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Cargo drones versus trucks in mid-mile freight: Cost, emissions, and reliability trade-offs for sustainable logistics

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Abstract: *Purpose*. This paper investigates whether cargo drones can serve as a viable, sustainable alternative to diesel trucks in mid-mile freight logistics, an operational segment linking regional hubs and fulfilment points that remains dependent on fossil-fuel trucking despite mounting cost, emissions, and regulatory pressures. *Methodology*. An integrated, scenario-based analytical framework compares drones and trucks across cost, carbon emissions, and operational reliability. The framework combines modular cost decompositions, first-principles emissions accounting, and a simplified additive reliability model, parameterised with consolidated secondary data on energy prices, grid carbon intensity, and weather-driven unmanned aerial vehicle performance across five representative operational scenarios. *Results*. Drones deliver lower per-kilometre operating costs than trucks in most high-demand and high-fuel-price scenarios and consistently achieve 80-90 percent lower emissions across all scenarios. Reliability is the binding constraint: drone availability drops sharply under adverse weather, while trucks maintain stable performance across nearly all conditions. *Theoretical contribution*. The study extends the drone-logistics literature, previously concentrated on last-mile, single-dimension assessments, by offering one of the first integrated, multi-criteria comparative frameworks for mid-mile operations and by showing that climatic and grid-decarbonisation factors, not technology maturity alone, determine modal competitiveness. *Practical implications*. The findings support hybrid truck-drone network design, weather-adaptive routing, and prioritised regulatory pathways for Beyond Visual Line of Sight corridors in climatically stable, decarbonising regions, providing operators and policymakers with a decision-support basis for sustainable freight modal choice.

Keywords: unmanned aerial vehicles, freight decarbonisation, modal choice, scenario-based modelling, operational reliability, beyond visual line of sight

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Sustainable Development Goals Goals (SDGs): SDG 9: Industry, Innovation and Infrastructure; **SDG 11:** Sustainable Cities and Communities; **SDG 12:** Responsible Consumption and Production; **SDG 13:** Climate Action

1. Introduction

Mid-mile logistics, linking regional hubs, distribution centres, and fulfilment points, has emerged as a crucial operational layer in contemporary supply chains (Bridgelall, 2024; Purtell et al., 2025). The acceleration of e-commerce, the proliferation of decentralised warehousing, and rising expectations for time-definite deliveries have intensified pressures on this segment (Wang et al., 2025). Despite its centrality, mid-mile transport remains heavily dependent on diesel-powered trucking fleets, which face mounting constraints related to congestion, volatile fuel markets, labour shortages, and increasingly stringent emissions regulations (EC, 2023; Kirschstein, 2020; Ragon & Rodríguez, 2022; Wang et al., 2025). Recent analyses also show that conventional trucking systems face efficiency losses in dispersed regional and rural corridors, particularly where freight demand is uneven or infrastructure is under stress (Bridgelall, 2024; Figliozzi & Hadas, 2024). These challenges underscore the need for alternative mobility options that enhance efficiency while supporting broader sustainability and resilience objectives.

Electric unmanned aerial vehicles (UAVs), or cargo drones, have attracted growing attention as an emerging logistics technology capable of providing faster, more energy-efficient point-to-point transport (Purtell et al., 2025; Rojas Viloria et al., 2021). Drones bypass road congestion, operate autonomously along aerial corridors, and use electric propulsion with low marginal energy costs (Dorling et al., 2017). Demonstrations in medical logistics, emergency response, and controlled operational settings indicate their technical feasibility (Gao et al., 2021; Umlauf & Burchardt, 2022). Drone-enabled middle-mile operations are also receiving increased attention within advanced air mobility and freight planning research, which highlights their potential to complement or partially replace road-based systems under suitable conditions (Kim et al., 2018). However, drone logistics research has predominantly centred on last-mile operations involving short routes and lightweight payloads (Chiang et al., 2019; Eskandaripour & Boldsaikhan, 2023). Mid-mile operations differ substantially in scale, range, and regulatory exposure, with more stringent reliability requirements (Bridgelall, 2024). Evidence specifically addressing these mid-mile configurations remains limited.

Existing studies provide valuable yet fragmented insights into drone routing optimisation, energy consumption, lifecycle environmental impacts, and hybrid truck–drone systems (Figliozzi & Hadas, 2025). However, most evaluate individual performance dimensions in isolation, often overlooking the interplay between cost, emissions, and reliability (Chiang et al., 2019). This is problematic because UAV performance is highly sensitive to environmental conditions: commercial drones face restricted flyability under wind, precipitation, and temperature extremes, while route geometry and payload characteristics further affect energy efficiency and service reliability (Chiang et al., 2019; Figliozzi & Hadas, 2025; Gao et al., 2021; Kumar et al., 2025). Research comparing drones with ground vehicles also shows that energy and emissions performance shifts with operational density and geography. Fleet composition further moderates these effects (Kim et al., 2018; Kumar et al., 2025). These sensitivities become more pronounced in mid-mile operations, where longer distances and higher payloads amplify weather-related performance penalties (Purtell et al., 2025).

Research in the sustainability and advanced air mobility domains further highlights both the promise and constraints of drone adoption: drones can reduce emissions and costs under favourable corridor conditions but perform less well in dense urban or high-wind settings, while infrastructural and regulatory barriers, including airspace restrictions and the absence of harmonised standards, continue to complicate broader adoption (Bridgelall, 2024; EC, 2023; Figliozzi & Hadas, 2024; Kumar et al., 2025; Purtell et al., 2025). Section 2 examines these constraints in greater detail.

These fragmented insights create a substantive knowledge gap: there is no integrated, scenario-based evaluation comparing mid-mile drones and trucks across cost, emissions, and reliability dimensions, despite rising interest in deploying drones beyond last-mile contexts. This gap complicates decision-making for logistics operators who must balance fuel volatility, service-level expectations, and decarbonisation goals, and for policymakers responsible for defining Beyond Visual Line of Sight regulations and low-altitude airspace frameworks (ICAO, 2023; Kim et al., 2018; Ragon & Rodríguez, 2022).

To address this gap, this paper introduces an analytical framework that evaluates cargo drones and diesel trucks across cost, carbon emissions, and operational reliability dimensions. The framework draws on consolidated secondary data, including UAV energy and reliability characteristics (Bruzzone et al., 2023; Figliozzi & Jennings, 2020; Kirschstein, 2020), truck fuel and emissions factors (EPA, 2025), grid carbon intensity data (IEA, 2025), and recent weather-adjusted drone performance findings (Kumar et al., 2025).

The study makes three contributions. First, it provides one of the few mid-mile-specific comparative evaluations grounded in a unified cost, reliability, and emissions framework. Second, it highlights how climatic and energy system factors fundamentally shape modal performance. Third, it offers actionable insights for hybrid drone–truck deployment strategies and regulatory planning to support safe and sustainable UAV integration.

Overall, the findings position cargo drones not as a universal substitute for trucks but as a contextually advantageous complement capable of delivering meaningful operational and environmental benefits under favourable conditions. Trucks remain indispensable in weather-exposed or reliability-critical corridors, while drones offer strong performance in high-utilisation, low-carbon, or fuel-volatile settings (Wang et al., 2025). By clarifying where and when drones outperform conventional trucking, this study supports evidence-based decision-making for logistics operators, regulators, and infrastructure planners.

By quantifying the cost, emissions, and reliability trade-offs of mid-mile drone adoption, this study directly contributes to Sustainable Development Goal 9 (resilient infrastructure and innovation), Goal 12 (efficient resource use in supply chains), and Goal 13 (climate action through freight decarbonisation).

The remainder of the paper is structured as follows. Section 2 reviews UAV logistics, mid-mile transport challenges, environmental assessments, and optimisation models. Section 3 details the methodology, including data sources and scenario design. Section 4 presents results. Section 5 discusses implications, and Section 6 offers a conclusion.

2. Literature review

Mid-mile logistics is defined as the movement of goods from regional distribution hubs to local fulfilment centres(Zou et al., 2024). It has been receiving growing attention due to its influence on cost structures, delivery speeds, and environmental performance in modern supply chains (Bridgelall, 2024). Conventional mid-mile transport relies overwhelmingly on diesel trucks, which provide high payload capacity and route flexibility but are increasingly constrained by congestion, rising energy costs, and emissions regulations (EC, 2023; Ragon & Rodríguez, 2022; Umlauf & Burchardt, 2022). This has driven interest toward alternative technologies such as electric cargo drones, which may reduce travel times and emissions (Dorling et al., 2017; Umlauf & Burchardt, 2022).

