

Stationary and mobile reload strategies for agricultural UAVs: A simulation study across field sizes and geometries within fertilizer application

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Frequent fertilizer refilling and battery exchange interrupt agricultural UAV operations and can substantially reduce effective field performance. This study quantifies how stationary and mobile reload configurations affect the operational performance of UAVs, using fertilizer application as a case study. A simulation framework combines field-coverage planning, reload-point selection, carrier movement, and mission-time optimization. Eight DJI agricultural UAV models, from the MG-1 to the Agras T100, were evaluated across standardized field sizes from 5 to 150 ha and three square or rectangular geometries. Six reload configurations were compared: two stationary positions and four mobile carrier paths with access to one to four field boundaries. The results show that mobile carrier support consistently reduces non-productive return travel and improves area performance relative to stationary reload points. The largest gains generally occur when mobile access first includes the field's longest operationally relevant boundary, while additional gains tend to become smaller once the most relevant boundaries are accessible. Newer UAV generations achieve higher area performance, but the absolute values remain conditional on the standardized model assumptions.

Keywords

agricultural UAVs, fertilizer application, reload logistics, mobile carrier systems, mission-time optimization, area performance

Digital technologies have become important components of precision agriculture, including sensor-based crop monitoring, decision-support systems, and automated field operations (DAPONTE et al. 2019, REJEB et al. 2022, TOSCANO et al. 2024). Within this development, unmanned aerial vehicles (UAVs) are increasingly used not only for monitoring and mapping, but also for field operations in which agricultural inputs are physically applied.

A general operational challenge of such UAV-based field operations arises from the limited payload and battery capacity of the aircraft. Whenever a UAV systematically covers a field while applying material, the mission must be interrupted repeatedly for refilling and battery exchange. These service events require the UAV to leave the active working area, travel to a reload location, undergo servicing, and subsequently return to the field operation. Therefore, a potentially substantial share of total mission time can consist of non-productive travel, waiting, and reloading activities rather than the actual field application. The organization and spatial positioning of these service activities therefore become an integral part of UAV mission design.

One possibility for reducing these non-productive movements is to replace a fixed reload location with mobile support that follows the progress of the UAV along accessible field boundaries. Vehicle-assisted UAV concepts can shorten return distances and reduce total mission time by positioning service capacity closer to the active operating area (XU et al. 2022). However, the magnitude of this advantage is likely to depend on field size and geometry, the orientation of the coverage path, the number and location of accessible field boundaries, and the technical characteristics of the UAV. Reload logistics therefore constitute a joint routing and service-location problem rather than merely an auxiliary component of UAV operation.

This general logistics problem is examined here using granular fertilizer application as a deliberately selected case study. Fertilizer spreading provides a particularly suitable setting because relatively high application rates combined with the limited hopper capacities of agricultural UAVs generate frequent and clearly identifiable reload events. Hopper capacity therefore directly determines how far the UAV can operate before returning for service, making the effect of reload-point location and carrier movement especially visible. Moreover, commercial agricultural UAVs offer well-defined granular spreading systems and payload specifications, allowing standardized operational scenarios to be constructed across several UAV generations. The analysis focuses exclusively on the logistical processes associated with field coverage, fertilizer replenishment, and battery exchange; spreading uniformity and agronomic application quality are outside the scope of the model.

The underlying logistics mechanism is nevertheless not restricted to spreading fertilizer. Similar operational problems occur whenever a UAV must systematically cover an area while carrying consumable input and periodically returning for both material replenishment and battery exchange. Agricultural spraying represents an obvious example. The present results should therefore be interpreted as evidence on the logistics of repeated UAV servicing under systematic field coverage, while fertilizer application provides the standardized empirical and technical setting through which this problem is investigated.

Against this background, the objective of this study is to determine how reload organization affects UAV mission time and area performance under standardized field conditions. Three questions guide the analysis: (1) How do stationary and mobile reload configurations differ in operational performance? (2) How do field size, field orientation, and boundary accessibility affect the benefit of mobile carrier support? (3) How does the effect vary across UAV generations with different payload capacities, spreading widths, and operating speeds?

To address these questions, a simulation framework combines deterministic field-coverage planning, reload-point selection, carrier movement, and mission-time optimization. Two stationary and four mobile reload configurations are evaluated for eight DJI UAV generations across standardized field sizes and square or rectangular geometries. The resulting contribution is therefore primarily a comparative logistics analysis of how service-point positioning and carrier accessibility shape the operational performance of UAV-based field missions.

Theoretical background

UAV-based granular fertilizer application

Agricultural UAVs can carry interchangeable liquid or granular application systems. Granular spreading systems use a hopper, a dosing mechanism, and typically a centrifugal disc (PATIL et al.

2024, ZHOU et al. 2024). Their operational performance depends on payload capacity, discharge rate, spreading width, flight speed, and the time required for repeated refilling.

Granular spreading differs from aerial spraying because solid particles, liquid droplets, and rotor downwash interact differently with the environment. Agronomic or distribution-related conclusions from pesticide spraying are therefore not transferred directly to fertilizer spreading. The present study considers only the logistical movement and reload processes required to distribute a specified fertilizer mass.

