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# Multi-Variable Regression Approach for Pavement Surface Distress Forecasting in Nepal

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**Abstract**

Accurate prediction of pavement surface deterioration is crucial for effective pavement management and efficient allocation of limited maintenance resources. In Nepal, pavement condition evaluation and maintenance prioritization mainly depend on the Surface Distress Index (SDI); however, robust SDI-based deterioration models aligned with national practices are still limited. This study develops and validates a multiple linear regression (MLR) model to predict SDI across Nepal's national highway network using nationally available pavement, traffic, and climatic data. The model links SDI to six explanatory variables: initial SDI, initial International Roughness Index (IRI), pavement age, total annual rainfall, temperature variation, and equivalent single axle loads (ESAL). Data from 157 highway sections, totaling 790 observations collected between 2012 and 2022, were used. Model development and validation involved an 80:20 data split, followed by a thorough out-of-sample forecast assessment with independent 2023 data from 125 highway sections. The MLR model shows strong explanatory and predictive performance, with coefficients of determination ($R^2$) of 0.724, 0.730, and 0.727 for the development, validation, and overall datasets, respectively. Error metrics reflect satisfactory accuracy, with mean absolute error (MAE) values between 0.292 and 0.358 and mean squared error (MSE) between 0.145 and 0.197. Sensitivity analysis highlights initial SDI, initial IRI, pavement age, and rainfall as the most influential factors in surface distress progression. Under true out-of-sample conditions, the model achieves an $R^2$ of 0.723, MAE of 0.359, RMSE of 0.460, and mean absolute percentage error (MAPE) of 16.93%, confirming its robustness and generalization ability. These results demonstrate that a well-specified deterministic regression model can reliably forecast SDI at the network level and serve as a practical, data-driven tool integrated into Nepal's Pavement Management System, assisting maintenance prioritization, budgeting, and long-term asset management.

*Keywords*: Surface Distress Index, International Roughness Index, Multiple Linear Regression, National Highway Network

## 1. Introduction

A Pavement Management System (PMS) is a decision-support tool that consolidates pavement condition, performance, and historical data to optimize maintenance and rehabilitation choices at both project and network levels (Haas et al., 1994). Its primary objectives are to identify cost-effective treatment options, efficiently allocate limited funds, and enhance overall pavement network condition through timely actions (AASHTO, 2001). Typically, a PMS includes pavement condition surveys, a comprehensive database, performance and cost models, decision criteria, and implementation procedures (Paterson, 1987). Pavement performance is assessed using indicators such as surface distress, ride quality, and structural capacity, while performance models forecast deterioration and support life-cycle cost analysis and maintenance prioritization (Babashamsi et al., 2016; Haas et al., 1994; Rajagopal, 2006). Road condition evaluation is vital to a PMS because it reflects the current functional and structural status of pavement sections. Road condition indices offer standardized and reliable measures for assessing pavement performance and aiding network-level decisions (Chamorro & Tighe, 2011; Reza et al., 2006; Standard, 2003). Common indices include the International Roughness Index (IRI), Pavement Condition Index (PCI), Surface Distress Index (SDI), Present Serviceability Index (PSI), and Structural Condition Index (SCI). In Nepal, pavement condition assessments primarily depend on IRI and SDI. The Department of Roads (DoR) gathers IRI data using Roughometer III, a portable response-type device equipped with an accelerometer, distance-measuring instrument, and GPS (Highway Management Information System-Information & Communication Technology (HMIS-ICT) Unit, 2022). The SDI is a visual-based index used to quantify surface deterioration by evaluating the type, extent, and severity of surface defects like cracking, rutting, potholes, and edge breaks (DoR, 1995). SDI employs a six-point rating scale from 0 (defect-free) to 5 (severe deterioration) and is widely used in

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Nepal for pavement condition assessment, maintenance prioritization, and performance monitoring over time (HMIS-ICT Unit, 2022).

Deterministic models predict pavement deterioration through mathematical relationships linking pavement condition with influencing factors such as age, traffic load, climate, structural properties, drainage, and maintenance history (Anyala et al., 2014; Gupta et al., 2014; Tighe, 2002). Compared to probabilistic models, deterministic approaches are widely adopted by road agencies because of their simplicity and ease of use (Sanabria et al., 2017; Wang et al., 2017). These models are generally categorized as mechanistic, empirical, or mechanistic–empirical. Mechanistic models rely on pavement structural responses—such as stresses and strains caused by traffic loads—and offer strong physical insights, but they require extensive data for calibration (Morosiuk & Riley, 2004; Prozzi & Madanat, 2002; Wang et al., 2017). Empirical models utilize statistical relationships, often regression-based, between pavement condition and key variables and are popular at the network level, though their precision may be limited by data availability and simplified assumptions (Anyala et al., 2014; Perera & Kohn, 2001). Regression-based deterministic models are the most practical for predicting pavement conditions when suitable model forms, variables, and calibration techniques are carefully chosen (George et al., 1989; Gong et al., 2019).

Nepal's 33,716 km road network is managed by multiple agencies, with the DoR overseeing 11,179 km of national highways (National Planning Commission, 2019). The DoR allocates around NRs 7 billion yearly for maintenance and employs the Annual Road Maintenance Plan (ARMP) within its PMS to prioritize work based on SDI, road age, traffic, and strategic significance (DoR, 2007; DoR, 2005). Although 73% of highways are rated as fair to good (HMIS-ICT Unit, 2022a), aging infrastructure and increasing traffic challenge the DoR's goal of maintaining over 95% of the network in good condition. Shrestha and Khadka (2021) created regression models connecting IRI with PCI and SDI using feeder road data from Kathmandu and Lalitpur, but they omitted key variables like pavement age, traffic, and environmental factors, reducing their applicability (Shrestha & Khadka, 2021). Sigdel and Pradhananga (2021) and Sigdel et al. (2024) proposed regression and ANN-based IRI models that include traffic and climate variables; however, these studies relied on highly aggregated traffic data, short time series, and did not account for factors like time since last maintenance or axle loads (Sigdel et al., 2024; Sigdel & Pradhananga, 2021). Their outputs also conflicted with the DoR's main decision metric, SDI. Shakya et al. (2023) used a Markov deterioration model with IRI and SDI, but only considered average traffic and excluded effects from commercial vehicles and environmental factors (Shakya et al., 2023). Existing research in Nepal is hindered by limited datasets, narrow variable selection, and a lack of exploration into alternative modelling approaches.

