Research on Quantitative Vehicle Mobility in a Region Based on Fuzzy Classification

Yunbo Zhou, Guangsheng Shi*, Ming Zhang, Bowen Zhang

Nanjing University of Science and Technology, Nanjing, China.

* Corresponding author email: 17660949361@163.com

Abstract

In the realm of terrain-driven vehicular navigation, achieving precise mobility assessment across heterogeneous landscapes remains a formidable challenge. This study proposes a quantitative evaluation model for vehicle mobility within a complex region by leveraging fuzzy classification techniques. Integrating topographic parameters—slope, elevation, and traversable speed—across four distinct soil environments, the model constructs a multilayered fuzzy inference system. Through the fusion of Digital Elevation Models, soil classification, and multibody dynamics simulations, we delineate GO/NO GO zones and generate a mobility cost map that reflects real-time navigability constraints. The application of Kriging interpolation enhances terrain resolution, while defuzzification via the "max–min" criterion ensures conservative yet realistic assessments. Ultimately, the proposed method provides a nuanced and visually interpretable classification of safe, low-risk, high-risk, and impassable zones, offering valuable insights into vehicle operability under multifactorial geospatial conditions.

Keywords

Soil terrain, vehicle mobility, geomechanics, fuzzy inference

1. Introduction

The notion of fuzziness refers to the presence of uncertainty and indistinct boundaries when evaluating or characterizing phenomena. In everyday life and professional contexts, numerous instances of fuzziness abound—for example, terms like "not bad" or "very" embody inherently vague definitions that resist precise depiction. In 1965, Professor L. A. Zadeh first articulated the concept of fuzziness in his seminal work ***Fuzzy Set***, marking the theoretical inception of fuzzy algorithms within the scientific domain. Later, in 1974, Professor H. Mamdani achieved the first successful application of fuzzy algorithms in the real-time control of industrial processes, signaling the transition of fuzzy logic from abstract theory to practical implementation—thereby igniting extensive scholarly discourse and exploration [1].

In taxonomy, fuzzy classification represents an emerging methodology that articulates problems through linguistic expressions rather that articulates problems through linguistic expressions rather than precise mathematical models, thereby accommodating the cognitive uncertainties—such as vagueness and ambiguity—inherent in real-world and everyday classification scenarios. The core process involves identifying a set of fuzzy rules pertinent to a specific classification task and applying these rules to input samples by interpreting the linguistic values of their attributes. As a result, fuzzy classification has found extensive applications in diverse fields such as image processing, handwriting recognition, speech recognition, text categorization, remote sensing, aerospace, meteorology, and industrial automation control [2].

In the evaluation and analysis of vehicle mobility, terrain is commonly categorized into GO/NO GO zones to indicate whether an area is passable or impassable for vehicles. Most studies typically label terrain points with gradients exceeding the vehicle's operational limits as impassable or classify soil areas with a cone index (CI) lower than the vehicle's cone index (VCI) as inaccessible. While such multi-factor fusion and weighting methods are efficient and convenient, they often yield routes with limited accuracy and fail to determine the optimal navigable path for ground vehicles within accessible zones [3,4]. Consequently, this thesis adopts a multi-factor fusion approach based on fuzzy classification. It integrates; this thesis adopts a multi-factor fusion approach based on fuzzy classification. It integrates an analysis of the vehicle's mobility across varying soil types while concurrently considering the influence of both terrain and soil parameters. This comprehensive evaluation yields a quantified assessment of the vehicle's maneuverability across composite terrains, categorizing the study area into safe zones, low-risk areas, high-risk areas, and impassable regions—thus more authentically reflecting the vehicle's operational capabilities in combat environments [5-8].

2. Related Work

When assessing a vehicle's mobility within a specific region, key inputs typically include the vehicle's maximum traversable speed, as well as the terrain's slope and elevation data. Open-source information is utilized to obtain the region's Digital Elevation Model (DEM), soil type data, and land use information. Additionally, the vehicle's maximum traversal speed under local soil conditions is computed through simulations [9].