Published work has examined distribution patterns and the influence of operating parameters for UAV-based granular spreaders (WANG et al. 2023, XUNWEI et al. 2024, ZHOU et al. 2024). The reported coefficients of variation and distribution patterns depend on the tested machine, fertilizer properties, flight settings, and experimental design. Because these agronomic outcomes are not part of the simulation, spreading accuracy is treated as an external requirement rather than a modeled advantage.

Potential operational advantages of UAVs include flexible deployment and access to terrain or crops where heavy ground machinery is difficult to use (PURI et al. 2017, DAPONTE et al. 2019, TOSCANO et al. 2024). At the same time, small hopper capacities and repeated service events constrain field performance. These opposing characteristics make reload logistics particularly relevant when assessing how an individual UAV completes a fertilizer mission.

In this study, battery exchange and fertilizer refilling are modeled as a combined reload event. This simplification reflects modular operating concepts in which batteries can be exchanged during fertilizer replenishment (PATIL et al. 2024, HAFEEZ et al. 2023). It does not imply that battery logistics are negligible in practice.

Reload logistics and mobile carrier systems

Frequent reload events are a fundamental operational limitation of fertilizer UAVs. Every return to a service point adds non-productive flight time, while coordination with a moving carrier can also create waiting time. The location and availability of service points therefore influence total mission duration.

Stationary concepts place the service point at a fixed field-boundary location. Mobile concepts allow a carrier to move along accessible boundaries and service the UAV closer to the active flight segment. Prior work indicates that such coordination can shorten return distances (XU et al. 2022).

The achievable benefit depends on field dimensions, sweep direction, boundary access, carrier speed, and the sequencing of flight segments and reload events. A carrier path along the long side of a rectangular field may produce a different result from the same path rotated by 90 degrees because the coverage direction remains fixed in the simulation.

The present analysis isolates these logistical relationships across field sizes, geometries, reload configurations, and UAV generations. It is an exploratory scenario comparison and is not intended to predict adoption or profitability in a particular country.

Operational context and scope

Conventional fertilizer application provides practical context for UAV operations, but the present study does not compare complete machinery systems. Ground spreaders and UAVs differ in working width, payload, labor organization, trafficability, regulation, and agronomic performance. A valid economic comparison would therefore require a separate system-level design and consistent cost data.

In general, fields include a wide range of sizes, shapes, access conditions, and mechanization levels. Square and rectangular scenarios cannot reproduce that diversity. They are used here because they permit controlled comparisons of carrier access and sweep orientation.

Possible niche applications, including steep terrain, vineyards, small fields, or traffic-sensitive crops, are relevant hypotheses for future empirical work. They are not outcomes of the current simulation because slope, irregular boundaries, crop conditions, and field trafficability are not represented. The simulation results apply to the specified standardized geometries and operating assumptions, irrespective of country.

Data

Eight DJI agricultural UAV models from different production years were used to represent changes in payload capacity, spreading speed, and spreading width (Table 1; DJI Agriculture, Shenzhen, China, <https://ag.dji.com/de>). Manufacturer specifications are shown together with standardized assumptions required by the simulation. The grey cells identify values held constant across scenarios, including carrier speed, non-spreading flight speed, reload time, and fertilizer application rate. Environmental conditions and payload-dependent battery consumption were not modeled. Battery endurance is not represented as a separate operational constraint. Instead, each fertilizer refill is assumed to coincide with a (potential) battery exchange, while hopper capacity determines the modeled frequency of these combined service events.

Table 1: UAV parameters used in the simulations; grey cells indicate standardized assumptions applied consistently across scenarios

UAV model	Year	Capacity in kg	Spreading Speed in m/s	Spreading width in m	Carrier speed in km/h	Drone flight speed in km/h	Reload time in s	Spread rate in kg/ha
DJI MG-1	2016	10	7	5	20	30	120	200
DJI Agras T16	2018	16	7	6	20	30	120	200
DJI Agras T20	2019	20	7	6	20	30	120	200
DJI Agras T30	2020	40	7	7	20	30	120	200
DJI Agras T40	2021	50	7	7	20	30	120	200
DJI Agras T50	2022	50	10	8	20	30	120	200
DJI Agras T60	2023	60	13,8	8	20	30	120	200
DJI Agras T100	2024	75	13,8	10	20	30	120	200

Across the selected model generations, payload capacity increases from 10 to 75 kg, spreading speed from 7 to 13.8 m s⁻¹, and spreading width from 5 to 10 m. These technical parameters affect simulated spreading time, the distance achievable per load, and the frequency and location of reload events.

Five standardized field sizes were selected to examine how reload logistics scale from short to extended missions (Table 2).

Table 2: Standardized field-size scenarios used in the simulation

Field size in ha	Role in the analysis	Interpretation
5	Small-field scenario	Short mission with a high relative influence of boundary access
20	Small-to-medium scenario	Increasing mission length and reload demand
50	Medium-field scenario	Intermediate scenario
100	Large-field scenario	Extended mission and boundary-travel distances
150	Upper large-field scenario	Stress test for reload logistics under long missions

The field-size range is analytical rather than geographically representative. No country-specific frequency or typicality is assigned to these scenarios, and the results should not be generalized to the complete diversity of field structures.

