Under-Canopy Robotic Systems for Precision Cover Crop Seeding: Advancing Sustainable and Climate-Resilient Agriculture Through Intelligent Field Automation

Dr. Dong Hyun Kang [1*], **Dr. Jonathan A. MacDonald** [2]
[1-2] Department of Agricultural Electrification and Automation, Northwest A&F University, Yangling 712100, China

* Corresponding Author: **Dr. Dong Hyun Kang**

Article Info

P-ISSN: 3051-3421
E-ISSN: 3051-343X
Volume: 05
Issue: 01
Received: 19-07-2024
Accepted: 21-08-2024
Published: 23-09-2024
Page No: 84-90

Abstract

Cover cropping has emerged as a critical practice in sustainable agriculture, offering benefits including soil erosion control, nutrient cycling enhancement, and carbon sequestration. However, conventional cover crop establishment methods face significant challenges in timing, precision, and integration with cash crop management. The development of autonomous under-canopy robotic systems represents a transformative approach to precision cover crop seeding, enabling interseeding operations without disrupting standing crops. This article reviews the state-of-the-art in autonomous agricultural robots designed for under-canopy operations, focusing on system architectures, sensing technologies, navigation strategies, and precision seeding mechanisms. Key technological components include multi-modal perception systems combining LiDAR, stereo vision, and RTK-GPS for robust localization; adaptive navigation algorithms for crop row following and obstacle avoidance in cluttered environments; and pneumatic or mechanical seeding actuators with variable rate control. Applications span diverse cropping systems where robotic interseeding supports soil health improvement, weed suppression, and climate adaptation strategies. Despite promising advances, challenges remain in system robustness, energy efficiency, economic viability, and scalability for widespread farmer adoption. Future research directions emphasize enhanced autonomy through deep learning-based perception, multi-robot coordination for large-scale deployment, and integration with precision agriculture decision support systems to optimize seeding parameters based on real-time soil and crop conditions.

Keywords: Autonomous agricultural robots, under-canopy navigation, precision seeding, cover crops, sustainable agriculture, climate-smart farming

Introduction

Background of Cover Cropping and Mechanization

Cover crops are non-harvested plant species grown primarily to protect and improve soil health, suppress weeds, enhance biodiversity, and contribute to climate change mitigation through carbon sequestration [1, 2]. Traditional cover crop establishment involves broadcasting seeds after cash crop harvest or using conventional drilling equipment before or after the main crop growing season [3]. However, these approaches present temporal and operational constraints that limit adoption, particularly in regions with short growing windows or intensive cropping rotations [4].

Limitations of Conventional Seeding Methods

Conventional cover crop seeding methods encounter several critical limitations. Post-harvest broadcasting often results in poor seed-soil contact, reduced germination rates, and uneven establishment [5]. Pre-planting incorporation can interfere with cash crop establishment timing and compete for moisture and nutrients during critical growth phases [6]. Aerial seeding, while enabling late-season establishment, suffers from high seed costs, poor placement accuracy, and vulnerability to weather conditions [7]. Furthermore, none of these methods allow for interseeding—the practice of establishing cover crops into standing cash crops—which maximizes cover crop growing time and soil protection benefits [8].

Role of Autonomous Under-Canopy Robots

Autonomous under-canopy robots offer a paradigm shift in cover crop establishment by enabling precise interseeding operations within standing crop canopies [9, 10]. These systems navigate between crop rows, avoiding obstacles while delivering seeds with spatial and temporal precision unattainable through conventional methods [11]. By operating autonomously, these robots reduce labor requirements, enable optimal seeding timing independent of operator availability, and facilitate data-driven decision-making through integrated sensing capabilities [12, 13]. The convergence of advances in agricultural robotics, precision agriculture, and sustainable farming practices positions under-canopy robotic seeding as a key technology for climate-resilient agricultural systems [14, 15].

Autonomous Agricultural Robotics: An Overview

Under-Canopy Robotic Platforms

Autonomous agricultural robots designed for under-canopy operations represent a specialized class of field robots optimized for navigation in spatially constrained and visually complex environments. Unlike open-field autonomous vehicles, under-canopy robots must operate within crop rows with limited overhead clearance, navigate around plant stems and leaves, and function effectively under variable lighting conditions created by canopy shade. Platform designs range from compact wheeled robots weighing 50-200 kg for vegetable and specialty crops to larger tracked or four-wheel-drive systems for row crop applications in corn and soybeans.