2.1. Terrain Model

In this study, the selected research area lies between 86°50′E~86°80′E and 29°52′N~29°85′N, encompassing a total area of approximately 1050.7 km^2. Upon identifying the target region, we downloaded satellite imagery and DEM data from the Geospatial Data Cloud platform. Additionally, soil type data for the region were obtained from open-source datasets, revealing four distinct soil categories: permafrost, chernozem, sandy loam, and upland sandy. Land use data were acquired through the same method. All datasets are illustrated on Fig.1.

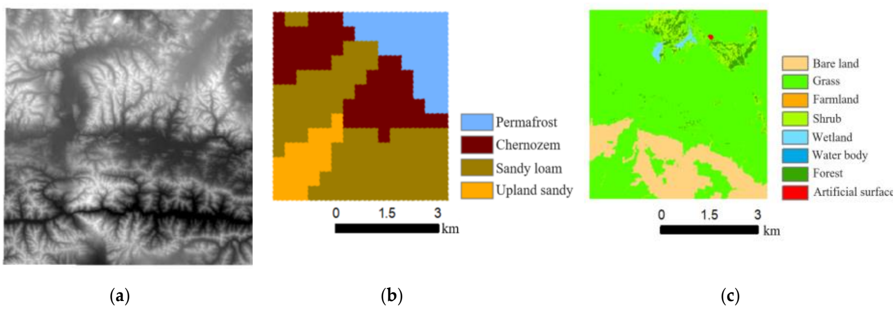


Fig 1. Multi source data with a resolution of 30 m in the target area.
(a) DEM(elevation), (b) Soil type distribution data, (c) Land use data

Under complex terrain conditions, slope is a critical factor that constrains vehicle mobility. Therefore, once the digital elevation model (DEM) is acquired, it is essential to calculate the slope at each terrain point. Specifically, based on the remote sensing data of the target area, a 3×3 window template is employed to traverse all raster cells of the terrain, allowing the slope value β_i of each cell to be computed. The calculation formula of the slope value of each point is

$$\beta_i = \arctan\sqrt{S_L^2 + S_T^2} \tag{1}$$

$$S_L = \left[(h_8 + 2h_1 + h_5) - (h_7 + 2h_3 + h_6) \right] / (8 \times d) \tag{2}$$

$$S_T = \left[(h_7 + 2h_4 + h_8) - (h_6 + 2h_2 + h_5) \right] / (8 \times d) \tag{3}$$

Where h_i (i= 1, ..., 8) represents the elevation values of the eight neighboring cells surrounding the target cell, and denotes the resolution of the data. The resulting slope map is shown in Fig.2, with the maximum slope within the region reaching 60%.

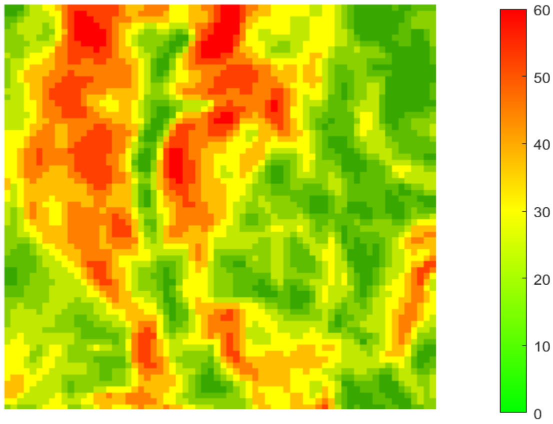


Fig 2. Slope map

After preprocessing the remote sensing data, the geographic coordinates (longitude and latitude) from the digital elevation model (DEM) were converted into Cartesian coordinates and extracted accordingly. Although the extracted dataset spans a broad geographic range, the inter-point distance remains approximately 30 meters, resulting in a resolution that is too sparse to ensure the accuracy of the constructed terrain model and rendering it inadequate for precise vehicle mobility prediction. Therefore, in fields such as Geographic Information Systems (GIS) and geology, interpolation methods are widely employed to fill data gaps, generate continuous surface models, and perform spatial analyses. Kriging interpolation, which utilizes a semivariogram to characterize spatial correlation, predicts the values of unknown points based on the spatial relationships among known points. Given its ability to account for spatial trends and autocorrelation, Kriging is particularly well-suited for datasets with inherent spatial continuity. Consequently, this study adopts the Kriging interpolation method to process and refine the terrain data of the target region. The reconstructed DEM is shown in Fig.3.

