Original scientific paper

Pavement Deterioration Modeling for Forest Roads Based on Logistic Regression and Artificial Neural Networks

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Abstract

The accurate prediction of forest road pavement performance is important for efficient management of surface transportation infrastructure and achieves significant savings through timely intervention and accurate planning. The aim of this paper was to introduce a methodology for developing accurate pavement deterioration models to be used primarily for the management of the forest road infrastructure. For this purpose, 19 explanatory and three corresponding response variables were measured in 185 segments of 50 km forest roads. Logistic regression (LR) and artificial neural networks (ANNs) were used to predict forest road pavement deterioration, Pothole, rutting and protrusion, as a function of pavement condition, environmental factors, traffic and road qualify. The results showed ANNs and LR models could classify from 82% to 89% of the current pavement condition correctly. According to the results, LR model and ANNs predicted rutting, pothole and protrusion with 83.5%, 83.00% and 81.75%, 88.65% and 85.20%, 80.00% accuracy. Equivalent single axle load (ESAL), date of repair, thickness of pavement and slope were identified as most significant explanatory variables. Receiver Operating Characteristic Curve (ROC) showed that the results obtained by ANNs and logistic regression are close to each other.

Keywords: forest road maintenance, pavement management system, pavement strength, pothole, protrusion, rutting

1. Introduction

The existence of qualitatively and quantitatively optimal forest transportation systems, which can be divided into primary and secondary network, is one of the basic requirements in today's modern, integrated, technologically advanced, rational, cost-effective, environmentally sound, socially responsible, biodiversity respectful and income sustainable management of forest ecosystems (Potočnik et al. 2015).

Similar to public roads, forest roads are deteriorated because of excessive load, transportation on negative weather condition, inconvenient drainage construction, planning the forest roads on low bearing capacity soils, using of unsuitable techniques for forest road construction (Eroglu et al. 2003). While it is important to do the right repair at the right place at the right time, it is cheaper to maintain roads in good shape than to fix broken roads. An excellent pavement maintenance program is usually part of an overall management plan. It can also be used as the starting point to develop such a plan (Ouma et al. 2015). One of the most important keys to successful pavement maintenance is to know what the proper repair is. This can range from doing nothing to reconstruct the entire road. It may be better to do nothing rather than to make a repair that fails prematurely (Santos and Ferreira 2013). Therefore, there must be a detailed plan for forest roads to keep their efficiency and reduce environmental damage and costs.

Pavement management is a program for improving the quality and performance of pavements and minimizing costs through good management practice (Bent et al. 2012, Roberts and Attoh-Okine 1998). Forest Roads Pavement Management System (FRPMS) is a set of defined procedures for collecting, analyzing, maintaining, and reporting forest road pavement data, to assist the decision makers in finding optimum strategies for maintaining forest road pavements in serviceable condition over a given period of time for the least cost (Rusu et al. 2015, Sen 2013). It is, moreover, designed to provide objective information and useful data for analysis so that road managers can make more consistent, cost-effective, and defensible decisions related to the preservation of a pavement network (Santos and Ferreira 2013, Yang 2004). The first step for a successful introduction of asset management systems is to develop a reliable deterioration model considering the heterogeneous deterioration process of their road network. Although most forest road pavement experts or researchers already understand the importance of this, the task is never easy due to insufficient data for statistical methods that usually demand a large amount of inspection data to draw characteristics of the deterioration process of their road network (Han et al. 2014).

The impact of various factors on pavement performance is complex. To understand the mechanism and predict the future state of pavement, it is essential to study the factors affecting pavement deterioration (Moreno-Navarro et al. 2015, Schlotjes 2013). Factors affecting pavement condition can be various factors such as the age of the pavement, traffic, environment, materials, thickness of pavement, pavement strength and properties of the substrate that affect the mechanical properties of the pavement (Salour and Erlingsson 2013). The effectiveness of maintenance planning depends on the accuracy of the predicted future performance and observed current condition of the pavement. If the deterioration models used in determining the maintenance policies cannot sufficiently represent the actual deterioration process, the planned maintenance strategies might be far from optimal. Therefore, performance measurement and deterioration models are essential components of the maintenance planning (Lin et al. 2014). Pavement deterioration models actually predict the future of pavement and it is useful for developing models of pavement maintenance management or maintenance priority index (MPI) (Saha et al. 2014). Pavement condition performance models, which simulate the deterioration process of pavement condition, play a pivotal role in FRPMS (Owolabi and Oladapo 2011). The ranking criteria used to prioritize pavement maintenance program are based on the severity of the stress and conditioned by it. The conditions governing the forest roads is different from the main roads maintenance management, and it is more complex (Sundin and Braban-Ledoux 2001). On the other hand, there is no special equipment to check the condition of roads or it is very expensive. For this reason it is recommended to use the techniques of linear and nonlinear models, as they are cheaper and faster (Hahne et al. 2014). Myriads of researches have been done with respect to pavement performance modeling in forest and public roads (Faghih-Imani and Amador Jimenez 2013, Forsyth et al. 2006, Tabatabaee et al. 2013, Tunay 2006). Regression technique is used by researchers as a traditional method to predict pavement deterioration rate (Kaur and Pulugurta 2008). Logistic regression is used when the target variable is binary or binomial and the independent variables are numerical and (or) categorical (Xu et al. 2014). Most specialists agree that no single prediction model is applicable to all pavements. This is due to the high variability in the manner in which each agency measures its pavement. For example, they may vary in the number, scale, type of pavement characteristics, and in the pavement deterioration indicators used (Roberts and Attoh-Okine 1998). In recent years, predicting the expected pavement deterioration has been the focus of many works (Attoh-Okine 1994) using traffic and time-related models, interactive time, traffic, or distress models. To date, approaches used in forecasting the pavement condition have included: regression models, artificial neural network, empirical model, mechanistic models and deterministic and probabilistic models in public roads. Within these approaches, logistic regression analysis and ANN are used by researchers as a new method to predict pavement deterioration rate in forest roads. Logistic regression is a data mining method that can be used to classify a given dataset. Logistic regression builds a linear model based on a transformed variable (Friedman et al. 2000) often referred to as logit variable (Hosmer Jr. et al. 2013), which is used to assess the relation between one dependent variable (binary, categorical or ordinal) and several predictor variables (continuous or categorical). Among the various methods of regression, according to the nature of data, logistic regression is a good method for pavement modeling and prediction for forest roads (Hosmer et al. 2013).

