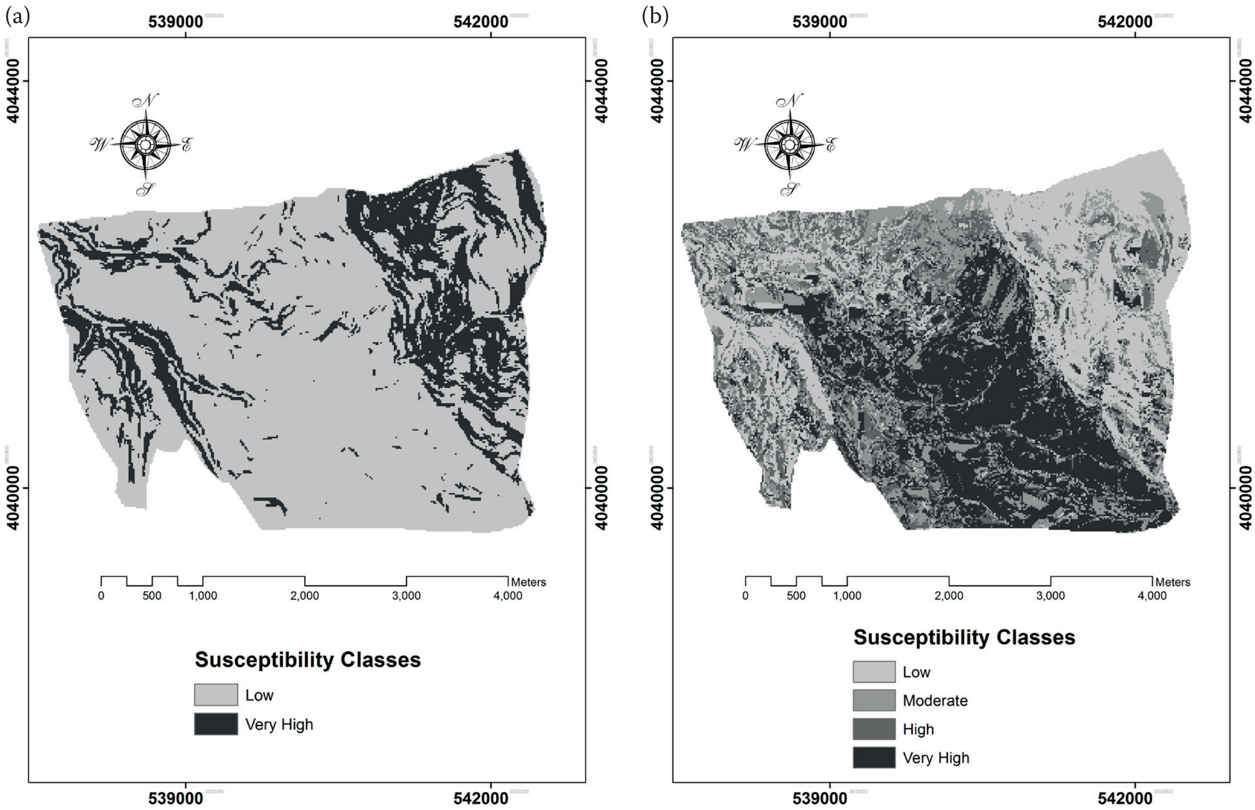

Fig. 4. Soil damage susceptibility map produced by classification and regression tree (a), random forest (b)

(De'ath, Fabricius 2000). CART builds one tree with several bins that assign pixels to a mean value, while RF builds thousands of trees that allow each pixel being assigned with a more refined value and making reliable RF findings (Peters et al. 2007).

Soil damage maps in the forest area show recognizable patterns; the outcomes of our study suggest that these maps are influenced by both physiological and soil factors nonlinearly; thus a non-parametric technique is considered desirable for modelling soil damage susceptibility. In their final form, both models consisted of a smaller number of variables selected from the original set of 10; CART consisted of one variable (slope aspect) and RF of 3 variables (slope degree, soil type and slope aspect). Other researchers also reported that a parsimonious prediction model could be more stable and easier to generalize, especially at a broad spatial scale (Peters et al. 2007; Oliveira et al. 2012). The previous studies showed a vast area of the Caspian forests, mostly located on steep slopes,

Table 6. Covered area percentage for soil damage zones in sub-classes

Model	Low	Moderate	High	Very high
CART	75.64	–	–	24.36
RF	30.40	21.83	16.65	31.12

CART – classification and regression tree, RF – random forest

highly sensitive to soil damage during forest harvesting (Najafi et al. 2009; Borrelli, Schütt 2014). When logs are pulled along a steep slope, load control and skidder movement would be difficult. As a result, the soil would experience high pressures. In the same conditions of soil tension, steep slope receives greater damage compared to gentle slope due to altering the forest hydrological function and soil morphological process (Laffan et al. 2001; Moore, Wondzell 2005). Therefore, it was assumed that slope aspect carries a high weight in determining the hazard zoning status and steep slope can be called an ample window of damage (Cerdà, Doerr 2005; Cerdà, Lasanta 2005). Additionally, exposing the mineral soil on steep slope is the result of the erosive power (according to high and very high sub-classes) which is related to the soil type impact (Imaizumi et al. 2007; Imaizumi, Sidle 2012). Sowa and Kulak (2008) reported that the terrain slope plays an important role in soil damage modelling of mountain forests, as the skidder travel is not likely restricted to designated skid trails.

According to Ampoorter et al. (2010), clayey and clay-loamy soils are more vulnerable to damage than coarse-grained soils. The high susceptibility level for clayey type is not therefore surprising, as these soils are prone to compaction and leaching, which are the representative characteristics in high and very high soil susceptibility sub-classes. Furthermore, the fine-textured soil has a higher vulnerability to degradation than other types (Aust et al. 1998).

Although slope aspect played a smaller role, it is still the most important in the level of soil damage resulting from timber skidding. Our results showed that forest sites with northeastern and eastern aspects are more exposed to damage than other aspects, probably due to microclimate-related conditions (Reeves et al. 2012).

The slope aspect conditions associated with slope and soil type make them conducive to the reduced impact of logging, which is often prescribed as the best management practice since it mitigates soil damage (Page-Dumroese et al. 2010a, b).

CONCLUSIONS

In the present work, the soil damage susceptibility was predicted by two tree ensemble techniques for a Caspian forest, Iran. The potentially high soil damage risks of the area were quantitatively observed on slope steeper than 30°, clayey and clay-loamy soil types, and northeast and eastern aspects. Our findings indicated that soil susceptibility maps predicted using RF provide a considerably higher prediction compared to maps developed using CART. The approach developed in the present work can support management objectives by providing soil conservation protocols and susceptibility maps in the other forest types.

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