Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

# How Realistic Are UAV Routing Studies? An Assessment of Operational Realism, Validation Maturity, and the Path to Deployable Missions

**Mehmet Çevik**

cevik2002@gmail.com

Izmir Kâtip Çelebi University https://orcid.org/0000-0002-6366-5566

**Latif Tibet Aktaş**

İzmir University of Economics https://orcid.org/0000-0002-0974-1759

**Systematic Review**

**Keywords:** Unmanned aerial vehicles (UAVs), UAV routing, operational realism, validation maturity, energy-aware routing, multi-UAV systems

**Posted Date:** September 29th, 2026

**DOI:** https://doi.org/10.21203/rs.3.rs-11178722/v1

**License:** This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

**Additional Declarations:** The authors declare no competing interests.

# Abstract

Unmanned aerial vehicle (UAV) routing research has advanced rapidly, yet the extent to which proposed methods reflect executable missions remains unclear. This systematic review evaluates operational realism, validation maturity, and reproducibility in mission-level UAV routing. Scopus and Web of Science were searched for studies published between 2015 and 2026, yielding a final corpus of 215 papers coded through an integrated two-phase framework covering mission domain, routing architecture, optimization paradigm, operational data, energy representation, dynamics and uncertainty, validation level, physical UAV use, and reproducibility. The results show a marked gap between algorithmic sophistication and deployment readiness. Although 35.3% of studies use explicit battery-energy or detailed energy models, 71.2% include neither dynamic operation nor explicit uncertainty. Validation remains predominantly computational: 67.0% of studies rely on synthetic or benchmark evaluation, only 9.8% involve an actual UAV, and just 1.9% reach operational field deployment. Reproducibility is also limited, with only 6.0% classified as High. Cross-dimensional analysis shows that greater modelling or algorithmic complexity does not systematically correspond to stronger empirical validation. The findings support a shift toward physics-aware, adaptive, system-level, progressively validated, and reproducible UAV-routing research aimed at narrowing the optimization-to-deployment gap. This perspective reframes review quality around executability rather than algorithmic novelty alone.


# 1. Introduction

Unmanned aerial vehicles (UAVs) are increasingly employed in logistics, infrastructure inspection, surveillance, emergency response, environmental monitoring, precision agriculture, mapping, and Internet of Things (IoT) applications. As these missions have diversified, UAV routing has evolved from comparatively simple shortest-path or traveling-salesman formulations into a broader mission-planning problem. Contemporary models increasingly couple route selection with task allocation, coverage requirements, service priorities and time windows, payload restrictions, charging and replenishment, communication constraints, collision avoidance, and vehicle endurance. This progression is evident in studies addressing joint charging-station location and delivery routing (Li et al., 2026), nonlinear payload- and flight-phase-dependent energy consumption in delivery missions (Wang et al., 2026), robust medical delivery with partial recharging (Peng et al., 2026), multi-UAV scheduling for large-scale three-dimensional reconstruction (Xia et al., 2025), priority-aware dynamic forest-fire monitoring (Utamima & Fano, 2026), and persistent mission planning under uncertain travel conditions (Radzki et al., 2021).

The solution methodologies applied to UAV-routing problems have expanded accordingly. Exact and mathematical optimization methods continue to play a major role, particularly for formulations involving energy, charging, scheduling, and location-routing decisions (Bhuiyan et al., 2024; Zheng et al., 2026). Heuristic and metaheuristic methods remain widely used for larger combinatorial problems, including adaptive large-neighborhood search for recharging-aware routing (Shi et al., 2023) and comparative metaheuristics for UAV data-collection routing (Abid et al., 2025). Hybrid and matheuristic approaches have also been developed for persistent monitoring, emergency response, and dynamic routing

problems (Tükenmez & Özkan, 2024; Calamoneri et al., 2024). More recently, learning has been incorporated directly into routing and recharging decisions. Ermağan et al. (2022) use machine learning to guide recharging decisions from high-quality optimization solutions, Büyüksan et al. (2026) employ surrogate modelling for energy-aware multi-trip routing, and Shokouhifar et al. (2026) combine metaheuristic optimization with machine learning for UAV-assisted wireless rechargeable sensor networks. Reinforcement-learning approaches have likewise been applied to collision-aware parcel delivery and waypoint sequencing for environmental monitoring (Chi et al., 2024; Oliveira et al., 2026). These developments demonstrate substantial algorithmic progress and an expanding decision-intelligence toolkit. However, increasing algorithmic sophistication does not by itself establish whether an optimized route can be executed by a UAV under realistic operating conditions.

This distinction is central to the present review. Operational realism depends on whether UAV-routing models represent the physical, environmental, operational, and uncertain conditions governing mission feasibility. Physical realism includes battery state, payload, speed, maneuvering, flight phase, and propulsion energy. Representative approaches include practical flight-energy modelling based on real measurements (Shan et al., 2022), nonlinear payload- and flight-phase-dependent energy consumption (Wang et al., 2026), and battery characteristics informed by UAV flight tests (Bhuiyan et al., 2024). Environmental realism encompasses wind, weather, terrain, obstacles, altitude, and spatial restrictions, including heterogeneous urban wind (Chen et al., 2023), load- and wind-dependent routing (Ito et al., 2022), and stochastic wind coupled with aerodynamic energy and recharging decisions (Liu et al., 2023). Operational realism also extends to charging, service requirements, communication, synchronization, multi-trip operation, and fleet coordination (Shi et al., 2023; Calamoneri et al., 2024; Diller et al., 2023). Finally, changing weather, moving targets, failures, newly arriving tasks, unreliable communication, and evolving mission information may require adaptation during execution rather than fixed pre-mission routing (Karabay et al., 2023; Zhang et al., 2022; Karim et al., 2026). These dimensions determine whether a mathematically feasible route remains executable under actual operating conditions.

A related but distinct issue is validation maturity. The use of realistic data does not necessarily demonstrate that an optimized route is physically executable. A study may employ actual demand, geographic, meteorological, or infrastructure data while evaluating its method entirely through numerical simulation (Grogan et al., 2021; Zheng et al., 2026; Wang et al., 2021). Li et al. (2026), for instance, use real metropolitan delivery data in a computational routing framework. By contrast, physical experimentation tests at least part of the proposed system using an actual UAV (Bhuiyan et al., 2024; Diller et al., 2023; Ghaziani et al., 2026), while field deployment demonstrates mission execution under operational conditions (Romanov et al., 2024; Zhang et al., 2024; Xia et al., 2025). Caballero et al. (2025) provide an example of the latter by autonomously inspecting more than 10 km of real overhead power lines with a heterogeneous multi-UAV team. These levels of evidence should therefore be distinguished rather than grouped under a broad notion of “real-world validation.” Recent UAV-routing studies situate the field in relation to earlier reviews emphasizing delivery operations, facility location, sustainability, and optimization approaches (Kumar et al., 2025), but these perspectives do not directly resolve the relationship between routing architecture, operational realism, and empirical maturity.

Whereas many existing reviews primarily classify UAV-routing problems, algorithms, and application domains, this study evaluates the literature through the lens of operational realism and validation maturity. The central question is not only how UAV routes are optimized, but how closely current routing studies represent executable missions and how far they have progressed toward physical experimentation and operational deployment.

Five research questions guide the analysis:

**RQ1.** What mission domains and routing architectures characterize UAV-routing research?

**RQ2.** Which mathematical, heuristic, hybrid, and learning-based optimization paradigms are used across these routing architectures?

**RQ3.** Operational realism. To what extent do UAV-routing models represent the physical, environmental, operational, and uncertain conditions that determine whether an optimized route can be executed in practice?

**RQ4.** Validation maturity. How far have UAV-routing methods progressed from synthetic and benchmark evaluation through real-data simulation to physical UAV experimentation and operational field deployment?

**RQ5.** Optimization-to-deployment gap. What mismatches exist between algorithmic sophistication, operational realism, and validation maturity, and what research priorities are required to narrow the gap between optimized routes and deployable UAV missions?

This review makes four main contributions. First, it develops an integrated analytical framework linking mission domain, routing architecture, and optimization paradigm with full-text measures of operational realism and validation maturity. Second, it distinguishes the use of real-world data from physical UAV experimentation and operational field deployment. Third, it evaluates how energy representation, dynamic and uncertain conditions, operational constraints, validation breadth, and reproducibility are addressed across the literature. Finally, using a common corpus of 215 studies, it identifies systematic gaps between algorithmic development and deployable mission planning and translates these gaps into an evidence-based research agenda.

## 2. Review Methodology and Integrated Coding Framework

# 2.1. Literature Search and Study Selection

A systematic literature search was conducted in Scopus and the Web of Science Core Collection, with the database searches finalized in September 2026. The search covered publications from 2015 to 2026 and used four complementary search blocks (A1, A2, B1, and B2) combining UAV-related terminology with terms describing routing, path and trajectory planning, mission planning, and optimization. The search was deliberately broad so that operational realism could subsequently be assessed as an

outcome of the review rather than imposed as an inclusion condition. Accordingly, terms such as realistic, energy, benchmark, wind, and reproducibility were not required in the search strings. The complete database-specific search strategy and exact queries are provided in Supplementary Material Section S1 and Table S1.

Eligible studies were English-language journal articles or full conference papers in which mission-level UAV movement constituted a substantive optimization decision, including routing, global or waypoint planning, coverage, inspection, search and surveillance, delivery, data collection, and related mission-level trajectory optimization. Studies limited to local or reactive obstacle avoidance, low-level flight control, packet or network routing, static UAV placement, or routing systems in which a non-UAV vehicle constituted an essential routing component were excluded. Reviews, pre-2015 publications, very short papers, and studies in which UAV routing was not a substantive methodological contribution were also excluded. The complete eligibility criteria and predefined exclusion rules (E1–E12) are reported in Supplementary Material Section S3 and Table S4.

Records were deduplicated using DOI, exact or normalized titles, and bibliographic information where necessary. Screening was then conducted sequentially at the title/abstract and full-text levels. An initial 48-paper calibration set was used to refine the eligibility boundaries; 22 studies remained eligible and 26 were excluded after application of the finalized criteria. Full-text exclusions were recorded using the predefined E1–E12 exclusion codes, preserving an auditable reason for each decision. Detailed screening accounting, including the calibration set and subsequent screening batches, is provided in Supplementary Material Section S2 and Tables S2–S3. The complete selection procedure, from database identification and duplicate removal through screening and full-text assessment to the final 215-study corpus, is summarized (Fig. 1) in the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) flow diagram (Page et al., 2021).

