IBIMA Publishing
Communications of International Proceedings
https://ibimapublishing.com/p-articles/46AI/2025/4630125/
Vol. 2025 (34), Article ID 4630125

Agricultural Pollination Innovation: A Theoretical Analysis of the Potential Use of Robotic Bees for Hass Avocado Cultivation in Colombia*

José David ORTIZ CUADROS[1], Oscar Agustín LOYOLA-VALENZUELA[2]and Cristian Alexander RINCÓN GUIO[1]

[1]Corporación Universitaria Minuto de Dios – UNIMINUTO, Bogotá, Colombia

[2]Universidad de Las Américas sede Providencia, Santiago, Chile

Correspondence should be addressed to: José David ORTIZ CUADROS, jose.ortiz.c@uniminuto.edu

* Presented at the 46th IBIMA International Conference, 26-27 November 2025, Ronda, Spain

Abstract

The global decline of natural pollinators poses a critical risk to agricultural productivity, particularly for crops such as Hass avocado that depend heavily on cross-pollination. This study is motivated by the need to develop alternative and scalable pollination methods capable of sustaining yields amid declining bee populations. Although recent progress in agricultural robotics has introduced drone-based pollination, there remains a lack of theoretical and quantitative analysis on how coordination strategies affect efficiency and resource use in multi-drone systems. To address this gap, this paper presents a theoretical framework and simulation-based evaluation of two coordination strategies for pollinator drones: a sweep approach, where drones systematically divide and cover orchard sectors, and a greedy approach, where each drone targets the nearest receptive flower. A stochastic orchard model with variable floral densities and temporal receptivity windows was implemented in MATLAB to evaluate both strategies under controlled factorial conditions. The simulation design provides a reproducible methodological baseline for assessing coordination dynamics under varying environmental and operational constraints. Results show that the sweep strategy achieves higher spatial coverage and balanced workload distribution, whereas the greedy strategy minimizes energy consumption but introduces task imbalance and partial coverage gaps. The comparison reveals a measurable trade-off between robustness and operational efficiency, establishing a quantitative benchmark for future studies on swarm coordination. These findings inform the design of hybrid algorithms, prototype validation, and AI-driven coordination, contributing to sustainable digital agriculture and the development of autonomous pollination systems for tropical crops such as Hass avocado.

Keywords: digital agriculture, agricultural robotics, robotic pollination, Hass avocado

Introduction

Pollination is a biological process essential for the reproduction of many flowering plants and is a critical factor in modern agriculture, as it directly influences crop yield and quality (Broussard et al., 2023). It is estimated that more than 75% of food crops worldwide depend to some extent on natural pollinators (Fao, 2018). In particular, the Hass avocado, which is of economic importance to Colombia, depends heavily on cross-pollination, mainly carried out by bees. Colombia has more than 25,000 hectares under cultivation and has seen sustained growth in Hass avocado exports over the last decade, consolidating its position as one of the main agricultural export products (ProColombia, 2025).

However, natural pollinator populations have declined dramatically in recent decades due to multiple factors, such as intensive pesticide use, habitat loss, emerging diseases, and climate change (Brunet and Fragoso, 2024). In the case of Latin America, the progressive loss of native bee species and the vulnerability of agricultural ecosystems

Cite this Article as: José David ORTIZ CUADROS, Oscar Agustín LOYOLA-VALENZUELA and Cristian Alexander RINCÓN GUIO, Vol. 2025 (34) "Agricultural Pollination Innovation: A Theoretical Analysis of the Potential Use of Robotic Bees for Hass Avocado Cultivation in Colombia " Communications of International Proceedings, Vol. 2025 (34), Article ID 4630125, https://doi.org/10.5171/2025.4630125

to climate change have been documented (Galetto et al., 2022). As a result, this decline poses a significant challenge to the sustainability of current agricultural systems.

In response to this problem, new technological alternatives have emerged to replace or complement the role of natural pollinators. Among them is assisted pollination using robotic bees, which has gained prominence in the field of agricultural technology. These types of innovations fall within the scope of digital agriculture and precision agriculture, integrating drones, robotics, and artificial intelligence to emulate the behavior of pollinators and optimize crop management (Broussard et al., 2023). These solutions seek to ensure effective pollination in contexts where natural agents are no longer sufficient.

