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Research Article

Analysis of factors influencing road stability in the hinterland connection of South Sumatra, Indonesia, using multi-linear regression

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Abstract
Palembang city is the capital of South Sumatra, a province in Indonesia known for its extensive hinterlands which serve as production areas for various agricultural commodities. To facilitate connectivity to these areas, robust road infrastructure capable of supporting heavy transport vehicles is essential. Currently, over-dimension overloading (ODOL) trucks are the primary cause of road damage. This research aimed to analyze factors influencing road stability, using independent variables. A multi-linear regression (MLR) model with a stepwise method was employed. The anticipated outcome of this study was to identify the factors affecting the stability of roads connecting Boom Baru port to hinterland production areas. The Durbin-Watson statistic, used to test for autocorrelation, showed a value of 1.612 for the sixth model, which indicates no autocorrelation (values range from 0 to 2). This suggests that the other five models are also free from autocorrelation. According to the coefficient table, model number 6 displayed the highest R-squared value of 0.676, though its constant was negatively high. Ideally, it should be positive or less than one. Thus, model number 3 is considered more suitable as it also has a high R-squared value of 0.650. The stability of roads depends on the volume of trips to agricultural areas, the type of pavement surface, and the ease of access to the port.

Keywords
Multi linear regression, Stability route, Hinterland connection.

1.Introduction
Ports are pivotal hubs for international trade, serving as gateways that link countries to the global marketplace. Ports are integral components of a competitive network, all competing for transport capacity. This competition has expanded beyond mere port operations to focus on hinterland connectivity those vital links that extend the reach of ports into the interior regions [1]. The main problem of the hinterland connection to the port of Palembang revolves around the need for improved coordination among multiple actors, often with conflicting mandates, who govern the development of port hinterland infrastructure. Merk and Notteboom (2015) discuss the critical role of hinterland connections in the competitiveness of seaports and the challenges involved in developing these connections [2]. Furthermore, they explained the importance of good policy response and multilevel governance in stakeholders in hinterland connections and ports.

The development of the hinterland area in South Sumatra, serving as a support region for Boom Baru port, warrants increased attention. Van and De [3] discussed the significance of port authorities actively monitoring their inland territories. The inland region, which includes the hinterland connections, functions as a regional hub for the collection and distribution of trucking operations. This arrangement is designed to expedite and streamline the transfer process to and from ports, to minimize prolonged container storage at the ports.

The route network of hinterland connection extends across multiple cities and districts within South Sumatra Province. A variety of goods have the potential to be marketed beyond the region via Boom Baru Palembang port. The majority of logistics rely

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on heavy-duty trucks for transporting goods to this port for export. Recognizing the vital links to nearby inland areas is essential for maintaining competitiveness. In another article, Van [4] stated the importance of developing an intermodal transportation strategy in supporting the performance of the hinterland to the Port.

Hinterland connectivity also increases competition between transport chains as investigated by Li et al. [5]. With the increasing distance of the hinterland from ports, competition becomes fiercer as intermodal services become increasingly viable. Visser et al. [6] investigate opportunities for the concept of inland transport at the Port of Rotterdam. Their study focuses on the types of transport systems used in its operations and evaluates existing conventional intermodal modes, such as rail and barge, as well as the potential of new transport technologies.

Multi-linear regression (MLR) analysis provides information about how strong the relationship is between the independent and dependent variables, as well as the relative contribution of each independent variable to the dependent variable. Regression analysis for ports identifies the relationship between various factors that influence port performance, helps in predicting future trends, optimizing operational efficiency, and identifying key factors that influence port performance, Uyanık and Güler [7].

Meanwhile, in determining road handling programs, it is often not following the priority needs of roads in the field. Roads that are frequently used by heavy vehicles, especially those overloaded, tend to be damaged more quickly. A long queue at the Boom Baru terminal gate resulted in long parking in two rows around the port. So, when the truck enters the ship there is a big hole in the road. Over dimension overloading (ODOL) trucks not only cause traffic jams but also cause narrow road space. This means it turns out that the loading variable alone is not enough to consider in pavement design. All methods used today only look at the technical side which only takes into account the traffic load and soil strength from the side that supports the load. So far only these two variables affect road conditions. It is necessary to anticipate other factors such as land use, accessibility, pavement structure, and road geometry factors.

The number of activities in an area generates movement, resulting in the frequent passage of heavy vehicles. It is necessary to investigate whether there are factors other than technical ones that contribute to road damage. Such as roads that connect to the port facility area or road sections that connect to agricultural areas and industrial areas known as hinterland. What factors can influence road stability? There has not been research that studies parameter models for supporting aspects of road stability infrastructure other than the technical aspects. Therefore, this analysis aims to examine the factors that affect the road stability of the hinterland connection to Boom Baru port.

The hinterland connections in South Sumatra face reduced support. This lack of support impacts road stability, hindering efficient transportation. The less accessible areas in South Sumatra province, especially its hinterlands, often face insufficient transportation connections, which hinder economic growth and market access. Polyzos and Tsiotas [8] stated that transportation infrastructure plays a crucial role in driving economic growth across all areas, especially at regional and local levels, where the components of spatial economic systems are typically established. Inadequate infrastructure investment and limited resources exacerbate the situation. Unstable roads lead to increased transportation costs. Businesses suffer due to delays, vehicle damage, and disruptions in supply chains. There is a relationship between transportation and economic development, which can have an impact on regional growth [8]; Economic growth in the region is directly linked to stable hinterland connections.

The diverse spatial constraints and topography constraints of South Sumatra pose challenges. Constructing stable roads across mountains, valleys, and forests requires innovative solutions. Spatial constraints impact route selection and stability [9].
Addressing these transportation challenges requires a comprehensive approach that involves strategic, sustainable planning, minimizing disruptions to road networks, investment in alternative modes of transport, and improving road safety. Effective collaboration among government agencies, private sector stakeholders, and communities is essential to address these complex transportation challenges comprehensively [10].

