

Traversability Driven Perception and Planning Coupling Mechanisms for Autonomous Driving in Unstructured Environments: A Review

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Abstract

Autonomous driving in unstructured environments faces challenges such as missing road boundaries, terrain variations, random obstacle distributions, and complex vehicle–terrain interactions, making it difficult to achieve safe navigation by relying on lane-level priors from structured roads. To address the problems of the relative separation between traversability analysis and trajectory planning, the ineffective propagation of perception uncertainty, and the insufficient scene adaptability of coupling mechanisms, this paper takes traversability as the main thread and systematically reviews the research progress of perception–planning coupling mechanisms in unstructured environments. First, traversability analysis methods based on geometric terrain, semantic understanding, and physical dynamics are reviewed, and the representation and propagation mechanisms of uncertainty in the perception–planning chain are analyzed. Second, the role of traversability information in global path search, local trajectory optimization, and data-driven planning is discussed, and the applicable boundaries of different coupling architectures are summarized from the perspectives of representation level and system organization form. Finally, datasets, simulation platforms, and evaluation metric systems are summarized, and a risk-state-oriented adaptive perception–planning coupling framework is proposed to dynamically adjust coupling strength based on risk-state information, thereby improving the safety, interpretability, and environmental adaptability of autonomous driving in unstructured environments.

Keywords: unstructured environments; autonomous driving; traversability analysis; perception and planning coupling; trajectory planning

Academic Editor: Fernando Viadero-Monasterio

Received: 15 May 2026

Revised: 14 June 2026

Accepted: 22 June 2026

Published: 23 June 2026

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1. Introduction

With the continuous advancement of autonomous driving technology, perception, decision-making, and control for structured road scenarios such as highways and urban arterial roads have formed a relatively mature autonomous driving technology system, and have been applied in assisted driving and some conditional autonomous driving scenarios. Meanwhile, autonomous driving technology is also accelerating its development toward unstructured environments such as agricultural operations [1–3], mining transportation [4], outdoor off-road driving [5], and forest patrol [6]. Compared with

structured roads such as highways and urban arterial roads, unstructured roads usually lack explicit constraint information such as road boundaries and lane markings. Meanwhile, terrain geometry, surface types, and obstacle distributions show significant irregularity and time-varying characteristics. Therefore, vehicles have difficulty relying on lane-level prior information in structured roads to complete driving area judgment and trajectory generation, which makes environmental perception, path planning, and vehicle control face greater uncertainty [7]. Typical unstructured road scenarios are shown in Figure 1.

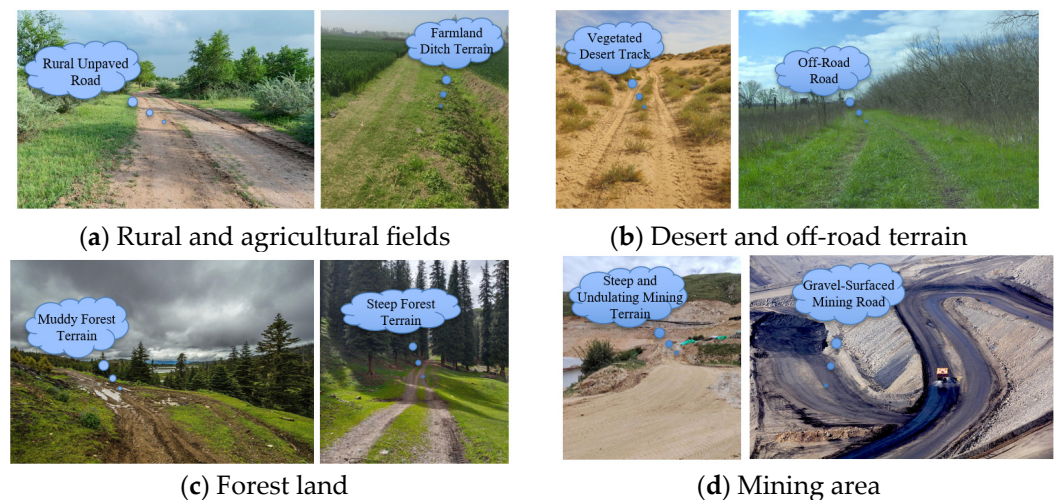


Figure 1. Typical unstructured road scenarios.

In unstructured environments, due to the diversity and complexity of scene types, roads contain not only various obstacles such as gravel and vegetation, but also negative obstacles such as gullies and pits. At the same time, factors such as terrain slope, soil mechanical properties, and ambiguous road boundaries make the environment present complex physical attributes and geometric structural characteristics. This brings great challenges to environmental perception, path planning, and autonomous navigation in autonomous driving systems. Therefore, whether a vehicle can travel safely in an unstructured environment depends not only on explicit road obstacles, but also on road slope, undulation, negative obstacles, soil bearing capacity, adhesion conditions, standing water, gravel, vehicle speed, load, and dynamic performance [8,9]. Unlike structured roads, where road boundaries, lane markings, and traffic rules jointly constrain vehicle behavior, the drivable space in unstructured environments is often not given in advance, but is dynamically formed during vehicle perception, terrain understanding, and motion execution. Especially in mining and off-road environments, negative obstacles, soft surfaces, and deformable terrain can significantly amplify the risks of vehicle posture instability, slip, getting stuck, and collision. However, in agricultural environments, although crop rows, boundaries, and operation paths provide certain weak structural priors, muddy ground, roadside gullies, crop occlusion, and disturbances still affect the stable passage of vehicles. Therefore, autonomous driving systems in unstructured environments cannot rely only on obstacle detection and drivable area segmentation, but also need to further determine whether a vehicle can safely pass through a specific area under the constraints of current speed, load, posture, and dynamic capability.

In autonomous driving systems, safe and executable trajectories are generated by evaluating the traversal risk and traversal cost of different regions while incorporating vehicle kinematic and dynamic constraints. As a key link between environmental perception and trajectory planning, traversability analysis aims to transform geometric,

semantic, and physical information in the environment into planning-usable representations, such as cost, risk, and drivable regions [10]. Therefore, trajectory planning is transformed from a problem constrained by rules into one constrained by terrain geometric states, vehicle kinematics, dynamics, and perception uncertainty [11,12]. When the planner of an autonomous driving system cannot fully utilize perception information, the system has difficulty generating safe trajectory information, which greatly affects the safety of the autonomous driving system. In this paper, traversability is regarded as a planning-oriented intermediate variable. Its role is to uniformly transform environmental geometric structures, surface semantic attributes, vehicle–terrain physical interactions, and perception uncertainty into cost terms, constraint boundaries, risk distributions, and feedback signals that can be used by the planner. As the core coupling element connecting perception and planning in autonomous driving systems, traversability cannot effectively improve system safety if its results remain only at the perception end and cannot be effectively converted into path search weights, trajectory optimization constraints, speed limits, and closed-loop feedback information.

In recent years, researchers have reviewed related studies from the perspectives of autonomous driving in unstructured environments, terrain traversability analysis, off-road perception, path planning, navigation, prediction–planning integration, and uncertainty propagation. A comparison of related reviews is shown in Table 1. As can be seen from Table 1, existing reviews on autonomous driving in unstructured environments mainly cover terrain traversability estimation, path planning, prediction–planning integration, uncertainty propagation, and end-to-end autonomous driving. In traversability estimation, the focus is mainly on how to estimate traversability, while the role of traversability in the planning stage is less discussed. In path planning studies, existing reviews systematically summarize graph search, sampling-based planning, optimization-based planning, and control methods. However, they often assume that upstream cost maps, occupancy maps, or traversable regions have already been reliably generated, while insufficient attention is paid to the sources and assumptions of traversability representations. In reviews on prediction–planning integration, uncertainty propagation, and end-to-end autonomous driving, the application scenarios are mainly structured roads, making it difficult to directly transfer these methods to unstructured scenarios involving soft terrain, negative obstacles, slip, sinkage, and vehicle–terrain coupling constraints.

Table 1. Comparison of related reviews on autonomous driving in unstructured environments.

Reference	Research Topic	Main Contributions	Limitations
Borges et al., 2022 [10]	Terrain traversability analysis for autonomous ground vehicles	Summarizes terrain classification, traversability estimation, sensor configuration, and application issues from the perspectives of methods, sensors, and challenges.	Mainly focuses on perception and estimation, with insufficient discussion on how traversability is transformed into path search costs, trajectory optimization constraints, and closed-loop feedback variables.
Wijayathunga et al., 2023 [13]	Learning-based perception and navigation for ground vehicles in unstructured environments	Summarizes the application of machine learning and deep learning methods in unstructured environment perception, scene understanding, and navigation.	Insufficient analysis of vehicle–terrain physical interaction, planning executability, and risk propagation.
Wang et al., 2024 [14]	Path planning for autonomous ground vehicles in unstructured environments	Summarizes path planning methods under complex terrain, harsh environments, and	Insufficient discussion of cost map generation assumptions, reliability, and uncertainty sources.

vehicle–terrain interaction conditions.			
Min et al., 2025 [8]	Autonomous driving in unstructured off-road environments	Covers mapping, localization, pose estimation, environmental perception, path planning, end-to-end driving, and datasets, with a broad review scope.	The coverage is broad and comprehensive, but less focused on traversability as an interface between perception and planning.
De Oliveira et al., 2025 [15]	Trajectory planning in low-structured and unstructured environments	Conducts a systematic review of methods and discusses global planning, local planning, motion control, and sensor fusion.	Insufficient discussion of how perception outputs affect trajectory feasibility and how planning feedback reversely corrects perception.
Musau et al., 2025 [16]	Off-road datasets, sensor technologies, and terrain traversability analysis	Reviews off-road datasets, sensor configurations, geometric methods, learning methods, and probabilistic traversability analysis.	Mainly focuses on data resources and perception, with insufficient discussion of the role of traversability results in path search, local optimization, and control execution.
Hagedorn et al., 2024 [17]	Prediction and planning integration in deep-learning-based autonomous driving	Classifies prediction and planning integration methods into modular, joint, and end-to-end forms, and discusses information coupling in deep learning systems.	Mainly focuses on structured road traffic and is difficult to directly explain vehicle–terrain constraints in unstructured terrain.
Jiang et al., 2025 [18]	Uncertainty in the perception, decision-making, and control chain of autonomous driving	Analyzes the generation, propagation, and amplification mechanisms of uncertainty, and emphasizes the influence of upstream perception errors on downstream decision-making and control.	It is a general review of uncertainty and lacks analysis of unstructured-scenario-specific uncertainties such as soft ground, negative obstacles, slip, and sinkage.

From the perspective of autonomous driving system architecture, traditional autonomous driving systems usually adopt a serially decoupled modular scheme. In this scheme, the perception module performs obstacle detection, semantic segmentation, and map construction, and then transmits results such as obstacle lists, semantic maps, occupancy grids, or cost maps to the planning module. The planning module completes path search, trajectory optimization, and motion control based on the perception results [19]. This architecture has the advantages of clear interfaces, easy engineering implementation, and convenient modular verification, but it also has obvious limitations in unstructured environments. First, high-dimensional terrain information is easily lost when it is converted into low-dimensional cost maps or semantic labels, making it difficult for the planner to distinguish regions that are geometrically traversable but physically high-risk. Second, the planning module usually has difficulty influencing perception strategies in reverse according to candidate trajectories, local risks, and vehicle execution states, resulting in an information mismatch between perception results and planning requirements. Therefore, the coupling between perception and planning in unstructured environments affects the driving safety and operational efficiency of vehicles. In addition, with the development of vision-language models and foundation models, their roles in natural language goal specification, open-scene semantic understanding, and high-level task reasoning have gradually attracted attention. Although vision-language models can provide assistance for task understanding and semantic interpretation in unstructured

environments, their outputs usually lack explicit physical interpretability, risk boundaries, and vehicle dynamic constraints, making it difficult for them to directly replace traversability modeling and safe trajectory planning. Therefore, this paper regards foundation models as high-level semantic enhancement modules in the traversability-driven coupling framework, rather than as independent safe planners.

In summary, research on autonomous driving in unstructured environments has been carried out around environmental perception, traversability analysis, and trajectory planning. However, most existing studies regard traversability analysis and trajectory planning as relatively independent problems, and there is still a lack of systematic discussion on how perception results are transformed into planning constraints, how traversal costs participate in trajectory generation, and how planning feedback influences perception modeling in reverse. Therefore, this paper reviews the mechanisms from sensor observation to risk representation, planning constraints, and coupling feedback in unstructured environments. The overall framework is shown in Figure 2.

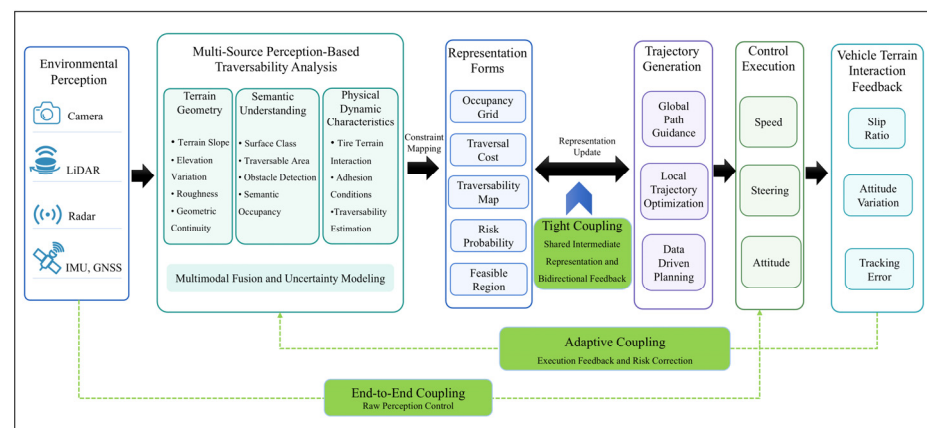


Figure 2. Overall framework of this review.

The main contributions of this paper are as follows:

- A review framework for autonomous driving in unstructured environments is constructed with traversability as the core theme. Traversability is defined as an intermediate variable connecting environmental perception and trajectory planning, and the transformation mechanisms of geometric, semantic, physical-dynamics, and uncertainty information into costs, constraints, and risk boundaries are systematically analyzed.
- The mechanisms of traversability-driven trajectory planning are systematically summarized. From the perspectives of global path search, local trajectory optimization, vehicle–terrain constrained planning, and data-driven planning, the ways in which different methods use traversability information, their applicable scenarios, and their main limitations are compared.
- A risk-state-based adaptive perception–planning coupling analysis framework is proposed. Based on the existing classification of coupling architectures, the applicable boundaries of modular weak coupling, tightly coupled closed-loop architectures, and end-to-end deep coupling are further analyzed from the perspectives of information loss, error propagation, closed-loop feedback, and safety verification. At the same time, it is pointed out that future systems should dynamically adjust coupling strength according to terrain risk, perception confidence, and vehicle execution state, so as to achieve a balance among real-time performance, safety, and interpretability.
- The testing and validation system for unstructured scenarios is systematically reviewed. Existing datasets and evaluation metric systems are compared in

combination with typical operating conditions such as agriculture, mining areas, and off-road environments, and the technical evolution and future development directions of perception–planning coupling mechanisms are summarized.

The remainder of this paper is organized as follows. Section 2 presents traversability analysis and representation forms in unstructured environments. Section 3 reviews trajectory planning methods driven by traversability. Section 4 analyzes the research progress and evolutionary trends of traversability-driven perception–planning coupling mechanisms. Section 5 discusses the testing and validation system, including public datasets, simulation platforms, and performance evaluation metrics. Section 6 analyzes existing challenges and future directions. Section 7 concludes this paper.

2. Traversability Analysis and Representation Forms in Unstructured Environments

In unstructured environments, traversability analysis serves as an important basis for determining whether a vehicle can travel safely. Its core task is to determine whether the vehicle can pass safely with an acceptable level of risk under the constraints of the current terrain, speed, load, and actuation capability. Compared with structured environments, road boundaries in unstructured environments are often unclear, and there is no fixed semantic boundary between obstacles and traversable regions. Vehicle traversal risk comes not only from explicit obstacles, but is also related to factors such as road conditions, ground physical properties, and vehicle driving states. In addition, risks vary across different scenarios. For example, agricultural scenarios usually have weak structural priors such as crop rows, furrows, and boundaries, but muddy ground, crop occlusion, and operation path constraints still affect stable traversal [20,21]. Mining scenarios pay more attention to the safe operation of heavy-duty vehicles under conditions such as slopes, gravel roads, dust occlusion, and long braking distances. Off-road and forest scenarios emphasize risks related to missing road boundaries, gullies, negative obstacles, soft terrain, weak GNSS signals, and posture stability during high-speed maneuvers [22]. Therefore, the core objective of traversability analysis is to transform geometric, semantic, physical, and uncertainty information obtained from environmental perception into risk constraints and cost representations that can be directly used by the planning module, and to continuously correct decision results through closed-loop feedback. The transmission mechanism of traversability risk from perception to planning is shown in Figure 3.

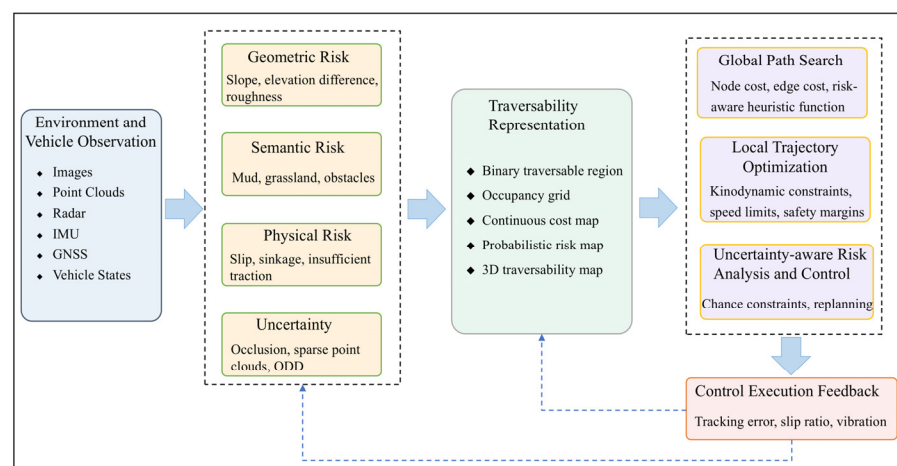


Figure 3. Transmission mechanism of traversability risk from perception to planning.