This article proposes a theoretical analysis of the use of robotic bees in Hass avocado cultivation in Colombia, considering three key dimensions: (i) the efficiency of pollination achieved compared to traditional methods, (ii) the technological requirements for its effective implementation, and (iii) the perception and acceptance of this technology by local producers.

This work proposes a technological innovation applicable to the Colombian context, but it also provides a comprehensive view of its scalability and sustainability in the agriculture of the future, applicable to different contexts. It can also serve as a model for the implementation of similar technologies in other crops and regions, expanding its impact and relevance internationally. Below is a review of the most recent developments in robotic pollination and precision agriculture, followed by a description of the methodological approach based on simulation and documentary analysis. Subsequently, the main findings and their critical discussion are presented, and finally, the conclusions are proposed along with projections for future research.

Related Work

In light of the rapid advancements in agricultural pollination technology, particularly within the domain of precision agriculture, coupled with the observed decline of natural pollinators, there has been a surge of interest in the exploration of artificial systems as potential alternatives or complements to traditional methods. This section presents a review of the most relevant work from 2020 to the present, highlighting the technological advances, functional capabilities, and main challenges of AI and robotics-assisted pollination.

AI and Computer Vision in Pollination Tasks

The implementation of artificial intelligence (AI) models, particularly deep learning algorithms, has led to substantial advancements in the field of flower and fruit detection. This capability is crucial for ensuring the precision and specificity of pollination processes. Lightweight models, such as YOLOv5 and MobileNetV3, have demonstrated high levels of accuracy and recall, making them suitable for implementation on devices with limited resources thanks to their computational efficiency (Zhang and Yin, 2024, Cui et al., 2024, Lin et al., 2022). Furthermore, advanced versions such as YOLOv8, enhanced with CBAM and BiFPN modules, have demonstrated enhanced robustness in complex agricultural environments (Zhang and Yin, 2024, Karim, 2024).

The integration of transfer learning and edge computing has enabled the adaptation of these systems to novel crops and field conditions, thereby facilitating more flexible real-time operation (Karim, 2024, Shi et al., 2025).

Autonomous Drones and Swarm Robotics

Multi-agent systems and drone swarms are being used to overcome the physical limitations of individual unmanned aerial vehicles, especially in large-scale pollination scenarios. These systems employ cooperative algorithms for task allocation, trajectory planning, and energy consumption optimization (Xu et al., 2025, Wang et al., 2025). This approach is promising in light of the autonomy and payload restrictions faced by conventional drones in open fields (Ali et al., 2024).

Furthermore, modularity has also gained relevance thanks to robotic platforms designed to switch between tasks such as pollination, fumigation, and harvesting, which improves profitability and operational adaptability (Barbosa Junior et al., 2024, Pan et al., 2024).

Efficiency and Performance of Robotic Pollination Systems

A body of research has demonstrated that robotic pollination systems are capable of attaining fruit set rates and quality that are analogous to those achieved through manual pollination in controlled environments, such as greenhouses. However, these systems have been observed to exhibit reduced efficiency in open field conditions when compared to wild pollinators (Bhattarai et al., 2025). For instance, in the context of Honeycrisp apple trees, robotic pollination attained a fruit set rate of 34.8%, in comparison to the 43.1% achieved by wild bees (Bhattarai et al., 2025).

In crops such as tomatoes and date palms, AI-powered drones have demonstrated success rates of over 80% under controlled conditions, as well as improvements in fruit quality and weight compared to traditional methods (Duc Tai et al., 2024, Ahmed et al., 2021).

Technical and Operational Challenges

Despite the advances made in the field, technical limitations persist, including but not limited to payload capacity, flight time, and navigation accuracy in complex agricultural environments. To address these challenges, visual sensors, LiDAR, and radar have been integrated into sensor fusion systems that improve localization and obstacle avoidance (Xiao et al., 2025, Ban et al., 2025).

