Libyan Journal of Sustainable Development Research
المجلة الليبية لأبحاث التنمية المستدامة
E-ISSN: 3136-313X
Volume 2, Issue 2, 2026
Page No: 22-53
Website: https://ljsdr.ly/index.php/ljsdr/index

Emerging Frontiers in Drone Technology Applications: Artificial Intelligence, Swarm Autonomy, Edge Computing, Smart Infrastructure, and Future Airspace Integration

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آفاق جديدة في تطبيقات تكنولوجيا الطائرات بدون طيار: الذكاء الاصطناعي، والاستقلالية الجماعية، والحوسبة الطرفية، والبنية التحتية الذكية، وتكامل المجال الجوي المستقبلي

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Received: April 6, 2026 Revised: June 27, 2026 Accepted: July 11, 2026
Published: July 22, 2026

Abstract:
Drone technology has evolved from remotely operated platforms into intelligent, connected, and increasingly autonomous systems supporting civilian, industrial, environmental, and humanitarian applications. This review examines recent advances, applications, challenges, and future research directions in drone technology. Key developments include artificial intelligence–enabled navigation, computer vision, obstacle avoidance, adaptive path planning, and autonomous decision-making. Drone swarms and multi-agent systems are also discussed, with emphasis on formation control, cooperative sensing, distributed task allocation, trajectory optimization, and reliable inter-drone communication. Edge AI and cloud–edge computing enable lightweight onboard processing, low-latency detection, real-time analytics, and scalable Drone-as-a-Service platforms. Major applications include precision agriculture, emergency response, wildfire monitoring, search and rescue, medical delivery, logistics, environmental monitoring, pollution detection, and biodiversity conservation. The review further highlights the role of 5G and future 6G networks in supporting high-speed communication, satellite connectivity, unmanned traffic management, and the Internet of Drones. However, deployment remains limited by endurance, payload capacity, computational requirements, communication instability, cybersecurity, privacy, regulations, and public acceptance. Future research should prioritize energy-efficient intelligence, secure cooperative autonomy, resilient communication, explainable AI, standardized traffic management, privacy-preserving analytics, and ethical governance.

Keywords: Drone Technology; Artificial Intelligence; Autonomous Navigation; Internet of Drones; Smart Applications.

الملخص:
تطورت تقنيات الطائرات بدون طيار من منصات جوية تُشغَّل عن بُعد إلى أنظمة ذكية ومتصلة ومتزايدة الاستقلالية، قادرة على دعم التطبيقات المدنية والصناعية والبيئية والإنسانية. تستعرض هذه الدراسة أحدث التطورات والتطبيقات والتحديات والاتجاهات البحثية المستقبلية في مجال الطائرات بدون طيار. وتشمل أبرز التطورات الملاحة المدعومة بالذكاء الاصطناعي، والرؤية الحاسوبية، وتجنب العوائق، والتخطيط التكيفي للمسارات، واتخاذ القرارات بصورة مستقلة. كما تناقش الدراسة أسراب الطائرات بدون طيار والأنظمة متعددة الوكلاء، مع التركيز على التحكم في التشكيلات، والاستشعار

التعاوني، والتوزيع الموزع للمهام، وتحسين المسارات، والاتصالات الموثوقة بين الطائرات. تتيح تقنيات الذكاء الاصطناعي الطرفي والحوسبة السحابية الطرفية تنفيذ المعالجة الخفيفة على متن الطائرة، والكشف منخفض التأخير، والتحليل الفوري للبيانات، وتطوير منصات قابلة للتوسع ضمن مفهوم الطائرات بدون طيار كخدمة. وتشمل التطبيقات الرئيسة الزراعة الدقيقة، والاستجابة للطوارئ، ومراقبة حرائق الغابات، وعمليات البحث والإنقاذ، وتوصيل الإمدادات الطبية، والخدمات اللوجستية، والرصد البيئي، وكشف التلوث، والحفاظ على التنوع الحيوي. كما تسلط الدراسة الضوء على دور شبكات الجيل الخامس وشبكات الجيل السادس المستقبلية في دعم الاتصالات عالية السرعة، والاتصال بالأقمار الصناعية، وإدارة حركة الطائرات غير المأهولة، وتطوير إنترنت الطائرات بدون طيار .ومع ذلك، لا يزال الانتشار الواسع لهذه التقنيات مقيدًا بمحدودية مدة الطيران، وسعة الحمولة، والمتطلبات الحاسوبية، وعدم استقرار الاتصالات، ومخاطر الأمن السيبراني، وقضايا الخصوصية، واللوائح التنظيمية، ومدى قبول المجتمع. لذلك، ينبغي أن تركز البحوث المستقبلية على تطوير ذكاء موفر للطاقة، واستقلالية تعاونية آمنة، واتصالات مرنة، وذكاء اصطناعي قابل للتفسير، وأنظمة موحدة لإدارة الحركة الجوية، وتحليلات تحافظ على الخصوصية، وأطر فعالة للحوكمة الأخلاقية.

الكلمات المفتاحية: تكنولوجيا الطائرات دون طيار؛ الذكاء الاصطناعي؛ الملاحة الذاتية؛ إنترنت الطائرات دون طيار؛ التطبيقات الذكية.

1. Introduction

Drone technology has progressed rapidly from remotely piloted aerial platforms to intelligent, autonomous, and interconnected systems capable of performing complex missions across diverse operational environments. Recent advances in artificial intelligence have significantly improved autonomous drone navigation through deep learning, computer vision, intelligent obstacle avoidance, adaptive route planning, and real-time decision-making [1,2]. These capabilities enable drones to perceive their surroundings, recognize objects, estimate position, and modify flight trajectories under uncertain or dynamically changing conditions. In parallel, drone swarms and multi-agent cooperative systems have introduced new possibilities for collective aerial operations through swarm intelligence, formation control, distributed task allocation, cooperative sensing, trajectory coordination, and resilient inter-drone communication.

The integration of edge artificial intelligence and cloud–edge computing has further enhanced the ability of drones to process large volumes of visual, thermal, spatial, and environmental data in real time. Lightweight AI models and onboard computing platforms support low-latency object detection and immediate mission responses, while edge servers and cloud infrastructure provide scalable storage, advanced analytics, fleet coordination, and Drone-as-a-Service capabilities [3,4]. All of these developments have expanded drone applications in smart agriculture and precision farming, where unmanned aerial systems are used for crop-health monitoring, disease and pest detection, precision spraying, irrigation assessment, yield prediction, soil mapping, and data-driven farm management. Figure 1 illustrates Several typical applications of Drones.

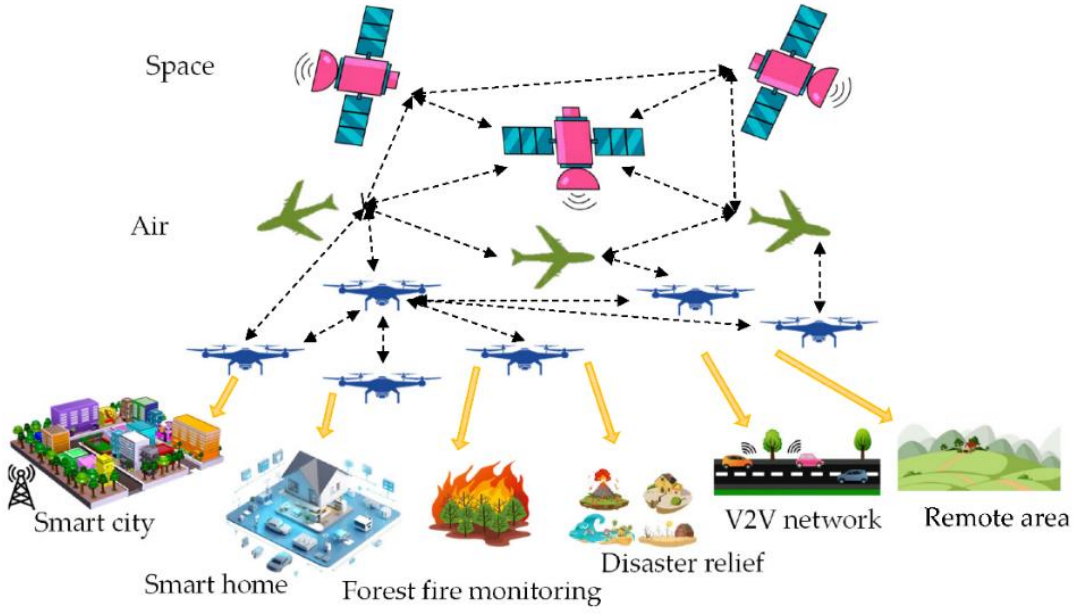

Figure 1. Several typical applications of Drones.

Drone systems have also demonstrated considerable value in emergency response, wildfire management, search-and-rescue operations, logistics, and environmental monitoring. During disasters, drones can support real-time mapping, victim identification, fire-front monitoring, hazardous-area assessment, medical-supply delivery, and coordinated rescue missions while reducing human exposure to dangerous locations [5,6]. In logistics, autonomous drones can facilitate parcel delivery, humanitarian distribution, route optimization, payload management, beyond-visual-line-of-sight operations, and urban last-mile delivery. Environmental and climate-smart applications include forest and wildlife monitoring, air-quality measurement, coastal surveillance, pollution detection, biodiversity assessment, flood mapping, and ecological conservation, thereby strengthening climate adaptation, ecosystem management, and environmental decision-making [7,8].

The future development of drone technology will increasingly depend on high-speed communication, secure connectivity, and effective airspace integration. Fifth-and sixth-generation networks are expected to support network slicing, UAV-assisted wireless systems, satellite–drone communication, cooperative sensing, edge connectivity, and integrated air-traffic management within an evolving Internet of Drones [9,10]. However, large-scale deployment remains constrained by limited endurance, communication instability, cyberattacks, privacy risks, operational safety concerns, airspace regulations, public acceptance, and ethical questions surrounding autonomous decision-making. Addressing spoofing, jamming, hijacking, data breaches, responsible AI governance, and regulatory compliance will therefore be essential for building secure, trustworthy, scalable, and socially acceptable drone ecosystems capable of supporting next-generation transportation, monitoring, communication, and decision-support services [11-13].

According to [14], the study presents a review of UAV swarm infrastructure, recent technological developments, and a wide range of practical applications. Particular attention is given to coordinated path planning, distributed task allocation, formation control, and security-related challenges, with emphasis on the integration of Artificial Intelligence (AI) and Machine Learning (ML) to enhance autonomous decision-making, adaptability, and operational efficiency.

Du et al. [15] provide a comprehensive survey of the fundamental technologies underpinning UAV swarm systems, including cooperative trajectory planning, task allocation, control strategies, localization, environmental perception, and inter-UAV communication. The study examines state-of-the-art algorithms and recent technological advances to highlight the potential for developing highly autonomous, intelligent, and coordinated swarm platforms.