2.1. Geometric, Semantic, and Physics Dynamics-Based Traversability Analysis

In unstructured environments, traversability analysis serves as feedforward information for trajectory planning in autonomous driving systems. Therefore, traversability analysis transforms sensor data into traversal cost representations required by the planning module, such as traversable regions, traversal costs, risk constraints, and feasible domains. Traversability analysis methods can be divided into geometric-terrain-based analysis, semantic-understanding-based analysis, and physical-dynamics-based analysis. A comparison of different analysis methods is shown in Table 2. Geometric-terrain-based analysis methods have the advantages of strong interpretability and constraint capability, but they have difficulty identifying surface materials and deformable terrain risks. Semantic-analysis-based methods can express surface categories and scene information, but they are easily affected by weather, illumination, seasons, and annotation accuracy. Physical-dynamics-based analysis methods can more directly describe whether a vehicle can pass through a certain region, but they depend on prior terrain and vehicle parameter information, and it is difficult to obtain these parameters in real time. A single method is difficult to cover traversal risks in unstructured environments. Therefore, traversability analysis needs to integrate multidimensional information to comprehensively determine vehicle traversability.

Table 2. Comparison of traversability analysis methods.

Modeling Type	Input Type	Output Form	Applicable Scenarios	Advantages	Limitations	Integration into Planning
Geometric terrain analysis	Point clouds, depth images, elevation maps, IMU	Slope, roughness, elevation difference, curvature, normal vectors	Off-road, forest, mining areas, farmland	Strong interpretability and easy integration with vehicle geometric constraints	Difficult to identify risks such as mud, standing water, and soft soil	Node costs, edge costs, slope constraints
Semantic understanding analysis	RGB images, point cloud semantics, BEV features	Surface categories, traversable regions, and semantic costs	Farmland, orchards, and weakly structured scenarios with unclear road boundaries	Can express surface categories and scene meanings	Weak mapping to actual traversability and easily affected by data distribution	Semantic costs, drivable regions, task constraints
Physical dynamics analysis	Wheel speed, IMU, vehicle states, terrain parameters	Friction, slip ratio, sinkage, traction force, roll stability margin	Off-road, high-speed maneuvers, heavy-load mining areas, soft terrain	Can describe the actual traversal capability of vehicles	Parameters are difficult to obtain, computation is complex, and model mismatch risk is high	Dynamic constraints, speed limits, stability constraints

2.1.1. Geometric Terrain-Based Traversability Analysis

Geometric-terrain-based traversability analysis mainly uses LiDAR point clouds, depth images, and multisensor fusion results to construct elevation maps, occupancy maps, and 3D maps, from which geometric features such as slope, elevation difference, roughness, local curvature, and surface normal vectors are extracted. These features can

be directly transformed into node costs, edge costs, or local trajectory constraints. When the terrain slope is too large, the elevation changes abruptly, or the local roughness is high, the vehicle may experience bottoming, collision, rollover, or posture instability. Therefore, these geometric indicators are usually used as basic safety constraints in path search and trajectory optimization.

In unstructured scenarios, researchers have conducted studies on point cloud mapping, elevation reconstruction, and local terrain assessment. Krüsi et al. [23] used point cloud maps for terrain assessment and motion planning, indicating that point cloud information can support 3D terrain traversability analysis without explicit surface reconstruction. The GridMap framework proposed by Fankhauser et al. [24] uses a two-dimensional grid structure to represent multilayer terrain attributes, and can store information such as elevation, slope, surface normal vectors, and roughness, providing structured geometric constraints for local obstacle avoidance and trajectory planning. Geometric-terrain-based traversability analysis usually relies on point clouds, elevation maps, or local terrain maps to extract features such as slope, elevation difference, roughness, curvature, and surface normal vectors. Therefore, its performance depends not only on the geometric decision rules themselves, but also on terrain mapping accuracy, map coverage, and real-time performance. In recent years, geometric mapping methods for off-road scenarios have gradually been compared on public datasets such as RELLIS-3D [25], providing a basis for evaluating different terrain modeling methods. Table 3 presents a comparison of typical geometric terrain representation methods. In the table, RMSE represents elevation reconstruction accuracy, coverage reflects the completeness of map construction, computational time affects online deployment capability, and P, R, and F1 are used to evaluate the consistency between traversable region reconstruction results and annotations. Overall, geometric methods have strong interpretability and engineering usability in identifying slopes, abrupt elevation changes, and rough terrain. However, existing methods still mainly focus on whether the terrain is correctly reconstructed, and have not sufficiently covered real traversal risks such as slip, sinkage, insufficient traction, and vehicle posture stability. Therefore, geometric terrain analysis can serve as a basic layer for traversability assessment in unstructured environments, but it still needs to be combined with semantic understanding, physical dynamics, and uncertainty modeling to more completely support safe planning.

Table 3. Performance comparison of traversability analysis methods based on geometric terrain representation.

Method	Dataset	Geometric Representation	Evaluation Metrics	Performance Results	Method Analysis
GPR [26]	RELLIS-3D	Traversable region reconstruction	P, R, F1, RMSE, coverage, time consumption	99.58%, 18.67%, 31.44%; 55.02 cm; 96.48%; 91.14 ms	High coverage, but low recall
NDT-TM [27]	RELLIS-3D	Local terrain distribution modeling	P, R, F1, RMSE, coverage, time consumption	98.67%, 52.65%, 68.66%; 8.58 cm; 68.39%; 11.35 ms	Low reconstruction error and good real-time performance, but limited detection accuracy
BGK [28]	RELLIS-3D	Probabilistic terrain inference	P, R, F1, RMSE, coverage, time consumption	82.10%, 69.85%, 75.48%; 14.39 cm; 89.57%; 128.23 ms	Low accuracy and high computational cost
Xue et al., 2023 [29]	RELLIS-3D	Online traversable region reconstruction	P, R, F1, RMSE, coverage, time consumption	99.69%, 73.61%, 84.69%; 7.28 cm; 92.70%; 47.80 ms	Better overall performance in accuracy, coverage, and real-time capability

Geometric-terrain-based methods are easy to combine with vehicle size, minimum ground clearance, maximum slope, and posture constraints. However, relying only on geometric information makes it difficult to fully reflect real traversal risks. Flat, muddy or waterlogged areas may appear geometrically as low-slope and low-roughness regions, and thus be regarded as low-risk areas, but slip, getting stuck, and insufficient traction may occur during actual traversal. In contrast, some hard terrains with large slopes may still be safely traversable when the vehicle has sufficient adhesion conditions and proper speed control. In addition, geometric methods are easily affected by sparse point clouds, vegetation occlusion, and the resolution of elevation maps. Negative obstacles may be underestimated in two-dimensional projections or sparse point clouds. Therefore, geometric traversability indicates whether the vehicle is allowed to pass in terms of spatial morphology, but it cannot represent whether the vehicle can pass stably under the current state.

2.1.2. Traversability Analysis Based on Semantic Understanding

Traversability analysis based on semantic understanding focuses on identifying surface categories, obstacle attributes, and scene structures, and constructs traversable regions or traversal costs according to the traversability attributes of different semantic objects. Compared with geometric terrain methods, semantic methods can express surface materials and scene meanings. In unstructured environments, hard dirt roads, slippery muddy ground, grass, gravel, puddles, and crop areas may have limited geometric differences, but their adhesion conditions, sinkage risks, controllability, and task constraints are clearly different. Therefore, semantic understanding can help the planner distinguish regions that are geometrically continuous but physically high-risk.

With the development of deep learning and multimodal perception technologies, image semantic segmentation, point cloud semantic segmentation, and bird's-eye-view representations have gradually become important methods for traversability analysis in unstructured environments. Maturana et al. [30] constructed a real-time semantic mapping system for off-road autonomous navigation. By combining semantic segmentation results with spatial maps, the autonomous driving system can distinguish categories such as roads, grass, vegetation, and obstacles, and use semantic information for navigation decisions. Shaban et al. [31] proposed BEVNet, which transforms sparse LiDAR input into a terrain cost category map from the bird's-eye view. It divides the environment into traversal levels such as free space, low cost, medium cost, and obstacles, thereby combining semantic categories with spatial structures. In agricultural and orchard scenarios, semantic understanding methods have also been widely used for crop row detection, navigation line extraction, and drivable region recognition [32–35]. Their essence is to transform semantic information such as crops, ground, inter-row areas, and obstacles into spatial constraints that can be used by local planning.

Traversability analysis based on semantic understanding usually identifies surface categories, obstacle attributes, and traversable regions through image semantic segmentation, point cloud semantic segmentation, or multimodal free-space detection. Related methods conduct off-road semantic segmentation and free-space detection tasks on existing public datasets such as RELLIS-3D and ORFD [36], and use F-score, IoU, and running speed to measure the detection capability of traversable region models. A comparison of semantic-understanding-based methods is shown in Table 4. As can be seen from Table 4, traversability analysis based on semantic understanding has formed a relatively mature evaluation system in off-road semantic segmentation and free-space detection tasks. Current vision-based semantic segmentation models are affected by factors such as class imbalance, ambiguous ground boundaries, and dramatic appearance changes in unstructured environments, and their performance still decreases significantly. In contrast,

multimodal methods show better traversable region recognition capability in free-space detection by fusing RGB and geometric information such as depth. Overall, semantic understanding can provide high-level semantic information for planning, such as surface categories, obstacle attributes, and free-space boundaries, making it an important way to compensate for the limitations of pure geometric methods. However, existing evaluation metrics mainly measure the consistency between semantic predictions and manual annotations, and it is difficult for them to directly reflect the actual traversal capability of vehicles under different surfaces and operating conditions. Therefore, semantic information is more suitable as a prior constraint for traversability modeling.

Table 4. Performance comparison of traversability analysis methods based on semantic understanding [36,37].

Method	Dataset and Task	Input Modality	Main Metrics	Performance Results	Method Analysis
HRNet + OCR [37]	RELLIS-3D, semantic segmentation	RGB	mIoU	51.55%	Maintains high-resolution features, but is significantly affected by class imbalance in off-road scenarios
Gated-SCNN [38]	RELLIS-3D, semantic segmentation	RGB	mIoU	52.92%	Strong boundary modeling capability, but still faces difficulties with ambiguous boundaries such as grass and bushes
SalsaNext [39]	RELLIS-3D, point cloud segmentation	LiDAR	mIoU	43.07%	Has real-time point cloud segmentation capability, but insufficient recognition of sparse classes
KPConv [40]	RELLIS-3D, point cloud segmentation	LiDAR	mIoU	19.97%	Sensitive to class imbalance and unstructured point cloud distributions
FuseNet [41]	ORFD, free-space detection	RGB, depth	F-score, IoU, speed	79.5%, 66.0%, 49 Hz	Fast, but has relatively low accuracy in traversable region detection
SNE-RoadSeg [42]	ORFD, free-space detection	RGB, normal vectors	F-score, IoU, speed	89.6%, 81.2%, 12.5 Hz	Normal vectors provide clear improvement, but the model is relatively complex
OFF-Net [36]	ORFD, free-space detection	RGB, normal vectors	F-score, IoU, speed	90.3%, 82.3%, 33.9 Hz	Achieves a relatively good balance between accuracy and real-time performance, and is suitable for online free-space detection

In summary, semantic understanding methods can compensate for the limitations of pure geometric methods in recognizing surface materials and scene categories. However, their limitation lies in the absence of a fixed mapping between category labels and traversal costs. The same grass category may correspond to different traversal risks under dry, slippery, compacted, or waterlogged conditions, and the same muddy ground may also correspond to different feasibility for small vehicles and heavy-duty vehicles. In addition, semantic models rely on large-scale annotated data and are easily affected by seasons, illumination, weather, crop growth stages, and changes in surface appearance. When the model encounters terrain materials outside the training set, it may produce high-confidence but incorrect semantic judgments. Therefore, to generate safety-critical

trajectory planning, semantic outputs cannot be directly regarded as traversal capability. Instead, they should be incorporated into cost modeling together with geometric structures, vehicle states, and uncertainty estimation, thereby improving the robustness of autonomous driving systems.

2.1.3. Traversability Analysis Based on Physical Dynamics

Physical-dynamics-based traversability analysis focuses on the mechanical interaction between the vehicle and the terrain. It aims to determine whether the vehicle can still pass stably under the constraints of current speed, load, posture, and actuation capability when a certain region is geometrically continuous and semantically feasible. Compared with geometric and semantic methods, physical-dynamics-based methods pay more attention to the actual traversal capability of vehicles. Therefore, they mainly evaluate physical factors such as the slip ratio between wheels and the ground, soil bearing capacity, sinkage, rolling resistance, and traction force. For off-road vehicles, mining trucks, tracked robots, and agricultural machinery, physical-dynamics modeling is directly related to whether a trajectory is executable.

In unstructured environments, terrain is often deformable, nonuniform, and time-varying. When vehicles travel on mud, sand, gravel, grass, paddy fields, or soft soil, wheel sinkage, track slip, insufficient traction, and posture instability may occur. The Bekker model [43] describes the pressure distribution of wheels on deformable ground through parameters such as soil cohesion modulus, internal friction angle, and sinkage exponent, and can be used to estimate sinkage, rolling resistance, and traction force. The online terrain parameter estimation method proposed by Dallas et al. [44] combines a ground mechanics model with state estimation to estimate parameters such as the sinkage exponent online, thereby improving the state prediction capability of vehicles on deformable terrain. For tracked operation machinery in hilly and mountainous areas, active leveling systems can reduce rollover risk and improve terrain adaptability [45]. Studies show that physical-dynamics information can elevate traversability from static terrain attributes to executability constraints related to vehicle states.

In recent years, related studies have begun to shift from manually set physical parameters to learning terrain responses using vehicle feedback. Wellhausen et al. used self-supervised feedback during robot driving to predict terrain properties from visual information, enabling the system to learn the relationship between surface appearance and wheel–terrain interaction responses [46]. Schmid et al. distinguished low-risk and high-risk terrain through reconstruction errors in regions covered by historical vehicle trajectories, thereby reducing the dependence on manual semantic annotations [47]. TerraPN combines RGB images, robot velocity, IMU vibration, and odometry errors to learn surface cost maps online and inputs them into the dynamic window approach to generate trajectories considering terrain costs [48]. This shows that physical-dynamics-based methods are not limited to traditional mechanics modeling, but can also learn the traction, vibration, and deformable characteristics of terrain through vehicle execution feedback.

Compared with geometric and semantic methods, the evaluation metrics of physical-dynamics-based methods are more diverse. Common metrics include terrain parameter estimation error, risk terrain recognition accuracy, navigation success rate, vibration cost, speed regulation, failure times, and vehicle posture stability. Table 5 presents a comparison of representative physical-dynamics-based traversability methods. As can be seen from Table 5, the quantitative evaluation of physical-dynamics-based methods has gradually expanded from single terrain parameter estimation to multidimensional metrics at the vehicle execution level, such as navigation success rate and failure times. These metrics are closer to actual vehicle traversal capability than simple semantic segmentation accuracy or geometric reconstruction error, and can reflect risks such as slip, sinkage,

impact, posture instability, and control failure. However, current studies still lack unified public test scenarios and evaluation systems, and different results are affected by factors such as vehicle mass, tire structure, speed range, surface material, and controller settings.

Table 5. Performance comparison of physical-dynamics-based traversability analysis methods.

Method	Platform	Physical and Feedback Information	Evaluation Metrics	Performance Results	Method Analysis
Dallas et al., 2020 [44]	Deformable terrain simulation	Wheel–terrain mechanics parameters, sinkage exponent	Parameter estimation error, computational cost	The estimation error of the sinkage exponent is less than 4%; the computational cost is reduced by about one order of magnitude	Estimates terrain parameters online, but is validated based on simulation
Schmid et al., 2022 [47]	Four-wheel off-road vehicle in field scenarios	Historical trajectories, self-supervised reconstruction error	Recognition accuracy of low- and high-risk terrain	The recognition accuracies on two test sets are 81.1% and 85.1%, respectively	Reduces dependence on manual annotation, but still requires historical vehicle experience
TerraPN [48]	Clearpath Husky in field scenarios	RGB, velocity, IMU vibration, odometry error	Success rate, vibration cost, speed regulation	The success rate is improved by up to 35.84%; the vibration cost is reduced by up to 21.52%; the speed on high-cost terrain is reduced by up to 46.76%	Transforms vehicle feedback into surface costs and is suitable for online navigation
Lee et al., 2023 [49]	High-speed off-road simulation	6-DoF states, terrain elevation, contact forces, model uncertainty	Failure times, lap time, control frequency	At 40 km/h, the number of failures is reduced from 19 to 0; the lap time is 134.69 ± 1.64 s; the control frequency is 10 Hz	Can directly incorporate dynamic risks into MPC, but is still mainly based on simulation

In summary, physical-dynamics-based methods have the advantages of clear mechanisms, strong interpretability, and easy integration into control constraints. However, they also face problems such as difficulty in parameter acquisition, complex real-time computation, and insufficient cross-platform generalization. Soil moisture content, compaction degree, gravel particle size, and vehicle load may vary over time, making it difficult for fixed-parameter models to adapt to real scenarios over the long term. Although purely data-driven models can learn complex terrain responses from vehicle feedback, their outputs may still produce overconfident judgments on unseen terrain if they lack physical constraints and uncertainty evaluation. Therefore, future research needs to combine terramechanics models, vehicle execution feedback, self-supervised learning, and risk-sensitive planning to establish unified dynamic traversability evaluation standards for different vehicle platforms and unstructured terrains.