However, the pavement deterioration process is so complex that it is difficult and sometimes impossible to find an appropriate functional form, as used by traditional modeling (Lee et al. 2013). Hence a new approach, which can be categorized as »biologically-inspired«, is taking the territory from its traditional counterpart. A typical model in this category is Artificial Neural Networks (ANNs) (Yang et al. 2003). Neural network abstracts the underlying relationship between dependent and independent variables from the exemplar data pairs and expresses it as forms of weight matrix (Russell C. Eberhart 1990, Yang 2004, Yang et al. 2003). Among the list of useful features of ANNs, many are favorable for FRPD prediction. The primary feature is that ANNs can represent any arbitrary nonlinear function, while in regression analysis relationships, or at best pre-specified nonlinearity, are needed (Xu et al. 2014). In ANN, the neural net discovers its own function with no limit associated with linearity. The other useful features are its ability to generalize a relationship from only a small subset of data, to remain generally vigorous in the presence of noisy inputs or missing input parameters, and to adapt and continue to learn even with evolving situations (Thube 2012). The main objective of this study was to introduce and develop a pavement performance model to predict Forest Road Pavement Deterioration (FRPD) and prioritize forest roads deterioration by applying artificial neural network and logistic regression model. The models can help forest engineers to define alternative ways of road maintenance, highly cost-effective and environmentally friendly in future. Moreover, the subgoal was to identify and quantify the new explanatory variables on FRPD. To date many models have been developed for forecasting of pavement conditions, most of them focusing on single index and all models relating to forest and public roads (Yang et al. 2003). Pavement deterioration models were developed in the present study to predict the forest roads deterioration based on current pavement conditions such as traffic loads, environmental, design, construction, and maintenance practices.

2. Methods

2.1 Data collection

The foundation of a successful FRPMS plan is the collection of data according to methods, standards, and protocols to be used in collecting pavement condition data. FRPMS rely on data from a variety of sources (e.g., roadway inventory, traffic data, materials, and construction history). This data maybe available or must be obtained by road inventory and managed so that it can be readily accessed by decision makers at all levels (McQueen and Timm 2005).

2.2 Road inventory

Necessary details of all the roads have been taken with the road inventory method. A road inventory (manual survey) was completed on 50 km including primary and secondary roads during Oct–Nov 2014. The roads were divided into a total of 185 road segments; road segments as defined by the road length between road drainage structures, intersections with other roads or trails, or changes in road condition (Coulter et al. 2006) and recorded by GPS. Within each segment, location of the initial sampling line was determined on the road by generating random value of 0–20 m and at 20 m interval away from the last line perpendicular to the wheel track (Fig. 1). Manual surveys were conducted by walking and noting the existing surface distress.

In a given segment, there were two main types of road inventory data, »Section« or »Continuous« data and »Event« or »Discrete« data to be collected, each of which needs a different and individual data collection treatment. Continues data such as grooves, pits and protrusions, checked rut and pothole were measured in linear or square meter. In contrast, event data such as road prism were described by a single change and an off-set from the center-line (Hill 2011).

A visual inspection is the first level of assessment and can be as simple as a walk-through the area. Rutting, protrusion and pothole were measured on cross-section as shown in Fig. 1. A stick marked in cm was used to measure the vertical distance between the road surface across the ruts, protrusion and pothole, and an aluminum bar mounted on a 1 m long rebar was driven into the ground on either side of the variables. The stick was aligned parallel to marks on the bar to ensure

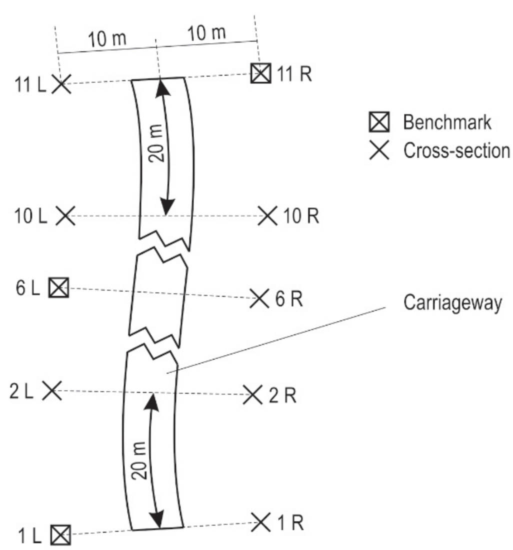

Fig. 1 Forest Roads Inventory for selected segments by generating random value of 0–20 m and at 20 m interval away from the last line

the vertical measurements were made in the same orientation with the stick. These vertical distances were measured at 2.5 cm horizontally across each rut and pothole unless more closely spaced vertical measurements were necessary to adequately define the shape of the road surface (Gatto 2001).

Within each segment, forest roads pavement condition was assessed based on pavement current condition (thickness of the component layers, materials, grooves, pits and protrusions checked), management history (traffics, maximum load, age of pavement), road prism (road slope, longitudinal and lateral drainage (and road location properties (distance to stream, ground slope, canopy density). The survey data were generally recorded on paper and then entered into the computer every day to create the pavement management system (PMS) database. Survey data was used in this study for both modeling and implementation purposes.

2.2.1 Study area

The Chob o kaghaz Mazandaran maintains approximately 400 km of primarily gravel surfaced low volume roads located in three separate forested tracts in Mazandaran province north of Iran, between 36°20′30′′ N and 36°23′58′′ N latitude and 45°17′30′′ and 52°18′35′′ E longitude. The area is part of the Caspian forest in northern Iran, with rough topography and dense vegetation cover (Jaafari et al. 2015). Elevations within the study area range from 150 to 800 meters above sea level. Mean annual precipitation for this area averages 867 millimeters, the primary and secondary roads were mostly under 30–40 years in age, and most have been reconstructed using current management practices in recent years; moreover, maintenance operations are done every six months. Average annual precipitation is about 872 mm and an average annual temperature ranges between 7 and 15 °C. The climate is humid and cold, according to Emberger climagram. The soil in this region includes soil type of brown forest and brown washed with argillic and calcic horizon.

