From Research to Deployment in Autonomous Agricultural Machinery: A Review of Path-Planning Technologies Against a Deployability Assessment Framework

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Wane, S., Shamshiri, R.R., Guo, W., Chen, H. and Cheein, F.A. (2026) 'From Research to Deployment in Autonomous Agricultural Machinery: A Review of Path-Planning Technologies Against a Deployability Assessment Framework', *Computation*, *14*(8), article number 194.

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Review

From Research to Deployment in Autonomous Agricultural Machinery: A Review of Path-Planning Technologies Against a Deployability Assessment Framework

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Abstract

Global labour shortages in the agricultural sector, combined with diminishing arable land and a growing population, are driving investment in autonomous agricultural machinery. Autonomous systems that can navigate crop environments and perform planting, treatment, and harvesting alongside humans are required, but the gap between published research and commercially deployed systems remains wide across most operational scenarios. Why are agricultural robots still not widely deployed in real farms despite decades of research in autonomous navigation and path planning, and what is preventing full farm autonomy? This paper reviews the principal enabling technologies for autonomous agricultural integration, with a specific focus on path planning as the differentiator between research-stage and deployed systems. Current research in human–robot integration, open-field navigation, row identification and following, crop sensing, and power efficiency is synthesised and evaluated against a deployability criterion. A Deployability Assessment Framework is introduced, comprising structured tables that assign Technology Readiness Levels to twelve path-planning families and benchmark eleven commercial and research platforms against field-validated accuracy data. The analysis shows that point-to-point GNSS navigation has reached TRL 9 with over one million commercial units deployed, vision-based crop row following is at TRL 5–7 depending on crop and season, and whole-farm autonomy with dynamic re-planning is at TRL 3–5. The primary barriers are the absence of standardised evaluation benchmarks, the failure of perception models to generalise across seasons and crop types, and the decoupling of terrain and slip feedback from global path planners. Our review reveals that open-field GNSS navigation is commercially mature, but true whole-farm agricultural autonomy remains unsolved because current systems are not robust enough across seasons, terrain, sensing conditions, and operational transitions.

Keywords: agricultural robot; path planning; crop row following; deployability; GNSS navigation; LiDAR; deep learning; Technology Readiness Level

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Academic Editor: Junlin Hu

Received: 29 June 2026
Revised: 31 July 2026
Accepted: 11 August 2026
Published: 21 August 2026

1. Introduction

In the West, farm ownership has become progressively consolidated under fewer, larger operators [1], while globally a structural agricultural labour shortage persists due

 https://doi.org/10.3390/computation14080194

to rural-to-urban migration, the unreliability of seasonal workforces, and the perceived hardship of farm work. These pressures create a direct demand for automation that can extend productive capacity without proportionally increasing headcount. Larger field sizes, tighter weather windows, and the agronomic requirement for precise, timely operations further accelerate this demand.

The complexity of the agricultural environment—unstructured terrain, seasonal change, unpredictable obstacles, variable soil conditions, and the co-presence of humans—explains the persistently low uptake of truly autonomous navigation for harvesting and crop treatment [2]. Reviews of navigation technology across plantation, livestock, and aquatic production confirm that no single platform or sensing modality covers all application types [2].

Path planning is the technological linchpin connecting a high-level farm management instruction ("spray field B") to the low-level motor commands that safely execute it. It determines how efficiently a machine covers a field, how reliably it follows crop rows, how it handles headlands and obstacles, and, ultimately, whether a system is suitable for commercial deployment. Despite hundreds of published path-planning algorithms, the gap between laboratory demonstrations and commercially viable, field-deployed systems remains wide [3,4]. This review argues that deployability—the measurable readiness of a complete system for autonomous field operation under realistic conditions—is the correct lens through which to evaluate progress in agricultural robotics.

This paper makes three specific contributions: (1) a critical review of enabling technologies—HRI, open-field navigation, row following, crop identification, and power management—evaluated against their contribution to deployability; (2) a Deployability Assessment Framework comprising structured tables that assign TRL values to twelve path-planning families and benchmark eleven commercial and research platforms against field-validated accuracy data; and (3) an identification of four technical gaps—standardised benchmarks, seasonal perception generalisation, terrain-integrated planning, and regulatory pathways—that currently block the transition from TRL 6–7 to TRL 9 for row following systems.

The review is organised as follows. Section 2 covers the principal technology areas (Sections 2.2–2.6). Section 3 presents the deployability analysis and tables. Section 4 identifies outstanding technical and regulatory challenges, and Section 5 provides conclusions.

2. Analysis of Current Problems and State of Solutions

2.1. Review Methodology

This review was developed through a targeted literature search with a goal of approximately 100 journal papers focused on path planning and its derivatives in agricultural settings. Scopus and Web of Science were the primary bibliographic databases. A total of 88 papers were investigated once duplicates were removed, with the remaining references referring to company websites or ISO specifications. Grey literature, vendor white papers and blogs were read for orientation but were not cited. Some of the figures were generated or enhanced with the aid of AI. Selection criteria: journal articles in English, published from 2019 to 2026, in Agricultural Sciences, Engineering, and Computer Science. Articles exclusively on teleoperation or without relevance to in-field path execution were excluded; earlier foundational studies were also included where the field cites them by convention. The search string combined the following:

(title:("farming" OR "precision agriculture") AND abstract:("robot" OR "automated")) AND keywords:("crop row following" OR "path planning" OR "autonomous navigation" OR "human-robot interaction")

The four main resulting pillars of deployability: human–robot interface (HRI), navigation and autonomous movement, crop identification and handling, and power efficiency and environmental impact—are illustrated in Figure 1 and structure the review.