**Note**

Search strings are omitted from the figure for readability and are reported in the Supplementary Material. The title/abstract screening sample comprised the 48-paper calibration set and 15 subsequent batches of 100 records each.

# 2.2. Phase 1: Problem-Structure Classification

Phase 1 characterized the structural features of each included study before the more detailed full-text assessment of operational realism and validation maturity. Three classification dimensions were retained for the final synthesis. First, the mission/service domain (G1) identified the primary operational purpose of the UAV mission using eight mutually exclusive categories: M1 delivery and logistics, M2 inspection and maintenance, M3 surveillance, reconnaissance and patrol, M4 search, disaster and emergency response, M5 coverage, mapping, imaging and reconstruction, M6 environmental and agricultural missions, M7 IoT/wireless sensor network (WSN) sensing and data collection, and M8 other

operational services. One primary mission category was assigned to each study, with a secondary category recorded only where a genuine cross-domain application was present.

Second, the routing/operational architecture (G2) captured how the UAV movement problem was structured. Twelve routing codes (R1–R12) represented architectures including single- and multi-UAV routing, joint task allocation and routing, coverage and revisit missions, dynamic/online routing, multi-trip operations, charging or replenishment, time-window scheduling, multi-depot systems, heterogeneous fleets, and integrated sequencing–trajectory problems. Unlike G1, G2 was explicitly multi-label, allowing multiple architectural characteristics to be assigned to the same study.

Third, the optimization paradigm (G4) classified the primary solution approach as exact/mathematical optimization, heuristic/metaheuristic, hybrid/matheuristic, ML/surrogate-assisted optimization, deep/neural combinatorial optimization, or reinforcement learning. A secondary paradigm was recorded only when substantively integrated with the primary method.

## 2.3. Phase 2: Operational Realism and Evidence Coding

Phase 2 consisted of a structured full-text assessment designed to evaluate how closely each routing study represented executable UAV operations and how strongly the proposed method was validated. Seven central dimensions were retained for the final synthesis. Validation type recorded the strongest level of empirical assessment actually demonstrated, using the progression Synthetic → Benchmark → Real-data simulation → Physical experiment → Field deployment. This distinction separated computational studies using artificial or standard instances from simulations based on real operational data, controlled experiments involving a physical UAV, and missions conducted in the intended operational context.

Real UAV was coded independently as Yes/No and required an actual physical UAV flight. Operational data identified whether locations, demand, weather, mission inputs, or related information were synthetic, benchmark-based, or derived from real-world sources. Dynamic/uncertain treatment distinguished static deterministic studies from those incorporating dynamic information, explicit uncertainty, or both. Robust, scenario-based, and related uncertainty formulations were grouped under the stochastic category for this reduced coding scheme.

The energy model captured increasing levels of physical representation: no energy treatment, range/time-based endurance proxies, explicit battery-energy accounting, or detailed models in which consumption depended on factors such as payload, speed, flight phase, maneuvering, or environmental conditions. Validation strength was classified as Basic, Comparative, or Extensive according to the breadth of computational or experimental evaluation, while reproducibility was coded as Low, Medium, or High according to the reporting of implementation details and the accessibility of code, data, or reusable instances.

Finally, “Key Constraints” was retained as a qualitative synthesis field. Because operational constraints are highly heterogeneous across applications, individual constraints were recorded descriptively rather

than forced into an overly rigid statistical taxonomy.

## 2.4. Integrated Analysis

The Phase 1 and Phase 2 datasets were merged using the common Paper_ID assigned to each included publication. The final integrated dataset contained 215 Phase 1 records and 215 Phase 2 records, with complete one-to-one matching (N = 215/215). Consequently, all subsequent cross-tabulations and comparisons were conducted on the same study population, avoiding inconsistencies that could arise from analyses based on partially overlapping samples. The integrated structure enabled mission domain, routing architecture, and optimization paradigm to be examined jointly with operational realism, validation maturity, and reproducibility. The complete list of the 215 included studies, together with their bibliographic information and coding characteristics, is provided in Supplementary Data S1 (sheet “Included_Studies_215”). For evidence-related analyses, the Phase 2 full-text validation coding was treated as the definitive classification because it was based on direct assessment of the complete articles. The preliminary evidence indicator assigned during Phase 1 was therefore not used in the final maturity analyses. Table 1 summarizes the coding dimensions retained in the integrated review framework.

Table 1
Integrated coding framework used in the systematic review

| Dimension | Code / variable | Categories or coding rule | Role in analysis |
|---|---|---|---|
| Mission/ service domain | G1 | M1 Delivery and logistics;<br>M2 Inspection and maintenance;<br>M3 Surveillance, reconnaissance and patrol;<br>M4 Search, disaster and emergency response;<br>M5 Coverage, mapping, imaging and reconstruction;<br>M6 Environmental and agricultural missions;<br>M7 IoT/WSN sensing and data collection;<br>M8 Other operational services | Primary mission context; one primary category per study, with secondary category where applicable |
| Routing/ operational architecture | G2 | R1–R12: single-UAV, multi-UAV, joint task allocation + routing, coverage, persistent/ revisit, dynamic/online, multi-trip, charging/replenishment, time-window/ service scheduling, multi-depot, heterogeneous fleet, integrated sequencing + trajectory | Multi-label representation of routing structure |
| Optimization/ decision intelligence | G4 | Exact/mathematical; heuristic/ metaheuristic; hybrid/ matheuristic; ML/surrogate-assisted; deep/neural combinatorial; reinforcement learning | Primary solution paradigm; secondary paradigm where substantively combined |
| Validation type | Validation Type | Synthetic; Benchmark; Real-data simulation; Physical experiment; Field deployment | Strongest validation actually demonstrated |
| Physical UAV use | Real UAV | Yes / No | Identifies whether an actual UAV was flown |
| Operational data | Operational Data | Synthetic; Benchmark; Real-world | Origin of mission, geographic, environmental, or operational inputs |
| Dynamic/ uncertain treatment | Dynamic or Uncertain | None; Dynamic; Stochastic; Both | Captures changing information and/or explicit uncertainty |

| Dimension | Code / variable | Categories or coding rule | Role in analysis |
|---|---|---|---|
| Energy representation | Energy Model | None; Range-time proxy; Battery-energy model; Detailed energy model | Indicates the level of energy/endurance realism |
| Validation breadth | Validation Strength | Basic; Comparative; Extensive | Breadth of numerical or experimental evaluation |
| Reproducibility | Reproducibility | Low; Medium; High | Reporting detail and availability of reusable code/data/instances |
| Operational constraints | Key Constraints | Short qualitative tags | Used for qualitative synthesis of heterogeneous mission constraints |

# 3. Landscape of UAV Routing Research

## 3.1. Evolution and Mission Domains

The final corpus shows a marked expansion of UAV-routing research over the 2015–2026 period (Fig. 2A). Only one study in the corpus was published in 2015, whereas annual output increased substantially after 2020, reaching 18 studies in 2021, 39 in 2022, 34 in 2023, 31 in 2024, and 43 in 2025. A further 29 studies were published in 2026 by the September search date. Overall, 194 of the 215 studies (90.2%) were published from 2021 onward, indicating that mission-level UAV routing has developed predominantly during the most recent period.

The application landscape is similarly diverse (Fig. 2B). Delivery and logistics constitutes the largest mission class (n = 44), encompassing increasingly complex formulations involving energy, moving recipients, charging, and service constraints. It is followed by coverage, mapping, imaging, and reconstruction (n = 35), including energy-aware coverage planning (Escobar & Pereira, 2025), and IoT/WSN sensing and data collection (n = 31), where routing is coupled with communication and data-acquisition requirements (Du et al., 2026; Houran et al., 2025). Inspection and maintenance accounts for 24 studies, environmental and agricultural missions for 22, surveillance/reconnaissance/patrol and other operational services for 21 each, and search/disaster/emergency response for 17 studies (Calamoneri et al., 2024).

These distributions show that UAV routing has evolved beyond a primarily delivery-oriented extension of the traveling salesman problem (TSP) and vehicle routing problem (VRP). It now encompasses substantially different mission structures, operational objectives, and execution conditions across multiple application domains.

## 3.2. Routing Architectures

Routing architecture provides a more informative structural view of the field than mission labels alone because it captures how the UAV movement problem is formulated. As noted in Section 2, G2 was coded as a multi-label classification, so a single study could simultaneously involve, for example, multi-UAV coordination, time windows, charging, and multi-depot operation. The resulting distribution shows that the literature is anchored in two near-equal core architectures: R1 single-UAV multi-target routing (n = 108) and R2 multi-UAV routing (n = 107). This near parity indicates that the field is no longer dominated by single-vehicle abstractions; coordination among multiple UAVs has become almost equally central (Xia et al., 2025; Caballero et al., 2025).

Beyond these two dominant forms, the most frequent secondary structures are R9 time-window/service scheduling (n = 40) (Zhen et al., 2024), R4 coverage path planning (n = 31) (Escobar & Pereira, 2025; de Souza et al., 2025), and R8 charging/replenishment-aware routing (n = 28) (Zhen et al., 2024). These categories indicate a clear shift away from purely geometric routing toward service- and resource-constrained operations, particularly in delivery, inspection, and persistent sensing contexts (Li et al., 2025; Zhen et al., 2024). Dynamic/online routing (R6, n = 23) is also increasingly visible, reflecting interest in changing mission states and replanning requirements (Radzki et al., 2021; Pu et al., 2025).

Several architectures remain comparatively uncommon. Integrated sequencing–trajectory problems (R12, n = 16), joint task allocation and routing (R3, n = 14), persistent/revisit routing (R5, n = 14), and multi-depot/distributed-base routing (R10, n = 14) are present but still clearly secondary to the dominant single- and multi-UAV formulations. Multi-trip/multi-sortie routing (R7, n = 12) is also relatively limited despite its practical relevance for battery-constrained UAV operations. Most notably, heterogeneous-fleet routing (R11, n = 3) remains extremely rare. This suggests that, although many studies claim operational relevance, the literature still only minimally addresses one of the most realistic features of real deployments: fleets composed of UAVs with differing capabilities, payloads, endurance limits, or sensing roles. Figure 3 summarizes the frequencies of all twelve routing architectures.

# 3.3. Optimization Paradigms

The solution-method distribution indicates that UAV-routing research remains predominantly grounded in operations research and combinatorial optimization, despite the growing visibility of AI-based methods. Exact or mathematical optimization is the largest category, accounting for 104 of 215 studies (48.4%). These studies typically formulate routing decisions through mixed-integer, nonlinear, dynamic-programming, or related mathematical models, sometimes complemented by decomposition or problem-specific solution procedures. Such approaches remain particularly important where feasibility, optimality bounds, or explicit representation of operational constraints is central (Wang et al., 2026).