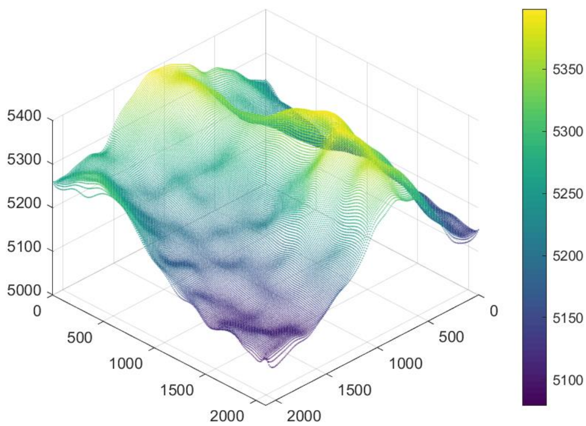


Fig 3. Terrain reconstruction with a resolution of 10 musing the ordinary Kriging method

2.2. Vehicle Traversal Speed

A multibody dynamics (MBD) model was constructed based on the empirical parameters of the research vehicle. Validated through experimental benchmarking, the model encompasses key components including the suspension system, tires, powertrain, and vehicle body. This framework is integrated with the established terrain model to enable DEM-MBD coupled simulation[10,11].

By simulating the vehicle's linear motion over four distinct soil types, the study investigates its mobility performance on soft ground surfaces. Given the relatively firm texture and dry condition of sandy loam, the Hertz-Mindlin (no slip) contact model was employed for its terrain modeling. The remaining three soil types were modeled using the Hertz-Mindlin with JKR contact model. As illustrated in Fig.4, the maximum traversable speeds of the vehicle under different soil conditions are presented: approximately 51.3 km/h on sandy loam, 33.7 km/h on chernozem soil, and 27.6 km/h on permafrost soil. Notably, due to the low traction coefficient and high slip rate on upland sandy soil, the vehicle achieves only a modest speed of about 14.7 km/h.

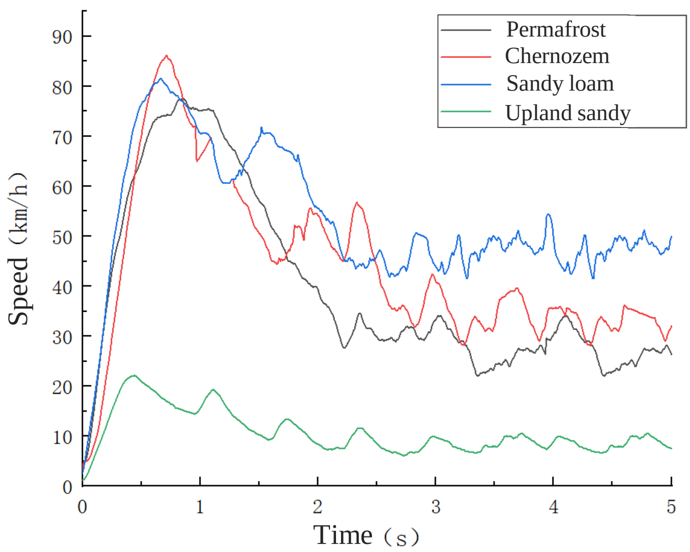


Fig 4. The maximum traversable speeds on four soil types

When navigating scenarios such as hill climbing and obstacle traversal, specialized vehicles often experience longitudinal body tilts. It is therefore essential to evaluate the vehicle's hill-climbing and obstacle-surmounting capabilities, as well as its reserve traction performance under varying gradients, to comprehensively assess its mobility—an evaluation that holds significant implications for understanding the vehicle's overall passability. In the simulations, the gradient was incremented by 5% with each run, with the ramp length set at 10 meters. A speed controller was configured to initiate the vehicle at an initial velocity of 5 km/h. The throttle was fully engaged at 100%, the gear was set to first, and full throttle was maintained throughout the simulation. It was required that the vehicle remain on the incline, maintaining a straight path until a steady speed was achieved. As depicted in Fig.5, the maximum gradient climbable by the research vehicle on different soil types is as follows: 50% on sandy loam with a corresponding speed of 7.3 km/h; 40% on chernozem soil with a speed of 6.8 km/h; 30% on upland sandy soil at 5.2 km/h; and 35% on permafrost soil with a speed of 5.5 km/h [12-14].