Average monthly traffic was 425. The recently-graded roads had more traffic because grading was generally a prerequisite to timber hauling. Most of the study sites were on the dry and wet season and average of timber hauling was 1200 m^3 with three and two axle trucks.

2.2.2 Response variables

Pavement management typically operates at two levels, (1) network level and (2) project level. At the network level, priority program and work schedule are developed within overall budget constraints. On the other hand, at the project level, specific physical improvements are implemented according to network decisions (Shahnazari et al. 2012). Information collected as part of a network-level data collection effort may involve many items, but a standard set of data typically collected as response variables, including rutting, pothole and protrusion, were identified as response variables through the literature, while standards were extracted from the PMS database.

When forest harvesting equipment and other vehicles move across a forest road, rutting can occur. Ruts are the trenches or furrows created by machine tires or tracks. Rutting displaces forest roads and damages it. Rutting is a normal occurrence for gravel roads. Ruts are indicators of maintenance need. If ruts exceed 5 cm in depth or direct water down the road, or surface roughness affects the ability to travel on the road, it is time to perform surface maintenance.

Potholes are impressions in the forest roads caused by heavy traffic and often occur at lower slope level. They are at least 3 cm wide and 3–5 cm long. Two different depth criteria (3 cm, 8 cm and 12 cm) apply, depending on the hazard of the standards being assessed. On sites with a high or very high deterioration hazard, or where the deterioration hazard has not been assessed, both depth criteria apply. On sites with a moderate or low deterioration hazard, only the greater than 12 cm depth criterion applies. This category does not require the survey point to be assessed for evidence of deterioration.

The category *repeated machine traffic* describes protrusion resulting from repeated heavy machine traffic. Such protrusion is typically found on roads and especially on repeatedly used skid trails, which are obvious linear features. However, it occurs on heavy traffic areas associated with roadside work areas and in middle slope or upper slope level. This disturbance also occurs on moderate or low compaction pavement logged under dry conditions, where random skidding operations have a limited use of trails – one or two passes.

2.2.3 Explanatory variables

Every variable that may affect pavement performance should be considered initially in road inventory. This list will typically be large. For their implementation within a FRPMS, however, predictive models must only use the variables that can be directly measured within acceptable cost and time constraints, retrieved from historical records, or computed or estimated (Zhang et al. 2013).

Previous studies prepared a summary of significant effective variables in FRPMS or highway or rural road (Dong 2011). Table 1 presents the list of variables for the current study.

Table 1 Important data elements in FRPMS deterioration

Main category	Input variable	Quality of variable	Value		Classes
			Min.	Max.	
Pavement condition	Thickness of pavement, cm	Ordinal	80.28	205.8	1,2
	Pavement material	Nominal	Mixed, river and mountain		1,2,3
	Age of pavement, year	Ordinal	30	44	1,2,3,4
	Maintenance historic, year	Nominal	0.60	1.20	1,2,3,4
Environmental factors	Precipitation, mm	Ordinal	433	1910	1,2,3,4,5,6
	Canopy, %	Scale	0	85	1,2,3,4
	Elevation, m	Ordinal	143	838	1,2,3,4
	Slope, %	Ordinal	1	23	1,2,3,4
	Aspect	Nominal	0	4	N,S,E,W
Traffic* (ADT and MADT)	ESAL, kN **	Scale	3	24	No
	Number of skids ***	Frequency	0	11	No
	Volume of timber, m^3	Scale	1067	2780	No
Road qualify	Loss of road	Presence or absence	0	1	Yes or No
	Sand in road ****	Presence or absence	0	1	Yes or No
	Drainage	Presence or absence	0	1	Yes or No
	Type of Road	Nominal	1	3	1,2,3
	Intersection	Presence or absence	0	1	Yes or No
	Status of ditch	Scale	0	8.79	No
	Turn	Frequency	0	4	No

* (ADT/MADT): ADT: Average daily traffic, MADT: Maximum ADT ocurred in this network (Gralund and Puckett 1996)

** Equivalent standard axle loads calculated in accordance with ESAL calculator program (Martin et al. 2000)

*** Total number of skids, timber trucks and truck brakes recorded by GPS

**** Amount of sand on road surface, as a result poor compaction

The identified variables could be categorized under major topics that are known to affect performance. A preliminary list of important explanatory variables is prepared under four major categories, which affect long-term pavement behavior. These categories include pavement condition; environmental factors, traffic and road qualify as listed in Table 1. This list will be the primary source for explanatory variables.

3. Data Analysis

LR and ANNs models were developed to model the overall pavement conditions, encompassing the individual pothole, protrusion and rut ratings. The SPSS version 16 was used for data analysis with logistic regression, and the default ANNs training algorithm of NeuroSolution Infinity software version 1.1.0.1 was used for neural network purpose.

Table 2 Subclasses of response variable (Reid and Dunne 1984, Smith 1993, Yee and Roelofs 1980)

Variable	Class 1	Class 2	Class 3	Class 4
Pothole	Depth < 3 cm	Depth = 3–8 cm	Depth 8–12 and < 12 cm and Area > 1 m^2	Depth >12 cm
Rutting	Depth < 5 cm	Depth = 5–10 cm	Depth = 10–15 cm	Depth > 15 cm
Protrusion	Height < 3 cm	Height = 3–5 cm	Height = 5–8 cm	Height > 8 cm or Area > 2 m * 3 m (6 m^2) in each class

3.1 Response Variable Classification

Initially, response variables including pothole, rutting and protrusion were divided into four sub-classes (Table. 2).

3.2 Logistic Regression Model

In this study, since the classification within the dependent variable has no meaning, ordinal logistic is used for each class. Logistic regression builds a linear model based on a transformed variable using a link function referred to as the Logit function or model, which is the log of the odds that an event occurs. The maximum likelihood estimation procedure is used to obtain the estimates of the regression coefficients by maximizing the value of log-likelihood function through an iterative process, with the aim of making the likelihood of observed data greater (Hosmer et al. 2013). The number of logistic regression equations required is usually lower by one category because one of the prediction categories is chosen as a reference category.