Zhu et al. [16] present a systematic and critical review of recent developments in spatial optimization for multi-agent intelligent systems, with particular emphasis on four principal domains: UAV swarm path planning, resource allocation, traffic-network analysis, and visualization technologies.

Javed et al. [17] provided a comprehensive review of the principal components of UAV swarm systems, including formation control, communication architectures, cooperative path planning, autonomy, coordination, and security. The study also examines recent advances in swarm algorithms that have enabled the development of increasingly complex, intelligent, and scalable multi-UAV platforms. In addition, it discusses the ethical considerations associated with swarm deployment and reviews a broad range of military, civilian, and entertainment applications.

This article provides a comprehensive and integrated review of recent developments in drone technology by connecting advances in artificial intelligence, autonomous navigation, swarm coordination, edge and cloud computing, precision agriculture, emergency response, logistics, environmental monitoring, next-generation communication networks, and regulatory governance within a single analytical framework. Its principal contribution lies in demonstrating how these technological domains interact to transform drones from isolated remotely operated platforms into intelligent, cooperative, connected, and service-oriented aerial systems. The study also identifies the main technical, operational, cybersecurity, privacy, ethical, and regulatory barriers limiting large-scale deployment and highlights measurable performance indicators for evaluating navigation accuracy, communication reliability, processing latency, energy efficiency, mission success, sensing quality, safety, and public acceptance. Furthermore, it proposes future research priorities involving explainable and trustworthy AI, resilient swarm architectures, energy-efficient edge intelligence, secure 5G/6G connectivity, autonomous charging, integrated air-traffic management, and standardized governance frameworks, thereby offering a structured foundation for researchers, industry stakeholders, and policymakers working toward safe, scalable, and sustainable drone ecosystems.

2. Methodology

This study adopted a structured review methodology to examine recent advances, application domains, technical limitations, and future research directions in drone technology. The review was

designed to integrate evidence from engineering, computer science, communication systems, environmental science, agriculture, logistics, emergency management, and aviation regulation. Relevant literature was identified from major scholarly databases, including Scopus, Web of Science, IEEE Xplore, ScienceDirect, SpringerLink, and Google Scholar. The search focused primarily on recent peer-reviewed journal articles, conference papers, review studies, technical reports, and authoritative regulatory documents. Earlier foundational studies were also considered when necessary to explain the evolution of key technologies and establish the theoretical background of current drone systems. Figure 2 depicts methodology flowchart.

A comprehensive keyword strategy was developed using combinations of terms related to unmanned aerial vehicles and their emerging applications. Core search terms included “drone technology,” “unmanned aerial vehicle,” “UAV applications,” “autonomous drone navigation,” “artificial intelligence for drones,” “deep learning UAV,” “computer vision drone,” “obstacle avoidance,” “adaptive path planning,” “UAV swarm,” “multi-agent drone systems,” “formation control,” “distributed task allocation,” “edge AI for drones,” “cloud–edge computing,” “real-time drone analytics,” “precision agriculture UAV,” “drone emergency response,” “wildfire monitoring,” “search and rescue drones,” “drone logistics,” “last-mile delivery,” “environmental monitoring UAV,” “Internet of Drones,” “5G UAV communication,” “6G drone networks,” “UAV cybersecurity,” “drone privacy,” and “UAS regulation.” Boolean operators such as AND, OR, and NOT were used to combine related concepts and refine the search results.

The review process followed four main stages: identification, screening, eligibility assessment, and final inclusion. During the identification stage, potentially relevant publications were collected from the selected databases. Duplicate records were removed before title and abstract screening. Studies were then assessed according to predefined inclusion and exclusion criteria. Publications were included when they addressed recent technological developments, operational applications, performance evaluation, implementation challenges, or future research directions related to drone systems. Studies presenting experimental results, simulation analyses, field demonstrations, systematic reviews, architectural frameworks, or regulatory guidance were prioritized. Publications were excluded when they lacked sufficient technical detail, focused exclusively on conventional manned aviation, were unrelated to the defined application areas, or provided unsupported commercial claims without scientific or technical validation.

The selected literature was classified into nine thematic categories. The first category addressed artificial intelligence–enabled autonomous navigation, including deep learning, computer vision, simultaneous localization and mapping, intelligent obstacle avoidance, adaptive route planning, and autonomous decision-making. The second category focused on drone swarms and multi-agent cooperative systems, covering swarm intelligence, formation control, distributed task allocation, cooperative sensing, trajectory optimization, and resilient inter-drone communication. The third category examined edge AI and cloud–edge computing, with emphasis on onboard processing, lightweight AI models, low-latency inference, intelligent computation offloading, cloud–edge coordination, and Drone-as-a-Service platforms.

The fourth thematic category covered smart agriculture and precision farming, including crop-health monitoring, disease and pest detection, precision spraying, irrigation assessment, yield forecasting, soil mapping, and data-driven farm management. The fifth category examined emergency response, wildfire management, and search-and-rescue operations, focusing on disaster mapping, victim identification, fire-front monitoring, hazardous-area assessment, medical-supply delivery, and coordinated rescue missions. The sixth category addressed drone-based logistics and last-mile delivery, including autonomous parcel transportation, medical and humanitarian logistics, route optimization, payload management, beyond-visual-line-of-sight operations, and urban delivery networks.

The seventh category considered environmental monitoring and climate-smart applications, including forest and wildlife surveillance, air-quality measurement, coastal monitoring, pollution detection, biodiversity assessment, flood mapping, and ecological conservation. The eighth category analyzed 5G/6G-enabled Internet of Drones and connected airspace, covering high-speed communication, network slicing, UAV-assisted wireless networks, satellite–drone connectivity, cooperative sensing, edge-assisted networking, and integrated air-traffic management. The ninth category examined cybersecurity, privacy, regulation, and ethical governance, including protection against spoofing, jamming, hijacking, data breaches, privacy violations, operational safety risks, regulatory noncompliance, public-acceptance concerns, and irresponsible AI deployment.

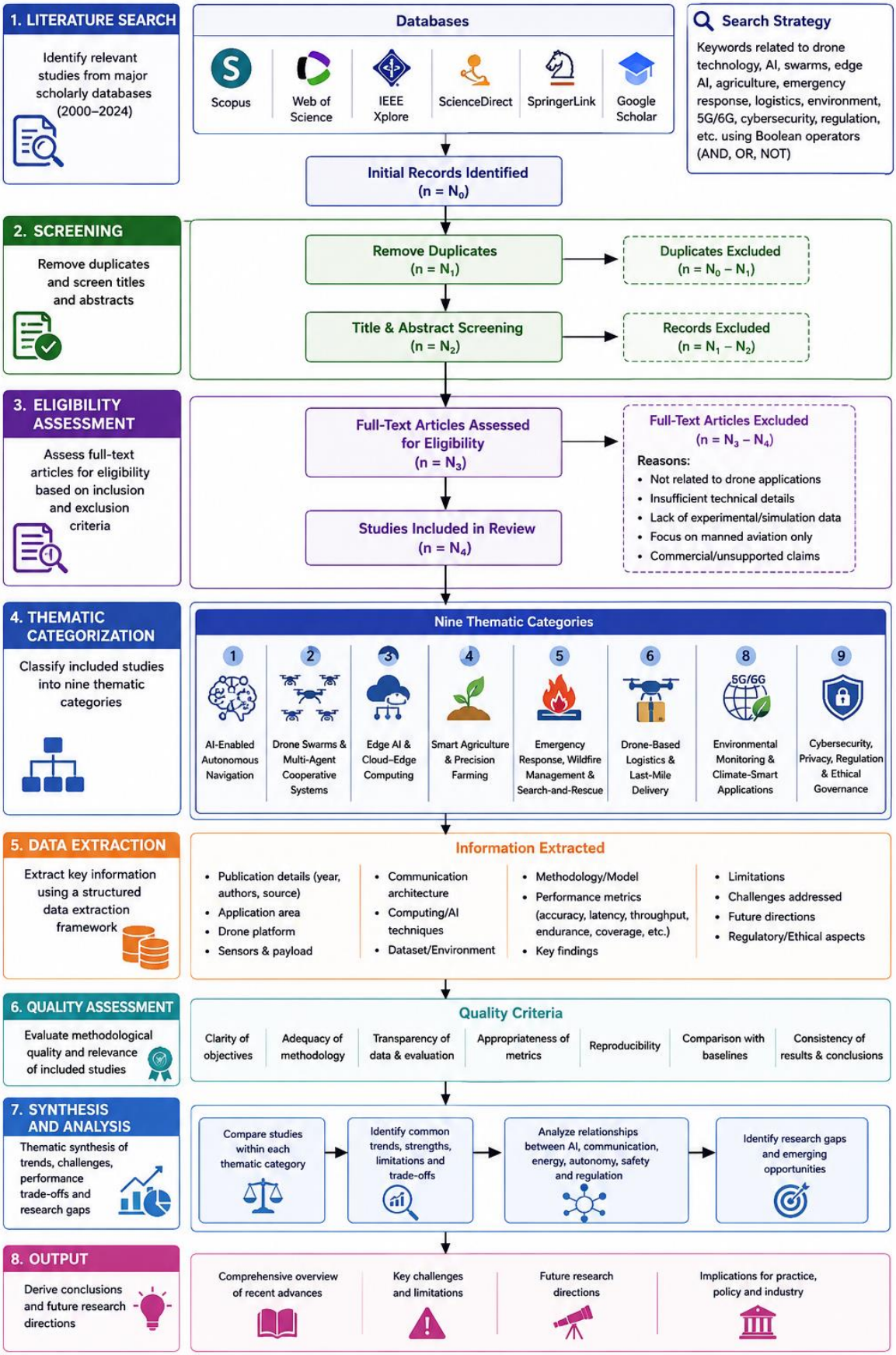

Figure 2. Methodology flowchart.

A structured data-extraction framework was used to compare the selected studies. The extracted information included publication year, application area, drone platform, sensor configuration, communication architecture, computational method, AI or optimization technique, experimental environment, dataset characteristics, and reported performance indicators. Depending on the application, the performance metrics included navigation accuracy, localization error, object-detection precision, recall, F1-score, inference latency, communication throughput, packet-loss rate, energy consumption, flight endurance, payload capacity, route-completion time, area coverage, mission-success rate, mapping accuracy, and cybersecurity detection performance. Information related to regulatory compliance, privacy protection, safety assurance, public acceptance, and ethical oversight was also recorded when available.

The methodological quality and relevance of the selected studies were assessed using several criteria. These included clarity of research objectives, adequacy of the experimental or simulation design, transparency of the dataset and evaluation procedure, appropriateness of the selected performance metrics, reproducibility of the proposed method, comparison with relevant baselines, and consistency between the reported findings and conclusions. Greater weight was assigned to studies supported by real-world experiments, field trials, open datasets, comparative analyses, or validated simulation environments. Review papers and regulatory documents were used primarily to establish broader research trends, standards, governance requirements, and unresolved challenges.