The second major group comprises heuristic and metaheuristic methods (n = 64; 29.8%). Their prevalence reflects the computational difficulty of increasingly large, constrained, and multi-UAV routing problems, for which exact solution methods may become impractical. Rather than treating individual methods such as the genetic algorithm (GA), particle swarm optimization (PSO), ant colony optimization

(ACO), tabu search, and simulated annealing as separate methodological streams, they are better interpreted as a common response to combinatorial complexity. Comparative metaheuristic frameworks such as that of Abid et al. (2025) illustrate this role.

A further 30 studies (14.0%) employ hybrid or matheuristic approaches, combining mathematical optimization with heuristics, metaheuristics, decomposition, or other complementary procedures. This represents an intermediate methodological stage between purely exact formulations and fully data-driven decision methods, seeking to retain structural knowledge while improving scalability (Calamoneri et al., 2024).

Learning-based optimization remains comparatively limited. Reinforcement learning accounts for 11 studies (5.1%), ML/surrogate-assisted optimization for four (1.9%), and deep/neural combinatorial optimization for only two (0.9%). These approaches represent just 17 studies (7.9%) of the corpus. Examples include reinforcement-learning-based routing under uncertain operating conditions (Liu et al., 2023) and ML-assisted optimization for UAV-supported sensor networks (Shokouhifar et al., 2026). Thus, the methodological landscape is better understood as a progression from mathematical optimization → metaheuristics → hybrids → learning-based decision methods, rather than a wholesale transition toward AI. AI-based approaches receive substantial conceptual attention, but their actual prevalence in mission-level UAV-routing research remains modest.

## 4. Operational Realism in UAV Routing Models

# 4.1. Operational Data Realism

The origin of the data used to construct or evaluate routing problems provides a first indication of operational realism, but it should not be interpreted as evidence of real-world deployment. Of the 215 studies, 120 (55.8%) rely primarily on synthetic data, 27 (12.6%) use established benchmark instances, and 68 (31.6%) incorporate real-world data. The latter category includes studies using observed customer or demand locations, geographic information system (GIS)-based geographic information, measured environmental conditions, infrastructure data, or records derived from actual operational settings.

Crucially, however, real-world data do not imply real-world UAV operation. A routing algorithm may be evaluated using genuine geographic coordinates or operational demand while all route generation, energy estimation, and feasibility testing remain computational. Li et al. (2026), for example, use real metropolitan delivery and charging-network information within a computational routing framework. Similarly, Utamima and Fano (2026) incorporate official forest-fire hotspot records while evaluating the proposed routing approach numerically, and Wang et al. (2026) construct scenarios using information derived from practical drone-delivery operations without conducting the reported optimization study as an operational field mission.

Operational-data origin must therefore be interpreted separately from validation type and physical UAV use. This distinction is fundamental throughout the review: realism of the input data can strengthen contextual relevance, but it does not by itself demonstrate that an optimized route is physically executable under real operating conditions.

## 4.2. Energy and Endurance Representation

Energy feasibility is one of the most fundamental requirements of executable UAV routing, yet its representation remains uneven across the literature. Of the 215 studies, 73 (34.0%) contain no substantive energy representation, while 66 (30.7%) model endurance primarily through a maximum flight time, route length, range, or comparable proxy. Consequently, 139 studies (64.7%) either omit UAV energy entirely or approximate feasibility without explicitly modelling battery state or propulsion-energy consumption. Only 26 studies (12.1%) employ an explicit battery-energy model, while 50 (23.3%) use a more detailed representation of energy consumption. Thus, only 76 of 215 studies (35.3%) move beyond simple distance/time/range constraints toward explicit energetic feasibility.

These categories represent a meaningful progression in operational realism. At the simplest level, a range-time proxy assumes that energy feasibility can be represented indirectly through distance or mission duration. Such formulations are computationally convenient but cannot capture situations in which two routes of similar length impose substantially different energy requirements. The next level introduces explicit battery accounting, tracking available charge, energy consumption, recharging, or state-of-charge constraints. The highest level incorporates operational factors that materially alter propulsion demand, such as payload, speed, acceleration, flight phase, maneuvering, altitude, wind, weather, or vehicle-specific power characteristics.

The difference is operationally significant. Wang et al. (2026), for example, model nonlinear energy consumption as a function of payload, flight phase, and flight time in shore-to-ship delivery. Similarly, Escobar and Pereira (2025) integrate an energy model directly into multirotor coverage-path optimization rather than relying solely on route distance (Han et al., 2025; Büyüksan et al., 2026). Such formulations illustrate the transition from distance/range proxy → explicit battery accounting → physics- and operating-condition-aware energy modelling (Stodola, 2020; Ermağan et al., 2022; Han et al., 2025). The overall distribution nevertheless shows that most UAV-routing studies still represent endurance at a relatively abstract level, despite energy consumption being a primary determinant of whether an optimized route can actually be flown (Tükenmez & Özkan, 2024; Utamima & Fano, 2026).

## 4.3. Dynamics and Uncertainty

A second major limitation in operational realism concerns how UAV-routing models represent changing conditions and uncertainty. Of the 215 studies, 153 (71.2%) were coded as having neither dynamic operation nor explicit uncertainty. Only 36 studies (16.7%) incorporated dynamic conditions, 13 (6.0%) incorporated stochastic or otherwise explicit uncertainty, and 13 (6.0%) included both. Thus, only 62 studies (28.8%) represented some form of dynamic operation or uncertainty.

This result is important because many intended UAV applications are inherently time-varying (Radzki et al., 2021; Karabay et al., 2023; Donipati et al., 2025). Operational conditions may change after route computation through weather and wind variation, newly arriving tasks, moving service targets, communication disruptions, sensor or vehicle failures, changing buffer states, obstacles, demand updates, or deviations in battery performance (Karim et al., 2026; Diller et al., 2023; Zhang et al., 2022; Donipati et al., 2025). A route that is feasible under fixed pre-mission assumptions may therefore become infeasible or suboptimal during execution (Radzki et al., 2021; Karabay et al., 2023; Vivaldini et al., 2019). For example, Wang et al. (2026) model continuously moving vessels in shore-to-ship delivery, requiring spatial and temporal synchronization between the UAV and its service targets. Liu et al. (2023) incorporate stochastic wind effects together with recharging decisions, demonstrating how uncertainty can directly affect energy-aware routing (Peng et al., 2026).

The overall distribution nevertheless indicates that deterministic, predominantly offline formulations remain the norm. This creates an important realism gap: applications such as emergency response, surveillance, logistics, sensing, and persistent monitoring frequently operate in environments in which mission information evolves during execution. Accordingly, greater algorithmic sophistication does not necessarily imply greater operational adaptivity unless the routing framework can respond to newly observed states and uncertainty during the mission.

## 4.4. Operational-Constraint Richness

The “Key constraints” field reveals substantial heterogeneity in how operational feasibility is represented across UAV-routing studies. Because individual constraints were reported using study-specific terminology and were not normalized into mutually exclusive statistical categories, they are synthesized here qualitatively rather than converted into frequency counts. Five recurring constraint families provide a clearer operational taxonomy (Fig. 4).

“Vehicle constraints” concern the physical capabilities of the UAV, including payload capacity, flight range, battery limits, speed, and endurance (Nishira et al., 2024; Han et al., 2026; Büyüksan et al., 2026). These constraints directly determine whether a mathematically feasible route can be flown; payload-dependent energy requirements provide a representative example (Büyüksan et al., 2026). “Service constraints” describe what must occur at mission locations, including time windows, service duration, visit frequency, priorities, and sequencing requirements (Tükenmez & Özkan, 2024; Zhen et al., 2024). Priority-sensitive monitoring and repeated visits illustrate this class. “Infrastructure constraints” include depot structure, charging stations, battery replacement, and other replenishment mechanisms, which increasingly link routing decisions with mission continuity (Ermağan et al., 2022; Lorenz et al., 2026; Sun et al., 2026).

“Environmental constraints” represent conditions external to the vehicle, including wind, weather, obstacles, terrain, and spatial restrictions (Xie et al., 2023; Wang & Qian, 2026). Their importance is particularly evident when environmental variation directly modifies energy consumption or route feasibility (Liu et al., 2023; Thibbotuwawa et al., 2019). Finally, system constraints arise from interactions

within the wider operational system, including communication availability, collision avoidance, synchronization among vehicles, sensor failures, and heterogeneous-fleet coordination (Diller et al., 2023; Caballero et al., 2025; Medani et al., 2025; Chen et al., 2024; Wang & Qian, 2026).

These five families show that operational realism is multidimensional: realistic UAV routing requires more than adding individual constraints to an optimization model; it requires representing the interacting vehicle, service, infrastructure, environmental, and system conditions under which the route must actually be executed.

## 5. Validation Maturity and Reproducibility

# 5.1. Validation Ladder

Validation maturity was classified according to the strongest level of evidence demonstrated in each study: Synthetic → Benchmark → Real-data simulation → Physical experiment → Field deployment. The distribution is strongly concentrated at the computational end of this progression (Fig. 5).

Synthetic evaluation is the dominant category, accounting for 117 of 215 studies (54.4%), while 27 studies (12.6%) use established benchmarks. Together, these categories represent 144 studies (67.0%). A further 50 studies (23.3%) reach real-data simulation. Li et al. (2026), for example, evaluate their routing framework using real metropolitan delivery and charging-network information, while Dong et al. (2026) use data from the 2020 Liangshan wildfire.

Only 17 studies (7.9%) include controlled physical UAV experiments and four (1.9%) reach operational field deployment. Representative physical experiments include the energy-aware coverage tests of Escobar and Pereira (2025) and the route-execution experiments of Liu et al. (2016) and Yang et al. (2025). At the highest maturity level, Caballero et al. (2025) demonstrate autonomous inspection of more than 10 km of real overhead power lines using a heterogeneous UAV team.

Only 21 studies (9.8%) involve an actual UAV. The evidence base therefore remains predominantly computational, with a sharp reduction in the number of studies progressing from simulation to physical testing and operational deployment.

# 5.2. Validation Breadth

Validation breadth shows a different pattern from validation maturity. Of the 215 studies, 191 (88.8%) were classified as Extensive, 14 (6.5%) as Comparative, and 10 (4.7%) as Basic. Extensive studies typically evaluated multiple instances and included sensitivity, scalability, robustness, ablation, or similarly broad analyses, whereas Comparative studies focused mainly on baseline comparisons and Basic studies relied on limited illustrative cases.