3.3 ANN Model

An ANN is a massively parallel distributed information processing system that has certain performance characteristics resembling biological neural networks of the human brain (Suman and Sinha 2012). ANNs have been developed as a generalization of mathematical models of human cognition or neural biology (Izenman 2008, Movagharnejad and Nikzad 2007, Rao 2000). A neural network is characterized by its architecture that represents the pattern of connection between nodes, its method of determining the connection weights and the activation function (Russell C. Eberhart 1990, Si et al. 2015). The basic structure of a network usually consists of three layers: the input layer, where the data are introduced to the network; the hidden layer or layers, where data are processed; and the output layer, where the results for given inputs are produced (Kumar et al. 2013, Suman and Sinha 2012).

3.3.1 Model Architecture

According to the database partitioning, the validation dataset has been considered statistically independent from the datasets used for training and testing purposes. Hence, the verification of ANN models through using the validation dataset can be considered a touchstone in examining the performance of the developed ANN models from an implementation point of view (Thube 2012). The selection of ANN architecture is not a decision making process. Most of the time, trial and error, combined with engineering judgment, is used to determine the appropriate architecture for a particular problem (Thube 2012). In the present study, a number of explanatory and response variables are kept constant, and variations are made in the hidden layers and in the neurons per hidden layers with the software default. First, the depth of the experiment search must be determined. The defaults are designed to choose the most commonly used preprocessing functions and neural network topologies, but if the computing resources are limited, the options can be changed to either limited, partial or none for a less thorough search (Abu Jamous 2013).

3.3.2 Data Optimization

It is necessary to determine how the data should be allocated for optimization. The database was divided into three datasets, and the first set has been used for training purposes. One set contains 70% (125 segments) of the data that are used for network training, and the remaining set contains 15% (30 segment) of the data used for network testing and 15% (30 segment) for validation.

3.4 The ROC Curve

Receiver Operating Characteristic (ROC) is used for evaluating two models. A ROC is a standard technique for summarizing classifier performance over a range of trade-offs between true positive (TP) and false positive (FP) error rates (Phillips et al. 2015). ROC curve is a plot of sensitivity (the ability of the model to predict an event correctly) versus 1-specificity for the possible cut-off classification probability values Π0 (Humphrey et al. 2012). For logistic regression, it is necessary to create a 2×2 classification table of predicted values from model for response if y^=0 or 1 versus the true value of y=0 or 1 (Sharma et al. 2011). A rough guide for classifying the accuracy of a diagnostic test is the traditional academic point system: 0.90–1 = excellent (A), 0.80–0.90 = good (B), 0.70–0.80 = fair (C), 0.60–0.70 = poor (D) and 0.50–0.60 = fail (F) (Hosmer Jr. et al. 2013).

While the ROC curve contains most of the information about the accuracy of a continuous predictor, it is sometimes desirable to produce quantitative summary measures of the ROC curve (Anifah et al. 2013). The most commonly used such measure is by far the area under the ROC curves (AUC) (Friedman et al. 2000). In an empirical ROC curve, this is usually estimated by the trapezoidal rule, which forms trapezoids using the observed points as corners, computing the areas of these trapezoids and then adding them up (Gonen 2006). This may be quite an effort for a curve with many possible thresholds. Fortunately, AUC is connected to a couple of well-known statistical measures that facilitates comparison and improves interpretation (Hosmer Jr. et al. 2013).

Table 3 Model summary of input explanatory response variable at four levels of pothole

Variable	Sig.	Wald Test	Standard deviation	Df	Coefficient
Iteration 1	0.300	4.7	1.234	1	–2.76
Iteration 2	0.233	1.4	1.231	1	–1.47
Iteration 3	0.599	0.2	1.224	1	0.643
Slope	0.206**	4.9	0.011	1	0.002
Date of repair	0.015***	24.5	1.08	1	–3.002
Turn	0.251**	1.5	0.086	1	–0.009
Percent of canopy	0.000***	14.74	0.007	1	–0.332
Thickness of pavement	0.222**	1.4	0.006	1	1.320
ESAL	0.000***	75.6	1.616	1	2.279
Drainage	0.599**	0.3	0.082	1	0.480
Material	0.025***	8.5	0.412	1	1.823
AUC 1,2,3,4	0.806	0.769	0.736	0.804	–

*** Strong relation ** Medium relation

4. Result

To simulate FRPD and evaluate Forest road pavement performance three response variables and 19 explanatory variables were defined based on literature review and field survey.

4.1 LR Models

4.1.1 Pothole Model

LR was applied to model pothole at four subclasses (Table 2). The result of pothole analysis and ROC evaluating model are presented in Table 3.

Table 4 Model summary of input explanatory response variable for rutting

Variable	Sig.	Wald Test	Standard deviation	Df	Coefficient
Iteration 1	0.492	0.47	1.124	1	0.772
Iteration 2	0.022	5.218	1.135	1	0.594
Iteration 3	0.000	12.45	1.126	1	4.078
Slope	0.06 ***	0.658	0.011	1	0.921
Date of repair	0.382 **	1.237	1.37	1	1.465
Turn	0.000 ***	72.241	0.111	1	–0.004
Percent of canopy	0.534 **	0.386	0.007	1	0.004
Thickness of pavement	0.049 ***	0.976	0.006	1	1.001
ESAL	0.081 ***	3.043	-1.880	1	–3.281
Drainage	0.266 **	0.1	0.078	1	0.012
Material	0.982 **	0.915	0.429	1	0.01
AUC 1,2,3,4	0.946	0.827	0.748	0.965	–

*** Strong relation ** Medium relation

Table 5 Model summary of input explanatory response variable for protrusion

Variable	Sig.	Wald Test	Standard deviation	Df	Coefficient
Iteration 1	0.000	16.526	1.295	1	–5.265
Iteration 2	0.004	8.281	1.281	1	–3.688
Iteration 3	0.371	0.8	1.249	1	–1.118
Slope	0.02 ***	4.132	0.013	1	0.525
Date of repair	0.05 ***	3.855	1.567	1	3.076
Turn	0.03 ***	4.196	0.091	1	0.047
Percent of canopy	0.375 **	0.856	0.008	1	–0.007
Thickness of pavement	0.328 **	0.957	0.006	1	–0.006
ESAL	0.000 ***	10.406	-2.280	1	5.258
Drainage	0.909 **	0013	0.083	1	0.009
Material	0.083 **	2.282	0.439	1	–0.064
AUC 1,2,3,4	0.921	0.923	0.806	0.935	–

*** Strong relation ** Medium relation

According to Wald test for all classes of pothole levels, the most important variables were date of repair, ESAL, percent of canopy and material.