A thematic synthesis approach was employed to integrate the findings. Rather than conducting a statistical meta-analysis, which was not appropriate because of the heterogeneity of drone platforms, datasets, operating environments, sensors, communication systems, and evaluation metrics, the studies were compared qualitatively and quantitatively within their respective thematic categories. Common technological trends, recurring limitations, performance trade-offs, and emerging research priorities were identified. Particular attention was given to the relationships among artificial intelligence, communication infrastructure, energy constraints, autonomy, scalability, safety, and regulatory compliance.

Finally, research gaps and future directions were derived by comparing current system capabilities with the requirements of large-scale real-world deployment. These gaps included limited battery endurance, insufficient generalization of AI models, unreliable operation under adverse weather, communication interruptions, computational constraints, swarm scalability, lack of interoperable standards, weak cybersecurity protection, privacy risks, fragmented airspace regulations, and limited public trust. Based on this analysis, the study proposes future research priorities involving energy-efficient onboard intelligence, explainable and trustworthy AI, resilient swarm coordination, secure 5G/6G connectivity, autonomous charging, integrated edge–cloud architectures, standardized performance evaluation, privacy-preserving analytics, and harmonized regulatory and ethical governance frameworks.

3. Artificial Intelligence–Enabled Autonomous Drone Navigation

Artificial intelligence–enabled autonomous drone navigation has emerged as a critical research domain within unmanned aerial systems, driven by the growing demand for intelligent, adaptive, and reliable aerial platforms. Unlike conventional drones that depend heavily on predefined routes and continuous human supervision, AI-powered drones can perceive their surroundings, interpret complex sensory data, and make autonomous navigation decisions in real time [18,19]. This capability is supported by advanced technologies such as deep learning, computer vision, sensor fusion, simultaneous localization and mapping, and reinforcement learning. Together, these techniques enable drones to perform object detection, environmental mapping, target recognition, obstacle avoidance, and dynamic path planning under uncertain and rapidly changing conditions.

The integration of AI into drone navigation has significantly expanded the scope of applications across infrastructure inspection, precision agriculture, logistics, surveillance, emergency response, environmental monitoring, and search-and-rescue operations. However, achieving dependable autonomy remains technically challenging because drones must operate under limited computational capacity, restricted battery endurance, communication uncertainties, and variable environmental conditions [20,21]. Figure 3 outlines artificial intelligence–enabled autonomous drone aspects.

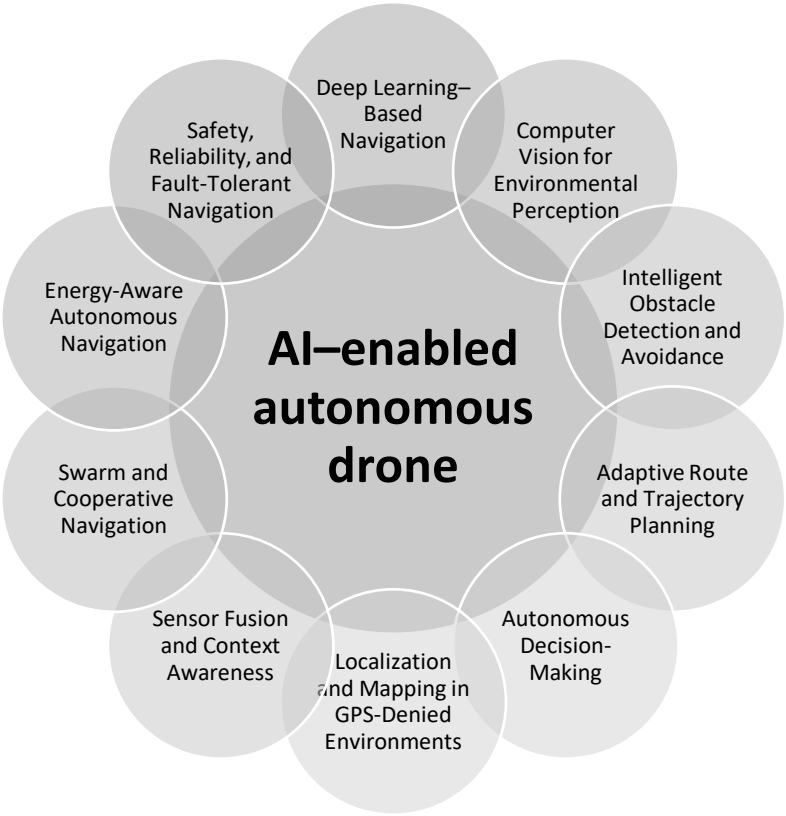

Figure 3. AI–enabled autonomous drone aspects.

Additional concerns related to safety assurance, cybersecurity, explainability, regulatory compliance, and decision-making reliability must also be addressed. Consequently, current research increasingly focuses on lightweight onboard AI, multimodal perception, adaptive route optimization, fault-tolerant control, and trustworthy autonomous decision architectures capable of supporting safe operation in complex environments [23,24]. Table 1 outlines artificial intelligence–Enabled Autonomous Drone Navigation.

Table 1. Artificial Intelligence–Enabled Autonomous Drone Navigation [25-32].

Research Area	AI Techniques	Primary Functions	Typical Sensors and Inputs	Major Applications	Key Advantages
Deep Learning–Based Navigation	Convolutional neural networks, recurrent neural networks, transformers, and deep reinforcement learning	Learns navigation policies, recognizes environmental patterns, predicts motion, and selects flight actions	Cameras, LiDAR, radar, inertial measurement units, GPS, and ultrasonic sensors	Urban navigation, industrial inspection, surveillance, and autonomous delivery	High adaptability, strong pattern recognition, and improved performance in dynamic environments
Computer Vision for Environmental Perception	Object detection, semantic segmentation, optical flow, visual odometry, and simultaneous localization and mapping	Detects obstacles and targets, estimates depth, localizes the drone, and constructs environmental maps	RGB, stereo, thermal, event-based, and depth cameras	Search and rescue, infrastructure inspection, precision agriculture, traffic monitoring, and security	Rich environmental understanding, accurate object recognition, and reduced dependence on GPS
Intelligent Obstacle Detection and Avoidance	Reinforcement learning, fuzzy logic, neural networks, evolutionary algorithms, and sensor-fusion models	Detects static and moving obstacles, estimates collision risk, and generates safe avoidance maneuvers	LiDAR, radar, cameras, ultrasonic sensors, proximity sensors, and inertial data	Indoor navigation, forest monitoring, warehouses, disaster zones, and low-altitude urban flight	Improved flight safety, reduced collision risk, and autonomy in cluttered environments
Adaptive Route and Trajectory Planning	A*, D*, rapidly exploring random trees, particle swarm optimization, genetic algorithms, ant colony optimization,	Generates optimal routes, replans trajectories, minimizes travel time, and avoids	Digital maps, GPS, weather data, obstacle maps, battery status, and mission objectives	Logistics, delivery, environmental monitoring, reconnaissance,	Reduced energy consumption, shorter mission duration, and

	and deep reinforcement learning	hazardous or restricted regions		and emergency response	improved mission reliability
Autonomous Decision-Making	Markov decision processes, reinforcement learning, expert systems, Bayesian networks, and multi-agent learning	Selects mission actions, prioritizes tasks, responds to unexpected events, and manages objectives	Sensor data, mission rules, environmental information, communication signals, and system-health data	Autonomous surveillance, disaster assessment, inspection, and high-risk missions	Reduced human intervention, faster response, and increased mission autonomy
Localization and Mapping in GPS-Denied Environments	Visual–inertial odometry, neural SLAM, graph-based optimization, and sensor fusion	Estimates position, creates three-dimensional maps, and maintains navigation without satellite signals	Cameras, inertial sensors, LiDAR, radar, and magnetometers	Underground inspection, indoor warehouses, tunnels, mines, and disaster-affected areas	Enables autonomous operation where GPS is unavailable or unreliable
Sensor Fusion and Context Awareness	Kalman filtering, particle filtering, Bayesian fusion, neural fusion networks, and attention-based models	Combines heterogeneous sensor information to improve perception, localization, and decision accuracy	Cameras, LiDAR, radar, GPS, inertial sensors, thermal sensors, and environmental sensors	Complex-terrain navigation, autonomous inspection, and all-weather operation	Higher reliability, redundancy, and robustness against individual sensor failure
Swarm and Cooperative Navigation	Multi-agent reinforcement learning, consensus algorithms, swarm intelligence, and distributed optimization	Coordinates multiple drones, maintains formations, shares maps, and allocates tasks cooperatively	Inter-drone communication, relative positioning, onboard sensors, and shared mission data	Large-area monitoring, disaster response, agriculture, defense, and communication support	Wider coverage, operational redundancy, scalability, and faster task completion
Energy-Aware Autonomous Navigation	Reinforcement learning, predictive energy models, optimization algorithms, and battery-state estimation	Selects energy-efficient routes, manages speed and altitude, and schedules charging or battery replacement	Battery state of charge, wind speed, payload, route length, motor data, and weather conditions	Long-duration inspection, delivery, environmental monitoring, and remote-area missions	Extended endurance, reduced power consumption, and improved mission-completion rate
Safety, Reliability, and Fault-Tolerant Navigation	Anomaly detection, predictive maintenance, fault diagnosis, redundant control, and safe reinforcement learning	Detects system faults, maintains stable flight, initiates emergency landing, and prevents unsafe actions	Motor currents, vibration signals, battery data, control signals, navigation data, and sensor-health indicators	Critical infrastructure inspection, urban air mobility, emergency operations, and medical delivery	Higher operational safety, lower accident risk, and increased system resilience

In this context, artificial intelligence has substantially transformed autonomous drone navigation by enabling unmanned aerial vehicles to perceive, analyze, and respond to their environments with reduced human intervention. Deep learning and computer vision have strengthened environmental perception, while reinforcement learning, and optimization algorithms have improved path planning, obstacle avoidance, and mission-level decision-making. These developments have allowed drones to operate more effectively in dynamic, cluttered, and partially unknown environments. In this direction, the combination of multiple sensing technologies, including cameras, LiDAR, radar, inertial measurement units, and global navigation systems, has further enhanced navigation accuracy and operational robustness. Sensor-fusion techniques help compensate for the limitations of individual sensors and support reliable localization, mapping, and obstacle detection. This is particularly important in GPS-denied environments such as tunnels, indoor facilities, forests, disaster zones, and densely built urban areas.

Despite these advances, several technical and operational challenges continue to limit the widespread deployment of fully autonomous drones. These challenges include high computational requirements, limited battery capacity, environmental uncertainty, communication delays, sensor failures, cybersecurity threats, and difficulties in validating AI-based decisions. The lack of explainability and standardized certification procedures also creates barriers to deployment in safety-critical applications, including medical delivery, urban air mobility, infrastructure inspection, and emergency response. Moreover, future research should therefore prioritize energy-efficient AI models, uncertainty-aware navigation, explainable decision systems, resilient sensor fusion, and formally verified control architectures. Greater attention should also be given to cooperative swarm navigation, edge computing, autonomous charging, and secure integration with 5G and 6G communication networks. Addressing

these research directions will be essential for developing autonomous drone systems that are intelligent, trustworthy, scalable, and suitable for operation in increasingly complex real-world environments.