These results indicate that UAV-routing research is generally characterized by substantial evaluation effort. However, breadth of testing should not be conflated with maturity of evidence. A method may be

examined across numerous computational scenarios, parameter settings, or baselines while still lacking direct evidence of physical executability. Validation breadth and validation maturity should therefore be interpreted as complementary but distinct dimensions.

## 5.3. Reproducibility

Reproducibility is similarly concentrated in the middle category. Of the 215 studies, 193 (89.8%) were classified as Medium, 13 (6.0%) as High, and 9 (4.2%) as Low. Medium reproducibility generally indicates sufficient methodological detail to understand and broadly reconstruct the reported procedure, including algorithm settings, software, hardware, or experimental configurations.

High reproducibility required stronger support for independent reuse, such as public code, accessible datasets, benchmark instances, instance generators, or sufficiently complete implementation resources. Only 13 studies met this standard.

This distinction matters because extensive evaluation and reproducibility are not equivalent. A method may be tested across numerous instances, baselines, or sensitivity analyses while remaining difficult to reproduce if code, data, parameter settings, random seeds, or software details are unavailable. Conversely, reusable research artifacts allow independent verification and more consistent comparison across methods.

The results show a clear asymmetry: UAV-routing studies are generally computationally extensive, but physical validation and high-level reproducibility remain comparatively limited.

# 6. Cross-Dimensional Synthesis and Maturity Gaps

## 6.1. Mission × Operational Maturity

Cross-dimensional analysis shows that operational maturity is not concentrated uniformly within any single mission domain (Fig. 6). Instead, different application families exhibit different combinations of data realism, energy representation, dynamic modelling, and empirical validation. This distinction is important because a mission class may appear mature on one dimension while remaining comparatively abstract on another.

The delivery and logistics mission family provides the clearest example. Although only 38.6% of delivery studies progressed to real-data simulation or higher validation, this domain shows comparatively strong modelling of physical feasibility: 63.6% employ an explicit battery-energy or detailed energy model and 40.9% incorporate dynamic conditions or uncertainty. Nevertheless, only 2 of 44 studies (4.5%) involved an actual UAV. Thus, delivery research has developed substantial operational modelling sophistication without a corresponding transition to physical validation.

The inspection and maintenance mission family exhibits a different maturity profile. Half of these studies reached at least real-data simulation, 45.8% used real-world operational data, and 25.0% involved

physical UAVs—the largest physical-validation share among the eight mission families. However, dynamic or uncertain operation was represented in only 8.3% of inspection studies. The coverage, mapping, imaging, and reconstruction mission family similarly shows comparatively greater physical validation (14.3%) than most domains, although explicit energy modelling remains limited to 25.7%. Notably, the four field deployments in the entire corpus were confined to these two mission families, with two in inspection/maintenance and two in coverage/mapping.

Other mission families reveal different mismatches. The search, disaster, and emergency response mission family has the largest share of studies reaching real-data simulation or higher (52.9%) and the same proportion using real-world data, yet explicit energy representation (5.9%) and physical UAV validation (5.9%) remain rare. Environmental and agricultural missions display a similar contrast: 50.0% use real-world data, but only 13.6% employ explicit energy models. Conversely, IoT/WSN sensing and data collection is relatively strong in energy modelling (54.8%) but highly simulation-dependent: only 3.2% use real-world operational data and 6.5% reach real-data simulation or higher validation. The surveillance, reconnaissance, and patrol mission family also remains weak in explicit energy modelling (4.8%) and physical UAV evidence (4.8%).

These results indicate that maturity should not be represented by a single score. Model realism and empirical maturity develop unevenly across mission families, and greater use of realistic data or sophisticated energy models does not necessarily correspond to physical or operational validation.

## 6.2. Routing Architecture × Validation Maturity

The integrated dataset provides no evidence that greater routing-architecture sophistication is systematically accompanied by greater empirical maturity. Because G2 is a multi-label classification, the architecture groups overlap and should not be interpreted as mutually exclusive populations. Nevertheless, their validation profiles reveal clear differences between formulation complexity and demonstrated operational evidence.

The two dominant architectures show almost identical maturity patterns. Among single-UAV multi-target studies (R1, n = 108), 66.7% remain at synthetic or benchmark validation, while 9.3% involve a physical UAV. The corresponding values for multi-UAV routing (R2, n = 107) are 67.3% and 10.3%, respectively. Thus, moving from single- to multi-UAV formulations has not produced a corresponding increase in empirical validation.

The pattern is even clearer for several structurally advanced architectures. Of the 23 dynamic/online-routing studies (R6), only 8 (34.8%) reach real-data simulation or higher and only one (4.3%) involves an actual UAV. Similarly, charging/replenishment-aware routing (R8, n = 28) shows strong physical modelling—23 studies (82.1%) use explicit battery-energy or detailed energy representations—but only one study (3.6%) includes physical UAV validation.

The rare heterogeneous-fleet studies (R11, n = 3) provide too small a sample for generalization, but none involved physical UAV validation. The strongest mismatch occurs in integrated sequencing–trajectory

formulations (R12, n = 16). Despite jointly optimizing discrete visit sequencing and continuous trajectory decisions, all 16 studies were validated synthetically, with no real-data simulation, physical experiment, or field deployment. Table 2 summarizes the validation and energy profiles of these selected routing architectures.

Table 2
Validation maturity and energy representation across selected UAV routing architectures.

| Routing architecture | N | Synthetic/ benchmark | ≥ Real-data simulation | Physical UAV | Explicit energy |
|---|---|---|---|---|---|
| R1 Single-UAV multi-target | 108 | 72 (66.7%) | 36 (33.3%) | 10 (9.3%) | 41 (38.0%) |
| R2 Multi-UAV | 107 | 72 (67.3%) | 35 (32.7%) | 11 (10.3%) | 35 (32.7%) |
| R6 Dynamic/online | 23 | 15 (65.2%) | 8 (34.8%) | 1 (4.3%) | 9 (39.1%) |
| R8 Charging/replenishment-aware | 28 | 18 (64.3%) | 10 (35.7%) | 1 (3.6%) | 23 (82.1%) |
| R11 Heterogeneous fleet | 3 | 2 (66.7%) | 1 (33.3%) | 0 | 0 |
| R12 Integrated sequencing + trajectory | 16 | 16 (100%) | 0 | 0 | 6 (37.5%) |

Note. G2 routing architectures are multi-label categories; therefore, studies may appear in more than one row. “≥ Real-data simulation” includes real-data simulation, physical experiment, and field deployment. “Physical UAV” denotes studies in which an actual UAV was flown. “Explicit energy” combines battery-energy and detailed energy models. Percentages are calculated within each routing-architecture group.

# 6.3. Optimization Paradigm × Validation Maturity

Crossing the primary optimization paradigm with validation type reveals a clear innovation–validation disconnect. Methodological novelty does not correspond systematically to stronger empirical evidence, and the newest decision-intelligence approaches remain concentrated largely at the simulation stage.

Exact or mathematical optimization (O1, n = 104) exhibits the broadest validation profile. Although 57 studies (54.8%) remain synthetic, 26 (25.0%) use real-data simulation, 13 (12.5%) include physical experiments, and 2 (1.9%) reach field deployment. Collectively, 41 O1 studies (39.4%) reach at least real-data simulation and 15 (14.4%) involve physical or field evidence. This is noteworthy because the more established mathematical-optimization literature currently contains a larger share of physically validated studies than the emerging learning-based methodological families.

Heuristic/metaheuristic approaches (O2, n = 64) are more strongly concentrated in synthetic and benchmark evaluation: 79.7% fall within these two categories, while only 5 studies (7.8%) progress to physical experiments or field deployment. Hybrid/matheuristic approaches (O3, n = 30) show a different

pattern. A relatively high 43.3% use real-data simulation, but none proceed to physical experimentation or field deployment.

The learning-based categories are much smaller and require cautious interpretation. All ML/surrogate-assisted studies (O4, n = 4) and deep/neural combinatorial studies (O5, n = 2) remain at synthetic or benchmark validation. Reinforcement learning (O6, n = 11) shows somewhat greater maturity, with 3 real-data simulations (27.3%) and 1 physical experiment (9.1%), but no field deployments.

Learning-based decision methods account for only 17 of 215 studies (7.9%) and have not, as a group, progressed beyond simulation more rapidly than conventional optimization approaches. Figure 7 shows the distribution of validation levels within each optimization paradigm.

## 6.4. Five Maturity Gaps

The cross-dimensional results indicate an uneven progression from optimization sophistication toward operationally demonstrated capability. Five recurring maturity gaps emerge from the integrated analysis.

1. Algorithmic sophistication vs empirical validation. Across routing architectures and optimization paradigms, greater methodological complexity does not consistently correspond to stronger empirical evidence. The maturity of a routing method should therefore be judged separately from the novelty of its optimization algorithm.
2. Routing abstraction vs vehicle physics. Many studies still represent UAV feasibility through route distance, maximum range, or flight-time constraints, while explicit battery accounting and physics-aware energy models remain substantially less common. Such abstractions can obscure the effects of payload, speed, maneuvering, flight phase, wind, and other factors that determine actual energy consumption. A route that satisfies a geometric range constraint is therefore not necessarily energetically executable.
3. Offline optimization vs dynamic operation. Most studies retain deterministic or static formulations despite the inherently time-varying nature of many UAV missions. Weather, wind, moving targets, newly arriving tasks, communication disruptions, failures, battery deviations, and changing demand can alter route feasibility during execution. Operational maturity therefore requires greater movement from pre-mission route optimization toward closed-loop planning and replanning based on newly observed system states.
4. Real data vs real deployment. The use of GIS layers, customer locations, delivery demand, weather records, disaster maps, or other real-world inputs improves contextual realism but should not be treated as equivalent to physical validation. Real-data simulation remains fundamentally different from controlled UAV experimentation, which in turn differs from deployment in the intended operational environment.
5. Experimental breadth vs reproducibility. UAV-routing studies are often computationally extensive, with multiple instances, baselines, sensitivity analyses, or scalability tests. However, extensive

experimentation does not guarantee independent reproducibility when code, datasets, benchmark definitions, parameter settings, software versions, or random seeds are unavailable.

These five gaps define the optimization-to-deployment gap identified in this review. Progress toward deployable UAV routing therefore depends on coordinated advances in physical realism, dynamic decision making, empirical validation, and reproducibility.

# 7. Research Agenda

The maturity gaps identified in this review suggest that future UAV-routing research should prioritize deployability over additional algorithmic variation. Five directions are particularly important.