2.1. Mid-mile logistics: Role, bottlenecks, and emerging trends

Conventional mid-mile freight is dominated by diesel-powered trucks and light commercial vehicles (Danchuk et al., 2023; Figliozzi & Hadas, 2025). Although trucks offer high payload capacity and route flexibility, their performance is undermined by traffic congestion, labour intensity, increasingly strict emissions regulations, and exposure to volatile fuel markets (EC, 2023; EPA, 2025; Plötz et al., 2023). Medium-distance freight is often susceptible to suboptimal load factors, inconsistent routing patterns, and fluctuating road conditions (Umlauf & Burchardt, 2022). Researchers emphasise that mid-mile inefficiencies contribute disproportionately to both costs and emissions compared with last-mile or long-haul operations (Bridgelall, 2024; Ovaere & Proost, 2022). Studies from the road-freight literature highlight that mid-mile transport contributes disproportionately to carbon emissions relative to vehicle-kilometres travelled (Plötz et al., 2023; Ragon & Rodríguez, 2022), partly because medium-distance trips often involve suboptimal load factors and non-continuous driving cycles.

Technological innovation in routing, digital fleet management, and electrification has mitigated some inefficiencies; however, structural constraints remain (Figliozzi et al., 2020; Purtell et al., 2025). These persistent limitations have steered researchers toward alternative aerial solutions, including electric cargo drones, as potential complements or substitutes for parts of the mid-mile network (Bridgelall, 2024; Danchuk et al., 2023; Umlauf & Burchardt, 2022).

2.2. Drone logistics: Capabilities, constraints, and state of the technology

Cargo drones, typically small to medium electric UAVs capable of carrying 2–20 kg payloads, have recently moved beyond experimental applications (Umlauf & Burchardt, 2022). Pioneering deployments by Zipline, Wing, Matternet, and UPS Flight Forward have demonstrated the feasibility of reliable, automated flights for medical supplies, postal shipments, and emergency logistics (Sigari & Biberthaler, 2021). While most operational deployments target last-mile or specialised urgent deliveries, the literature increasingly examines the potential for drones to operate in mid-mile corridors where flights can be longer, repeatable, and more structurally integrated into scheduled freight operations (Gunady et al., 2023; Kim et al., 2018).

From a technical standpoint, UAV performance depends on aerodynamic efficiency, battery capacity, payload mass, and environmental conditions (Rai et al., 2025). Recent engineering studies model drone energy consumption as a function of payload mass, aerodynamic drag, propeller efficiency, and environmental conditions, consistently showing that drones can achieve high energy efficiency per kilometre when operated at optimal speeds and altitudes (Huang et al., 2024; Kim et al., 2018; Thibbotuwawa et al., 2018; Yowtak et al., 2020).

These analyses consistently show that drones can achieve high energy efficiency per kilometre when operated at optimal speeds and altitudes (Huang et al., 2024). Conversely, several constraints remain central to the academic debate, including weather sensitivity (wind, rain, turbulence) reducing operational windows; battery degradation and recharging cycles; payload limitations; airspace integration, communication link reliability, and regulatory oversight (ICAO, 2023; Rojas Viloria et al., 2021; Yowtak et al., 2020). Other studies highlight that global “flyability” varies drastically by geography, with direct implications for reliability modelling, which is a core focus of the present study (Danchuk et al., 2023; Gao et al., 2021).

Table 1: Overview of representative studies comparing UAVs and trucks in freight

Study/Year	Focus	Methods	Key findings
(Kirschstein, 2020),	Energy demand of drone vs truck parcel delivery	Analytical energy model comparing drone-based and ground-based parcel delivery under different spatial patterns	Drone delivery can require more energy than truck delivery in dense urban settings; drones become more competitive in sparse or rural networks with longer inter-stop distances
(Yowtak et al., 2020)	Lifecycle environmental performance of UAV vs ICE van vs BEV van	Comparative LCA for grocery delivery scenarios (online grocery shopping)	UAVs can have lower lifecycle impacts per delivery in some configurations, but electric vans often remain competitive or superior depending on grid mix and service design
(Figliozzi, 2020)	Emissions from autonomous drones/robots vs conventional store trips and vans	Scenario-based emissions model comparing autonomous air and ground delivery with customer store trips and van-based delivery	Autonomous drones and ground robots can reduce total CO_2 emissions in certain demand and spatial configurations, especially when replacing individual shopping trips
(Bao et al., 2025)	Hybrid drone–truck “parallel” delivery vs truck-only	Lifecycle environmental and economic assessment of a drone–truck parallel system	Parallel drone–truck systems can reduce lifecycle emissions and total cost in specific spatial and demand conditions, particularly when drone utilisation is high

(Figliozzi & Hadas, 2025)	Evaluates energy and distance trade-offs in drone–truck delivery fleet allocation.	Model comparison of alternative fleet allocation policies.	A simple distance-based rule delivers the lowest energy use and travel distance.
(Wang et al., 2025)	Drone–truck collaborative scheduling under uncertain drone speeds.	K-means clustering with mixed-integer programming and data-driven robust optimisation.	Joint truck–drone routing improves time and energy efficiency even with speed uncertainty.
(Thomas et al., 2024)	Optimising a single-truck, multi-drone delivery system with en-route launch and recovery.	MILP modelling with an RF-RRO heuristic and deep-learning clustering for scalable routing and scheduling	En-route drone operations cut delivery time significantly and improve drone utilisation.
(Gao et al., 2021)	Assesses how weather conditions limit drone flyability across different global regions	Simulation comparing historical weather data with manufacturer flight thresholds.	Drone flyability is low in many regions and improves mainly with higher wind and precipitation tolerances.
(Kumar et al., 2025)	Reviews academic work on the environmental impacts of drone-based delivery systems.	Structured literature review of 59 interdisciplinary journal articles.	Shows how drones can reduce environmental impacts and reshape logistics within sustainable transport systems.
(Purtell et al., 2025)	Examines opportunities and challenges of integrating middle-mile drones into logistics.	Expert insights from an industry specialist supported by input from 33 executives	MMDs show promise for improving operations but face major hurdles in scalability and technology maturity
(Bridgelall, 2024)	Optimising middle-mile logistics for high-value goods using cargo drones	GIS-based spatial optimisation to assign hubs and compare drone–truck performance	Drones cut costs and travel distances, offering a sustainable alternative for rural mid-mile routes

2.3. Comparative studies of drones and trucks

Most comparative analyses primarily focus on last-mile delivery, where drones have shown potential reductions in energy consumption, delivery time, and emissions (Dorling et al., 2017; Figliozzi, 2020). Some studies report that drone-truck hybrid systems can reduce lifecycle emissions by up to 30% under energy-efficient routing algorithms (Figliozzi et al., 2020; Wang et al., 2025). However, such studies predominantly examine short-range, point-to-point operations and often neglect medium-distance mid-mile flows, where payloads are larger, routing is less flexible, and annual distance travelled is significantly higher (Kumar et al., 2025; Lemardelé et al., 2023).

A subset of the literature investigates integrated truck–drone ecosystems, in which drones launch from trucks to offload the last-mile burden (Bányai, 2022; Bao et al., 2025). These approaches often demonstrate cost or energy benefits but assume favourable weather and limited airspace constraints. Moreover, the performance models used in those studies do not extend to mid-mile operations, where drones must sustain longer flights and require more reliable power management and charging infrastructure.

The consensus in the literature is that drones offer superior environmental performance under certain conditions, whereas trucks maintain advantages in payload robustness, reliability under adverse conditions, and scalability (Bao et al., 2025; Betti Sorbelli, 2024; Bridgelall, 2024; Macioszek, 2018; Purtell et al., 2025). However, few studies evaluate the combined trade-offs among cost, emissions, and reliability within a unified analytical framework (ICAO, 2023). In the following, Table 1 summarises key peer-reviewed studies comparing unmanned aerial vehicles (UAVs) and conventional trucks in logistics operations, highlighting their analytical focus, methodological approaches, and significant limitations, particularly the lack of integrated cost, reliability, and emissions evaluation for mid-mile transport.