4. Drone Swarms and Multi-Agent Cooperative Systems

Drone swarms and multi-agent cooperative systems represent a major transition from individually operated unmanned aerial vehicles toward distributed aerial networks capable of coordinated perception, decision-making, and action. Inspired by collective behaviors observed in biological systems, drone swarms use decentralized control, swarm intelligence, consensus mechanisms, and multi-agent learning to accomplish missions that would be inefficient or impractical for a single platform. Through continuous exchange of position, velocity, sensing, energy, and mission-status information, multiple drones can maintain formations, divide operational areas, allocate tasks, avoid collisions, and adapt their collective behavior to dynamic environmental conditions [33,34].

Recent advances in artificial intelligence, wireless communication, embedded computing, sensor fusion, and distributed optimization have substantially expanded the capabilities of cooperative drone systems. Swarms are increasingly applied in search and rescue, environmental monitoring, infrastructure inspection, precision agriculture, logistics, surveillance, disaster assessment, and temporary communication-network deployment. Nevertheless, reliable swarm operation remains constrained by communication instability, limited energy resources, computational complexity, cybersecurity threats, heterogeneous platform characteristics, and the difficulty of guaranteeing safe collective behavior. Consequently, current research focuses on resilient inter-drone communication, distributed task allocation, cooperative sensing, adaptive formation control, energy-aware trajectory optimization, fault-tolerant coordination, and trustworthy human–swarm interaction [35,36]. Table 2 illustrates drone swarms and multi-agent cooperative systems.

Table 2. Drone swarms and multi-agent cooperative systems [37-44].

Research Area	Principal Methods and Algorithms	Core Functions	Communication and Data Requirements	Representative Applications	Key Advantages
Swarm Intelligence	Particle swarm optimization, ant colony optimization, artificial bee colony, evolutionary algorithms, bio-inspired coordination	Enables collective behavior, decentralized decision-making, adaptive movement, and mission-level cooperation	Local neighbor information, relative position data, shared mission objectives, and intermittent communication	Environmental monitoring, surveillance, disaster assessment, precision agriculture, and defense	Scalability, adaptability, robustness, and reduced dependence on a central controller
Formation Control	Leader-follower control, virtual structure, behavior-based control, consensus algorithms, model predictive control	Maintains geometric formations, regulates inter-drone spacing, and supports coordinated maneuvering	Relative distance, heading, altitude, velocity, and neighbor-state information	Cooperative mapping, aerial displays, convoy monitoring, search missions, and communication relays	Improved coverage, collision reduction, structured coordination, and efficient sensing
Distributed Task Allocation	Auction-based methods, market-based algorithms, game theory, contract-net protocols, multi-agent reinforcement learning	Assigns tasks among drones according to capability, location, urgency, and available energy	Mission priorities, drone availability, payload capacity, battery state, and estimated task cost	Search and rescue, parcel delivery, inspection, crop monitoring, and military reconnaissance	Efficient resource utilization, parallel task execution, and reduced mission completion time
Cooperative Sensing and Perception	Distributed sensor fusion, Bayesian estimation, federated learning, collaborative SLAM, consensus filtering	Combines observations from multiple drones to improve environmental awareness and target detection	Shared camera, LiDAR, radar, thermal, GPS, and inertial data	Wildlife tracking, infrastructure inspection, border surveillance, disaster mapping, and pollution monitoring	Wider sensing coverage, improved accuracy, redundancy, and reduced blind spots
Cooperative Localization and Mapping	Collaborative SLAM, visual-inertial odometry, graph optimization, relative localization,	Estimates individual and collective positions while constructing shared maps	Relative range, visual features, inertial measurements, GPS when available, and map updates	Indoor exploration, underground inspection, urban mapping, and GPS-denied navigation	Improved localization accuracy, map consistency, and operational

	distributed Kalman filtering				continuity without GPS
Trajectory and Path Optimization	A*, D*, rapidly exploring random trees, genetic algorithms, particle swarm optimization, deep reinforcement learning	Generates collision-free, energy-efficient, and time-optimal trajectories for multiple drones	Environmental maps, obstacle locations, flight constraints, battery status, and predicted drone motion	Logistics, monitoring, inspection, aerial mobility, and reconnaissance	Reduced travel time, lower energy consumption, improved safety, and coordinated movement
Collision Avoidance and Airspace Deconfliction	Velocity-obstacle methods, reciprocal collision avoidance, potential fields, safe reinforcement learning, model predictive control	Prevents inter-drone collisions and resolves conflicting trajectories	Relative position, velocity, acceleration, predicted trajectory, and safety-zone information	Dense swarm operations, urban air mobility, warehouse drones, and emergency response	Enhanced flight safety, increased swarm density, and reliable autonomous operation
Resilient Inter-Drone Communication	Ad hoc networking, mesh networks, multi-hop routing, software-defined networking, cognitive radio, network coding	Maintains reliable command, coordination, and data exchange within the swarm	Low-latency links, routing updates, synchronization, authentication, and spectrum awareness	Large-area monitoring, military missions, emergency networks, and communication restoration	Extended communication range, redundancy, decentralized connectivity, and network flexibility
Multi-Agent Reinforcement Learning	Centralized training with decentralized execution, actor-critic models, Q-learning, policy-gradient methods	Learns cooperative policies for navigation, task allocation, pursuit, and resource management	Local observations, reward signals, shared policies, and limited inter-agent information	Cooperative exploration, target tracking, delivery, surveillance, and defense	Adaptation to complex environments, reduced reliance on predefined rules, and emergent cooperation
Energy-Aware Swarm Coordination	Multi-objective optimization, battery-state prediction, energy-aware routing, reinforcement learning	Balances workload minimizes propulsion and communication energy, and schedules charging	Battery state of charge, payload, wind conditions, route length, and charging availability	Long-duration monitoring, inspection, logistics, and remote sensing	Extended mission endurance, improved task completion, and balanced energy consumption
Fault-Tolerant and Resilient Swarm Control	Redundant control, anomaly detection, adaptive consensus, distributed fault diagnosis, reconfiguration strategies	Detects failures, isolates malfunctioning drones, and reorganizes the swarm to continue the mission	Vehicle-health data, motor status, communication quality, and neighbor-state information	Critical infrastructure inspection, defense, disaster response, and medical delivery	Improved reliability, mission continuity, and resistance to individual drone failures
Heterogeneous Multi-Drone Cooperation	Hierarchical control, capability-based task assignment, cross-platform data fusion, distributed optimization	Coordinates drones with different sizes, sensors, endurance levels, and payloads	Platform capabilities, sensor types, task requirements, and shared operational data	Search and rescue, agriculture, inspection, logistics, and environmental monitoring	Broader mission capability, complementary sensing, and improved resource utilization
Cybersecurity and Trust Management	Blockchain, intrusion detection, lightweight cryptography, trust evaluation, secure consensus	Protects swarm communication, prevents malicious control, and identifies compromised agents	Authentication credentials, encrypted messages, trust scores, and network-behavior data	Defense, public safety, industrial inspection, and critical-infrastructure monitoring	Improved data integrity, secure coordination, and resistance to spoofing and hijacking
Human-Swarm Interaction	Shared autonomy, natural-language interfaces, gesture control, supervisory control, explainable AI	Allows human operators to guide, monitor, and intervene in swarm missions	Operator commands, mission visualization, swarm status, and decision explanations	Emergency response, military operations, logistics, and environmental management	Reduced operator workload, and improved situational awareness

Swarm Validation, Regulation, and Ethical Governance	Formal verification, simulation, digital twins, safety assessment, risk analysis	Evaluates swarm reliability, compliance, accountability, and operational safety	Flight logs, communication records, safety constraints, and regulatory requirements	Urban operations, public safety, commercial delivery, and critical missions	Greater public trust, improved certification, and safer deployment

Drone swarms and multi-agent cooperative systems have emerged as a transformative approach for conducting complex aerial missions through coordinated and distributed intelligence. By combining swarm algorithms, formation-control strategies, cooperative sensing, distributed task assignment, and multi-agent decision-making, multiple drones can operate as an integrated system rather than as isolated platforms. This collective architecture improves mission scalability, spatial coverage, operational flexibility, and resilience to individual vehicle failures. In addition, the effectiveness of a drone swarm depends heavily on reliable coordination among its members. Formation control and trajectory optimization allow drones to maintain safe spatial configurations while adapting to obstacles, weather disturbances, and changing mission requirements. Distributed task-allocation techniques further improve operational efficiency by assigning responsibilities according to each drone's location, battery level, payload, sensing capability, and mission priority. Cooperative perception and mapping also enhance environmental awareness by integrating observations from multiple aerial viewpoints.

Despite considerable progress, several limitations continue to restrict the large-scale deployment of autonomous swarms. Dynamic communication topologies, bandwidth constraints, latency, interference, jamming, and packet loss can disrupt coordination and compromise mission performance. Additional challenges include collision avoidance in dense airspace, computational scalability, energy imbalance, cybersecurity vulnerabilities, heterogeneous-system interoperability, and the verification of learning-based control policies. Regulatory uncertainty, privacy concerns, accountability, and public acceptance must also be addressed before swarm technology can be widely adopted in commercial and civilian environments. To sum up, future research should prioritize decentralized and self-healing swarm architectures capable of maintaining stable operation under communication failures, vehicle faults, and adversarial conditions. Greater emphasis is also required on safe multi-agent reinforcement learning, explainable collective decision-making, 5G/6G-enabled communication, autonomous recharging, digital-twin validation, and joint optimization of trajectories, communication, and energy consumption. The development of standardized communication protocols, certification frameworks, and human–swarm interfaces could be essential for establishing drone swarms as reliable, secure, and scalable platforms for next-generation aerial operations.

5. Edge AI and Cloud–Edge Computing for Real-Time Drone Analytics

Edge artificial intelligence and cloud–edge computing have become essential enabling technologies for real-time drone analytics, particularly in applications that require rapid perception, immediate decision-making, and continuous processing of large sensor streams. Conventional cloud-only architectures often suffer from communication latency, unstable connectivity, bandwidth limitations, and high data-transmission costs [45,46]. By shifting part of the computational workload to the drone or to nearby edge servers, aerial systems can process images, video, LiDAR, thermal, acoustic, and environmental data closer to the point of acquisition. This architecture supports low-latency object detection, autonomous navigation, anomaly recognition, target tracking, and mission adaptation without relying entirely on remote cloud infrastructure. Figure 4 outlines cloud-assisted cooperative drone–vehicular communication architecture for intelligent urban transportation networks.

The effectiveness of edge-enabled drone systems depends on the integration of lightweight AI models, embedded processors, intelligent computation offloading, adaptive communication, and scalable cloud services. Onboard processing provides immediate responses, while edge servers and cloud platforms offer higher computational capacity, centralized data storage, fleet coordination, and long-term analytics. This collaborative framework is especially valuable in infrastructure inspection, precision agriculture, emergency response, logistics, environmental monitoring, and smart-city surveillance [47,48]. However, its deployment remains constrained by limited onboard energy, restricted processing resources, variable network quality, cybersecurity risks, model accuracy–latency trade-offs, and the complexity of coordinating distributed computing resources. Table 3 demonstrates edge AI and cloud–edge computing for real-time drone analytics.