This study develops a multi-variable regression model for predicting SDI on Nepal's national highways, incorporating initial pavement condition, traffic loading, climatic variables, and pavement age. The model is trained on 2012–2022 data from 157 highway sections, validated on a held-out dataset, and evaluated under a true out-of-sample forecasting framework using 2023 data. The proposed approach aims to provide a practical, statistically robust tool for network-level pavement performance prediction.

## 2. Methodology

### 2.1 Variables

The study defined SDI as a function of six independent variables: Initial International Roughness Index ($IRI_0$), Initial Surface Distress Index ($SDI_0$), pavement age (Age), total annual rainfall (RF), annual temperature difference (TD), and Equivalent Single Axle Load per day (ESAL), based on an extensive review of relevant literature, as expressed in Equation 1. The variable Age represents the number of full years elapsed since the most recent major renewal or rehabilitation activity that effectively reset the pavement's deterioration lifecycle. The variable RF denotes the cumulative depth of precipitation recorded during the twelve months preceding the year of prediction. The TD variable represents the annual thermal range experienced at the road section, calculated as the difference between the average daily maximum and minimum temperatures over a continuous twelve-month period. The variable $IRI_0$ refers to the pavement roughness measured at the beginning of the service life (age zero), while $SDI_0$ represents the surface distress condition at the same reference point. Lastly, ESAL indicates the standardized number of equivalent 80 kN single axle load applications per day, capturing the cumulative damaging effect of commercial traffic on the pavement. ESAL values were derived from classified traffic counts using Nepal-specific VDFs (DoR, 2014).

$$\mathrm{SDI} = \mathrm{f}\,[\mathrm{SDI_0}, \mathrm{IRI_0}, \mathrm{Age}, \mathrm{RF}, \mathrm{TD}, \mathrm{ESAL}] \text{ ………Equation 1}$$

## 2.2 Study Area

In Nepal, the Highway Management Information System (HMIS) includes traffic data from only 160 permanent traffic survey stations, meaning that accurate traffic information is available for a limited number of road sections. Among these, three sections lacked roughness data because they were unpaved at the time of classification under the Strategic Road Network and were later excluded once paved. Consequently, only road sections with complete and consistent traffic and roughness data were considered in this study. Based on this criterion, 157 road sections were selected, with an average section length of 15.7 km, covering a total network length of 15,783 km over the period 2012–2022. Although SDI and IRI measurements by the DoR began in 1995, a systematic web-based database was only established after 2012. As a result, this study was constrained to use data collected from 2012 onwards (DoR, 2023). The selected road sections, illustrated in Figure 1, represent those segments for which reliable and complete datasets were available. The selection of a limited number of road sections was a deliberate methodological decision aimed at preserving data accuracy and spatial representativeness. While including a larger number of road sections could increase network coverage, it would require extrapolating traffic data from distant survey stations to unsurveyed sections. Given Nepal's highly heterogeneous traffic conditions—driven by variations in settlement patterns, land use, topography, access density, and road functional class—such extrapolation would introduce significant uncertainty and potential systematic bias. Furthermore, the spatial distribution of traffic survey stations across the national highway network is uneven, with stations concentrated primarily along major corridors and sparse coverage in secondary and remote routes, as shown in Figure 2.

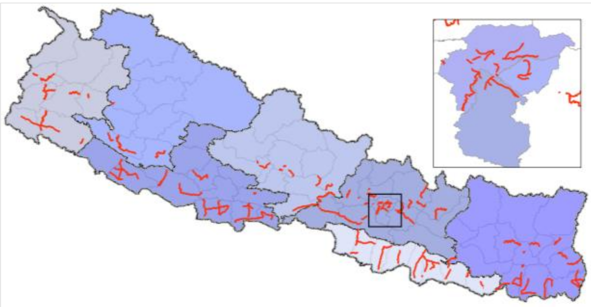


Figure 1 Road Sections taken for study

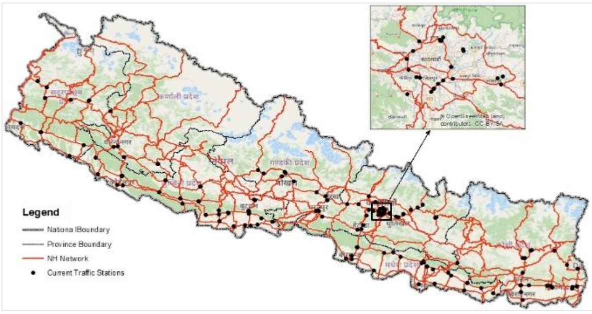



Figure 2 NH Network and Traffic Stations

As illustrated in Figure 3, only national highway sections with both direct traffic measurements and complete roughness records were included in the analysis. This approach minimizes reliance on assumed traffic conditions, enhances the reliability of model inputs, and strengthens the overall credibility of the pavement performance modelling results.


Figure 3 Selected Road sections with available traffic data and excluded NH

## 2.3 Data Collection and Preprocessing

Data on SDI, IRI, and traffic were obtained from the HMIS of the DoR (DoR, 2023), as described previously. Climatic data were sourced from the nearest Department of Hydrology and Meteorology (DHM) stations (Figure 4), which constitute the only authoritative long-term climate records available in Nepal. For each road section, average annual rainfall and annual temperature difference were computed to represent regional climatic exposure.

Although localized microclimatic variations may exist, these datasets provide the most reliable representation of climatic influences on pavement deterioration. Due to the absence of direct pavement age records, pavement age was inferred indirectly by identifying abrupt reductions in SDI or IRI values, which are indicative of overlays or major rehabilitation activities. The inferred intervention years were subsequently cross-validated using maintenance and rehabilitation records from the Road Board Nepal (RBN). Pavement age was assigned a value of zero in years corresponding to detected major structural improvements.