For every field size, three geometries were simulated: a square field ($x = y$), a rectangle with $x = 2y$, and the rotated rectangle with $2x = y$. Although the two rectangular shapes are geometrically equivalent under rotation, they are not operationally identical in the model because coverage sweeps are generated in the y -direction and carrier access is defined relative to the x - and y -boundaries. The three orientations therefore distinguish long flight lanes from a larger number of shorter lanes. In total, 15 field scenarios were evaluated.

Methodology

A simulation framework was developed to compare UAV field coverage and reload logistics under standardized conditions. It combines deterministic coverage-path generation, candidate reload-point selection, carrier movement, and metaheuristic mission sequencing. The objective is to minimize total mission time, including spreading, non-productive flight, reload, and waiting time.

The framework is an exploratory operational model. It is designed to compare scenario differences rather than to produce validated real-world predictions or economic estimates.

General simulation approach

Six reload configurations were evaluated and are denoted consistently as S1, S2, and M1-M4 (Table 3).

Table 3: Reload configurations used consistently throughout the analysis

Code	Type	Reload or carrier access	Interpretation
S1	Stationary	Fixed point at a field corner	Stationary baseline
S2	Stationary	Fixed point at the midpoint of the y -side	Alternative stationary position
M1	Mobile	Carrier access along the y -side	One accessible field edge
M2	Mobile	Carrier access along the y - and x -sides	Two adjacent accessible edges
M3	Mobile	Carrier access along the y -, x -, and opposite y -side	Three accessible edges
M4	Mobile	Carrier access along all four field boundaries	Full boundary access

The two stationary configurations use fixed service points at the field boundary:

- S1: reload at a field corner;
- S2: reload at the midpoint of the y -side.

The four mobile configurations use a carrier that supplies fertilizer and replacement batteries while moving along one to four accessible field boundaries. The carrier remains restricted to pre-defined boundary paths representing field tracks or other accessible edges. Carrier travel is modeled as a separate support activity; the model therefore represents either a dedicated carrier operator or autonomous carrier movement and does not assume that the remote pilot drives the carrier while supervising an active UAV flight.