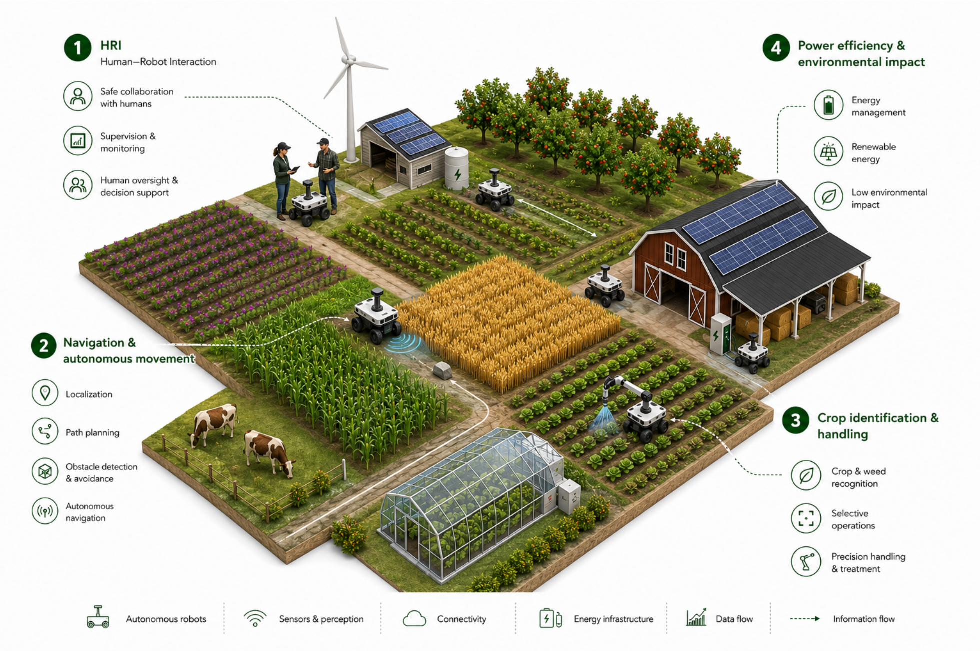

Figure 1. Summary of key areas: (1) HRI, (2) navigation and autonomous movement, (3) crop identification and handling, (4) power efficiency and environmental impact.

2.2. Integration with Humans and Existing Machinery (HRI)

The transition to field autonomy is constrained by the cost of replacing existing machinery and the time required for farm workers to adopt new operational practices. The scope of this transition across plantation, livestock, and aquatic applications is reviewed in [2]. Overall, HRI research accounted for less than 12% of the research papers reviewed, with the majority originating in the USA, Northern Europe, and Japan. Integration of the Robot Operating System (ROS) with legacy farm machinery is demonstrated in [5], which presents an effective graphical user interface enabling high-level commands (go to field, follow leader, go to charging station) across a mixed fleet of conventional and robotic vehicles. A modular hardware-software framework using ROS, standardised sensors, and replaceable 3D-printed chassis components has been validated across cotton-crop field trials [6].

Machines operating near humans must approach from predictable directions, maintain defined safety distances, and respond to operator gestures. A Human-Aware Module (HAM) applied to soft-fruit picking[7] shown in Figure 2, models the human movement envelope using cameras to infer intent through gesture recognition, and legs detected by the LiDAR coverage as shown in (a) blue and pink with the red arrow in (b) demonstrates the leg's detection and likely movement direction.The new generation of collaborative robots (cobots [8]) and sensitive electronic "skin" [9] (Airskin [7]) are making close-proximity human–robot operation viable on agricultural manipulators. Risk assessment frameworks for autonomous agricultural machinery are becoming standardised practice [10], and deep-learning-based human-intention recognition with safety zones is advancing rapidly [11]. A comprehensive review of human–robot collaboration (HRC) in agriculture covering 55 studies identifies sensing infrastructure, safety certification, and operator training as the dominant barriers to deployment [12].

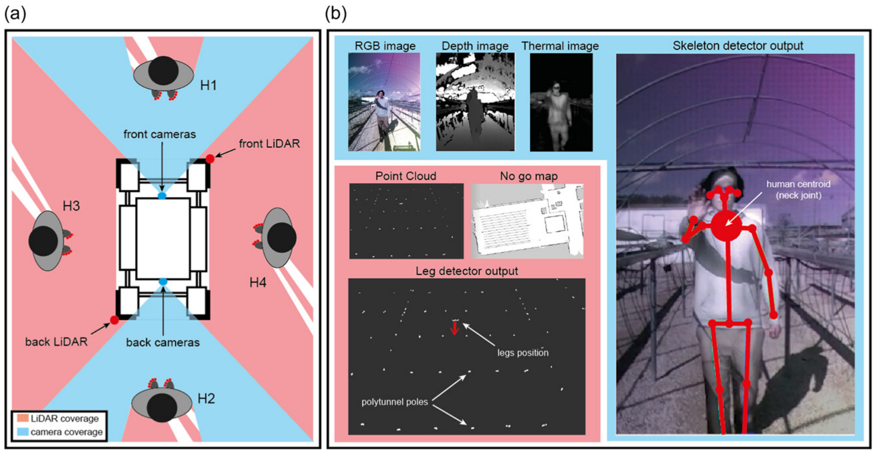

Figure 2. Human-aware navigation module for cooperative fruit-picking (**a**) Detection coverage areas according to the sensor used. (**b**) Inputs and outputs of the camera-based skeleton detector (blue) and the LiDAR-based leg detector (red) [7].

Fleet coordination extends HRI beyond individual platforms. A decentralised framework for allocating vehicles, implements, and raw materials dynamically across a farm, accounting for soil stability, time horizon, and shared ownership, is proposed in [13]. The leader–follower architecture in [14] allows a human-driven tractor to lead a swarm of autonomous robots, with the swarm pattern, spacing, and headland-turning logic managed autonomously. Route descriptions using controlled natural language and ISO 8373:2021 vocabulary [15] are encoded in the Mission Planner [16], enabling routes from the machine shed through gates and across fields to be expressed in a human-readable farm description.

The analysis of trailer dynamics during headland turning [17] addresses a common cause of crop damage and wasted headland in towed implements, providing analytical paths for N-trailer vehicles that prevent corner cutting. Vehicle rollover risk as a function of terrain slope, speed, and turning radius is tabulated in [18] and minimised through dynamic path constraints in [19].

2.3. Open-Field Navigation

Open-field navigation—locomotion without crop row constraints—is the most mature segment of agricultural autonomy, covering 27% of the reviewed papers, with a majority of them originating from China and Europe. Summarised in Figure 3, navigation relies on Global Navigation Satellite Systems (GNSS) to derive position and heading, with the pure-pursuit algorithm [20] the most widely deployed controller. A comprehensive review of path-planning methods (pure pursuit, Linear Quadratic Regulator (LQR), Fuzzy Logic, Model Predictive Control (MPC)) and motion-control methods (Proportional–Integral–Derivative (PID), neural networks, sliding mode) in an agricultural context is provided in [21].