The model developed in this study is expected to provide a holistic solution that captures every aspect of the problem. The motivation behind this research lies in addressing critical challenges related to road stability in South Sumatra, Indonesia.
Here are some of the key drivers:

Economic growth and transportation support:
- South Sumatra's economic growth heavily relies on efficient transportation.
- The region experiences a mix of heavy vehicles, necessitating robust hinterland connections.
- These connections are vital for supporting economic activities, trade, and development.

Infrastructure development and route selection:
- The study aims to identify optimal routes for hinterland connections.
- By analyzing road stability conditions, researchers seek to compile the best routes.
- These routes will enhance transportation efficiency and contribute to economic prosperity.

Overcoming existing obstacles:
- Road damage and decreased support for hinterland transportation pose challenges.
- The research intends to overcome these obstacles while maintaining the existing level of service.
- Stable roads are essential for sustaining economic activities and minimizing disruptions.

Strategic policies for economic growth:
- By understanding hinterland connection performance, the study informs infrastructure development.
- The road stability value approach guides decision-making for the best route selection.
- Strategic policies can then be formulated to support South Sumatra's economic growth.

This research makes contributions at both strategic and operational levels. It bridges the gap between theory and practice, offering actionable insights for policymakers, engineers, and stakeholders. By ensuring stable hinterland connections, South Sumatra can achieve economic growth while preserving its natural environment.

From the background of the problems described above, the formulation of the problem in this study is as follows:
1) How to model road stability to predict the future condition of hinterland connection from port to hinterland.
2) How to get the factors that can affect road stability.

The objectives of this study are as follows:
1) To find an MLR model of road stability to predict the future condition of the hinterland connection from port to hinterland.
2) To analyze the correlation between road stability and the variables of land use, accessibility, pavement structure, and road geometry factors.

The outline of this paper is as follows: Section 1 explains the background, problem formulation, research objectives, and motivation of this study. Section 2 discusses the literature review. Section 3 explores the methodology in detail. Section 4 presents the research details. Section 5 describes the discussion related to the results obtained. Finally, the conclusions are presented in Section 6.

2. Literature study

Many researchers have used MLR as a good starting point for understanding the factors that support port productivity and how MLR can be applied to analyze them. Wang et al. (2023) [11] established a model within a container yard context to predict the arrival time of container transportation and its influencing factors, using data from the yard's control center.

In the present paper Dwarakish [12], has examined the relationship between various observed performance parameters and the productivity (total traffic handled) of the port. Ali et al. [13] conducted a study for a statistical logistic regression model of technical data that analyzes the relationship between various variables. Likewise, Yang [14] in his research has built several regional freight transportation demand (RFTD) prediction models demand using a comparison of several MLR, nonlinear regression (NLR), and simple linear regression (SLR) methods that depend on specific contexts and the relationship between model complexity and prediction accuracy.

Vyas and Varia [15] used MLR and soft computing approach, artificial neural networks to predict urban environmental noise with the results of comparing mean square error (MSE) values of 5.4% and 9.3%. In addition to noise studies on material waste indicators, there was research that obtained the most dominant design factors and procurement factors that were effective for reducing material waste in a construction project [16]. Zhang et al. [17] forecasted the transport energy demand for 2010, 2015, and 2020 based on the partial least square regression (PLSR) method in China by reaching 468.26 Mtce [18]. Other research was conducted on the empirical assessment of sustainable transportation indicators that have an impact on increasing economic productivity [19].

Research that contributes to the field of land suitability evaluation using multi-criteria analysis (MCA) and geographic information system (GIS). Integration shows that variables of soil quality, topography, and erosion risk are most influential in the study area [20].

Road infrastructure development is part of the transportation system for socio-economic development in a country, road infrastructure is important to be considered, which provides access to markets, jobs, and resources [21]. The selection of road sections as a support for the best alternative routes can contribute to the development of the road network system along with the development of the region [22].

For this reason, an analysis is needed that supports the level of accessibility based on several variables, such as distance, infrastructure conditions, and the availability of comfortable and safe facilities. The better the port's connection to various inland areas, the greater the potential to expand the overall captive area [23]. Rosada and Arliansyah [24]. stated that road infrastructure burdened with a continuous high volume of traffic will lead to a decrease in road stability which can affect safety, comfort, and economy.

In the same view, Mulyono [25] thinks that the decline in road pavement performance is caused by excessive vehicle loads and inaccuracy in determining implementation standards. A pavement structure is a layer of material that has been calculated, and its function is to support traffic loads without causing significant damage to road construction [26]. According to Octaviansyah et al. [27], in Puteri and Sulandari [28] the main requirement of each pavement surface layer must be safe, comfortable, and economical. In addition to that industrial estates will add strategic and fast-growing areas with new economic growth centers [29].

The availability of a stable road network as a transportation infrastructure that connects all cities and production centers throughout the region provides opportunities and encourages the development and increase of regional economic growth [30]. The category of road stability level used by the Directorate General of Highways is the stability of road construction based on the availability of sufficient data seen from the parameters of roughness, road width average daily traffic (ADT) volume [31], Roughness parameters can be performed by measuring the internationally accepted international roughness index (IRI) as an important indicator for evaluating pavement conditions [32]. Meanwhile, according to Putranto [33], the direction of providing reliable transportation infrastructure services translates into regional connectedness and road service stability.

In the road network system, several road sections with various conditions will get priority lanes, thus making the inland transportation system to the port more sustainable [34]. Land connectivity is a description of the relationship between a port and the area around its buffer, where there is no relative boundary of a province depending on the presence or absence of ports adjacent to the area [35]. Likewise, according to [36], port productivity is greatly updated with the condition of road infrastructure as a link between the port production area and the market.