Design Constraints and Field Challenges

Key design constraints for under-canopy robots include dimensional compatibility with crop row spacing, ground clearance sufficient to avoid crop damage, and mechanical robustness to withstand uneven terrain and plant contact. The under-canopy environment presents unique challenges: GPS signal degradation due to canopy interference, visual occlusion from dense foliage, dynamic obstacles from wind-induced plant movement, and soil surface variability affecting traction and stability. Successful platforms incorporate low center-of-gravity designs, independent suspension systems, and redundant sensing modalities to maintain reliable operation despite these challenges.

Relevance to Sustainable Agriculture

Under-canopy robotic systems directly support sustainable agriculture objectives by enabling conservation practices that would be impractical with conventional equipment. Precision interseeding reduces the need for tillage, minimizes soil disturbance, and extends ground cover duration, thereby reducing erosion and nutrient leaching. Autonomous operation enables optimal timing aligned with crop phenology and weather conditions, maximizing cover crop establishment success. Integration with variable rate technology allows site-specific seed application based on soil properties and crop vigor, optimizing resource use efficiency.

Robotic Systems for Under-Canopy Cover Crop Seeding

Mobile Robotic Platforms

Contemporary under-canopy seeding robots employ diverse mobility architectures tailored to specific crop systems and field conditions. Four-wheeled platforms with adjustable track width dominate row crop applications, offering stability and compatibility with standard row spacing (76 cm for corn, 38-50 cm for soybeans). These platforms typically feature electric or hybrid powertrains providing 4-8 hours of autonomous operation per charge, with power distribution supporting locomotion, sensing, computation, and seeding actuation. Advanced platforms incorporate active suspension systems that maintain chassis levelness on slopes up to 15 degrees while preserving ground clearance of 60-90 cm for mid-to-late season operations.

Table 1: Types of Autonomous Agricultural Robots Used for Under-Canopy Operations

Robot Type	Weight Range (kg)	Row Width Compatibility (cm)	Typical Crops	Primary Power Source
Compact wheeled	50-100	30-50	Vegetables, specialty crops	Battery electric
Medium row-crop	100-200	50-76	Soybeans, cotton	Hybrid electric
Heavy-duty tracked	200-400	76-90	Corn, sorghum	Diesel-electric
Multi-unit modular	40-80 per unit	30-76	Various row crops	Battery electric

Sensing and Perception Technologies

Robust perception constitutes the foundation of autonomous under-canopy navigation and operation. Multi-modal sensor suites combine complementary technologies to achieve reliable environmental understanding despite canopy-induced challenges. Light Detection and Ranging (LiDAR) sensors provide three-dimensional point clouds for crop row detection, obstacle identification, and terrain mapping, with 2D scanning LiDARs mounted horizontally for row-edge detection and 3D units for volumetric environment reconstruction. Stereo camera systems enable visual crop row following and plant-specific obstacle classification through depth perception, though performance degrades under low-light canopy conditions.

Table 2: Sensors and Perception Technologies for Under-Canopy Navigation

Sensor Type	Primary Function	Advantages	Limitations	Typical Range/FOV
2D Scanning LiDAR	Crop row detection	Lighting-independent, accurate	Limited vertical information	30 m range, 270° FOV
3D LiDAR	Obstacle detection, mapping	Full 3D reconstruction	High cost, data processing	100 m range, 360° horizontal
Stereo cameras	Visual navigation, classification	Rich semantic information	Light-sensitive, occlusion	10 m effective depth
RTK-GNSS	Absolute positioning	Global reference, cm-accuracy	Canopy signal degradation	N/A
IMU	Orientation, motion	High-rate, reliable	Drift over time	N/A
Ultrasonic sensors	Proximity detection	Low cost, simple	Limited range and resolution	0.5-5 m

Real-Time Kinematic Global Navigation Satellite Systems (RTK-GNSS) provide centimeter-level absolute positioning in open-field conditions, but signal quality and availability degrade significantly under dense canopies, necessitating sensor fusion with odometry and relative navigation methods. Inertial Measurement Units (IMUs) contribute orientation estimation and motion prediction, enabling robust state estimation when integrated with other modalities through Extended Kalman Filtering or particle filtering approaches.