2.2. Uncertainty Representation and Propagation Mechanisms in the Perception–Planning Chain

In unstructured environments, traditional traversability analysis often transforms perception results into deterministic cost maps or traversable regions, but this representation easily conceals risks caused by insufficient observation and model mismatch. However, when vehicles operate in scenarios such as mud, standing water, soft soil, low vegetation, negative obstacles, and obstacle occlusion, low-cost regions do not necessarily

indicate real driving safety. They may also be incorrectly estimated as low-risk areas due to insufficient sensor observation, semantic mis-segmentation, or unknown terrain physical parameters. Therefore, traversability representation for unstructured environments should not only output deterministic costs but also describe the confidence level of these costs, thereby further affecting path search, trajectory optimization, and control execution.

In unstructured environments, uncertainty can be divided into environmental uncertainty, perception uncertainty, and model uncertainty. Environmental uncertainty mainly comes from factors such as changes in soil moisture content, time-varying surface materials, muddy conditions, standing water depth, gravel distribution, and vegetation occlusion. Perception uncertainty mainly includes sensor noise, illumination changes, rain, fog and dust, sparse point clouds, semantic class confusion, occlusion, and annotation bias. Model uncertainty mainly comes from unknown wheel–terrain dynamic parameters, vehicle load changes, friction coefficient estimation errors, sinkage model mismatch, and vehicle state estimation bias. However, these uncertainties are not independent of the system, but propagate progressively during traversability mapping, trajectory planning, and control execution. When the planner only receives a single deterministic cost value, the system has difficulty distinguishing truly low-risk regions from regions with high uncertainty that are temporarily estimated as low-risk, which may guide the vehicle into dangerous terrain.

In the perception process, Bayesian mapping and Gaussian-process-based methods can be used to express terrain attribute uncertainty under sparse observation conditions. Shan et al. used Bayesian generalized kernel inference to estimate terrain elevation and traversal attributes, enabling traversability results under sparse point cloud conditions to contain probabilistic confidence [28]. The advantage of this type of method is its strong interpretability, making it suitable for handling sparse point clouds, local occlusion, and incomplete maps. However, it implicitly assumes that terrain attributes are spatially stationary or continuous. In actual off-road environments, negative obstacles, steep edge regions, vegetation-occluded areas, and strongly heterogeneous surfaces often show obvious discontinuities, which may lead to over-smoothing and local distortion in model prediction results. Deep-learning-based methods have further promoted environmental uncertainty modeling from probabilistic inference based on prior assumptions to data-driven learning. EVORA uses evidential deep learning to simultaneously estimate aleatoric uncertainty and epistemic uncertainty in traction prediction, and applies them to risk-aware off-road planning [50]. Aleatoric uncertainty mainly comes from sensor noise, random terrain disturbances, and irreducible observation errors. Epistemic uncertainty reflects the decline in prediction confidence caused by insufficient model knowledge of unseen scenarios, long-tail samples, or out-of-distribution data. From the decision-making perspective, these two types of uncertainty have different physical meanings and control requirements. Aleatoric uncertainty usually needs to be mitigated through risk margin design, conservative speed planning, or robust optimization, while epistemic uncertainty is more suitable as an important basis for triggering active perception, online learning, or exploration behaviors. However, current studies only use uncertainty as a weight in the cost function and a basis for path selection, without forming a closed-loop risk reasoning mechanism between perception and planning. Therefore, how to realize interpretable uncertainty expression, cross-module transmission, and decision-level utilization remains an important direction for building safe and reliable autonomous off-road systems.

In the planning process, the key to uncertainty propagation lies in whether it can change planning decisions. The STEP framework combines stochastic traversability assessment, conditional value-at-risk, and model predictive control, enabling the planner to consider tail risks in unknown off-road environments [51]. Compared with methods that only optimize expected costs, CVaR pays more attention to low-probability but high-loss

hazardous events, and is suitable for handling safety-critical problems such as getting stuck, rollover, collision, and entering unrecoverable regions [52]. Chance-constrained MPC and distributionally robust optimization can also transform uncertainty into constraint violation probabilities or worst-case risk boundaries, allowing the planner to automatically adopt more conservative trajectories under low-confidence conditions. However, these methods usually increase computational burden and may reduce traversal efficiency due to excessive conservatism. For autonomous driving in unstructured environments, risk-sensitive planning does not mean that more conservative planning is always safer. Instead, an adjustable mechanism needs to be established among task efficiency, real-time performance, and risk level.

Conformal prediction provides a statistical learning framework for uncertainty quantification and propagation. Its core idea is to construct prediction sets or prediction intervals with coverage guarantees under relatively weak distributional assumptions, so that prediction results can be clearly linked to a preset confidence level. In recent years, conformal prediction has been used in tasks such as safe planning, trajectory prediction, and reachable set calibration in autonomous driving. Lindemann et al. [53] combined conformal prediction with model predictive control to provide statistical safety guarantees for safe planning in unknown dynamic environments. Muthali et al. [54] used conformal prediction to calibrate multi-agent trajectory prediction errors, enabling prediction uncertainty to be integrated into the planning process in the form of confidence boundaries. Although these studies mainly focus on structured traffic environments, their ideas can be transferred to terrain risk boundary estimation in unstructured environments. For example, conformal prediction can provide confidence interval estimation for terrain traversability assessment, ground bearing capacity prediction, and risk cost modeling, thereby realizing the explicit transmission of environmental uncertainty to the planning module. However, this method relies on the assumption of approximately identical distribution between calibration data and operational data. When a vehicle moves from farmland to mining areas, or from dry roads to slippery mud, such environmental distribution shifts will weaken the effectiveness of the system. In addition, conformal prediction provides statistical reliability guarantees rather than physical safety guarantees.

Therefore, uncertainty in unstructured environments is not auxiliary information at the perception end, but should be transformed into risk variables that can be used by the planning module. To illustrate how uncertainty is transmitted from traversability estimation to path search, trajectory optimization, and risk control, Table 6 compares typical uncertainty modeling methods and their planning interfaces. As shown in the table, Bayesian and Gaussian process mapping usually output the mean and variance of terrain attributes, making them suitable for constructing probabilistic traversability maps under sparse observation conditions. Evidential deep learning can distinguish aleatoric uncertainty caused by data noise from epistemic uncertainty caused by insufficient model knowledge, and is therefore more suitable for unseen terrains or out-of-distribution scenarios. Conformal prediction and distributionally robust optimization place more emphasis on constructing risk boundaries or worst-case guarantees under predictive uncertainty, while chance-constrained MPC and CVaR-based risk planning are closer to the planning end and can directly transform uncertainty into constraint violation probabilities, tail-risk costs, and safety margins.

Table 6. Comparison of uncertainty modeling methods and planning interfaces.

Method	Output Form	Basic Assumptions	Suitable Scenarios	Planning Interface	Main Limitations
Bayesian and Gaussian process mapping	Mean, variance, confidence interval	Terrain attributes are spatially correlated	Sparse point clouds, unknown terrain mapping	Risk cost	High computational cost

Evidential deep learning	Aleatoric uncertainty, episodic uncertainty	The model can express confidence through evidence distributions	Unseen terrain, traction prediction, risk-aware planning	Penalty for high-uncertainty regions, conservative planning	Requires calibration and is unstable in extreme OOD scenarios
Conformal prediction	Prediction set, confidence boundary	Calibration data and test data satisfy certain exchangeability conditions	Safety boundary estimation, risk region screening	Chance constraints, safety margins	Sensitive to distribution shift, and the real-time update mechanism is complex
Distributionally robust optimization	Risk boundary under the worst-case distribution	The true distribution lies within an uncertainty set	High-risk off-road driving, heavy-load planning in mining areas	Robust cost, conservative constraints	Strong conservatism and complex computation
Chance-constrained MPC	Constraint probability	State and obstacle uncertainty can be probabilistically modeled	Local trajectory optimization, dynamic obstacle avoidance	Chance constraints, speed limits	Depends on probabilistic models
CVaR-based risk planning	Tail-risk cost	Focuses on low-probability and high-loss scenarios	Muddy ground, negative obstacles, unknown off-road environments	Risk penalty term, path selection	Risk-level parameters need to be set according to tasks

From the perspective of perception–planning coupling, the key to uncertainty modeling does not lie in whether confidence can be estimated at the perception end, but in whether this confidence can enter path search, trajectory optimization, and control constraints in a computable form. In global path planning, uncertainty can act as a risk penalty term to affect path selection. In local trajectory optimization, uncertainty can be transformed into safety margins, chance constraints, or speed limits. During closed-loop execution, vehicle slip ratio, posture changes, and tracking errors can, in turn, correct traversability estimation. Therefore, multidimensional fusion and uncertainty modeling are not only issues of improving perception accuracy, but also key to achieving stable transmission of traversability information to planning constraints. Future research needs to solve the unified representation of geometric, semantic, physical, and vehicle state information, and establish a continuous propagation mechanism from perception uncertainty to planning risk boundaries.

2.3. Traversability Representation Forms

In the perception–planning coupling chain, the form of traversability representation determines whether perception results can be stably used by the planner. Currently, according to different application scenarios, traversability representation forms can be divided into binary traversable regions, occupancy grids, continuous cost maps, probabilistic risk maps, and 3D traversability maps. These representation forms not only provide spatial feasibility information but also reflect environmental complexity, obstacle distribution, and terrain characteristics, thereby supporting the planning module in path search, motion planning, and trajectory optimization. Traversability representation forms are shown in Figure 4, and the characteristics of different representation forms are compared in Table 7.

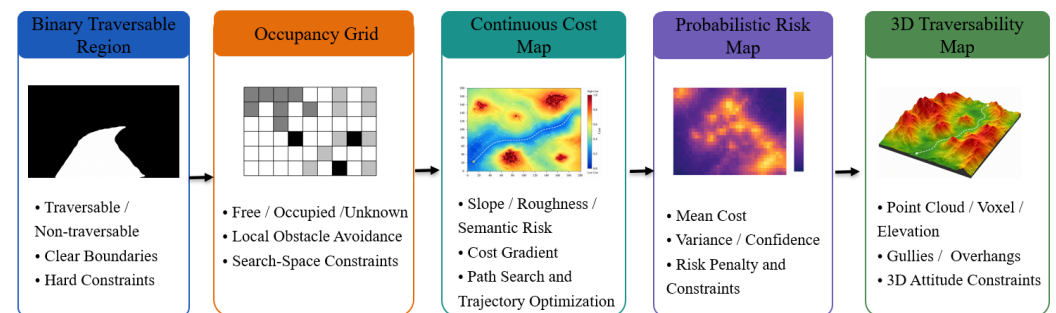


Figure 4. Representative forms of traversability representation.

Table 7. Comparison of characteristics of different representation forms.

Representation Form	Expressed Content	Applicable Scenarios	Integration into Planning
Binary traversable region [55]	Determines whether a region is traversable or non-traversable	Low-risk scenarios with structured environments, clear rules, and clear risk boundaries	Hard constraints
Occupancy grid [56]	Obstacle occupancy probability distribution based on sensor observations	Local dynamic obstacle avoidance, unknown environment mapping, and scenarios with perception noise	Search space constraints
Continuous cost map [57]	Continuously varying traversal costs, such as slope, roughness, and semantic risk	Most unstructured off-road scenarios with continuous terrain variations	Path search costs, trajectory optimization
Probabilistic risk map [51]	Probability distribution of traversal costs, with explicit modeling of mean and variance	Regions with high perception uncertainty and significant randomness in terrain–vehicle interaction	Risk penalty terms, chance-constrained planning
3D traversability map [58]	3D structural information, such as dense point clouds, voxels, and semantic scene completion	Off-road, mining, and forest scenarios with complex 3D structures such as gullies, negative obstacles, and overhanging objects	Path search cost evaluation, 3D posture constraints, obstacle-crossing constraints

As the simplest form of traversability representation, binary traversable regions usually divide the environment into traversable and non-traversable regions, and participate in planning in the form of hard constraints [55]. This method is suitable for scenarios with clear boundaries, low risks, or explicit task rules, such as inter-ridge navigation in some agricultural operations, greenhouse mobile robot path planning, and rural road path planning. However, binary representation usually assumes that the traversal risk boundary is clear and stable, and this assumption is not sufficient in mud, standing water, soft soil, low vegetation, and weakly structured off-road roads. Therefore, many regions are not absolutely traversable or non-traversable, but are related to vehicle speed, load, wheel–terrain adhesion conditions, and posture stability. This may cause the planner to lose risk gradients, making it difficult to tradeoff between detouring through low-risk regions and passing through high-cost regions at low speed. Occupancy grids are used to describe the division of free regions, obstacle regions, and unknown regions in space, and are suitable for local obstacle avoidance, unknown environment mapping, and graph-search planning [56]. However, occupancy grids mainly describe whether space is occupied by objects, and cannot fully express surface materials, adhesion conditions, sinkage risks, and slip risks. On structured roads, unoccupied regions can usually be approximately regarded as drivable space. However, in unstructured environments, unoccupied regions do not mean safe traversal. Therefore, occupancy grids are more suitable as a basic obstacle avoidance

method, and cannot be used alone as the final traversability criterion in complex unstructured terrain.

As a commonly used traversability interface form in trajectory planning for unstructured environments, continuous cost maps can map information such as slope, roughness, elevation difference, semantic category, obstacle distance, and physical risk into unified traversal cost values, and directly embed them into the cost function of path search or trajectory optimization [57]. Compared with binary regions and occupancy grids, continuous cost maps can express risk gradients among different regions, so that the planner no longer only judges whether a region can be passed through, but can compare the cost of passing through it. In farmland, mining roads, and general off-road scenarios, continuous cost maps can better support global path search and local trajectory optimization. However, their main problem is that the cost fusion process often relies on manually designed weights or empirical rules. There is no unified dimension among slope, roughness, semantic category, obstacle distance, and vehicle dynamic risk, and different weight settings may lead to completely different planning results. When cost sources are not decomposable, although the planner can avoid high-cost regions, it is difficult to explain whether the high cost comes from geometric obstacles, semantic risks, slip risks, or model uncertainty. This will weaken the interpretability and verifiability of the system, and also make cross-scenario transfer more difficult.

To improve the risk representation capability in complex off-road environments, researchers have used environmental representation methods such as probabilistic risk maps [51] and 3D traversability maps [58] to represent traversability. Probabilistic risk maps introduce uncertainty information, such as cost mean, variance, confidence, or risk boundaries, on the basis of continuous cost maps, enabling the planner to distinguish truly low-risk regions from insufficiently observed regions, and further transform uncertainty into risk penalty terms and chance constraints. Meanwhile, 3D traversability maps use point clouds, voxels, and 3D grids to preserve terrain height variations and spatial occupancy relationships, and can more accurately describe complex structures such as gullies, negative obstacles, overhanging objects, and local abrupt elevation changes. Compared with traditional two-dimensional deterministic representations, both methods help reduce planning failures caused by missing terrain information or underestimated risks. However, the reliability of probabilistic risk maps depends on the quality of uncertainty estimation and probabilistic calibration, and high-confidence misjudgments may bring more serious safety risks than ordinary prediction errors. Three-dimensional maps require higher perception accuracy, storage resources, and computational costs, and it is difficult to maintain high-resolution real-time updates over large-scale scenarios for a long time. In addition, the settings of both risk probability parameters and 3D map resolution affect planning efficiency and safety margins. Therefore, the core of unstructured environment representation does not lie in adding more risk dimensions or spatial information, but in whether this information can be effectively transmitted to the planning and decision-making modules, thereby achieving real risk-aware and safety-constrained planning.

Therefore, traversability representation in unstructured environments should not remain at the level of whether a certain region on the map is traversable, but should gradually shift toward expressing at what cost, risk, and constraints a vehicle can pass under its current state. In the process of perception–planning coupling, the traversability interface should simultaneously include information such as geometric structure, semantic attributes, physical risk, uncertainty confidence, and vehicle dynamic constraints. In low-risk agricultural scenarios with relatively clear rules, binary regions, occupancy grids, or lightweight cost maps can be used to ensure real-time performance. In off-road scenarios involving mud, slopes, occlusion, negative obstacles, and unknown terrain, probabilistic risk maps and 3D maps should be introduced to describe complex spatial structures, so

as to improve the planner's ability to judge risk and execution feasibility. Selecting the representation granularity according to the risk state provides a basis for adaptive perception–planning coupling mechanisms.

3. Trajectory Planning Methods Driven by Traversability

Trajectory planning in unstructured environments differs significantly from that in structured road scenarios. In structured roads, planners can generate trajectories under relatively clear reference lines and constraints. However, unstructured environments lack stable lane-level priors, and terrain slope, local undulation, surface material heterogeneity, and obstacle distribution all have strong uncertainty. Therefore, whether a vehicle trajectory is safe and feasible depends not only on avoiding obstacles [59] but also on the contact state between the vehicle and the terrain, slip risk, posture stability, and traction capability. Traversability analysis not only provides a judgment of traversable or non-traversable regions. Instead, it needs to transform geometric risk, semantic attributes, physical constraints, and uncertainty information into cost terms, constraint boundaries, and sampling distributions that can be handled by the planner. Therefore, this chapter mainly reviews the role of traversability information in trajectory generation from three aspects: global path guidance, local trajectory optimization, and data-driven planning.

3.1. Global Path Search Based on Traversal Cost

In unstructured environments, global path search aims to find a topologically connected path from the start point to the goal point in a large-scale space, providing long-horizon guidance for local trajectory planning. Unlike path planning in structured roads, which relies on lane markings, road network topology, and traffic rules, unstructured environments usually lack clear road boundaries. Vehicles need to autonomously determine the traversal direction and path topology in continuous terrain space. Traversability information needs to be entered into the search process through cost mapping. Specifically, it is encoded into the weights of search nodes or edges through a cost function, and the search algorithm generates the optimal path according to the principle of minimizing cumulative cost. Therefore, global path search should not only take path length or geometric connectivity as the optimization objective, but should also transform traversability information, such as slope, roughness, semantic risk, obstacle distance, slip risk, and perception uncertainty, into search costs.