Safira et al. [37] have carried out research regarding the pre-clearance time equation model. Analysis of the pre-clearance time equation model at the Boom Baru Port can be searched by modeling the existing data using multiple linear regression analysis. The best model obtained is Y = 1,384 + 0,380 X1 + 1,078 X2 + 0,290 X#, where X1 is the prohibited and restricted goods permit process, X2 is quarantine process, X3 is document preparation, and Y is pre-clearance time. All in units of time (day).

Mokhtar et al. [38] have done research regarding a regression model for vessel turnaround time. Their study results show that time solution vessels are highly correlated with crane allocation as well as the amount of loaded and unloaded containers.

Yousefi et al. [39] have another MLR research, that has been applied to analyzing Canada's freight transportation framework. It revealed that weight, distance, and quantity delivery had a positive and sufficiently strong correlation with gaining income. These three factors have been found to have a positive and strong correlation with revenue generation. This means that as the weight and distance of the freight increase, along with the quantity delivered, there is a corresponding increase in income.

Research regarding models to predict balance sheet future trade has been published under the name of Gan and Ahmad [40]. In their research, an MLR model was developed for forecasting balance sheet future trade, which shows Y= -164+ 0.001 (export palm oil) + 0.001 (exports of crude petroleum) – 0.001 (imports of f petroleum product) – 0.003 (import of motor cars) + 0.002 (export of plywood plain).

Iwu and Uchendu [41] carried out research regarding the application of artificial neural networks and MLR models for forecasting container throughput in the application performance management (APM) terminal Apapa port A. The result of this MLR model is as follows: Y = 0.323+0698 X1 – 0.105X2, where Y= Container Throughput, X1= GDP and X2= Inflation Rate.

Owalabi and Abiola [42] in 2021 they studied the development of a priority index assessment model for road pavements in Nigeria. The results of their research which uses the MLR method to get a method of management pavement effective way in Nigeria and developing countries and others in the world with conditions climate, soil, and traffic are similar.

As it is mentioned above the Limited Terminal area of Boom Baru port in Palembang causes long queues before and during the loading of exported goods onto ships. As a result, the roadside, and in some locations, the entire road, including drainage, was damaged [43]. In many cases. Terminal operators tend to make stacking decisions based mostly on factors such as the container's weight, size, and type. To enhance the Terminal processing time. Kourounioti et al. [44] develop a methodological framework that relates the various factors that affect the dwelling time of container terminals.

On the other hand, Zheng et al. [45] have studied the efficiency of container terminals in Korea and China. This study aims to analyze efficiency improvement and management level enhancement by selecting container terminals in Korea and China as comparison units. The results show that the efficiency of major terminals in Korea was similar efficiency of China's terminals. Furthermore, Burdzik et al. [46] have tried to assess the impact of processing handling efficiency on the transport process. The research was done in a real object, the same technology and handling equipment. The results confirm the importance of the loading and unloading process in palletized cargo [47].

Based on the review and analysis, it is observed that MLR can be adopted for predicting factors that affect road stability. It is anticipated that road stability on hinterland route connections can be improved and managed effectively. As a result, port management may receive recommendations from the public works department of the local government on how to reduce queues outside the port area.

3. Methodology

3.1Flow chart of research

This study presents the steps to analyze the hinterland connectivity problems in South Sumatra. The analysis begins with identifying the traffic problems encountered and establishing expected outcomes, clearance problems encountered in the field, and the data and analysis needed to determine the best route in domestic connection.

This study was carried out on the national road network of South Sumatra province. The method used in this study with multi-linear regression, while variables and parameters were obtained by analyzing management policies and roads in the southern province of Sumatra in terms of road stability. The assessment was achieved by distributing questionnaires to road operators and experts to find out their perceptions of the criteria and sub-criteria based on expertise, as well as questionnaires to road users. Participants get an idea of road performance about what they experience and feel in their daily lives. The resulting dimensions and indicators are used to develop strategic policies and set priorities for road treatment programs that can bring added value to economic growth and enhance investment. The research flow chart has been prepared as a guideline to find the aim of this research. It is shown in *Figure 1*.

3.2Data collection

Data resources are the primary data from the field survey. The Slovin method is used to determine a representative sample size from a larger population. The population is obtained from the number of ADTs on the observed roads, which is the national highway agency in South Sumatra. The number of samples used is calculated based on Slovin's theory with a confidence level of 95%. The Slovin Equation is as follows (Equation 1):

$$n = N/(1+(N\times e^2)) \qquad (1)$$

Where: n = number of samples

N = Average Daily Traffic

e = percent limit error (5%).

So, the calculation of the number of samples becomes $N = 135531/\ (1+(135531\times(0.05)^2))) = 398.29$.

A total of 398 potential respondents representing the interests of road users were obtained using the Slovin calculation.