The heading accuracy achievable from two spatially separated GNSS antennas fused with an Inertial Measurement Unit (IMU) is critically assessed in [22], which proposes an adaptive Kalman filter that significantly reduces bias on narrow, bumpy terrain. Centimetre-level accuracy using the Quasi-Zenith Satellite System correction signal has been validated in mountainous farmland [23]. RTK-GNSS evaluation on dynamic and static platforms against a total station ground truth is described in [24].

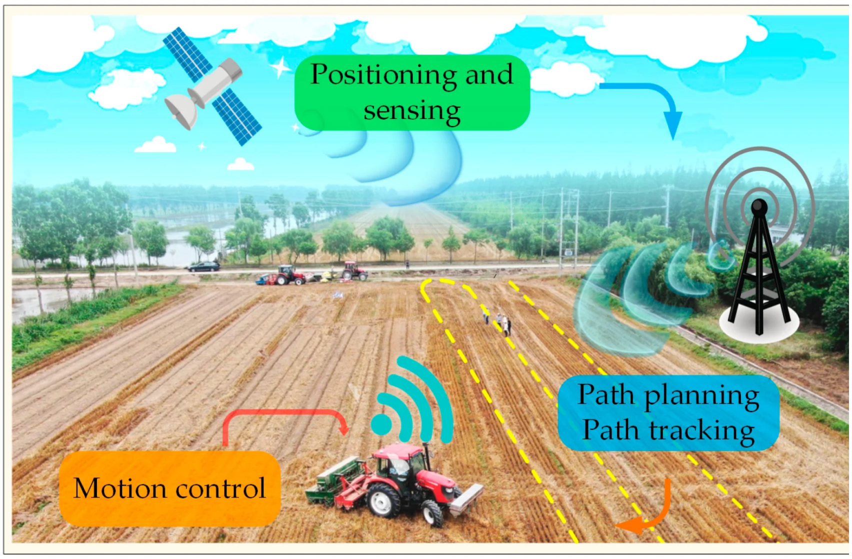

Figure 3. Path-planning and motion-control taxonomies for unmanned agricultural tractors [21].

A complete navigation stack ("FiWare"/Smart Navigation Manager) is developed in [25,26]: a high-level GOTO-GOAL command produces a motion profile, including orientation; Dubins and Spiral controllers manage Ackermann steering; and LiDAR-segmented safety zones trigger real-time path re-planning. The Reeds–Shepp curve [27] improves coverage efficiency over irregular field boundaries. Smooth headland turns using Dubins curves and spiral controllers with actuation-rate constraints are formalised in [28]. The entry/exit path planner in [29] uses the A* algorithm with vehicle turning-radius constraints and was validated on a 60 kW tractor.

Complete Coverage Path Planning (CCPP) has received substantial recent attention. The work in [3] presents a systematic CCPP approach for wheeled robots addressing field entry, irregular boundaries, and headland coverage; Ref. [30] extends this to 3D fields with terrain-inclination effects on soil erosion and energy consumption. The review in [4] proposes a three-stage methodology: guidance-track generation, traversal sequencing, and smooth drivable path generation. Headland coverage planning with continuous curvature and full tractor-implement geometry constraints is solved in [31], the first work to guarantee that field borders are not crossed during manoeuvres.

Obstacle avoidance using binarised Google Maps imagery is demonstrated in [32,33]; the minimum-snap algorithm adds vehicle kinematics (minimum curvature, jerk, and snap constraints) to obstacle-circumnavigation planning [34]. A hybrid semantic–topological–metric map with a novel switching algorithm [35] enables low-energy path planning by incorporating surface type and inclination. Multi-robot cooperative planning, where a UAV and UGV coordinate to locate and service insect traps in olive groves using YOLO-based identification and fiducial-marker landing, represents an emerging frontier [36]. It must be mentioned that the use of UAV imagery, proximal sensing, multispectral or hyperspectral data, and AI-based crop monitoring can provide useful information for autonomous robots, such as disease distribution, weed patches, crop growth status, and prescription maps, giving a dual use for real-time UAV imagery.

Path planning in agriculture is often task-dependent. For example, the best path for crop scouting, disease monitoring, selective spraying, weeding, or harvesting may not be the same. Table 1 uses information in [37] to show the relationship of different agricultural tasks with different navigation requirements, such as coverage efficiency, row following accuracy, target localisation, repeatability, and avoidance of crop damage.

A recent review of the control systems of agricultural robotics [38] emphasises that navigation requirements vary significantly across field operations. Tasks such as scouting prioritise coverage efficiency and mapping consistency, whereas precision operations like weeding or selective spraying demand centimetre-level trajectory tracking and accurate target localisation to avoid crop damage and minimise chemical use. Harvesting further introduces fine-scale positioning and safe interaction constraints, while many applications require repeatability across multiple passes for temporal monitoring or treatment alignment. Consequently, modern agricultural navigation systems must balance coverage planning, row following accuracy, perception-driven localisation, and robustness to unstructured terrain, with task-specific optimisation rather than a universal solution.

Table 1. Agricultural tasks and corresponding navigation requirements.

Agricultural Task	Primary Objective	Key Navigation Requirements	Why It Matters
Crop scouting/monitoring	Map crop health, detect stress	High coverage efficiency; moderate localisation accuracy; robust sensing	Efficient large-area coverage with consistent geo-referenced observations
Disease/pest monitoring	Detect specific plants/patches	Accurate localisation; revisit accuracy; sensor stability	Links observations reliably over time
Selective spraying	Apply chemicals selectively	cm-level localisation; precise path tracking; repeatability	Avoids over/under-application and reduces waste
Weeding	Remove weeds within/between rows	Very high row following accuracy; low lateral error; crop avoidance	Prevents crop damage from navigation errors
Harvesting	Pick crops or fruits	Precise positioning; stable motion; obstacle avoidance	Enables safe and accurate crop interaction
Field coverage	Uniform treatment (e.g., fertilisation)	Efficient coverage planning; obstacle avoidance; moderate accuracy	Optimises time and energy efficiency

A recent systematic review [39] of path-planning and trajectory-tracking methods covering 95 papers (2020–2025) identifies the absence of unified evaluation metrics as a critical barrier to cross-study comparison and proposes a unified framework based on lateral deviation, heading error, and RMSE (root mean square error).