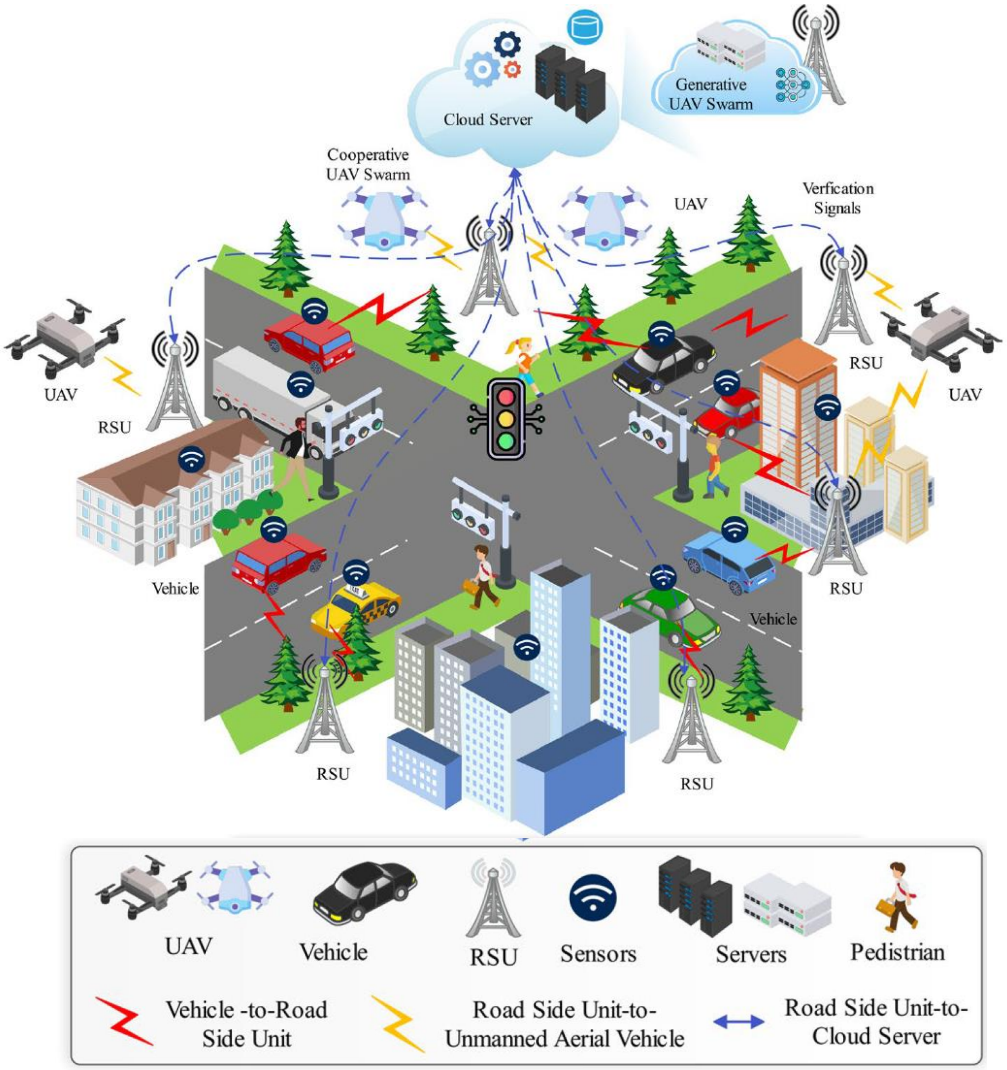

Figure 4. Cloud-Assisted Cooperative Drone–Vehicular Communication Architecture for Intelligent Urban Transportation Networks

Table 3. Edge AI and Cloud–Edge Computing for Real-Time Drone Analytics [49-54].

Research Area	Principal Technologies and Methods	Core Functions	Computing and Data Requirements	Representative Applications	Key Advantages
Onboard Edge-AI Processing	Embedded GPUs, neural processing units, field-programmable gate arrays, system-on-chip devices, and edge inference engines.	Processes images, video, navigation data, and sensor measurements directly onboard the drone.	Compact processors, optimized memory use, low-power accelerators, and real-time operating systems.	Infrastructure inspection, autonomous navigation, surveillance, agriculture, and disaster assessment.	Reduces dependence on remote servers, preserves communication bandwidth, and supports immediate decisions.
Lightweight AI Models	MobileNet, EfficientNet, Tiny-YOLO, lightweight transformers, depthwise-separable convolution, and compact vision networks.	Performs object detection, classification, segmentation, and target recognition using resource-constrained hardware.	Reduced parameters, low memory consumption, limited floating-point operations, and compact model storage.	Traffic monitoring, crop analysis, wildlife detection, search and rescue, and security operations.	Faster inference, lower hardware requirements, and reduced energy consumption.
Model Compression and Acceleration	Quantization, pruning, knowledge distillation, low-rank approximation,	Reduces AI-model size and accelerates inference without requiring major	Representative calibration datasets, compressed weights, optimized inference libraries,	Real-time aerial imaging, onboard analytics, autonomous inspection, and	Lower memory use, faster inference, reduced power demand, and

	operator fusion, and tensor optimization.	hardware upgrades.	and hardware-specific compilers.	persistent surveillance.	improved deployment feasibility.
Low-Latency Object Detection	YOLO-based detectors, single-shot detectors, attention mechanisms, feature-pyramid networks, and vision transformers.	Detects vehicles, people, defects, obstacles, fires, and other mission-critical objects in real time.	High-frame-rate cameras, optimized preprocessing, GPU or NPU acceleration, and efficient inference pipelines.	Crowd monitoring, emergency response, road inspection, border surveillance, and autonomous landing.	Enables rapid environmental interpretation and immediate mission responses.
Edge-Cloud Collaborative Inference	Split computing, hierarchical inference, model partitioning, early-exit neural networks, and edge-cloud cooperation.	Executes latency-sensitive processing onboard while transferring computationally intensive tasks to edge or cloud servers.	Reliable network connectivity, model-partitioning policies, synchronized software environments, and resource monitoring.	Large-scale mapping, precision agriculture, smart-city monitoring, industrial inspection, and remote sensing.	Balances local responsiveness with cloud-scale computing and storage.
Intelligent Computation Offloading	Deep reinforcement learning, game theory, Lyapunov optimization, fuzzy neural networks, and multi-objective optimization.	Determines whether tasks should be processed onboard, at a nearby edge server, or in the cloud.	Task size, channel condition, deadline, processor workload, battery level, and server availability.	Video analytics, autonomous monitoring, Internet-of-Things services, and multi-drone missions.	Reduces latency, balances computing workloads, and extends drone endurance.
Real-Time Video and Sensor Analytics	Stream processing, online learning, frame prioritization, event detection, temporal analysis, and multimodal fusion.	Extracts actionable information from continuous visual, thermal, acoustic, LiDAR, and environmental data.	High-throughput input pipelines, temporary edge storage, synchronized sensors, and real-time analytics engines.	Wildfire detection, pollution monitoring, security surveillance, structural inspection, and wildlife observation.	Reduces raw-data transmission and enables event-driven responses.
Bandwidth-Aware Data Compression	Video encoding, feature compression, semantic compression, region-of-interest transmission, and adaptive bitrate control.	Reduces the volume of aerial data transmitted to ground, edge, or cloud infrastructure.	Channel-quality estimation, compression processors, mission-priority rules, and scalable encoding.	Long-range inspection, disaster mapping, agricultural monitoring, and multi-drone surveillance.	Saves bandwidth, lowers transmission energy, and improves communication continuity.
Cloud-Based Data Management and Analytics	Distributed databases, data lakes, GPU clusters, serverless computing, big-data analytics, and digital dashboards.	Stores mission data, conducts large-scale analysis, trains AI models, and delivers information to end users.	High-capacity storage, cloud APIs, secure connectivity, scalable processors, and standardized metadata.	Regional mapping, fleet management, long-term environmental analysis, and predictive maintenance.	Provides scalable storage, computational elasticity, centralized visualization, and historical analysis.
Multi-Drone Cooperative Edge Computing	Distributed computing, collaborative caching, swarm task offloading, multi-agent reinforcement learning, and workload sharing.	Distributes processing tasks across drones and nearby edge nodes according to available resources.	Inter-drone links, workload status, energy information, shared task queues, and distributed scheduling.	Swarm surveillance, collaborative mapping, search and rescue, and large-area inspection.	Increases processing capacity, improves scalability, and provides computational redundancy.
Energy-Aware Edge Analytics	Dynamic voltage and frequency scaling, battery-aware scheduling, energy-latency optimization, and adaptive inference.	Adjusts computing intensity, transmission activity, and model complexity according to available energy.	Battery state, processor power, communication energy, workload deadlines, and flight requirements.	Long-duration monitoring, delivery, inspection, and environmental sensing.	Extends mission endurance and avoids premature mission termination.
Federated and Distributed Drone Learning	Federated learning, decentralized learning, transfer learning, collaborative model updating, and privacy-	Trains shared AI models using data generated by multiple drones	Local training resources, model-update exchange, aggregation	Distributed surveillance, agricultural monitoring, fleet intelligence, and	Improves privacy, reduces raw-data transmission, and enables

	preserving aggregation.	without centralizing all raw information.	servers, and secure coordination.	environmental classification.	collective learning.
Cybersecurity and Privacy Protection	Lightweight encryption, authentication, intrusion detection, trusted execution, blockchain, and zero-trust access control.	Protects aerial data, AI models, communication links, edge nodes, and cloud services.	Cryptographic keys, security policies, behavior logs, integrity checks, and authenticated channels.	Critical-infrastructure monitoring, defense, public safety, and commercial drone services.	Improves confidentiality, data integrity, service reliability, and user trust.
5G/6G-Enabled Drone Analytics	Ultra-reliable low-latency communication, network slicing, multi-access edge computing, massive machine-type communication, and integrated satellite networks.	Supports real-time data transmission, computation offloading, remote control, and fleet coordination.	High-throughput wireless links, edge base stations, adaptive resource allocation, and mobility management.	Smart cities, emergency networks, urban logistics, autonomous inspection, and aerial communication relays.	Provides higher capacity, lower delay, wider coverage, and improved service continuity.
Drone-as-a-Service Platforms	Cloud-native applications, microservices, containerization, application programming interfaces, fleet orchestration, and subscription-based service models.	Provides on-demand drone deployment, mission planning, analytics, storage, reporting, and fleet supervision.	Scalable cloud infrastructure, service-level agreements, interoperable APIs, remote-identification systems, and secure user access.	Mapping, inspection, delivery, agriculture, media, emergency response, and environmental monitoring.	Reduces ownership costs, improves accessibility, enables scalable deployment, and supports specialized analytics.
Digital Twins and Lifecycle Management	Virtual drone models, simulation, telemetry synchronization, predictive analytics, and cloud-based asset management.	Reproduces drone, edge, network, and mission behavior for testing, optimization, and maintenance.	Real-time telemetry, system-health data, environmental models, and simulation platforms.	Fleet maintenance, mission rehearsal, fault diagnosis, and infrastructure-inspection planning.	Enables risk-free testing, predictive maintenance, performance optimization, and system validation.