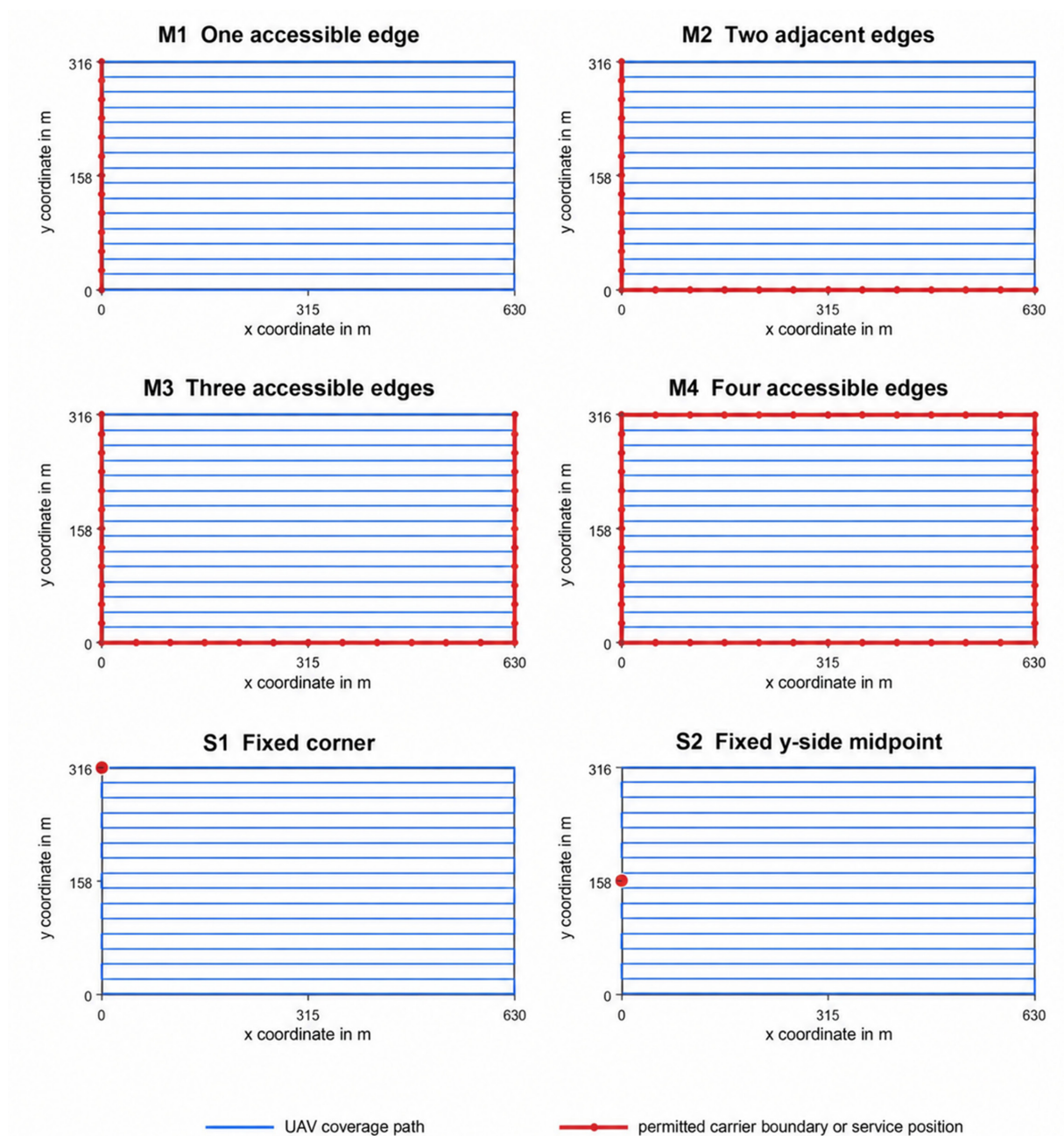


Figure 1: Reload configurations for a DJI MG-1 on a 20 ha field; top row: M1 and M2; middle row: M3 and M4; bottom row: S1 and S2; blue lines show the UAV coverage path; red boundaries and points show the permitted carrier path or fixed service position

Figure 1 illustrates the six configurations for a DJI MG-1 on a 20 ha field. Blue lines show the UAV coverage path and red markers show stationary or mobile reload positions. The comparison isolates how the position and extent of boundary access influence non-productive travel and synchronization.

Drone parameters and field representation

Each drone model $d \in D$ is characterized by the following parameters:

- payload capacity C_d in kg,
- spreading speed v_s in m/s,
- spreading width w_s in m,
- reload time t_r in s.

The simulation considers rectangular fields $F_i = (w_i, h_i)$, where w_i and h_i denote field width and height. For consistency with the graphical representation, field width w_i is denoted by x and field height h_i by y . Three orientations are evaluated for each field size:

- square fields ($x = y$),
- rectangular fields with $x = 2y$,
- rectangular fields with $2x = y$.

The UAV starts at the upper-left field corner. Because the sweep direction is fixed, rotating a rectangular field changes lane length, lane count, and the relationship between the carrier path and the active flight segment.

Coverage path planning

Field coverage is represented by parallel horizontal flight segments generated in the y -direction. These segments define the complete set of field-coverage tasks. Their execution sequence is subsequently optimized within the mission-planning procedure rather than being fixed ex ante as a single sequential zigzag path.

For a given spreading width w_s , the number of required flight lanes is calculated according to equation 1:

$$N_y = \left\lceil \frac{h_i}{w_s} \right\rceil \quad (\text{Eq. 1})$$

Each flight segment spans the full field width.

Reload point planning and carrier modes

Reload points are generated according to the active configuration S1-S2 or M1-M4. In S1 and S2, the reload position remains fixed. In M1-M4, candidate reload points are distributed along the permitted carrier boundary path. The carrier travel time between selected service positions is calculated using the standardized speed in Table 1, and synchronization delays enter the waiting-time component. For example, M1 permits repositioning only along the y -side, whereas M2 also permits service positions along the adjacent x -side.

To identify suitable reload-point configurations, a greedy search procedure is first applied prior to the global optimization step. The greedy search samples between 2 and 200 evenly spaced candidate

reload points along the carrier path and evaluates their operational feasibility through preliminary mission simulations. The best-performing candidate configurations are then transferred to the genetic algorithm as feasible reload-point sets. This two-stage procedure reduces the search space of the genetic algorithm and improves computational efficiency.

Mission time calculation

The total mission time T is decomposed into four operational components according to equation 2:

$$T = T_{fly} + T_{spread} + T_{reload} + T_{wait} \quad (\text{Eq. 2})$$

where:

T_{fly} represents travel time between flight segments and reload points,

T_{spread} denotes active fertilizer spreading time,

T_{reload} describes time required for fertilizer refilling and battery replacement,

T_{wait} accounts for potential waiting times caused by carrier movement or reload synchronization.

The effective fertilizer application rate per meter of flight path is defined according to equation 3:

$$\gamma = \frac{w_s \cdot r}{10000} \quad (\text{Eq. 3})$$

where:

w_s is the spreading width in m,

r is the fertilizer application rate in kg ha^{-1} ,

the factor 10,000 converts hectares into square meters.

All simulations used a fixed fertilizer application rate of $r = 200 \text{ kg ha}^{-1}$. This standardized rate is used in every scenario as a standardized case-study assumption rather than as a crop-specific agronomic recommendation. The maximum spreading distance achievable per load is calculated according to equation 4:

$$L_{max} = \frac{c_d}{\gamma} \quad (\text{Eq. 4})$$

If a flight segment exceeds the spreading distance available from one load, a reload event is inserted and the nearest feasible service position under the active configuration is selected. Because application rate directly determines fertilizer consumption per meter, the absolute results are conditional on the fixed value of 200 kg ha^{-1} .

