

Article

A Rapid Assessment Model for Off-Road Tracked-Vehicle Trafficability Based on a Multilayer Perceptron

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Abstract

Rapid and accurate assessment of tracked-vehicle trafficability on off-road terrain is essential for vehicle mobility evaluation and path planning. Traditional empirical formulas for tracked-vehicle terramechanics are computationally complex and require numerous measured parameters. To address this issue, this study proposes a vehicle trafficability inversion method that combines a multilayer perceptron with numerical simulation. First, a parametric tracked vehicle–terrain trafficability model was constructed using numerical calculations, and a vehicle trafficability dataset was generated from typical influencing parameters. Next, an MLP surrogate model was trained using these data. The model takes terrain slope, basic mechanical properties of the ground soil, track geometric parameters, vehicle weight, and vehicle speed as inputs and outputs vehicle trafficability information. The optimal model architecture was then identified through Bayesian optimization, and the results show that the surrogate model achieves high accuracy and real-time performance. In addition, an engineering case study demonstrates the potential application of this method in path planning.

Keywords: track-soil interaction; terramechanics; MLP; Bayesian optimization

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1. Introduction

The prediction of off-road vehicle mobility is critical in military logistics, agricultural automation, planetary exploration, and disaster response [1–14]. Rapid and accurate determination of terrain traversability is essential for path planning, autonomous navigation, and mission feasibility assessment [15,16]. In these scenarios, vehicles often operate in complex and heterogeneous environments, where abrupt variations in soil behavior may cause bogging or loss of traction, making further movement impossible [17,18].

The study of vehicle–terrain interaction, known as terramechanics, has traditionally relied on a hierarchy of models ranging from purely empirical formulations to highly detailed physics-based simulations [19]. Empirical and semi-empirical models, such as the well-known Bekker–Wong pressure–sinkage relationship and the Janosi–Hanamoto shear stress formulation, are computationally efficient and have been widely adopted for vehicle

mobility assessment [20–22]. However, traditional empirical formulas in terramechanics have clear limitations in practical applications. First, their calculation procedures are often complex and cumbersome, involving numerous intermediate variables and iterative operations, which makes it difficult to satisfy the real-time requirements of online prediction and path planning. Second, these models require a set of empirically derived parameters (e.g., cohesive modulus k_c , frictional modulus k_ϕ , sinkage exponent n , cohesion c , and internal friction angle ϕ) that characterize the mechanical behavior of soil. Accurate determination of these parameters remains challenging. Conventional methods rely on costly and time-consuming laboratory tests, such as bevameter tests, or field-based cone penetrometer measurements, which often fail to capture the spatial variability of natural terrain and may not be feasible for every environment of interest [23,24].

Concurrently, vehicle dynamics simulation has advanced significantly with the development of high-fidelity physics-based models. The Discrete Element Method (DEM), which represents soil as an assembly of individual particles, is a powerful tool for capturing the complex nonlinear behavior of granular materials under vehicular loading, including large deformation and soil flow [25,26]. Although DEM provides a high degree of accuracy, its computational cost is prohibitive for applications that require real-time feedback or large-scale mapping [27]. Conversely, empirical models offer high computational speed but are limited in generality and precision, which are essential for novel vehicle designs or previously untested terrains [28].

Recent research shows that machine learning (ML) surrogate models can approach the accuracy of high-fidelity simulations while retaining the computational speed of empirical approaches [29,30]. Machine learning has considerable potential for efficiently predicting the mechanical behavior of materials [31–33]. For instance, deep neural networks have been successfully used to predict vehicle behavior, including traction and energy consumption, on sloping terrain [34] and to estimate soil parameters from wheel-interaction data [35,36]. Furthermore, Bayesian inference has been used to calibrate simplified terramechanics models using data generated from high-fidelity DEM simulations [37,38]. Empirical and semi-empirical terramechanics models are computationally efficient but often require many soil parameters and have limited adaptability outside calibrated conditions. DEM/FEM-based high-fidelity models can describe complex soil deformation and track-soil interaction mechanisms more explicitly, but their computational cost limits their direct use in real-time or large-area assessment. Machine learning surrogate models offer a practical compromise by learning nonlinear mappings from simulation or experimental data and enabling rapid prediction; however, their reliability is limited by the quality and parameter coverage of the training data. Although empirical terramechanics, high-fidelity numerical simulation, and machine learning models have all been used for mobility prediction, a lightweight workflow is still needed to map measurable soil, terrain, and tracked-vehicle parameters directly to multiple trafficability indicators for rapid large-area grid evaluation. These studies collectively indicate the feasibility of a hybrid strategy in which high-cost numerical simulations generate a comprehensive dataset that supports the training of an efficient and accurate machine learning predictor for mobility.

In this study, a fast and accurate method is developed by integrating numerical simulation with machine learning to assess off-road vehicle mobility. The core concept is to first build a parameterized numerical model of a tracked vehicle interacting with deformable terrain using high-fidelity simulation. A comprehensive dataset is then generated by systematically varying key input parameters, including terrain slope, fundamental soil mechanical properties (cohesion, friction angle, and sinkage exponent), track geometry, vehicle weight, and vehicle speed. A Multilayer Perceptron (MLP) surrogate model is trained on this dataset to map these input parameters to vehicle mobility outcomes, such as

drawbar pull, sinkage, and traversability. The model structure is optimized using Bayesian optimization to ensure high accuracy and real-time inference capability. Finally, a case study demonstrates the practical utility of the proposed approach for path planning. By combining the fidelity of physics-based simulation with the computational efficiency of machine learning, this work provides a practical solution for rapid vehicle mobility assessment in complex off-road environments.

2. Methodology

2.1. Research Framework

To address the computational complexity and extensive parameter requirements of traditional empirical formulas for tracked-vehicle terramechanics, this paper proposes an MLP [39] inversion surrogate model based on three-dimensional numerical simulation for rapid vehicle trafficability assessment. As a standard feedforward neural network, the MLP is theoretically known for its strong function-approximation capability, enabling it to learn highly nonlinear and complex mappings effectively [40]. This study constructs a surrogate model that takes vehicle parameters (speed, weight, geometric dimensions, etc.), basic soil mechanical parameters (elastic modulus, internal friction angle, cohesion, etc.), and terrain parameters (slope) as inputs and outputs four trafficability indicators: drawbar pull, slip rate, sinkage, and trafficability. Figure 1 illustrates the complete research process.