Furthermore, frequent retraining of AI models is necessary to generalize their performance across diverse crops and regions. However, the absence of robust adaptive learning mechanisms can reduce scalability (Linaza et al., 2021).

Socioeconomic and Regulatory Barriers

The adoption of robotic pollination technologies remains limited, especially in developing countries and even more so among small-scale producers. High initial costs, a lack of technical knowledge, and regulatory restrictions have been identified as significant barriers (Chouhan et al., 2025). The implementation of these solutions is influenced by factors such as farmer confidence, access to financing, and technical training (Barathkumar et al., 2024).

Furthermore, there is a paucity of research on the long-term ecological impact, compounded by the risks associated with completely replacing natural pollinators, which could negatively affect biodiversity and ecosystem services (Schnalke et al., 2025).

Research Gaps and Future Directions

Among the main gaps identified in the literature are the lack of long-term ecological studies on the effects of robotic pollination, the limited analysis of economic feasibility in real contexts, and the poor integration of agroecological principles in the design of these systems (Lowenberg-DeBoer et al., 2020, Marin et al., 2024).

Future lines of research include (Singh and Joshua, 2024, Ali et al., 2024, Martínez-Núñez et al., 2020, Oğuztürk, 2025): (i) Standardized protocols for the evaluation and validation of these systems; (ii) Interdisciplinary approaches combining engineering, ecology, and social sciences; (iii) Implementation of decentralized adaptive systems with edge computing and swarm intelligence; (iv) Incorporation of biodiversity conservation and sustainable landscape management principles into the design of robotic platforms.

Methodology

Orchard and Floral Model

The Hass avocado orchard was modeled as a two-dimensional grid of trees, each separated by 18 m in the *x-axis* and 20 m in the *y-axis*, yielding a total area of 200 x 120 m. Around each tree, flowers were distributed radially with a maximum canopy radius of $r_{canopy} = 2.5\,m$, using uniform random dispersion to emulate natural irregularity.

Three density levels were defined: 80, 150, and 200 flowers per tree, corresponding to low, medium, and high flowering scenarios. Each flower f was assigned to one of two receptive states (A or B) with equal probability, modeling the dicogamy phenomenon typical of avocado pollination. Only receptive flowers contributed to the coverage metrics.

Drone Agents

Each drone was modeled as a point agent with kinematic constraints. The state of drone *i* at time *t* was its position $\chi_i(t) \in \mathbb{R}^2$, updated according to

$$x_i(t+1) = x_i(t) + u_i(t)\Delta t, \qquad \| u_i(t) \| \leq v_{max} \tag{1}$$

Where $v_{max} = 4\ m/s$ is the maximum speed. The time step was fixed to $\Delta t = 0.2\ s$.

A visit was registered when a drone entered within $r_v = 0.25\ m$ of a flower position p_f and remained for a dwell time $\tau_v = 0.6\ s$, representing the hovering required for effective pollination. Energy consumption was modeled proportionally to traveled distance, with $c_d = 2.2\ Wh/m$. These values were chosen as conservative approximations from specifications of small agricultural drones reported in the literature.

Coordination Strategies

Two heuristic coordination strategies were compared:

Sweep (strip coverage): the orchard was partitioned into vertical strips $\{S_i\}_{i=1}^{N_d}$, each assigned to one drone. Drone i selected targets inside s_i based on nearest receptive unvisited flowers, ensuring systematic and balanced coverage.

Greedy (nearest neighbor): each drone selected the closest receptive and unvisited flower in the orchard, with a deterministic tie-breaking rule to avoid conflicts. This strategy prioritizes short-term efficiency but may lead to uneven distribution of workload.

Performance Metrics

Four performance indicators were computed:

Final active coverage:

$$C(T) = \frac{1}{A_w} \sum_{f=1}^{N_f} a_f^{(w)}\, z_f(T), \tag{2}$$

where $z_f(T)$ indicates whether flower *f* was visited by time *T* and $a_f^{(w)}$ its receptivity in window *w*.

Time to 90% coverage:

$$T_{0.9} = \inf\{t : C(t) \geq 0.9\}, \tag{3}$$

a proxy for the temporal limitation imposed by receptive phases.