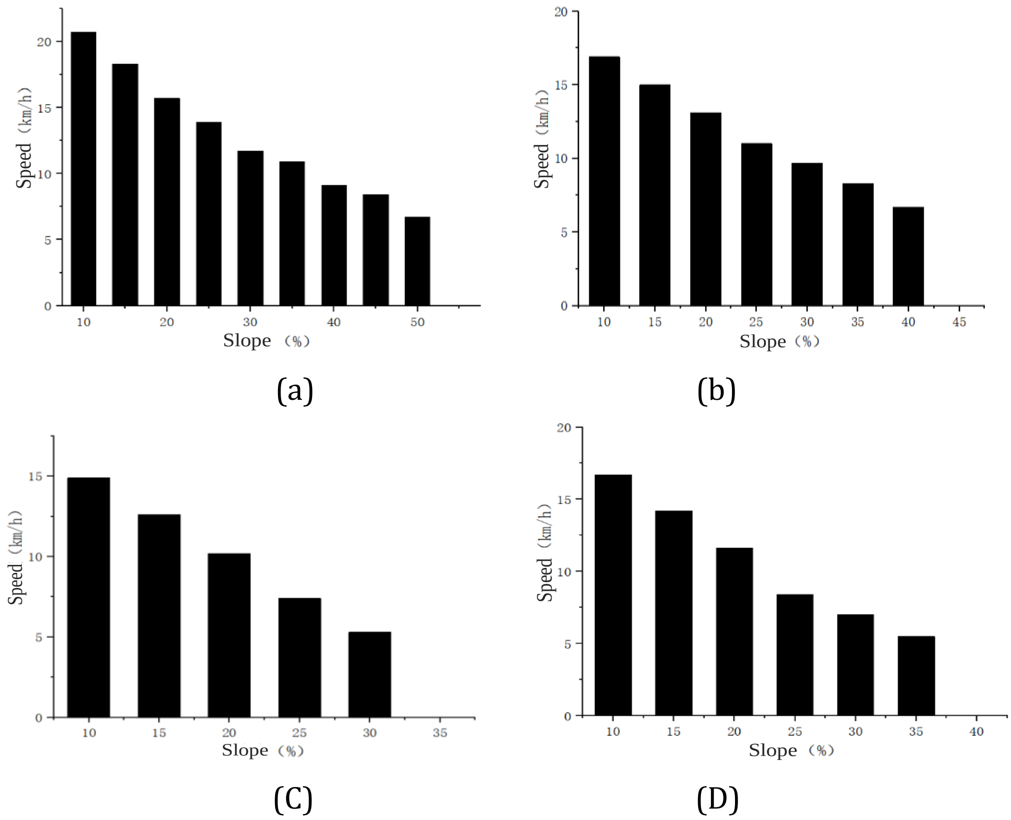


Fig 5. This figure illustrates the vehicle's climbing performance across four distinct soil types, along with the corresponding maximum climbing speeds. (**a**) The result of sandy loam; (**b**) The result of chernozem soil; (c) The result of upland sandy soil; (d) The result of permafrost soil

2.3. Fuzzy Classification

When conducting fuzzy classification, the initial step involves the fuzzification of both input and output variables. Fuzzification refers to the process of transforming the input data for the fuzzy classifier into corresponding linguistic variables, such as "low," "medium," and "high." This requires the prior determination of a membership function, which defines the degree to which each input belongs to these linguistic categories, thereby ensuring the stability and responsiveness of the fuzzy system.

Within a given interval, if the membership functions are densely concentrated in specific regions, the classifier becomes more sensitive to incoming inputs, resulting in faster system responses but potentially reduced stability. Conversely, if the membership functions are more dispersed, the system's reaction may slow, but its stability improves. Commonly used membership functions include triangular, Z-shaped, and S-shaped functions. These functions are used to partition the input and output domains into intervals, each of which is assigned a descriptive name.