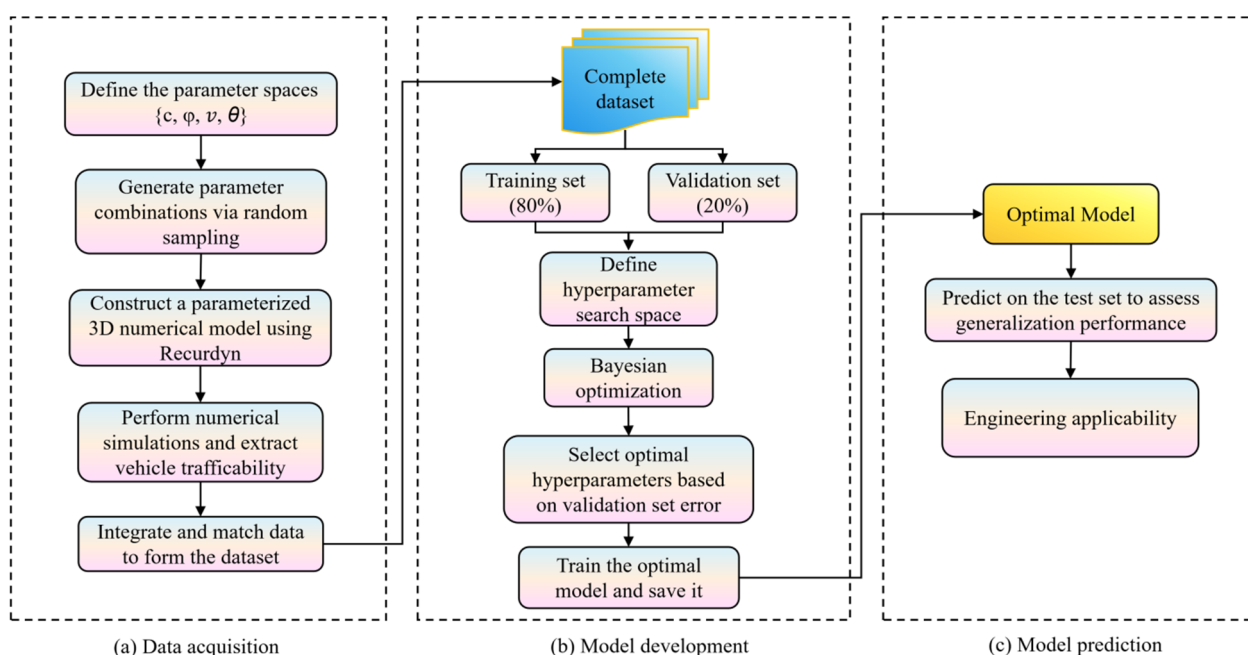


Figure 1. Research flowchart.

Uniform random sampling over a predefined parameter space was first used to generate parameter combinations during model construction. Using Recurdyn software(version: V9R4), a sample set containing 50 vehicle trafficability outcomes was then established and computed. This database was used to train an MLP model, whose hyperparameters [41] were optimized by Bayesian optimization [42]. After systematic evaluation of the model's generalization ability, the optimal trafficability inversion model was obtained.

2.2. Introduction to Tracked Vehicle Terramechanics

Classical vehicle terramechanics theory is mainly based on the Bekker model, in which vehicle trafficability is related to drawbar pull:

$$D_P = (F_t - F_{TR})N \quad (1)$$

where N is the number of tracks of the tracked vehicle, F_{RT} is the total resistance (N), and F_t is the soil thrust (N).

The total resistance imposed on the vehicle by the terrain consists of three main components: compaction resistance, bulldozing resistance, and slope resistance.

Compaction resistance:

$$F_{Rc} = \frac{1}{(n+1)b_l^{1/n} \left(\frac{k_c}{b_l} + k_\varphi \right)^{1/n}} \left(\frac{W_l}{L} \right)^{\frac{n+1}{n}} \quad (2)$$

Bulldozing resistance:

$$F_{Rb} = \frac{b_l \sin(\alpha + \varphi)}{2 \sin \alpha \cos \varphi} (2zcK_c + \gamma z^2 K_\gamma) \quad (3)$$

where c is the soil cohesion (Pa), φ is the soil internal friction angle ($^\circ$), γ is the soil density (kg/m^3), k_c is the soil cohesive modulus ($\text{N}/\text{m}^2(n+1)$), and k_φ is the soil frictional modulus ($\text{N}/\text{m}^2(n+2)$). K_c is the soil cohesion modulus, K_γ is the soil friction modulus, and z is the total sinkage of the track (m). The expressions for α , K_c , and K_γ are as follows:

$$\alpha = \arctan\left(\frac{z}{L}\right) \quad (4)$$

$$\begin{cases} K_c = (N_c - \tan \varphi) \cos^2 \varphi \\ K_\gamma = \left(\frac{2N_\gamma}{\tan \varphi} + 1 \right) \cos^2 \varphi \end{cases} \quad (5)$$

where N_c and N_γ are the Terzaghi bearing capacity factors.

The total sinkage of the vehicle consists of two parts: static sinkage and slip sinkage. The formula for calculating the static sinkage of a tracked vehicle is as follows:

$$z_0 = \left[\frac{W_l / b_l L}{k_c / b_l + k_\varphi} \right]^{\frac{1}{n}} \quad (6)$$

where W_l is the vertical load on a single track (kg), L is the track ground contact length (m), and b_l is the track width (m).

The vertical load W_l on a single track can be calculated using the following formula:

$$W_l = \frac{G_l \cos \theta}{N_l} \quad (7)$$

where G_l is the total weight of the tracked vehicle (N), N_l is the number of tracks, and θ is the slope ($^\circ$).

The slip sinkage of the vehicle is

$$z_s = \frac{hi}{1-i} \quad (8)$$

where h is the characteristic height (m), which in tracked vehicles is the grouser height, and i is the slip rate.

The total sinkage is calculated as

$$z = z_0 + z_s \quad (9)$$

Slope resistance:

$$F_{Rs} = W_i \sin \theta \quad (10)$$

where W_i is the weight borne by a given track (N).

Finally, the total resistance is calculated:

$$F_{RT} = F_{Rb} + F_{Rc} + F_{Rs} \quad (11)$$

The soil thrust of a tracked vehicle is calculated by the following formula:

$$F_t = \left\{ b_l L c \left(1 + \frac{2h}{b_l} \right) + W_l \tan \varphi \left[1 + 0.64 \left(\frac{h}{b_l} \operatorname{arccot} \left(\frac{h}{b_l} \right) \right) \right] \right\} \times \left\{ 1 - \frac{k}{iL} \left(1 - e^{-iL/k} \right) \right\} \quad (12)$$

where b_l is the track width (m), L is the track ground contact length (m), h is the grouser height (m), i is the slip rate, and k is the shear deformation modulus (m).

2.3. Establishment of a Vehicle Trafficability Sample Set Based on Numerical Simulation

The tracked vehicle used in the calculations in this paper is shown in Figure 2. The total vehicle weight is 20 tons, and its geometric dimensions are 4716 mm × 2576 mm × 1945 mm. The track ground-contact length is 2.64 m, the track width is 0.49 m (ground-contact width: 0.38 m), and the grouser height is 0.06 m.