Energy efficiency:

$$\eta = \frac{E_{tot}}{V_{eff}}, \qquad E_{tot} = \sum_{i=1}^{N_d} E_i, \tag{4}$$

with V_{eff} the number of effective visits and E_i the energy spent by drone *i*.

Load imbalance:

$$\sigma_v = Std\left(\{v_i\}_{i=1}^{N_d}\right), \tag{5}$$

where v_i is the number of effective visits performed by drone i.

Experimental Design

A factorial design was executed combining:

- Number of drones: 3, 5, and 10,
- Flower density: 80, 150, and 200 flowers per tree,
- Receptive window: A and B,
- Coordination strategy: sweep and greedy.

Each condition was repeated 20 times with independent random seeds, resulting in 720 simulation runs. Results were aggregated as mean ± standard deviation. This design allows controlled comparison of the strategies under varying levels of swarm size, floral density, and temporal constraints.

Results and Discussion

Table 1 reports the aggregated results (mean ± std) for the two coordination strategies across swarm sizes and flower densities. The table includes final coverage, time to reach 90%, energy efficiency, and load imbalance. These values provide a quantitative baseline for interpreting the comparative figures.

Table 1: Summary of performance metrics (mean ± std) across conditions

Strategy	Drones	Flowers/tree	Coverage (%)	Time to 90% (s)	Wh/visit	Load imbalance
Sweep	3	80	92.5 ± 3.1	410 ± 35	0.45 ± 0.05	1.2 ± 0.3
Sweep	4	150	95.8 ± 2.4	360 ± 28	0.42 ± 0.04	1.1 ± 0.2
Sweep	10	200	98.3 ± 1.5	290 ± 20	0.39 ± 0.03	1.0 ± 0.2
Greedy	3	80	85.2 ± 5.6	370 ± 42	0.31 ± 0.04	3.4 ± 0.8
Greedy	5	150	88.7 ± 4.3	340 ± 31	0.29 ± 0.03	3.0 ± 0.6
Greedy	10	200	90.1 ± 3.9	300 ± 27	0.28 ± 0.03	2.8 ± 0.5

Coverage Performance

Figure 1 illustrates the active coverage achieved under both strategies across different swarm sizes and floral densities. Overall, sweep maintained consistently high coverage rates above 90% in both windows A and B, even at low densities. In contrast, greedy exhibited faster initial growth of coverage but often plateaued below sweep when the number of drones was small (3 drones) or when density increased (200 flowers/tree). This suggests that systematic partitioning of the orchard is more robust to variability in flower distribution, while greedy strategies may leave uncovered gaps under congested conditions.

