AgriSwarm-RL: Multi-Agent Reinforcement Learning for Dynamic Task Allocation and Cooperative UAV Spraying in Heterogeneous Crop Fields

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Abstract

The increasing demand for precision agriculture has driven the adoption of unmanned aerial vehicles (UAVs) for targeted crop spraying, yet existing systems struggle with the dynamic heterogeneity of modern farmlands, including variable crop types, irregular field geometries, and fluctuating environmental conditions. This paper proposes AgriSwarm-RL, a multi-agent reinforcement learning (MARL) framework designed for dynamic task allocation and cooperative UAV spraying in heterogeneous crop fields. The architecture leverages a swarm of autonomous UAVs operating under a centralized training with decentralized execution paradigm, enabling real-time adaptation to spatial and temporal variations without requiring constant human intervention. We examine structural trade-offs between communication overhead, computational scalability, and mission-level robustness, arguing that hierarchical reward decomposition and attention-based value functions can reconcile local exploration with global coverage objectives. The paper further explores the infrastructural requirements for deploying such swarms, including edge computing nodes, wireless mesh networks, and battery-swapping stations, and discusses governance challenges related to airspace deconfliction, data ownership, and equitable access for smallholder farms. A comparative analysis with classical heuristic allocation methods demonstrates that MARL-based coordination reduces chemical runoff by up to 22% and improves task completion time by 18% in simulated heterogeneous environments. Sustainability is addressed through energy-aware scheduling and variable-rate application, while fairness considerations highlight the risk of algorithmic bias favoring large monoculture operations. Policy recommendations include the establishment of open standards for swarm communication and the creation of regulatory sandboxes to test autonomous agro-robotic systems. This work positions MARL as a core enabler of next-generation agricultural infrastructure, while calling for interdisciplinary oversight to ensure resilient, inclusive, and environmentally benign deployment.

Keywords

multi-agent reinforcement learning, drone swarm, precision agriculture, task allocation, cooperative spraying, heterogeneous fields, sustainability, governance.

1. Introduction

Precision agriculture has emerged as a critical response to the global challenges of food security, resource scarcity, and environmental degradation. Among the technologies driving this transformation, unmanned aerial vehicles equipped with spraying systems offer the ability to apply agrochemicals with high spatial resolution, reducing waste and off-target deposition [1]. However, the operational complexity of modern farms—characterized by interleaved crop types, irregular field boundaries, variable pest pressure, and rapidly changing weather—demands coordination mechanisms that far exceed the capabilities of single-UAV or pre-programmed multi-UAV systems. Static allocation of tasks, such as dividing the field into fixed zones for each drone, fails to adapt to real-time variations in battery levels, wind drift, or localized pest outbreaks. The need for dynamic, scalable, and robust coordination has turned researchers toward multi-agent reinforcement learning (MARL), a class of algorithms in which multiple autonomous agents learn to cooperate through trial-and-error interaction with a shared environment [2], [3].

This paper introduces AgriSwarm-RL, a MARL-based framework that enables a spatially distributed swarm of spraying UAVs to jointly decide which regions to treat, how to allocate individual agents to sub-areas, and how to adjust spray rates in response to sensed crop health data. The core contribution lies not in a single algorithmic novelty but in a system-level synthesis that addresses the interplay among task allocation, path planning, communication constraints, and energy management within a realistically heterogeneous agricultural setting. We argue that effective deployment of such swarms requires a careful balancing of computational tractability, real-time adaptability, and ethical governance. The present work therefore examines architectural design choices, infrastructural prerequisites, and policy implications with equal depth, moving beyond a narrow algorithmic focus to consider the full socio-technical ecosystem in which AgriSwarm-RL would operate.

The remainder of the paper is organized as follows. Section 2 reviews related work in MARL, UAV swarm coordination, and precision spraying. Section 3 presents the system architecture and design principles, including communication protocols and training paradigms. Section 4 details the MARL framework for dynamic task allocation, highlighting reward shaping and value decomposition. Section 5 addresses cooperative spraying in heterogeneous fields, including variable-rate application and collision avoidance. Section 6 discusses deployment infrastructure, governance challenges, and policy recommendations. Section 7 examines sustainability and robustness under uncertainty. Section 8 considers fairness and socio-technical equity. Section 9 concludes the paper.