1. Physics-aware routing. Routing models should move beyond distance, range, and flight-time proxies when these abstractions materially affect feasibility. Relevant factors include payload, speed, maneuvering, altitude, flight phase, wind, and battery state. The objective is to achieve sufficient physical fidelity to determine whether an optimized route can actually be flown.
2. Adaptive routing under uncertainty. Routing should increasingly be treated as a closed-loop process integrating sensing, state estimation, execution monitoring, and replanning. Stochastic, robust, scenario-based, or adaptive methods are needed where weather, communication, demand, target motion, battery state, or vehicle availability can change during execution.
3. System-level multi-UAV operation. Future models should move beyond fleets of identical vehicles toward heterogeneous, coordinated systems. Communication constraints, collision avoidance, synchronization, shared airspace, coordinated charging, distributed decision making, and differentiated vehicle roles should be incorporated where operationally relevant.
4. Progressive validation. Validation should advance systematically from computational testing to real-data simulation, controlled physical flight, and, where appropriate, operational deployment. Claims of practical applicability should be aligned with the strongest validation level actually demonstrated.
5. Reproducible research infrastructure. UAV-routing benchmarks should include not only coordinates and route costs, but also vehicle characteristics, energy parameters, environmental conditions, service requirements, and validation scenarios. Public code, reusable datasets, instance generators, parameter settings, and software details would enable independent replication and fairer comparison.

Table 3 summarizes the empirical basis, methodological implications, and recommended validation pathways associated with these five priorities.

Table 3
Evidence-based research agenda for deployable UAV routing

| Observed gap | Evidence from N = 215 | Required methodological advance | Recommended validation |
|---|---|---|---|
| Simplified physical/energy representation | 139 studies (64.7%) use no energy model or only range/time proxies | Physics-aware routing incorporating relevant payload, speed, maneuver, wind, and battery effects | Energy-model calibration and controlled flight testing |
| Predominantly static and deterministic planning | 153 studies (71.2%) include neither dynamics nor explicit uncertainty; only 62 (28.8%) include either | Closed-loop routing with state estimation, replanning, and stochastic/robust/adaptive treatment of uncertainty | Dynamic stress testing followed by real-time flight experiments |
| Limited system-level fleet realism | Multi-UAV routing is common (n = 107), but heterogeneous-fleet routing is rare (n = 3) | Heterogeneous fleets, communication constraints, collision avoidance, synchronization, and coordinated charging | Multi-UAV controlled experiments progressing to operational trials |
| Weak progression to physical deployment | 144 studies (67.0%) remain at synthetic/benchmark validation; 21 (9.8%) use an actual UAV; 4 (1.9%) reach field deployment | Explicit progression from computational testing toward operational execution | Simulation → real-data simulation → controlled flight → field deployment |
| Limited high-level reproducibility | Only 13 studies (6.0%) achieve High reproducibility | Open code, datasets, benchmark generators, reusable instances, and complete implementation settings | Independent replication on common benchmark and real-data scenarios |

Therefore, the research priority is no longer simply to compute better routes, but to develop physically credible, adaptive, system-aware, validated, and reproducible routing methods that can transfer to real UAV missions.

# 8. Conclusions

This systematic review shows that UAV-routing research has developed into a broad and methodologically sophisticated field spanning logistics, inspection, sensing, surveillance, environmental monitoring, emergency response, coverage, and other operational applications. The literature now addresses a wide range of routing architectures, including multi-UAV coordination, charging-aware routing, time-window scheduling, dynamic operation, and integrated sequencing–trajectory decisions.

Despite the growing prominence of artificial intelligence and learning-based decision methods, the field remains dominated by mathematical optimization, heuristics, metaheuristics, and hybrid approaches.

Learning-based methods represent an important emerging direction, but their actual prevalence remains modest relative to the attention they receive.

The more consequential finding is that operational maturity has not progressed at the same rate as algorithmic maturity. Many studies continue to rely on simplified endurance assumptions, deterministic or offline formulations, synthetic or benchmark evaluation, and limited physical validation. Real-world data improve contextual realism, but they do not by themselves demonstrate that an optimized route can be executed by an actual UAV under operational conditions. Likewise, extensive numerical experimentation should not be confused with reproducibility or deployment readiness.

The resulting optimization-to-deployment gap suggests that future UAV-routing research should place greater emphasis on physics-aware energy modelling, dynamic and uncertain operation, heterogeneous multi-UAV systems, progressive physical validation, and reusable research artifacts. Methodological innovation remains valuable, but its practical significance ultimately depends on whether routing decisions remain feasible when confronted with real vehicles, real environments, and changing mission conditions.

Future progress in UAV routing should therefore be measured not only by shorter routes, lower objective values, or faster algorithms, but by the ability to produce physically feasible, adaptive, reproducible, and operationally validated UAV missions.

# References


1. Abid M, El Kafhali S, Amzil A, Hanini M (2025) Optimization of UAV flight paths in multi-UAV networks for efficient data collection. Arab J Sci Eng 50(10):7207–7232. https://doi.org/10.1007/s13369-024-09369-9
2. Bhuiyan TH, Walker V, Roni M, Ahmed I (2024) Aerial drone fleet deployment optimization with endogenous battery replacements for direct delivery of time-sensitive products. Expert Syst Appl 252:124172. https://doi.org/10.1016/j.eswa.2024.124172
3. Büyüksan AT, Demir KU, Utku DH, Özgün K (2026) Energy consumption optimization of multi-trip UAV routing using surrogate modeling with heuristic and metaheuristic algorithms. Drones 10(6):430. https://doi.org/10.3390/drones10060430
4. Caballero A, Roman-Escorza FJ, Maza I, Ollero A (2025) A multi-UAV approach for fast inspection of overhead power lines: From route planning to field operation. J Intell Robotic Syst 111(2):67. https://doi.org/10.1007/s10846-025-02277-6
5. Calamoneri T, Corò F, Mancini S (2024) Management of a post-disaster emergency scenario through unmanned aerial vehicles: Multi-depot multi-trip vehicle routing with total completion time minimization. Expert Syst Appl 251:123766. https://doi.org/10.1016/j.eswa.2024.123766
6. Chen L, Liu G, Zhu X, Li X (2024) A heuristic routing algorithm for heterogeneous UAVs in time-constrained MEC systems. Drones 8(8):379. https://doi.org/10.3390/drones8080379

7. Chen M, Smyth AW, Giometto MG, Li MZ (2023) Drone delivery routing with stochastic urban wind. In *2023 IEEE 26th International Conference on Intelligent Transportation Systems (ITSC)* (pp. 2260–2267). https://doi.org/10.1109/ITSC57777.2023.10422533
8. Chi C-Y, Chen D-F, Doan H-P, Kuo C-H (2024) UAV parcel delivery system with deep reinforcement learning based collision avoidance and route optimization. Int J Autom Smart Technol 14(1):8–18. https://doi.org/10.5875/p25fht10
9. de Souza BCF, Marques TB, Arroyo JEC (2025) GRASP metaheuristic for energy-efficient drone coverage path planning. In *Proceedings of the Genetic and Evolutionary Computation Conference Companion* (pp. 2190–2197). https://doi.org/10.1145/3712255.3734543
10. Diller J, Hall P, Han Q (2023) Holistic path planning for multi-drone data collection. In *2023 19th International Conference on Distributed Computing in Smart Systems and the Internet of Things (DCOSS-IoT)* (pp. 222–226). https://doi.org/10.1109/DCOSS-IoT58021.2023.00046
11. Dong Y, Li P, Guo X, Li Z (2026) Towards effective forest fire response: A cloud–edge collaborative UAV deployment strategy for rapid situational awareness. Fire 9(4):160. https://doi.org/10.3390/fire9040160
12. Donipati M, Jaiswal A, Hazra A, Mazumdar N, Singh J (2025) Optimizing UAV-based data collection in IoT networks with dynamic service time and buffer-aware trajectory planning. IEEE Trans Netw Serv Manage 22(2):1450–1460. https://doi.org/10.1109/TNSM.2024.3500778
13. Du P, Zhao S, Jia Z, Cao H, Liu L, Du J, Qing C (2026) Multi-drone cooperative path planning for data collection in large-scale IoT networks. IEEE Internet Things J 13(12):27154–27165. https://doi.org/10.1109/JIOT.2026.3678884
14. Ermağan U, Yıldız B, Salman FS (2022) A learning based algorithm for drone routing. Comput Oper Res 137:105524. https://doi.org/10.1016/j.cor.2021.105524
15. Escobar L, Pereira GAS (2025) Energy-aware coverage path planner for multirotor UAVs. In *2025 International Conference on Unmanned Aircraft Systems (ICUAS)* (pp. 777–784). https://doi.org/10.1109/ICUAS65942.2025.11007830
16. Ghaziani M, Yaman U, Turgut AE (2026) Optimized multi-unmanned aerial vehicle coverage path planning for efficient solar panel cleaning: A rectilinear and vehicle routing problem-based approach. J Dyn Syst Meas Contr 148(4). https://doi.org/10.1115/1.4070721
17. Grogan S, Pellerin R, Gamache M (2021) Using tornado-related weather data to route unmanned aerial vehicles to locate damage and victims. OR Spectrum 43(4):905–939. https://doi.org/10.1007/s00291-021-00640-1
18. Han C, Zhang M, Zhang J, Ma X (2026) A guided collaborative optimization framework for the stability-constrained UAV routing and three-dimensional loading problem. Algorithms 19(5):403. https://doi.org/10.3390/a19050403
19. Han Z, Fang C, Wang W, Xu J (2025) Energy-efficient UAV routing problem based on approximate cellular decomposition for geohazards monitoring. Comput Oper Res 183:107154. https://doi.org/10.1016/j.cor.2025.107154