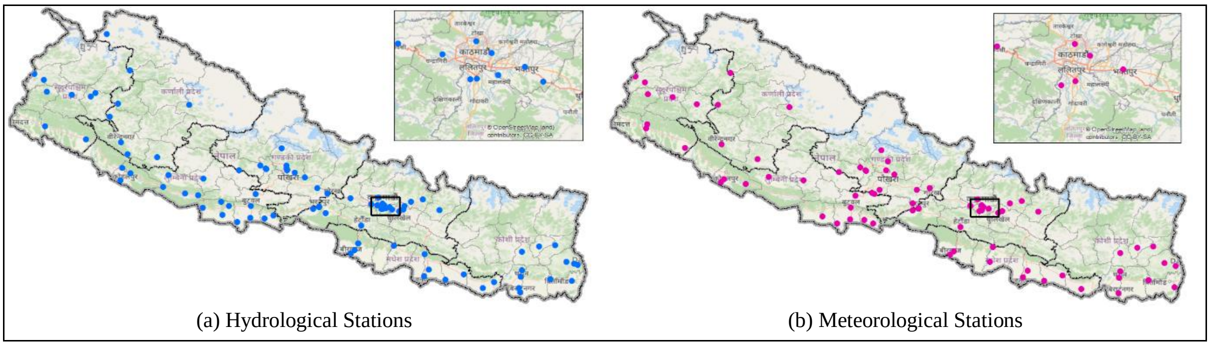



Figure 4 Climate Stations used

Before model development, the dataset was organized and pre-processed to address inconsistencies and extreme values. Missing observations were handled using imputation to retain incomplete records, while outliers were controlled through capping by replacing extreme values with predefined thresholds. These procedures helped preserve data integrity and robustness. In addition, Pearson's correlation coefficients were calculated to evaluate multicollinearity among the independent variables.

### 2.4 Multi-linear Regression Analysis

The study divided the overall collected dataset into two parts: a model development dataset (used for model development), which comprised 80% of the total data, and a validation dataset, which accounted for the remaining 20%. The research developed the MLR model using the model development dataset and validated it using the validation dataset using a number of evaluation metrics. The purpose of regression analysis is to create a model that can be used to predict the value of the dependent variable based on the values of the independent variables. A typical multiple variable regression equation takes the form of an Equation 2.

$$y = b0 + b1x1 + b2x2 + \ldots + bnxn \text{ .........Equation 2}$$

Where, y is the dependent variable; x1, x2, ..., xn are the independent; b0, b1, b2, ..., bn are the regression coefficients that represent the slope of the line for each independent variable (Neter et al., 1996).

The MLR model was developed in Microsoft Excel using the model development dataset. The statistical significance and explanatory power of the model were evaluated using ANOVA (Analysis of Variance) and coefficient of determination ($R^2$) values. ANOVA was employed to assess whether the regression model significantly explained the variance in the dependent variable. The $R^2$ value was used to determine the proportion of variance in SDI that could be explained by the independent variables, indicating the model's goodness-of-fit. To ensure the reliability and accuracy of the model, validation was performed using the validation dataset. The framework for the MLR model development has been shown in Figure 5.

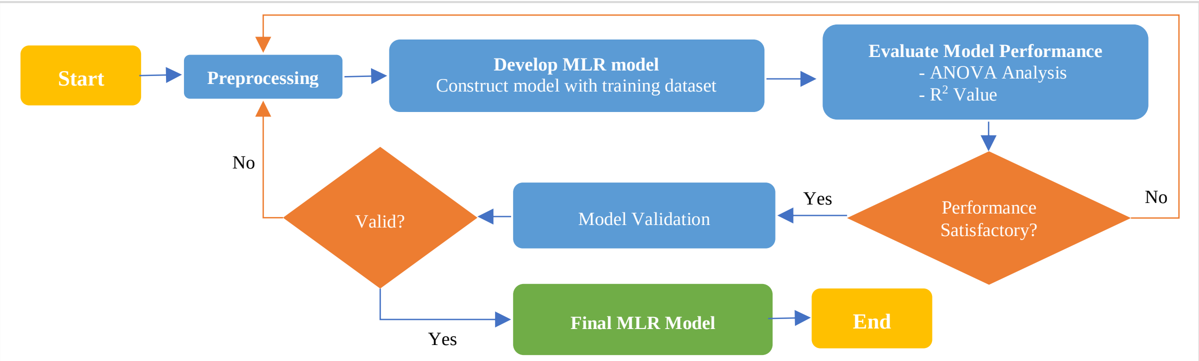



Figure 5 MLR Model Development Framework

The developed models were further evaluated using various parameters such as coefficient of determination ($R^2$), mean squared error (MSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and mean absolute deviation (MAD). Equation 3 through Equation 7 are employed to calculate each of these criteria (Asteris et al., 2020; Golafshani et al., 2020; Kooshkaki & Eskandari-Naddaf, 2019; Piro et al., 2022; Rasmussen & Williams, 2006). The value of $R^2$ ranges from 0 to 1, with a value of 1 considered optimal. For MSE, MAE, MAPE, and MAD, the values range from 0 to ∞, with lower values being preferred, and a value of zero being the best.

$$R^2 = \left(\frac{\sum_i (yp-\bar{x}) \times (yi-\bar{y})}{\sqrt{\sum_i (yp-\bar{x})^2} \times \sqrt{\sum_i (yi-\bar{y})^2}}\right)^2 \quad \text{.........Equation 3}$$

$$MSE = \frac{\sum_{i=1}^{N} (yi-yp)^2}{N} \quad \text{.........Equation 4}$$

$$MAE = \frac{\sum_{i=1}^{N} (|yi-yp|)}{N} \quad \text{.........Equation 5}$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N} \left|\frac{yi-yp}{yi}\right| \quad \text{.........Equation 6}$$

$$MAD = \frac{1}{N}\sum_{i=1}^{N} |xi - m(x)| \quad \text{.........Equation 7}$$

Where, yp = predicted value of SDI; yi = observed value of SDI; $\bar{x}$ = mean of predicted SDI values; $\bar{y}$ = mean of observed SDI values; xi = data values in the set; m(x) = average value of the data set; N = total number of data in the dataset.