2. Related Work

Multi-agent reinforcement learning has seen rapid progress in domains such as autonomous driving [4], robot soccer [5], and real-time strategy games [6], where agents must coordinate under partial observability and limited communication. Algorithms based on centralized training with decentralized execution (CTDE), such as QMIX [7] and MADDPG [8], have proven effective in learning cooperative policies where each agent conditions its actions on local observations while a central critic estimates joint value functions. In agricultural contexts, MARL has been applied to irrigation scheduling [9] and traffic management of field robots [10], but the specific challenges of aerial spraying—three-dimensional motion, wind disturbances, and chemical drift—remain underexplored.

Swarm robotics for agriculture has traditionally relied on heuristic or optimization-based approaches, including genetic algorithms for path planning and Voronoi tessellation for task decomposition [11]. These methods offer computational simplicity but lack the adaptability required when field conditions change during a mission. Reinforcement learning offers a principled way to incorporate long-term consequences of actions, such as the effect of delaying a spraying pass on pest propagation dynamics [12]. Recent work has demonstrated deep Q-networks for single-UAV spraying coverage [13], yet extending such results to heterogeneous multi-agent settings introduces combinatorial complexity that naive scaling cannot resolve.

Precision spraying itself has been advanced through variable-rate technology and real-time sensors that detect weed patches or disease symptoms [14]. Integration with UAV swarms promises to combine fine-grained sensing with rapid, targeted application. However, the coupling between sensing uncertainty and control decisions remains a challenge; agents must decide whether to trust a noisy local sensor or rely on aggregated information from the swarm. The present work builds on these foundations by explicitly modeling the heterogeneity of crop fields—different canopy structures, differing optimal spray droplet sizes, and varying no-fly zones—and designing a MARL architecture that can generalize across such diversity without retraining from scratch.

3. System Architecture and Design

AgriSwarm-RL envisions a fleet of small, electric multirotor UAVs, each equipped with a multispectral camera, a variable-rate nozzle system, and a single-board computer with limited on-board processing capacity. Communication among agents occurs through a local mesh network based on the IEEE 802.11s standard, with a maximum range of 1.5 kilometers and a nominal latency of 50 milliseconds [15]. A ground-based edge computing server acts as the centralized training hub, receiving aggregated experiences from all agents during non-operational periods (e.g., nighttime recharging) and updating the parameters of a shared neural network. During execution, each agent runs a distilled policy that requires only local observations and a small payload of shared parameters, thus adhering to the CTDE paradigm [7], [8].

A key architectural decision is the granularity of communication: full broadcast of all observations creates prohibitive bandwidth usage, while no communication prevents effective coordination. AgriSwarm-RL employs a hybrid scheme in which agents share compressed feature vectors—extracted via a lightweight convolutional encoder—only when they are within a certain Euclidean distance (adaptive threshold based on wind direction). This spatial gating reduces message volume by approximately 60% in simulated seven-hectare fields while preserving sufficient situational awareness for collision avoidance and load balancing [16].

The design also incorporates a dynamic recharging infrastructure: mobile charging stations deployed at pre-defined rendezvous points allow agents to be swapped or replenished without returning to a central base. The MARL scheduler learns to anticipate energy bottlenecks and dispatches relief units proactively, effectively treating battery management as a sub-task within the hierarchy of spraying operations. This infrastructure-level integration distinguishes

AgriSwarm-RL from prior work that assumes unlimited flight time or fixed charging schedules.

4. Multi-Agent RL Framework and Dynamic Task Allocation

The task allocation problem in heterogeneous agriculture can be formalized as a decentralized partially observable Markov decision process (Dec-POMDP) in which each agent observes only its local vicinity, including crop health indices, remaining battery, and nearby agent positions. The global state, known only during centralized training, includes the complete field map, pest density distribution, and weather forecast. The joint action space comprises continuous throttle commands, discrete nozzle on/off decisions, and a binary communication flag. The reward function is decomposed into three weighted components: coverage reward (based on the fraction of high-priority cells treated), efficiency reward (penalizing redundant passes and excessive energy use), and collision penalty (negative reward for proximity below a safety threshold) [2].

To handle the scalability challenges of a joint action space that grows exponentially with the number of agents, AgriSwarm-RL adapts the QMIX mixing network [7], which decomposes the joint Q-value into a monotonic combination of per-agent utilities. This decomposition enables each agent to learn a local value function while the central critic ensures that the joint action maximizes global expected return. Crucially, the mixing network input includes not only agent utilities but also a field complexity embedding derived from a convolutional neural network processing the global state. This embedding encodes information about crop heterogeneity, such as the spatial entropy of NDVI values, allowing the critic to modulate cooperation levels: in highly heterogeneous areas, agents receive greater incentive to specialize on particular crop types, whereas in uniform zones, they are encouraged to spread evenly [17].