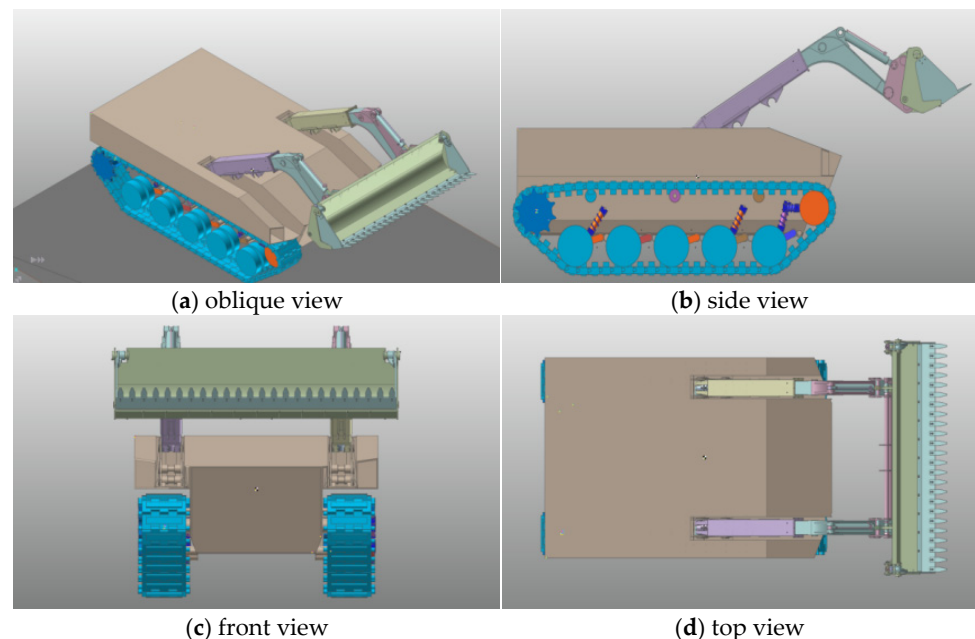


Figure 2. Computational model.

Because traditional fine-grained soil modeling methods require substantial computational resources, their numerical solution efficiency is low. Therefore, this study adopts the simplified ground-model function in the RecurDyn software system, which represents vehicle–soil interaction through the contact parameters between the vehicle track and the ground [43]. RecurDyn is multibody system dynamics simulation and optimization software developed based on recursive algorithms. It uses relative-coordinate equations of motion and a fully recursive algorithm, providing relatively high computational speed. Nu-

merical simulation of tracked-vehicle trafficability on soil must comprehensively consider terrain factors, terramechanics, and vehicle dynamic-performance parameters. This paper focuses mainly on parameters with significant influence, selecting terrain slope, vehicle speed, soil internal friction angle, and cohesion as influencing variables. The parameter space is determined based on engineering experience. A random function is used to generate parameters to avoid subjective bias in the manual selection of parameter values, while other parameters are kept constant, as shown in Table 1.

Table 1. Parameters used in the numerical model.

Density/kg/m ³	Elastic Modulus/MPa	Poisson's Ratio	Cohesion/kPa	Internal Friction Angle/°	Theoretical Vehicle Speed/km/h	Slope/°
1800	10	0.3	1–50	2–40	5–60	0–30

The maximum time step in this study was set to 1/10–1/20 of the highest response period of the system. Considering the large number of collision and contact events among the driving sprocket, road wheels, track shoes, and soil, the contact-related time scale is generally much smaller than the overall vehicle motion time scale. Therefore, the maximum time step was set to 1.0×10^{-3} s, the minimum time step was set to 1.0×10^{-6} s, and the local time step during contact was controlled within 1.0×10^{-4} s.

To further verify time-step independence, trial simulations of the same operating condition were conducted using maximum time steps of 5.0×10^{-4} s, 1.0×10^{-3} s, and 2.0×10^{-3} s. The stabilized vehicle velocity, mean drawbar pull, and sinkage were compared. When the maximum time step was reduced from 2.0×10^{-3} s to 1.0×10^{-3} s, the relative change in sinkage was less than 3%, and the relative change in drawbar pull was less than 2%. When the time step was further reduced to 5.0×10^{-4} s, the difference in the results was less than 1%. Considering both computational efficiency and accuracy, a maximum time step of 1.0×10^{-3} s was adopted for all simulations.

Track-ground soft contact was modeled using the built-in soft-soil contact model in RecurDyn/Track (HM). The normal force was calculated based on the Bekker pressure–sinkage equation, while the tangential force was calculated using the Janosi–Hanamoto shear stress–displacement equation. The contact stiffness and damping coefficients were determined according to the soil modulus and the geometric parameters of the track shoes. The normal contact stiffness was set to 10–100 times the soil-bearing stiffness, and the damping coefficient was set to 0.1–0.3 times the critical damping to balance numerical stability and contact-penetration control.

A Coulomb friction model was used, with the static and dynamic friction coefficients set to 0.6 and 0.4, respectively. A critical sliding velocity threshold was introduced to avoid numerical oscillations caused by friction switching at near-zero velocity. All contact parameters were determined through parameter sensitivity analysis to ensure convergence of their influence on the results.

In a multibody contact system, numerical stability is a prerequisite for obtaining reliable results because of the presence of constraint equations and contact nonlinearities. In this simulation, the relative error tolerance was set to 1.0×10^{-4} , the absolute error tolerance was set to 1.0×10^{-6} , the maximum number of Newton–Raphson iterations was set to 25, and the Jacobian matrix was updated at each step. To monitor numerical stability, the total system energy, constraint violation, and maximum contact penetration depth were recorded during the simulation. The results showed that, during the stable driving stage, the total system energy varied smoothly, the constraint violation was less than 10^{-5} m, and the maximum contact penetration depth was less than 1 mm.

The simulated track sinkage was compared with the theoretical value calculated using the Bekker pressure–sinkage equation. Under the selected soil test parameters, the relative error between the theoretical sinkage and the simulation result was within 20%. In addition, five independent simulations were performed for the same typical operating condition, and the stabilized velocity, mean drawbar pull, and maximum sinkage were compared. The maximum relative deviation among the five simulations was less than 3%, demonstrating the repeatability of the simulation.

The numerical simulation results show that the drawbar pull is generally maintained between 65 kN and 105 kN; the slip rate is generally maintained between 30% and 40%; the stable vehicle speed is maintained between 3.24 km/h and 39.96 km/h; the maximum sinkage is 0.367 m, whereas the minimum sinkage is only 0.054 mm. Among the 50 simulation cases, six cases are classified as impassable.

3. Rapid Assessment Surrogate Model for Vehicle Trafficability

3.1. Multilayer Perceptron Artificial Neural Network

A Multilayer Perceptron (MLP) is a typical feedforward artificial neural network and one of the most fundamental model architectures in modern deep learning systems. Its basic idea is to use a network structure composed of multiple neuron layers to transform input data through a series of linear transformations and nonlinear mappings, thereby gradually extracting, combining, and reconstructing features to model and approximate complex nonlinear relationships. Compared with traditional linear regression models, the MLP has strong nonlinear representation and adaptive learning capabilities, enabling it to learn hidden patterns and regularities automatically from large amounts of data.