2.4. Row Identification and Path Following

Crop row following imposes tighter navigation constraints than open-field traversal and is the primary operational mode for treatment, scouting, and harvest robots. The physical crop provides a navigable feature, but its variability—missing plants, wind motion, irregular growth, seasonal change—means that no deployed system handles all four failure modes reliably across a full growing season. Research publications accounted for 12% of the papers included in this review, with the majority originating from China and Southern Europe.

2.4.1. Classical Machine Vision and LiDAR

The monocular camera with classical machine vision (MV) remains competitive for edge computing in terms of speed and low power consumption [40], using Hough transforms, linear regression, blob analysis, and stereo disparity for weed/crop height discrimination [41]. The orchard vision system of [42] identifies the vanishing point against the sky background; Ref. [43] uses 3D LiDAR point-cloud histograms to locate crop row peaks without any camera. Fusing LiDAR with a camera [44] allows fast clustering, convex hull, and rotating-calipers algorithms, and the HSI colour space is shown to be optimal for green-vegetation segmentation.

The 3D row-sensing template method [45] matches a probabilistic voxel template to the current point cloud for pose estimation, as can be seen in Figure 4, the position can be approximated from the transition of the path to the foliage; at 5 m from the row end, the system automatically switches to a rear-looking camera to avoid template-matching degradation. Semantic 3D point-cloud interpretation using a convex canopy hull and polynomial approximation reduces computational cost for vineyard navigation [46]. LiDAR-only navigation under a broad-leaf canopy using heuristic stalk detection is validated on a small phenotyping robot [47]; the same principle applied to polytunnel mounting-pole detection is demonstrated in [48]. K-means clustering of LiDAR points for stalk-based row detection under dense canopy is described in [49].

Figure 4. 3D row-sensing template matching for localisation relative to orchard row centrelines [45].

Sensor fusion of 3D vision, LiDAR, and ultrasonics for inside-orchard row guidance is evaluated in [50]. A combination of ultrasonic distance sensors and mechanical feelers navigates vine trunk rows in [51]. AprilTag fiducial markers at row starts, combined with ultrasonic collision detection, support minimum-time row-transition control in [52]. GNSS–crop row switching for headland navigation is achieved in [53], where a feature map weighted by vegetation likelihood "snaps" the GNSS position onto a priori parallel line models.

Real-time crop row detection using unsupervised computer vision on a deployed agricultural robot—achieving detection at 15 Hz on embedded hardware—is reported in [54]. An RGB-D-based line-following sprayer using Otsu thresholding demonstrates classical MV scalability in semi-structured polytunnels [55]. Actively controlled NIR illumination substantially improves row-crop contrast against soil background in variable-light conditions [56]. A detailed comparison of camera types (monocular, stereo, RGB-D, NDVI) concludes that the monocular camera with classical processing remains the most deployable for edge devices, while deep learning methods handle challenging cases better [57].

2.4.2. Deep Learning for Row Identification

Deep learning methods are more robust than classical MV to occlusion, missing plants, plastic debris, varying illumination, and wind-induced crop motion under controlled conditions [57]. YOLO-based real-time weed identification is identified as optimal for variable-rate technology application under outdoor agricultural conditions [58]. The DGLNet neural network fuses crop row recognition with navigation-line extraction from a single RGB image, using a priori row-spacing as a prior [59]. Semantic segmentation of 3D LiDAR point clouds using a deep-learning downsampling strategy is presented in [60].

Monocular depth estimation through learned data augmentation eliminates the need for calibrated stereo pairs or active ranging in structured environments [61]. End-to-end navigation combining a depth image, a Convolutional Neural Network (CNN) heading classifier, and a parabolic speed–depth relation operates at 47 Hz with a reduced resolution (640 × 480) and MobileNet compression [62]. A complete virtual-world framework in Blender/Gazebo generates synthetic 3D crop datasets for rapid deep-learning iteration across seasons, times of day, and lighting conditions [63]. Weakly supervised area segmentation using edge-detection priors to reduce the manual labelling burden is validated on a combine harvester [64]. A tightly coupled GNSS–stereo–inertial SLAM system, providing a public benchmark dataset ("Rosario"), achieves smooth trajectories and reliable loop closure in arable fields [65].

Deep learning for real-time crop row detection achieving sub-row lateral deviations at commercial field speeds is validated in [66] across 11 crop varieties and initial heading offsets up to ±20°. The real-time segmentation approach of [67] uses a Deep Dual-Resolution Network (DDRNet23-slim) model with domain-generalisation and attention mechanisms, trained on a RUGD-based dataset with shared ontological classes (roads, trees, vegetation, obstacles), suitable for multi-season deployment.

2.5. Crop Identification and Handling

Crop identification underpins weed detection, row following, ripeness assessment, and infestation monitoring, and ref. [68] provides a comprehensive review of real-time phenotyping platforms across 142 papers, covering cable gantries, push carts, tractor-mounted systems, mobile robots carrying RGB sensors, and thermal, hyperspectral, LiDAR, stereo, and fluorescence sensors. Segmentation, feature extraction, classification, and SVM on RGB images form the dominant processing pipeline, with yield estimation, disease detection, and plant height as primary outputs. This is a mature research topic, accounting for over 40% of the reviewed papers, which are based in USA, Europe, China and Australia.

According to [69], weed losses account for 33% of crop loss with only 0.1% of conventional spray typically reaching the target area. Precision nozzle control (on/off, variable-rate, micro-dose at 4 g ha^{-1}) guided by in situ vision has been demonstrated commercially (Ecorobotix ARA, See & Spray from John Deere). Robot arms have demonstrated the ability to rotate the spray angle for better deposition and accurate quantity control [70] and Figure 5 shows the development of a light-weight robot arm mounted to a mobile base for spraying[71]. Selective harvesting using a robotic arm remains slower than human picking—a single pepper averages 24 s per pick [72]—with robotics currently deployed for strawberries [73], raspberries [74], and broccoli [75]. No robotic grape harvester has been demonstrated at commercial scale, primarily due to the irregular geometry of grape clusters and the sensitivity of fruit to contact forces.

Diode-laser weeding in cotton fields integrating YOLOv4 object detection with a finite state machine and ROS demonstrates autonomous weeding at TRL 5–6 [76]. UAV–UGV cooperation for insect trap monitoring in olive groves using YOLO and fiducial markers represents an early example of heterogeneous multi-robot crop management [36]. Space-Geometry-Intensity (SGI) fusion of LiDAR and camera for 3D obstacle detection and language-annotated object classification is advancing towards semantically rich scene understanding for crop environments [77].

https://doi.org/10.3390/computation14080194

Figure 5. Precision light-weight pesticide spraying robotic arm mounted to a mobile base [71].