20. Houran MA, Srivastava G, Mirza J, Ranjha A, Javed MA, Zafar MH (2025) Centralized task allocation for multiple UAVs in time-constraint industrial IoT operations. IEEE Internet Things J 12(18):37529–37537. https://doi.org/10.1109/JIOT.2025.3584277
21. Ito S, Akaiwa K, Funabashi Y, Nishikawa H, Kong X, Taniguchi I, Tomiyama H (2022) Load and wind aware routing of delivery drones. Drones 6(2):50. https://doi.org/10.3390/drones6020050
22. Karabay N, Köksalan M, Tezcaner Öztürk D (2023) Biobjective UAV routing for a mission to visit multiple mobile targets. OR Spectrum 45(3):925–954. https://doi.org/10.1007/s00291-023-00715-1
23. Karim AA, Majed H, Abbas N (2026) Hazard-aware multi-UAV mission coordination using DQN for disaster relief supply delivery. In *2026 IEEE 23rd Consumer Communications & Networking Conference (CCNC)* (pp. 1–6). https://doi.org/10.1109/CCNC65079.2026.11366551
24. Kumar G, Tanvir O, Kumar A, Goswami M (2025) Optimal drone deployment for cost-effective and sustainable last-mile delivery operations. Int Trans Oper Res 32(6):3259–3295. https://doi.org/10.1111/itor.13527
25. Li J, Ni X, Hua M, Wang Q, Wu Q, Zhao X, Xu M (2026) Energy-efficient large-scale low-altitude delivery: Integrating charging station location and UAV route planning by a cascade optimization framework. Aerosp Sci Technol 168:111119. https://doi.org/10.1016/j.ast.2025.111119
26. Li M, Lyu T, Guo C, Lin F (2025) A novel ant colony inspection scheme for satellite integrated smart grid. Discover Artif Intell 5:218. https://doi.org/10.1007/s44163-025-00478-4
27. Liu R, Shin H, Tsourdos A (2023) Edge-enhanced attentions for drone delivery in presence of winds and recharging stations. J Aerosp Inform Syst 20(4):216–228. https://doi.org/10.2514/1.I011171
28. Liu X, Gao L, Guan Z, Song Y, Zhang R (2016) A multi-objective optimization model for planning unmanned aerial vehicle cruise route. Int J Adv Rob Syst 13(3). https://doi.org/10.5772/64165
29. Lorenz C, Mimmo N, Otto A, Vigo D (2026) Very large-scale neighborhood search for drone routing with energy replenishment. OR Spectrum 48(2):587–626. https://doi.org/10.1007/s00291-026-00849-y
30. Medani K, Gherbi C, Mabed H, Aliouat Z (2025) Energy-efficient Q-learning-based path planning for UAV-aided data collection in agricultural WSNs. Internet Things 33:101698. https://doi.org/10.1016/j.iot.2025.101698
31. Nishira M, Nishikawa H, Kong X, Tomiyama H (2024) Multi-trip routing of delivery drones with load-dependent flight speed. In *2024 International Conference on Electronics, Information, and Communication (ICEIC)* (pp. 1–4). https://doi.org/10.1109/ICEIC61013.2024.10457090
32. Oliveira KR, Dias LMA, Balieiro WG, Cukla AR, Gamarra DFT, Drews PLJ, Brito AS, Silva VJ, Pio JLS, Oliveira FG (2026) Distance-optimized waypoint sequencing for UAV environmental monitoring. In *2026 Brazilian Conference on Robotics (CROS)* (pp. 316–321). https://doi.org/10.1109/CROS69211.2026.11565710
33. Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, Shamseer L, Tetzlaff JM, Akl EA, Brennan SE, Chou R, Glanville J, Grimshaw JM, Hróbjartsson A, Lalu MM, Li T, Loder EW,

Mayo-Wilson E, McDonald S, Moher D (2021) The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. BMJ 372:n71. https://doi.org/10.1136/bmj.n71

34. Peng W, Wang D, Yang H, Cheng T (2026) Robust drone delivery with partial recharging strategy in urban medical logistics. Transp Res E 209:104732. https://doi.org/10.1016/j.tre.2026.104732
35. Pu Q, Yang L, Li T (2025) Dynamic coverage path planning method for UAV formations in multi-region aerial tasks. Aerosp Sci Technol 167:110683. https://doi.org/10.1016/j.ast.2025.110683
36. Radzki G, Bocewicz G, Golińska-Dawson P, Jasiulewicz-Kaczmarek M, Witczak M, Banaszak Z (2021) Periodic planning of UAVs' fleet mission with the uncertainty of travel parameters. In *2021 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE)* (pp. 1–8). https://doi.org/10.1109/FUZZ45933.2021.9494491
37. Romanov AM, Gyrichidi N, Volkova MA, Eroshenko SA, Matrenin PV, Khalyasmaa AI (2024) Automated mission planning for aerial large-scale power plant thermal inspection. J Field Robot 41(5):1313–1348. https://doi.org/10.1002/rob.22320
38. Shan F, Huang J, Xiong R, Dong F, Luo J, Wang S (2022) Energy-efficient general PoI-visiting by UAV with a practical flight energy model. IEEE Trans Mob Comput 1–17. https://doi.org/10.1109/TMC.2022.3199237
39. Shi J, Mao H, Zhou Z, Zheng L (2023) Adaptive large neighborhood search algorithm for the unmanned aerial vehicle routing problem with recharging. Appl Soft Comput 147:110831. https://doi.org/10.1016/j.asoc.2023.110831
40. Shokouhifar M, Khoshvaght S, Mirjalili S, Smerat A, Almazyad AS, Mohamed AW (2026) Real-time metaheuristic-driven machine learning model for UAV-assisted wireless rechargeable sensor networks in smart agriculture. Appl Soft Comput 199:115309. https://doi.org/10.1016/j.asoc.2026.115309
41. Stodola P (2020) Unmanned surveillance problem: Mathematical formulation, solution algorithms, and experiments. Military Oper Res 25(2):31–48. https://doi.org/10.5711/1082598325231
42. Sun Y, Qi G, Guan W, Guo R (2026) Minimizing costs in UAV inspection routing: Trade-offs between fleet size and recharging strategies. In *2026 International Conference on Robotics, Automation and Intelligent Transportation Systems (RAITS)* (pp. 1–5). https://doi.org/10.1109/RAITS68656.2026.11580185
43. Thibbotuwawa A, Bocewicz G, Nielsen P, Banaszak Z (2019) Planning deliveries with UAV routing under weather forecast and energy consumption constraints. IFAC-PapersOnLine 52(13):820–825. https://doi.org/10.1016/j.ifacol.2019.11.231
44. Tükenmez İ, Özkan Ö (2024) Matheuristic approaches for multi-visit drone routing problem to prevent forest fires. Int J Disaster Risk Reduct 112:104776. https://doi.org/10.1016/j.ijdrr.2024.104776
45. Utamima A, Fano NF (2026) Priority-aware unmanned aerial vehicles route planning for forest fire monitoring using Bayesian-tuned hybrid metaheuristics. IEEE Access 14:118436–118451. https://doi.org/10.1109/ACCESS.2026.3719107

46. Vivaldini KCT, Martinelli TH, Guizilini VC, Souza JR, Oliveira MD, Ramos FT, Wolf DF (2019) UAV route planning for active disease classification. Auton Robots 43(5):1137–1153. https://doi.org/10.1007/s10514-018-9790-x
47. Wang K, Song M, Li M (2021) Cooperative multi-UAV conflict avoidance planning in a complex urban environment. Sustainability 13(12):6807. https://doi.org/10.3390/su13126807
48. Wang M, Chen S, Meng Q (2026) Drone routing problem for shore-to-ship delivery services considering non-linear energy consumption. Transp Res Part B: Methodological 206:103410. https://doi.org/10.1016/j.trb.2026.103410
49. Wang W, Qian H (2026) A battery-aware integrated genetic algorithm with K-means and 2-optimization for multi-UAVs discrete coverage path planning in unstructured environment. Adv Eng Inform 73:104574. https://doi.org/10.1016/j.aei.2026.104574
50. Xia Y, Xu X, Xu Y, Li A, Wang J, Fu C, Wu W (2025) An efficient task scheduling framework for large-scale 3D reconstruction in multi-UAV edge-intelligence systems. Symmetry 17(10):1758. https://doi.org/10.3390/sym17101758
51. Xie D, Hu R, Wang C, Zhu C, Xu H, Li Q (2023) A simulation framework of unmanned aerial vehicles route planning design and validation for landslide monitoring. Remote Sens 15(24):5758. https://doi.org/10.3390/rs15245758
52. Yang Q, Zhang Y, Shao S (2025) Dynamic siting and coordinated routing for UAV inspection via hierarchical reinforcement learning. Machines 13(9):861. https://doi.org/10.3390/machines13090861
53. Zhang J, Zhu Y, Wang T, Wang W, Wang R, Li X (2022) An improved intelligent auction mechanism for emergency material delivery. Mathematics 10(13):2184. https://doi.org/10.3390/math10132184
54. Zhang T, Shen H, Yin Y, Xu J, Yu J, Pan Y (2024) LECES: A low-bandwidth and efficient collaborative exploration system with distributed multi-UAV. IEEE Rob Autom Lett 9(9):7795–7802. https://doi.org/10.1109/LRA.2024.3433200
55. Zhen L, Yang Z, Laporte G, Yi W, Fan T (2024) Unmanned aerial vehicle inspection routing and scheduling for engineering management. Engineering 36:223–239. https://doi.org/10.1016/j.eng.2023.10.014
56. Zheng Y, Gai W, Zhang J, Zhong M (2026) A collaborative bi-level optimization approach for smart logistics: Depot location and unmanned aerial vehicle-based pickup-delivery services. Eng Appl Artif Intell 165:113453. https://doi.org/10.1016/j.engappai.2025.113453