Graph-search-based methods are widely used in global path planning. Traditional Dijkstra and A* algorithms can search for minimum-cost paths on explicit cost maps, but they still have certain limitations when directly applied to unstructured environments [60]. On the one hand, ordinary two-dimensional grid search has difficulty expressing vehicle nonholonomic constraints and minimum turning radius, and may generate paths that are geometrically connected but kinematically infeasible. On the other hand, traditional cost functions often consider path length or obstacle occupancy state, and have difficulty fully encoding multidimensional traversability information such as slope, roughness, semantic risk, slip risk, and vehicle posture constraints. However, in a traversability-driven graph search framework, terrain risk usually enters the planner through node costs and edge costs. Compared with distance-based search alone, graph-search-based methods can enable the planner to actively avoid high-risk terrain, rather than only performing local avoidance near obstacles. Zhu et al. proposed a two-layer Hybrid A* method, which compresses the search space through a guidance layer and a planning layer, and introduces a multi-cost function and a phase window mechanism to improve search efficiency and path quality in complex unstructured terrain [61]. In addition, some studies encode slope, soil type, vehicle geometric parameters, and dynamic parameters together as edge weights in improved A* algorithms, so that the generated paths can avoid regions with

high sinkage risk or slope limitations [62]. However, traversability planning based on graph search still depends on the quality of the upstream cost map. When the cost map only contains obstacle distance or slope information, and does not express slip, sinkage, semantic uncertainty, and vehicle state constraints, the search result can only ensure low cost at the map level, but cannot guarantee real vehicle execution safety. In off-road scenarios involving mud, standing water, grass-covered gullies, and soft sand, the geometric cost may be low, but the dynamic risk may be high. In this case, even if A* and Hybrid A* can find the minimum-cost path, they may still guide the vehicle to regions with insufficient traction or posture instability. Therefore, graph search methods are more suitable as global topological guidance, and their outputs still need to be further verified by local trajectory optimization and vehicle–terrain dynamic constraints.

In environments with obvious three-dimensional undulations, two-dimensional cost maps have difficulty fully expressing spatial structures such as negative obstacles, gullies, steps, and local abrupt elevation changes. Some studies integrate elevation, slope, and surface attributes into a grid traversal index and introduce this index into improved A* algorithms, thereby considering both path connectivity and traversal safety [63]. This method has good engineering interpretability, but the two-dimensional gridding process compresses three-dimensional spatial information, especially for negative obstacles, overhanging objects, and local abrupt elevation changes. Therefore, two-dimensional cost maps are more suitable for global path guidance, while local 3D maps and vehicle posture constraints are still needed for further verification in high-risk regions. Sampling-based planning is another important method for global path planning in unstructured environments. RRT and its asymptotically optimal variant RRT* can rapidly explore feasible paths in high-dimensional continuous spaces, and are suitable for complex terrain and high-dimensional state-space planning problems [64]. However, in unstructured scenarios, uniform sampling easily generates a large number of invalid nodes in non-traversable or low-value regions, leading to reduced search efficiency. Therefore, traversability information should not only be used to evaluate generated paths, but should also participate in the design of sampling distributions. Lv et al. incorporated terrain undulation and land cover information into global off-road path planning, enabling the search process to consider both spatial connectivity and traversal cost [65]. These studies show that traversability can improve the search efficiency of sampling-based planning in complex terrain, but its effect is still constrained by the quality of the cost field. When traversability estimation contains errors, sampling bias may cause the planner to focus too early on local low-cost regions, thereby reducing global exploration capability.

As the complexity of unstructured environments increases, a single graph search or sampling-based planning method is often difficult to satisfy the requirements of global connectivity, local executability, and computational efficiency at the same time. Therefore, multi-stage hybrid planning has gradually become an important development trend [66]. Shen et al. proposed a three-stage global trajectory planner that combines A* search, RRT expansion, and local trajectory refinement, enabling path planning to consider vehicle nonholonomic constraints and local executability while ensuring search efficiency [67]. However, this method shifts from path search to trajectory generation, and the system complexity also increases. Therefore, the cost functions, constraints, and traversability representations between different stages need to remain consistent. Otherwise, the problem of a mismatch between global path objectives and local trajectory optimization objectives may occur. In recent years, data-driven methods have also begun to participate in global path guidance. For example, monocular images can be used to generate candidate paths, and then a traversability risk model can evaluate the terrain risks of different candidate paths, thereby combining learning-based candidate generation with traditional risk evaluation [68]. This method can effectively reduce the difficulty of manually

constructing cost functions. However, monocular vision is sensitive to scale, illumination, occlusion, and cross-scenario generalization. If uncertainty estimation and physical constraint verification are lacking, the candidate paths generated by the system may still be infeasible in real terrain.

Traversability-driven global path search usually introduces slope, surface type, terrain undulation, traversal speed, and vehicle motion constraints into the search process through node costs, edge costs, or heuristic functions. Unlike path planning on structured roads, global paths in unstructured environments do not necessarily take the shortest distance as the only objective, but place more emphasis on achieving a balance among traversability risk, path efficiency, search time, and vehicle executability. Since existing studies mostly use self-built terrain, remote sensing DEM, simulation environments, or specific field scenarios, evaluation metrics and experimental standards have not been unified. Table 8 summarizes representative quantitative results to illustrate how different global planning methods use traversal costs and their performance characteristics. As shown in Table 8, global path search based on traversal costs has gradually shifted from traditional shortest-path optimization to executable path optimization under risk constraints. Two-layer Hybrid A* and improved A* methods mainly improve path quality by modifying search costs and neighborhood expansion mechanisms, and show obvious advantages in metrics such as path length, slope, threat exposure, and turning points. Methods based on mobility prediction further incorporate soil type, slope, and vehicle traversal speed into the cost function, enabling planning results to reflect the actual traversal capability of vehicles on different surfaces. Planning methods for 3D exploration further show that traversability can be used not only for path evaluation, but also for goal selection and exploration strategy generation.

Table 8. Performance comparison of global path search methods based on traversal cost.

Method	Scenario and Data	Traversability Information	Main Metrics	Result Summary	Result Analysis
Two-layer Hybrid A* [61]	DEM-based unstructured terrain	Elevation, slope, threat areas	Path length, slope, planning time	Shorter path, lower slope, and faster planning speed	Balances safety and efficiency
Global planning based on mobility prediction [62]	Off-road remote sensing terrain and soil data	Slope, soil type, mobility cost	Distance, speed, cost, time	Reduces overall traversal risk	Planning oriented to vehicle mobility
3D traversability exploration planning [63]	Complex off-road scenarios	Slope, roughness, dynamic constraints	Exploration time, distance, cost	Improves exploration efficiency and reduces cost	Suitable for autonomous exploration tasks
Improved 3D off-road A* [65]	Field terrain simulation	Slope, land cover, obstacles	Path length, time, turning points	Generates a better path and shorter traversal time	Improves safety and traversal efficiency

In summary, global path search based on traversal costs is shifting from finding the shortest path to finding executable guidance paths under risk constraints. Graph search methods have clear structures and strong interpretability, and are suitable for low-speed agricultural operations, mining roads, and relatively regular off-road scenarios. However, their results depend on the quality of the cost map and cannot independently guarantee dynamic executability. Sampling-based methods are suitable for complex spatial exploration, but require traversability information to guide sampling and depend on subsequent

trajectory optimization for feasibility verification. Multi-stage hybrid methods can consider both search efficiency and local executability, but place higher requirements on system interface consistency and parameter design. Therefore, global path planning in unstructured environments should not only focus on the search algorithm itself, but should pay more attention to how geometric, semantic, physical-dynamics, and uncertainty information can be reliably transformed into node costs, edge costs, and heuristic functions. Only when the global path can provide risk-consistent and constraint-consistent guidance for local trajectory optimization can traversability-driven planning have engineering significance.

3.2. Local Trajectory Optimization Based on Vehicle Terrain Coupling Constraints

In unstructured environments, local trajectory optimization is the key link between global path guidance and actual vehicle execution. Unlike structured roads, unstructured terrain often has slope variations and local undulations. When a vehicle travels in an unstructured environment, whether the trajectory is feasible depends not only on geometric obstacle avoidance results, but also on the contact state between the wheels and the ground, slip ratio, traction capability, and rollover risk. Therefore, local trajectory optimization must transform the geometric, semantic, physical, and uncertainty information provided by traversability analysis into cost terms, constraint boundaries, or vehicle feasible domains, so as to generate trajectories that are geometrically safe and dynamically executable.

Model predictive control has become an important method for local trajectory optimization in unstructured environments because it can handle vehicle dynamics, terrain constraints, and control boundaries during rolling optimization. In the MPC framework, traversability information is usually optimized through costs and constraints in the objective function. Dallas et al. jointly modeled terrain-adaptive trajectory planning and trajectory tracking to handle the coupling between trajectory generation and execution on deformable terrain [12]. This method incorporates terrain response and vehicle control into a unified planning framework, making the planning results less dependent on the assumption of ideal rigid ground and more consistent with the actual traversal capability of the vehicle. However, its performance still depends on terrain parameters, vehicle models, and state estimation accuracy. When soil properties are unknown, the environment changes rapidly, or vehicle operating conditions change, online parameter estimation and feedback correction mechanisms are still needed to reduce the deviation between the model and the actual terrain response. Gai et al. combined a global traversability cost map with local nonlinear MPC, and comprehensively considered vehicle kinematic constraints, rollover risk, and path smoothness in local replanning [69]. This method can directly integrate traversability analysis results into optimization objectives and constraints. Compared with planning methods that rely only on geometric paths, NMPC, integrating traversability cost maps and vehicle dynamic constraints, is more suitable for off-road scenarios with complex terrain and slope variations. When the cost map fails to fully reflect key risks such as slip, sinkage, and perception uncertainty, the optimizer may still generate suboptimal or even dangerous trajectories based on incomplete environmental information. Therefore, this type of method should be comprehensively evaluated from the perspectives of optimization performance and environmental risk representation capability.

When a vehicle travels on deformable terrain, relying only on the rigid-ground assumption makes it difficult to accurately describe the vehicle's motion state. Wheel sinkage, slip, and traction loss may occur, causing trajectories that are geometrically feasible to fail during actual execution. Yu et al. combined a terramechanics model with an unscented Kalman filter and used hard and soft constraints in MPC to improve the

robustness of vehicle trajectory planning on deformable terrain [70]. By explicitly incorporating wheel–terrain interaction into planning constraints, trajectory optimization can reflect the physical characteristics of the terrain. However, terramechanics models usually depend on accurate terrain parameters, while soil states and vehicle operating conditions in real environments often change dynamically. Therefore, physical models are more suitable as interpretable constraints and risk boundaries, rather than complete descriptions of complex unstructured terrain. Knaup et al. applied covariance-steering stochastic model predictive control to off-road driving, and explicitly handled state uncertainty during control to improve trajectory execution safety [71]. By extending uncertainty from the perception layer to the planning layer, uncertainty directly participates in state prediction and safety constraint construction. For off-road scenarios, stochastic MPC and covariance control can effectively deal with the risk of state deviations near dynamic limits. However, such methods require high-quality uncertainty modeling, computational resources, and real-time solving capability.

The combination of physical priors and data-driven models is an important development direction for current local trajectory optimization. Pure physical models have strong interpretability but rely on accurate terrain and vehicle parameters. Pure data-driven methods can learn complex terrain responses, but they still have limitations in safety verification and cross-scenario generalization. Therefore, an increasing number of studies attempt to combine the two. Lee et al. learned the influence of terrain on vehicle dynamics through onboard sensors, and combined MPPI with proprioceptive and exteroceptive information to predict the six-degree-of-freedom motion of the vehicle. They also penalized unstable motion, unsafe contact, and model uncertainty in cost design [49]. Learning-based dynamics models cannot replace traditional models, but they can supplement local planners in modeling complex terrain responses. However, the reliability of learning-based models is usually related to the coverage of training scenarios. When a vehicle enters unseen terrain, extreme slopes, or different load states, uncertainty estimation, physical constraints, or safety protection mechanisms are still needed for joint limitation. Sakayori et al. introduced changes in slip ratio into the path planning cost function, showing that traversal costs in unstructured terrain dynamically change with motion states [72]. The key to this type of method is that incorporating the slip ratio into the cost function helps extend traversability from a static environmental attribute to a state-related variable, thereby more accurately reflecting the actual traversal risk of the vehicle. However, slip ratio is affected by multiple factors, such as terrain, vehicle state, and control input, and is difficult to predict accurately in advance. Therefore, it is more suitable for use together with online state estimation and feedback mechanisms.

Slip and sideslip are non-negligible factors in local trajectory optimization for agricultural vehicles, mining vehicles, and off-road platforms [73]. When a vehicle travels on slippery, soft, or rough heterogeneous ground, the actual motion between the tires or tracks and the ground may deviate from the ideal kinematic model, leading to increased trajectory tracking errors or even instability. Therefore, local trajectory optimization needs to incorporate slip ratio, sideslip angle, and adhesion conditions into control constraints [74]. Fnadi et al. established a dynamic model for a dual-steering off-road robot on slippery ground, considering road geometry, wheel–terrain slip, and friction, and designed constrained MPC to improve dynamic path tracking capability [75]. For tracked platforms, a slip-based nonlinear double-track prediction model can use contact force estimation to improve trajectory tracking accuracy [76]. Prado et al. constructed an adaptive framework combining moving horizon estimation and MPC for mining skid-steering mobile robots, improving vehicle adaptability to terrains such as slag, gravel, and loose soil through online estimation of slip dynamic parameters [77]. This method combines parameter estimation with control optimization and can adapt to the dynamic changes in terrain

parameters in unstructured environments. However, its performance is greatly affected by parameter estimation accuracy, and estimation instability may occur under sensor noise, terrain abrupt changes, or low-adhesion conditions. Therefore, when evaluating such methods, in addition to tracking performance, attention should also be paid to parameter convergence, abnormal estimation handling, and failure protection mechanisms. In addition to MPC and its extended methods, sliding mode control, adaptive control, and disturbance observers are also commonly used to improve trajectory tracking robustness in unstructured environments. Fixed-time super-twisting sliding mode adaptive control based on RLS-ELM [78], and nonsingular terminal sliding mode control based on adaptive disturbance observers [79], can improve path tracking performance of agricultural vehicles or mobile platforms under external disturbances and model uncertainty. These methods can strongly suppress disturbances and parameter uncertainty, and mainly act at the control execution layer. When slip ratio, posture changes, and trajectory tracking errors are not used to update traversability costs and local planning constraints, the system still remains at the level of control compensation and does not form a complete risk correction loop among perception, planning, and execution.

To further compare the performance of local trajectory optimization methods under vehicle–terrain coupling constraints, Table 9 lists representative local trajectory optimization methods based on vehicle–terrain coupling constraints. As shown in Table 9, the evaluation metrics of local trajectory optimization have expanded from simple path tracking errors to metrics that are closer to real execution safety, such as failure times, posture stability, slip risk, real-time performance, and uncertainty constraints. MPC and its extended methods can explicitly handle vehicle constraints and local risks, but their performance depends on the quality of models, parameters, and traversability inputs. Physical models enhance system interpretability, but require online estimation and feedback correction to adapt to time-varying terrain. Learning-based dynamics models can compensate for complex terrain responses, especially in high-speed off-road and strongly nonlinear scenarios, but still require uncertainty evaluation and physical boundary protection. Vehicle proprioceptive feedback signals, such as slip ratio, sideslip angle, and posture changes, provide an important basis for shifting traversability from static environmental attributes to dynamic vehicle-related risks.

Table 9. Comparison of local trajectory optimization methods based on vehicle–terrain coupling constraints.

Method	Scenario and Data	Traversability Information	Main Metrics	Result Summary	Characteristics
Terrain-adaptive MPC [12]	Vehicle on deformable terrain	Terrain parameters, vehicle dynamics	Tracking error, control input	Verifies the effectiveness of tracking in complex terrain	Terrain-aware control
Traversability cost map-NMPC [69]	Undulating unstructured terrain	Traversal cost map, dynamic constraints	Smoothness, obstacle avoidance capability, stability	Generates safer and smoother trajectories	Combines global cost with local optimization
Real-time terrain-adaptive local planning [70]	High-speed off-road deformable terrain	Terramechanics model, state estimation	Real-time performance, tracking error, slip risk	Achieves real-time planning capability	Strengthens physical constraints
Covariance stochastic MPC [71]	High-performance off-road driving	State uncertainty propagation	Safety, control performance	Improves safety in high-speed off-road driving	Risk-aware control
Terrain-aware MPPI [49]	High-speed off-road simulation	Terrain geometry, dynamics, uncertainty	Failure times, lap time, posture stability	Significantly reduces failure risk	Suitable for high-speed dynamic scenarios

Slip-ratio-related traversal cost [72]	Sandy/rough terrain	Slip ratio, wheel–terrain interaction	Slip estimation accuracy, slip risk	Reduces path slip risk	Introduces wheel–terrain interaction information
Constrained MPC for slip tracking [75]	Off-road robot on slippery ground	Wheel–terrain slip, friction model	Tracking error, control constraints	Improves tracking performance on slippery ground	Oriented toward execution-layer control
Adaptive NMPC for mining robots [77]	Mining skid-steering robot	Online parameter estimation, vehicle dynamics	Tracking error, stability	Improves adaptability to dynamic terrain	Online model adaptation

Local trajectory optimization based on vehicle–terrain coupling constraints is gradually shifting from rigid kinematic planning to integrated optimization that combines terrain dynamics, slip constraints, and uncertainty risks. Overall, MPC-based, physical-model-based, and learning-based methods show complementary advantages, but their reliability still depends on model quality, parameter estimation, uncertainty evaluation, and execution feedback. Data-driven models can compensate for complex terrain responses, but require uncertainty evaluation and physical boundary protection. Therefore, for agricultural vehicles, mining trucks, and off-road platforms, the core of local trajectory optimization is not only to generate geometrically collision-free trajectories, but also to generate trajectories that can be stably executed under real terrain, vehicle states, and uncertainty constraints. In the future, traversability cost maps, uncertainty risk boundaries, and execution feedback should be jointly incorporated into local planning, so that trajectory optimization can shift from static cost minimization to risk control oriented toward actual traversal capability.