2.6. Power Use and Environmental Impact

Autonomous path planning must consider energy consumption as a first-class constraint. The hybrid map used in path planning [35] incorporates surface type, inclination, and proximity to charging stations into path cost. Slip estimation and feedback control on tracked vehicles are addressed in [78–80], with the latter demonstrating superior curved-path guidance by reducing lateral deviation on low-traction surfaces. A model-free adaptive predictive path-tracking controller that accommodates heading deviation in real time is presented in [81].

Effector rotation direction is shown to affect power balance between drive wheels, opening a feedback loop for operational optimisation [51]. Battery-charge depletion logged per operational configuration provides the data for charge-informed speed profiling, analogous to eco-driving under low-fuel conditions [82] and Figure 6 demonstrates the permutations of the tasks in this work whereby a variety of tasks and autonomy are monitored and compared to assess efficiency.A comparison of navigation algorithms in terms of fuel consumption and operation time is made in [83]. The full lifecycle environmental performance of an autonomous laser weeder—from material specification through to disposal—is assessed in [84]. A 3D simulation environment for testing traversability from satellite-derived terrain models before field deployment is provided by AgROS [85].

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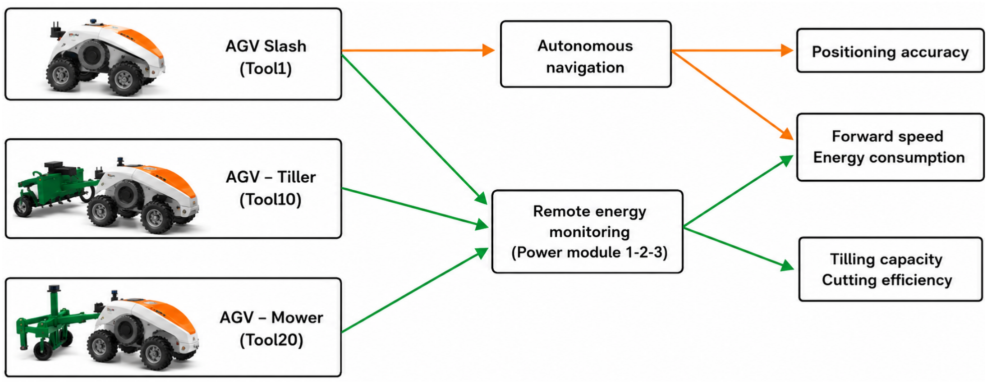

Figure 6. Energy consumption monitoring of an electric agricultural robot across operational configurations, taken from [82].

3. Deployability of Agricultural Path-Planning Systems

3.1. Deployability Assessment Framework

Technology Readiness Levels (TRLs), as defined by the European Commission and used in agricultural robotics contexts [86], provide a structured vocabulary for describing the maturity of a system from TRL 1 (basic principles observed) to TRL 9 (system proven in an operational environment). In agricultural robotics, "operational environment" implies uncontrolled field conditions across multiple seasons, crop types, and weather states, with human workers present and commercial service uptime requirements. The descriptive list of TRL levels applied to agricultural robots is used as follows:

1–3: Basic research and proof of concept.
4: Prototype system performance validated in test environment.
5: Prototype system performance validated in field trials, e.g., crop row following robots with real plant geometry and GNSS validation.
6: Prototype deployments in an operational environment, with a limited navigation scope and use of a sensor modality.
7: Application proven for a limited season, e.g., selective harvesting, pruning, and seeding.
8: Confidence in prototype through repeated testing throughout seasons.
9: Large-scale autonomous tractors and harvesters in commercial use, with a large navigation scope integrated with a precision input application and AI monitoring.

The Deployability Assessment Framework (DAF) introduced here extends the TRL taxonomy with three dimensions specific to agricultural path planning: navigation scope (open-field, row following, headland turning, or whole-farm), sensor modality (GNSS/IMU, monocular camera, stereo/RGB-D, LiDAR, or fused combinations), and validated performance (lateral deviation in cm, operational speed in $\mathrm{m\,s^{-1}}$, field area covered in ha, and number of seasons tested). Most published agricultural navigation systems report single-season, single-crop, single-site results, which corresponds to TRL 4–6 depending on replication.

Table 2 summarises TRL assignments for the principal path-planning families reviewed in this paper. Table 3 benchmarks commercially available or near-commercial platforms. Table 4 compares path-tracking accuracy from field-validated experiments.

Table 2. Technology Readiness Level assessment of agricultural path-planning approaches.

Planning Approach	TRL	Evidence Base	Key Limitation	Ref.
GNSS waypoint (open field)	9	Mass-market autosteer (John Deere, CNH, AGCO); >1 M units deployed	Requires RTK correction signal; sub-2 cm accuracy only with RTK	[24]
Pure pursuit/LQR (straight-line)	8–9	Validated on tractors and sprayers; core commercial autosteer algorithm	Degraded performance on curved paths and sloped terrain	[21]
CCPP with headland (Reeds–Shepp)	6–7	Laboratory and field trials on tractors and ground robots; irregular fields tested	No commercial product; headland geometry constraints only recently solved	[3,31]
Dubins/spiral controller (Ackermann)	7–8	Validated on full navigation stacks in arable fields; real-time re-planning demonstrated	Requires accurate vehicle kinematic model; limited slip compensation	[25,26]
Classical MV row following (Hough, regression)	6–7	Multi-crop trials; deployed in polytunnel and orchard settings	Fails with missing plants, strong shadows, and seasonal variation	[40,41]
LiDAR-only row following	6–7	Validated in orchards and maize; 3D histogram and template matching	Dust, rain, and dense low canopy degrade the point cloud	[43,49]
Sensor-fused (LiDAR + camera) row following	6–8	Demonstrated in vineyards, orchards, and maize; TRL varies by crop	Calibration drift; high computational demand; integration complexity	[44,53]
Deep learning row detection (CNN/YOLO)	5–7	Validated across 11 crop types [66]; real-time at 47 Hz [62]	Training data seasonally limited; domain shift across farms	[57,63]
SLAM-based localisation (outdoor)	5–7	GNSS–stereo–inertial SLAM validated in arable fields; public benchmark released	Loop closure in dynamic environments (crop growth, harvest) remains open	[65,87]
Whole-farm mission planning (semantic maps)	4–5	Prototype farm descriptions validated in simulation and controlled trials	Dynamic map updates, temporal consistency, and weather resilience unresolved	[16]
Multi-robot cooperative path planning	4–5	Leader–follower swarms validated; fleet routing demonstrated	Communication latency; decentralised conflict resolution at scale	[13,14]
Dynamic re-planning with real-time obstacle prediction	3–5	Research frameworks (AgriPath, A* variants) validated in simulation; limited field testing	Real-time computation on edge hardware; sensor-latency integration	[39,88]

Table 3. Commercially available and near-commercial autonomous agricultural platforms with path-planning capability.