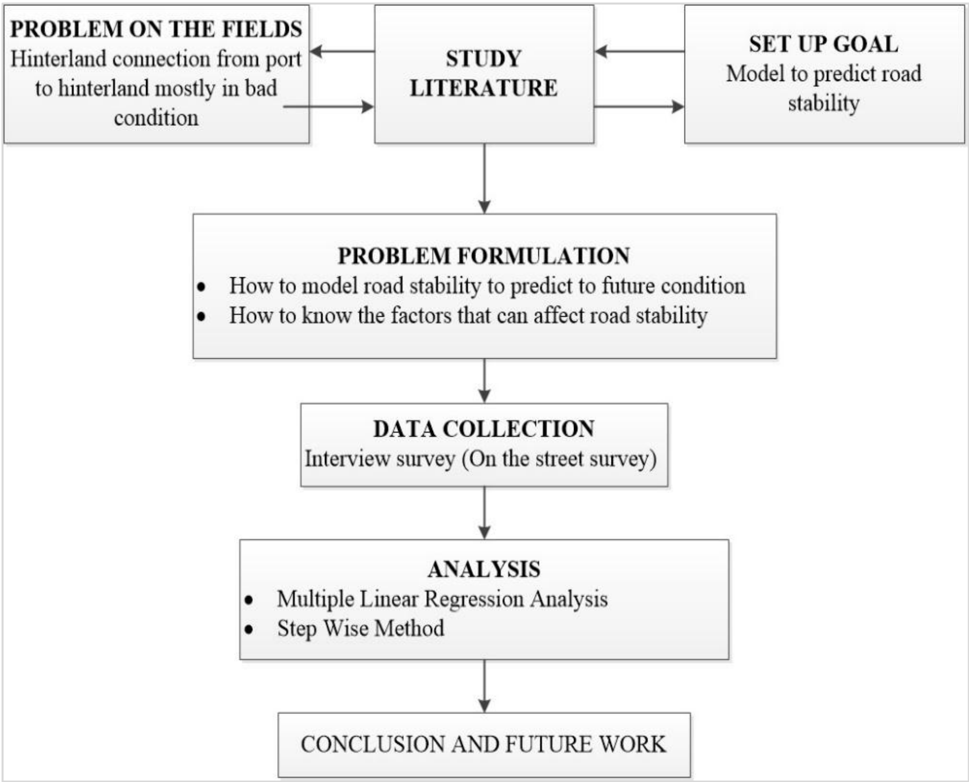

Figure 1 Flow chart of research

3.3Analysis steps using multi-linear regression

The MLR is a statistical technique that uses several explanatory variables to predict the outcome of a response variable. The goal of multiple linear regression is to model the linear relationship between the explanatory (independent) variables and response (dependent) variables [48]. In essence, multiple regression is the extension of ordinary least-squares (OLS) regression because it involves more than one explanatory variable.

Most of the statistically analyzed data does not necessarily have one response variable and one explanatory variable. In most cases, the number of variables can vary depending on the study. To measure the relationships between these multidimensional variables, multivariate regression is used. This method has been further developed because, in many cases, there are numerous variables and parameters. The basic equation remains the same even though it is more complex [46]. The following Equation 2 shows the general equation of MLR methods.

$$Y = a1X1 + a2X2 + \ldots anXn + C \qquad (2)$$

Where :

Y= Dependent Variable.

X1... Xn = Independent variable.

C= regression constant

a1... an = regression coefficient

The assumption method used to verify data in this study is a stepwise method. Some tests were done, including:

1. Normality Test
2. Multi – Collinearity Test
3. Heteroskedasticity Test
4. Autocorrelation
5. Linearity Test

The variables used to find a model of road stability of hinterland connection routes for supporting port productivity were sought and obtained according to the amount of influence on the dependent variable, which is road stability. The independent variables to be used for multiple regression analysis, namely:

X1= Pavement surface (Percentage of good Surface)
X2= Load of Heavy Good Vehicles (Tonnage)
X3= Road Width (m)
X4=Vertical Alignment (Percentage of slope).
X5= Super Elevation (Percentage of Superelevation).
X6=Accessibility from Port to hinterland (kph)
X7=Accessibility route to Industrial Area (kph)

X8=Percentage residential area passed by the Route (percentage area)
X9=Percentage agriculture and plantation area passed by the Route (percentage area)
X10=Connectivity level the route (percentage)
X11=The easiness of route Accessibility (kph)

The MLR analysis involves more than simply fitting a linear line through a cloud of data points. It consists of three stages: (1) analyzing the correlation and directionality of the data, (2) estimating the model, which includes fitting the line, and (3) evaluating the validity and usefulness of the model.

Before performing MLR, it is essential to understand how the independent variables (predictors) relate to each other and to the dependent variable (outcome). The relationships between predictors and the dependent variable should be linear. Analyzing correlation and directionality helps us understand the relationships among variables, which is crucial for building an effective MLR model.

The determination of dependent variables and independent variables used in this study was obtained from literature studies, adequate secondary data surveys and interviews, and questionnaire distribution to expert sources by their expertise fields.

This method allows us to understand how multiple independent variables relate to a single dependent variable. Here's a step-by-step guide:
Understand the problem and data: Ensure that the data meets the assumptions of MLR.
Formulate the hypotheses: Hypothesis testing helps us determine whether the predictors collectively or individually contribute significantly to explaining the variation in the dependent variable.
Check assumptions:
- Ensure that the assumptions of linear regression hold:
- The error variance is constant across all levels of predictors.
- Data points are collected independently.
- The residuals follow a normal distribution.
- The relationship between predictors and the dependent variable is linear.

Data preparation: Properly preparing data ensures accurate and meaningful results.
Build the model: Use software (such as R, Python, or Statistical Package for Social Science (SPSS) to fit the multiple linear regression model. Specify the dependent variable and the independent variables.
Interpret the coefficients (slopes) for each predictor.
Evaluate model fit: Check the overall model fit using metrics like R-squared (proportion of variance explained) and adjusted R-squared.
Assess the significance of the model using the F-test.
Check for collinearity: Assess if predictors are highly correlated (multicollinearity). High correlations may affect coefficient interpretation.
Make predictions: Use the model to predict the dependent variable for new data points. Interpret the predictions based on the coefficients.
Present results: Report the model summary, coefficients, p-values, and any other relevant statistics. Explain the practical implications of the findings.

4. Result

From a total of 398 samples collected through field questionnaires, normality distribution tests were conducted. The results indicate that the samples are representative and valid for analysis. The recapitulation of the complete data provides a descriptive analysis, including the mean and standard deviation, as shown in *Table 1*.

The data provided in *Table 1* includes statistical measures for a set of variables (Y1, X1, X2, etc.). Here's an explanation of each measure:

- Mean is the average value of the observations for each variable. For example, Y1 has a mean of 2.35, which is the average of all 398 observations for Y1.
- Standard Deviation: This indicates how much the values of each variable deviate from their mean. A higher standard deviation means more variability. For instance, X1 has a standard deviation of 1.159, suggesting its values are spread out over a wider range than X5, which has a standard deviation of 0.474.
- N: The number of observations or data points for each variable. In this case, each variable has 398 observations.