According to the results, the maximum and minimum AUC were found in class 1 and class 3, 0.806 and 0.736, respectively (Table 3). Table 3 shows four AUC representing excellent, good, and fair.

4.1.2 Rutting Model

The results of rutting analysis and evaluating (AUC) model are presented in Table 4.

Wald test for rutting showed that the most important variable for this responsible variable were turn, thickness of pavement, ESAL and slope. Similar to the results obtained for pothole, the results showed that the maximum AUC was found in class 4 and minimum in class 3 (Table 4).

4.1.3 Protrusion Model

Protrusion LR analysis and evaluating (AUC) are presented in Table 5.

According to Wald test ESAL, date of repair, material, number of turn and slope are the effective factors in protrusion formation. In protrusion, maximum AUC was found in class 4 (Table 5) and minimum in class 3. The best tested plot in protrusion showed that all classes were excellent excluding class 3 (Table 5).

Table 6 Model overview for Pothole

Variable	Model	Experiment	Project	Input	Percent of Issue
Pothole	Dataset	Optim.	Leave-N-Out	Date of Repair	20.6
	Score	98.82	65.75	Canopy	19.6
	Percent correct	100	85.23	Material	18.3
	Avg. area ROC	1	0.880	ESAL	15.2
	Avg. correlation	0.91	0.78	Slope	15.1
	Avg. norm. MSE	0.0892	0.0377	Drainage	9.5
	Avg. norm. MAE	0.099	0.234	Precipitation	1.7
	Max. abs. error	0.044	1	–	–
	Training epochs	3	–	–	–

4.2 ANN Modeling

4.2.1 Pothole Model

Based on the prediction of pothole, a satisfactory prediction model has been developed. Given the various ANNs model overview for pothole (Table 6), the weights of links among the neurons are determined through the training process. The training process has been carried out for a fixed number of epochs (10,000) (Semeida 2015).

The model comparisons for different ANN models are carried out by comparing the normal mean square error (NMSE) values during testing stage. The details of NMSE and average correlation variations for different ANN models are shown in Table 6.

The results indicated that the final model has a very good NMSE, NMAE and AUC (Table 6). Based on Table 6, the higher values of Percent of Issue indicate that the variable is relatively more important. The five most influential variables on the failure of the pavement and pothole were the date of repair (20.6), material (18.3), ESAL (15.2), Slope (15.1) and drainage (9.5). Finally, the ANN models correspond to the ROC curve and average correlation at the testing stage was selected. Another critical step, prior to the actual application of the developed model, is to evaluate the performance of the model. The details of the evaluation for pothole ANN models are shown in Fig. 2 and 3 as an example, while those for other models were removed to reduce the volume of figures.

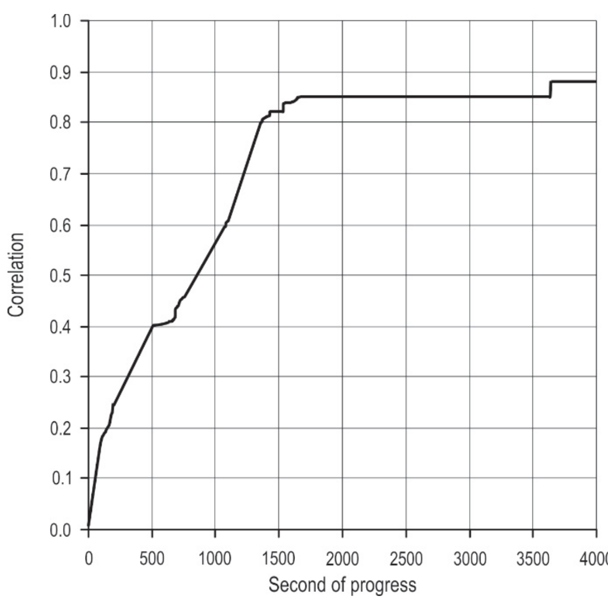

Fig. 2 Correlation between explanatory variable in Pothole ANN model

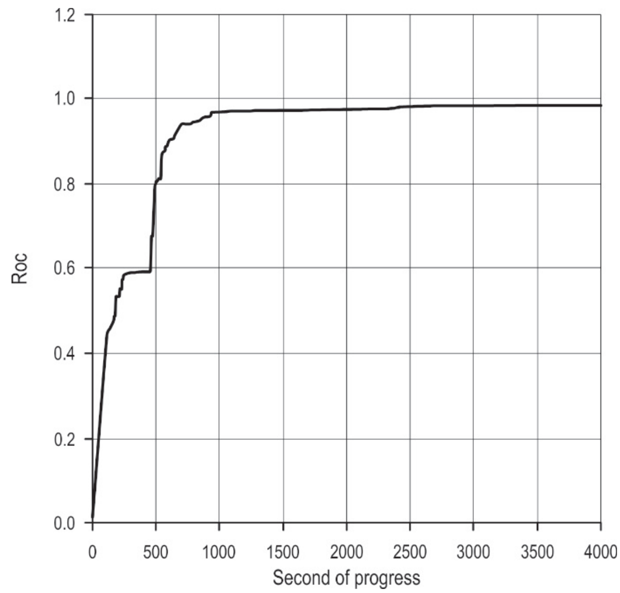

Fig. 3 Pothole ROC Curve in ANN model

The correlation of pothole model showed that maximum correlation was achieved in thirty minutes after running the model, after which there was no performance. However, the disturbances of explanatory variable got better and Maximum performance came to 0.9. AUC was used to compare the evaluation of this model with pothole model generated by LR (Fig 3).