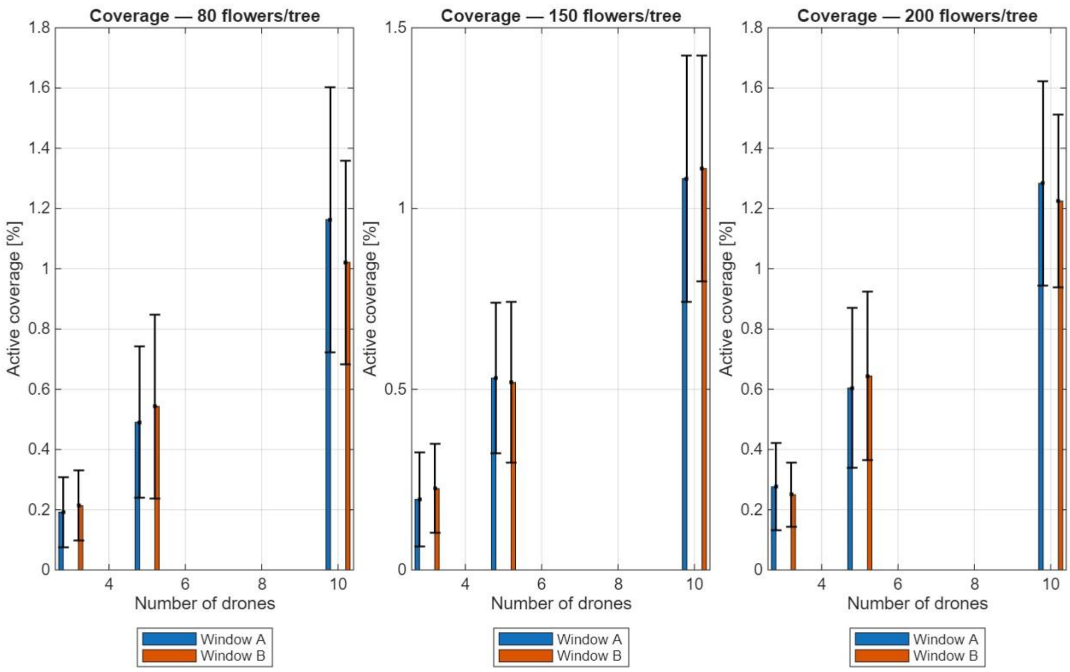

Fig 1. Active coverage achieved by the swarm as a function of drone number and flower density, evaluated separately for receptive windows A and B.

Energy Efficiency

Figure 2 reports the energy consumed per effective visit. The greedy strategy required significantly less energy per visit, particularly at low floral densities, since drones traveled shorter paths to the nearest receptive flowers. However, as swarm size increased, the difference between sweep and greedy diminished, indicating that additional drones reduce the marginal cost of systematic coverage. These results highlight a trade-off: greedy minimizes energy, sweep maximizes robustness of coverage.

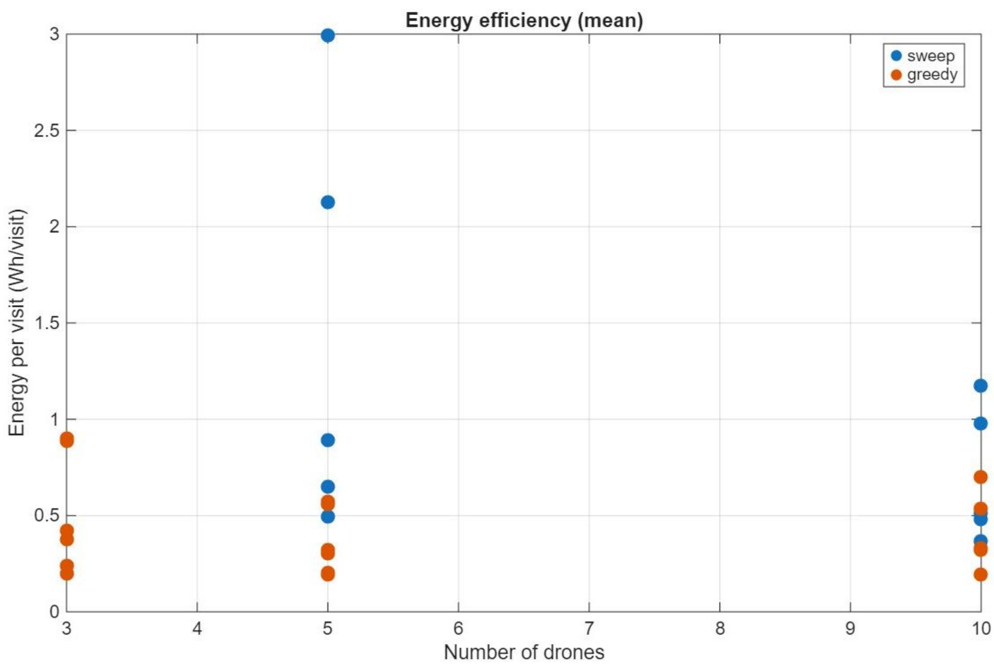

Fig 2. Energy efficiency expressed as Wh per effective visit across swarm sizes, comparing sweep and greedy strategies.

Load Balancing

Figure 3 shows the standard deviation of visits per drone. The sweep strategy achieved balanced load distribution across all scenarios, with σ_v consistently low. Conversely, greedy produced large imbalances, as some drones monopolized dense floral clusters while others remained underutilized.