Structurally, a multilayer perceptron typically consists of three parts: an input layer, one or more hidden layers, and an output layer, as shown in Figure 3. The input layer receives external data, with each input node corresponding to a feature variable. The hidden layers transform and abstract the input information through operations such as weighted summation and nonlinear activation. The output layer produces the final prediction result according to the task type. MLP training is mainly divided into two stages: forward propagation and backpropagation. During forward propagation, the input data sequentially pass through each layer to generate the output. During backpropagation, the model calculates the error between the predicted and true values and uses gradient descent to update the parameters in the reverse direction. Through multiple iterations, the network gradually converges to a near-optimal set of parameters, approximates the input–output mapping, and learns the functional relationship between the inputs and outputs.

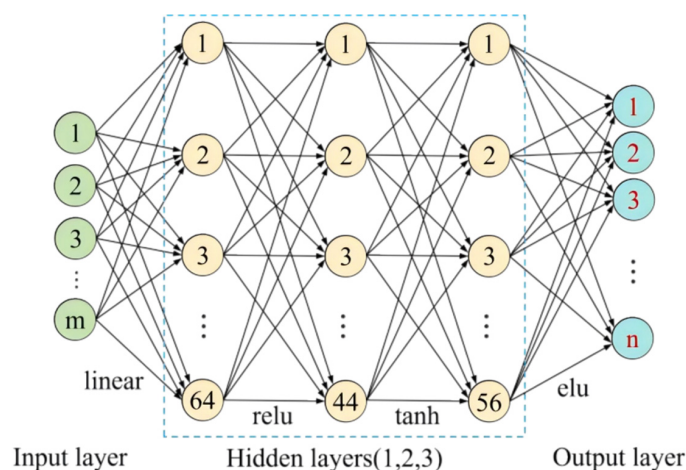


Figure 3. Schematic diagram of the MLP model.

3.2. Bayesian Optimization

Hyperparameter optimization plays an essential role in improving the predictive performance of machine learning models. In this study, the Tree-Structured Parzen Estimator (TPE), a sequential model-based Bayesian optimization algorithm implemented in Optuna, was employed to search automatically for the optimal hyperparameter configuration. Compared with conventional grid search and random search, TPE substantially reduces the number of expensive model evaluations while efficiently identifying high-quality hyperparameter combinations.

Unlike Gaussian process (GP)-based Bayesian optimization, TPE does not directly construct a probabilistic model of the objective function. Instead, it estimates the probability density of hyperparameter configurations conditioned on the observed objective values, making it particularly suitable for high-dimensional and heterogeneous search spaces.

(1) Optimization objective

The hyperparameter optimization problem can be formulated as

$$\mathbf{x}^* = \operatorname{argmin}_{\mathbf{x} \in \mathcal{X}} f(\mathbf{x}) \quad (13)$$

where

$\mathbf{x}$ denotes a hyperparameter configuration;

$f(\mathbf{x})$ denotes the objective function;

$\mathcal{X}$ represents the hyperparameter search space.

(2) Density estimation

After evaluating several hyperparameter configurations, TPE divides all observations into two groups according to a threshold y^* , which is usually chosen as the γ -quantile of the observed objective values.

The probability density of promising configurations is

$$l(\mathbf{x}) = p(\mathbf{x} \mid y < y^*) \quad (14)$$

The probability density of less promising configurations is

$$g(\mathbf{x}) = p(\mathbf{x} \mid y \geq y^*) \quad (15)$$

where

$l(\mathbf{x})$ is the density function of hyperparameters associated with better objective values;

$g(\mathbf{x})$ is the density function of hyperparameters associated with worse objective values.

Both density functions are estimated using kernel density estimation (KDE).

(3) Bayesian inference

According to Bayes' theorem, the posterior probability can be expressed as

$$p(y|\mathbf{x}) = \frac{p(\mathbf{x}|y)p(y)}{p(\mathbf{x})} \quad (16)$$

Instead of directly estimating $p(y|\mathbf{x})$, TPE estimates the inverse conditional probability $p(\mathbf{x}|y)$, which is easier to model in high-dimensional search spaces.

(4) Expected Improvement

The next hyperparameter configuration is selected according to the expected improvement (EI). In the TPE framework, EI is proportional to the ratio between the two density functions.

$$EI(\mathbf{x}) \propto \frac{l(\mathbf{x})}{g(\mathbf{x})} \quad (17)$$

A larger value of $l(\mathbf{x})/g(\mathbf{x})$ indicates that the hyperparameter configuration has a higher probability of producing a better objective value.

The next hyperparameter configuration is therefore determined by

$$\mathbf{x}_{next} = \operatorname{argmax}_{\mathbf{x}} \frac{l(\mathbf{x})}{g(\mathbf{x})} \quad (18)$$

This strategy naturally balances exploration and exploitation during the optimization process.

(5) Optimization procedure

The TPE optimization process is summarized as follows [44]:

- (1) Define the hyperparameter search space.
- (2) Randomly sample several initial hyperparameter configurations.
- (3) Train the model using each configuration and evaluate the objective function.
- (4) Divide the observations into two groups according to the threshold y^* .
- (5) Estimate the density functions $l(\mathbf{x})$ and $g(\mathbf{x})$ using kernel density estimation.
- (6) Select the next hyperparameter configuration by maximizing the ratio $l(\mathbf{x})/g(\mathbf{x})$.
- (7) Update the density estimation model using the newly observed result.
- (8) Repeat the above procedure until the maximum number of optimization trials is reached.

3.3. Hyperparameter Optimization

Traditional theoretical formulas of vehicle terramechanics provide a rich theoretical foundation and empirical parameters, offering useful references for selecting input parameters for reduced-order modeling. According to the vehicle terramechanics theory described above, the parameters affecting vehicle trafficability can be divided into three categories: soil mechanical parameters, vehicle parameters, and terrain parameters. Therefore, the surrogate model takes density, elastic modulus, Poisson's ratio, cohesion, internal friction angle, theoretical vehicle speed, slope, total vehicle weight, track width, grouser height, and track ground-contact length as inputs and outputs drawbar pull, slip rate, sinkage, and trafficability. Trafficability is output as a 0/1 mask, where 1 indicates passable and 0 indicates impassable. Through supervised learning, a nonlinear mapping between inputs and outputs is established, thereby obtaining the functional relationship between them.

To obtain better predictive performance, Bayesian optimization was employed to optimize the hyperparameters of the Support Vector Regression (SVR), Random Forest (RF), Extreme Gradient Boosting (XGBoost), and Multilayer Perceptron (MLP) models. The search ranges of the hyperparameters for each model are summarized in Table 2.