3.3. Data Driven Traversability Learning and Trajectory Planning

With the rapid development of deep learning and self-supervised learning technologies, data-driven methods have gradually been introduced into traversability planning in unstructured environments [80]. Compared with methods that rely on manually designed rules or explicit physical models, data-driven planning methods can learn the complex mapping relationships among terrain appearance, vehicle responses, and traversal costs from real driving experience, expert trajectories, vehicle perception feedback, and multi-modal sensor data. This reduces the dependence on manually designed cost functions and complex physical parameter calibration. For environments such as farmland, mining areas, and off-road roads, terrain materials, illumination conditions, and vehicle–terrain interaction relationships vary significantly. Fixed rules alone are difficult to adapt to complex scenarios. Therefore, data-driven methods provide a new way for traversability modeling and planning strategy adaptation.

Traversability in unstructured environments is not only related to surface appearance, but also to vehicle speed, load, wheel–terrain contact state, and terrain response. Manual annotation alone is difficult to accurately express this conditional dependence. Self-supervised learning automatically generates training labels by using vehicle sensor feedback. The BADGR system proposed by Kahn et al. learns navigation policies from self-supervised off-policy data in real environments, enabling robots to understand physical traversability from their own experience rather than relying only on geometric obstacle avoidance [81]. This method can identify some regions that are geometrically irregular but actually traversable from its own experience, allowing the system to learn the influence of grass, obstacles, and local terrain on driving outcomes. However, from the perspective of traversability-driven planning, when the learning results cannot be explicitly transformed into cost maps, risk constraints, or vehicle feasible domains, it is difficult for the planner to determine whether a failure comes from perception data or the control

policy. The SALON framework proposed by Sivaprakasam et al. further introduces online adaptability into traversal cost estimation. It rapidly generates risk-aware cost maps and speed maps based on a small amount of online experience, thereby improving the system's adaptability to new environments [82]. This online adaptation method can alleviate the problem of insufficient offline data coverage and is suitable for scenarios with significant terrain changes or large platform differences. However, its performance improvement is often accompanied by safety exploration risks, and the vehicle may come into contact with unknown or high-risk regions during learning. Therefore, this type of method needs to be combined with uncertainty evaluation, conservative control, and failure protection mechanisms to balance adaptability and operational safety.

Vehicle perception feedback has also been used to learn traversal costs. Castro et al. used perception information such as vibration, posture changes, and slip ratio during vehicle driving as self-supervised signals, and trained a traversability cost prediction network so that vehicle dynamic responses could participate in terrain traversability modeling [83]. By using actual vehicle responses to construct training signals, traversability assessment is directly linked to vehicle–terrain interaction results. However, this method is limited by the vehicle platform, suspension characteristics, and sensor configuration. Different vehicles may respond differently to the same terrain, so the learned cost model is usually difficult to transfer directly to other platforms.

The combination of visual models and contrastive learning has also gradually been used to improve traversability estimation in unstructured environments. V-STRONG, proposed by Jung et al. [84], introduces visual foundation models into traversability prediction. It combines contrastive learning with human driving data so that the model can learn the relationship between terrain semantics and traversal attributes, thereby showing good zero-shot and few-shot generalization capability in unseen scenarios. This indicates that data-driven methods no longer completely rely on large-scale annotations from specific scenarios, but attempt to use pretrained visual representations, a small amount of experience feedback, and task-related data to jointly construct transferable traversability models. However, for complex unstructured environments, visual semantic similarity does not necessarily mean the same dynamic response. Therefore, visual foundation models are more suitable as surface semantic and cost priors, rather than directly replacing vehicle state feedback, physical constraints, and risk calibration mechanisms.

Cost map learning is a way to combine data-driven planning with traditional planners. Traditional cost maps usually rely on manual rules to combine slope, roughness, obstacle distance, and semantic categories into traversal costs according to empirical weights. However, this approach requires extensive parameter tuning and is prone to inaccurate cost estimation due to design bias. Vecchio et al. used self-supervised learning and unsupervised domain adaptation for traversability prediction, reducing the dependence on large-scale manual annotations [85]. The CAMEL framework [86] learns the relative cost relationships among different terrains through constraints. This framework does not require accurate regression of the absolute cost value of each region, thereby reducing annotation difficulty and improving the robustness of the model to noise. These methods restrict the outputs of learning models to cost map representations that can be used by planners, making them easier to integrate with traditional planning frameworks than end-to-end control. However, cost map learning still needs to solve the problems of cost-source interpretability and cross-scenario comparability. When the learned cost cannot distinguish geometric obstacles, semantic risks, slip risks, and model uncertainty, the planner can use the cost map, but it is difficult to explain and verify high-risk decisions.

To further illustrate the practical effects of data-driven methods in traversability learning and trajectory planning, Table 10 summarizes the quantitative results of representative methods reported in the literature. As shown in Table 10, data-driven methods

have gradually developed from simply learning traversable regions to learning cost maps, speed maps, and online risk adaptation oriented toward planning interfaces. BADGR and HDIF show that the vehicle's own experience can provide supervision signals for traversability that are closer to physical traversal capability than manual semantic labels. V-STRONG indicates that visual foundation models and contrastive learning can improve traversability generalization capability in unseen scenarios. SALON further shows that online experience, proprioceptive feedback, and uncertainty estimation can jointly support risk-aware planning, enabling the system to quickly adjust cost maps and speed constraints in new environments. CAMEL and domain-adaptation-based methods reflect the engineering feasibility of combining learning-based cost maps with traditional planners.

Table 10. Performance comparison of data-driven traversability learning and trajectory planning methods.

Method	Scenario and Platform	Learning Signal	Planning Interface	Main Metrics	Result Summary	Characteristics
BADGR [81]	Urban and off-road robots	Self-supervised driving data	Learning-based navigation policy	Arrival rate, bumpiness, speed	Achieves cross-scenario autonomous navigation	Learns implicit traversability
SALON [82]	ATV off-road platform	Visual features, proprioception	Cost map, speed map, MPPI	Number of interventions, speed, roughness	Achieves online adaptive navigation	Jointly learns cost and speed
HDIF [83]	Large-scale off-road robot	Proprioceptive feedback	Self-supervised cost map	Number of interventions, smoothness	Significantly reduces manual interventions	Integrates vehicle dynamic feedback
V-STRONG [84]	RELLIS-3D and real off-road scenarios	Visual features, contrastive learning	Cost map, MPPI	AUROC, F1, collision rate	Improves traversability prediction accuracy	Has strong generalization capability
SSL and UDA traversability prediction [85]	Simulation and real scenarios	Self-supervised learning, domain adaptation	Traversability prediction	Cross-domain prediction performance	Improves cross-scenario transfer capability	Enhances generalization and transfer performance
CAMEL [86]	Simulation and real off-road scenarios	Demonstration data, multi-modal information	Learned cost map + path planning	Collision rate, path feasibility	Achieves collision-free off-road navigation	Demonstration-learning-driven planning

The key role of data-driven methods is not to completely replace geometric modeling, physical constraints, and optimization-based planning, but to supplement complex terrain experience that is difficult to cover using manual rules, and to correct traversability estimation through self-supervised feedback and online adaptation. The main risks of this type of method lie in insufficient cross-scenario generalization, safety verification, and output interpretability. Since the data distribution in unstructured environments is significantly affected by seasons, weather, soil conditions, vehicle loads, and terrain materials, the traversal cost learned in one farmland, mining area, or off-road scenario may not be directly transferable to other scenarios. The cost maps output by deep models often lack

a clear physical meaning. Without intermediate constraints or risk interpretation, it is difficult for the planner to determine whether a high cost comes from geometric obstacles, semantic categories, slip risk, or model uncertainty. In extreme scenarios, purely data-driven methods may suffer from overconfidence; that is, the model may produce seemingly reasonable but actually dangerous cost estimates for unseen terrain. Therefore, for autonomous driving in unstructured environments, the future development direction is to integrate data-driven cost learning, vehicle execution feedback, physically interpretable constraints, and uncertainty risk modeling. In this way, learning models can be embedded into interpretable planning frameworks in the form of functional modules such as traversability assessment, risk prediction, and candidate trajectory generation, thereby balancing environmental adaptability, decision reliability, and system safety.

4. Traversability-Driven Perception and Planning Coupling Mechanisms

4.1. Interface Levels of Perception and Planning Coupling Mechanisms

In autonomous driving systems for unstructured environments, the coupling between perception and planning is not a simple process of directly transmitting perception results to the planning module. Instead, it involves effective information interaction among environmental observations, traversability representations, vehicle states, and planning constraints. For unstructured environments, the key to the coupling mechanism does not lie in whether perception and planning belong to the same network or the same module, but in whether geometric structures, semantic attributes, physical-dynamics risks, and uncertainty information can be completely, stably, and interpretably used by the planner. When terrain information output from the perception end is excessively compressed at the interface, even if the planner adopts complex optimization algorithms, it can only generate trajectories based on incomplete risk information. Therefore, from the perspective of information interface levels, this paper divides perception and planning coupling into three categories: data-level coupling, feature-level coupling, and decision-level coupling, as shown in Figure 5.

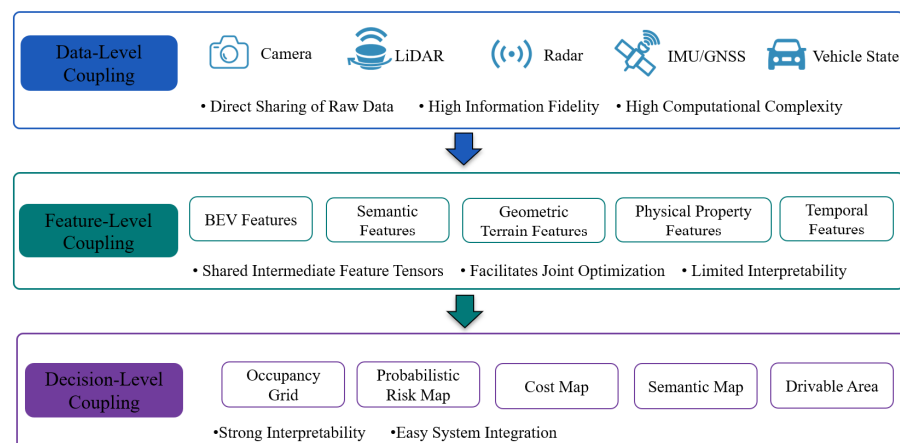


Figure 5. Hierarchical classification of coupling mechanisms.

Data-level coupling means that the planning module directly uses raw data such as images, point clouds, radar, IMU, GNSS, and vehicle states for fusion modeling. This type of method can preserve detailed information such as terrain texture, local geometric undulations, low vegetation, and obstacle boundaries to the greatest extent, thereby reducing information loss caused by interface compression [87]. In unstructured environments, some key factors affecting traversal safety may exist only in the details of raw data, such

as soft surface textures, local depressions, or small elevation changes. When this information is excessively compressed into binary traversable regions at the perception output stage, the planning module will have difficulty accurately judging real traversal risks. Data-level coupling has obvious limitations, as it places high requirements on sensor calibration, time synchronization, computational resources, and closed-loop safety verification. For agricultural vehicles, mining vehicles, and off-road platforms, continuously maintaining high-resolution data-level coupling often makes it difficult to balance real-time performance and engineering deployability. Therefore, a more reasonable strategy is to use compressed maps or cost interfaces in regular regions, and dynamically improve data fidelity in high-risk and high-uncertainty regions to support local re-perception and risk verification. Therefore, data-level coupling is more suitable as a risk-driven local enhancement mechanism rather than a fixed architecture for all scenarios.

Feature-level coupling means that the perception module and the planning module share intermediate representations, including bird's-eye-view features, occupancy features, spatiotemporal features, vectorized maps, latent space states, or multimodal fusion features. Compared with data-level coupling, feature-level coupling reduces computational burden through encoding and compression while retaining certain spatial structure and semantic information. Therefore, it is more suitable for joint optimization in deep learning models. BEV features can express terrain structures and semantic information in a unified space, providing a more compact spatial interface for path planning [88]. Multimodal modeling methods based on spatiotemporal Transformers further enhance cross-sensor information fusion and temporal environmental understanding [89]. In unstructured environments, the key to feature-level coupling lies in whether intermediate representations can simultaneously express terrain geometry, surface semantics, physical risk, and uncertainty information, and be stably used by the planner, thereby compensating for the excessive information compression of decision-level interfaces. Compared with decision-level methods, feature-level coupling retains richer environmental information, but its physical meaning and decision-making process often lack interpretability. When planning fails, it is difficult for the system to accurately determine whether the problem comes from feature representation, feature mapping, or planning constraint design. Since traversal risk is affected by multiple factors, such as terrain features, vehicle states, and wheel-terrain interactions, this limitation is particularly prominent in unstructured environments. Therefore, relying only on high-dimensional feature inputs is difficult to effectively support risk decision-making. Feature-level coupling still needs to be combined with interpretable cost construction, uncertainty estimation, and vehicle dynamic constraints to serve safe planning more reliably.

Decision-level coupling is currently the most common interface form between perception and planning. In this method, the perception module outputs standardized results such as occupancy grids, obstacle lists, traversable regions, semantic maps, cost maps, probabilistic risk maps, or vehicle feasible domains, and the planning module then performs path search, trajectory optimization, or control decision-making based on these results. The advantage of decision-level coupling lies in its clear interface and strong interpretability, which facilitate independent module development and testing. Therefore, it has high engineering applicability in agricultural vehicle and mining vehicle platforms. In low-speed scenarios with relatively clear rules or controllable risks, decision-level coupling can achieve stable deployment at low computational cost. However, decision-level coupling also has the typical problem of information loss. During transmission, perception results are often compressed into deterministic cost maps, traversable regions, or obstacle boundaries, making it difficult to completely preserve terrain details, uncertainty, and vehicle-related risks. For example, occupancy information is difficult to reflect ground adhesion characteristics and sinkage risks, semantic categories cannot directly represent

the actual traversal capability under different vehicle operating conditions, and deterministic cost maps cannot distinguish truly low-risk regions from insufficiently observed regions. Therefore, decision-level coupling should not remain at the level of obstacle lists or deterministic cost maps, but should gradually expand into an integrated risk interface that includes geometric structures, semantic attributes, physical constraints, and uncertainty boundaries [51].

From the perspective of the requirements of autonomous driving in unstructured environments, data-level, feature-level, and decision-level coupling do not have absolute advantages or disadvantages. Instead, they form different trade-offs among information fidelity, computational complexity, and engineering feasibility. Data-level coupling can preserve raw environmental information to the greatest extent, but its computational and verification costs are high. Feature-level coupling balances information compression and joint optimization capability, but its interpretability is relatively limited. Decision-level coupling has advantages such as clear interfaces, modular decoupling, and convenient engineering deployment, but it is prone to losing fine-grained risk information. Therefore, the advantage of a coupling architecture does not lie in the depth of the coupling level, but in whether environmental risk information can be effectively perceived, transmitted, and used by the planning module. For open, low-risk regions with high perception confidence, decision-level coupling based on cost maps or traversable regions can usually meet real-time planning requirements. In muddy, sloped, occluded, negative-obstacle, and high-uncertainty scenarios, feature-level or even data-level information should be introduced to enhance local risk perception capability. For vehicle-dynamics-related problems such as slip, sinkage, and posture stability, vehicle states and execution feedback should be further incorporated into traversability representation and planning decision-making to construct a closed-loop coupling mechanism for vehicle–terrain interaction.

Therefore, perception and planning coupling in unstructured environments should evolve from fixed-level interfaces to risk-driven multi-level collaborative mechanisms. According to environmental risks and task requirements, the system should dynamically balance information fidelity, computational cost, and interpretability, rather than relying on a single data-level, feature-level, or decision-level architecture. In low-risk regions, decision-level interfaces can be used to meet the requirements of real-time performance and stability. In local high-risk regions, shared intermediate features or improved perception resolution can be used to enhance risk perception capability. In unknown or high-uncertainty scenarios, probabilistic risk representations, local re-perception, and execution-feedback correction mechanisms should be further introduced. By constructing such a hierarchical and adaptive collaborative framework, traversability can truly become a carrier of risk information connecting environmental perception and trajectory planning, rather than merely serving as a static map representation output by the perception module.

4.2. System Organization Forms of Perception and Planning Coupling

According to differences in information flow topology and feedback mechanisms between the perception and planning modules, the system organization forms of autonomous driving in unstructured environments can be divided into three typical architectures: modular weak coupling, tightly coupled closed-loop architectures, and end-to-end deep coupling. These three architectures have essential differences in module boundaries, information interface forms, and the degree of closed-loop feedback. The modular weak coupling architecture adopts a cascaded serial link, in which perception, traversability representation, decision planning, and control execution are connected through standardized interfaces with one-way transmission. The module boundaries are clear, but high-dimensional terrain information and uncertainty are easily lost during interface compression. The tightly coupled closed-loop architecture introduces reverse information flow on

this basis, allowing planning requirements to actively guide perception updates and execution feedback to correct traversability estimation online. Perception and planning achieve dynamic collaboration through shared BEV features, risk maps, and feasible domains. The end-to-end deep coupling architecture directly inputs raw sensor data into a unified neural network, completes joint reasoning from environmental understanding to trajectory generation in the latent space through shared representations, and performs closed-loop updates driven by planning objectives. The organization forms of perception and planning coupling are shown in Figure 6.

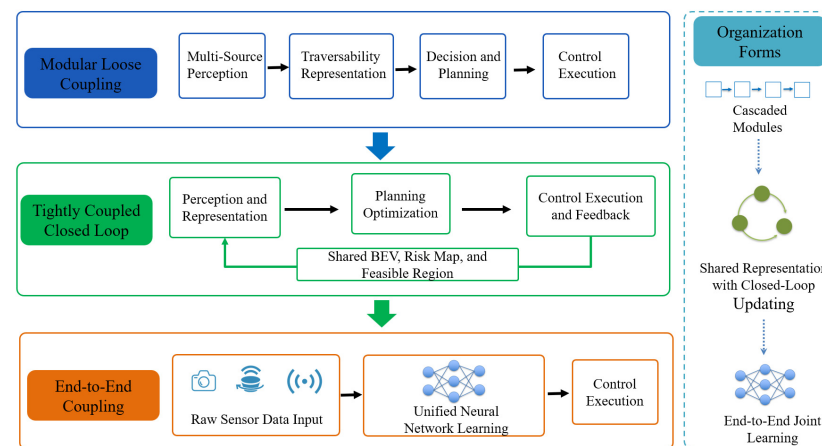


Figure 6. Representative architectures for perception–planning coupling.