Following fuzzification, it is necessary to establish fuzzy classification rules to map input variables to output variables. These rules, forming part of the classifier's rule base, are generally constructed using linguistic variables. The number and accuracy of the rules directly affect the classifier's performance. Each fuzzy rule is structured as an if-then statement, such as: if A1 is N and A2 is N ... and An is N, then B is M, where A1, A2, ..., An are input variables, B is the output variable, and N and M represent their respective fuzzy subsets. These rules can be summarized in a table, allowing outputs to be directly queried based on given inputs. Thus, precise values from the universal set are mapped to fuzzy subsets via the membership function, replacing exact values with linguistic terms (e.g., large, medium, small). This mirrors the human approach to variable observation in control processes, producing fuzzy outputs based on fuzzy inputs and rules.

Since the result of fuzzy inference is a fuzzy output, a defuzzification process must be applied. Common methods include the maximum membership principle, the median method, and the weighted average method. Depending on the specific system requirements or operational conditions, the most suitable defuzzification approach is selected to convert the fuzzy result into a precise value for final classification.

3. Fuzzy Classifier

As a system grounded in fuzzy inference, the core of a fuzzy classification system lies in the design of its classifier. In the context of quantifying vehicle mobility assessments, the design of the fuzzy classifier is primarily composed of three key components. First, the input set comprises the vehicle's maximum traversable speed, terrain slope, and terrain elevation across four distinct soil environments. During the fuzzy inference process, the classifier transforms the numerical data from these inputs into fuzzy sets. In other words, the input variables are represented according to their degrees of membership under various membership functions. Second, the “if–then” rule structure is employed to associate the input set with the output set. The inference engine interprets the input set and determines, based on the rule base, which rules should be activated to generate the corresponding output set. Finally, the classifier’s fuzzy output set undergoes defuzzification, yielding a concrete result—whether a given area is passable or impassable—and producing a quantified classification of vehicle mobility. Figure 6 illustrates the composition and procedural flow of this system.

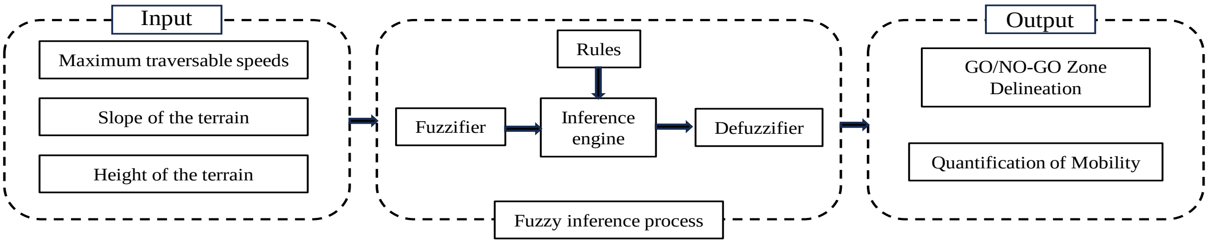


Fig 6. Block diagram of the proposed mobility quantification method

3.1. Fuzzification

The vehicle's traversable speed, terrain slope, and elevation altitude are designated as the three input variables of the fuzzy classifier, three input variables of the fuzzy classifier, while vehicle mobility serves as the output variable. For each of these, three linguistic variables—"High (H)," "Medium (M)," and "Low (L)" — are defined. Regarding the determination of membership functions, it is generally accepted that the steeper the shape, the higher the resolution of the system; conversely, the slower the variation, the greater the system's stability. Accordingly, the membership functions corresponding to the three linguistic variables are set as S-type, triangular, and Z-type, respectively. Based on research into the vehicle’s maximum traversable speed and maximum climbing gradient across four soil environments, the speed domains are defined as follows: [0, 51.3] for sandy loam, [0, 33.7] for calcareous black soil, [0, 14.7] for upland sandy soil, and [0, 27.6] for permafrost-thin layer soil. The domain for slope is uniformly defined as [0, 30°]. Furthermore, digital elevation data indicates that the elevation of the study area ranges from 5000 to 5400 meters above sea level, so the elevation domain is set as [5000, 5400]. After normalizing the input and output variables, the corresponding membership functions are defined as illustrated in Fig.7.