During the hyperparameter optimization process, the dataset was randomly divided into a training set (80%), a validation set (10%), and a test set (10%). The mean squared error (MSE) on the validation set was adopted as the optimization objective. For each model, 100 hyperparameter optimization trials were performed using the TPE-based Bayesian optimization algorithm. This number of optimization trials was sufficient to ensure the accuracy and stability of the optimization results. The optimal hyperparameter configurations and the corresponding optimization times are summarized in Table 3. The results indicate that the computational time required for 100 hyperparameter optimization

trials followed the order SVR < Random Forest < XGBoost < MLP, with SVR requiring the shortest optimization time and MLP requiring the longest.

Table 2. Hyperparameter optimization range.

Model	Parameters	Search Space
SVR	C value	Log space (0.1, 1000)
	Gamma	Log space (1×10^{-3} , 10)
	Epsilon	Log space (1×10^{-4} , 0.1)
RF	Number of trees	(50, 200)
	Maximum tree depth	(2, 10)
	Number of trees	(50, 200)
XBoost	Maximum tree depth	(2, 10)
	Learning rate	Log space (0.01, 0.2)
	Subsample ratio of columns for each tree	(0.5, 1.0)
MLP	Number of hidden layers	(2, 4)
	Number of neurons per hidden layer	(8, 16)
	Activation function	[Relu, Tanh, Silu, Elu]
	Learning rate	Log space (1×10^{-4} , 5×10^{-3})
	Batch size	(5, 8, 10)
	L2 regularization coefficient	Log space (1×10^{-6} , 1×10^{-3})

Table 3. Hyperparameter optimization results.

Model	Parameters	Result	Time (s)
SVR	C value	403.7	5.39
	Gamma	1.26×10^{-2}	
	Epsilon	3.26×10^{-4}	
RF	Number of trees	75	16.50
	Maximum tree depth	8	
	Number of trees	150	
XGBoost	Maximum tree depth	2	35.91
	Learning rate	3.21×10^{-2}	
	Subsample ratio of columns for each tree	0.94	
MLP	Number of hidden layers	4	2119.46
	Number of neurons per hidden layer	(8, 12, 14, 12)	
	Activation function	[Elu, Tanh, Relu, Silu]	
	Learning rate	2.87×10^{-3}	
	Batch size	(5, 8, 10)	
	L2 regularization coefficient	4.16×10^{-6}	

These experiments were implemented in Python v.3.12 using Scikit-Learn and Keras on a computer equipped with a Core i5-1035G1 CPU (1.00 GHz), 16 GB of RAM, and a 64-bit operating system.

3.4. Model Evaluation

To comprehensively evaluate the predictive performance of the hyperparameter-optimized models, fivefold cross-validation was employed for model validation. Since the dataset contained only 50 samples, each fold included only 10 test samples. Consequently, the coefficient of determination (R^2) calculated on individual test folds was susceptible to fluctuations caused by variations in sample distribution, resulting in relatively high variability. Therefore, the average Weighted Absolute Percentage Error (WAPE) obtained from the fivefold cross-validation was adopted as the primary evaluation metric, while R^2 was used as a supplementary performance indicator. The average WAPE values for

the training and test sets and the overall R^2 obtained from the fivefold cross-validation are presented in Table 4 and Figure 4.

Table 4. Model evaluation.

Model	Train Set WAPE (%)	Test Set WAPE (%)	WAPE Gap (%)	All Set R^2
SVR	3.65 ± 0.41	5.51 ± 1.92	1.86	0.469 ± 0.058
RF	2.90 ± 0.34	7.58 ± 2.71	4.68	0.816 ± 0.045
XGBoost	2.54 ± 0.39	6.85 ± 1.61	4.31	0.872 ± 0.056
MLP	3.04 ± 0.88	5.99 ± 1.89	2.95	0.846 ± 0.083

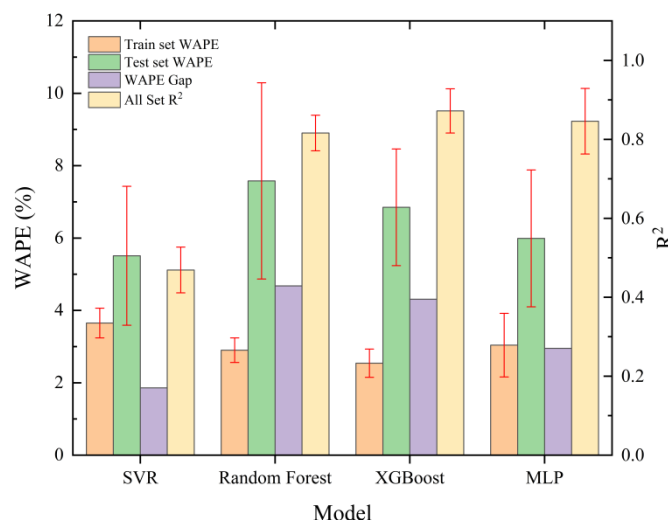


Figure 4. Model evaluation.

Table 4 compares the performance of the four machine learning models in terms of the training WAPE, test WAPE, WAPE gap, and the overall R^2 . Among the four models, the SVR model achieved the lowest test WAPE ($5.51 \pm 1.92\%$), indicating superior prediction accuracy for unseen samples. However, its overall R^2 was only 0.469 ± 0.058 , suggesting a relatively limited ability to capture the overall relationship between the input variables and the target variable.

In contrast, XGBoost achieved the highest overall R^2 (0.872 ± 0.056), demonstrating excellent overall fitting capability. Nevertheless, its test WAPE ($6.85 \pm 1.61\%$) and WAPE gap (4.31%) were both noticeably higher than those of the MLP model, indicating a certain degree of overfitting. A similar trend was observed for the Random Forest model, which exhibited the highest test WAPE ($7.58 \pm 2.71\%$) and the largest WAPE gap (4.68%).

Overall, the MLP model achieved a relatively low test WAPE ($5.99 \pm 1.89\%$) while maintaining a relatively high overall R^2 (0.846 ± 0.083) and a relatively small WAPE gap (2.95%). These results indicate that the MLP model provides a better balance among prediction accuracy, overall fitting capability, and generalization performance. Therefore, considering overall model performance rather than any single evaluation metric, the MLP model was selected as the final predictive model.

3.5. Prediction Results of the Surrogate Model

During the Bayesian hyperparameter optimization process, 90% of the samples were used as the training set, without reserving a separate validation set, to fully utilize the available training data and obtain the final optimized model. The remaining 10% of the samples were then used as the test set (Table 5) to evaluate the generalization performance of the optimized model.

Table 5. Test set.