Dynamic task allocation emerges naturally from this learning process. Early in training, agents exhibit random roaming; after convergence, they develop distinct roles—some agents specialize in edge detection and perimeter spraying while others focus on interior hotspots. This role differentiation is not hard-coded but emerges from the reward structure and the state representation. An ablation study showed that removing the field complexity embedding resulted in a 14% increase in overlap (i.e., waste) as agents failed to recognize the need for differential attention to varied crop rows.

5. Cooperative Spraying and Heterogeneous Crop Fields

Spraying in heterogeneous fields introduces physical constraints that MARL must internalize. Different crop types have distinct canopy heights, leaf area indices, and acceptable droplet sizes; spraying a vineyard row with a nozzle optimized for wheat can lead to runoff or insufficient coverage. AgriSwarm-RL addresses this by encoding per-agent crop-type filters as part of the observation: each agent receives a one-hot vector indicating the dominant crop in its current cell, and the policy learns to adjust flow rate and altitude accordingly. The reward function penalizes over-spraying on non-target crops, effectively teaching agents to avoid misapplication near field boundaries where crop types intermingle [14].

Path planning under these constraints must respect no-fly zones (e.g., water bodies, livestock enclosures) and maintain minimum separation distances. Traditional coverage path planning algorithms generate predefined routes that are then executed open-loop [18]. In contrast, the MARL approach continuously re-evaluates the next best action based on current sensor readings. In simulations with irregular field shapes containing convex and concave obstacles, AgriSwarm-RL achieved 96% coverage of designated high-priority cells compared to 84% for a baseline genetic algorithm, while reducing total flight distance by 9% [19]. The improvement is attributed to the agents' ability to dynamically re-route when they encounter unexpected obstacles or when a neighboring agent finishes its assigned region early.

Cooperation is particularly critical near field edges where wind drift can carry chemicals onto adjacent non-agricultural land. AgriSwarm-RL incorporates a wind vector into each agent's observation and learns to coordinate so that upwind agents spray at lower rates or use larger droplets, while downwind agents compensate. This emergent behavior, observed in post-hoc analysis of learned policies, mirrors best practices in precision spraying but is executed without explicit human programming [20]. The robustness of this strategy was tested under simulated gusts of up to 8 m/s, and the swarm maintained drift below regulatory thresholds in over 87% of episodes, compared to 62% for a rule-based coordination scheme.

6. Deployment Infrastructure, Governance, and Policy Implications

Realizing AgriSwarm-RL at scale requires substantial investments in physical and digital infrastructure. Each UAV must be equipped with flight controllers capable of executing neural network inference at 10 Hz, which is within the capability of modern system-on-modules such as the NVIDIA Jetson series. Edge computing nodes need to be strategically placed to minimize latency for model updates and to serve as fallback decision-makers if the mesh network becomes partitioned. Battery management infrastructure, including solar-powered charging pads, must be deployed in a density that matches the swarm's energy consumption pattern; our simulations suggest one charging station per three hectares for a 10-UAV swarm operating continuously during daylight hours [21].

Governance of autonomous agricultural swarms touches on multiple regulatory domains. Airspace authorities require deconfliction with manned aircraft and other drones; AgriSwarm-RL can be integrated with existing UAS traffic management (UTM) systems by broadcasting a geofenced operation volume and a real-time flight intent. However, current UTM standards are designed for single-operator scenarios and do not account for swarm-level emergent behavior. Policy makers must develop new frameworks that allow swarms to operate with a single authorization but with robust fail-safe mechanisms—such as automatic return-to-base if network connectivity is lost for more than 30 seconds [22].

Data governance is another critical layer. The multispectral data collected by the swarm can reveal proprietary information about crop yields and pest susceptibility. Farmers must retain ownership of their data, but the training of centralized models on pooled data from multiple farms raises privacy concerns. Federated learning approaches, where model updates are aggregated without sharing raw data, could be mandated as a condition for regulatory approval. The trade-off is between model accuracy—which improves with larger, more diverse datasets—and farmer autonomy. Our analysis suggests that a federated variant of AgriSwarm-RL achieves within 5% of centralized performance on coverage metrics while preserving data locality [23].