Genetic algorithm optimization

A genetic algorithm (GA) was used to optimize two decision components simultaneously: the sequence in which coverage segments are executed and the subset of feasible reload points used during the mission. GAs are established search methods for complex nonlinear and combinatorial optimization problems (HOLLAND 1973, GALLAGHER and SAMBRIDGE 1994, MIRJALILI 2019). The preceding greedy search generates candidate reload-point sets and reduces the search space; the GA then minimizes simulated total mission time.

Each chromosome therefore contains (1) a permutation of coverage segments and (2) a selected subset of candidate reload positions. Fitness is the total simulated mission time, so lower values indicate a better operational solution under the specified assumptions.

The optimization process applies a two-point crossover operator to the sequence of flight segments, while reload-point configurations are combined through union and intersection operations. Mutation is implemented through random swapping of flight segments and optional modification or removal of reload points. In addition, elitism is applied by preserving the three best-performing individuals in each generation to ensure solution stability throughout the optimization process.

The GA uses a population of 20 individuals over 30 generations, a mutation probability of 10%, and elitist retention of the three best individuals. These settings provide a consistent exploratory search across the scenario set; they are not presented as proof of global optimality.

Model assumptions

The model applies simplifying assumptions to maintain comparability across all scenarios. It is an exploratory operational assessment rather than a validated prediction model.

Wind, precipitation, terrain, temperature, communication delays, irregular field boundaries, payload-dependent battery use, fertilizer-distribution quality, staffing schedules, and depot replenishment are excluded. Flight and spreading parameters remain constant, and each fertilizer refill is combined with a battery exchange. The mobile modes assume a separate driver or autonomous carrier; one-person operation in which the remote pilot must stop supervising the UAV to move the carrier is outside the model scope.

Several parameters are based on manufacturer information or standardized assumptions instead of field measurements, particularly spreading speed, reload duration, and carrier behavior. Results should therefore be interpreted as relative operational indicators under controlled assumptions.

The framework supports a systematic comparison of reload configuration, field size, field orientation, and UAV generation. It does not estimate full machinery costs, regional adoption, or agronomic performance.

Output metrics

The simulation was executed for every combination of drone type, field geometry, and reload scenario. For each configuration, the best-performing operational solution was recorded. The resulting output metrics include total mission time, spreading time, flight time, reload time, waiting time, as well as the number and spatial distribution of reload points.

In addition, the reload-point coordinates and the number of reload events at each coordinate were stored. Distinct service positions were ordered along the continuous accessible boundary. The minimum number of carrier relocations was defined as the number of distinct service positions minus one; repeated reloads at the same position did not add a relocation. Minimum boundary-travel distance was defined as the shortest open traverse along the permitted boundary that visits every distinct service position once, with free start and end points. These values represent the minimum movement requirements.

Area performance was calculated as the ratio between field size and total mission duration according to equation 5:

$$P_a = \frac{a}{T/60} \quad (\text{Eq. 5})$$

where a denotes the field size in hectares and T represents the total mission time in minutes.

Results

For an overview, area performance was averaged across all six reload configurations and all three field geometries for each UAV and field size. Figure 2 shows that mean area performance generally increases across successive UAV models. At the same time, mean area performance decreases as field size increases from 5 to 150 ha. This pattern reflects the increasing contribution of reload-related and non-productive travel as missions become longer.

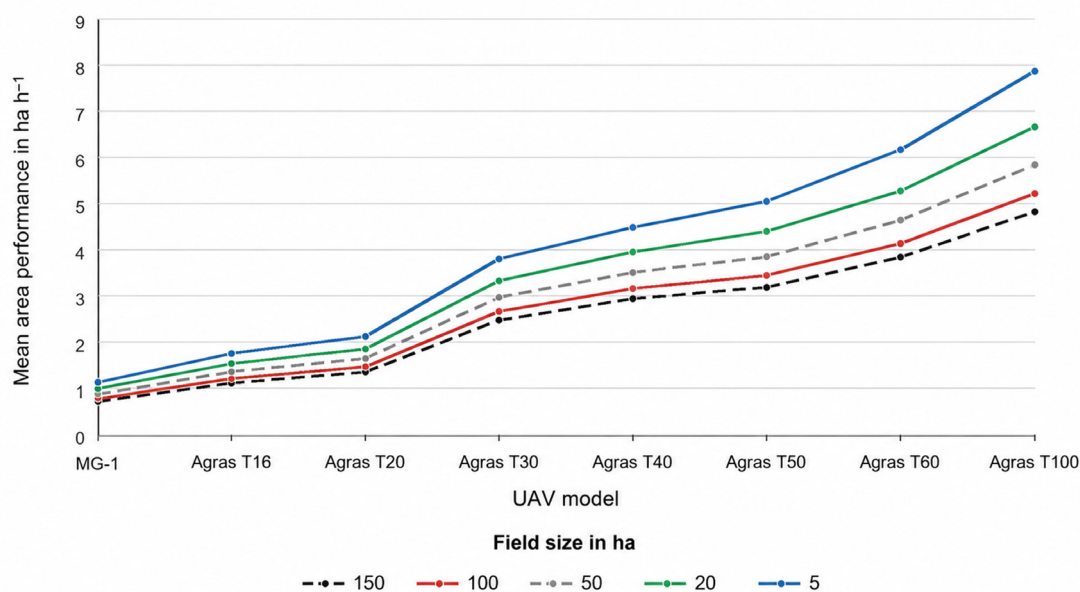


Figure 2: Mean area performance across the six reload configurations for different UAV generations and field sizes; legend entries indicate field size in hectares

Detailed operational results are presented in Figure 3 for 5, 50, and 150 ha fields. The figure compares the two stationary configurations (S1-S2) and four mobile configurations (M1-M4) across UAV generations. The $x = 2y$, $x = y$, and $2x = y$ scenarios are shown separately because the fixed sweep orientation makes the geometries operationally different.