Platform/Company	Application	Navigation	Path Planning	Sensing	TRL	Ref.
John Deere See & Spray	Selective herbicide	RTK-GNSS + vision	Pre-planned rows; vision-triggered spray	RGB cameras, RTK	9	[57]
CNH/Case IH AFS Connect	Arable tractor autosteer	RTK-GNSS	CCPP guidance tracks; headland assist	GNSS/IMU	9	[21]
Ecorobotix ARA	Precision weeding	RTK-GNSS + vision	Row-aligned spray path	RGB + AI	9	[57]
Kubota X-tractor concept	Arable tillage/mowing	6-motor electric drive, GNSS	Autonomous field coverage	GNSS, sensors	6–7	[54]
Carbon Robotics Laserweeder	Broadacre weeding	RTK-GNSS	Pre-planned pass coverage	RGB + deep learning	8–9	[58]
Burro (Augean Robotics)	Harvest assist	Vision + GNSS	Row following; harvest-assist path	RGB-D, GNSS	7–8	[89]
Dogtooth Tech	Strawberry harvesting	Row following	Fixed row traversal	RGB-D stereo	7–8	[73] [a]
Fieldwork Robotics	Raspberry harvesting	Row following	Fixed row traversal	RGB-D + arm	7	[74] [a]
EarthRover	Broccoli scouting/harvesting	Row following	Fixed row traversal	RGB + spectral	6–7	[75] [a]
Farm-ng Amiga	Multi-tool carrier	GNSS + vision	Between-row path	GNSS, cameras	7	[90]

[a] Vendor-claimed rather than independently reviewed.

Table 4. Field-validated path-tracking accuracy for agricultural robots: indicative but not comparable.

Reference	Platform Type	Terrain	Sensing	Mean Dev. (cm)	Max Dev. (cm)	Speed ($m\,s^{-1}$)
[91]	Orchard ground robot	Orchard	GNSS + SVM/A*	9.9	—	0.50
[24]	RTK-GNSS tractor	OVGH [b]	RTK-GNSS	<2	<5	1.40
[22]	Agricultural robot	Vineyard	Dual GNSS + IMU	3–8	—	0.80
[39] [a]	Tracked field robot	OVGH [b]	GNSS + vision	22.8	56.6	0.50
[92]	Tracked vehicle	Cultivated land	LiDAR slip-aware PP	7	18	0.75
[93]	High-clearance sprayer	Flat field	UAV-planned + RTK	±5.5	—	0.80
[28]	Ackermann tractor	Simulated open field	GNSS + Dubins	<10	—	0.50
[66]	Crop row follower	Sugar beet/maize	RGB CNN	5–15	—	0.40

[a] RMSE reported as 36.9 cm; uneven terrain identified as the dominant error source. [b] Open field, vineyard, greenhouse, and hilly terrain.

3.2. TRL Assessment of Path-Planning Approaches

Table 2 assigns TRL values to twelve path-planning families. The most significant finding is that the TRL gap between GNSS waypoint navigation (TRL 9) and vision-based row following (TRL 5–7) spans four to five levels despite extensive published work on the latter. In every sub-TRL 7 category, the limiting factor is the absence of multi-season, multi-crop field validation rather than algorithmic immaturity.

3.3. Commercial and Near-Commercial Platform Benchmarks

Table 3 lists eleven platforms; three (John Deere, CNH, Ecorobotix) of them have reached TRL 9 through GNSS-guided, pre-planned path operations where the sensor system activates a discrete output (spray or laser) rather than navigating dynamically within the row. Platforms that depend on row following for navigation—Burro, Dogtooth, Fieldwork Robotics, EarthRover—are rated TRL 7–8, reflecting vendor-claimed performance within constrained environments that do not yet cover all seasonal conditions.

3.4. Field-Validated Path-Tracking Accuracy

Comparing published tracking performance across studies is complicated by inconsistent evaluation protocols [39]. Table 4 collects field-experiment results where lateral deviation is explicitly reported under realistic field conditions. This table is indicative rather than comparable because of the variety of sensing modalities. RTK-GNSS-based systems consistently achieve <5 cm RMSE, while vision-only and LiDAR-only systems report 5–20 cm under ideal conditions, worsening with missing plants, low light, or terrain roughness.

3.5. Deployability Gaps and Transition Requirements

Drawing on Tables 2–4, four specific gaps impede the transition from TRL 6–7 to TRL 9 for whole-farm path planning.

(1) Unified evaluation protocols. The absence of standardised metrics (lateral deviation, RMSE, heading error, coverage completeness) and standardised test fields prevents cross-study comparison and slows community progress [39]. Although unified evaluation metrics have previously been proposed [39], the Deployability Assessment Framework is used to increase these metrics to compare and evaluate the application of autonomy in

functional agricultural scenarios. A benchmark analogous to KITTI for road vehicles is urgently needed for agricultural row following.

(2) Seasonal and cross-crop generalisation. Deep-learning navigation models trained on one crop, season, or lighting regime fail under domain shift. Further permutations are caused by disease stage, canopy structure, planting density, illumination, soil background and management practices. Synthetic dataset generation [63] and domain-adaptation techniques [77] are promising but not yet validated at scale. Shared ontological vocabularies (DDRNet23-slim classes; ISO 8373:2021 [15]) will accelerate this work.

(3) Headland and task-transition autonomy. Headland turning combines CCPP, kinematic constraints, terrain awareness, and implement management into a single complex event. While recent work [30,31] has substantially advanced headland path generation, real-world headland turning under degraded GNSS (canopy, terrain) with varying implements remains TRL 5–6.