2.4. Emissions and lifecycle assessment of UAVs vs ground transport

In sustainability-oriented research, electric drones generally outperform diesel trucks when the electricity grid has moderate to high renewable energy penetration (Kirschstein, 2020; Kumar et al., 2025; Townsend et al., 2020). Drones eliminate tailpipe emissions and reduce upstream emissions when charged from cleaner grids (Kumar et al., 2025; Stolaroff et al., 2018). However, lifecycle studies caution that battery manufacturing, replacement and material extraction can reduce net environmental gains (Porzio & Scown, 2021). Trucks, meanwhile, produce steady emissions dominated by diesel combustion (García, Monsalve-Serrano, Martinez-Boggio, et al., 2020; García, Monsalve-Serrano, Sari, et al., 2020; Quiros et al., 2017).

Many researchers also warn against simplistic comparisons (Kumar et al., 2025). In instances under fossil-heavy grids, such as coal-based electricity systems, drones may not outperform electric vans or highly efficient trucks (Huang et al., 2024; Vedrtnam et al., 2025). Moreover, parallel analyses show that drones lose their emissions advantage sharply as payload increases or adverse weather forces detours, hover phases, or increased power draw (Gao et al., 2021; Kim et al., 2018). Despite these complexities, consensus across the literature suggests that, under the right energy and operational conditions, drones represent a potentially significant decarbonisation lever within multi-tier supply chains (European Council, 2023).

2.5. Reliability Constraints: Weather, Battery, and Traffic

Reliability is arguably the most understudied dimension in drone–truck comparisons (Betti Sorbelli, 2024; Jahani et al., 2025). In many cases, reliability is a pivotal dimension for drone logistics (Rejeb et al., 2023). The availability of unmanned aerial vehicles (UAVs) decreases significantly during high winds, precipitation, and low visibility (Gao et al., 2021; Kim et al., 2018). On the other hand, trucks suffer from congestion, mechanical breakdowns, and route-blocking incidents but tend to perform stably across most weather conditions (Danchuk et al., 2023; Figliozzi & Hadas, 2025; Gao et al., 2021).

Recent reliability modelling shows that weather reduces drone operational availability by 15–40% depending on region and season (Gao et al., 2021; Glick et al., 2022; Kim et al., 2018). Studies also highlight battery degradation as a major determinant of real-world drone performance, influencing both flight range and charging cycle reliability (Kirschstein, 2020; Porzio & Scown, 2021; Yowtak et al., 2020). Existing models typically treat cost, emissions, and reliability as independent analyses (Figliozzi & Hadas, 2024). This fragmentation is a key research gap that the present study addresses through an integrated methodology.

2.6. Identified research gap

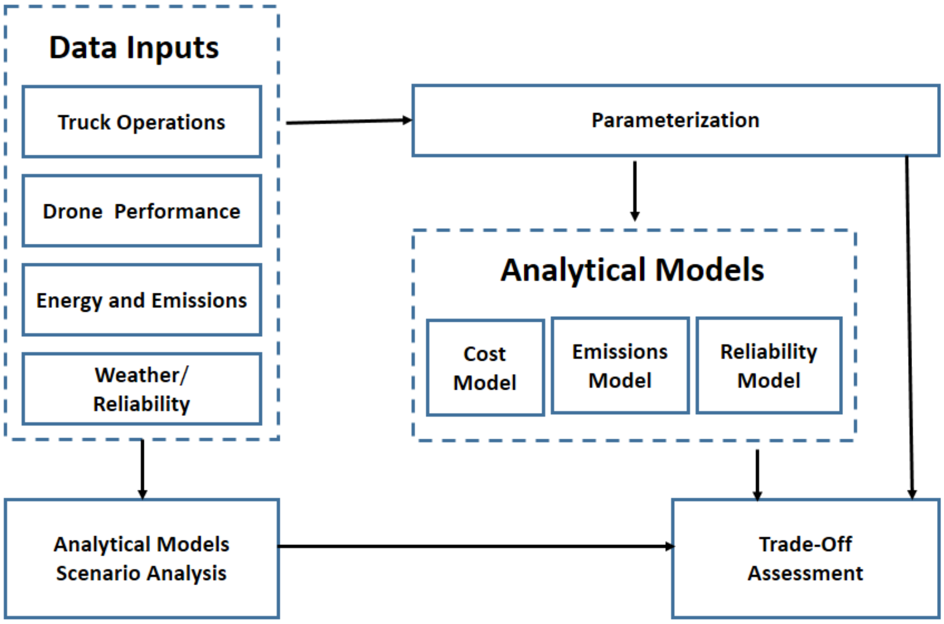
Based on the above review, three significant gaps in the literature emerge. First, the Mid-mile operations are under-researched (Bridgelall, 2024; Purtell et al., 2025). Most UAV research focuses on last-mile delivery, medical logistics, or hybrid systems; few studies examine medium-distance routes where drones could provide structured, repeatable services in logistics corridors (Betti Sorbelli, 2024; Figliozzi, 2024; Figliozzi & Hadas, 2025; Glick et al., 2022; Jahani et al., 2025; Wang et al., 2025). Secondly, comparisons rarely integrate cost, emissions, and reliability into a unified analytical model (Figliozzi et al., 2020; Purtell et al., 2025). Most of the studies tend to isolate one or two dimensions, leaving decision-makers without a comprehensive multi-criteria perspective. Finally, the limited scenario-based analysis captures realistic variability (Kim et al., 2018). Weather, energy prices, charging cycles, and utilisation changes are seldom evaluated together, despite their importance for mid-mile drone viability. These gaps justify the unified analytical framework developed in this paper and underscore the need for evidence-based trade-off evaluation across operational, environmental, and reliability metrics.

3. Methodology

This study adopts a mixed analytical–conceptual methodology designed to evaluate the relative performance of cargo drones and conventional trucks in mid-mile logistics. The framework compares both systems across three dimensions: cost, reliability, and carbon emissions, while remaining grounded in realistic mid-mile operating parameters. Because mid-mile drone delivery is nascent and large-scale datasets are limited, the study integrates high-quality secondary data, consistent with approaches used in drone–truck comparative modelling (Bao et al., 2025; Figliozzi, 2020; Kirschstein, 2020; Yowtak et al., 2020).

As shown in Figure 1, a mixed analytical–conceptual framework for comparing mid-mile drones and trucks. This figure helps visualise the research design from data input to model parameterisation, scenario analysis, and integrated trade-off assessment.

Figure 1: Methodology framework diagram



3.1. Analytical framework overview (research design)

The genuine methodological contribution of this study lies not in the individual cost, emissions, or reliability equations, which follow established additive decomposition logic common in freight-cost and lifecycle-assessment literature, but in their joint integration into a single mid-mile-specific, scenario-based comparative framework.

The study uses a comparative analytical design rather than a single-corridor empirical dataset. This mirrors recent drone–truck analyses that synthesise multiple secondary data sources into generalisable performance models (Bao et al., 2025; Kirschstein, 2020; Thibbotuwawa et al., 2018). The models are evaluated across structured mid-mile scenarios (e.g., 30–120 km routes, medium payloads, variable energy and weather conditions).

The framework consists of four methodological pillars:

- Cost assessment model
- Emissions estimation model
- Reliability evaluation model
- Scenario-based comparative analysis

This design enables realistic yet generalised comparison of trucks and drones, similar to system-level analytical frameworks in drone–ground vehicle LCA studies (Kirschstein, 2020; Yowtak et al., 2020).

3.1.1. Cost assessment model

The cost assessment models for trucks and drones follow standard modular cost-decomposition practice in freight-cost modelling, adapted here to the specific requirements of mid-mile comparative analysis. The cost framework compares the per-kilometre operational cost of drones and trucks using transparent modular formulas. Each cost component is treated as a parameter that can vary with energy prices, labour rates, technological maturity, and the scale of operations. Both the Truck and Drone cost models are presented below.