This data can be used to understand the distribution and variability of each variable, which is essential for statistical analysis and hypothesis testing.

Table 1 Descriptive statistics of the distribution and variability of each variable

	Mean	Standard deviation	N
Y1	2.35	1.070	398
X1	2.77	1.159	398
X2	1.73	0.820	398
X3	3.97	0.667	398
X4	3.90	0.676	398
X5	2.89	0.474	398
X6	3.54	0.789	398
X7	3.19	0.903	398
X8	2.24	0.815	398
X9	2.85	0.856	398
X10	3.55	0.569	398
X11	3.26	0.667	398

4.1Normality Test

The normality test is used to determine the spread of the data distribution, whether the data spreads normally or not. In this study, testing was carried out using the international business machines (IBM) SPSS statistical 22 viewer program. The results of the normality test, shown in *Figure 2*, indicate that the data is normally distributed.

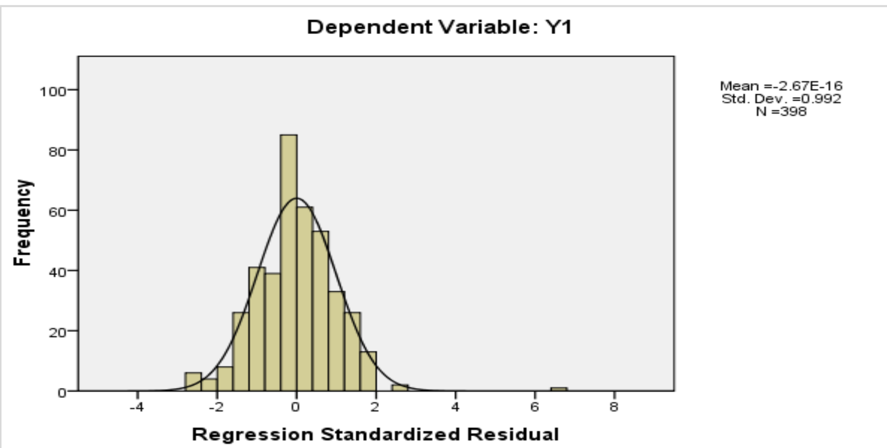

Figure 2 Plot of regression standardized residual

4.2The Pearson correlation

The correlation of each independent variable with the dependent variable is shown in *Table 2*. The Pearson correlation in *Table 2* indicates a linear relationship between two variables.

The Pearson correlation value ranges from -1 to 1, where:

- **1** indicates a perfect positive correlation,
- **0** indicates no correlation,
- **-1** indicates a perfect negative correlation.

The variables used in the table are as follows:

- **Y1** is the variable measured against all other variables (X1 to X11).
- Values above **0.5** or below **-0.5** indicate a strong correlation.
- The **Sig. (1-tailed)** value indicates the statistical significance of the correlation. Values below **0.05** are usually considered significant.
- **N** is the number of samples used to calculate the correlation, in this case, **398** for each pair of variables.
- **Y1** and **X1** have a strong positive correlation ($r = 0.718$) that is significant ($p < 0.05$). Y1 and X6 have also a strong positive correlation ($r = 0.629$). Y1 and X9 have an r-value of 0.723, which is also a strong correlation.
- **Y1** and **X2** have a weak negative correlation ($r = -0.239$) that is significant ($p < 0.05$). This suggests that as the value of X1 increases, the value of Y1 also tends to increase, and vice versa for X2. For a deeper interpretation, it may be needed to look at the context of the research and the variables involved.

Table 2 The correlation of each independent variable with the dependent variable

		Y1	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11
Pearson Correlation	Y1	1.000	.718	-.239	.009	.096	.270	.629	.575	.500	.723	.402	.556
	X1	.718	1.000	-.378	-.085	.065	.262	.510	.491	.496	.679	.408	.425
	X2	-.239	-.378	1.000	.150	-.057	-.136	-.289	-.277	-.221	-.292	-.110	-.238
	X3	.009	-.085	.150	1.000	.312	.156	-.072	-.002	.061	-.004	.121	.019
	X4	.096	.065	-.057	.312	1.000	.297	.155	.184	.156	.162	.036	.146
	X5	.270	.262	-.136	.156	.297	1.000	.300	.267	.250	.400	.246	.323
	X6	.629	.510	-.289	-.072	.155	.300	1.000	.631	.441	.635	.333	.538
	X7	.575	.491	-.277	-.002	.184	.267	.631	1.000	.544	.569	.152	.435
	X8	.500	.496	-.221	.061	.156	.250	.441	.544	1.000	.553	.228	.377
	X9	.723	.679	-.292	-.004	.162	.400	.635	.569	.553	1.000	.441	.550
	X10	.402	.408	-.110	.121	.036	.246	.333	.152	.228	.441	1.000	.422
	X11	.556	.425	-.238	.019	.146	.323	.538	.435	.377	.550	.422	1.000
Sig. (1-tailed)	Y1	.	.000	.000	.429	.028	.000	.000	.000	.000	.000	.000	.000
	X1	.000	.	.000	.046	.098	.000	.000	.000	.000	.000	.000	.000
	X2	.000	.000	.	.001	.127	.003	.000	.000	.000	.000	.014	.000
	X3	.429	.046	.001	.	.000	.001	.076	.483	.114	.466	.008	.351
	X4	.028	.098	.127	.000	.	.000	.001	.000	.001	.001	.234	.002
	X5	.000	.000	.003	.001	.000	.	.000	.000	.000	.000	.000	.000
	X6	.000	.000	.000	.076	.001	.000	.	.000	.000	.000	.000	.000
	X7	.000	.000	.000	.483	.000	.000	.000	.	.000	.000	.001	.000
	X8	.000	.000	.000	.114	.001	.000	.000	.000	.	.000	.000	.000
	X9	.000	.000	.000	.466	.001	.000	.000	.000	.000	.	.000	.000
	X10	.000	.000	.014	.008	.234	.000	.000	.001	.000	.000	.	.000
	X11	.000	.000	.000	.351	.002	.000	.000	.000	.000	.000	.000	.
N	Y1	Y1	398	398	398	398	398	398	398	398	398	398	398
	X1	X1	398	398	398	398	398	398	398	398	398	398	398
	X2	X2	398	398	398	398	398	398	398	398	398	398	398
	X3	X3	398	398	398	398	398	398	398	398	398	398	398
	X4	X4	398	398	398	398	398	398	398	398	398	398	398
	X5	X5	398	398	398	398	398	398	398	398	398	398	398
	X6	X6	398	398	398	398	398	398	398	398	398	398	398
	X7	X7	398	398	398	398	398	398	398	398	398	398	398
	X8	X8	398	398	398	398	398	398	398	398	398	398	398
	X9	X9	398	398	398	398	398	398	398	398	398	398	398
	X10	X10	398	398	398	398	398	398	398	398	398	398	398
	X11	X11	398	398	398	398	398	398	398	398	398	398	398