# Figures

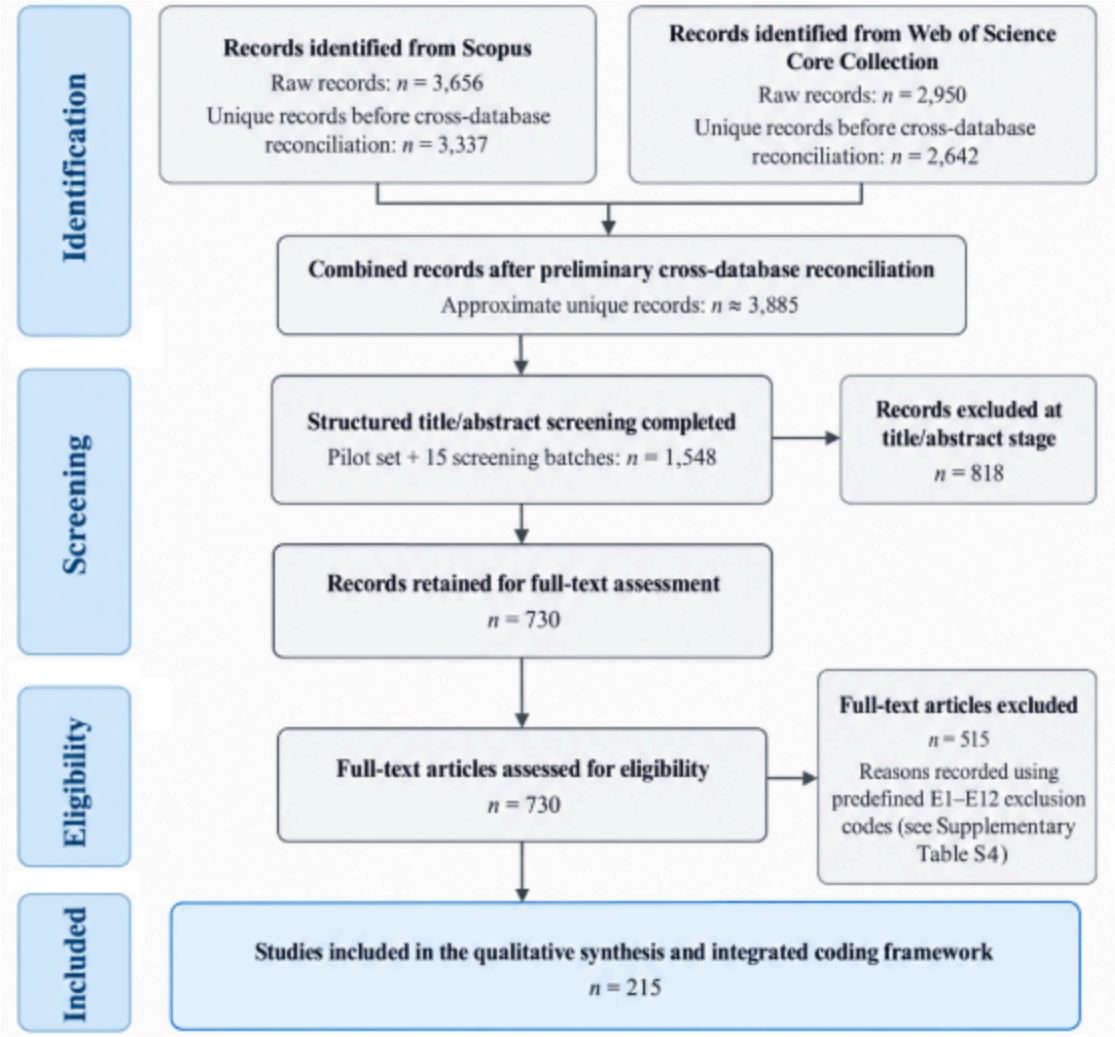



**Figure 1**

PRISMA-style flow diagram of literature identification, screening, and inclusion

Note. Search strings are omitted from the figure for readability and are reported in the Supplementary Material. The title/abstract screening sample comprised the 48-paper calibration set and 15 subsequent batches of 100 records each.

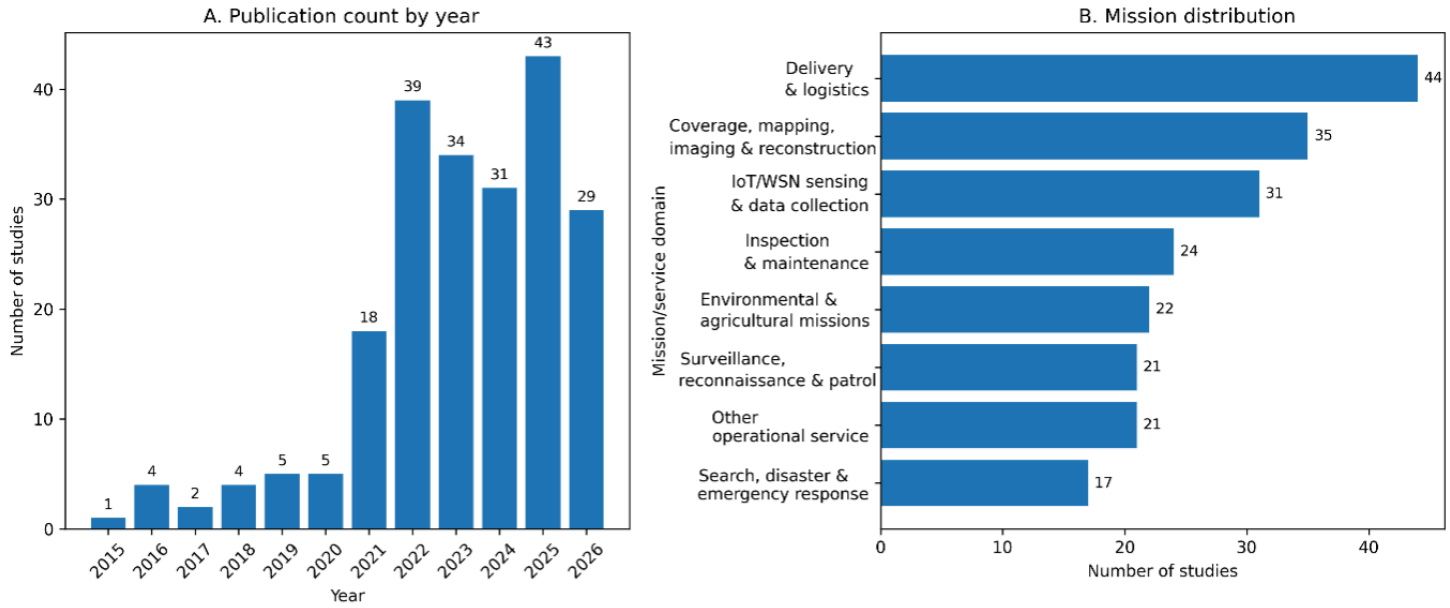



**Figure 2**

Evolution and mission domains of UAV routing research (N = 215)

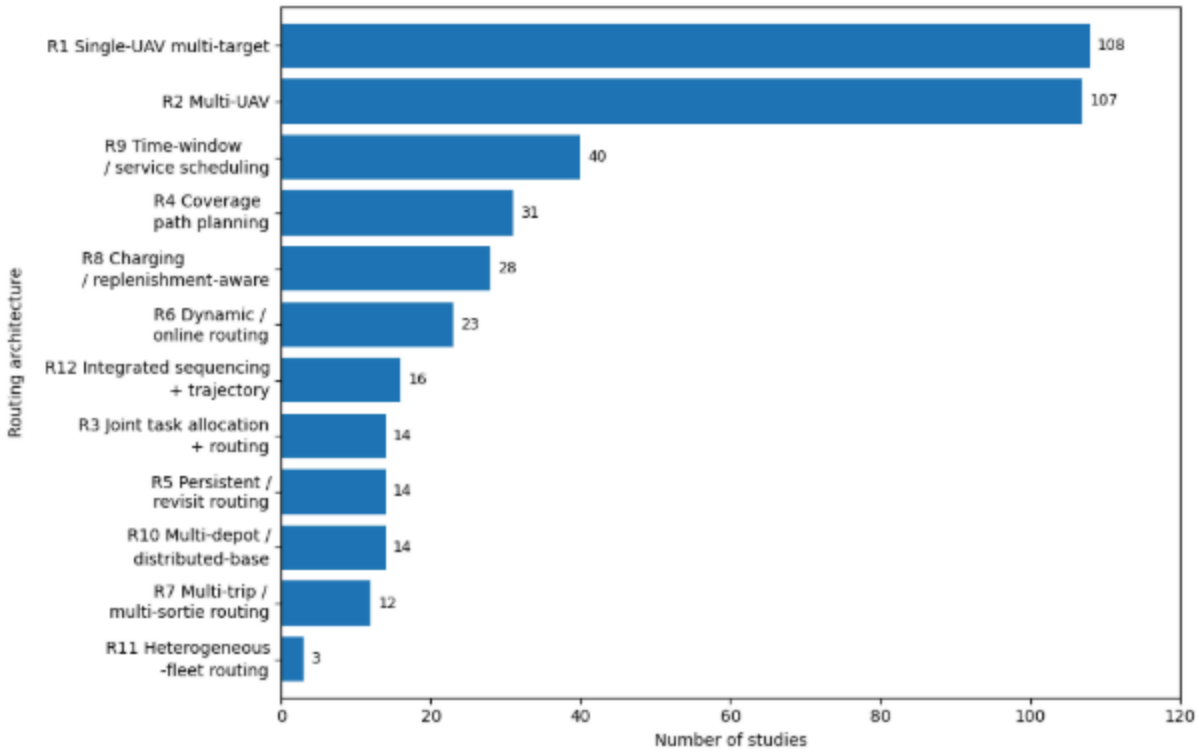
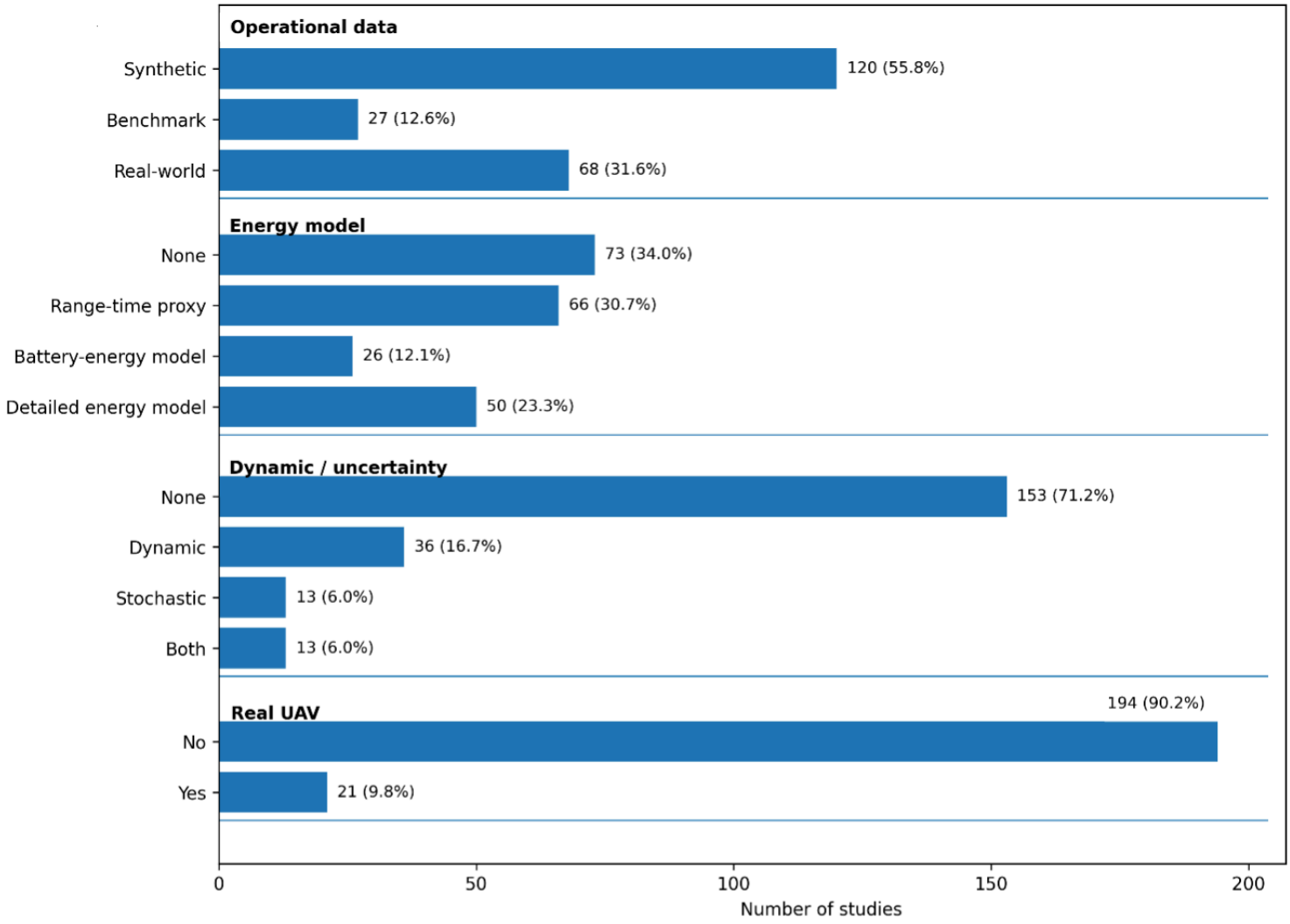