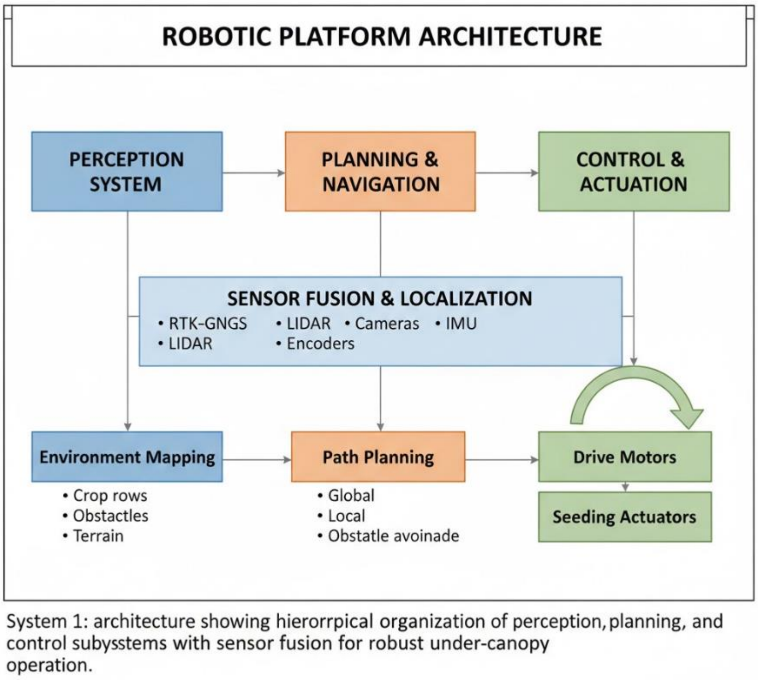
Seeding Mechanisms and Actuation Systems

Precision seeding under canopies requires actuation systems capable of accurate seed placement while accommodating variable crop residue and soil conditions. Pneumatic seeding systems dominate current implementations, utilizing vacuum or positive air pressure to singulate seeds and deliver them through flexible tubes to furrow openers positioned behind the robot chassis. These systems achieve seed spacing accuracy of ±2-5 cm at travel speeds of 0.5-1.5 m/s, with electric motor-driven metering wheels enabling dynamic rate adjustment based on prescription maps or real-time sensor inputs.

Table 3: Seeding Mechanisms and Precision Control Strategies

Mechanism Type	Seed Singulation Method	Placement Accuracy	Speed Range (m/s)	Suitable Seed Types
Pneumatic vacuum	Vacuum plate/belt	±2-3 cm	0.8-2.0	Small to medium grains, legumes
Pneumatic positive pressure	Air stream metering	±3-5 cm	0.5-1.5	Medium to large seeds
Mechanical cell	Rotating cell wheel	±4-6 cm	0.3-1.2	Large seeds, irregular shapes
Broadcast spreader	Centrifugal distribution	±10-20 cm	1.0-3.0	Small seeds, high-rate applications

Furrow opening mechanisms vary from simple coulter discs creating shallow trenches (2-4 cm depth) for small-seeded species to double-disc openers with depth-control wheels for larger-seeded legumes and brassicas. Closing wheels or drag chains follow the opener to ensure seed-soil contact and moisture retention. Variable rate control algorithms adjust seeding rates based on spatial prescription maps derived from soil electrical conductivity, elevation, or previous yield data, optimizing cover crop establishment for site-specific conditions.



s

Fig 1: Architecture of an Autonomous Under-Canopy Robotic System for Cover Crop Seeding

Navigation, Control, and Precision Seeding Strategies

Under-Canopy Localization and Mapping

Robust localization under crop canopies requires fusion of multiple complementary sensing modalities to overcome GNSS signal degradation and visual occlusion. State estimation frameworks typically implement Extended Kalman Filters or factor graph optimization combining RTK-GNSS measurements (when available), wheel odometry, IMU data, and visual or LiDAR-based relative positioning. In regions with complete canopy coverage, vision-based crop row detection and LiDAR edge tracking provide relative positioning references, enabling dead-reckoning navigation over distances of 50-100 m between GNSS updates.

Simultaneous Localization and Mapping (SLAM) techniques adapted for agricultural environments enable construction of local maps representing crop rows as geometric features (lines or curves) and obstacles as point clusters or polygonal boundaries. Graph-based SLAM implementations maintain pose graphs with nodes representing robot positions and edges encoding spatial constraints from sensor observations, enabling consistent map building over multi-hectare fields. These maps support path planning, enable return-to-position for interrupted operations, and facilitate multi-season data integration for temporal crop monitoring.