The AUC shows very good disturbance of explanatory variable a few minute after running the model. The AUC in this pothole ANN model was at first 0.6 and after thirty minutes it reached the maximum performance (0.88).

4.2.2 Rutting Model

Similar to LR modeling, to develop the rutting model, rutting data was classified into four classes. Total rutting results showed that the most important variables were: the thickness of pavement, Elevation, turn and ESAL over timeline (Table 7).

As can be seen from Table 7, the percentage of Thickness (30.3) has a strong impact on the rutting followed by Elevation (22) and ESAL (13.6).

4.2.3 Protrusion Model

To develop the protrusion model, the data was classified similar to those in LR modeling. To analyze the influence of explanatory factors on FRPD, the relatively effective and ineffective maintenance were distinguished. Pavement that received relatively effective treatment can be determined using protrusion condition. These types of response (Correlation and ROC) are illustrated in Table 8.

Table 7 Rutting model overview

	Model	Experiment	Project	Input	Percent of Issue
Rutting	Dataset	Optim.	Leave-N-Out	Thickness of pavement	30.3
	Score	99.985	68.56	Elevation	22
	Percent Correct	100	83	Turn	15
	Avg. Area ROC	1	0.854	ESAL	13.6
	Avg. Correlation	1	0.74	Material	9.6
	Avg. Norm. MSE	0	0.043	Slope	3.4
	Avg. Norm. MAE	0	0.0198	Date of Repair	5.8
	Max. Abs. Error	0	1	Drainage	2.8
	Training Epochs	3	–	Precipitation	1.5

Table 8 Protrusion model overview

	Model	Experiment	Project	Input	Percent of Issue
Protrusion	Dataset	Optim.	Leave-N-Out	ESAL	36.1
	Score	99.275	75.376	Slope	35.7
	Percent Correct	100	98.65	Material	12.9
	Avg. Area ROC	1	0.921	Drainage	7.5
	Avg. Correlation	0.99	0.83	Turn	6
	Avg. Norm. MSE	0.0592	0.0283	Canopy	1.7
	Avg. Norm. MAE	0.065	0.140	–	–
	Max. Abs. Error	0.103	0.92	–	–
	Training Epochs	3	–	–	–

As can be seen from Table 8, the percentage of ESAL (36.1), slope (35.7) and material (12.9) were considered the most significant variables influencing the protrusion. It is important to note that more explanatory variables mentioned in Table 8, such as channel and canopy, is included in the functional form of models. Finally, the protrusion models corresponding to the correlation and ROC curve at the testing stage were selected.

The effect of important explanatory variable on response variable is shown in Fig 4. These figures show the effect of management operations in output model and FRPMS.

4.3 Comparison of models

The models developed by LR and ANNs were then applied to the data set and their performances were compared by AUC, and Percent of Correct Prediction (PCP) and Root Mean Square Error (RMSE) (Table 10). The LR and ANNS were able to classify precisely 89% and 82% of the pavement segments, respectively.

Table 9 Comparison of LR and ANNs models in assessing pavement deterioration condition

Pavement deterioration	Model description	AUC	PCP	RMSE
Pothole	ANN model	0.880	85.2%	0.194
	LR model	0.832	81.2%	0.253
Rutting	ANN model	0.854	83%	0.207
	LR model	0.910	83.5%	0.265
Protrusion	ANN model	0.921	88.6%	0.168
	LR model	0.817	81.7%	0.244