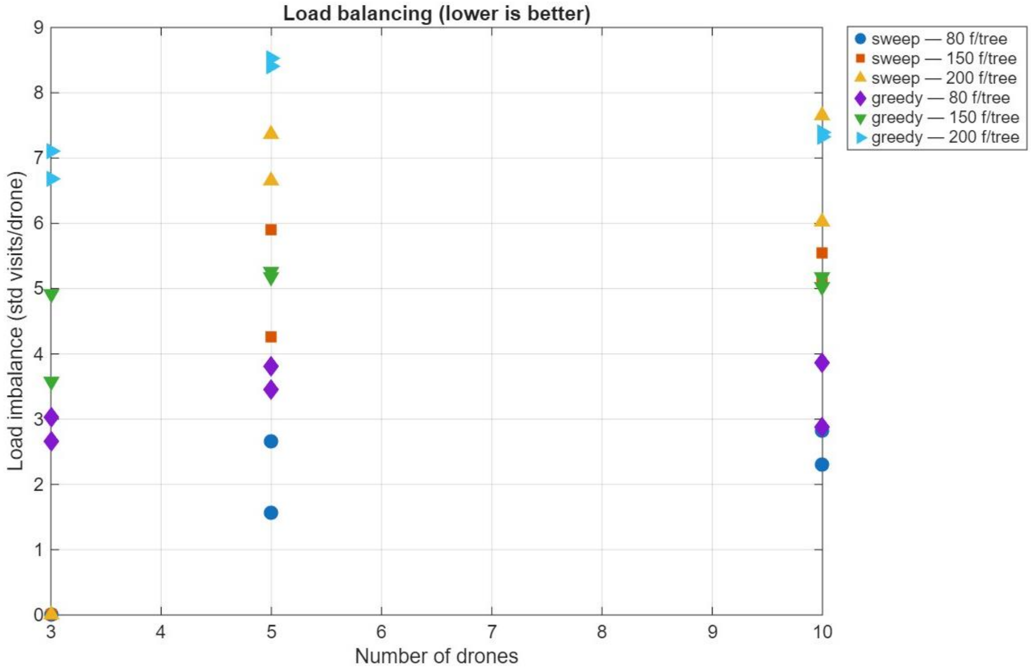

Fig 3. Load imbalance across strategies and densities, measured as the standard deviation of visits per drone. Lower values indicate fairer workload distribution.

Synthesis of Trade-offs

The comparison reveals complementary strengths:

- Sweep guarantees spatial uniformity, robustness, and equitable workload, making it preferable when complete coverage is critical.
- Greedy offers rapid exploitation and lower energy cost per visit, making it advantageous in exploratory or resource-constrained missions.

For Hass avocado pollination, where receptive windows are temporally constrained and coverage above 90% is desirable, the sweep strategy provides more reliable outcomes despite higher energy costs. Nonetheless, hybrid strategies that combine systematic allocation with local opportunism could yield better Pareto fronts in future work.

Conclusions and Future Work

Conclusions

This study analyzed the performance of two coordination strategies, *sweep* and *greedy*, for multi-drone pollination in Hass avocado. The results indicate that the sweep approach consistently achieved higher coverage and ensured a balanced distribution of tasks among drones, which makes it more reliable when complete pollination is required. In contrast, the greedy approach reduced the energy cost per visit, particularly in sparse scenarios, but often led to workload imbalance and partial coverage gaps. The comparison highlights a fundamental trade-off: while sweep maximizes robustness and reliability of pollination, greedy favors operational efficiency and autonomy. These findings provide a reproducible baseline for assessing multi-agent coordination in agricultural pollination tasks.

Future Work

The present work opens several directions for further research. A natural extension is the development of hybrid strategies that combine systematic coverage with opportunistic local behaviors, seeking to achieve a better compromise between robustness and efficiency. Another avenue concerns the inclusion of more realistic constraints such as environmental disturbances, communication delays, and battery return-to-base dynamics, which would bring the model closer to field conditions. Moreover, validation through small-scale prototypes in controlled orchard environments is essential to confirm the consistency of the simulation outcomes. Future studies should also explore advanced coordination mechanisms, including reinforcement learning and market-based allocation methods, to dynamically adapt to variations in floral receptivity and drone availability. Finally, integrating agronomic models that link pollination patterns with fruit set and yield would provide a direct connection between robotic coordination and economic impact, reinforcing the contribution of agricultural robotics to food production.