Obstacle Avoidance and Crop Row Following

Crop row following constitutes the fundamental navigation behavior for under-canopy robots, maintaining centered positioning within the inter-row space to avoid crop damage while enabling effective seeding operations. Vision-based approaches employ Hough transforms or Ransac line fitting to detect row edges from camera imagery, computing lateral offset and heading error for feedback control. LiDAR-based methods cluster point clouds into distinct row segments and extract medial axes or edge features, providing robust performance under variable lighting and plant density conditions.

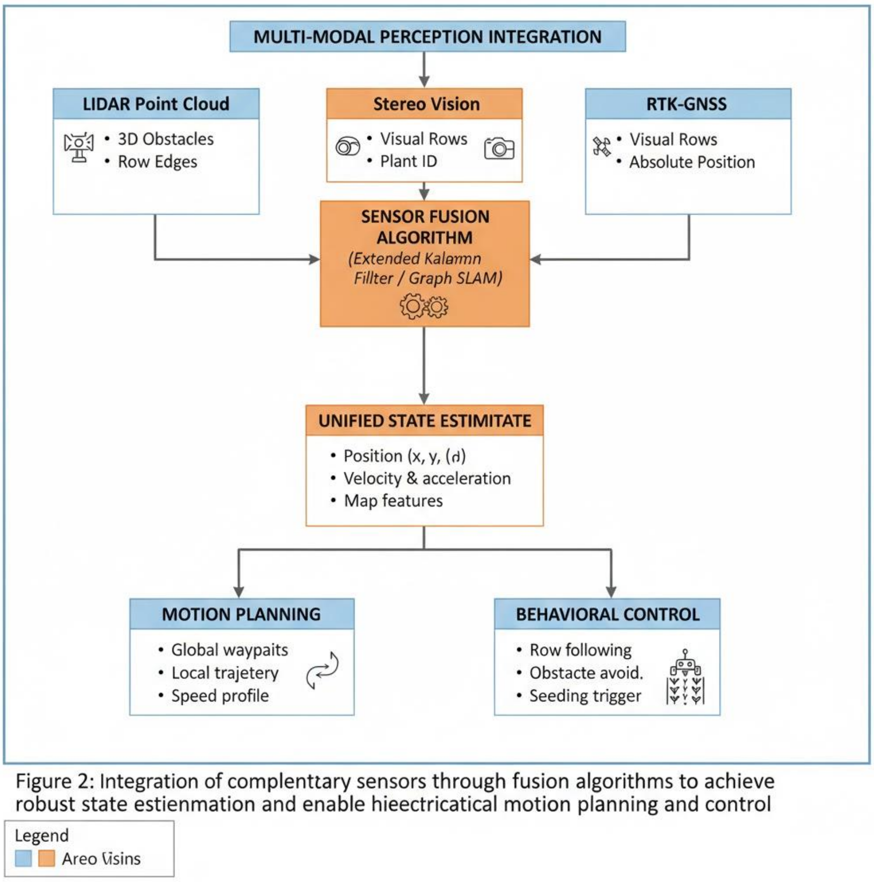


Fig 2: Sensor Fusion and Navigation Strategies for Under-Canopy Environments

Obstacle avoidance strategies distinguish between static obstacles (rocks, equipment, trees) and dynamic crop elements (leaves, stems) that may be safely contacted or deflected. Machine learning approaches, particularly convolutional neural networks trained on field imagery, enable semantic segmentation classifying scene elements as navigable space, crop plants, or obstacles requiring avoidance. Dynamic window approaches and model predictive control generate collision-free trajectories by predicting robot motion over short time horizons and selecting control inputs that maintain safety margins while progressing toward navigation goals.

Precision Seed Placement and Rate Control

Precision seed placement requires tight integration between navigation, actuation control, and real-time decision-making based on environmental sensing. Seed metering systems receive control commands from the central processing unit specifying target seeding rates (seeds per meter or per hectare) adjusted for travel speed and site-specific prescriptions. Feed-forward compensation accounts for system delays between metering activation and seed deposition, ensuring accurate placement despite robot motion.