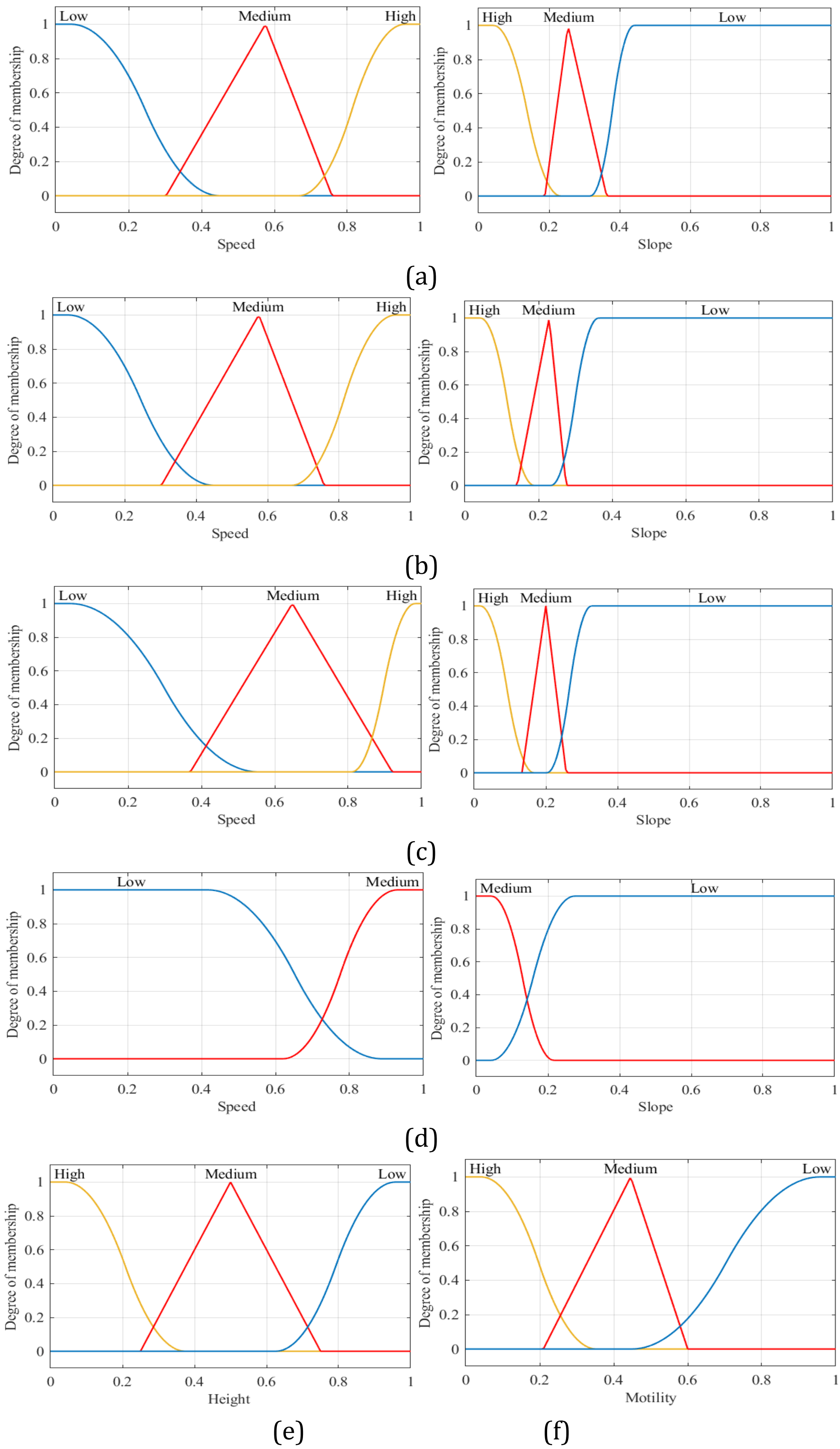


Fig 7. Membership of fuzzy rules. (**a**) Degree of membership of the sandy loam; (**b**) Degree of membership of the chernozem soil; (c) Degree of membership of the permafrost soil; (d) Degree of membership of the upland sandy soil; (e) Degree of membership of the height; (f) Degree of membership of the motility

3.2. Fuzzy Rules

The fuzzy rule system established in this study comprises in this study comprises three input variables—slope, elevation, and traversable speed—and one output variable: vehicle mobility. Each input and output variable is characterized by three linguistic states: "Low (L) ", "Medium (M) ", and "High (H) ".