4.2.1. Modular Weak Coupling Architecture

The modular weak coupling architecture is currently the most mature and easiest-to-deploy organization form in autonomous driving systems. Its basic process is that the perception module first independently completes object detection, semantic segmentation, and traversability assessment, and then transmits standardized results such as obstacle lists, occupancy grids, semantic maps, cost maps, or local feasible domains to the planning module. The planning module then generates paths or trajectories based on the input information, which are finally executed by the control module. In unstructured environments, the core feature of this architecture is that one-way information transmission is dominant between perception and planning. Most practically deployed planning systems for unstructured vehicles still adopt explicit decision-level interfaces, that is, cost maps or reachable regions output by the perception module are transmitted to the planner, thereby facilitating the explicit incorporation of vehicle dynamic constraints, safety redundancy, and task rules into the planning process.

In agricultural, greenhouse, and mining scenarios, modular weak coupling architectures are relatively common. The autonomous navigation system for greenhouse mobile robots proposed by Jiang et al. [90] completes autonomous navigation through LiDAR point cloud fusion, Cartographer mapping, Dijkstra global planning, and DWA local planning, and its perception–planning interface reflects a typical hierarchical transmission feature. Guo et al. [91] constructed an autonomous navigation system for greenhouse electric tracked tractors, in which the perception module outputs an environmental map and the planning module completes path search and local obstacle avoidance based on the map. In field operation environments, an automatic navigation system based on dynamic path search and a fuzzy Stanley model also achieves high-precision tractor operation through explicit decoupling between planning and tracking modules [92]. For large rear-wheel-steering combine harvesters, a standardized control interface integrating feedforward PID and a preview Ackermann algorithm further verifies the engineering reliability of this

architecture under complex actuator control [93]. In autonomous mining driving, the parallel intelligent autonomous mining framework proposed by Chen et al. [94] uses digital twins and field systems to coordinate multi-vehicle operations in mining areas, and its clear modular interfaces facilitate safety verification under heavy-load conditions. Li et al. [95] proposed a coordinated control strategy for longitudinal speed and vertical posture for articulated unmanned mining trucks, indicating the characteristics of standardized perception input and vehicle structural constraints in control-layer integration.

The modular weak coupling architecture has a clear structure, strong interpretability, and low system integration difficulty, and is convenient for module-level testing and fault localization. For engineering platforms that require long-term stable deployment, such as agricultural tractors, combine harvesters, and mining trucks, this architecture remains relatively mature. However, its limitations are also obvious. First, when perception results are transmitted to the planning module, they are usually compressed into deterministic cost maps, obstacle lists, or semantic labels, and high-dimensional terrain information, surface details, and perception uncertainty are easily lost during interface conversion. For example, the planner can use a cost map to avoid obstacles, but may not be able to determine whether the cost comes from slope, mud, soft soil, negative obstacles, or insufficient perception confidence. In this case, although the planning module formally completes path generation, its safety is still limited by the quality of upstream risk representation.

Therefore, the modular weak coupling architecture is not equivalent to an outdated architecture. The key is not to eliminate module boundaries, but to enhance the risk expression capability of module interfaces. For unstructured environments, perception outputs should not remain only at the level of obstacle lists and deterministic cost maps, but should include geometric structures, semantic categories, physical constraints, and uncertainty boundaries as much as possible. Only when the planning module can understand the source of costs and adopt different planning strategies according to different risk types can the modular architecture be further transformed from perception result transmission into risk information transmission.

4.2.2. Tightly Coupled Closed-Loop Architecture

The tightly coupled closed-loop architecture introduces reverse information flow based on modular systems, forming dynamic interaction among perception, planning, and control. Unlike the one-way information flow of perception output, planning, and control execution in the modular weak coupling architecture, the tightly coupled closed-loop architecture emphasizes that the planning module can actively influence the attention regions of perception and the update strategy of traversability according to task goals, candidate trajectories, and local risks. When candidate trajectories pass through occluded regions, mud, slopes, negative obstacles, or high-uncertainty regions, the planner can trigger local re-perception, improve the map resolution of key regions, or re-estimate risk boundaries. When a slip, abnormal posture, or increased tracking error occurs during vehicle execution, control feedback can also reverse the traversability cost.

The SPIN framework proposes the ideas of perceiving to move and moving to perceive, and emphasizes that motion affects perception quality, while perception determines motion strategies. Therefore, perception and motion processes need to be jointly optimized in a unified framework [96]. In unstructured environments, vehicles should not only passively accept existing perception results, but should actively adjust observation behaviors according to task goals and risk regions. TerraPN uses online self-supervised signals generated during robot–terrain interaction to update traversability estimation [48], while the WVN system combines pretrained models and online self-supervised learning to improve rapid traversability learning in complex wild environments [97]. These studies show that traversability should not be only offline training or static mapping, but should

be continuously corrected according to real feedback during vehicle execution, so that the system shifts from static perception to dynamic risk updating.

The tightly coupled closed-loop architecture can alleviate the information mismatch between perception results and planning requirements. For high-risk regions such as mud, standing water, occlusion, slopes, negative obstacles, and soft terrain, static cost maps are often insufficient to support safe decision-making. The planner needs to actively focus on key regions according to candidate trajectories, and the execution module also needs to feed back terrain risks according to the real response of the vehicle. Adaptive off-road navigation studies such as NAUTS reflect the idea of dynamically adjusting navigation strategies according to terrain and tasks [98]. In agricultural vehicles and towed vehicles, studies on robust trajectory tracking and fuzzy sliding mode control also show that vehicle execution is affected by model uncertainty, external disturbances, and complex terrain, and planned trajectories cannot be completely based on the assumption of ideal tracking [99,100]. However, while the tightly coupled closed-loop architecture improves environmental adaptability, it also brings higher system complexity, verification cost, and real-time computational pressure. As planning and execution feedback enter the perception and traversability assessment process, environmental representation is no longer a static result, but changes dynamically with task goals, vehicle states, and historical interaction information. If feedback variables, update mechanisms, and risk correction rules are not clearly defined, the system may suffer from error accumulation and feedback-coupling instability. Therefore, tightly coupled architectures need to clarify the functional boundaries of different types of feedback information, such as using candidate trajectories to trigger local re-perception, correcting terrain costs through slip ratio, adjusting speed constraints according to tracking errors, and dynamically updating rollover risk boundaries based on vehicle posture changes, so as to ensure system interpretability, stability, and verifiability.

In summary, the tightly coupled closed-loop architecture is more suitable for local high-risk and high-uncertainty scenarios, but it is not necessarily suitable as a fixed operating mode for all regions. In open, low-risk regions with high perception confidence, modular interfaces can ensure real-time performance and engineering stability. In regions involving mud, slopes, occlusion, standing water, negative obstacles, or abnormal vehicle execution states, local closed-loop enhancement should be enabled, so that planning requirements and execution feedback jointly participate in traversability updating. The core value of tightly coupled closed-loop architecture does not lie in increasing system complexity, but in forming a traceable risk correction chain among perception results, planning requirements, and real vehicle responses.

4.2.3. End-to-End Deep Coupling Architecture

The end-to-end deep coupling architecture incorporates environmental perception, traversability assessment, trajectory planning, and low-level control into a unified learning framework, enabling the system to directly generate planned trajectories or control commands from multisource sensor inputs. Compared with modular architecture, end-to-end methods reduce manually designed interfaces and can learn the relationships among complex terrain appearance, spatial structures, and navigation behaviors through shared features. The early ALVINN system used a neural network to predict vehicle steering from camera and laser rangefinder inputs, serving as an early representative of end-to-end vehicle navigation [101]. Modern end-to-end autonomous driving further introduces BEV representations, occupancy prediction, vectorized scene representations, differentiable planners, and multitask supervision to improve system interpretability and planning orientation [102].

In terms of structural form, end-to-end deep coupling can be divided into weakly interpretable end-to-end methods and planning-oriented end-to-end methods. The former directly maps sensor inputs to control commands and trajectory parameters, thereby minimizing module interfaces and manual rules, but its internal decision-making process lacks interpretability. In contrast, planning-oriented end-to-end methods retain explicit intermediate representations and use auxiliary tasks such as perception and prediction for trajectory planning, thereby achieving a balance between joint optimization and engineering interpretability. MP3 generates interpretable planning results through online maps and dynamic object prediction [103], while InterFuser uses a multisensor Transformer to generate intermediate semantic features and enhances the interpretability of action outputs through safety-related constraints [104]. This shows that the key to end-to-end deep coupling is not to completely remove intermediate interfaces, but to design intermediate representations as learnable interfaces serving planning objectives. For unstructured environments, end-to-end deep coupling can enhance the system's ability to express weak road priors, complex terrain, and implicit traversal risks. UniAD incorporates perception, prediction, and planning into a unified network, achieving joint optimization from visual input to planned trajectories [105]. VAD further represents dynamic objects and map elements as vectorized scene constraints to improve planning efficiency and safety [106]. Therefore, traversability does not have to be expressed only as traditional grid cost maps, but can also be embedded into the end-to-end planning process in forms such as vectorized terrain boundaries, candidate trajectory constraints, and vehicle feasible domains. PathFormer for off-road scenarios decodes free-space semantics from visual inputs to achieve mapless path planning [107], while TerrainSense completes vision-driven mapless off-road navigation based on Transformer [108]. MTG uses a conditional variational autoencoder to generate multiple candidate trajectories satisfying traversability constraints, and combines coverage and feasibility constraints to improve candidate trajectory quality. This shows that generative models can be embedded into end-to-end planning frameworks as candidate trajectory generation tools [109]. Therefore, end-to-end deep coupling does not rely only on final control outputs, but can achieve more controllable joint optimization through intermediate structures such as differentiable planners, cost maps, or candidate trajectories.

In recent years, world models and vision-language models have further expanded the representation capability of end-to-end coupling. Drive-WM constructs a driving world model through multiview video prediction, enabling the system to evaluate future scene changes that may result from different actions [110]. Chib et al. summarized the development of end-to-end autonomous driving from the perspectives of input modalities, interpretability, and safety, showing that this direction has gradually expanded from a single perception-to-control mapping to a more complex unified modeling framework [111]. However, for autonomous driving in unstructured environments, such models are more suitable as auxiliary modules for high-level scene understanding, task interpretation, and candidate strategy generation, and cannot directly replace interpretable traversability modeling, physical constraints, and safe planners. Compared with structured roads, end-to-end deep coupling in unstructured environments faces more prominent data, physical, and verification problems. First, farmland, orchards, mining areas, and wild roads lack large-scale high-quality closed-loop driving data, and annotations for 3D traversability and vehicle-terrain interaction are insufficient. Second, traversal capability in unstructured environments depends not only on terrain appearance, but also on physical factors such as friction coefficient, sinkage, slip ratio, vehicle load, and structural form, which are difficult to fully learn only from images or point clouds. The reliability of end-to-end models under unfamiliar terrain, extreme weather, and long-tail operating conditions is difficult to fully prove through open-loop metrics. The closed-loop multi-ability

evaluation benchmark proposed by Bench2Drive shows that closed-loop evaluation is irreplaceably important for truly measuring end-to-end driving capability [112].

In summary, modular weak coupling, tightly coupled closed-loop architectures, and end-to-end deep coupling correspond to different information flow structures and engineering trade-offs. Modular weak coupling is suitable for stable deployment and safety review, but needs to enhance risk expression in the interface. Tightly coupled closed-loop architectures are suitable for high-risk and high-uncertainty regions, but need to control system complexity and error propagation. End-to-end deep coupling has the potential to learn complex representations and reduce manual interface loss, but must be protected by interpretable intermediate representations, physical constraints, and closed-loop verification. For autonomous driving in unstructured environments, future systems are more likely not to replace one architecture with another, but to introduce local closed-loop feedback and learning-enhanced modules on the basis of modular architectures, so that the system can dynamically adjust coupling strength according to terrain risk, perception confidence, and vehicle execution state.

4.3. Role Boundaries of Foundation Models and Vision-Language Models in Traversability Coupling

With the development of vision-language models and visual navigation foundation models, open-scene semantic understanding, natural language goal parsing, and task-level reasoning have gradually been introduced into robot navigation and autonomous driving systems. Compared with traditional perception models based on closed-category learning, foundation models are pretrained on large-scale image-text data, robot interaction data, and navigation trajectory data. Therefore, they have stronger capabilities in open-vocabulary recognition, cross-scenario knowledge transfer, and semantic reasoning. For autonomous driving in unstructured environments, agricultural fields, mining areas, forests, and off-road scenarios often contain complex and dynamically changing environmental elements, and terrain types, obstacle forms, and task constraints that are not sufficiently covered in the training data frequently appear. In this context, traditional semantic segmentation methods are limited by predefined category systems and have difficulty effectively handling open-category targets and new scene semantics. In contrast, foundation models can use natural language prompts, visual-semantic associations, and prior knowledge to achieve open-category target recognition and high-level task understanding, thereby providing richer semantic prior information for traversability assessment, environmental risk analysis, and path planning.

CLIP achieves open-vocabulary visual representation learning through large-scale image-text contrastive learning, laying the foundation for the application of vision-language models in open-scene perception [113]. In robot task planning, SayCan combines the task reasoning capability of large language models with robot skill executability constraints, achieving hierarchical decision-making from natural language instructions to action sequences [114]. PaLM-E combines multimodal perception inputs such as vision and state estimation with language models, enabling the model to handle embodied reasoning and robot task understanding problems [115]. In navigation tasks, LM-Nav integrates pretrained language models, visual models, and navigation policies to achieve natural-language-driven long-distance autonomous navigation [116]. These studies show that foundation models can provide new technical pathways for task understanding, open-category recognition, and high-level behavior decision-making in unstructured environments.

For autonomous driving in unstructured environments, the potential value of foundation models is mainly reflected in the ability of vision-language models to interpret natural language task constraints, such as avoiding muddy ground, driving along flatter

areas, and not driving over crops, thereby providing high-level semantic goals for the planner. Foundation models can assist in identifying open-category terrains and semantic regions, thus alleviating the problems of closed categories, high annotation cost, and insufficient cross-scenario generalization in traditional semantic segmentation models. Foundation models can serve as traversability prior generation modules, providing prompts for cost map construction, candidate region screening, or local re-perception. Galimzhanov et al. combined vision-language terrain reasoning with A* path planning, indicating that vision-language models can serve as an auxiliary information source for terrain semantic understanding and path cost adjustment [117]. Mattamala et al. used pre-trained models and online self-supervised learning to achieve rapid traversability learning in wild visual navigation, showing that the combination of pretrained visual representations and online feedback helps improve adaptability to unknown outdoor scenarios [97]. Castro et al. used proprioceptive feedback during vehicle driving to learn off-road traversability cost maps, further indicating that the outputs of foundation models and learning models still need to be combined with real vehicle terrain responses [83].

In unstructured scenarios, the semantic understanding capability of vision-language models is not equivalent to the judgment of actual vehicle traversal capability. Traversal risk in unstructured environments depends not only on visual appearance and semantic categories, but also on friction coefficient, soil bearing capacity, slip ratio, sinkage, vehicle load, speed, and posture stability. Visually similar dry soil and wet mud may correspond to completely different adhesion conditions, and regions semantically classified as grassland or dirt roads may also present different risks due to changes in moisture content, compaction degree, and slope. Therefore, if the output of a vision-language model is directly used as the basis for traversability cost or planning decisions, semantic understandability may be mistaken for physical executability. Learning-based off-road traversability cost maps combine vision, geometry, and proprioceptive feedback, thereby improving cost map prediction and navigation performance. This indicates that if foundation models are to serve traversability-driven planning, they must be connected with geometric structures, vehicle states, and physical feedback, rather than relying only on general visual semantic judgment.

In addition, the application of foundation models in unstructured environments still has limitations. First, when models produce overconfident judgments on unseen terrain, extreme weather, dust occlusion, and low-light scenarios, especially when the training data lack mining areas, forests, muddy ground, and complex off-road samples, semantic generalization does not necessarily lead to safety generalization. Then, vision-language models usually lack explicit modeling of wheel–terrain interaction, making it difficult to directly estimate planning constraints such as sinkage, traction force, roll stability margin, and braking distance. Finally, foundation models have high inference costs, and their real-time performance and deployment stability still need to be evaluated in combination with onboard computing resources. Studies on language-guided off-road 3D trajectory planning have begun to align language annotations with vehicle actions and terrain geometry, and evaluate trajectory quality through traversability consistency and elevation consistency metrics. Therefore, language description alone is insufficient to support safe planning, and the outputs of foundation models still need to be verified through terrain geometry, trajectory feasibility, and vehicle constraints.

Therefore, in the framework of this paper, foundation models and vision-language models should be positioned as high-level semantic enhancement components in traversability-driven coupling mechanisms, rather than independent safe planners. Their outputs can enter the traversability analysis module as semantic priors, task constraints, cost map prompts, or candidate path prompts, and then be jointly verified by geometric terrain, physical dynamics, uncertainty estimation, and vehicle states. For low-risk scenarios,

foundation models can assist in interpreting task goals and scene semantics. For semantically ambiguous or open-category terrains, foundation models can help identify potential risk regions. For muddy ground, slopes, negative obstacles, and unknown off-road scenarios, their outputs must be filtered by probabilistic risk maps, vehicle-related feasible domains, and local trajectory optimization constraints. Therefore, foundation models and vision-language models are not substitutes for the perception–planning coupling chain, but upper-level modules that enhance semantic understanding and task adaptability. Only when semantic reasoning results can be transformed into verifiable costs, constraints, and risk boundaries can they truly serve safe planning in unstructured environments.