Cohesion (kPa)	Internal Friction Angle (°)	Theoretical Vehicle Speed (km/h)	Slope (°)	Traction Force (kN)	Slip Ratio	Total Sinkage (mm)	Passability
13.44	33.97	55.38	2.26	50	31.1	71	1
4.57	24.62	29.05	10.99	80	34.3	122	1
25.37	35.3	5.47	14.3	91	34.1	68	1
44.55	28.82	6.15	28.09	109	35.7	94	1
6.92	35.27	8.11	20.03	95	35.6	85	1

The predicted traction force, slip ratio, sinkage, and passability were compared with the corresponding numerical simulation results. On the test set, the WAPE values for traction force, slip ratio, and sinkage were 4.56%, 5.27%, and 15.20%, respectively, while the prediction accuracy for passability reached 100%. Across the entire dataset, the corresponding WAPE values were further reduced to 2.62%, 3.13%, and 4.49%, respectively, and the prediction accuracy for passability remained 100%, as shown in Figure 5. In addition, the residual distributions are shown in Figure 6.

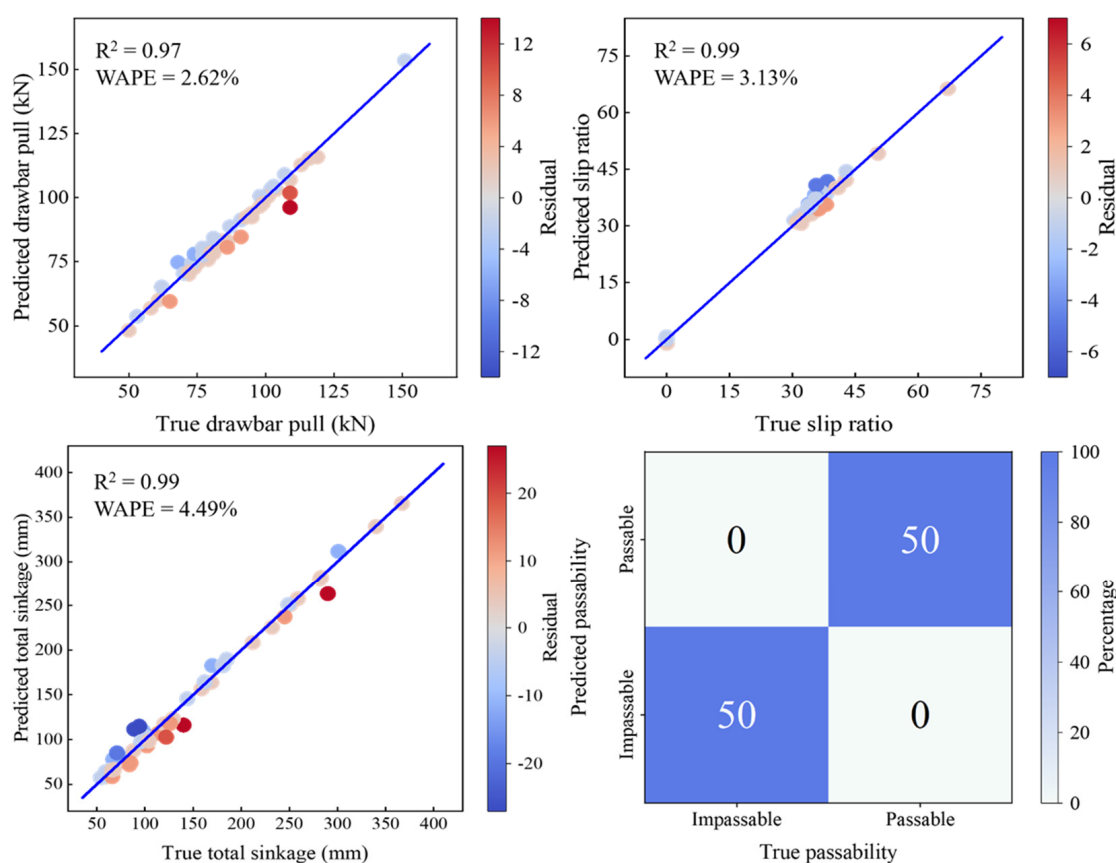


Figure 5. Comparison between predicted and true values.

The results demonstrate a high degree of agreement between the predicted and simulated values, indicating that the proposed model accurately captures the complex nonlinear relationships between the input parameters and the output responses.

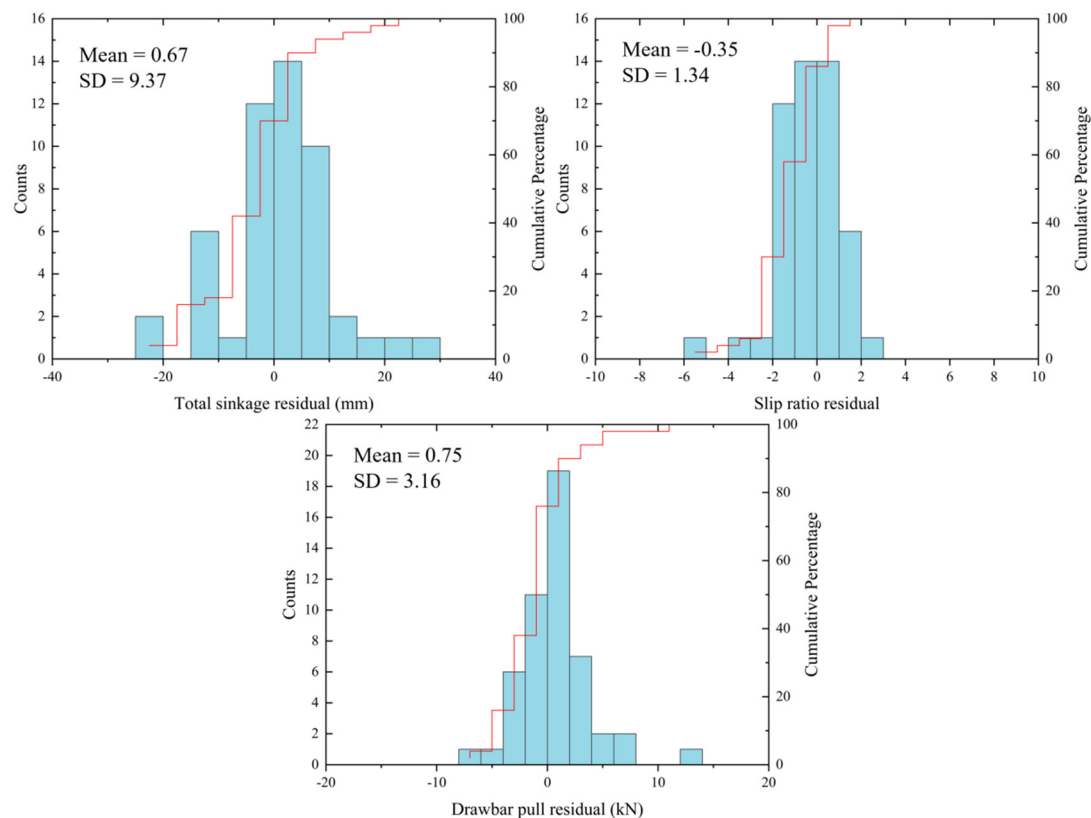


Figure 6. Residual distribution.