Variable rate seeding algorithms process prescription maps defining seeding rates as functions of field position, derived from multi-year yield data, soil survey information, or real-time sensor measurements of soil moisture and organic matter. Look-ahead controllers anticipate seeding zone boundaries and adjust rates preemptively, minimizing transition errors at prescription zone edges. Some advanced systems incorporate real-time biomass sensing to detect gaps in cash crop stands and increase cover crop seeding rates in under-utilized areas, optimizing spatial resource allocation.

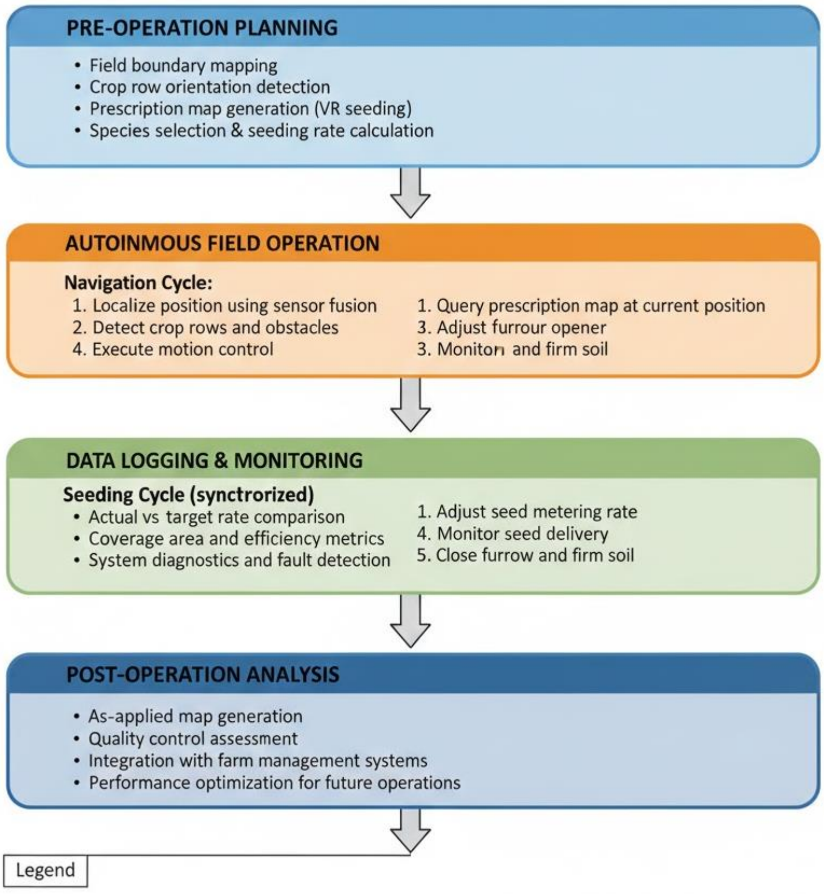


Fig 3: Workflow of Precision Cover Crop Seeding Using Autonomous Robots

Agricultural and Environmental Applications

Soil Health and Erosion Control

Robotic precision interseeding of cover crops provides substantial benefits for soil health improvement and erosion mitigation in intensive agricultural systems. Early establishment of cover crops through autonomous interseeding extends the period of living root presence in soil, supporting microbial communities and enhancing soil aggregate stability. Cover crop biomass produced through extended growing periods increases organic matter inputs, improving soil water holding capacity and nutrient retention. Research demonstrates that interseeded cover crops reduce soil erosion by 40-70% compared to post-harvest establishment, with robotic precision placement enabling optimal spatial distribution for erosion-prone field areas.

Weed Suppression and Nutrient Cycling

Strategic cover crop interseeding facilitated by autonomous robots supports integrated weed management by establishing competitive ground cover before weed emergence windows. Precision placement of allelopathic species such as cereal rye in specific field zones provides targeted weed suppression while minimizing interference with cash crops. Variable rate seeding algorithms enable increased cover crop density in weed-prone areas identified through historical weed mapping, optimizing suppression effectiveness.

Cover crop species selection and placement affect nutrient cycling dynamics, with legume covers fixing atmospheric nitrogen and non-legumes scavenging residual soil nutrients. Robotic systems enable species-specific seeding in precision patterns, such as alternating rows of nitrogen-fixing and nutrient-scavenging species to optimize nutrient capture and subsequent release timing. Multi-species cover crop mixtures established through sequential passes or multi-hopper seeding systems provide complementary rooting architectures and phenologies, enhancing overall ecosystem services.