Sequential relative gains were calculated from the underlying results: S1 serves as the stationary baseline, while S2 relative to S1 captures the effect of changing the stationary service-point location. M1 relative to S2 captures the transition from stationary to mobile support, and M2-M4 are each compared with the preceding mobile-access configuration. The measure captures the marginal operational effect of service-point placement and progressively extended mobile boundary access; it is not an economic indicator. The marginal benefit depends strongly on field geometry and on which boundary becomes accessible. For $x = 2y$ fields, the largest gain generally occurs when M2 adds access to the long x -boundary. For $2x = y$ fields, the long y -boundary is already accessible under M1, producing a pronounced gain from S2 to M1. Square fields show a more balanced distribution of gains. Overall, boundary location and orientation matter more than the number of accessible sides alone, and further access generally provides smaller gains once the operationally most relevant boundaries are available.

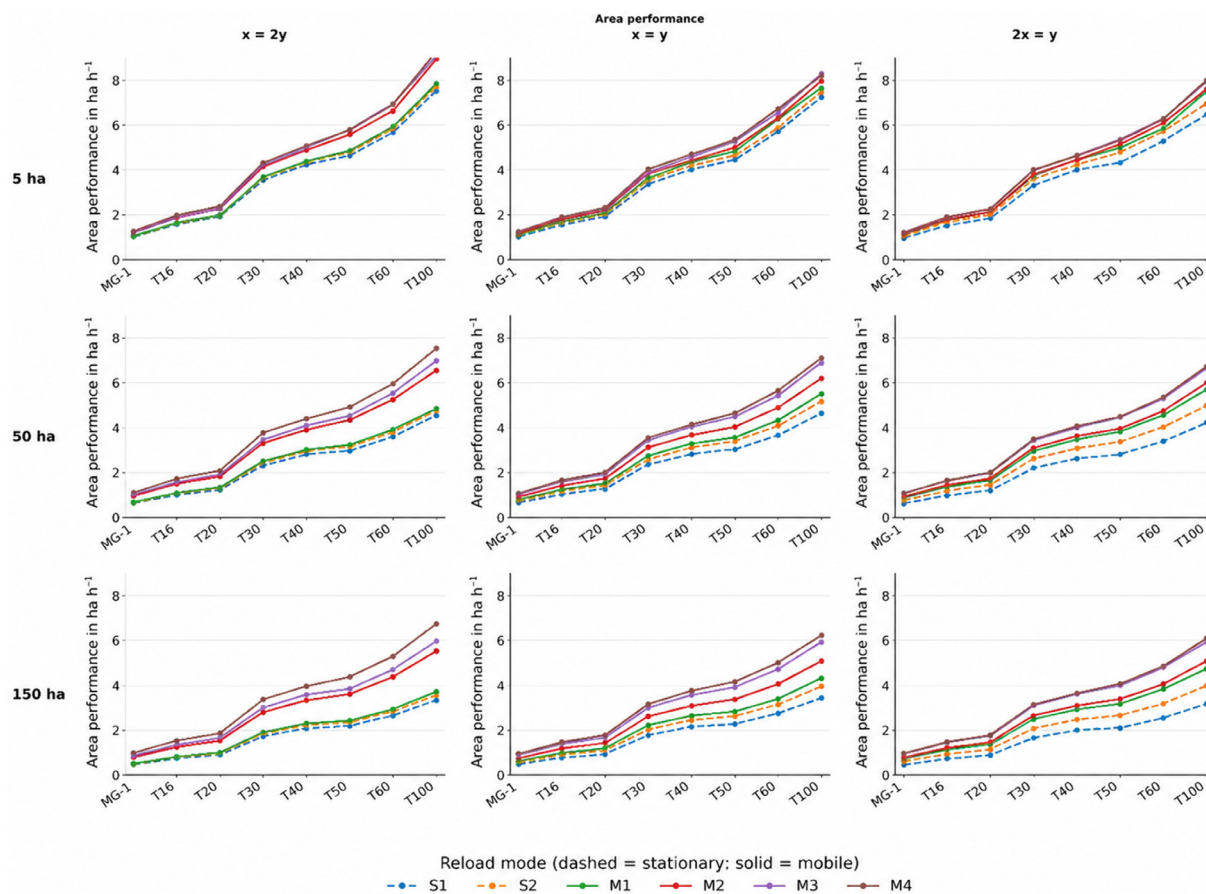


Figure 3: Area performance for (a) $x = 2y$ fields, (b) $x = y$ fields, and (c) $2x = y$ fields at 5, 50, and 150 ha; dashed lines indicate stationary configurations; solid lines indicate mobile configurations

Figure 4 provides two spatial examples for the 5 ha field with the DJI Agras T40. In M1, all 19 reload events occurred at 19 distinct positions along the accessible y-boundary. In M2, the same 19 events were distributed across 19 positions on the adjoining y- and x-boundaries. The numbers indicate the post-processed minimum-distance visit order along the permitted carrier path.