3.6. SHAP

The SHAP method, originally proposed by Lundberg and Lee, is a game-theoretic framework for interpreting machine learning models. Its fundamental idea is to decompose the prediction of a model into the additive contributions of individual input features, which can be formulated as

$$f(x) = \phi_0 + \sum_{i=1}^M \phi_i \quad (19)$$

Here, $f(x)$ is the model prediction for a given set of input features; ϕ_0 is the average prediction across all samples; ϕ_i is the SHAP value associated with feature x_i , reflecting its contribution to the current prediction; and M is the total number of features.

Figure 7 illustrates the mean feature importance and SHAP value distributions of the four normalized input features for four output labels. The bar plot shows the mean absolute SHAP values, which quantify the global importance of each feature. The results indicate that slope is the most influential factor when predicting traction force and total sinkage, whereas the dilation angle contributes most significantly to the prediction of slip ratio and passability.

In addition, the beeswarm plot displays the distribution of SHAP values for each feature, providing insight into how individual features influence model predictions. Each point corresponds to the SHAP value of a single sample for a given feature, with colors ranging from blue to red to represent low to high feature values. The SHAP values quantify the relative importance of each feature and reveal the direction of its effect on the output variable. A positive SHAP value indicates that an increase in the feature value leads to an increase in the predicted output, whereas a negative SHAP value indicates a reduction in the predicted output. As shown in the results, slope is negatively correlated with passability: larger slope values reduce passability, while smaller slope values enhance it.

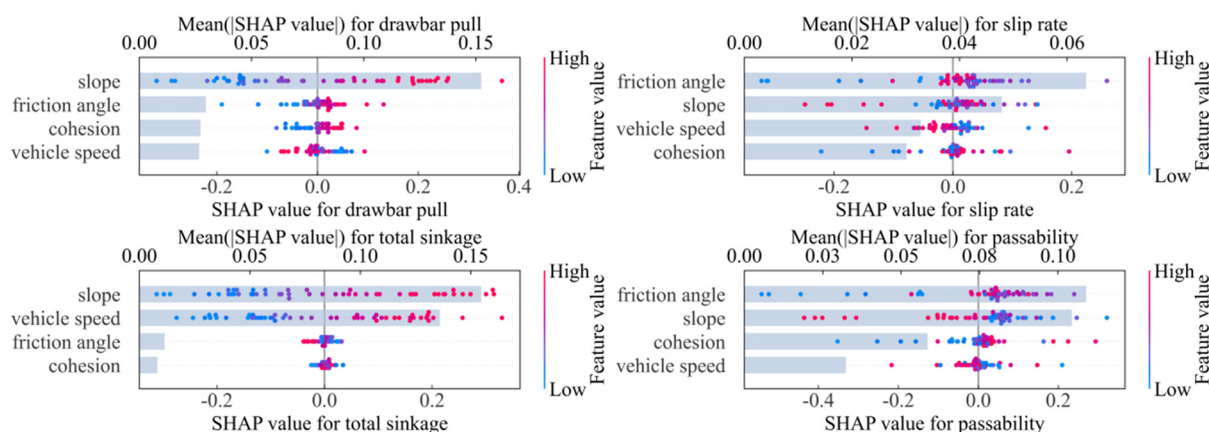


Figure 7. Feature importance analysis and SHAP value distributions.

4. Engineering Application

When the terrain and ground mechanics information of a point is known, the vehicle trafficability information of the point can be quickly obtained based on the rapid evaluation model established in this paper. Therefore, the rapid assessment of vehicle trafficability in an area can be divided into the following steps, as shown in Figure 8:

- (1) Grid the target area, with each grid cell serving as a basic unit;
- (2) Input the terrain and ground-mechanics information for each grid unit;
- (3) Use the surrogate model to obtain the vehicle trafficability results for the grid unit;
- (4) Finally, output the cloud map of vehicle trafficability for the entire area.

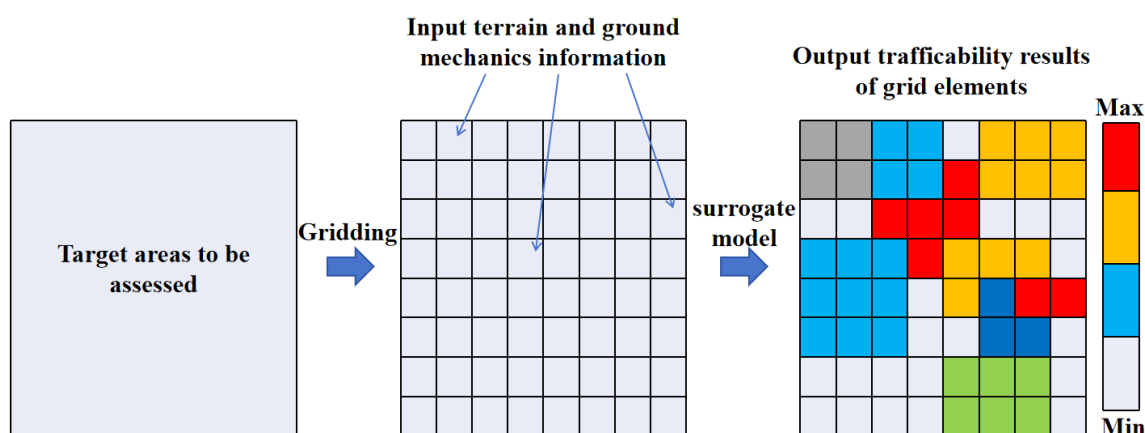


Figure 8. Rapid assessment of vehicle trafficability.

The evaluation module is developed based on the self-developed CDEM [45] simulation platform. It consists of two functional submodules: a 3D geological-terrain construction submodule and a vehicle trafficability assessment submodule. The terrain construction submodule inputs scattered terrain and geomechanical data and interpolates them to form geological-terrain fused raster data with uniform resolution. Based on the gridded geological-terrain fused data and vehicle characteristics, the vehicle trafficability assessment submodule evaluates trafficability and passing capacity at different spatial grid points.

Based on the prediction model presented in this paper, a test case was conducted to assess the trafficability of an area with given terrain and geological conditions and to provide the trafficability indicators and drawbar pull for each grid cell. The test terrain is shown in Figure 9. The area size is 1000 m × 1000 m, including 1.44 million grid points. The maximum elevation of the test terrain was 995.398 m, the minimum elevation was