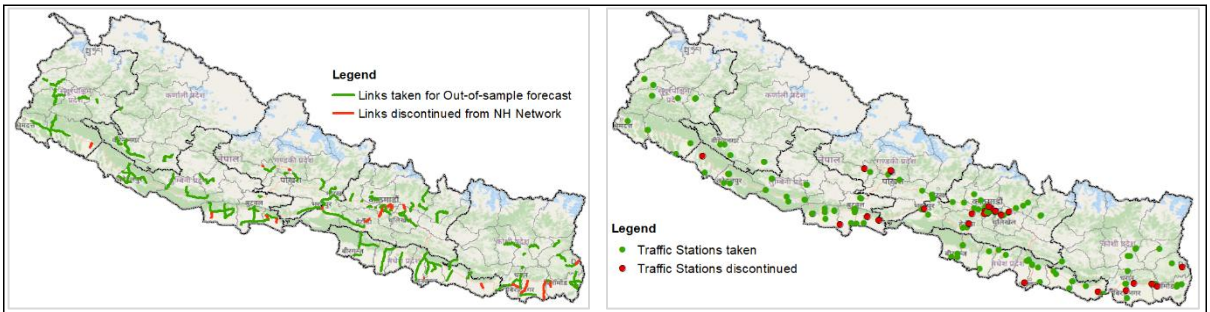
A sensitivity analysis was performed on the developed prediction models to quantify the relative influence of individual input variables on SDI predictions and to identify the most and least influential parameters. The study employed the Equation 8 to compute the sensitivity index (Chang & Liao, 2012).

$$S = \left\{\left(\frac{O2-O1}{I2-I1}\right) * \left(\frac{Iavg}{Oavg}\right)\right\} \quad \text{.........Equation 8}$$

Where, S: Sensitivity Index; $I_1$, I2: Minimum and Maximum Input values respectively; $O_1$, O2: Output values corresponding to $I_1$ and $I_2$ respectively; $I_{avg}$, $O_{avg}$: Average $I_1$, $I_2$ and Average $O_1$, O2 respectively.

## 2.5 True Out-of-Sample Forecasting

To rigorously evaluate the forward-looking predictive performance and practical applicability of the developed models, a true out-of-sample forecasting framework was implemented. This framework was designed to replicate real-world pavement management conditions, in which future pavement condition data are unavailable at the time of model development. All stages of model formulation were conducted exclusively using data available up to the year 2022. Pavement condition, traffic, and climatic information for 2023 became accessible only after the models had been finalized, ensuring that no data leakage or temporal bias influenced the model development process. For out-of-sample evaluation, the newly available 2023 dataset was used as an independent test set. However, 32 of the original sections were discontinued from the national highway network in 2023 and were therefore excluded due to the absence of pavement condition surveys. Consequently, the forecasting assessment was performed on the remaining 125 pavement sections with complete 2023 data. Figure 6(a) shows the sections taken for out-of-sample forecasting and sections discontinued from the NH network, while Figure 6(b) shows the traffic stations used for data collection in the sections taken along with the traffic stations discontinued.




(a) Sections (b) Traffic Stations

Figure 6 Sections and Stations for Out-of-Sample Forecasting

Predicted SDI values for 2023 were generated using only information that would realistically be available before or during the forecasting year. Model inputs included IRI obtained from the 2023 condition survey, pavement age updated to 2023, climatic variables aggregated up to 2022, and traffic data corresponding to 2023. This input configuration ensures that the forecasting exercise accurately reflects operational implementation scenarios faced by highway agencies. Once model structures and parameters were finalized using pre-2023 data, the trained models were applied directly to the 2023 dataset without any recalibration or adjustment. Forecasted SDI values were produced for each of the 125 pavement sections and compared with observed SDI measurements from the 2023 survey. Model performance was assessed using multiple statistical indicators as discussed earlier, including graphical diagnostics and error distribution analyses.

## 3. Results and Discussion

### 3.1 Data Statistics

Table 1 presents the descriptive statistics of the variables used for model development. To minimize potential bias, the dataset was compiled from road sections representing a wide range of pavement conditions, ages, traffic loading, and environmental characteristics. The dataset includes wide variations in pavement condition, age, climate, and traffic loading. The observed ranges and standard deviations indicate sufficient variability in the dataset, supporting the development of a robust and representative prediction model.

Table 1 Statistics of the variables used for model development

| Statistical Parameters | $SDI_0$ | $IRI_0$ | Age | RF | TD | ESAL |
|---|---|---|---|---|---|---|
| Max. | 2.3 | 6.7 | 10 | 4345 | 24.2 | 15138 |
| Min. | 0.5 | 1.9 | 0 | 365 | 3.9 | 100 |
| Average | 1.3 | 3.4 | 3 | 1577 | 11.8 | 2894 |
| Standard Deviation | 0.4 | 0.8 | 3 | 551 | 1.8 | 2877 |

### 3.2 Assessment of multi-collinearity

Pearson's correlation coefficient is utilized to assess the collinearity among independent variables. Before model development, the relationships between individual independent variables were evaluated through the creation of a correlation coefficient matrix. The computed correlation coefficients for these variables range from 0.01 to 0.23. Thus, the variables exhibit weak correlations. This suggests the absence of significant multicollinearity among the independent variables. Therefore, all six independent variables, Initial IRI, Initial SDI, Age, RD, TD, and ESAL, are considered for the development of the prediction model. The absolute Pearson correlation coefficient matrices have been illustrated in Figure 7. Since all the absolute Pearson correlation coefficients are below 0.8, this suggests a low probability of substantial collinearity (Kim, 2019).

| | Initial SDI | Initial IRI | Age | Rainfall | Temp. Diff. | ESAL |
|---|---|---|---|---|---|---|
| Initial SDI | 1.00 | 0.18 | 0.16 | 0.08 | 0.10 | 0.08 |
| Initial IRI | 0.18 | 1.00 | 0.14 | 0.08 | 0.01 | 0.10 |
| Age | 0.16 | 0.14 | 1.00 | 0.23 | 0.05 | 0.05 |
| Rainfall | 0.08 | 0.08 | 0.23 | 1.00 | 0.01 | 0.19 |
| Temp. Diff. | 0.10 | 0.01 | 0.05 | 0.01 | 1.00 | 0.03 |
| ESAL | 0.08 | 0.10 | 0.05 | 0.19 | 0.03 | 1.00 |