In this direction, Edge AI and cloud–edge computing has significantly expanded the analytical capabilities of modern drone systems by enabling faster, more autonomous, and more context-aware operation. Processing mission-critical data directly onboard or at nearby edge nodes reduces response time and communication dependency, allowing drones to detect objects, identify hazards, interpret environmental conditions, and adapt their actions in real time. This capability is particularly important in dynamic or safety-critical missions where delayed cloud responses may reduce operational effectiveness. Lightweight neural networks, model compression, hardware acceleration, and efficient inference frameworks are central to the practical implementation of onboard intelligence. These techniques reduce memory use, computational demand, and energy consumption while preserving sufficient analytical accuracy. At the same time, cloud–edge collaboration enables complex tasks such as large-scale mapping, historical data analysis, digital-twin simulation, predictive maintenance, fleet management, and AI-model training to be performed using more powerful computing infrastructure.

Despite these advantages, several challenges continue to limit large-scale deployment. Drone platforms operate under strict battery, payload, thermal, and processing constraints, while wireless links are affected by interference, mobility, congestion, and coverage gaps. Additional concerns include data privacy, malicious computation offloading, adversarial attacks, service reliability, platform interoperability, and the difficulty of selecting optimal processing locations under rapidly changing mission conditions. The balance among latency, energy consumption, communication cost, and analytical accuracy therefore remains a major research problem. Future research should focus on adaptive edge–cloud orchestration, hardware-aware AI design, semantic communication, energy-efficient processors, and intelligent workload partitioning. Further advances are also needed in federated learning, secure distributed analytics, cooperative multi-drone computing, 5G/6G connectivity, and autonomous Drone-as-a-Service platforms. Integrating these developments with digital twins and standardized service architectures will support the transition toward scalable, secure, and commercially viable drone ecosystems capable of delivering reliable real-time intelligence across diverse operational environments.

6. Drone Applications in Smart Agriculture and Precision Farming

Drone technology has become a central component of smart agriculture and precision farming by enabling rapid, non-destructive, and high-resolution monitoring of crops, soils, water resources, and field conditions. Equipped with RGB, multispectral, hyperspectral, thermal, and LiDAR sensors, agricultural drones can collect spatially detailed information that is difficult to obtain through conventional ground-based inspection [55,56]. These data support crop-health assessment, disease and pest detection, weed identification, nutrient-status evaluation, irrigation analysis, soil mapping, and yield estimation. When combined with artificial intelligence, geographic information systems, and Internet of Things platforms, drones can transform raw aerial observations into actionable agronomic information. Figure 5 represents collaborative Drone-WSN-IoT in an agricultural field.

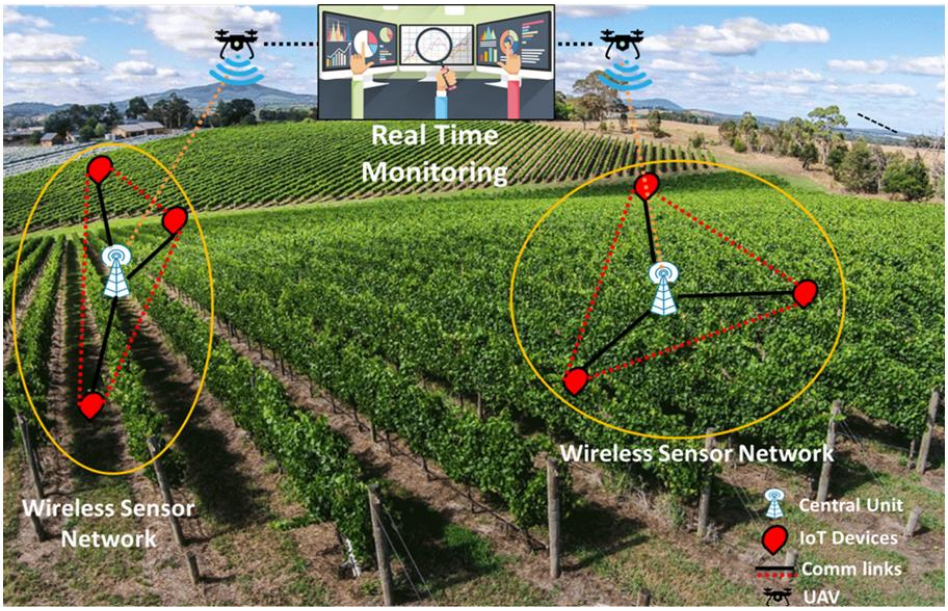

Figure 5. Collaborative Drone-WSN-IoT in an agricultural field.

The integration of drones into data-driven farm management improves the timing, precision, and efficiency of agricultural operations. Variable-rate spraying, targeted fertilization, water-stress detection, crop counting, and damage assessment allow farmers to respond to spatial variability rather than applying uniform treatments across entire fields [57,58]. This approach can reduce chemical consumption, water use, labor requirements, and operational costs while improving productivity and environmental performance. Nevertheless, the effectiveness of drone-based precision agriculture remains influenced by sensor accuracy, weather conditions, battery endurance, regulatory constraints, data-processing requirements, and the availability of reliable ground-truth information. Table 4 highlights drone applications in smart agriculture and precision farming.

Figure 4. Drone applications in smart agriculture and precision farming [59-65].

Application Area	Sensors and Data Sources	Analytical Methods	Main Functions	Agricultural Outputs	Key Benefits
Crop-Health Monitoring	RGB, multispectral, hyperspectral, thermal cameras, LiDAR, and weather sensors	Vegetation-index analysis, image segmentation, machine learning, deep learning, and temporal change detection	Evaluates crop vigor, canopy development, chlorophyll content, nutrient status, and physiological stress	Crop-health maps, stress zones, growth-stage classification, and intervention recommendations	Provides rapid field-scale assessment, supports early intervention, and reduces dependence on manual scouting
Disease Detection and Diagnosis	RGB, multispectral, hyperspectral, fluorescence, and thermal imagery	Convolutional neural networks, vision transformers, object detection, semantic segmentation, and anomaly detection	Identifies disease symptoms, estimates infection severity, and maps spatial disease distribution	Disease-presence maps, severity classes, infected-plant locations, and treatment zones	Enables earlier diagnosis, targeted treatment, and reduced spread of crop diseases

Pest Infestation Monitoring	High-resolution RGB, multispectral and thermal sensors, pheromone-trap data, and field observations	Object detection, pattern recognition, density estimation, spatial clustering, and predictive modeling	Detects pests, pest-induced crop damage, and infestation hotspots	Pest-density maps, risk zones, outbreak forecasts, and targeted-control plans	Reduces scouting time, supports localized pest management, and limits unnecessary pesticide application
Weed Detection and Management	RGB, multispectral and hyperspectral cameras	Semantic segmentation, object detection, spectral classification, and deep neural networks	Separates weeds from crops and identifies weed species and density	Weed-distribution maps, spot-spraying prescriptions, and mechanical-removal routes	Supports site-specific weed control, reduces herbicide use, and limits crop exposure
Precision Spraying	Crop maps, variable-rate prescription maps, altitude sensors, flow meters, radar, LiDAR, GPS, and wind sensors	Variable-rate control, route optimization, droplet-deposition modeling, computer vision, and feedback control	Applies pesticides, herbicides, fungicides, fertilizers, and biological agents at selected locations and rates	Application records, treated-area maps, chemical-use reports, and coverage assessments	Improves application precision, reduces worker exposure, and enables treatment in difficult terrain
Irrigation and Water-Stress Assessment	Thermal, multispectral and hyperspectral imagery, soil-moisture sensors, weather stations, and IoT devices	Crop-water-stress indices, evapotranspiration estimation, thermal analysis, regression, and machine learning	Detects water stress, irrigation deficiencies, leakage, overwatering, and spatial moisture variation	Irrigation-zone maps, water-demand estimates, and variable irrigation schedules	Improves water-use efficiency, detects stress before visible wilting, and supports timely irrigation
Nutrient-Deficiency Assessment	Multispectral, hyperspectral and RGB cameras, leaf and soil measurements	Spectral-index analysis, feature selection, regression, deep learning, and chemometric modeling	Estimates nitrogen, phosphorus, potassium, chlorophyll, and other nutrient conditions	Nutrient-status maps, fertilizer prescription maps, and deficiency alerts	Supports variable-rate fertilization, lowers input waste, and reduces nutrient runoff
Yield Prediction and Production Forecasting	Multitemporal RGB and multispectral imagery, canopy height, vegetation indices, weather, soil, and historical yield data	Random forests, support-vector regression, gradient boosting, CNNs, recurrent networks, transformers, and crop-growth models	Forecasts field-level and within-field yield before harvest	Yield maps, production estimates, harvest planning, and storage and marketing forecasts	Supports resource planning, supply-chain management, insurance, and food-security assessment
Soil Mapping and Soil-Property Estimation	Multispectral and hyperspectral imagery, LiDAR, thermal sensors, topographic data, and ground soil samples	Digital soil mapping, geostatistics, machine learning, spectral regression, and spatial interpolation	Estimates soil moisture, texture, salinity, organic matter, compaction, drainage, and erosion risk	Soil-property maps, management zones, and land-suitability classifications	Provides high-resolution spatial information and improves sampling efficiency
Crop Counting and Plant-Density Estimation	High-resolution RGB and multispectral imagery	Object detection, instance segmentation, feature matching, and density-estimation networks	Counts plants, trees, fruits, flowers, seedlings, and missing stands	Plant-population maps, emergence rates, stand-uniformity indicators, and replanting recommendations	Accelerates crop inventory, supports early stand assessment, and improves yield estimation
Crop Phenotyping and Breeding	RGB, multispectral, hyperspectral, thermal and LiDAR sensors	Three-dimensional reconstruction, trait extraction, temporal modeling, and machine learning	Measures canopy height, biomass, leaf area, flowering, lodging, stress response, and growth rate	Genotype rankings, trait databases, and breeding-selection indicators	Enables high-throughput evaluation of large experimental plots and reduces manual measurement