Climate-Resilient Farming Systems

Autonomous cover crop interseeding contributes to climate change adaptation and mitigation objectives in multiple ways. Extended cover crop growing periods achievable through robotic interseeding increase photosynthetic carbon capture, with studies indicating 20-35% greater biomass accumulation compared to post-harvest seeding. This additional biomass enhances soil carbon sequestration rates, with long-term adoption potentially sequestering 0.3-0.6 Mg C ha^{-1} yr^{-1} in temperate agroecosystems.

Climate adaptation benefits include improved water infiltration and storage through enhanced soil structure, reducing vulnerability to both drought and excessive precipitation events. Deep-rooted cover crops established early via robotic interseeding access deeper soil moisture reserves and create macropore networks facilitating water movement, reducing surface runoff and flooding risk. Diversification of cropping systems through cover crop integration increases overall system resilience to climate variability and extreme weather events.

Challenges and Future Perspectives

Technical and Economic Barriers

Despite technological advances, several technical challenges constrain widespread adoption of autonomous under-canopy seeding robots [76]. Energy density limitations of current battery technologies restrict operational duration, with typical systems requiring recharging after 4-8 hours of continuous operation, limiting daily field coverage to 3-8 hectares depending on travel speed and field configuration. Robust operation under diverse environmental conditions—including wet soil, dense residue, and extreme temperatures—remains challenging, with reliability rates of 85-95% falling short of the >98% reliability expected for commercial agricultural equipment.

Economic barriers present significant adoption constraints, with current robotic seeding systems costing $150,000-$300,000, substantially higher than conventional seeding equipment. Return on investment calculations depend on labor cost savings, yield improvements from optimized cover crop establishment, and avoided soil degradation, with break-even farm sizes typically exceeding 200 hectares. Sharing economy models and custom robotic seeding services may reduce adoption barriers for smaller operations.

Table 4: Advantages and Limitations of Robotic Cover Crop Seeding Systems

Aspect	Advantages	Limitations
Operational	Enables optimal timing; reduces labor; operates in narrow windows	Limited daily area coverage; weather-dependent; requires field accessibility
Agronomic	Precise placement; variable rate capability; extended growing period	Soil compaction from traffic; potential crop damage; species/variety constraints
Technical	Data collection; repeatability; integration with precision ag	High initial cost; maintenance requirements; technology complexity
Environmental	Reduced soil disturbance; targeted input use; improved sustainability	Energy consumption; manufacturing footprint; end-of-life disposal
Economic	Labor savings; improved establishment; long-term soil benefits	High capital investment; uncertain ROI; limited service infrastructure

Scalability and Farmer Adoption

Scalability challenges encompass both technical capacity for large-field operations and socioeconomic factors affecting farmer decision-making. Current single-robot systems with coverage rates of 0.5-1.0 ha h^{-1} require multi-robot fleets or significant speed increases to service large commercial farms within narrow operational windows. Fleet coordination algorithms enabling multiple robots to work cooperatively while avoiding redundancy and collisions represent an active research frontier.

Farmer adoption requires not only demonstrated agronomic and economic benefits but also user-friendly interfaces, reliable service support, and integration with existing farm management workflows. Participatory design approaches involving farmers in robot development and field testing improve technology acceptance and identify practical usability requirements. Educational programs and demonstration projects reduce perceived risk and build operational competence among early adopters.

Future Research Directions

Future research directions span technological innovation, agronomic optimization, and system integration domains. Deep learning-based perception systems offer potential for more robust crop row detection, obstacle classification, and predictive modeling of plant growth dynamics to optimize seeding decisions. Reinforcement learning approaches could enable adaptive navigation strategies that learn optimal behaviors for diverse field conditions through experience.

Multi-robot systems with heterogeneous capabilities—including scouting robots for crop monitoring, seeding robots for cover crop establishment, and weeding robots for integrated weed management—could provide comprehensive autonomous crop management. Swarm robotics concepts may enable scalable field coverage through coordination of large numbers of small, low-cost robots.

Integration with digital agriculture ecosystems connecting robotic operations to farm management information systems, weather forecasting, soil sensing networks, and market information platforms will enable holistic decision optimization. Digital twin technologies creating virtual representations of fields and crops could support predictive simulation of cover crop performance under different seeding strategies, guiding autonomous robot planning.