Figure 7 Pearson Correlation Coefficient Heatmap

### 3.3 Multi-linear Regression Analysis

The results of the ANOVA test have been presented in Table 2. The ANOVA results indicate a highly significant regression model, with an F-statistic of 341, demonstrating that the variance explained by the model is substantially greater than the unexplained variance. The associated p-value ($< 0.05$) confirms rejection of the null hypothesis, indicating a statistically significant relationship between SDI and the selected independent variables. The regression and residual degrees of freedom were 6 and 783, respectively, corresponding to the number of estimated model parameters and the remaining unexplained variability in the dataset. The regression mean square (MSR = 68.8) was considerably higher than the residual mean square (MSE = 0.2), suggesting a strong explanatory capability and good model fit. Additionally, the regression sum of squares (SSR = 412.8) exceeded the residual sum of squares (SSE = 157.7), indicating that a substantial proportion of the total variability in SDI is captured by the regression model.

Table 2 ANOVA Results (Approach 1)

| | Degree of freedom (df) | Sum of Squares (SS) | Mean of Squares (MS) | F Statistics | Significance F (p-value) |
|---|---|---|---|---|---|
| Regression | 6 | 412.800 | 68.800 | 341.631 | 9.4073E-215 |
| Residual | 783 | 157.686 | 0.201 | | |
| Total | 789 | 570.486 | | | |

The regression statistics presented in Table 3.2 indicate strong model performance. The multiple correlation coefficient (R = 0.851) reflects a strong positive linear relationship between the independent variables and SDI. The coefficient of determination ($R^2 = 0.724$) shows that 72.4% of the variability in SDI is explained by the model, while the adjusted $R^2$ value (0.721) confirms that the selected predictors contribute meaningfully without overfitting. The standard error of the estimate (0.449) indicates relatively small deviations between observed and predicted values, demonstrating good predictive accuracy of the regression model.

Table 3 Regression Statistics

| Regression Statistics | |
|---|---|
| Multiple R | 0.851 |
| $R^2$ | 0.724 |
| Adjusted $R^2$ | 0.721 |
| Standard Error | 0.449 |
| Observations | 790 |

Table 4 presents the test statistics and coefficients of Multilinear regression analysis. The most influential predictor is Initial SDI, with a coefficient of 0.528, a very small P-value (8.59E-33), and a 95% confidence interval between 0.445 and 0.611, indicating a strong, positive, and highly significant relationship with the dependent variable. Initial IRI also shows a positive, though smaller, effect (coefficient of 0.045) and is statistically significant with a P-value of 0.039. Age is another critical variable, with a coefficient of 0.206, indicating that pavement age contributes significantly to the outcome, confirmed by its P-value of 3.19E-137. RF and TD both have significant effects, with coefficients of 0.282 and 0.035, respectively, showing that higher rainfall and greater temperature variation are associated with higher pavement distress. Lastly, ESAL has a coefficient of 0.012 and is statistically significant (P-value of 0.033), suggesting that heavier traffic increases distress, though its effect is relatively smaller compared to other factors, which is likely to be because of the trend of increase in maintenance activities with increase in ESAL. The standard errors are provided for each coefficient, ensuring the precision of estimates, and the t-statistics further affirm the significance of most predictors.

Table 4 Test Statistics and Coefficients (Approach 1)

| | Coefficients | Standard Error | t Stat | P-value | Lower 95% | Upper 95% |
|---|---|---|---|---|---|---|
| Intercept | -0.164 | 0.138 | -1.194 | 0.233 | -0.434 | 0.106 |
| Initial SDI | 0.528 | 0.042 | 12.494 | 8.5865E-33 | 0.445 | 0.611 |
| Initial IRI | 0.045 | 0.022 | 2.063 | 0.039 | 0.002 | 0.087 |
| Age | 0.206 | 0.007 | 30.822 | 3.1881E-137 | 0.193 | 0.219 |
| RF (in m) | 0.282 | 0.031 | 8.963 | 2.28344E-18 | 0.220 | 0.344 |
| TD (in °C) | 0.035 | 0.009 | 4.057 | 5.47127E-05 | 0.018 | 0.052 |
| ESAL (in tsa) | 0.012 | 0.006 | 2.139 | 0.033 | 0.001 | 0.023 |

Based on the outcomes of the multiple linear regression analysis, the model for SDI concerning Nepal's national highway pavements is formulated as represented in the Equation 9.

$$\mathrm{SDI} = -0.164 + 0.528\ \mathrm{SDI}_0 + 0.045\ \mathrm{IRI}_0 + 0.206\ \mathrm{Age} + 0.282\ \mathrm{RF} + 0.035\ \mathrm{TD} + 0.012\ \mathrm{ESAL} \quad \text{...Equation 9}$$

Where, SDI: Surface Distress Index; $IRI_0$: Initial International Roughness Index / Performance function (m/Km); $SDI_0$: Initial Surface Distress Index; Age: Pavement Age in years; RF: Total Rainfall in m; TD: Annual Max and Min Temperature Difference in °C; ESAL: Number of Equivalent Single Axle Load in thousands (thousand standard axles, tsa)

For model validation, the developed model was used to predict the SDI using the validation dataset consisting of 189 observations (20% of the overall dataset), which was set aside as discussed earlier. The $R^2$ value for the validation dataset was computed at 0.7298, marginally surpassing the $R^2$ value of the model. This indicates that approximately 72.98% of the SDI values predicted by the model matched the observed dataset, which is greater than the percentage accounted for by the model. This outcome suggests that, on the whole, the model demonstrates satisfactory statistical performance and possesses the capability to reasonably forecast SDI for the various pavement sections. Figure 8 illustrates the scatter plots comparison between observed (measured) and predicted SDI across the model development phase, validation phase, and overall dataset for the MLR model. In the model development phase, the model demonstrates a strong correlation between observed and predicted SDI, capturing a significant portion of the variability in the data. During the validation phase, the model slightly improves in predictive performance on unseen data, suggesting good generalization beyond the training dataset. The overall performance plot, which combines both development and validation datasets, confirms the model's consistency across different phases. The results indicate that MLR explains approximately 72.7% of the variance in SDI, reflecting a good fit. The observed pattern shows a strong correlation between observed and predicted SDI values in the 0–2 range, with greater scatter appearing in the 2–4 range, which is typical in pavement condition modeling. At lower SDI levels, pavements are usually in good to fair condition, with more gradual and uniform distress development, making it easier for the MLR model to identify relationships. Conversely, in the moderate to poor condition range (SDI 2–4), pavement behaviour becomes more non-linear and diverse due to mixed types of distress, faster and uneven deterioration, and greater variability in field assessments. The linear nature of the MLR model also restricts its ability to capture complex interactions in this range, and data imbalance further hampers model training for severely distressed pavements. Hence, the model is effective for early-stage deterioration but loses accuracy as pavement conditions decline and deterioration processes grow more complex.