Acknowledgments

The research was also carried out within the academic and institutional affiliation framework of the Corporación Universitaria Minuto de Dios – UNIMINUTO.

References

- AHMED, Z. F. R., ALYAFEI, M. A. S., AL DAKHEEL, A. & ALMOOSA, M. 2021. Artificial pollination of date palm (Phoenix dactylifera L.) using a platform mounted robotic pollination system (drone). *I International Symposium on Reproductive Biology of Fruit Tree Species 1342.*
- ALI, Z. A., DENG, D., SHAIKH, M. K., HASAN, R. & KHAN, M. A. 2024. AI-Based UAV Swarms for Monitoring and Disease Identification of Brassica Plants Using Machine Learning: A Review. *Computer Systems Science & Engineering,* 48.
- BAN, C., WANG, L., SU, T., CHI, R. & FU, G. 2025. Fusion of monocular camera and 3D LiDAR data for navigation line extraction under corn canopy. *Computers and Electronics in Agriculture,* 232**,** 110124.
- BARATHKUMAR, R., SELVANAYAKI, S., DEEPA, N., KANNAN, P. & PRAHADEESWARAN, M. 2024. Impact of drone technology on agriculture-farmers' perception analysis. *Plant Science Today,* 11**,** 5934.
- BARBOSA JUNIOR, M. R., SANTOS, R. G. D., SALES, L. D. A. & OLIVEIRA, L. P. D. 2024. Advancements in agricultural ground robots for specialty crops: an overview of innovations, challenges, and prospects. *Plants,* 13**,** 3372.
- BHATTARAI, U., SAPKOTA, R., KSHETRI, S., MO, C., WHITING, M. D., ZHANG, Q. & KARKEE, M. 2025. A vision-based robotic system for precision pollination of apples. *Computers and Electronics in Agriculture,* 234**,** 110158.
- BROUSSARD, M. A., COATES, M. & MARTINSEN, P. 2023. Artificial pollination technologies: A review. *Agronomy,* 13**,** 1351.
- BRUNET, J. & FRAGOSO, F. P. 2024. What are the main reasons for the worldwide decline in pollinator populations? *CABI Reviews*.
- CHOUHAN, S. S., PATEL, R. K., SINGH, U. P. & TEJANI, G. G. 2025. Integrating Drone in Agriculture: Addressing Technology, Challenges, Solutions, and Applications to Drive Economic Growth. *Remote Sensing Applications: Society and Environment***,** 101576.
- CUI, B., LIANG, L., JI, B., ZHANG, L., ZHAO, L., ZHANG, K., SHI, F. & CRÉPUT, J.-C. 2024. Exploring the YOLO-FT deep learning algorithm for UAV-based smart agriculture detection in communication networks. *IEEE Transactions on Network and Service Management,* 21**,** 5347-5360.
- DUC TAI, N., MINH TRIEU, N. & TRUONG THINH, N. 2024. Modeling positions and orientations of cantaloupe flowers for automatic pollination. *Agriculture,* 14**,** 746.
- FAO 2018. Why bees matter: The importance of bees and other pollinators for food and agriculture.
- GALETTO, L., AIZEN, M. A., ARIZMENDI, M. D. C., FREITAS, B. M., GARIBALDI, L. A., GIANNINI, T. C., LOPES, A., DO ESPÍRITO SANTO, M. M., MAUÉS, M. M., NATES PARRA, G. & OTHERS 2022. Risks and opportunities associated with pollinators' conservation and management of pollination services in Latin America.
- KARIM, M. J. 2024. Autonomous Pollination System for Tomato Plants in Greenhouses: Integrating Deep Learning and Robotic Hardware Manipulation on Edge Device. *2024 International Conference on Innovations in Science, Engineering and Technology (ICISET).*