Policy recommendations emerging from this work include the creation of a certification category for autonomous agricultural swarms, similar to the European Union's class C5 for large drones, but with specific requirements for MARL-based systems regarding auditability of learned policies and transparency of decision-making. Furthermore, subsidies should be structured to favor systems that demonstrate environmental benefits, such as documented reductions in chemical use, rather than simply subsidizing drone hardware.

7. Sustainability and Robustness

Sustainability in UAV spraying is measured not only by reduced chemical consumption but also by energy efficiency and lifecycle impacts. AgriSwarm-RL's energy-aware reward component encourages agents to select actions that minimize throttle variations and avoid unnecessary altitude changes, which are major power drains. In long-duration missions, the policy learns to schedule high-power activities (e.g., altitude climbs for cross-field transit) during periods of strong solar irradiance when auxiliary solar panels on the UAV can supplement battery power. This integrated energy management reduces total grid energy draw by an estimated 12% compared to time-optimal planning that ignores renewable supply [24].

Robustness to individual agent failures is inherent in the swarm architecture because task allocation is continuously re-optimized. If one UAV suffers a motor failure, the remaining agents dynamically expand their coverage zones within seconds, guided by the QMIX value function that reassigns high priority to the now-underserved regions. Stress tests in which 20% of agents failed mid-mission showed only a 7% drop in overall coverage, whereas a static allocation system would lose the entirety of the failed agents' assigned areas. This graceful degradation is an essential property for deployment in rural areas where immediate technical support may be unavailable.

Environmental robustness to weather variability is achieved through domain randomization during training. The simulation environment randomizes wind speed and direction, ambient temperature (affecting battery discharge), and solar glare (affecting sensor noise). The resulting policy generalizes to unseen conditions, although performance degrades gracefully beyond the training envelope. A formal robustness verification using reachability analysis—though computationally expensive—indicated that the policy remains within safety constraints for 92% of perturbed scenarios at the extreme edge of the training distribution [25].

8. Fairness and Socio-Technical Considerations

While AgriSwarm-RL promises efficiency gains, its deployment may exacerbate existing inequities in agricultural technology access. Large-scale agribusinesses with contiguous monoculture fields stand to benefit most because their fields align well with the assumptions of the simulation training environments. Smallholder farms, with irregular patches and mixed cropping, may receive suboptimal service if the swarm's policy has not been trained on such heterogeneous patterns. To mitigate this, the training dataset should deliberately include a wide range of field geometries and crop combinations, and a fairness metric—such as the Gini coefficient of coverage completeness across different farm types—should be part of the benchmark evaluation [26].

Algorithmic bias can also arise from the reward function. If the global coverage reward prioritizes treating large areas quickly, agents may systematically neglect small or distant patches that are difficult to reach, effectively redlining marginal lands. The inclusion of a minimum service constraint in the reward function—ensuring that every field cell receives at least a baseline spray within a mission time window—can enforce equity without requiring explicit centralized scheduling [27]. This constraint increases mission duration by about 8% but ensures that no area is entirely skipped.

Community governance models, such as cooperative ownership of the swarm infrastructure, could democratize access. Instead of each farmer purchasing an expensive fleet, a local agricultural cooperative could own and operate AgriSwarm-RL, scheduling services on demand. The MARL system would then have to be designed for multi-client tasks, learning to prioritize jobs based on urgency while avoiding favouritism. This sociotechnical perspective underscores that the algorithm is not value-neutral; it encodes priorities that must be aligned with societal goals through careful, participatory design.

9. Conclusion

AgriSwarm-RL represents a comprehensive attempt to apply multi-agent reinforcement learning to the pressing challenge of cooperative UAV spraying in heterogeneous crop fields. By integrating dynamic task allocation, variable-rate application, energy management, and robust coordination within a single CTDE framework, the system outperforms classical heuristics in both coverage efficiency and chemical reduction. However, the paper has argued that technical optimization alone is insufficient; the deployment of such swarms requires careful attention to physical infrastructure, regulatory governance, data privacy, sustainability, and fairness. The trade-offs among communication overhead, model complexity, and real-time adaptability must be resolved through iterative field trials and policy experimentation. Future work should focus on transfer learning across diverse agro-ecological zones, incorporating crop growth models to enable predictive spraying, and developing open-source testbeds for community validation. The path toward truly intelligent agricultural swarms will demand interdisciplinary collaboration among computer scientists, agronomists, regulators, and farmers—a collaboration that the AgriSwarm-RL framework aims to facilitate.

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