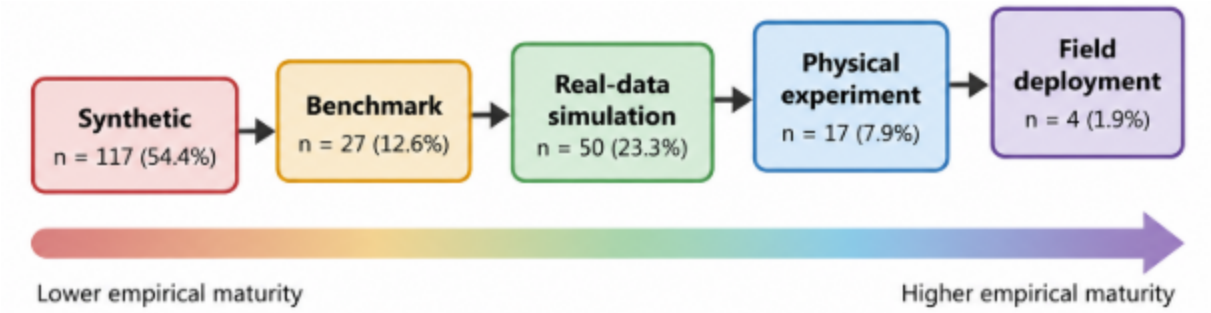

**Figure 3**

Distribution of UAV routing architectures (G2; N = 215)




## Figure 4

Operational realism profile of the reviewed UAV-routing studies




## Figure 5

Validation maturity ladder for UAV-routing studies (N = 215)

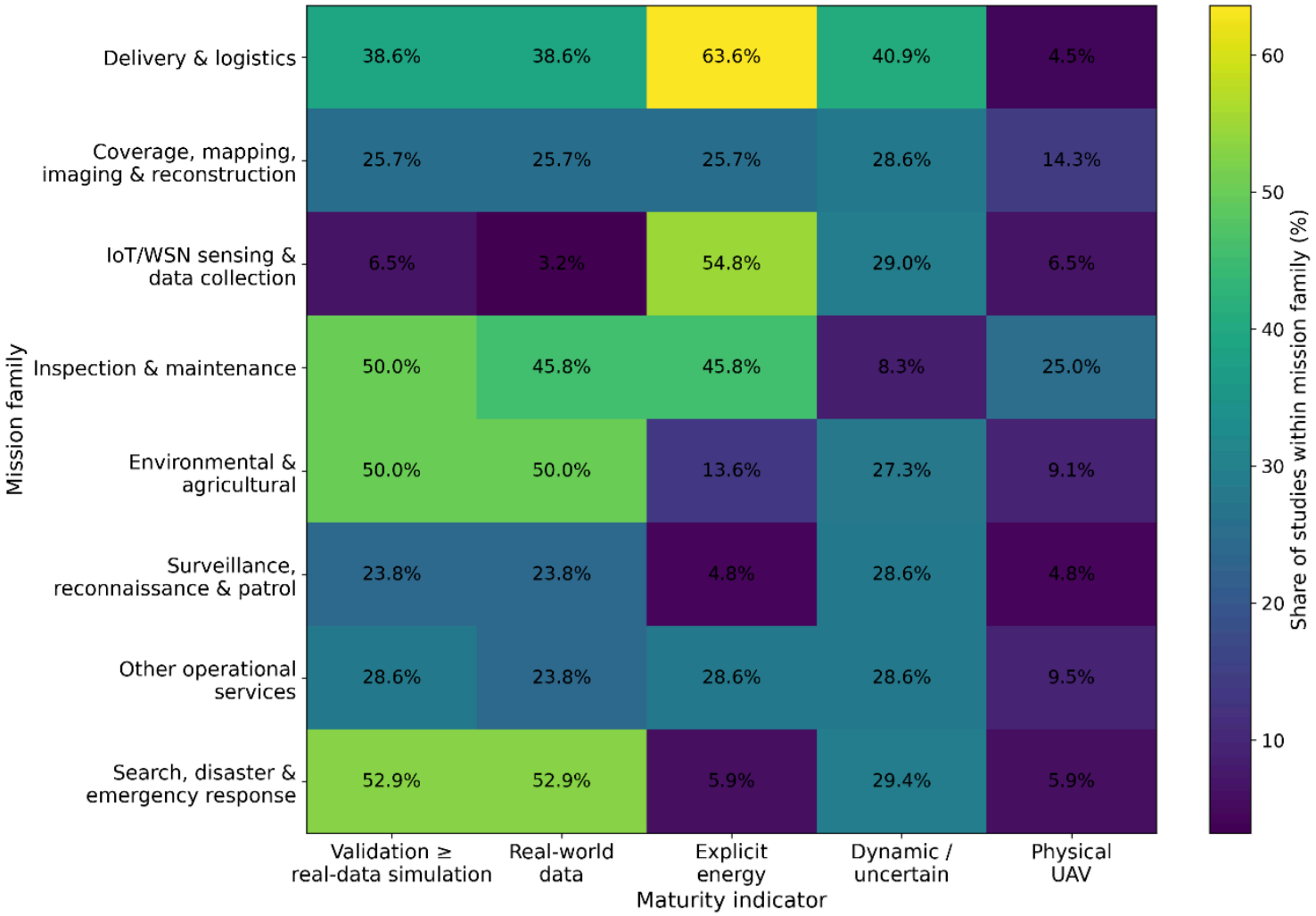



**Figure 6**

Mission family × operational and validation maturity indicators heatmap

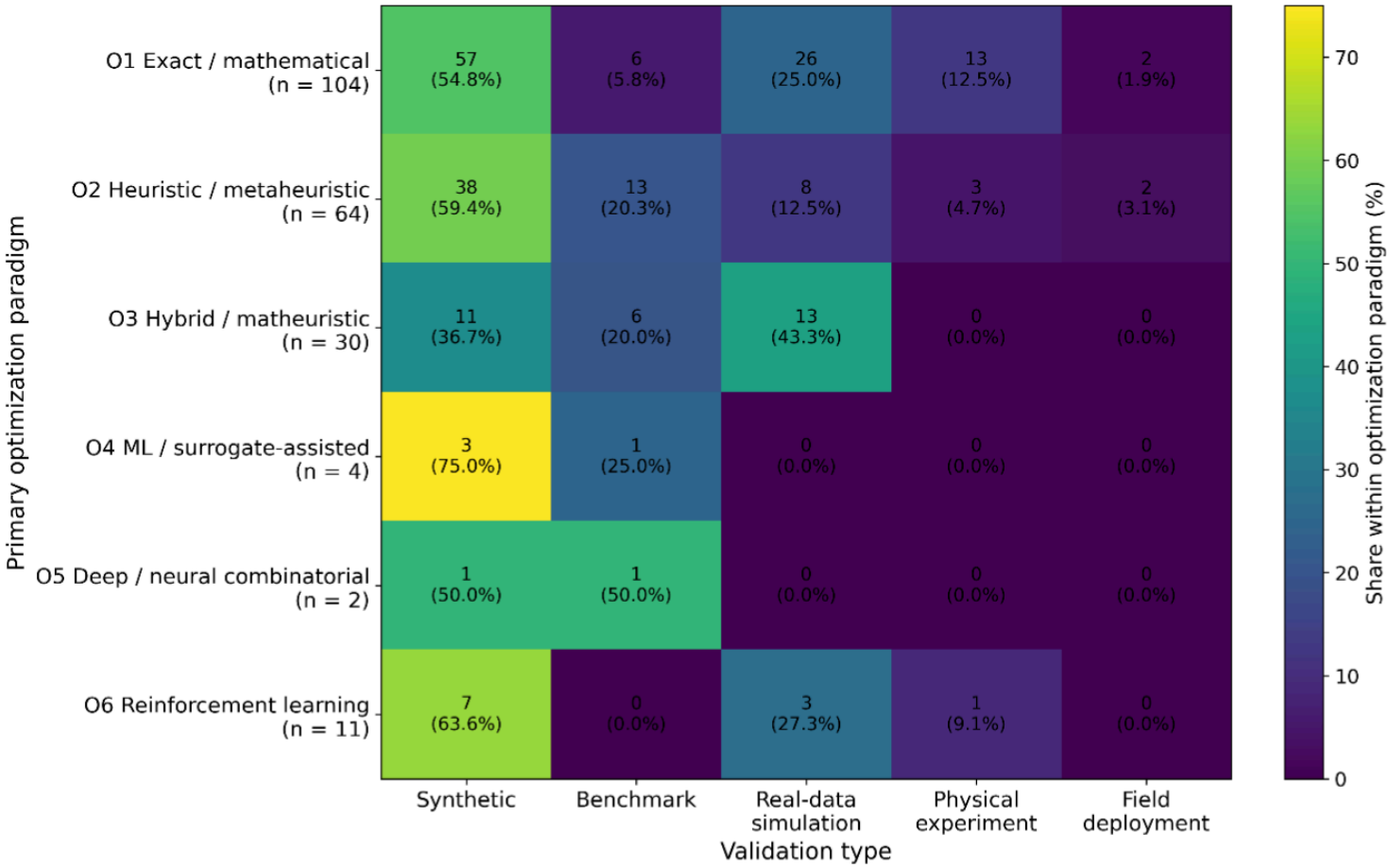



**Figure 7**

Optimization paradigm × validation maturity heatmap