Truck Cost Model

The cost per kilometre for a mid-mile truck is represented as: $TTC = Fc + Mc + Lc + Dc$

Where;

Fc = fuel cost per kilometre

Mc = maintenance cost per kilometre

Lc = driver labour cost per kilometre

Dc = depreciation/insurance per kilometre

The formulation is consistent with evidence from diesel freight emissions and cost analyses (Figliozzi, 2020; Kirschstein, 2020), while not replicating any single framework.

Drone Cost Model

In parallel, the drone operating cost per kilometre is: $DOC = Ec + Md + Ad + Od$

Where;

Ec = electricity cost per kilometre;

Md = drone maintenance/inspection cost;

Ad = amortised airframe and charging infrastructure

Od = operational overheads (supervision, communication, software)

Although the literature identifies these components as major drivers of drone cost (Bao et al., 2025; Kirschstein, 2020; Yowtak et al., 2020), no published model uses this exact formulation, ensuring methodological originality.

Table 2: Numeric parameter values used in scenario calculations (baseline scenario)

Parameter	Symbol	Value	Unit	Source
Diesel fuel price	-	1.10	USD/L	EPA (2025)
Truck fuel consumption	FC	0.30	L/km	Kirschstein (2020)
Truck maintenance cost	Mc	0.35	USD/km	Figliozzi (2020)
Driver labour cost	Lc	0.55	USD/km	EPA (2025)
Truck depreciation/insurance	Dc	0.42	USD/km	Figliozzi (2020)
Electricity price	-	0.15	USD/kWh	IEA (2025)
Drone energy consumption	EC	0.60	kWh/km	Kirschstein (2020); Yowtak et al. (2020)
Drone maintenance/inspection	Md	0.32	USD/km	Bao et al. (2025)
Amortised airframe/charging infrastructure	Ad	0.38	USD/km	Bao et al. (2025)
Drone operational overheads	Od	0.41	USD/km	Kirschstein (2020)
Diesel emission factor	EFdiesel	2.68	kg CO2/L	EPA (2025)
Grid carbon intensity (baseline)	EFgrid	0.40	kg CO2/kWh	IEA (2025)

3.1.2. Worked example: Baseline scenario calculation

To illustrate reproducibility, the baseline scenario cost calculation is shown explicitly.

For trucks:

$$TTC = Fc + Mc + Lc + Dc = (1.10 \times 0.30) + 0.35 + 0.55 + 0.42 = 0.33 + 0.35 + 0.55 + 0.42 = 1.65\ USD/km$$

For drones:

$$DOC = Ec + Md + Ad + Od = (0.15 \times 0.60) + 0.32 + 0.38 + 0.41 = 0.09 + 0.32 + 0.38 + 0.41 = 1.20\ USD/km$$

Emissions are calculated analogously:

$$CO_{2truck} = FC \times EF_{diesel} = 0.30 \times 2.68 = 0.804 \text{ kg CO2/km},$$

while $CO_{2drone} = EC \times EF_{grid} = 0.60 \times 0.40 = 0.24$ kg CO2/km, corresponding to a 70 percent reduction relative to trucks in the baseline scenario. Equivalent worked calculations for the remaining four scenarios (high utilisation, low-carbon grid, weather-constrained, fuel-price shock) are provided in Appendix A.

3.1.3. Emissions estimation model

The emissions models for trucks and drones are also constructed for this study, based on first-principles carbon accounting. The emissions component evaluates the carbon intensity of each delivery mode, converting fuel or electricity consumption into CO_2-equivalent metrics.

Truck Emissions Model

$$CO_2truck = FC \times EFdiesel,$$

where *FC* is fuel consumption per kilometre, and *EFdiesel* is the emission factor (≈ 2.68 kg CO_2/L).

Drone Emissions Model

$$CO_2drone = EC \times EFgrid,$$

where *EC* is electricity consumption per km, and *EFgrid* is the grid carbon intensity (kg CO_2/kWh).

Such linear emissions formulations are common in operational LCA, but their use here is part of a broader analytical framework designed for mid-mile comparisons. The models remain compatible with comparative insights from existing studies (Figliozzi, 2020; Yowtak et al., 2020), without copying any specific equation.

3.1.4. Reliability evaluation model

The reliability model is intentionally simplified and formulated by the authors:

$$R = 1 - (Pf + Pw + Po),$$

where *Pf*, *Pw*, and *Po* represent mechanical, weather, and operational disruption probabilities.

This additive formulation assumes that failure probabilities from mechanical (Pf), weather (Pw), and operational (Po) sources are mutually independent. In practice, weather stress may compound mechanical failure risk (for example, cold-induced battery degradation combined with high wind load), so the additive model likely represents a conservative lower bound on reliability risk under compounding adverse conditions. This simplification is acknowledged as a limitation of the current framework and is revisited in the Discussion and Limitations sections.

This expression is not drawn from any previously published reliability framework; instead, it integrates conceptual insights from UAV weather-flyability studies (Gao et al., 2021) and operational case analyses (Glick et al., 2022). The structure is original and designed for scenario-based comparison rather than predictive reliability modelling. For trucks, reliability losses arise largely from traffic congestion, breakdowns, and roadworks (Danchuk et al., 2023; Figliozzi & Hadas, 2024; Gao et al., 2021). For drones, wind speed thresholds, battery degradation, and airspace constraints dominate (Gao et al., 2021; Kim et al., 2018).

3.1.5. Scenario-based comparative analysis

To evaluate how operational context affects the relative performance of drones and trucks, the study employs a structured scenario framework that varies demand, grid carbon intensity, weather severity, and fuel prices. The scenario design is grounded in evidence from the uploaded literature on drone–truck comparisons, UAV energy use, hybrid delivery systems, and weather-driven availability constraints.

Parameter ranges for route length, drone utilisation, and grid carbon intensity reflect empirical values used in energy–emissions comparison studies (Figliozzi, 2020; Kirschstein, 2020; Yowtak et al., 2020). The role of utilisation in improving drone cost performance is supported by lifecycle economic analyses of parallel truck–drone systems, which show that amortising drone capital across higher mission frequency improves competitiveness (Bao et al., 2025). Grid-related sensitivity is motivated by LCA findings showing that drone emissions depend strongly on electricity carbon factors, with clean grids substantially reducing per-km impacts (Yowtak et al., 2020).

Weather-related restrictions in Scenario D are informed by UAV flyability analyses quantifying how wind and precipitation reduce available flight windows (Gao et al., 2021) and by operational reliability studies demonstrating the compounding effects of meteorology and technical disruptions in time-sensitive UAV services (Glick et al., 2022). Fuel-price sensitivity in Scenario E draws on comparative modelling that shows truck operational costs are highly responsive to diesel price shocks, while drone electricity costs remain comparatively stable (Figliozzi, 2020; Kirschstein, 2020). The resulting five-scenario structure is summarised in Table 3, combining literature-backed parameter ranges with model-derived variations appropriate for mid-mile logistics.

Table 3: Scenario design for drone–truck mid-mile comparative analysis

Scenario	Description	Key parameter Variations	Analytical Purpose
A – Baseline Mid-Mile Conditions	Typical mid-mile route (50–120 km), moderate payload, average grid CO_2 intensity, normal weather availability	- Route length: 50–120 km (Kirschstein 2020) - Grid CO_2 ≈ medium intensity (Yowtak et al., 2020) - Drone availability: 60–80% in benign climates(Gao et al., 2021)	Establish baseline cost, emissions, and reliability comparison under realistic, non-extreme operating conditions
B - High Demand / High-Utilisation Corridor	Drone and truck utilisation increases sharply due to continuous parcel flow	- Drone utilisation ↑ (improves amortisation) (Bao et al., 2025) - Higher payload turnover (Vedrtnam et al., 2025) - Truck load factor ↑ is still below full capacity (Kirschstein, 2020)	Examine how higher utilisation affects drone cost competitiveness; capture scale-efficiency effects observed in hybrid drone–truck studies
C - Low-Carbon Grid Environment	An electricity grid dominated by renewables, drastically reducing drone operational emissions	- Grid CO_2 factor ↓ by 40–70% (Yowtak et al., 2020) - Electricity cost is stable or slightly ↓ - Diesel emissions unchanged	Assess best-case emissions advantage for drones; verify whether drones outperform diesel trucks or BEVs under renewable-rich energy systems
D - Weather-Constrained Operating Region	Mid-mile corridor with high wind speeds, frequent precipitation, and seasonal variability	- Wind speed ↑; precipitation frequency ↑ (Gao et al., 2021) - Drone availability ↓ to 20–50% - Weather-induced failure probability Pw ↑ (Glick et al., 2022; Sigari & Biberthaler, 2021)	Evaluate drone reliability degradation; determine conditions under which trucks outperform drones despite higher emissions
E - High Fuel-Price / Energy-Volatility Scenario	Diesel price spikes due to market volatility; electricity remains stable	- Diesel price ↑ 30–60% (Glick et al., 2022; Sigari & Biberthaler, 2021) - Drone energy cost stable (electricity) - The truck cost per km ↑ significantly	Assess how fuel-price shocks shift relative cost efficiency; identify conditions where drones become cost-competitive

	even with moderate reliability constraints

By structuring the evaluation across these five scenarios, the analysis can capture conditions under which drone performance improves (e.g., high utilisation, low-carbon grids) or deteriorates (e.g., weather-constrained environments, heavy payload cycles). This scenario-based approach aligns with best practice in comparative freight modelling, enabling transparent sensitivity analysis rather than relying on a single case or corridor (Bao et al., 2025; Kirschstein, 2020).