Livestock and Pasture Monitoring	RGB and thermal cameras, GPS collars, acoustic sensors, and pasture imagery	Animal detection, tracking, behavior recognition, thermal anomaly detection, and biomass estimation	Locates livestock, assesses health and behavior, detects missing animals, and evaluates forage availability	Herd-location maps, health alerts, grazing-pressure maps, and pasture-condition assessments	Improves large-area supervision, reduces labor, and supports rotational grazing
Field Mapping and Management-Zone Delineation	RGB, multispectral, hyperspectral and LiDAR data, GPS, and elevation measurements	Orthomosaic generation, digital elevation modeling, clustering, geostatistics, and geographic information systems	Maps field boundaries, crop variability, drainage, elevation, erosion, and operational obstacles	Orthomosaics, elevation models, management zones, drainage maps, and machinery routes	Provides detailed spatial information for targeted input management and farm planning
Damage and Disaster Assessment	RGB, multispectral, thermal and radar data	Change detection, image classification, anomaly mapping, and damage-severity estimation	Evaluates damage caused by drought, flooding, frost, hail, wind, wildfire, and lodging	Damage maps, loss estimates, insurance evidence, and recovery priorities	Enables rapid post-event assessment and supports targeted recovery operations
Data-Driven Farm Management	Drone imagery, IoT sensors, machinery records, weather forecasts, soil data, and farm-management information systems	Data fusion, predictive analytics, decision-support systems, digital twins, cloud computing, and AI optimization	Integrates crop, soil, weather, energy, water, labor, and input information into operational decisions	Dashboards, prescriptions, alerts, forecasts, cost analyses, and farm-management recommendations	Converts drone observations into actionable decisions and supports resource-efficient farm operation
Autonomous Agricultural Drone Fleets	RTK-GPS, computer vision, edge AI, fleet-management software, 5G, IoT, and cloud platforms	Autonomous mission planning, fleet coordination, task allocation, recharging, and data synchronization	Coordinates large-scale monitoring, spraying, pollination, seeding, and continuous surveillance missions	Fleet mission plans, synchronized field data, service records, and coverage reports	Expands coverage, increases operational scalability, and reduces dependence on individual operators

Note: UAV = unmanned aerial vehicle; IoT = Internet of Things; LiDAR = light detection and ranging; RTK-GPS = real-time kinematic global positioning system.

Drone-based smart agriculture has significantly improved the capacity of farmers and agricultural managers to observe field conditions with greater spatial and temporal detail. Applications such as crop-health monitoring, disease detection, pest surveillance, weed mapping, and nutrient assessment provide early warnings of emerging problems and support faster intervention. These capabilities help shift agricultural management from reactive practices toward predictive and preventive decision-making. In addition to that, precision spraying and irrigation assessment are among the most valuable operational applications of agricultural drones. By identifying localized treatment requirements, drones can support variable-rate application of pesticides, herbicides, fertilizers, and water. This reduces unnecessary input use, limits environmental contamination, and improves resource-use efficiency. Drone-derived thermal and multispectral data are also increasingly valuable for identifying water stress, irrigation failures, and uneven crop development before such problems become visually severe.

The integration of drone imagery with artificial intelligence, IoT sensors, weather information, soil measurements, and farm-management platforms further strengthens agricultural decision support. Machine-learning models can use these combined data to estimate yield, classify crop conditions, delineate management zones, and forecast production risks. However, important limitations remain, including inconsistent data standards, limited rural connectivity, high equipment and processing costs, model-transferability problems, and the technical skills required to interpret complex datasets. Thus, future research should prioritize autonomous agricultural drone fleets, lightweight onboard AI, real-time edge analytics, multimodal sensor fusion, and interoperable farm-data platforms. Greater attention is also required for explainable decision-support systems, automated docking and recharging, cooperative drone–robot operations, and region-specific models adapted to different crops and climates. Addressing regulatory, economic, and technical barriers will be essential for making drone-enabled precision

agriculture accessible, scalable, and sustainable across both large commercial farms and smallholder agricultural systems.

7. Emergency Response, Wildfire Management, and Search-and-Rescue Operations

Drone technology has become an increasingly important component of emergency response and disaster-management systems because it enables rapid access to hazardous, inaccessible, or geographically extensive areas. Unlike conventional ground-based assessment methods, drones can be deployed immediately after floods, earthquakes, industrial accidents, landslides, wildfires, and severe storms to collect high-resolution visual, thermal, and geospatial information [66,67]. Equipped with RGB cameras, thermal sensors, LiDAR, multispectral imaging systems, and communication devices, drones provide emergency teams with timely situational awareness while reducing the exposure of personnel to dangerous conditions. Their ability to operate at low altitude and transmit live data makes them particularly valuable during the early stages of a disaster, when accurate information is essential for allocating resources and planning rescue activities [68,69].

Real-time disaster mapping is one of the principal applications of drones in emergency management. Aerial imagery can be processed to generate orthomosaic maps, three-dimensional terrain models, flood boundaries, structural-damage assessments, and accessibility maps. These outputs help emergency authorities identify collapsed buildings, damaged roads, blocked evacuation routes, isolated communities, and areas at risk of further deterioration. When integrated with geographic information systems, satellite data, and artificial intelligence, drone-generated maps can support dynamic decision-making and continuous updating of disaster conditions [70,71]. This capability improves the coordination of rescue teams, emergency vehicles, medical units, and humanitarian organizations.

Victim identification and localization are also critical functions in search-and-rescue missions. Thermal cameras can detect human body heat in darkness, smoke, forests, collapsed structures, and other visually challenging environments. Computer-vision algorithms can assist in recognizing people, vehicles, clothing, movement patterns, and emergency signals within aerial images and video streams. Drones equipped with loudspeakers, spotlights, microphones, and two-way communication systems can establish contact with survivors, provide instructions, and determine their immediate medical needs [72,73]. However, the effectiveness of these systems may be affected by thermal interference, dense vegetation, debris, adverse weather, and the difficulty of distinguishing human targets from environmental heat sources.

In wildfire management, drones provide continuous information on fire location, intensity, direction, and rate of spread. Thermal and infrared sensors can identify active fire fronts, hidden hotspots, and areas vulnerable to renewed ignition, even when smoke reduces the visibility of conventional cameras. Real-time fire-front monitoring enables emergency commanders to evaluate evacuation zones, protect firefighting personnel, and deploy resources more effectively. Drones can also monitor wind-driven changes, inspect inaccessible terrain, and assess post-fire damage [74,75]. The integration of drone observations with meteorological data, fire-propagation models, and AI-based prediction systems can improve short-term forecasts of wildfire behavior and support proactive containment strategies.

Hazardous-area assessment is particularly important in chemical spills, nuclear incidents, industrial explosions, volcanic activity, and damaged infrastructure. Drones carrying gas detectors, radiation sensors, thermal cameras, and environmental-monitoring instruments can measure dangerous conditions without requiring direct human entry [76,77]. They can identify gas leaks, structural instability, excessive heat, toxic emissions, and contaminated zones while creating risk maps for emergency responders. In addition, drones can inspect bridges, buildings, pipelines, power networks, and communication infrastructure to determine whether these systems remain safe and operational after a disaster.

Drones can further support humanitarian operations through the delivery of medical supplies, blood products, vaccines, communication equipment, food, water, and emergency tools. This capability is especially valuable when roads are damaged, communities are isolated, or conventional transport is delayed. Coordinated drone fleets can divide affected regions into operational zones, distribute supplies according to urgency, relay communication signals, and support simultaneous search missions. Swarm intelligence, multi-agent task allocation, autonomous route planning, and resilient inter-drone communication can increase coverage and reduce mission time [78,80]. Future developments should focus on longer flight endurance, all-weather operation, reliable victim-recognition systems, secure communication, autonomous charging, and integration with national emergency-management platforms. Clear regulations standardized operating procedures, and effective human–drone collaboration will also be essential for ensuring that drone-assisted emergency operations remain safe, ethical, and dependable.

8. Drone-Based Logistics and Last-Mile Delivery Systems

Drone-based logistics and last-mile delivery systems are emerging as an important extension of modern supply-chain networks, particularly for transporting lightweight, time-sensitive, and high-value items. Autonomous delivery drones can travel directly between distribution points and customers without being constrained by road congestion, thereby supporting parcel delivery, pharmaceutical distribution, humanitarian assistance, and emergency supply operations. Their performance should be evaluated using measurable indicators, including average delivery time (min/order), delivery-distance efficiency (actual flight distance/shortest feasible distance), on-time delivery rate, mission-success rate, deliveries per drone-hour, and cost per completed delivery (USD/order). A recent synthesis of the last-mile literature reported highly context-dependent delivery costs ranging from approximately USD 0.03 to USD 0.67 per parcel, with potential cost reductions of up to 96.5% relative to conventional truck delivery under selected assumptions; however, such values vary substantially with demand density, labor costs, regulations, infrastructure, and fleet utilization [81,82].

Autonomous parcel delivery requires the integration of navigation, sensing, flight control, customer-location verification, and secure package-release mechanisms. Drones may deliver goods by landing, lowering packages through a tether, releasing them into secure lockers, or transferring them at designated collection points. Key operational metrics include delivery accuracy (m), defined as the distance between the intended and actual drop locations; failed-delivery rate; average customer-service time (s/order); package-damage rate; and fleet availability. Delivery reliability can be represented by the ratio of successfully completed missions to total dispatched missions, while service productivity can be measured through the number of completed deliveries per aircraft per operating day. These indicators are particularly important in dense urban environments, where obstacles, restricted zones, signal interference, and limited landing space can affect delivery consistency [83,84].

Medical and humanitarian logistics represent especially valuable applications because delivery speed may directly influence patient care and disaster-response effectiveness. Drones can transport blood products, laboratory samples, vaccines, medicines, diagnostic equipment, and emergency supplies to remote clinics, isolated communities, or disaster-affected locations. Performance assessment should include emergency response time (min), order-to-delivery lead time (min or h), population coverage, cold-chain compliance, temperature-excursion duration (min), critical-delivery completion rate, and medical payload integrity. For humanitarian operations, additional indicators include beneficiaries served per flight, kilograms delivered per operating hour, service-area coverage (km^2), and delivery continuity during road-network disruption [85,86].

Route optimization is essential because drone endurance is constrained by battery capacity, wind, payload mass, airspace restrictions, and the requirement to maintain a safe reserve for diversion or return-to-base operations. Optimization models commonly seek to minimize a weighted combination of total mission time, energy consumption, travel distance, number of vehicles, late deliveries, and operating cost. Relevant metrics include route-completion time or makespan (min), energy consumed per mission (Wh), energy intensity (Wh/km or Wh/kg-km), battery-reserve margin, distance reduction, and average deviation from the optimal route. Hybrid truck–drone systems can use trucks as mobile depots for transporting, charging, launching, and recovering drones. In one data-driven simulation study involving 93 scenarios, the configuration of three drones operating from five truck stops reduced energy consumption by 36% relative to the least-efficient tested configuration, illustrating the importance of fleet size and launch-point selection [87,88].