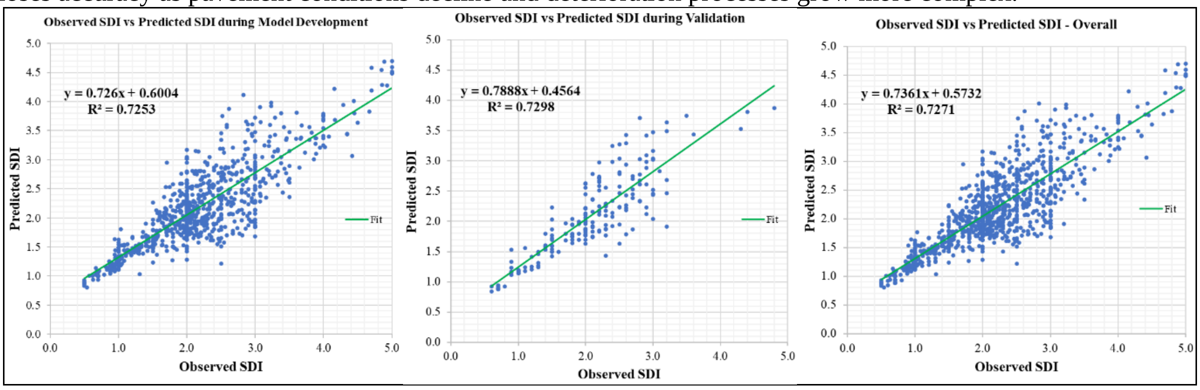
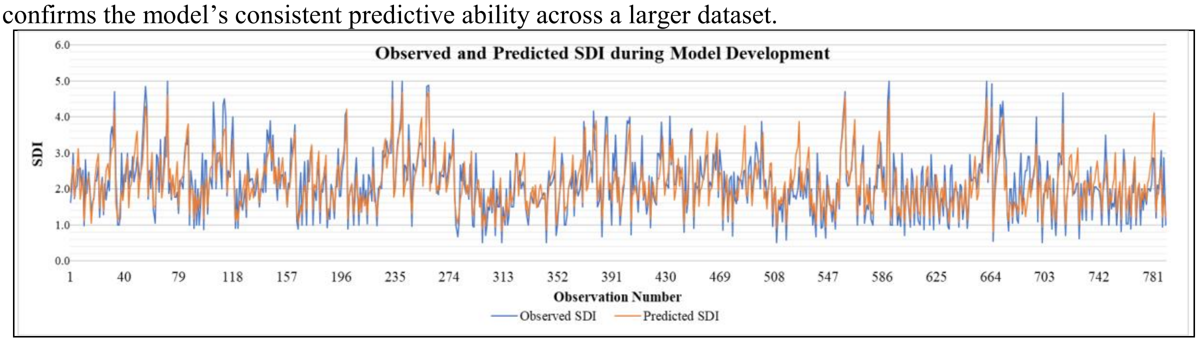



Figure 8 Predicted SDI Vs measured SDI

Figure 9 presents a comparison between observed (measured) and predicted SDI using MLR across three different evaluation phases. In the model development phase, the predicted SDI values (orange line) closely follow the observed SDI values (blue line), demonstrating that the MLR model captures key trends and patterns. During the validation phase, the model continues to perform well, with predicted SDI values aligning closely with observed values. The overall performance graph, which consolidates both development and validation datasets, confirms the model's consistent predictive ability across a larger dataset.