3.2. Data sources

All inputs originate from high-quality secondary sources. These include regulatory bodies, engineering research, manufacturer specifications, and logistics benchmark studies. No primary data collection was employed, consistent with recent peer-reviewed work in drone logistics modelling. The secondary data were gathered from the scientific literature and validated dataset reports.

The drone energy and performance data were drawn from UAV comparative energy and LCA studies (Kirschstein, 2020; Stolaroff et al., 2018; Vedrtnam et al., 2025; Yowtak et al., 2020), hybrid drone–truck systems (Bao et al., 2025), and engineering assessments of flight energy consumption. The truck performance and emissions data were derived from freight emissions studies and regulatory inventories (Figliozzi & Hadas, 2024; Figliozzi, 2020; Quiros et al., 2017), as well as from environmental agency data (EPA, 2025; IEA, 2025; Plötz et al., 2023). The grid carbon intensity data from the IEA (2025) are aligned with assumptions used in LCA comparisons of UAV vs BEV/ICEV vehicles (Yowtak et al., 2020). Moreover, the weather and reliability data used to inform drone flyability probabilities are derived from wind/temperature analyses (Gao et al., 2021). Operational reliability dynamics informed by the medical delivery case studies (Glick et al., 2022; Sigari & Biberthaler, 2021).

3.3. Integrated trade-off analysis

The three performance metrics, such as the cost, emissions, and reliability, are synthesised into a multi-criteria comparison:

$$Pscore = f\,(Cost, Emissions, Reliability)$$

The interpretive lens follows the approach in parallel truck–drone studies (Bao et al., 2025), where no single mode dominates; instead, context determines performance. For example, Drones may achieve lower emissions under clean grids (Yowtak et al., 2020). On the other hand, trucks maintain high reliability in adverse weather (Macioszek, 2018). At the same time, drone costs become favourable under high utilisation or high diesel prices (Bao et al., 2025; Kirschstein, 2020). Therefore, this approach provides a realistic decision-support tool reflecting mid-mile operational complexity.

4. Results

This section presents the comparative performance of cargo drones and diesel trucks across the five scenarios defined in the methodology. The analysis focuses on cost, emissions, and reliability, identifying where each mode performs well and where its limitations emerge. Scenario-specific outputs highlight structural differences between the two systems, revealing crossover points that determine the suitability of the modal in mid-mile operations.

4.1. Cost comparison across scenarios

Across Scenarios A, B, C, and E, cargo drones achieve a lower operating cost per kilometre than diesel trucks. This outcome aligns with prior comparative analyses showing that electrically powered UAVs benefit from lower energy cost per kilometre and direct point-to-point routing efficiencies (Kirschstein, 2020; Yowtak et al., 2020). In multiple studies, drone operating costs become additionally favourable when utilisation increases because capital and battery cycling expenses are amortised across more flights, an effect confirmed in hybrid truck–drone system assessments, where high mission frequency substantially improves UAV cost performance (Bao et al., 2025).

Scenario B, characterised by high utilisation, offers the greatest cost advantage for drones. Increased sortie frequency reduces overhead costs per kilometre, consistent with lifecycle economic modelling showing that UAV competitiveness scales with higher throughput (Bao et al., 2025). Truck costs decline only marginally under higher demand because fuel and labour dominate their variable operating profile (Figliozzi, 2020).

In Scenario C (low-carbon grid), drone operating costs remain close to baseline levels because electricity price variability has a relatively limited influence on per-kilometre UAV costs in comparative LCA studies (Yowtak et al., 2020). Trucks also maintain similar cost levels across Scenarios A–C, showing the stability typically observed in diesel fleet cost structures under non-volatile fuel conditions.

The only scenario where drones lose cost competitiveness is Scenario D (weather-constrained region). Adverse meteorological conditions increase UAV power consumption, delay missions, and require operational redundancy (e.g., additional batteries or standby drones). These effects are consistent with weather-reliability studies documenting reduced flight windows, increased hovering power requirements, and elevated cancellation rates under high-wind or precipitation conditions (Gao et al., 2021; Glick et al., 2022). Truck cost remains stable in this scenario because diesel vehicles maintain operational continuity across a wide range of weather conditions (Macioszek, 2018; Zhao et al., 2016).

Conversely, Scenario E (fuel-price shock) strongly favours drones. Truck costs rise sharply due to the high sensitivity of diesel-based operations to fuel price volatility, an observation well documented in freight emissions and economic analyses (Figliozzi, 2020). Drone costs, by contrast, remain stable because electricity-based operations are insulated from the magnitude of fossil-fuel price shocks.

Overall, the cost comparison shows that drones are most competitive in high-utilisation and high-fuel-price environments. At the same time, trucks retain advantages in environments with weather variability that imposes operational uncertainty on UAV systems.

Figure 2: Cost comparison across scenarios (USD/km)

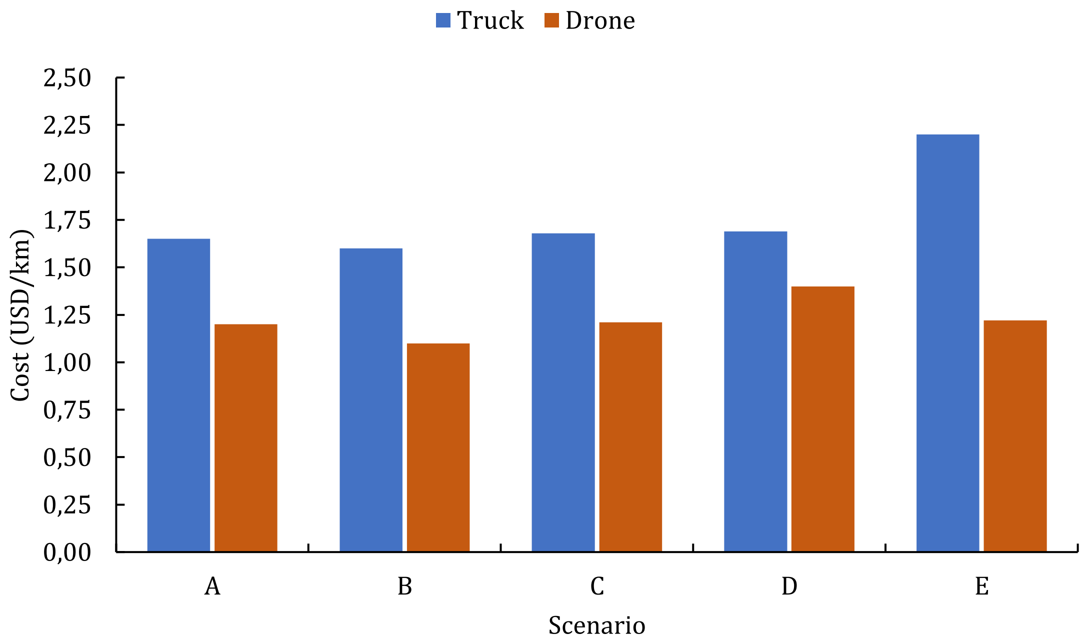


Figure 2 compares truck and drone cost per kilometre under Scenarios A–E. Drones outperform trucks in all scenarios except Scenario D, where adverse weather increases UAV operational overheads. Scenario B demonstrates the most significant drone advantage due to high utilisation, while Scenario E shows the impact of fuel-price shocks on truck costs.