(4) Slip, terrain, and energy integration. Path planning rarely integrates real-time terrain feedback. Slip-aware controllers [79,92] improve tracking accuracy on soft soil by 50–78% but are not yet integrated with global CCPP planners. Energy-optimal path planning [35] remains largely decoupled from slip and traction estimation.

4. Current and Future Challenges in Agri-Tech

4.1. Workforce and Training

Early deployments of autonomous agricultural machines require operators who understand both crop agronomy and the failure modes of autonomous systems. A robot that loses GNSS fix at the field boundary or whose vision system fails on a cloudy afternoon in late October must be recovered by someone who can diagnose the cause and restart the mission safely. This hybrid agronomist-technologist role does not yet exist as a defined profession; a UK white paper identifies the gap and recommends multi-disciplinary curricula spanning agronomy, robotics, data science, and machine operation [94]. The problem is particularly acute in developing-country contexts, where rural communities face competing pressures of labour displacement and the absence of the technical support infrastructure needed to maintain complex autonomous systems. Training programmes need to be designed around the actual on-farm failure modes documented in field trials, not around laboratory demonstrations.

4.2. Environmental Robustness and Dataset Coverage

Current path-planning and perception systems are routinely validated in good conditions—clear daylight, dry soil, healthy fully grown crop—and reported performance figures reflect this selection bias. Published lateral deviation results from Table 4 range from under 2 cm (RTK-GNSS on firm ground) to 57 cm (GNSS-vision fusion on uneven terrain), a range that reflects experimental conditions at least as much as algorithmic quality. No published study reports row following performance systematically across rain, mud, partial crop failure, and seasonal growth stages in a single trial.

Perception models are affected not only by crop type and season but also by disease stage, canopy structure, planting density, illumination, soil background, and management practices. LiDAR point clouds degrade under heavy rain due to water droplet backscatter; RGB cameras produce motion blur and reduced contrast; GNSS suffers multipath in wet soil and shadowing under dense canopy [22]. Addressing this requires deliberate data collection in adverse conditions, not just post hoc testing. Field datasets should be published in ROS2 bag format with documented topic schemas, GPS ground-truth tracks, and weather metadata, enabling models to be benchmarked under known conditions. The community has accumulated substantial data on typical sunny-day field conditions; the gap is in structured coverage of the failure envelope.

4.3. Platform Size, Power, and Communication

Power availability in rural fields constrains both vehicle size and operational duration. Large tractors drawing 100–400 kW can work continuously because their diesel tanks can be refilled at the field edge; battery-electric platforms of equivalent size would require either very large battery packs or frequent return trips to charge, both of which reduce effective field coverage. The engineering response has been to develop smaller platforms operating in swarms [6,14], which reduce soil compaction per pass and offer greater task flexibility. However, swarm coordination requires reliable low-latency communication, and LTE or 5G coverage in rural fields beyond 1 km from farm buildings is inconsistent in most agricultural regions [95]. Path planning for swarms must therefore be robust to communication dropout: each vehicle needs sufficient local autonomy to complete its assigned pass and return safely if contact with the fleet manager is lost. In-field charging using an autonomous tanker or fixed charging point has been demonstrated at TRL 6 [5] but adds logistical complexity that has not been analysed at whole-farm scale. Path-planning algorithms that explicitly minimise energy consumption per hectare covered, rather than treating energy as a post hoc metric, are needed and remain a research gap [35,83].

4.4. Computational Cost, Power Use, and Edge-Compute Dimension

Energy consumption is an essential consideration not only for the conservation of energy but also for the longevity of the hardware. Electrification is becoming a strong contender for vehicles in the farming environment; however, due to the limitations of energy storage, efficiency has become a priority. Systems are required to be 'self-aware' of their energy use and to optimise their functionality. High-performance edge computation—where the computing power is mounted on the robot—offers a faster sampling rate due to lower latency in computation at the expense of higher power use compared to a low-performance controller. Such a low-performance controller can introduce delays due to a reduced sample rate; similarly, cloud computing—where the computation is offloaded onto a remote server—can introduce delays due to communication and requires continuous connectivity. Sensor data from IMU, GNSS, LiDAR, ground RADAR, and encoders are combined using sensor fusion algorithms, which also require high computation capacities and sample rates.

4.5. Regulatory and Liability Frameworks

The transition from TRL 7 to TRL 8–9 requires navigating a regulatory environment that was not designed for autonomous field machinery. In the European Union, the EU AI Act classifies autonomous systems operating near humans as high-risk AI, requiring conformity assessment, technical documentation, and ongoing post-market monitoring [86]. Autonomous agricultural vehicles operating at speeds above 6 $\mathrm{km\,h^{-1}}$ in fields accessible to the public additionally fall under Machinery Regulation (EU) 2023/1230, which references EN ISO 25119 as the applicable functional safety standard for agricultural machinery control systems. EN ISO 25119 requires a systematic hazard analysis and risk assessment, definition of Agricultural Performance Levels (AgPL), and validation of safety functions to the specified AgPL—a process that typically takes 18–36 months for a new platform. No research-stage agricultural robot has publicly completed this process. The consequence is that any system reaching TRL 7 in a field trial cannot legally operate as an unsupervised commercial service in the EU without completing the certification process, regardless of demonstrated technical performance. Even if fully autonomous navigation becomes technically reliable, agricultural robots will still require human supervision because of regulatory constraints, liability concerns, safety around humans, unexpected field situations, communication failures, and environmental uncertainty. Liability for harm caused by an autonomous decision—crop damage from incorrect path execution, personal injury from a collision, equipment damage from a rollover—remains legally undefined in most jurisdictions. Current product liability frameworks assign responsibility to the manufacturer of a defective product, but when an AI system makes a decision that a human operator would not have made, responsibility is contested between the platform developer, the AI model supplier, the operator, and the farm owner. Until these liability questions are resolved, commercial insurers are unwilling to cover autonomous agricultural operations without a human supervisor present, which removes much of the economic case for autonomy. Standards bodies including ISO TC 23/SC 15 and ISO TC 299 are working on definitions and liability frameworks, but the timescale for resolution is likely a decade rather than years. Despite recent advances in autonomous navigation, regulatory, liability, and operational safety concerns continue to limit the deployment of fully unsupervised agricultural robots. As a result, near-term agricultural autonomy is likely to evolve through supervised and assisted-autonomy frameworks in which human operators remain actively involved in mission supervision and intervention. Technologies such as geofencing, remote teleoperation, digital shadow systems, and human-in-the-loop control architectures provide practical pathways for increasing operational safety while maintaining autonomous functionality in complex agricultural environments. Recent studies have demonstrated the feasibility of long-range teleoperation of agricultural mobile robots using local LoRa-based communication networks combined with digital shadow representations and ROS-integrated supervisory control, enabling remote intervention during challenging operations such as row-end turning and obstacle negotiation [96].