4.4. Risk-State-Driven Adaptive Coupling Mechanism

Modular weak coupling, tightly coupled closed-loop architectures, and end-to-end deep coupling represent different levels of perception and planning collaboration. Modular weak coupling has clear interfaces, high real-time performance, and convenient engineering verification, but it easily compresses high-dimensional terrain information and uncertainty information at the perception–planning interface. Tightly coupled closed-loop architectures can use planning requirements and execution feedback to correct traversability estimation, but they have higher system complexity and verification difficulty. End-to-end deep coupling has the potential to learn complex scene representations and generate candidate trajectories, but its safety, interpretability and cross-scenario generalization capability are limited. Therefore, perception–planning coupling in unstructured environments cannot be simply understood as a transition from weak coupling to strong coupling, nor should end-to-end methods be regarded as the final replacement. A more reasonable future direction is to construct a risk-state-driven adaptive coupling mechanism, so that the system can dynamically adjust the information interaction mode according to terrain risk, perception confidence, vehicle state, and task requirements. The framework of the risk-driven adaptive coupling mechanism is shown in Figure 7.

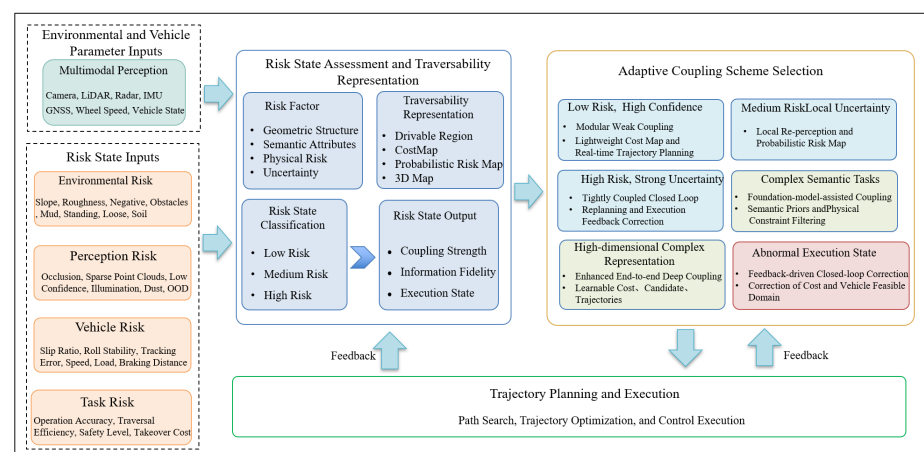


Figure 7. Framework of the risk-state-driven adaptive coupling mechanism.

Risk state is the key factor that determines coupling strength. For autonomous driving systems in unstructured environments, risk state is not determined only by obstacle distance, but is jointly formed by multiple factors related to the environment, perception, vehicle, and task. Environmental risks include slope, roughness, negative obstacles, gullies, standing water, mud, soft soil, and gravel. Perception risks include sparse point clouds, occlusion, low semantic segmentation confidence, illumination changes, dust interference, and out-of-distribution terrain. Vehicle risks include slip ratio, roll stability margin, trajectory tracking error, speed, load, and braking distance. Task risks are related

to operation accuracy, traversal efficiency, safety level, transport load, and human takeover cost. Only by comprehensively analyzing these risk factors can the system determine whether the current region is suitable for a lightweight modular interface, or whether local re-perception, probabilistic risk planning, or execution-feedback correction should be enabled.

In low-risk and high-confidence scenarios, modular weak coupling becomes the key choice for the system. For example, in open farmland, regular greenhouse passages, flat mining roads, or off-road sections with small terrain variations, the perception module can output traversable regions, occupancy grids, or continuous cost maps, and the planning module can complete path search and local trajectory optimization based on these standardized interfaces. In this case, excessive introduction of data-level coupling or complex end-to-end reasoning not only increases computational burden but may also reduce system verifiability. For such scenarios, the focus of the coupling mechanism is to ensure stable interfaces, clear cost meanings, and plan real-time performance. In medium-risk or locally uncertain scenarios, the system should shift from a one-way modular interface to locally enhanced coupling. For example, when a candidate trajectory approaches mud, standing water, slopes, crop boundaries, occluded regions, or sparse point cloud regions, the planner should not only passively use the existing cost map, but should send local re-perception requirements to the perception module, improve the resolution of key regions, or update the probabilistic risk map. At this time, feature-level coupling and decision-level coupling can work together. The perception end retains local BEV features, semantic confidence, and 3D structural information, while the planning end adjusts paths, safety margins, and speed according to risk costs, confidence, and vehicle states. This mechanism can improve the judgment accuracy of local high-risk regions without significantly increasing the global computational burden. In high-risk and highly uncertain scenarios, a tightly coupled closed-loop mechanism should be enabled. Typical scenarios include regions with dense negative obstacles, soft soil, slippery mud, steep slopes, gravel roads in mining areas, high-speed off-road turning, and abnormal increases in vehicle tracking error. In these cases, traversability cannot be completely determined only by forward perception, but should be continuously corrected using vehicle execution feedback. Signals such as slip ratio, posture changes, wheel speed differences, acceleration, trajectory tracking error, and control input saturation can be reversely used to update terrain costs, friction estimation, and vehicle feasible domains. The planner should also adopt conservative strategies according to the updated risk boundaries, such as reducing speed, increasing safety distance, replanning paths, or triggering human takeover. In such scenarios, the core of the coupling mechanism is not to pursue high traversal efficiency, but to prevent getting stuck, rollover, collision, and entering unrecoverable regions.

End-to-end deep coupling and foundation models are more suitable as enhancement modules in adaptive coupling mechanisms, rather than fixed replacement modules. In scenarios involving complex semantic understanding, open-category terrain recognition, and natural language task constraints, vision-language models and foundation models can provide high-level semantic priors, such as identifying mud, crops, gravel, or ditches, or prompting potential non-traversable regions. However, their outputs must be verified by geometric structures, physical dynamics, uncertainty, and vehicle state constraints. For high-risk regions, foundation models can be used to propose candidate risk regions or interpret task intentions, while the final trajectory should still be jointly constrained by interpretable planners, probabilistic risk maps, and vehicle-related feasible domains. In this way, the open semantic capability of foundation models can be used while avoiding their use as unverifiable safety decision-makers. The relationship between risk states and adaptive coupling strategies is shown in Table 11.

Table 11. Relationship between risk states and adaptive coupling.

Risk State	Typical Scenarios	Recommended Coupling Mode	Triggering Basis	Planning Response
Low risk and high confidence	Flat farmland, regular greenhouse passages, gentle mining roads	Modular weak coupling	Low traversal cost, high perception confidence, small trajectory tracking error	Use lightweight cost maps to maintain real-time path planning and trajectory tracking
Medium risk and local uncertainty	Muddy edges, slopes, occluded areas, crop boundaries, sparse point cloud regions	Combination of decision-level interface and local feature enhancement	Decreased semantic confidence, increased local cost, candidate trajectory approaching risk regions	Trigger local re-perception, update probabilistic risk maps, and adjust safety margins and speed
High risk and strong uncertainty	Negative obstacles, soft soil, slippery roads, steep slopes, high-speed off-road scenarios	Tightly coupled closed loop	Increased slip ratio, abnormal posture, increased trajectory tracking error, unstable risk boundary	Reduce speed, expand safety boundaries, perform local replanning, and trigger human takeover when necessary
Complex semantic tasks	Natural language goals, open-category terrain, unknown scenarios, areas with complex task constraints	Foundation-model assistance combined with interpretable planning filtering	Scene semantic ambiguity, insufficient existing category system, and task goals requiring high-level semantic interpretation	Generate semantic priors or candidate risk regions, and verify them through geometric, physical, and risk constraints
Abnormal execution state	Increased trajectory deviation, control input saturation, abnormal vehicle posture, abnormal wheel speed difference	Closed-loop correction driven by execution feedback	Tracking error, slip ratio, wheel speed difference, abnormal IMU posture, or control saturation	Correct traversability costs and vehicle feasible domains, and re-plan local trajectories

The risk state-driven adaptive coupling mechanism can form a closed-loop process involving risk assessment, coupling selection, planning response, and execution feedback. The perception module generates traversability representations related to geometry, semantics, physics, and uncertainty based on multimodal observations. The risk assessment module determines the current coupling level according to environmental risk, perception confidence, vehicle state, and task constraints. The planning module selects lightweight cost maps, probabilistic risk maps, 3D local maps, and vehicle-related feasible domains according to the coupling level. After vehicle execution, traversability estimation is further corrected through feedback such as slip ratio, posture changes, and trajectory errors. This process makes traversability no longer a separately generated static map, but a coupling variable that is dynamically updated with environmental observations, planning requirements, and vehicle responses.

Therefore, the risk-state-driven adaptive coupling mechanism can coordinate the dual requirements of real-time performance and safety in unstructured environments. It maintains an efficient, stable, and verifiable decision-making process in low-risk regions, while enhancing information fidelity, feedback correction capability, and planning conservatism in high-risk or unknown regions. Compared with fixed coupling architectures, this mechanism can achieve a balance among engineering reliability, environmental adaptability, and intelligent decision-making. For complex scenarios such as agriculture, mining areas, off-road environments, and forests, future perception–planning coupling

systems should not simply pursue deeper coupling but should dynamically select appropriate coupling modes according to risk states so that traversability becomes the core risk interface throughout perception, planning, and execution feedback.

5. Testing and Validation Systems and Evaluation Metrics

5.1. Public Datasets

High-quality public datasets are the basis for reproducible comparison of autonomous driving algorithms in unstructured environments. Compared with urban autonomous driving datasets, unstructured datasets pay more attention to terrain categories, traversable regions, off-road free space, multimodal point clouds, and different illumination and weather conditions. A comparison of different public datasets is shown in Table 12. Early datasets for unstructured environments mainly focused on visual semantic understanding and free-space detection. The RUGD dataset [118] is designed for visual perception of small ground robots in unstructured outdoor environments. It provides pixel-level semantic annotations and covers various weakly structured terrains such as grass, soil, gravel, and road edges, and can be used to evaluate the robustness of terrain semantic segmentation models in scenarios with irregular boundaries. The RELLIS-3D dataset further introduces annotations for camera images and LiDAR point clouds. It contains 13,556 LiDAR scans and 6235 images, providing a commonly used benchmark for 3D semantic understanding and multimodal perception of off-road robots. The ORFD dataset is directly oriented toward off-road free-space detection. It covers scenarios such as forests, farmland, grassland, and rural roads, and annotates traversable regions, non-traversable regions, and unreachable regions under sunny, rainy, foggy, snowy, and different illumination conditions. It is suitable for evaluating whether free-space detection results can be stably transformed into drivable regions usable for planning.

Table 12. Comparison of commonly used datasets for autonomous driving and traversability analysis in unstructured environments.

Dataset	Main Scenarios	Sensors/Data Forms	Main Annotations or Tasks	Applicability and Limitations
RUGD [118]	Off-road and semi-natural outdoor environments	RGB video images	Pixel-level semantic segmentation	Suitable for visual terrain understanding; lacks vehicle physical parameters and 3D traversal costs
RELLIS-3D [25]	Off-road robot scenarios	RGB images, 3D LiDAR	2D/3D semantic segmentation	Suitable for multimodal off-road perception, the annotation scale is still limited compared with urban datasets
ORFD [36]	Forests, farmland, grassland, and rural roads	RGB images, LiDAR point clouds	Off-road free-space detection	Directly oriented toward traversable regions; limited semantic categories and physical attributes
TOMD [119]	Narrow trails and environments with strong illumination changes	128-beam LiDAR, stereo cameras, GNSS, IMU, illumination information	Traversable path segmentation	Suitable for evaluating narrow trails and illumination robustness; still biased toward robot trail scenarios
GND [120]	Outdoor environments	3D LiDAR, RGB, 360-degree images	Multi-class traversability maps and global navigation	Suitable for global navigation and multi-class traversability reasoning;

				not fully equivalent to vehicle off-road dynamic scenarios
IDD-AW [121]	Adverse weather and unstructured traffic scenarios	RGB-NIR images	Safe semantic segmentation, Safe mIoU	Suitable for robustness and dangerous mis-segmentation evaluation; insufficient terrain physical attributes
R2S100K [122]	Roads with potholes, soil, gravel, and standing water	Large-scale road images	Road region segmentation, semi-supervised learning	Covers non-ideal road surfaces; focuses more on road region recognition than complete off-road traversability
STONE [123]	Off-road environments such as grassland, farmland, construction sites, and lakesides	Surround-view cameras, LiDAR, 4D radar	Voxel-level 3D traversability prediction	Has multimodal and 3D advantages; currently remains a relatively new preprint benchmark

As research on autonomous driving in unstructured environments shifts from two-dimensional semantic recognition to three-dimensional traversability estimation and task-oriented navigation, datasets have gradually shown a trend toward multimodality, three-dimensional representation, and planning orientation. The TOMD dataset targets narrow, trail-like off-road environments and integrates 128-beam LiDAR, stereo images, GNSS, IMU, and illumination measurement information. It is suitable for evaluating traversable path segmentation capability under strong illumination changes and narrow passages. From the perspective of global navigation, the GND dataset provides 3D LiDAR, RGB images, 360-degree panoramic images, and multi-class traversability maps, and can be used to evaluate global path planning and multi-class traversability reasoning in large-scale outdoor environments. The IDD-AW dataset targets safe semantic segmentation under adverse weather and unstructured traffic conditions, and proposes the Safe mIoU metric to penalize dangerous mis-segmentation, which provides a reference for robust perception and safety evaluation. The R2S100K dataset focuses on unstructured road regions such as potholes, standing water, soil, and gravel, and provides large-scale image data and partial fine annotations. It is suitable for semi-supervised road region understanding. As a recently proposed large-scale multimodal surround-view 3D traversability dataset, the STONE dataset integrates 128-beam LiDAR, six cameras, and 4D imaging radar, and automatically generates trajectory-guided 3D traversability maps, providing a new data basis for vehicle-scale 3D traversability prediction.

Existing public datasets have supported terrain semantic segmentation, free-space detection, multimodal perception, and 3D traversability prediction in unstructured environments, but they are still difficult to fully meet the needs of perception–planning coupling research. First, most datasets mainly provide semantic labels or traversable region annotations, but lack terrain physical attribute labels, making it difficult to support vehicle–terrain coupling constraint modeling. Second, existing datasets are mostly used for open-loop perception evaluation and lack closed-loop evaluation information directly related to trajectory planning, control execution, and task completion performance. Therefore, future datasets for unstructured environments need to move from single perception annotation toward integrated annotation of perception, traversability, planning, and execution. That is, they should simultaneously provide terrain semantics, geometric structures, physical responses, vehicle states, and trajectory results to support the validation of traversability-driven perception–planning coupling mechanisms.

5.2. Simulation Platforms and Testing Validation

Simulation testing is an important part of autonomous driving systems. This approach can greatly reduce the cost of real-vehicle testing, while supporting the reproduction of extreme scenarios and large-scale algorithm iteration. A comparison of typical simulation testing platforms is shown in Table 13. CARLA [124], as a widely used open-source autonomous driving simulator, can provide urban roads, sensor configurations, environmental conditions, and vehicle control interfaces, and is commonly used in autonomous driving perception and trajectory planning research. CARLA-GymDrive, proposed by Morgado [125], further encapsulates CARLA as a Gymnasium-style reinforcement learning environment and provides convenient interfaces for autonomous driving agent training, scenario configuration, and scenario-based testing. However, CARLA itself is mainly oriented toward urban structured road scenarios, and its native support for farmland, mining areas, and complex off-road terrain is limited. Therefore, in studies on unstructured environments, secondary development of terrain and vehicle dynamics models is usually required. Compared with general autonomous driving simulators, dedicated simulation platforms for specific unstructured scenarios can better cover specific scenario applications. MineSim [126] is designed for autonomous mining truck planning tasks in open-pit mining areas. It can provide components such as scenario parsing, ego-vehicle state updating, state information of other traffic participants, metric evaluation, scenario visualization, and construct static and dynamic obstacle avoidance benchmarks from real mining-area data.

Table 13. Comparison of typical simulation platforms.

Platform	Target Scenarios	Core Capabilities	Advantages	Limitations
CARLA [124]	Urban structured roads	Sensor simulation, vehicle control, and environmental condition configuration	Mature open-source platform, rich ecosystem, and convenient for end-to-end and reinforcement learning research	Insufficient support for off-road, farmland, and mining terrain
CARLA-GymDrive [125]	Reinforcement learning training based on CARLA	Gymnasium-style task interface, scenario configuration, sensor configuration	Lowers the barrier for RL experiments and facilitates reproducible experimental workflows	Performance still depends on the realism of CARLA scenarios and dynamics
MineSim [126]	Unstructured roads in open-pit mining areas	Closed-loop planning testing for mining trucks, obstacle benchmarks, scenario visualization	Suitable for heavy-duty mining vehicles and roads without lane markings	Scenarios are concentrated in mining areas, with limited applicability to agriculture and rescue
Chrono [127]	Off-road and unstructured terrain	Vehicle multibody dynamics, wheel–terrain interaction, deformable terrain modeling	Describes vehicle–terrain coupling and the physical mechanisms of traversability, and is suitable for off-road vehicle dynamics and traversability validation	Traffic flow, complex scenario ecosystem, and visualization resources are not as mature as those in CARLA
MAVS [128]	Off-road autonomous ground vehicles	Digital terrain, vehicle dynamics, and sensor simulation, such as cameras, LiDAR, and GPS	Oriented toward off-road scenarios and suitable for joint validation of perception and navigation algorithms	General ecosystem and scenario reusability are weaker than those of large general-purpose platforms
Gazebo [129]	General robots and outdoor mobile robots	Three-dimensional dynamics, multi-robot modeling	Mainstream robot simulation platform with strong extensibility	Requires secondary modeling for soft soil, sinkage, and high-

				fidelity wheel–terrain contact
ANVEL [130]	Unmanned ground vehicles and off-road scenarios	Real-time vehicle dynamics, complex terrain and obstacle interaction simulation	Oriented toward UGV and military scenarios, and suitable for off-road system-level validation	Not open source

For terrain variations and vehicle–terrain interaction problems in unstructured environments, Chrono [127] and MAVS [128] are more representative. Chrono can support multibody dynamics of wheeled and tracked vehicles, wheel–terrain contact, and complex terrain modeling, making it suitable for mechanism verification of off-road vehicle dynamics and traversability. MAVS is oriented toward off-road autonomous vehicles and can integrate vehicle models and sensors such as cameras, LiDAR, and GPS in digital terrain for real-time simulation. It is more suitable for joint testing of perception and navigation algorithms. Gazebo [129] and ANVEL [130] are used for system-level validation of mobile robots or unmanned ground vehicles. Gazebo is designed to construct three-dimensional, dynamic multi-robot environments to facilitate robot algorithm development and joint debugging. ANVEL provides controllable and repeatable testing environments for unmanned ground vehicles and can simulate the interaction among vehicles, terrain, and obstacles in repeatable environments. However, both platforms have relatively limited native capability in representing physical properties of unstructured surfaces, such as soft soil and sinkage.