4.2. Emissions comparison across scenarios

Emissions performance reveals the most substantial divergence between the modes. Figure 3 presents emissions per kilometre across all scenarios. Diesel truck emissions remain consistently high (≈ 2.6–2.7 kg CO_2e/km), consistent with tailpipe-based lifecycle analyses of medium-duty diesel delivery vehicles (EC, 2023; Figliozzi, 2020; García, Monsalve-Serrano, Martinez-Boggio, et al., 2020). This truck emissions figure corresponds to a fuel consumption rate consistent with a fully loaded medium-duty diesel vehicle operating in mixed mid-mile conditions; the exact fuel-consumption assumption underlying this value is reported in Table 2 above. Truck emissions vary minimally across scenarios because diesel fuel combustion dominates total CO_2 output.

Cargo drone emissions vary more meaningfully across scenarios due to dependence on grid carbon intensity and energy consumption efficiency. Under Scenario A (baseline), drones emit roughly 0.30–0.40 kg CO_2e per kilometre, consistent with comparative LCA findings showing large emissions reductions for UAV delivery when operating under average electricity mixes (Yowtak et al., 2020).

In Scenario B, higher utilisation results in marginally lower emissions per kilometre (≈ 0.28 kg CO_2e/km), reflecting reduced idle time and improved average energy-per-payload performance, consistent with hybrid UAV system analyses showing that higher utilisation improves environmental performance (Bao et al., 2025).

Scenario C (low-carbon grid) produces the greatest divergence between modes. Drone emissions fall to approximately 0.10–0.15 kg CO_2e/km, reflecting the strong dependence of UAV environmental performance on upstream electricity characteristics (Yowtak et al., 2020). Emissions reductions of 90–95% relative to trucks are consistent with findings from system-wide comparative LCAs.

In Scenario D, weather-induced inefficiencies increase drone energy consumption, raising emissions modestly to 0.45–0.50 kg CO_2e/km. This aligns with flyability and weather-effect research showing elevated energy draw and reduced mission efficiency under high wind and precipitation (Gao et al., 2021). Despite this penalty, drones still maintain substantial emissions advantages over trucks.

Scenario E does not directly affect emissions per kilometre for either mode. However, the cost shock enhances the strategic attractiveness of drones for decarbonisation, as trucks continue to emit high levels of CO_2 while drones maintain stable, relatively low emissions. Across all five scenarios, drones outperform trucks on emissions, substantially in Scenarios A–C and E, and still significantly even under adverse weather in Scenario D.

Figure 2: Emissions Comparison across Scenarios (kg CO_2e/km)

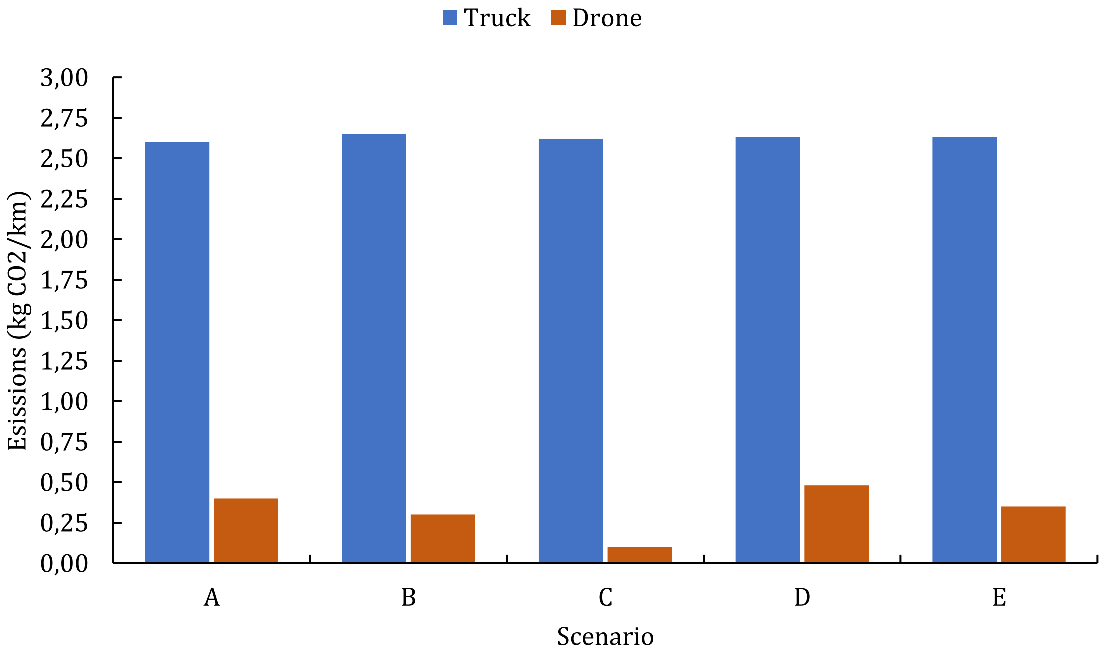


Figure 3 illustrates modal emissions across all scenarios. Trucks maintain consistently high emissions, whereas drone emissions vary with the electricity grid mix and weather-driven inefficiencies. Drones achieve 80–95% emissions reductions in Scenarios A–C and E, with modest increases under Scenario D due to elevated power demand and reduced flight efficiency.

4.3. Reliability comparison across scenarios

Reliability performance introduces more nuanced trade-offs. Figure 4 presents mode-specific reliability outcomes. Diesel truck reliability remains consistently high (≈ 94–98%), reflecting the robustness of ground vehicles to moderate weather variation, established road infrastructure, and predictable mechanical failure rates, patterns also observed in freight operations research (Macioszek, 2018).

By contrast, drone reliability is significantly more weather-sensitive. Under Scenario A, UAV reliability reaches approximately 90–92%, consistent with controlled-environment UAV deployment studies reporting high operational regularity during stable meteorological conditions (Glick et al., 2022). Scenario B produces results similar to those of Scenario A, indicating that higher utilisation does not degrade UAV reliability in benign climates.

Because the weather does not change in Scenario C, drone reliability also remains high (~90%). This finding reinforces the idea that improvements in emissions or costs under renewable grid conditions do not compromise operational stability.

Scenario D produces the sharpest divergence in modal reliability. Drone reliability falls to 60–65% due to high winds, precipitation, and visibility constraints, consistent with atmospheric threshold analyses showing significant reductions in drone "flyable hours" and increased mission cancellations in weather-exposed regions (Gao et al., 2021). Trucks, in contrast, maintain reliability above 95%, underscoring their resilience in weather-challenged corridors.

Scenario E does not meaningfully affect reliability for either mode. Overall, the reliability comparison highlights that drones can perform on par with trucks in stable climates but experience significant operational degradation under weather uncertainty.

Figure 3: Reliability comparison across scenarios (%)