The formulation of these rules is primarily grounded in the analysis of the test vehicle's maximum traversable speed and climbing gradient across four types of soil. Taking sandy loam as an example, where the vehicle achieves a peak speed of 51.3 km/h, the speed domain is accordingly segmented as follows: a speed between 0–20 km/h is classified as Low, 15–35 km/h as Medium, and 30–51.3 km/h as High. Regarding slope, given the vehicle's maximum climbing capability on sandy loam is 50%, equivalent to a gradient of 26.5°, the slope domain is partitioned such that slopes from 0–10° are considered High, 8–21° as Medium, and those exceeding 20° as Low. Moreover, since the selected study area lies in a high-altitude plateau region with an average elevation exceeding 5000 meters, atmospheric pressure decreases by approximately 5.9 mmHg for every 100-meter rise above sea level. This rare air results in reduced engine air intake and consequently diminished fuel injection, air intake and consequently diminished fuel injection, thereby slightly impairing vehicle power performance. As such, the elevation-related fuzzy rules are defined as follows: altitudes from 5000–5150 meters are classified as High, 5100–5300 meters as Medium, and 5250–5400 meters as Low. Detailed specifications of the fuzzy rules are presented in TABLE I.

Table 1. Fuzzy inference rules

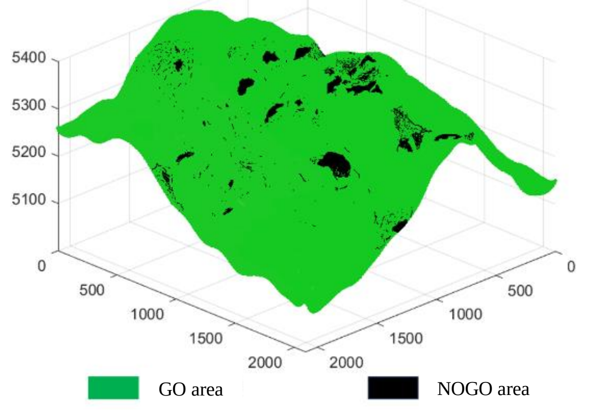
Input			Output
Speed	Slope	Height	Mobility
L	L	L	L
L	L	M	L
L	L	H	L
L	M	L	L
L	M	M	L
L	M	H	L
L	H	L	L
L	H	M	L
L	H	H	L
M	L	L	M
M	L	M	M
M	L	H	L
M	M	L	M
M	M	M	L
M	M	H	L
M	H	L	L
M	H	M	L
M	H	H	L
H	L	L	H
H	L	M	H
H	L	H	M
H	M	L	M
H	M	M	M
H	M	H	L
H	H	L	L
H	H	M	L
H	H	H	L

3.3. Defuzzification

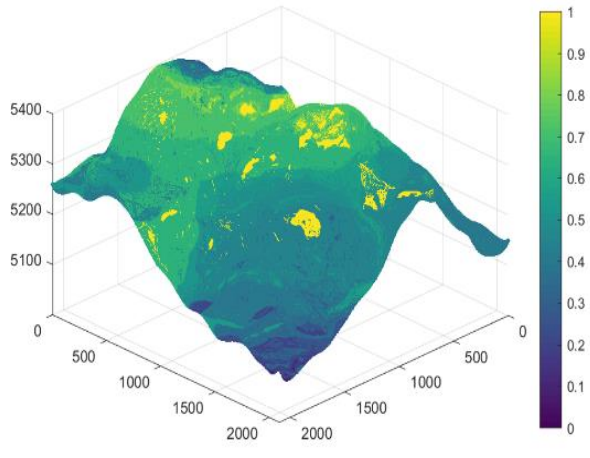
In the realm of fuzzy inference, a unified theoretical framework for the construction of fuzzy relations has yet to be established. This implies a diversity of methodologies in defining fuzzy relations, variations in the associated fuzzy operations, and, consequently, discrepancies in the inference outcomes. In practical applications of fuzzy reasoning, the "max–min" criterion—also known as the pessimistic criterion—is commonly employed. Rooted in the principles of decision-making under uncertainty, this approach adopts a cautious and conservative stance. It functions by identifying the worst possible outcome (i.e., the minimum value) for each alternative and subsequently selecting the alternative with the highest value among these minimums. This strategy, to some extent, minimizes the potential adverse consequences of the decision. In this study, the "max–min" criterion is utilized for defuzzification, thereby yielding a relatively conservative evaluation of regional mobility. Such an approach is aimed at mitigating the risk of vehicular damage to the greatest extent possible.