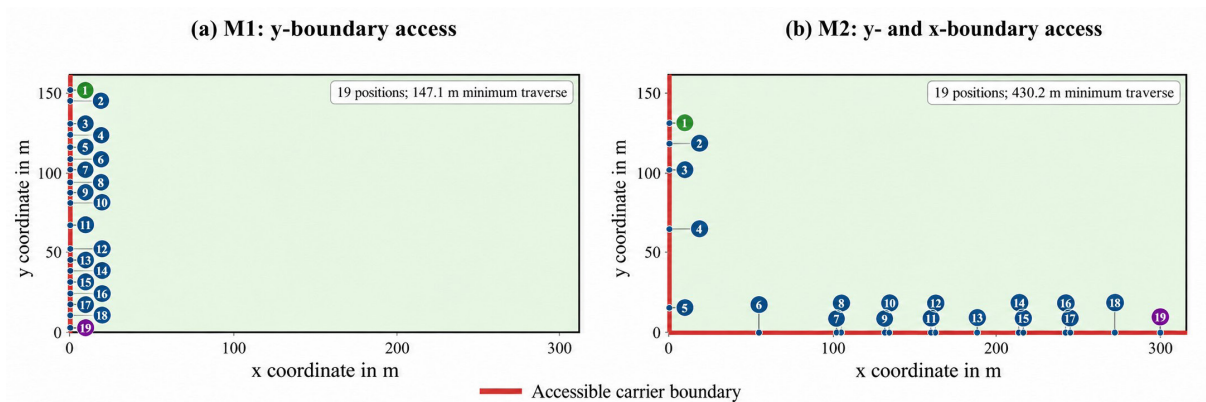


Figure 4: Representative mobile reload-point distributions for a 5 ha field and the DJI Agras T40; a) M1: carrier access along the y-boundary, b) M2: carrier access along the adjacent y- and x-boundaries; numbered markers show the post-processed minimum-distance visit order; the shaded rectangle is the treated field

The representative calculations in Table 4 show the carrier movement associated with extended boundary access. M1 requires a minimum boundary traverse of 147.1 m, compared with 430.2 m in M2, 609.9 m in M3, and 791.6 m in M4. Over the same sequence of configurations, total mission time falls from 68.4 min to 59.1 min because the UAV can reload closer to the active field segment. These values illustrate the additional carrier movement required to obtain the modeled reduction in UAV return travel.

Table 4: Minimum carrier movement requirements for the representative 5 ha scenario (DJI Agras T40)

Mode	Carrier access	Reload positions	Reload events	Minimum relocations	Minimum boundary distance (m)	Mission time (min)
M1	y-side	19	19	18	147.1	68.4
M2	y- and x-sides	19	19	18	430.2	61.5
M3	y-, x-, and opposite y-side	19	19	18	609.9	59.9
M4	all four boundaries	18	19	17	791.6	59.1

Notes: Minimum relocations equal the number of distinct reload positions minus one. Minimum boundary distance is the shortest open traverse along the permitted carrier boundaries that visits each distinct position once. Repeated reloads at the same position do not add a relocation.

Discussion

The results identify reload organization as a central determinant of operational performance in granular fertilizer UAV missions. Across field sizes, orientations, and UAV generations, mobile carrier configurations reduced non-productive return travel relative to stationary service points. A fixed corner location (S1) generally produced the longest return paths, whereas mobile access allowed the service position to follow the active work area. This is an operational effect on mission time and area performance, not evidence of economic or agronomic superiority.

The benefit was not proportional to the number of accessible field sides. Instead, the results show that the operational value of additional access depends primarily on which boundary becomes available and how that boundary relates to field geometry and the coverage direction. Access to the longest operationally relevant boundary generally produces the strongest improvement. Once such access is available, further extensions of the carrier route tend to generate smaller marginal gains.

This pattern is consistent with the vehicle-assisted scheduling mechanism analyzed by Xu et al. (2022), in which positioning service capacity closer to the active flight area reduces empty travel. It also connects the agricultural application to broader UAV logistics research, where the coordinated positioning and scheduling of mobile resources are treated as system-level design decisions (REJEB et al. 2023). The present results add a controlled comparison of six reload configurations for single-UAV operations across field sizes, orientations, and platform generations.

Across the modeled UAV generations, higher payload capacities, wider spreading widths, and higher operating speeds translated into greater area performance. The direction of this result is consistent with reviews documenting the rapid technical development of agricultural UAV platforms (HAFEZ et al. 2023, PATIL et al. 2024, TOSCANO et al. 2024). However, the comparison is based on parameterized product specifications and should not be interpreted as a causal time trend, a profitability assessment, or evidence that UAVs can replace conventional spreaders.