4.3Regression coefficients

Table 3 is a regression coefficient from an MLR analysis. Here is an explanation of the key components:

- **Unstandardized coefficients (B)**: These values represent the change in the response variable for a one-unit change in the predictor variable, holding all other predictors constant.
- **Standard Error (Std. Error)**: This measures the average distance that the observed values fall from the regression line.
- **Standardized coefficients (Beta)**: These are the coefficients that have been standardized so that the variances of dependent and independent variables are 1. They are useful for comparing the relative importance of each predictor variable in the model.
- **t**: This is the t-statistic, which is used to test the hypothesis that the coefficient is different from 0 (no effect).
- **Sig. (Significance)**: This is the p-value associated with the t-statistic. A low p-value (typically ≤ 0.05) indicates that it can be rejected the null hypothesis that the coefficient is zero.

For each model in the table, the constant term represents the expected value of the response variable when all predictors are held at zero. The coefficients for X1, X6, X9, X11, and X2 represent the expected change in the response variable for a one-unit change in the predictor variable, assuming all other variables are held constant.

For example, in Model 5:

- The constant term is **-1.561**, which is the expected value of the response variable when all predictors are 0.
- The coefficient for **X9** is **0.330**, meaning that for each one-unit increase in X9, the response variable is expected to increase by 0.330 units, assuming all other variables are held constant.
- The **Sig.** values for all variables are less than 0.05, indicating that these predictors are statistically significant at the 5% level.

This table is used to understand which variables are significant predictors of the response variable, the direction of their relationship (positive or negative), and their relative strength of association.

In Model 1, the beta coefficient for X9 is 0.723, indicating a strong positive relationship with the dependent variable, and this model explains 52.2% of the variance. Model 2 introduces X1 alongside X9, both showing high significance and increasing the explained variance to 61.6%. Model 3 further adds X6, with all predictors remaining highly significant and the model explaining 64.7% of the variance. Model 4 includes an additional predictor, X11, and Model 5 adds X2, with all predictors in both models being highly significant, except for X2 which has a p-value of 0.008. The explained variance slightly increases with each model, reaching 67.0% in Model 5. The analysis concludes that Model 3 offers a good balance between simplicity and explanatory power, making it a reasonable choice for predicting the dependent variable due to its significant predictors and good fit, as indicated by an adjusted R-squared value of 0.647. the constant for model 3 is –0.871 (< 1). This figure is better when compared to Model 5 and Model 6 which have a larger constant, it is important to conduct further validation and consider domain-specific knowledge before making a final decision.

Table 3 Coefficients of regression models

Model		Unstandardized coefficients		Standardized coefficients	Collinearity statistics	
		B	Standard error	Beta	t	Significance
1	(Constant)	-.226	.129	NA	-1.750	.081
	X9	.904	.043	.723	20.834	.000
2	(Constant)	-.286	.116	NA	-2.471	.014
	X9	.547	.053	.438	10.341	.000
	X1	.388	.039	.421	9.939	.000
3	(Constant)	-.871	.148	NA	-5.889	.000
	X9	.391	.057	.313	6.866	.000
	X1	.357	.038	.386	9.430	.000
	X6	.316	.053	.233	5.979	.000
4	(Constant)	-1.240	.171	NA	-7.245	.000
	X9	.332	.058	.266	5.746	.000
	X1	.350	.037	.379	9.416	.000
	X6	.253	.054	.187	4.689	.000
	X11	.239	.059	.149	4.063	.000
5	(Constant)	-1.561	.208	NA	-7.492	.000
	X9	.330	.057	.264	5.747	.000
	X1	.374	.038	.405	9.849	.000
	X6	.266	.054	.196	4.948	.000
	X11	.246	.058	.154	4.222	.000
	X2	.110	.041	.084	2.660	.008

4.4Analysis variance of the predictive models

Table 4 presents an analysis of variance (ANOVA), a statistical method used to compare the means of different groups and determine if at least one group significantly differs from the others. Here is a breakdown of the key components of the ANOVA table:

Sum of squares: This measures the total variation within the data and is divided into: **Regression:** Variation explained by the model.

Residual: Variation not explained by the model, also known as error.

Total: The sum of regression and residual variations.

Degree of freedom (df): This represents the number of values in the final calculation of a statistic that are free to vary. **For regression:** It is the number of predictors in the model. **For residual:** It’s the total number of observations minus the number of predictors minus one. **For total:** It is the total number of observations minus one.