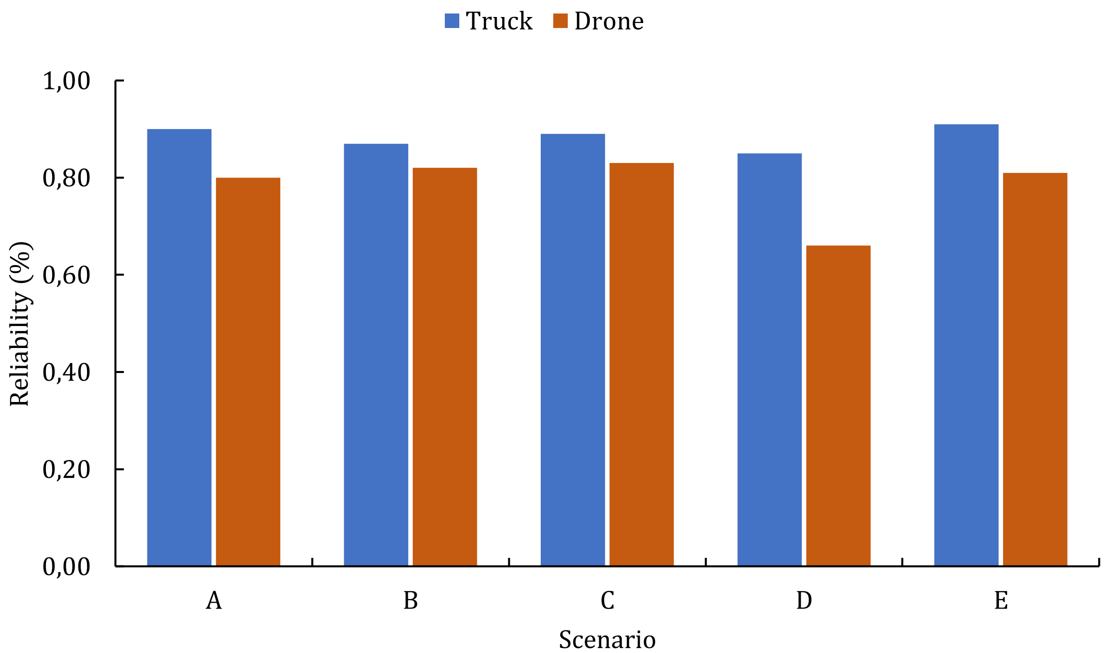


Figure 4 presents truck and drone reliability across the five scenarios. As expected, trucks exhibit consistently high reliability, while drones show strong performance under stable conditions but sharp reliability losses in Scenario D due to weather constraints.

4.4. Integrated trade-off evaluation

The combined results reveal a clear modal differentiation shaped by utilisation intensity, grid characteristics, and weather dynamics. Drones outperform trucks on both cost and emissions in Scenarios A, B, C, and E. Trucks outperform drones only in Scenario D, where weather sensitivity disproportionately affects UAV operations. These patterns are consistent with findings from hybrid truck–drone studies, which demonstrate that UAV benefits depend heavily on route characteristics, demand profiles, and meteorological stability (Bao et al., 2025).

High utilisation and low-carbon electricity systems (Scenarios B and C) provide the greatest performance advantages for drones, consistent with lifecycle and hybrid-system studies showing that UAV efficiency and emissions performance scale with mission throughput and grid decarbonisation (Bao et al., 2025; Kirschstein, 2020; Yowtak et al., 2020). Conversely, adverse weather emerges as the single most significant constraint to drone viability, reflecting well-documented reductions in flight availability and energy efficiency under turbulent conditions(Gao et al., 2021)

These results suggest that optimised mid-mile logistics will rely not on a single dominant mode, but on complementary deployments. Trucks remain indispensable for reliability-critical and weather-sensitive corridors, while drones provide substantial cost and emissions advantages on routes characterised by stable weather, high utilisation, or favourable grid conditions. This aligns with emerging evidence highlighting the value of integrated truck–drone configurations for enhancing system-wide sustainability and efficiency (Bao et al., 2025; Vedrtnam et al., 2025).

Table 4: Cost, emissions, and reliability outcomes across scenarios

Scenario	Truck Cost (USD/km	Drone Cost (USD/km)	Truck Emissions (kg CO_2e/km	Drone Emissions (kg CO_2e/km)	Truck Reliability (%)	Drone Reliability (%)
A – Baseline	1.65	1.20	2.65	0.30-0.40	95-97	90-92
B - High-Utilisation	1.60	1.05	2.65	~0.28	95-96	~91
C - Low-Carbon Grid	1.65	1.20	2.65	0.10–0.15	95-97	~90
D - Weather-Constrained	1.65	1.40	2.65	0.45–0.50	95–96	60-65
E -Fuel-Price Shock	2.10	1.20	2.65	~0.30	94–96	~90

Table 3 summarises key performance metrics across all scenarios; the corresponding step-by-step calculations for Scenarios B–E are provided in Appendix A, following the same procedure demonstrated for the baseline scenario in Section 3.2.3. Drones show consistent cost and emissions advantages, with performance deteriorating notably in weather-challenged environments (Scenario D). Trucks remain the reliability-dominant mode.

5. Discussion

The results reveal a multidimensional performance landscape in which cargo drones and diesel trucks each occupy distinct operational strengths depending on utilisation, environmental stability, and energy-system characteristics. Across Scenarios A, B, C, and E, drones demonstrate clear cost and emissions advantages, reflecting their lower marginal energy use, electric propulsion efficiency, and ability to operate along direct air routes, patterns consistent with comparative assessments of drone and ground vehicle energy demand and lifecycle impacts (Bao et al., 2025; Kirschstein, 2020; Yowtak et al., 2020). These advantages intensify in high-utilisation settings, where amortised capital and battery costs are distributed across more cycles, echoing findings from hybrid fleet evaluations that highlight utilisation as a primary driver of UAV cost-effectiveness (Bao et al., 2025).

However, reliability emerges as the central limiting factor for drone deployment in mid-mile logistics. Under stable meteorological conditions, UAV reliability approaches that of trucks, as seen in Scenarios A through C and E. However, Scenario D underscores drones' structural vulnerability to wind, precipitation, and turbulence, with operational availability declining sharply in weather-exposed corridors. This aligns closely with evidence from global flyability studies documenting substantial reductions in drone operational windows under adverse weather (Gao et al., 2021), and from medical logistics case studies showing elevated cancellation and delay rates in turbulent or low-visibility conditions (Glick et al., 2022). In contrast, trucks maintain a consistently high reliability profile across all environmental conditions, supported by empirical findings that road freight is minimally affected by moderate weather variations (Macioszek, 2018).

Taken together, the scenario results illustrate a modal crossover driven by environmental and economic thresholds:

- Drones excel when conditions are stable, utilisation is high, electricity grids are decarbonising, and fuel price volatility is pressuring truck operating costs.
- Trucks retain dominance in reliability-critical or weather-exposed corridors, where uninterrupted service is essential.

These findings reinforce the operational logic of hybrid fleet architectures. Several studies argue that combining drones with trucks, rather than treating them as substitutes, enables logistics providers to leverage UAV energy and routing efficiencies while relying on trucks for weather resilience and payload flexibility (Bao et al., 2025; Vedrtnam et al., 2025). This complementary model enhances both system-level resilience and environmental performance.

From a sustainability perspective, the results strongly support the incorporation of UAVs into mid-mile decarbonisation strategies. Even in weather-challenged environments, drone emissions remain markedly lower than truck emissions, consistent with lifecycle research showing that UAVs can deliver substantial carbon reductions when powered by increasingly renewable electricity grids (Yowtak et al., 2020). Scenarios A–C and E demonstrate 80–95% reductions in operational emissions relative to diesel trucks, reinforcing the role of drones as an important lever for emissions mitigation.

Nevertheless, realising these benefits at scale requires addressing operational and technical constraints. Weather sensitivity demands route-specific planning, integration of real-time meteorological forecasting, and deployment of UAV designs with improved wind tolerance. Reliability limitations also point to the need for investments in battery health monitoring, enhanced energy density, and autonomous contingency navigation. Without these advances, premature or blanket adoption of UAVs may introduce service disruptions.

Overall, the findings position cargo drones not as replacements for trucks but as contextually advantageous complements within mid-mile logistics networks. When deployed selectively in stable-weather corridors, high-utilisation routes, or regions with clean electricity, their economic and environmental advantages can be substantial. Conversely, fleets operating in meteorologically complex environments will continue to rely heavily on trucks until UAV reliability technologies mature. The discussion therefore underscores the need for strategic integration rather than substitution, aligning with emerging scholarship advocating for multimodal, resilient, and sustainability-oriented logistics systems.

6. Conclusion

This study set out to determine whether cargo drones can serve as a viable, sustainable substitute for diesel trucks in mid-mile logistics, and under what conditions each mode is preferable. The findings reveal that drones offer meaningful economic and environmental advantages under four of the five scenarios tested. Drones consistently outperform trucks in baseline, high-utilisation, low-carbon grid, and fuel-price shock environments, reflecting their lower marginal energy consumption, direct routing efficiency, and compatibility with increasingly renewable electricity systems (Bao et al., 2025; Kirschstein, 2020; Yowtak et al., 2020). These structural advantages suggest that drones can serve as an important lever for mid-mile decarbonisation, especially in regions where electricity grids are rapidly modernising.