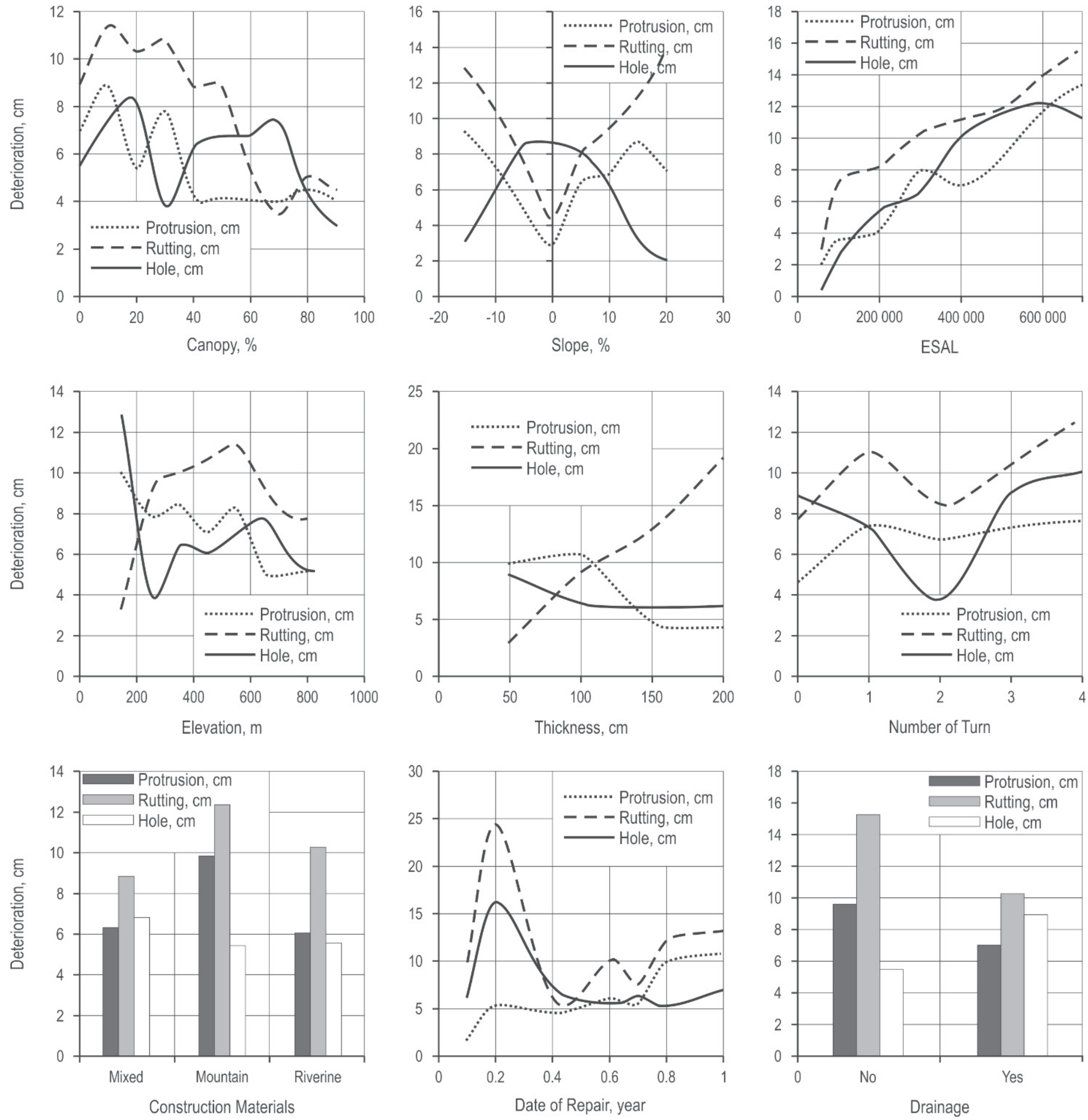

Fig. 4 Effect of important explanatory variable on response variable in FRP

Predictions of rutting, pothole and protrusion are carried out by using the trained ANN models of selected architectures, as well as by using the LR model. The maximum protrusion accuracy (88.6%) was achieved with ANN model. Pothole and rutting achieved the maximum accuracy with ANN and LR model.

5. Discussions and Conclusions

Forest Road Pavement Management is a topic of great significance in forest engineering. It is essential to develop reliable pavement management systems, which have the ability to estimate the overall pavement condition and the ability to forecast when and what kind of repair will be needed on certain pavements. The models of the pavement performance prediction are developed using the past pavement performance data. Thus Pavement Performance Prediction models are integrated into the decision making process and help to schedule the repairs and estimate the budgets (Kaur and Pulugurta 2008).

ESAL had the most significant effect on FRPD (pothole, ruts and protrusion) in both models. By definition, it removes the effect of pavement design, age, and condition variables. For example, one ESAL on a strong pavement corresponds to a much lower proportion of its fatigue life than one ESAL on a weak pavement (Sun et al. 2007). For this reason, its effect is significant in our forest roads because the average age of the road is 35. In the study area, the transporting machines with maximum capacity of logs are used to reduce the logging and timber transportation costs. Max ESAL found in forest roads was more than 20 kN and in this segment max deterioration was observed. ADT and MADT sized pieces resulting from the weight of the truck and friction between the tire and the aggregate (Miller 2014). These smaller, fine particles are then more easily mobilized. During wet weather hauling, the weight of the truck on the road layer may also cause fine sediment from the subgrade to move upward indicate the traffic impact on pavement performance; it merges with ESAL or at least includes the percentage of truck information in our model. It is a well-known fact that roads with high levels of traffic, especially truck traffic, need to be repaired more often than roads with lower levels of traffic. Higher traffic levels increase the ESAL as well as the volume of fine material, and this is a major reason why traffic increases pavement deterioration (Smith 1993). Log truck traffic increases pavement deterioration by increasing the availability of fine sediment on the road surface (Fassman and Blackbourn 2011). Degradation of the surface aggregate into smaller sized pieces is the result of the truck weight and friction between the tire and the aggregate (Miller 2014). These smaller, fine particles are then more easily mobilized. During hauling in wet weather, the weight of the truck on the road layer may also cause fine sediment from the subgrade to move upward to the surface in a process known as pumping (Schaefer et al. 2008). Larger logs on trucks can cause breaking of the pavement's upper layer providing conditions for the water to get into roadbed and cause deterioration and rutting of pavements (Wang 2011). Heavy vehicles will do far more damage to pavements than lighter vehicles. In the current research, ESAL in LR and ANNs model had a most significant role in FRPD and this is in line with the research of (Adlinge and Gupta 2013, Fassman and Blackbourn 2011, Miller 2014, Peshkin 2011, Schaefer et al. 2008, Smith 1993, Wang and Al-Qadi 2009).

The most common maintenance activity that influences pavement deterioration is the date of the last repair of pavements (Zhang et al. 2010). The results of this research showed that the increased maintenance activity resulted in lower pavement deterioration. These results indicate that roads that are not adequately maintained become deteriorated, and are more deteriorated than well maintained roads. The mentioned pavements should be blocked to be repaired and maintained after the logging operations (Miller 2014). With the start of maintenance operations, road traffic increases and hence at the beginning of the road maintenance, deterioration is significant. However, with time, after maintenance operations, the deterioration of the road surface is reduced. We also believe that increasing the thickness of pavements, in the course of maintenance, is a reason to increase FRPD (Fig. 4), because maintenance operations do not improve compaction in these segments.

The composition (mixed, riverine and mountain) and thickness of road surface materials influences the FRPD, as high quality rock will not degrade into smaller, more mobile particle sizes (Pérez and Gallego 2010). Segments covered by the mountain material (40%) deteriorated more rapidly than those paved by mix or riverine materials. Mixed materials were found in 35 percent of segments, and they had lower deterioration. The lowest deterioration was measured in the segment with riverine material pavement (Fig. 4). Thickness of pavement provides insurance against deterioration from the bottom layer (Giroud and Han 2004). There is correlation between the rate of pavement deterioration and pavement thickness (Giroud and Han 2004). Apparently, low thickness in higher traffic has a much greater effect causing deterioration (protrusion and pothole). The results showed that, with the decrease in thickness, pothole and protrusion increase, while rutting appears in high thickness (Fig. 4). When thickness is low, soil strength is not sufficient to support the applied load from vehicles or equipment traffic (ESAL) and thus potholes and protrusions occur on forest roads and trails (Cambi et al. 2015). High thickness of forest roads provide the surface for rutting in wet season, and after maintenance operations, traffic increases and tire pressure causes rutting (Fig. 4). The increase of water pressure can make completion material unsuitable and unstable and this may result in permanent deformation of the road surface and cause rutting (Rodgers et al. 2014). With the increase of thickness, rutting decreases. This is quite the contrary with protrusion, because with high thickness, first rutting occurs and after that protrusion appears. Protrusion is the result of soil compaction of heavy machinery during high traffic and dry season.