4. Quantitative Results

By integrating topographic slope data with land use with land use information, the GO/NO GO zoning of the vehicle's mobility under comprehensive terrain conditions is delineated using the aforementioned fuzzy classification method. According to the slope data and constrained by the vehicle's dynamic model, any terrain with a gradient exceeding the vehicle's maximum climbing capability is designated as a NO GO zone. Additionally, areas classified as wetlands, water bodies, or forested land based on land use data are also defined as impassable (NO GO), while all other regions are considered traversable (GO). This classification yields a GO/NO GO map, as illustrated in Fig.8a, where green denotes passable zones—constituting 90.74% of the study area—and black signifies impassable zones—accounting for 9.26%. Furthermore, after computing each factor through fuzzy classification, the attribute parameters of each terrain point are translated into corresponding mobility cost values, as depicted in Fig.8b. These values range from 0 to 1, where 0 indicates no velocity hindrance, and 1 denotes impassability. The closer the value approaches 1, the more diminished the vehicle's mobility becomes.



(a)



(b)

Fig 8. Distribution map of GO/NOGO and Fuzzy inference results.
(a) GO/NOGO map; (b) Fuzzy inference result for the mobility cost of [0, 1]

Based on the derived mobility cost values, the range [0, 0.3] is defined as a safe driving zone for the vehicle, [0.3, 0.5] as a low-risk traversable zone, [0.5, 0.9] as a high-risk traversable zone, and [0.9, 1] as an impassable zone. This classification enables a more intuitive visualization of the vehicle's mobility performance under comprehensive terrain conditions, as illustrated in Fig.9.

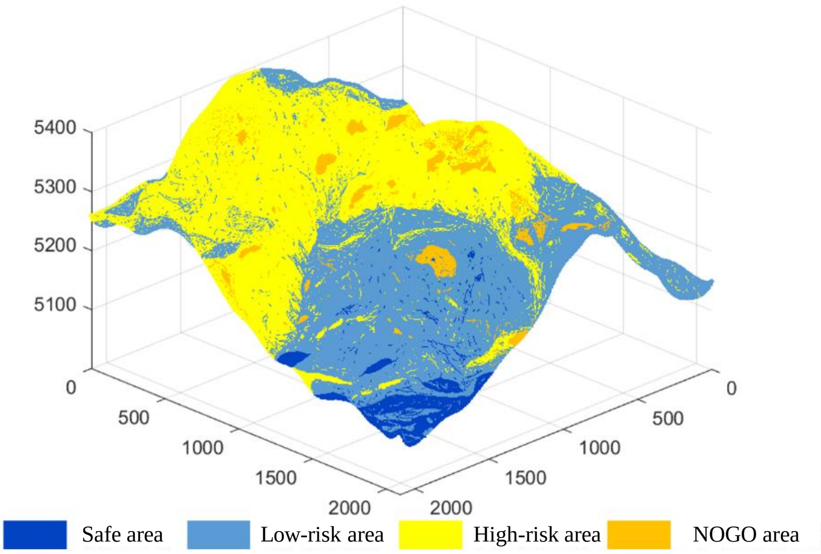


Fig 9. Fuzzy inference result for four categories:
NOGO area, high-risk area, low-risk area and safe area

5. Conclusions

This research establishes a comprehensive framework for quantifying vehicle mobility using fuzzy classification, effectively addressing the uncertainties inherent in terrain evaluation. By synthesizing terrain features and vehicular dynamics within a fuzzy logic paradigm, the proposed model transcends traditional binary GO/NO GO distinctions. The integration of elevation, slope, and soil characteristics enables a granular analysis of mobility across varied landscapes, while the application of fuzzy rules and conservative defuzzification ensures both responsiveness and stability in classification. The resulting mobility map facilitates strategic path planning and risk-aware navigation in real-world scenarios, particularly in geomechanically challenging or combat-critical environments. This method paves the way for intelligent vehicle routing systems that harmonize computational precision with environmental complexity.

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