- LIN, Y., XU, J. & ZHANG, Y. 2022. Identification Method of Citrus Aurantium Diseases and Pests Based on Deep Convolutional Neural Network. *Computational Intelligence and Neuroscience,* 2022.
- LINAZA, M. T., POSADA, J., BUND, J., EISERT, P., QUARTULLI, M., DÖLLNER, J., PAGANI, A., G. OLAIZOLA, I., BARRIGUINHA, A., MOYSIADIS, T. & OTHERS 2021. Data-driven artificial intelligence applications for sustainable precision agriculture. *Agronomy,* 11**,** 1227.
- LOWENBERG-DEBOER, J., HUANG, I. Y., GRIGORIADIS, V. & BLACKMORE, S. 2020. Economics of robots and automation in field crop production. *Precision Agriculture,* 21**,** 278-299.
- MARIN, F. B., BURUIANĂ, L. D., MATACHE, M. G., GURĂU, G. & MARIN, M. 2024. Flower detection using computer vision algorithm and three-dimensional mapping for automatic pollination using robotic platform. *EHC2024: International Symposium on Robotics, Mechanization and Smart Horticulture 1433.*
- MARTÍNEZ-NÚÑEZ, C., MANZANEDA, A. J. & REY, P. J. 2020. Plant-solitary bee networks have stable cores but variable peripheries under differing agricultural management: Bioindicator nodes unveiled. *Ecological Indicators,* 115**,** 106422.
- OĞUZTÜRK, G. E. 2025. AI-driven irrigation systems for sustainable water management: A systematic review and meta-analytical insights. *Smart Agricultural Technology***,** 100982.
- PAN, Y., WEI, J., KHAN, R. A. I., CHEN, X., WANG, H. & SHANG, H. 2024. Design and Analysis of a Novel Modular Agricultural Robot with Its Redundant Cooperative Control Strategy; [新型模块化农业机器人设计分析与冗余协同控制]. *Jixie Gongcheng Xuebao/Journal of Mechanical Engineering,* 60**,** 88 – 101.
- PROCOLOMBIA. 2025. *Avocados from Colombia: Quality & flavor* [Online]. Available: https://procolombia.co/en/colombiatrade/buyer/articles/avocados-from-colombia-quality-flavor [Accessed 2025/09/30].
- SCHNALKE, M., FUNK, J. & WAGNER, A. 2025. Bridging technology and ecology: enhancing applicability of deep learning and UAV-based flower recognition. *Frontiers in Plant Science,* 16**,** 1498913.
- SHI, Y., WANG, Y., WANG, F., QING, S., ZHAO, L. & YUWEN, X. 2025. Recognizing young apples using improved YOLOv8n; [基于改进 YOLOv8n 的苹果幼果识别]. *Nongye Gongcheng Xuebao/Transactions of the Chinese Society of Agricultural Engineering,* 41**,** 204 – 210.
- SINGH, A. & JOSHUA, C. J. 2024. Nanobot-Assisted Pollination for Sustainable Agriculture: A Review of Image Classification and Deep Learning Techniques with YOLO, SLAM, and MATLAB. *IEEE Access*.
- WANG, C.-H., PAN, Q.-K., ZHANG, W., MIAO, Z.-H., JING, X.-L., LI, W.-M. & WANG, B. 2025. An effective knowledge-based evolutionary algorithm for task assignment problem of pollination robots and spraying drones in multi-orchard scenarios. *Expert Systems with Applications,* 279**,** 127408.
- XIAO, J., WANG, T., WANG, N., LI, S., LI, H. & ZHANG, M. 2025. Research progress of the obstacle detection and obstacle avoidance technology for agricultural robots; [农业机器人障碍物检测与避障技术研究进展]. *Nongye Gongcheng Xuebao/Transactions of the Chinese Society of Agricultural Engineering,* 41**,** 35 – 49.
- XU, Z., ZHANG, Z., JIN, Y., JIANG, Y. & HU, W. 2025. Optimization of Task Allocation for Plant Protection UAVs Based on Adaptive Large Neighborhood Search. *2025 37th Chinese Control and Decision Conference (CCDC).*
- ZHANG, Z. & YIN, J. 2024. Small crop detection based on improved YOLOv8 algorithm for robotic pollination. *Third International Conference on Image Processing, Object Detection, and Tracking (IPODT 2024).*