Road slope and elevation are two characteristics that often correlated with increased FRPD. This is physically intuitive because, as the slope and elevation of a road increase, potential energy increases and leads to higher erosive power of the skid log trucks (Loizos and Plati 2008). Pavement deterioration is the decisive deterioration process on inclined roads. While potholes dominate on horizontal road segments, rutting and protrusion are found in high slope segments (Moghadami Rad et al. 2014). Fig. 8 shows the probability of maximum pothole occurrence at zero percent gradients, reducing at 5–8% gradient. The study layout results at lower road gradients (Reid and Dunne 1984). Ruts in upslope and high elevation can be filled with water causing it to drain along the road instead of draining away from the road (Caliskan 2013). Heavily sloped roads (those with slopes greater than 10%) can become rutted very easily, because the driver/operator uses extra capacity of the road when driving with heavy loads or under wet conditions. The probability of protrusion occurrence containing pothole distresses has been recorded at low slope, being significant at 5–8% gradient, disappearing at 0–2% gradient (Fig. 4). Protrusions behave like ruts in slope and elevation.

The results indicate that road surface drainage was effective in preventing the development of deterioration (Fu et al. 2010). Engineered points were less than 20 percent of the pavement deterioration. The average road segment length that was drained by cross-drain culverts or live-stream crossing culverts was appreciably different from the average for the entire database (Fig. 4). As the contact pressure from a tire is mainly supported by the completion layer, the load from the tire can increase the pore water pressure in the road material when drainage is restricted. When water remains on the road surface on low slope segments, potholes appear, while protrusion is seen in mountain roads.

The percentage of canopy that covers the road pavement is an important factor in pothole and protrusion risk and has a significant influence on FRPD as well (Eskioglou 2003). Dense canopies protect the road surface from the water drop. However, when interception decreases in high precipitation, deterioration increases. When canopy tends to be denser, light that reaches the road surface is reduced, and in this case, the road surface remains wet and severe deterioration occurs. The results showed that high canopy, the highest measured was 80%, was sufficient to protect the road surface very well against precipitation and was enough open to let light reach the road surface. Potholes were observed in road classes one and two that have low slope and canopy density. While the concentrated flow of surface water is the cause of erosion, protrusions are formed by pounding water. Therefore, the total amount of water falling on a certain area in high slope is an indicator for the occurrence of protrusions.

A FRP is susceptible to variations in climatic conditions of the area in which the road is located. Since the segments are neighbors, the historical precipitation data did not vary significantly (Table 6 and 7), while pothole and rutting precipitation varied significantly. In rainy season, the moisture content in the road becomes higher and consequently the bearing capacity of the FRP is generally reduced causing rutting of the roads. In dry season, the moisture content of the FRP is reduced and this causes road protrusion.

Turns with drainage conditions were the effective variables on road deterioration in both models. The results showed that pavement deterioration increased with decreasing horizontal curve radius in turn. According to the results, due to drainage lakes and uneven load distribution, deterioration was more severe in turns. One reason is that, in view of higher stress on curves, material is dislodged and thrown into the ditches. When the speed is constant, the centrifugal force of the moving trucks increases with the decrease in the radius of the horizontal curve (Kordani and Molan 2014). This can distribute the uneven load on the road surface. If the specific slope was not considered on horizontal curves, the water would be collected on the road surface and the rutting and protrusion would occur severely. Moreover, the pavement layer of the road is damaged by increasing brake on horizontal curves and high longitudinal slopes (Burton et al. 2014). In order to prevent pavement deterioration on road surface, the longitudinal slope should be decreased on horizontal curve to five degrees (Aricak 2015). By increasing the number of turns, pavement deterioration increased but with only two turns, deterioration was less. This is due to the lack of deceleration of the truck driver when he makes two consecutive turns not reducing the vehicle speed due to good visibility.

The pavement deterioration of forest roads varies as a result of length of time since construction, date of maintenance, pavement condition and traffic. The 19 major explanatory variables were considered to investigate the type of deterioration of forest roads with LR and ANN models. The factors that cause deterioration, potholes, ruts, and protrusion, will be the final input parameters for FRPMS. Hassan (2015) reported that logistic regression modeling is feasible for developing deterioration models of subjective distress data of pavement surfaces.

This paper develops two type models using pavement distress data for forest roads. The deterioration modeling was based on FRP condition and response variable (pothole, rutting and protrusion) using two different models (ANN and LR). The results showed that ANN and LR models could be applied for the pothole, rutting, protrusion, and deterioration progression modeling of forest roads. These results are the same as those of Kaur and Pulugurta (2008) with the accuracy of the logistic regression model. Both models predicted two indices on rutting, pothole and protrusion: extent and severity. ANN and LR models were examined by carrying out various trials. The models showed a high area under ROC curve (AUC) between observed and predicted distresses of more than one ratio. This shows an efficacy of the suggested ANN and LR models (Hassan 2015). Although ANN models showed higher efficiency, the results obtained from LR were desirable. LR can describe very well the relationship between pothole, rutting and protrusion and a set of predictor variables due to model responsibility in terms of natural data involving an environmental condition. The models that have been chosen in this study are relevant to all forest environments. The origin of the model as well as the places and diversities of applications of the models provide an indication of suitability.

Forest road pavement management database consists of many different attributes that are both continuous and categorical in nature. In pavement management, it is often required to determine the type of repair needed for a pavement. This decision is based on the condition of the pavement - whether it is in good condition or fair condition, and also on different attributes such as traffic, weather conditions, etc. It is a complicated process to develop a statistical model based on all these attributes. In this study, a more straightforward approach was used using the actual data. An Artificial Neural Network was generated and then converted to simple rules. The rules were then tested on a test data set and the results showed that the accuracy of the model was approximately 85%. Furthermore, a logistic regression was used to classify the dataset and the results of the logistic regression model were compared to the ANNs. The accuracy of the logistic regression model was 82%.

There are several directions for future work because these generated models are the first models applied to forest roads. Further study is recommended to validate their performance in other forest roads and other conditions. Models that predict the pavement performance in feature years based on the current pavement distress condition can be a very crucial tool for allocating budget among alternative pavement managements and preservation projects for forest management authorities.

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