534.344 m, the mean elevation was 776.924 m, and the median elevation was 787.838 m. The highest point of the terrain was located in the west–southwestern region, whereas the lowest point was located near the southeastern boundary, indicating an overall pattern of higher elevation in the west and lower elevation in the east. The maximum slope angle was 79.82, the mean slope angle was 36.62, and the median slope angle was 36.9. Overall, the terrain exhibited strong relief, with locally steep slopes. The vehicle parameters used in the test were kept consistent with those used in the numerical simulations. The soil parameters were assigned uniformly, with a density of 1800 kg/m³, an elastic modulus of 10 MPa, a Poisson’s ratio of 0.3, a cohesion of 3 kPa, and an internal friction angle of 15°. The test results are shown in Figure 10, and the computation time of the evaluation module was 0.33 s. As shown in Figure 10, the rapid assessment model can output drawbar-pull and passability results for each grid cell in the study area. In Figure 10a, the drawbar pull exhibits a clearly nonuniform spatial distribution, with a color scale ranging from approximately 48.32 to 175.10 kN. The area is generally dominated by medium drawbar-pull values, while high-value zones mainly appear as local patches. In contrast, low-value zones are mostly distributed continuously along gullies, abrupt slope transitions, or areas with large terrain undulations, indicating that complex terrain can significantly reduce the tractive capability of the vehicle. Figure 10b presents the binary passability classification results, where red indicates passable areas and blue indicates impassable areas. The results show that impassable areas occupy a relatively large proportion, whereas passable areas are mainly distributed as scattered patches or strips, suggesting that the overall trafficability of this area is strongly constrained by terrain undulation and tractive capability. The spatial distribution of drawbar pull is generally consistent with the passability results; however, passability is not determined solely by drawbar pull but is also jointly affected by factors such as slope, sinkage, and slip. Overall, Figure 10 demonstrates that the proposed rapid assessment model can effectively identify low-traction zones and potential impassable areas in complex terrain, providing an intuitive basis for path planning and trafficability risk assessment of off-road tracked vehicles. This rapid assessment module can provide real-time reference data for trafficability-based path planning of tracked vehicles in off-road environments.

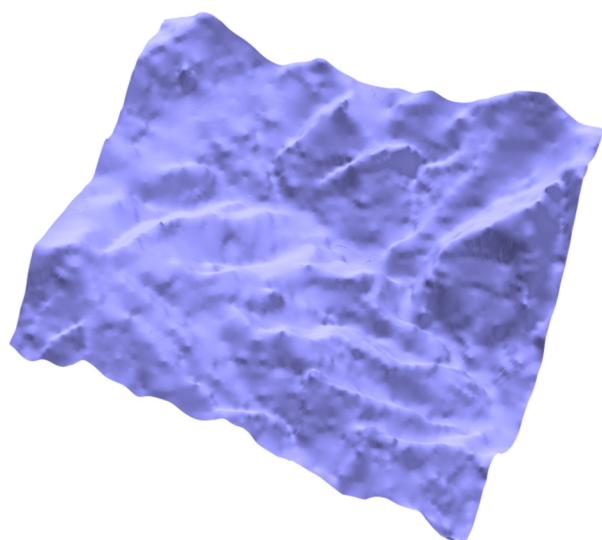


Figure 9. Test terrain.

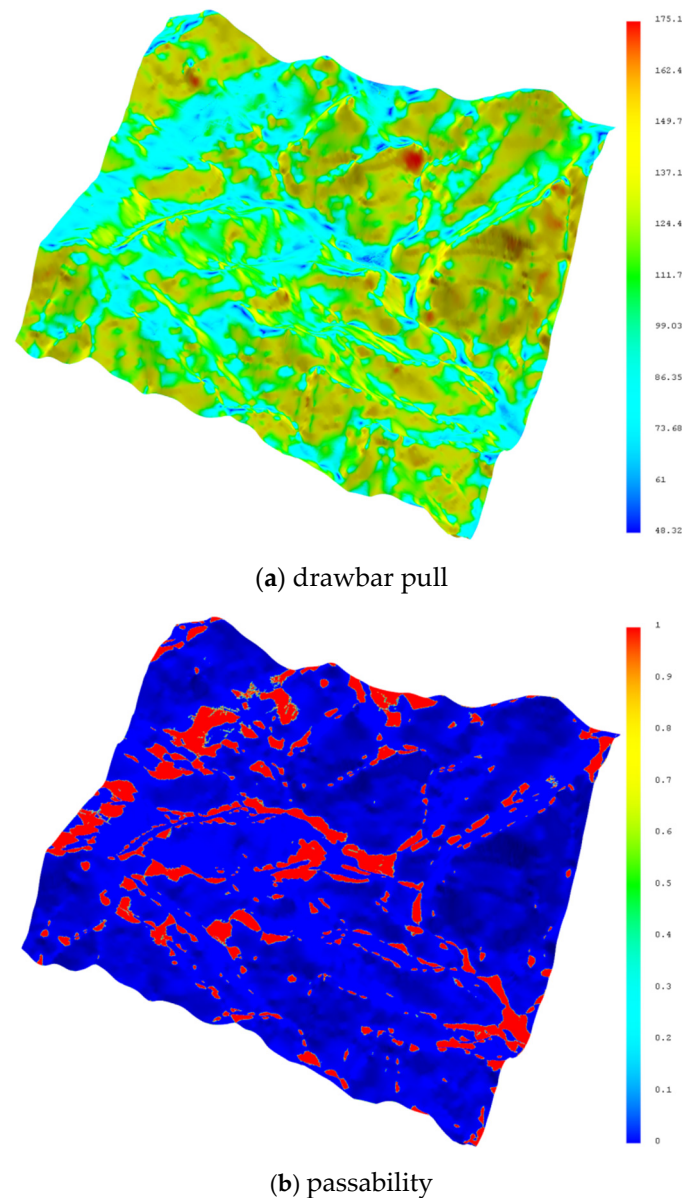


Figure 10. Rapid assessment of vehicle trafficability.

5. Conclusions

To address the computational complexity and extensive parameter-measurement requirements of traditional empirical formulas for tracked-vehicle terramechanics, this paper proposes a rapid vehicle trafficability assessment method that combines numerical simulation with a multilayer perceptron. The proposed method ensures prediction accuracy while significantly improving computational performance. The main conclusions are as follows:

- (1) The tracked-vehicle trafficability inversion model exhibits reliable prediction performance even on a small dataset (50 samples), and the model approaches convergence rapidly during the learning process.
- (2) Based on the functional relationship between inputs and outputs obtained from training, the maximum WAPE for the predicted drawbar pull, slip rate, and sinkage is 4.49%; the minimum R^2 is 0.97; and the accuracy of trafficability prediction is 100%, indicating that the prediction model can effectively characterize the relationship between the input and output variables.

- (3) The field application shows that the model can provide evaluation results within 0.33 s for a one-square-kilometer test terrain with 1,440,000 grid points. This rapid assessment module can provide real-time reference data for trafficability-based path planning of tracked vehicles in off-road environments.

6. Limitations and Future Work

Although this model exhibits a certain degree of predictive performance, its scope is mainly limited to the most significant influencing factors, including soil cohesion, internal friction angle, and a single terrain slope, as well as a single vehicle type. The limited number of factors cannot fully reflect the complex geometric characteristics and soil mechanical properties of off-road terrain, such as soil heterogeneity, dynamic properties, and vehicle-type effects. Nevertheless, this framework provides a reliable foundation and can be further extended to a wider range of vehicle types, complex terrain conditions, and soil characteristics by establishing a more comprehensive sample set.

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