Conclusion

Autonomous under-canopy robotic systems for precision cover crop seeding represent a transformative technology at the intersection of agricultural robotics, sustainable farming practices, and climate-smart agriculture. These systems overcome critical limitations of conventional cover crop establishment methods by enabling interseeding operations that extend growing periods, improve soil health, and enhance agroecosystem resilience. Technical advances in multi-modal perception, sensor fusion localization, and precision actuation have demonstrated feasibility of reliable autonomous operation in the challenging under-canopy environment. Key applications span soil erosion control, weed suppression, nutrient cycling optimization, and climate change adaptation, with quantifiable benefits for both environmental sustainability and long-term agricultural productivity.

Despite promising technological maturity, challenges remain in system robustness, energy efficiency, economic viability, and scalability for diverse farm sizes and cropping systems. Addressing these challenges requires continued interdisciplinary research integrating robotics, agronomy, economics, and social sciences. Future developments in artificial intelligence-based perception, multi-robot coordination, and digital agriculture integration promise to enhance system capabilities and accelerate adoption. As agriculture confronts increasing pressures from climate change, resource constraints, and environmental regulations, autonomous under-canopy seeding robots offer a practical pathway toward sustainable intensification—producing more food while regenerating soil resources and mitigating environmental impacts. The continued evolution and deployment of these systems will play a vital role in transitioning global agriculture toward more resilient and sustainable production paradigms.

References

1. Blanco-Canqui H, Shaver TM, Lindquist JL, *et al*. Cover crops and ecosystem services: insights from studies in temperate soils. Agronomy Journal. 2015;107(6):2449-2474.
2. Poeplau C, Don A. Carbon sequestration in agricultural soils via cultivation of cover crops – a meta-analysis. Agriculture, Ecosystems & Environment. 2015;200:33-41.
3. Appelgate SR, Lenssen AW, Wallander R, *et al*. Cover crop seeding systems: a review of alternative approaches. Agronomy Journal. 2021;113(4):3021-3038.
4. Singer JW, Nusser SM, Alf CJ. Are cover crops being used in the US corn belt? Journal of Soil and Water Conservation. 2007;62(5):353-358.
5. Kornecki TS, Price AJ, Raper RL, *et al*. Performance of different roller designs in terminating rye cover crop and reducing vibration. Applied Engineering in Agriculture. 2009;25(5):633-641.
6. Kaspar TC, Bakker MG. Biomass production of 12 winter cereal cover crop cultivars and their effect on subsequent no-till corn yield. Journal of Soil and Water Conservation. 2015;70(6):353-364.
7. Hunter MC, Sheaffer CC, Culman SW, *et al*. Effects of defoliation and row position on growth of an alfalfa-perennial grass mixture. Agronomy Journal. 2020;112(3):2287-2299.
8. Wilson ML, Allan DL, Baker JM. Aerially seeding cover crops in the northern US Corn Belt: limitations, future research needs, and alternative practices. Journal of Soil and Water Conservation. 2014;69(3):67A-72A.
9. Bakker T, van Asselt K, Bontsema J, *et al*. A vision based row detection system for sugar beet. Computers and Electronics in Agriculture. 2006;60(1):87-95.
10. Slaughter DC, Giles DK, Downey D. Autonomous robotic weed control systems: a review. Computers and Electronics in Agriculture. 2008;61(1):63-78.
11. Bergerman M, Billingsley J, Reid J, *et al*. Robotics in agriculture and forestry. In: Siciliano B, Khatib O, editors. Springer Handbook of Robotics. 2nd ed. Cham: Springer; 2016. p. 1463-1492.
12. Bawden O, Ball D, Kulk J, *et al*. A lightweight, modular robotic vehicle for the sustainable intensification of agriculture. In: Proceedings of the Australasian Conference on Robotics and Automation; 2014 Dec 2-4; Melbourne, Australia.
13. Grimstad L, From PJ. The Thorvald II agricultural robotic system. Robotics. 2017;6(4):24.
14. Lowenberg-DeBoer J, Huang IY, Grigoriadis V, *et al*. Economics of robots and automation in field crop production. Precision Agriculture. 2020;21:278-299.
15. Rose DC, Chilvers J. Agriculture 4.0: broadening responsible innovation in an era of smart farming. Frontiers in Sustainable Food Systems. 2018;2:87.