The development of end-to-end autonomous driving and large models has also promoted the expansion of simulation platforms from single planning tests to comprehensive multitask evaluation. In autonomous driving for unstructured environments, simulation platforms are shifting from single-algorithm testing to system-level closed-loop validation. An ideal testing platform should be able to construct typical unstructured scenarios, simulate traversability-related terrain factors such as slope, roughness, soft soil, standing water, gravel, and low adhesion, and integrate vehicle dynamics, sensor noise, and actuation delay models. It should finally output comprehensive evaluation metrics related to perception, planning, control, and task completion. Therefore, simulation platforms should not remain only at the level of visual perception or single-path planning testing.

5.3. Evaluation Metric System

The evaluation of autonomous driving in unstructured environments should not rely only on single metrics such as perception segmentation accuracy or path length, but should cover the processes of environmental perception, traversability modeling, trajectory planning, vehicle control, and task completion. Unlike structured roads, safe traversal in unstructured environments depends not only on obstacle detection, but also on whether terrain risks are correctly quantified and whether planned trajectories satisfy vehicle dynamic constraints. Therefore, the evaluation metric system should reflect perception accuracy, traversal risk, trajectory quality, control stability, and task completion performance. The testing and evaluation metric system for autonomous driving in unstructured environments is shown in Table 14.

Table 14. Evaluation metrics for autonomous driving testing in unstructured environments.

Evaluation Level	Representative Metrics	Applicable Objects	Evaluation Content	Limitations
Perception and traversability	mIoU, Precision, Recall, F1, point cloud IoU, Safe mIoU	Semantic segmentation, free-space detection, traversable region recognition	Evaluates terrain category recognition, traversable region	Difficult to directly reflect the vehicle trajectory safety and actual traversal capability

				detection, and spatial perception accuracy
Uncertainty modeling	ECE, NLL, Brier score, OOD detection rate, correlation between confidence and error rate	Probabilistic traversability maps, evidential learning, risk-aware planning	Evaluates whether model confidence is reliable and whether high-uncertainty regions can be identified	Reliable confidence does not equal planning safety, and still needs to be transformed into planning constraints or risk costs
Trajectory planning	Success rate, collision rate, path length, minimum safety distance, replanning times, computational latency	Global path planning, local trajectory generation	Evaluates the safety, efficiency, and real-time performance of planned paths	If vehicle dynamic constraints are lacking, it is difficult to reflect trajectory executability in real terrain
Vehicle dynamics	Slip ratio, roll stability margin, slope passability, sinkage risk, curvature, acceleration	Off-road vehicles, mining trucks, agricultural vehicles	Evaluates vehicle stability, traversal capability, and dynamic safety boundaries on real terrain	Requires vehicle states, terrain physical attributes, and execution feedback data, which are rarely provided in public datasets
Path tracking control	Average lateral error, maximum lateral error, heading error, RMS error	Tractors, combine harvesters, mining trucks, rescue vehicles	Evaluates whether planned trajectories can be stably executed by real vehicles	If not associated with terrain risk and traversability estimation, it is difficult to explain whether the perception–planning coupling mechanism is effective
Tasks and applications	Operation coverage, missed operation rate, overlap rate, transportation cycle time, rescue arrival time, number of human interventions	Agriculture, mining areas, off-road environments	Evaluates system-level application effects and engineering value	Different scenarios, vehicle platforms, and task objectives vary greatly, making cross-study results difficult to compare directly

In the process of perception and traversability modeling, commonly used metrics include mIoU, Precision, Recall, F1, boundary F1, and point cloud segmentation IoU, which can be used to evaluate terrain semantic segmentation, free-space detection, and 3D point cloud recognition. However, traditional mIoU has difficulty fully reflecting safety risks in unstructured environments, because the consequences of mis-segmentation among different categories are not the same. In addition, for traversability modeling, attention should also be paid to metrics such as slope estimation error, roughness estimation error, traversable region recall, non-traversable region miss rate, cost map consistency, and risk ranking accuracy. For probabilistic risk maps and uncertainty modeling, confidence calibration error, negative log-likelihood, Brier score, and OOD detection metrics can be further used to evaluate whether model confidence is consistent with real risk.

At the trajectory planning and control execution level, evaluation should consider safety, feasibility, and smoothness. Common planning metrics include task success rate, collision rate, path length, driving time, minimum obstacle distance, trajectory curvature, curvature change rate, replanning times, and computational latency [131]. For vehicles in unstructured environments, further attention should be paid to metrics such as slope

passability, roll stability margin, slip ratio, sinkage risk, accumulated terrain cost, and energy consumption per unit distance, so as to reflect the physical executability of trajectories on real terrain. At the control execution level, average lateral error, maximum lateral error, heading error, speed tracking error, and control input smoothness can be used to evaluate whether the vehicle can stably execute the planned trajectory [132]. For agricultural vehicles, operation accuracy is closely related to trajectory tracking accuracy. Therefore, lateral error, headland turning error, and operation-width deviation are particularly important [133]. At the task scenario and coupling mechanism level, evaluation metrics should further reflect whether the system truly meets application requirements. Agricultural scenarios can focus on operation coverage, missed operation rate, overlap rate, crop damage, and soil compaction [134], while mining scenarios can focus on transportation cycle time, transportation distance, heavy-load braking distance, and docking error at loading and unloading points [135].

Existing evaluation metrics still show obvious hierarchical separation. Perception metrics can measure terrain recognition capability, but they cannot prove whether the vehicle can pass safely. Planning metrics can evaluate path length, collision rate, and computational efficiency, but without evaluation of slip, sinkage, and posture stability, they are still difficult to prove that a trajectory is executable in real terrain. Control metrics can reflect trajectory tracking performance, but if they are not associated with terrain risk and traversability estimation, they also cannot explain whether the perception–planning coupling mechanism is effective. Therefore, the evaluation system in unstructured environments should shift from single-module accuracy evaluation to cross-level closed-loop evaluation. It should simultaneously focus on whether perception is correct, whether risk is reasonably represented, whether planning uses risk information, and whether the vehicle can execute stably. Since different studies use different vehicle platforms, sensor configurations, terrain types, speed ranges, task objectives, and evaluation protocols, the performance results reported in existing literature are often difficult to compare directly across studies.

Therefore, the evaluation of autonomous driving in unstructured environments should shift from single-module accuracy to full-chain closed-loop capability assessment. Perception metrics are used to measure environmental understanding capability, traversability metrics are used to evaluate the quality of terrain risk modeling, planning and control metrics are used to evaluate trajectory generation and execution stability, and task metrics are used to reflect the engineering value of the system in real applications. In the future, a more reasonable evaluation method should combine open-loop dataset evaluation, closed-loop simulation testing, and real-vehicle scenario validation, so as to more accurately measure the overall performance of traversability-driven perception–planning coupling systems.

6. Key Challenges and Future Directions

Autonomous driving technology in unstructured environments has made significant progress in environmental perception, traversability analysis, and trajectory planning. However, many problems remain in achieving long-term reliable operation in complex open scenarios, such as the lack of unified traversability representation, the difficulty of obtaining physical properties of vehicle–terrain interaction, the difficulty of effectively propagating uncertainty, and the insufficiency of closed-loop validation systems. Unlike structured roads, traversal risks in unstructured environments come not only from obstacles, but are also closely related to surface properties and vehicle attributes. Therefore, future research should not only focus on improving perception accuracy or the performance of a single planning algorithm, but should pay more attention to how traversability

information is uniformly represented, how it enters trajectory planning, and how it is corrected online through vehicle execution feedback.

In the process of planning-oriented unified traversability representation, current studies usually describe traversal risks from the perspectives of geometry, semantics, and physical dynamics, but the expression scales and planning interfaces of different types of information are not consistent. Geometric information can reflect slope, elevation difference, and roughness. Semantic information can identify grass, mud, crops, and obstacles. Physical-dynamics information further describes risks such as friction, slip, sinkage, and posture stability. However, many methods still rely on manual weights or empirical rules to combine these types of information into a single cost map, which can easily lead to the loss of key risks. A more reasonable future direction is to construct a unified representation that simultaneously includes traversal cost, confidence, risk boundaries, and vehicle feasible domains, so that traversability can shift from a static environmental attribute to a dynamic expression related to vehicle type, motion state, and task requirements.

In the online estimation of physical properties of vehicle–terrain interaction, factors such as friction coefficient, soil bearing capacity, sinkage, and slip ratio directly affect whether the vehicle can pass stably. However, these parameters are often difficult to obtain in advance and may change with soil moisture content, compaction degree, vehicle load, and weather conditions. If the system relies only on offline calibration or fixed models, it is difficult to adapt to time-varying terrain in real environments. Therefore, future research needs to combine vehicle proprioceptive feedback, terramechanics models, and data-driven methods, and use signals such as wheel speed, acceleration, posture changes, slip ratio, and trajectory tracking error to correct traversability estimation online. In this way, the system can gradually develop from pre-judging terrain risks to dynamically updating traversal risks according to the real response of the vehicle.

In uncertainty propagation within the perception–planning chain, many perception models can output confidence or probabilistic results, but these uncertainties often do not stably enter path search, trajectory optimization, and control constraints. As a result, the planner still makes decisions based on deterministic cost maps. In scenarios such as mud, standing water, occlusion, gullies, and low vegetation, if low-confidence regions are mistakenly regarded as low-risk regions, the vehicle may be guided to dangerous terrain. Future research should further establish a propagation mechanism from perception uncertainty to planning risk boundaries, so that cost mean, variance, confidence, and risk margins can directly affect path selection, speed planning, and safety constraints, thereby improving system robustness in unknown and high-risk regions.

In terms of the interpretability and adaptability of perception–planning coupling mechanisms, modular weak coupling architectures have clear interfaces and are easy to verify, but they easily compress high-dimensional terrain information and uncertainty information during interface transmission. Tightly coupled closed-loop architectures can use planning requirements and execution feedback to dynamically correct traversability estimation, but their internal information flow is more complex, and how feedback variables affect perception updating, cost correction, and trajectory adjustment still needs to be clearly explained. End-to-end deep coupling architectures have strong high-dimensional representation learning capability, but their decision-making processes often lack transparency and interpretability. Therefore, a more feasible future direction is not to simply pursue stronger coupling, but to construct a risk-state-oriented adaptive coupling mechanism, so that different coupling modes can be selected in different scenarios. In open, low-risk regions with high perception confidence, modular interfaces can be used to ensure real-time performance and verifiability. In muddy, sloped, occluded, waterlogged, or highly uncertain regions, local re-perception, risk boundary expansion, and execution-feedback correction can be enabled. In complex semantic understanding and high-

dimensional cost learning, deep representations or large-model-assisted reasoning can be introduced, but their outputs should still be constrained by physical constraints, risk boundaries, and interpretable planning modules. In this way, the system can maintain efficiency and stability in low-risk scenarios, enhance safety redundancy in high-risk scenarios, and improve environmental understanding in unknown scenarios, thereby achieving a balance between safety interpretability and environmental adaptability.

Finally, the testing and validation system needs to shift from single-module evaluation to closed-loop system evaluation. Existing datasets and simulation platforms mostly focus on semantic segmentation, free-space detection, or single path planning, and are still difficult to use for fully evaluating the traversability capability. In the future, comprehensive datasets that include terrain geometry, semantic categories, physical properties, vehicle states, and execution feedback should be constructed, and simulation platforms capable of modeling ground and vehicle properties should be developed. Evaluation metrics should also be expanded from single metrics such as mIoU and path length to system-level metrics such as traversability cost accuracy, uncertainty calibration, and trajectory execution stability. Only by incorporating environmental perception, traversability modeling, trajectory planning, and vehicle execution into a unified closed-loop validation framework can the performance of autonomous driving systems in unstructured environments be evaluated more accurately.

7. Conclusions

This paper reviews traversability-driven perception and planning coupling mechanisms for autonomous driving in unstructured environments, covering traversability analysis, trajectory planning methods, coupling architectures, and testing and validation systems. In terms of traversability analysis, geometric terrain methods can provide basic spatial constraints such as slope, elevation difference, and roughness; semantic understanding methods can identify surface categories and scene structures; and physical-dynamics methods further describe vehicle-related risks such as friction, slip, sinkage, and posture stability. In terms of trajectory planning, traversability information enters global path guidance and local trajectory optimization through node costs, edge costs, dynamic constraints, and uncertainty penalties, so that the planning objective shifts from geometric collision avoidance to safe executability on real terrain.

In terms of perception and planning coupling, this paper analyzes the problem from two perspectives: information interface levels and system organization forms. Data-level, feature-level, and decision-level interfaces correspond to different computational complexities and engineering interpretability, while modular weak coupling, tightly coupled closed-loop architectures, and end-to-end deep coupling reflect the development trend of systems from clear interfaces and bidirectional feedback to joint learning. For autonomous driving in unstructured environments, a more reasonable future direction is not to simply pursue strong coupling, but to introduce risk-aware feedback, local re-perception, and deep representation enhancement on the basis of modular and verifiable architectures, so that the system can dynamically adjust coupling strength according to terrain risk, perception confidence, task requirements, and vehicle execution state. In terms of testing and validation, this paper summarizes public datasets, simulation platforms, and evaluation metric systems. Existing datasets and simulation tools can already support semantic segmentation, free-space detection, multimodal perception, and partial closed-loop testing, but they still have limitations in physical attribute annotation, vehicle dynamic response, execution feedback, and task-level evaluation. In the future, datasets and testing platforms should be constructed with a stronger focus on traversability and closed-loop planning, and a multitask comprehensive evaluation system covering perception, traversability modeling, trajectory planning, and control execution should be established.

In summary, traversability analysis serves as the core link between perception and trajectory planning in unstructured environments. Future research needs to further address key problems such as unified representation, online estimation of physical properties, uncertainty propagation, adaptive coupling, and closed-loop validation. It should also promote the system from identifying drivable regions to understanding whether a vehicle can pass safely, thereby improving the safety, robustness, and engineering applicability of autonomous driving systems in complex scenarios such as agriculture, mining areas, and off-road environments.

Author Contributions: Conceptualization, Q.G., H.J. and S.M.; methodology, Q.G., H.J. and S.M.; investigation, Q.G., Y.C. and L.Y.; resources, H.J., S.M. and L.Y.; data curation, Q.G. and Y.C.; formal analysis, Q.G., Y.C. and L.Y.; writing—original draft preparation, Q.G.; writing—review and editing, H.J., S.M., Y.C. and L.Y.; visualization, Q.G. and Y.C.; supervision, H.J. and S.M. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Data Availability Statement: No new data were created or analyzed in this study.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

A*	A-star search algorithm
ALVINN	Autonomous Land Vehicle In a Neural Network
ANVEL	Autonomous Navigation Virtual Environment Laboratory
BEV	Bird's-Eye View
BEVNet	Bird's-Eye View Network
CARLA	Car Learning to Act
CLIP	Contrastive Language-Image Pre-training
CVaR	Conditional Value at Risk
DWA	Dynamic Window Approach
ECE	Expected Calibration Error
ELM	Extreme Learning Machine
ENet	Efficient Neural Network
EVORA	Evidential Traversability Learning Framework
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
IDD-AW	Indian Driving Dataset-Adverse Weather
IMU	Inertial Measurement Unit
LiDAR	Light Detection and Ranging
LM-Nav	Language Model Navigation
MAVS	Mississippi State University Autonomous Vehicle Simulator
MineSim	Mining Simulation Platform
mIoU	mean Intersection over Union
MPC	Model Predictive Control
MP3	Map-Predict-Plan Framework
MTG	Multiple Trajectory Generation
NIR	Near-Infrared
NLL	Negative Log-Likelihood
OOD	Out-of-Distribution
ORFD	Off-Road Freespace Detection
PaLM-E	Pathways Language Model-Embodied
PID	Proportional-Integral-Derivative
R2S100K	Road Region Segmentation 100K

RELLIS-3D	RELLIS-3D Dataset
RGB	Red-Green-Blue
RLS-ELM	Recursive Least Squares-Extreme Learning Machine
RMS	Root Mean Square
RRT	Rapidly exploring Random Tree
RRT*	Rapidly exploring Random Tree Star
RT-2	Robotics Transformer 2
RUGD	Robot Unstructured Ground Driving
Safe mIoU	Safety-aware mean Intersection over Union
SARO	Space-Aware Robot System
SLAM	Simultaneous Localization and Mapping
SPIN	SPIN Framework
STEP	Stochastic Traversability Evaluation and Planning
STONE	Surround-View 3D Traversability Dataset for Off-Road Robot Navigation
TOMD	Trail-based Off-road Multimodal Dataset
UGV	Unmanned Ground Vehicle
UniAD	Unified Autonomous Driving
VAD	Vectorized Autonomous Driving
ViNT	Visual Navigation Transformer
VLM	Vision-Language Model
VLM-GroNav	Vision-Language Model-Grounded Navigation

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