Mean square: This is the sum of squares divided by the corresponding degrees of freedom. It’s used to calculate the F-statistic. **For regression:** It is the mean square for the model. **For residual:** It is the mean square for the error. **F (F-statistic):** This is the ratio of the mean square for the model to the mean square for the error. It’s used to determine the significance of the predictors in the model. **Significance (Sig.):** This is the p-value associated with the F-statistic. A low p-value (typically ≤ 0.05) indicates that the model is statistically significant.

In *Table 4*, multiple models are compared, with each model adding more predictors. As more predictors are added, the regression sum of squares increases, indicating that the model explains more variation. However, the F-statistic decreases because the variance explained by each additional predictor is less impactful. Despite these changes, the p-value remains significant across all models, suggesting that the predictors effectively explain the variation in the response variable.

Table 4 Analysis variance of the predictive models

Model		Sum of Squares	Degree of freedom (df)	Mean Square	F-statistic (F)	Significance
1	Regression	237.649	1	237.649	434.072	.000[a]
	Residual	216.805	396	.547	-	-
	Total	454.455	397	-	-	-
2	Regression	281.025	2	140.512	320.027	.000[b]
	Residual	173.430	395	.439	-	-
	Total	454.455	397	-	-	-
3	Regression	295.453	3	98.484	244.041	.000[c]
	Residual	159.002	394	.404	-	-
	Total	454.455	397	-	-	-
4	Regression	301.862	4	75.465	194.360	.000[d]
	Residual	152.593	393	.388	-	-
	Total	454.455	397	-	-	-
5	Regression	304.567	5	60.913	159.306	.000[e]
	Residual	149.888	392	.382	-	-
	Total	454.455	397	-	-	-
6	Regression	307.434	6	51.239	136.269	.000[f]
	Residual	147.021	391	.376	-	-
	Total	454.455	397	-	-	-

4.5Model summary

The Durbin-Watson statistic is a test for autocorrelation in the residuals from statistical regression analysis. Here, the Durbin-Watson value for the 6th model is 1.612, which falls within the range of 0 to 2. This indicates a lack of positive autocorrelation. However, it's important to note that this statistic alone for the 6th model does not automatically imply that the previous five models are also free from autocorrelation, as each model should ideally be tested separately for autocorrelation.

It is observed from *Table 5* that Model No. 6 has the highest R2 value at 0.676. However, the constant in this model is notably high and negative, which may be undesirable depending on the context. Ideally, the constant should be positive or closer to zero. Given this, Model No. 3 is more suitable as its R2 value is also high at 0.650, suggesting a strong fit with a more acceptable constant value. Based on the discussion of the results, the selected model is Model No. 3.

From the results, it can be concluded that the selected model is (Equation 3):

$$Y = 0.391X9 + 0.357\,X1 + 0.316\,X6 - 0.871 \qquad (3)$$

Where:

X9 = Percentage of agriculture and plantation area passed by the route

X1 = Pavement surface

X6 = Accessibility from port to hinterland

Y = Road stability

Analysis of model summary:

- **Model 3** has the highest $\mathbf{R^2}$ value (65.0%), indicating that it explains the highest variance in the dependent variable.
- The **Adjusted** $\mathbf{R^2}$ values are similar across models, but Model 3 still performs well.
- The **Standard error of the estimate** is lowest in Model 3 (0.635), suggesting better prediction accuracy.
- The Durbin-Watson statistic is consistent across all models, with a value of 1.612, indicating mild positive autocorrelation. This table shows that the Durbin-Watson statistics have been calculated for all variances in the prediction model, meaning that the other models also have the same score and meet the conditions. Considering the balance between model complexity and explanatory power, Model 3 appears to offer a good trade-off.

Therefore, based on these statistics, **Model 3** is likely the best choice for predicting the dependent variable. However, further validation and practical considerations are essential before making a final decision.

The regression modeling can be explained as follows:

- Any increase in the unit number of agriculture and plantation area roads results in an increase of 0.391 in the level of road damage, assuming other variables remain constant. This suggests a direct correlation between the expansion of agricultural and plantation areas and the need for road stability support.
- Any increase in the unit number of pavement surfaces in the area results in an increase of 0.357 in the level of road stability, assuming other variables remain constant. This condition implies that another important variable is the pavement structure, which refers to the percentage of good pavement surface in an area.
- Any increase in accessibility factors such as travel time, capacity, and connectivity leads to an increase in road stability by 0.316. This means that accessibility from the port to the hinterland is crucial to maintain. A decline in road stability will adversely affect the level of accessibility and connectivity to the port.
- A constant of - 0.871 indicates that factors other than the technical ones considered also influence road damage.

Table 5 Summary of the regression model's performance metrics

Model	R	R^2	Adjusted R^2	Standard error of the Estimate	Durbin-Watson
1	.723[a]	.523	.522	.740	1.612
2	.786[b]	.618	.616	.663	1.612
3	.806[c]	.650	.647	.635	1.612
4	.815[d]	.664	.661	.623	1.612
5	.819[e]	.670	.666	.618	1.612
6	.822[f]	.676	.672	.613	1.612

a. Predictors: (Constant), X9
b. Predictors: (Constant), X9, X1
c. Predictors: (Constant), X9, X1, X6
d. Predictors: (Constant), X9, X1, X6, X11
e. Predictors: (Constant), X9, X1, X6, X11, X2
f. Predictors: (Constant), X9, X1, X6, X11, X2, X7

5. Discussion

The key findings from the analysis of influence factors on road stability for hinterland connections in South Sumatra, Indonesia, using the MLR method are as follows:

1) Performance of hinterland Connections: The study aims to identify the performance of hinterland connections in South Sumatra Province. These connections play a critical role in supporting economic growth, especially considering the heavy vehicle mix that requires efficient transportation.
2) Methodology: The road stability value through the MLR approach can be used to develop the optimal route. The focus is on maintaining the existing level of service while addressing obstacles related to decreased support for hinterland transportation and road damage.
3) Strategic perspective: The study provides an overview of the road network for hinterland connections in South Sumatra Province. By analyzing road-handling policies from various perspectives, the research informs infrastructure development. The goal is to strategically support economic growth in the region.
4) Implications and recommendations: Improved hinterland connections can enhance port productivity and overall economic development. Addressing road stability issues is essential for efficient transportation and sustained economic growth. Recommendations include prioritizing road maintenance, investing in infrastructure, and collaborating with stakeholders.