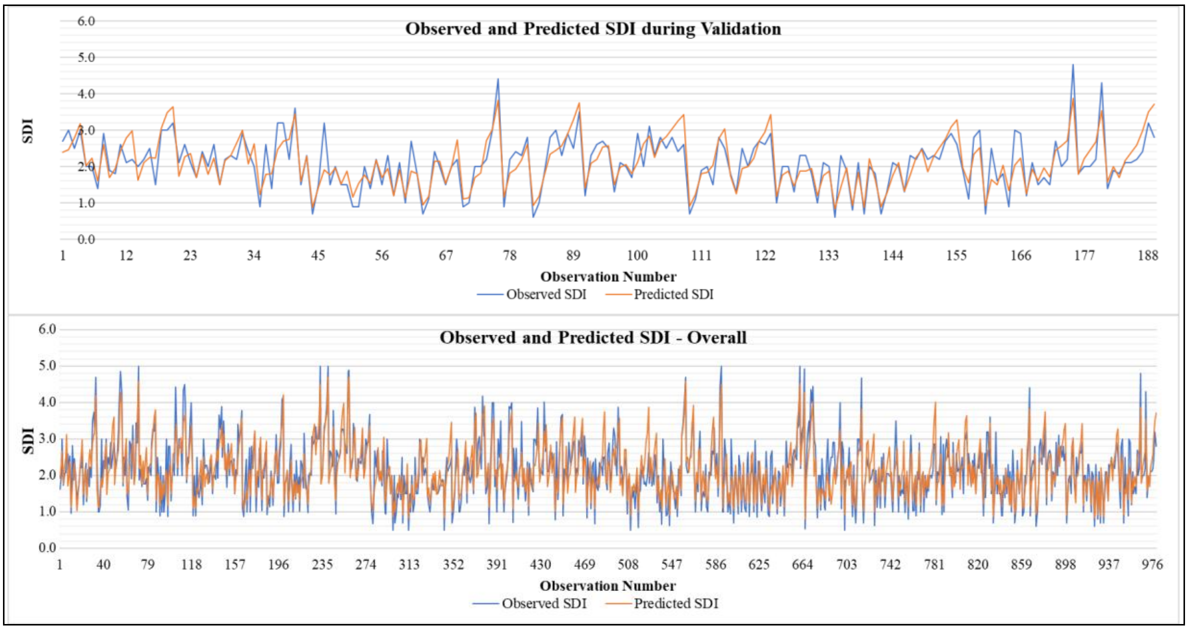



Figure 9 Comparison between predicted and observed SDI

Figure 10 compares the developed models in terms of the evaluation parameters computed during model development, validation, and overall data. During the model development phase, the model demonstrates an MSE of 0.197, an MAE of 0.358, and an $R^2$ value of 0.725, indicating a good fit but with some prediction errors. In the Validation phase, the MSE and MAE slightly improve to 0.145 and 0.292, respectively, with an $R^2$ value of 0.730, suggesting better performance on unseen data. The overall performance across all datasets remains stable, with an $R^2$ of 0.727, showing the model's consistency but also its limitations in fully capturing SDI variations.

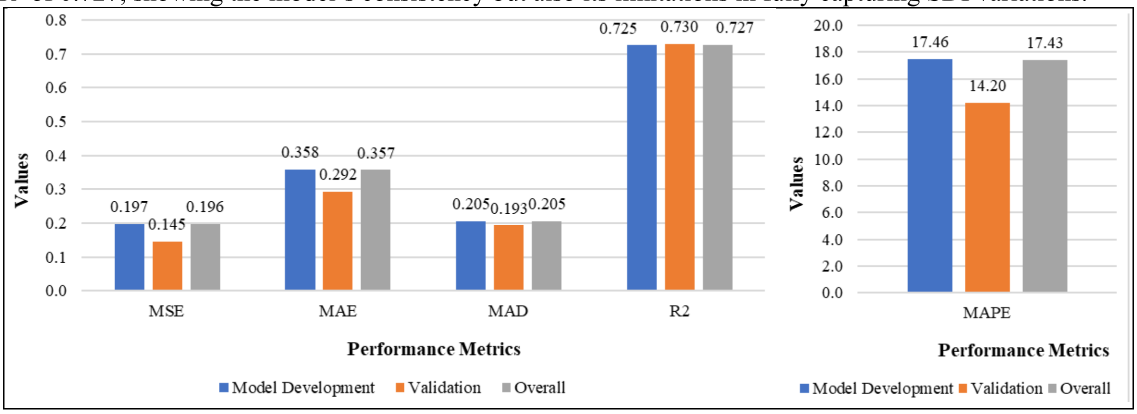



Figure 10 Comparison of evaluation parameters

Figure 11 illustrates an error histogram representing the occurrences of error in the overall dataset, which shows a roughly normal distribution centered around zero, indicating minimal bias in predictions. Most errors fall within the range of -0.356 to 0.094, suggesting accurate predictions, while extreme errors are rare. The symmetrical distribution implies the model performs well without significant overestimation or underestimation. However, some large errors at the extremes may indicate outliers or difficult-to-predict cases.

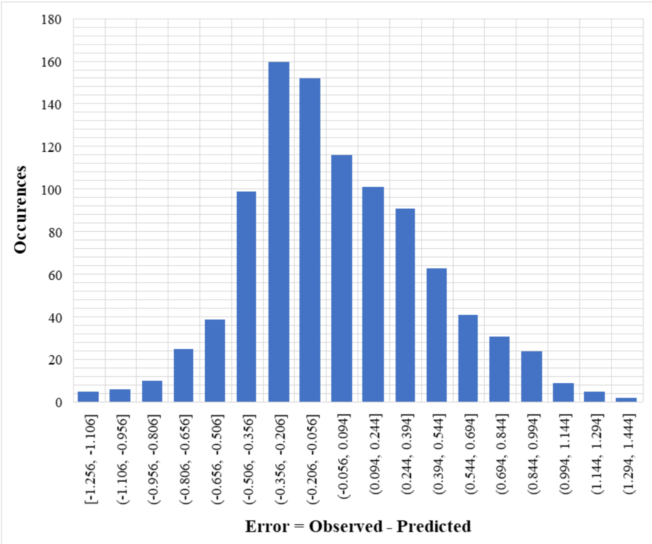



Figure 11 Error Histogram under Regression

The sensitivity index computed for the variables used in the research has been presented in Table 5. The computed indices show that Initial SDI is the most sensitive parameter, followed by Initial IRI, while ESAL is found to be the least sensitive parameter. A lower value of the sensitivity index in ESAL signifies pavement interventions in the selected road sections with an increase in ESAL.

Table 5 Sensitivity Index in Variables

| | **Initial SDI** | **Initial IRI** | **Age** | **Rainfall** | **Temp Difference** | **ESAL** |
|---|---|---|---|---|---|---|
| Sensitivity Index | 0.68 | 0.78 | 0.38 | 0.51 | 0.64 | 0.16 |

### 3.4 True Out-Of-Sample Forecasting

This section presents a comprehensive evaluation of the out-of-sample forecasting performance of the developed model for the year 2023. The model was developed using historical data up to 2022, while the 2023 dataset, comprising 125 observations, was treated as completely unseen, thereby providing a rigorous assessment of the model's true forward-looking predictive capability.

Figure 12 illustrates the scatter plot comparing observed (measured) and predicted SDI values under the true out-of-sample framework. The strong positive linear relationship, reflected by an $R^2$ value of 0.723, indicates that the model generalizes well beyond the calibration period and effectively captures the overall magnitude of pavement surface distress. The concentration of points around the 1:1 reference line suggests satisfactory predictive accuracy. Figure 13 presents the distribution of prediction errors (Observed − Predicted SDI) for the out-of-sample dataset. The error histogram is approximately symmetric and centered near zero, indicating the absence of systematic bias in the model predictions. Most errors fall within a narrow range, demonstrating stable and consistent forecasting performance.