4.6. Path Planning for Whole-Farm Integration

The current state of the art treats individual navigation sub-problems—open-field coverage, row following, headland turning, obstacle avoidance—as separate research topics. Each has seen substantial progress when considered in isolation, as the TRL assignments in Table 2 confirm. The unsolved problem is integration: a deployed system must transition between all of these modes in a single uninterrupted operation, handling the degraded GNSS that occurs at field boundaries and under canopy, the change in sensor regime when entering and exiting crop rows, the implement state changes during headland turns, and the refuelling logistics at the field edge. The Mission Planner of [16] provides a semantic framework for representing these transitions, but does not resolve the sensor-switching and path-continuity problems that occur at each transition point. Even if fully autonomous navigation becomes technically reliable, agricultural robots will still require human supervision because of regulatory constraints, liability concerns, safety around humans, unexpected field situations, communication failures, and environmental uncertainty. Leader–follower systems [14] reduce the integration burden by keeping a human in the loop for the high-level sequencing, but the long-term research direction requires a unified path planner that maintains situational awareness across the full operational sequence. This requires tight integration of the global CCPP layer, the local row following controller, real-time terrain and traction feedback [79,92], and the fleet management layer [13]—a system-of-systems engineering challenge that has not yet been addressed as a whole.

5. Conclusions

Using a targeted literature search, this review assessed path-planning studies and enabling technologies for agricultural robotics against a deployability criterion based on Technology Readiness Levels (TRLs), field-validated performance, and operational robustness. The analysis confirms that GNSS-based open-field autosteer has reached TRL 9 with widespread commercial adoption, while crop row navigation based on classical machine vision, LiDAR, and deep-learning approaches remains largely within TRL 5–7 due to limited multi-season and multi-crop validation. Whole-farm autonomous operation, including seamless transitions among open-field traversal, row following, headland turning, obstacle avoidance, and task coordination, remains below TRL 5 on most reported platforms. The review demonstrates that the principal challenge in agricultural autonomy is no longer the absence of navigation algorithms, but the lack of robust system integration under real agricultural conditions. Open-field GNSS navigation is commercially mature, but true whole-farm agricultural autonomy remains unsolved because current systems are not sufficiently robust across seasonal variability, terrain conditions, sensing uncertainty, communication limitations, and operational transitions between navigation modes. Existing approaches typically solve isolated sub-problems under controlled conditions, whereas deployable agricultural robots must continuously adapt to changing illumination, crop morphology, wheel slip, degraded GNSS, weather variability, and the co-presence of humans and machinery within a unified operational framework. Four major barriers currently impede the transition from research-stage systems to fully deployable autonomous agricultural platforms: (1) the absence of standardised evaluation protocols and benchmark datasets for agricultural navigation; (2) limited generalisation capability of perception and deep-learning models across seasons, crops, and environmental conditions; (3) insufficient integration of terrain, traction, slip, and energy awareness into global path-planning frameworks; and (4) unresolved regulatory, safety, and liability pathways for autonomous operation in commercial farming environments. Future progress in agricultural robotics will therefore depend less on incremental improvements in isolated path-planning algorithms and more on the development of adaptive, integrated, and resilient system architectures. Robust multi-sensor fusion, distributed sensing networks, edge-based decision-making, communication-aware autonomy, and real-time terrain-adaptive navigation are likely to become the defining technologies enabling the transition from experimental field robots to scalable whole-farm autonomous systems.

Author Contributions: Data curation, F.A.C.; supervision, F.A.C.; visualisation, S.W. and F.A.C.; writing—original draft preparation, S.W. and F.A.C.; writing—review and editing, R.R.S., H.C. and W.G. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: No new data were created or analysed in this study. Data sharing is not applicable to this article.

Acknowledgments: During the preparation of this manuscript, the authors used ChatGPT 5.6-Sol for the purposes of creating Figure 1, enhancing Figure 6, and creating the graphical abstract. The authors have reviewed and edited the output and take full responsibility for the content of this publication.

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

Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
AIOTI	Alliance for Internet of Things Innovation
AgPL	Agricultural Performance Level
APC	Article Processing Charge
CCBY	Creative Commons Attribution
CCPP	Complete Coverage Path Planning

CNN	Convolutional Neural Network
Cobot	Collaborative Robot
DAF	Deployability Assessment Framework
DDRNet	Deep Dual-Resolution Network
DGLNet	Deep Guidance Line Network
EN ISO 25119	Agricultural Machinery Functional Safety Standard
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
GOTO	Go-To-Goal Navigation Command
HAM	Human-Aware Module
HRC	Human–Robot Collaboration
HRI	Human–Robot Interaction
HSI	Hue–Saturation–Intensity
IMU	Inertial Measurement Unit
ISO	International Organization for Standardization
KITTI	Karlsruhe Institute of Technology and Toyota Technological Institute Dataset
LiDAR	Light Detection and Ranging
LoRa	Long Range
LTE	Long-Term Evolution
LQR	Linear Quadratic Regulator
MPC	Model Predictive Control
MV	Machine Vision
NDVI	Normalised Difference Vegetation Index
NIR	Near-Infrared
PID	Proportional–Integral–Derivative
PP	Pure Pursuit
RGB	Red–Green–Blue
RGB-D	Red–Green–Blue with Depth
RMSE	Root Mean Square Error
ROS	Robot Operating System
ROS2	Robot Operating System 2
RTK	Real-Time Kinematic
RTK-GNSS	Real-Time Kinematic Global Navigation Satellite System
SGI	Space–Geometry–Intensity
SLAM	Simultaneous Localisation and Mapping
SVM	Support Vector Machine
SVR	Support Vector Regression
TRL	Technology Readiness Level
UAV	Unmanned Aerial Vehicle
UGV	Unmanned Ground Vehicle
UK RAS	United Kingdom Robotics and Autonomous Systems
YOLO	You Only Look Once

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