Operationally, mobile reload should be understood as an integrated support-system design issue rather than an isolated flight-path choice. Carrier access, service positioning, battery exchange, fertilizer supply, and the coverage sequence must be coordinated. Strategically selected partial-boundary access may therefore offer a practical compromise between short return paths and infrastructure requirements, but the resulting carrier movements and service times require validation in field trials (XU et al. 2022, REJEB et al. 2023).

While absolute area performance differs substantially across UAV models, the relative advantages of the reload configurations follow broadly similar patterns across platform generations. Field geometry and boundary orientation therefore appear to be more important determinants of the relative logistics gain than UAV generation itself.

Logistics gains must also be separated from spreading quality. Experiments with UAV granular systems show that discharge consistency and distribution patterns depend on the machine, fertilizer material, and operating settings (WANG et al. 2023, XUNWEI et al. 2024, ZHOU et al. 2024). Research on conventional variable-rate spreaders likewise treats distribution uniformity as a distinct technical performance dimension (SHI et al. 2018). Area performance alone therefore cannot establish agronomic equivalence; future field experiments should evaluate logistics and distribution quality together.

It should be emphasized that fertilizer application was deliberately selected as a case study for a broader UAV reload-logistics problem. The underlying logistics mechanism and the simulation framework may also be relevant to other applications in which a field is systematically covered by a UAV and regular stops are required for both battery replacement and material replenishment, for example in agricultural spraying operations. The application-specific quantitative results should, however, not be transferred directly to such settings.

The operational gains identified in this study have potential economic relevance, but higher area performance does not automatically translate into lower application costs. Extending carrier access reduces UAV mission time by shortening non-productive return flights, while simultaneously increasing the distance travelled by the carrier. Partial boundary access may therefore be economically preferable to full mobility if the additional carrier movement, labor, energy use, or infrastructure cost exceeds the value of the UAV time saved. A system-level assessment would need to include UAV and carrier investment, depreciation, batteries and charging, labor, fuel or electricity, maintenance, transport, setup time, annual utilization, and fertilizer supply logistics. Comparable cost components would also be required for conventional spreading equipment. The present results therefore identify operational trade-offs relevant to an economic assessment but do not establish cost competitiveness or profitability.

Personnel requirements depend strongly on the level of automation. A manually operated mobile-carrier system would normally require at least two simultaneous operational roles: a remote pilot supervising the UAV and a separate operator driving and positioning the carrier. Automated waypoint flight does not necessarily remove the pilot's supervisory responsibility. Practical implementation may also require qualifications in UAV operation, fertilizer handling, battery safety, maintenance, and digital mission planning. Future autonomous or remotely coordinated carriers could reduce the need for a dedicated driver and may eventually allow one qualified operator to supervise the combined system, subject to the applicable safety and regulatory requirements. A fully electrified configuration combining agricultural UAVs with an electric truck or field carrier is also conceivable,

although its performance would depend on charging capacity, battery logistics, payload, and electricity supply.

Further efficiency gains may be possible by coordinating several UAVs with one carrier. Such a multi-UAV system could increase carrier utilization and field capacity but would introduce additional scheduling, charging, loading, communication, safety, and supervision constraints that are not represented in the present single-UAV model. Shared-service arrangements may therefore be particularly relevant. Agricultural cooperatives, machinery rings, or specialized contractors could pool the investment, employ qualified personnel, and increase annual system utilization across several farms. The economic viability of these arrangements would depend on transport distances, seasonal capacity, scheduling, regulatory requirements, and the total area served.

Several limitations frame the interpretation. The deterministic model relies on manufacturer specifications and standardized values, omits weather, terrain, staffing constraints, and operational variability, and cannot establish global optimality. Results are conditional on 200 kg ha⁻¹, rectangular fields, and simplified carrier access; other rates, irregular fields, obstacles, depot replenishment, and labor coordination require field validation. Agronomic distribution quality was not tested. A system-level cost comparison would require consistent data for complete UAV and conventional-spreader systems, batteries, charging, labor, maintenance, certification, carrier support, and annual utilization.

Conclusions

This study examined reload logistics for agricultural UAV field operations using granular fertilizer application as a case study. Two stationary and four mobile reload configurations were compared across standardized field sizes, field orientations, and UAV models. The results show that reload-point placement and carrier access are integral components of UAV mission design.

Mobile carrier support improved area performance relative to stationary reload points by reducing non-productive return travel. The largest gains generally occurred when mobile access first included the longest operationally relevant field boundary. Once access to the most relevant boundaries was available, further extensions tended to provide smaller incremental gains. Strategically selected partial-boundary access may therefore capture a substantial share of the attainable logistics benefit.

Later UAV models achieved higher simulated area performance because of their parameterized payloads, spreading widths, and operating speeds. This finding remains conditional on the fixed application rate, simplified field geometries, and deterministic operating assumptions; it does not establish cost competitiveness or agronomic equivalence with conventional machinery.

The practical contribution is therefore a logistics principle: service positioning and boundary access should be designed together with the coverage direction. Future research should test this principle in real fields, include irregular geometries and different application rates, evaluate distribution quality, and validate optimization robustness. A separate system-level full-cost analysis should follow once reliable and comparable data are available.

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