The advantages, limitations, and potential future work related to the MLR model for hinterland connection in South Sumatra Province, Indonesia:

Advantages

- Comprehensive evaluation: The multilinear regression model allows for a comprehensive assessment of various factors influencing hinterland connections. It considers multiple variables simultaneously, providing a holistic view.

- Quantitative approach: Regression models provide quantitative relationships between input variables (such as road stability, climate conditions, etc.) and output (hinterland connection performance). This facilitates data-driven decision-making.
- Predictive capability: Once calibrated, the model can predict hinterland connection performance based on specific input conditions, aiding in planning and optimization.

Limitations

- Data requirements: Multilinear regression models rely heavily on data availability and quality. Insufficient or inaccurate data can affect model performance.
- Assumptions: Regression models assume linear relationships between variables. If the underlying relationships are nonlinear, the model may not capture the true dynamics.
- Overfitting: If the model is too complex (overfit), it may perform well on training data but poorly on unseen data. Proper regularization techniques are essential to mitigate overfitting.

Another factor to consider is the pavement structure, which refers to the percentage of good pavement surface in an area. Maintaining accessibility from the port to the hinterland is crucial. When there is a long queue at the port that extends to the surrounding area, it causes road damage. Significant damage has been observed in the area around Boom Baru Port. Road damage occurs not only in the vicinity of the port but also in the hinterland connections. Although roads classified as national roads can support heavier loads compared to provincial and district roads, ODOL trucks often carry loads exceeding 30 tons, whereas the roads are designed for lesser capacities. Using the MLR method, it has been demonstrated that the route for overload trucks should be diverted to specially designed roads capable of handling heavy loads.

A complete list of abbreviations is summarized in *Appendix I.*

6. Conclusion and future work

A model of road stability for hinterland connection routes was developed by modeling existing data using an MLR approach with the stepwise method, facilitated by the SPSS program. The best-fit model for the hinterland connection route, which supports port productivity, is expressed as $Y = 0.391\ X9 + 0.357\ X1 + 0.316\ X6 - 0.871$. Where, Y represents the condition of road stability, X9 denotes the percentage of agricultural and plantation areas traversed by the route, X1 is the pavement surface type (% Surface), and X6 reflects the ease of access of the route to the port (kph).

The influence of each factor on the stability of the hinterland connection route in supporting port productivity is quantified as follows:

- The coefficient X9, which is 0.391, indicates that every unit increase in the percentage of agricultural and plantation areas traversed by the route improves the stability of the route by 0.391, assuming other variables remain constant.
- The coefficient X1, which is 0.357, suggests that every unit increase in the pavement surface type (% Surface) enhances the steadiness of the route by 0.357, assuming other variables remain constant.
- The X6 coefficient of 0.316 shows that every unit increase in the ease of access of the route to the port (kph) increases the stability of the route by 0.316, provided other variables are constant.

Future research on road stability in Palembang City focuses on several key areas to deepen insights and improve management strategies:

- Enrich the MLR model by integrating additional variables such as traffic volume, weather conditions, and maintenance schedules to assess their influence on-road stability.
- Monitor the long-term effects of various factors on road stability through extended observational studies.
- Examine the impact of ODOL truck traffic on road stability by comparing different routes with varying traffic levels.
- Analyze the effectiveness of policies targeting ODOL issues and their influence on road conditions.
- Evaluate the cost-effectiveness of different pavement types and their relationship with road stability.
- Conduct thorough geotechnical surveys to assess underlying soil and subsoil conditions affecting stability.
- Explore innovative materials and technologies in road construction and maintenance to improve road stability.
- Collect insights from stakeholders such as drivers, local communities, and businesses to identify practical challenges and solutions.
- Investigate how road instability affects the economic output of hinterland agriculture and supply chain efficiency.

By addressing these areas, the research can provide a comprehensive understanding of the factors affecting road stability and offer actionable insights for infrastructure development and policymaking. The ultimate goal would be to enhance the connectivity and support the economic growth of the hinterland areas in South Sumatra.

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Conflicts of interest

The authors have no conflicts of interest to declare.

Data availability

The secondary data considered in the study obtained from officials of national roads in South Sumatra provinces and districts, and primary data collected from direct surveys of road users. The supporting data and findings of this study are available from the corresponding author upon reasonable request.

Author's contribution statement

Hardayani Haruno: Conceptualization, investigation, data collection, interpretation of result, writing – original draft. **Decky Oktaviansyah:** Conceptualization, investigation, data collection, writing – original draft. **Erika Buchari:** Conceptualization, writing-review, and supervision. **Joni Arliansyah:** Conceptualization, supervision. **Ermatita:** Writing review and editing. **Nobel Nawawi:** Analysis result and editing.

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Appendix I

S. No.	Abbreviation	Description
1	ADT	Average Daily Traffic
2	Anova	Analysis of Variance
3	APM	Application Performance Management
4	df	Degree of Freedom
5	GIS	Geographic Information System
6	IBM	International Business Machines
7	IRI	International Roughness Index
8	MCA	Multi-Criteria Analysis
9	MLR	Multi-Linear Regression
10	MSE	Mean Square Error
11	NLR	Nonlinear Regression
12	ODOL	Over Dimension Overloading
13	OLS	Ordinary Least-Squares
14	PLSR	Partial Least Square Regression
15	RFTD	Regional Freight Transportation Demand
16	SLR	Simple Linear Regression
17	SPSS	Statistical Package for Social Science