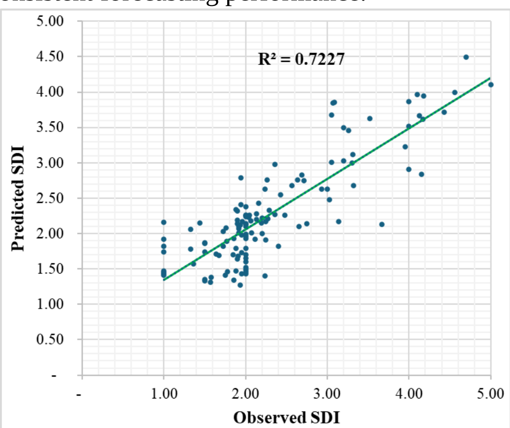



Figure 12 Predicted SDI Vs measured SDI (Out-of-Sample)

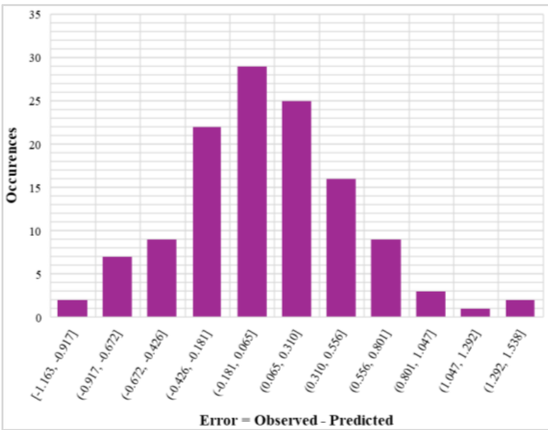



Figure 13 Error Histogram (Out-of-Sample)

Figure 14 further compares the observed and predicted SDI values across all out-of-sample observations. The predicted SDI series closely follows the overall trend and variability of the observed data, confirming the model's ability to track spatial and temporal changes in pavement condition. Nonetheless, localized discrepancies are observed during abrupt peaks and troughs, indicating limited sensitivity to sudden changes in distress progression.

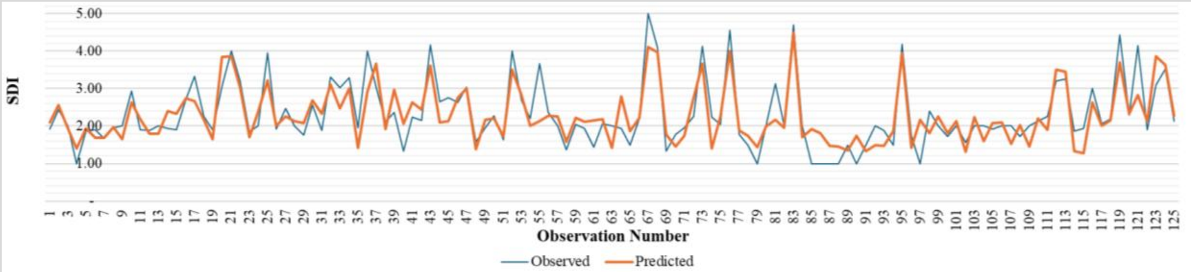



Figure 14 Comparison between predicted and observed SDI (Out-of-Sample)

The numerical performance indicators are summarized in Table 6 verify these graphical observations. The model achieves an MSE of 0.211, MAE of 0.359, RMSE of 0.460, and an $R^2$ of 0.723, reflecting satisfactory accuracy and robustness under out-of-sample conditions. The MAPE value of 16.93% indicates moderate relative error, which is acceptable for network-level pavement performance modelling.

Table 6 Performance evaluation parameters (Out-of-sample)

| Observations | MSE | MAE | MAPE | MAD | R2 | RMSE |
|---|---|---|---|---|---|---|
| 125 | 0.211 | 0.359 | 16.928 | 0.225 | 0.723 | 0.460 |

## 4. Conclusion

This study developed, validated, and thoroughly tested a deterministic multiple linear regression (MLR) model to predict the Surface Distress Index (SDI) of Nepal's national highway pavements within the operational framework of the Department of Roads' Pavement Management System. The model includes six explanatory variables—initial SDI, initial IRI, pavement age, annual rainfall, annual temperature difference, and ESAL—chosen to represent pavement condition, traffic load, and climate exposure using nationally available datasets. Using data from 157 national highway sections and 790 observations collected from 2012 to 2022, the MLR model showed strong statistical performance. It achieved an $R^2$ of 0.724 during model development and 0.730 during validation, with an overall $R^2$ of 0.727, meaning about 72–73% of the variation in SDI is explained by these predictors. Performance metrics based on errors further confirm the model's reliability, with mean squared error (MSE) values of 0.197 and 0.145, and mean absolute error (MAE) values of 0.358 and 0.292 for the development and validation datasets, respectively. The error distribution was roughly symmetric and centered near zero, indicating minimal systematic bias. Regression analysis shows initial SDI as the most influential predictor, followed by pavement age, and climatic factors, especially rainfall. Sensitivity analysis supports these findings, with sensitivity indices of 0.68 for initial SDI, 0.78 for initial IRI, and 0.51 for rainfall, while ESAL had the lowest sensitivity index (0.16), reflecting the impact of maintenance measures on heavily trafficked sections. The model's true forecasting ability was further tested through a strict out-of-sample prediction exercise using 125 highway sections from the 2023 dataset, which were completely separated from the model development and calibration process. Under this real-world testing framework, the model achieved an $R^2$ of 0.723, an MSE of 0.211, an MAE of 0.359, an RMSE of 0.460, and a MAPE of 16.93%. These results demonstrate consistent and stable performance in forecasting, confirming the model's capacity to generalize beyond the historical data and reliably support network-level decision-making.

The developed SDI prediction model offers a statistically sound, operationally practical, and nationally applicable tool for pavement performance forecasting in Nepal. Its high explanatory power, acceptable prediction errors, and proven robustness in out-of-sample tests make it suitable for integration into the Annual Road Maintenance Plan, helping to improve maintenance prioritization, budgeting accuracy, and long-term asset management. Future research could focus on including detailed axle-load spectra, explicit maintenance history variables, longer post-rehabilitation performance records, and comparative analyses with advanced machine learning or hybrid models.

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