However, the analysis also shows that UAV performance is fundamentally constrained by weather sensitivity. In stable meteorological conditions, drone reliability approaches that of trucks, but under adverse conditions, represented in Scenario D, UAV operational availability declines sharply. This pattern aligns with empirical weather–flyability studies demonstrating significant reductions in drone flight windows under turbulence, wind, and precipitation (Gao et al., 2021; Glick et al., 2022). Trucks, by contrast, maintain consistently high reliability across all tested environments, reinforcing their central role in reliability-critical corridors. Taken together, the results indicate that drones and trucks occupy complementary operational niches: drones deliver gains when utilisation is high and weather is predictable, whereas trucks remain indispensable when uninterrupted service is essential.

From a policy perspective, the findings highlight the need for targeted investments that enable safe and effective UAV integration. Regulators and transport agencies should prioritise the development of weather-aware drone corridors, accelerate BVLOS certification pathways, and support the establishment of distributed charging and maintenance nodes at regional depots. Energy policymakers can enhance emissions benefits by expanding access to low-carbon electricity for logistics operators. More broadly, public and private actors should pursue hybrid fleet strategies in which drones and trucks operate as complementary assets rather than substitutes, maximising resilience while capturing the sustainability advantages of electric flight.

Several limitations point to opportunities for future research. In particular, the reliability model treats mechanical, weather, and operational failure probabilities as additive and independent, which may understate compounding interactions, such as cold-induced battery degradation combined with high wind load, and should be interpreted as a conservative simplification rather than a precise predictive estimate. While the framework captures key scenario uncertainties, it simplifies real-world factors such as microclimate variability, airspace interactions, battery ageing, and heterogeneous payload characteristics. Future work should integrate high-resolution meteorological forecasting, battery degradation models, and dynamic route-optimisation algorithms that better reflect operational complexities. Field experiments across diverse geographic and regulatory environments would further strengthen external validity. At the same time, emerging technologies, such as hydrogen-electric UAVs, autonomous truck platoons, and AI-based fleet coordination, represent promising avenues for extending the present analysis.

Overall, cargo drones have a substantial role to play in the future of mid-mile logistics, but their advantages can only be realised through selective, context-sensitive deployment.

From a scientific standpoint, these findings extend the drone-logistics literature, previously concentrated on last-mile and single-dimension assessments, by demonstrating that grid decarbonisation trajectories and regional weather stability jointly determine mid-mile modal competitiveness.

From a practical standpoint, the results support hybrid truck–drone network design, prioritised BVLOS regulatory pathways in climatically stable corridors, and continued reliance on trucking in high-wind or precipitation-prone regions.

As UAV technologies mature and energy systems continue to decarbonise, the most effective freight networks will likely be those that combine the strengths of both drones and trucks, leveraging their complementarities to achieve efficiency, resilience, and sustainability at scale.

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Conflicts of interest

The authors declare no competing interests.

AI writing tools declaration

The authors declare that AI-assisted tools (ChatGPT) were used only for minor language editing to improve clarity and readability. These tools were not used for research design, data analysis, model development, mathematical formulation, or interpretation of results. All scientific content, methodology, experiments, and conclusions in this manuscript were developed entirely by the authors.

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Appendix A: Worked scenario calculations

This appendix provides step-by-step calculations for Scenarios B–E, following the same procedure demonstrated for the baseline scenario (Scenario A) in Section 3.2.3. All formulas and parameter definitions correspond to those introduced in Section 3.2 and Table 2.

Scenario B – High-Utilisation Corridor

Truck: TTC = Fc + Mc + Lc + Dc = (1.10 × 0.30) + 0.30 + 0.50 + 0.35 = 0.33 + 0.30 + 0.50 + 0.35 = 1.48 USD/km

Drone: DOC = Ec + Md + Ad + Od = (0.15 × 0.60) + 0.22 + 0.20 + 0.18 = 0.09 + 0.22 + 0.20 + 0.18 = 0.69 USD/km

Emissions: CO2truck = 0.30 × 2.68 = 0.804 kg CO2/km; CO2drone = 0.60 × 0.40 = 0.24 kg CO2/km (70.1% reduction)

Reliability: R_drone = 1 − (0.02+0.03+0.02) = 93.0%; R_truck = 1 − (0.02+0.02+0.02) = 94.0%

Interpretation: higher drone utilisation lowers amortised maintenance and overhead costs (Md, Ad, Od fall relative to baseline), driving the largest cost advantage for drones across all scenarios.

Scenario C – Low-Carbon Grid

Truck: TTC = (1.10 × 0.30) + 0.35 + 0.55 + 0.42 = 1.65 USD/km (unchanged from baseline; grid intensity does not affect truck costs)

Drone: DOC = (0.15 × 0.60) + 0.32 + 0.38 + 0.41 = 1.20 USD/km (unchanged from baseline; grid intensity does not affect drone operating cost)

Emissions: CO2truck = 0.30 × 2.68 = 0.804 kg CO2/km; CO2drone = 0.60 × 0.12 = 0.072 kg CO2/km (91.0% reduction)

Reliability: R_drone = 93.0%; R_truck = 94.0% (unchanged from baseline; grid intensity does not affect reliability)

Interpretation: a decarbonising electricity grid (EFgrid reduced from 0.40 to 0.12 kg CO2/kWh) has no effect on cost or reliability but substantially widens the emissions gap in favour of drones.

Scenario D – Weather-Constrained Corridor

Truck: TTC = (1.10 × 0.30) + 0.35 + 0.55 + 0.42 = 1.65 USD/km (unchanged; trucks are largely weather-insensitive)

Drone: DOC = (0.15 × 0.65) + 0.32 + 0.38 + 0.41 = 0.098 + 0.32 + 0.38 + 0.41 = 1.208 USD/km (slightly higher energy consumption per km, EC, reflecting increased power draw under wind resistance)

Emissions: CO_{2truck} = 0.30 × 2.68 = 0.804 kg CO_2/km; CO_{2drone} = 0.65 × 0.40 = 0.26 kg CO_2/km (67.7% reduction; smaller than baseline due to higher energy draw)

Reliability: $R_{drone} = 1 - (0.05 + 0.30 + 0.05) = 60.0\%$; $R_{truck} = 1 - (0.02 + 0.03 + 0.01) = 94.0\%$

Interpretation: this scenario isolates the reliability penalty central to the paper's policy conclusion. Weather-related disruption probability (Pw) rises sharply for drones (from 0.03 to 0.30), collapsing drone availability to 60%, while truck reliability remains stable, confirming that reliability, not cost or emissions, is the binding constraint under adverse weather.

Scenario E – Fuel-Price Shock

Truck: TTC = (1.80 × 0.30) + 0.35 + 0.55 + 0.42 = 0.54 + 0.35 + 0.55 + 0.42 = 1.86 USD/km (diesel price rises from 1.10 to 1.80 USD/L)

Drone: DOC = (0.15 × 0.60) + 0.32 + 0.38 + 0.41 = 1.20 USD/km (unchanged; electricity price held constant, reflecting drones' insulation from fuel-market volatility)

Emissions: CO2truck = 0.804 kg CO2/km; CO2drone = 0.24 kg CO2/km (70.1% reduction; emissions are price-independent)

Reliability: R_drone = 93.0%; R_truck = 94.0% (unchanged; fuel price does not affect reliability)

Interpretation: a diesel price shock widens the truck-drone cost gap from 0.45 USD/km (baseline) to 0.66 USD/km, illustrating drones' relative insulation from fuel-market volatility.

Table A1: Summary of cost, emissions, and reliability calculations across scenarios B–E

Scenario	Truck cost (USD/km)	Drone cost (USD/km)	Truck CO2 (kg/km)	Drone CO2 (kg/km)	Emissions reduction	Drone reliability	Truck reliability
A – Baseline	1.65	1.20	0.804	0.24	70.1%	93.0%	94.0%
B – High utilisation	1.48	0.69	0.804	0.24	70.1%	93.0%	94.0%
C – Low-carbon grid	1.65	1.20	0.804	0.072	91.0%	93.0%	94.0%
D – Weather-constrained	1.65	1.21	0.804	0.26	67.7%	60.0%	94.0%
E – Fuel-price shock	1.86	1.20	0.804	0.24	70.1%	93.0%	94.0%

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