Payload management strongly affects flight range, energy demand, propulsion loading, and mission safety. The principal indicators are payload capacity (kg), payload utilization, payload-to-vehicle mass ratio, energy consumed per kilogram delivered (Wh/kg), maximum safe range at a specified payload (km), and remaining battery state of charge at landing [89,89]. Payload utilization may be calculated as the actual package mass divided by the drone's rated payload capacity. High payload utilization improves transport productivity, but heavier packages increase power demand and may reduce range, climb capability, and reserve energy. Consequently, logistics platforms should dynamically match package weight, dimensions, urgency, destination, weather conditions, and aircraft capability. Predictive energy models should also account for wind speed and direction, because adverse wind can increase delivery time and energy consumption even when drone-assisted systems remain more efficient than truck-only alternatives [90,91].

Beyond-visual-line-of-sight operations are fundamental to scaling drone delivery beyond small local service areas. BVLOS refers to flights conducted outside the remote pilot's direct visual observation and therefore requires reliable command-and-control links, detect-and-avoid capability, remote identification, contingency planning, and airspace coordination [92,93]. The Federal Aviation Administration identifies unmanned-aircraft traffic management as an enabling framework for

coordinating multiple low-altitude BVLOS operations, including package delivery, generally below 400 ft above ground level in the described operating environment. Important BVLOS metrics include command-and-control link availability, communication latency (ms), packet-loss rate, navigation continuity, detect-and-avoid success rate, loss-of-link events per 100 flight hours, and unscheduled landing rate per 1,000 missions. Regulatory compliance should also be assessed through authorization-processing time, operational restriction frequency, incident rate, and the percentage of routes that can be legally served [93-95].

Urban delivery networks require coordinated infrastructure that may include micro-depots, rooftop stations, charging hubs, parcel lockers, vertiports, edge-computing nodes, and digital fleet-management platforms. Network performance can be quantified using customers served per square kilometre, average depot-to-customer distance (km), charging-station utilization (%), vehicle turnaround time (min), deliveries per hub per day, and network coverage. Artificial intelligence and Internet of Things technologies can support demand forecasting, dynamic routing, fleet assignment, real-time monitoring, and coordination among drones, ground robots, trucks, and collection lockers. Hybrid networks can increase operational range and reduce energy expenditure, although scalability, infrastructure readiness, and regulation remain central constraints [96-98].

The future development of drone-based logistics will depend on integrating autonomous aircraft with intelligent route optimization, predictive maintenance, automated charging, secure communications, airspace-management systems, and interoperable logistics platforms. A comprehensive evaluation framework should combine technical metrics, such as range, payload, energy, latency, and reliability, with economic, environmental, safety, and service-quality indicators. Particular attention should be given to cost per successful delivery, mission success above 99% for safety-critical services, minimal cold-chain violations, low loss-of-link frequency, and high fleet utilization without compromising battery reserves or maintenance requirements. Such multidimensional assessment will support the design of scalable delivery networks that are not merely faster, but also safe, resilient, economically viable, and environmentally responsible.

9. Environmental Monitoring and Climate-Smart Applications

Drone-based environmental monitoring has become an important component of climate-smart observation systems because it provides high-resolution, repeatable, and geographically flexible measurements between field surveys and satellite observations. Drones equipped with RGB, multispectral, hyperspectral, thermal, LiDAR, and environmental sensors can document ecosystem structure, detect disturbances, measure atmospheric pollutants, map floods, and monitor environmental changes in locations that are difficult or dangerous to access. Overall system performance should be assessed using ground-sampling distance (cm/pixel), area covered per flight (km²), survey duration (min/km²), revisit interval (days or hours), geolocation error (m), data-completeness rate (%), and cost per surveyed hectare or square kilometre. These indicators determine whether a drone platform can deliver sufficiently accurate and timely information for conservation planning, climate-risk management, and environmental decision-making [99].

In forest monitoring, drone imagery can be used to estimate canopy height, tree density, crown dimensions, species composition, biomass, carbon stocks, deforestation, fire damage, and forest-health conditions. RGB photogrammetry provides three-dimensional canopy models, while multispectral, hyperspectral, and LiDAR systems improve the characterization of vegetation structure and spectral condition. Important metrics include tree-detection precision and recall (%), species-classification overall accuracy, canopy-height RMSE, biomass-estimation RMSE (Mg/ha), coefficient of determination (R^2), crown-delineation Intersection over Union, and annual forest-cover change (ha/year). A 2025 tree-species classification study using UAV RGB and multispectral information reported overall accuracy above 83% for its best-performing configuration, illustrating the potential of high-resolution drone data for species-level forest inventories [100].

Wildlife monitoring applications use high-resolution optical cameras, thermal imaging, and AI-based object detection to locate, count, classify, and track animals across forests, grasslands, wetlands, and protected areas. Drone surveys can support population estimation, habitat-use analysis, migration monitoring, anti-poaching surveillance, and human–wildlife conflict assessment while reducing the need for researchers to enter sensitive habitats. Relevant metrics include animal-detection precision, recall or probability of detection, false-positive rate, mean average precision, counting error, animals detected per flight hour, survey coverage (km²/h), and disturbance distance (m). Detection performance is strongly influenced by flight altitude, thermal contrast, vegetation density, animal size, weather, and sensor resolution; therefore, ecological surveys should report both detection accuracy and the proportion of the habitat that was effectively observable [101]. Experimental studies using drone-based

thermal imagery have demonstrated the feasibility of automated wildlife detection, while also identifying occlusion, environmental heat, and limited image detail as major sources of error.

For air-quality monitoring, drones can carry compact sensors for particulate matter, carbon monoxide, carbon dioxide, ozone, nitrogen oxides, sulfur dioxide, volatile organic compounds, temperature, humidity, and wind. Unlike fixed stations, drones can measure pollutants in both horizontal and vertical dimensions and can characterize concentration gradients around roads, industrial facilities, landfills, mines, wildfires, and urban street canyons. Performance should be quantified through pollutant concentration (μg/m³, mg/m³, ppm, or ppb), sensor bias, calibration R^2, RMSE and MAE, limit of detection, response time (s), vertical sampling resolution (m), and measurements collected per flight. Sensor placement must also be evaluated because propeller-induced airflow can alter particle transport and affect onboard measurements. Drone platforms equipped with electrochemical sensors have been developed for mobile and stationary measurement of CO, O_3, NO, and NO_2 in inaccessible locations, demonstrating the value of calibrated UAV systems for three-dimensional air-quality mapping [102].

Coastal surveillance uses UAV photogrammetry, LiDAR, multispectral cameras, and thermal sensors to monitor shoreline migration, beach erosion, dune change, coastal flooding, wetland degradation, coral and seagrass condition, and unauthorized human activities. Repeated surveys can generate orthomosaics, point clouds, digital elevation models, and three-dimensional coastal profiles at substantially finer spatial scales than many satellite products. Key metrics include shoreline-position RMSE (m), horizontal and vertical mapping accuracy (cm or m), sediment-volume change (m³), erosion or accretion rate (m/year), coastal area lost or gained (m²/year), point-cloud density (points/m²), and digital elevation model completeness. UAV photogrammetry and GNSS surveys have been successfully applied to quantify coastal morphological change, while UAV-derived elevation models have also been used to assess short-term beach-system changes and coastal vulnerability [103].

Pollution-detection applications include the identification of oil spills, wastewater discharges, floating plastics, solid waste, mine drainage, thermal effluents, and illegal dumping. AI models can classify pollutants and segment contaminated areas using RGB, thermal, multispectral, hyperspectral, or radar-compatible datasets. Appropriate performance indicators include classification accuracy, precision and recall, F1-score, Intersection over Union, minimum detectable object size (cm²), polluted area (m² or km²), pollutant-volume estimate, false-alarm rate, and detection-to-alert time (min). In a drone-based river-pollution study using more than 1,000 aerial images, a random-forest model achieved classification accuracies of 94% for oil spills, 92% for wastewater, and 95% for debris. Such results show that drone imagery combined with machine learning can support rapid pollution screening, although performance must be validated under different illumination, water-surface, weather, and background conditions [104].

Biodiversity assessment extends beyond individual-species detection to the mapping of plant communities, habitat types, invasive species, ecosystem fragmentation, and ecological diversity. High-resolution aerial data can be used to calculate species richness, vegetation-cover fractions, habitat connectivity, canopy heterogeneity, and changes in sensitive ecosystems. Recommended metrics include species richness, Shannon or Simpson diversity indices, habitat-classification accuracy, Cohen's kappa, species-detection probability, occupied habitat area (ha), fragmentation or connectivity indices, and change in habitat extent. A UAV-based AI study of forest plant-community composition reported a correlation of $r = 0.87$ between model-derived and reference community estimates. In another application, multispectral UAV imagery mapped kelp canopy with 93% accuracy, compared with 67% using RGB imagery, demonstrating the benefit of selecting sensors that capture ecologically informative spectral bands [105].

Flood mapping is a major climate-adaptation application because drones can rapidly document inundation boundaries, water depth, damaged infrastructure, isolated communities, and blocked transport routes. Drone-derived digital terrain models can also improve hydrodynamic simulations by representing roads, channels, embankments, buildings, and local drainage features at fine resolution. Performance should be evaluated using flood-classification accuracy, Intersection over Union, boundary-position error (m), water-depth RMSE (m), inundated area (km²), mapped area per hour, processing latency (min), and time from deployment to operational map delivery. Research on drone-derived terrain data has evaluated resolutions ranging from 6 cm to 30 m, demonstrating that terrain-data resolution can materially affect simulated flood extent and flow pathways. Deep-learning flood-mapping studies have also reported classification accuracy close to 97%, although results depend on water turbidity, shadows, vegetation, reflections, and the availability of validation data [106,107].

The ecological value of drone monitoring ultimately depends on whether collected information leads to effective conservation action. Ecological-conservation programs should therefore measure not only mapping accuracy but also time to management intervention, protected habitat restored (ha), reduction in illegal activities, decline in pollutant exposure, increase in monitored population size, cost per

conservation outcome, and percentage of priority areas surveyed [108,109]. Integration with satellite imagery, ground sensors, environmental DNA, camera traps, geographic information systems, and ecological models can provide a more complete representation of ecosystem condition than any single observation platform. Future research should emphasize automated docking, longer endurance, low-noise operation, edge-AI processing, standardized sensor calibration, uncertainty reporting, and autonomous multi-drone surveys. These developments will support environmental-monitoring systems that are more continuous, scalable, scientifically reproducible, and capable of providing timely evidence for climate adaptation and ecological conservation.

10. 5G/6G-Enabled Internet of Drones and Connected Airspace

The Internet of Drones (IoD) represents a networked aerial ecosystem in which drones, ground-control stations, edge servers, cloud platforms, satellites, air-traffic authorities, sensors, and other aerial vehicles continuously exchange operational and mission data. Fifth-generation networks already provide an important foundation for command-and-control communication, high-definition video transmission, remote identification, fleet coordination, and beyond-visual-line-of-sight operations. The effectiveness of an IoD architecture should be evaluated using end-to-end latency (ms), uplink and downlink throughput (Mbit/s), packet-loss rate, jitter (ms), link availability, communication outage duration (s), handover-success rate, and command-and-control message-delivery reliability. 3GPP Release 18 includes NR enhancements specifically intended to integrate aerial user equipment into 5G networks, including UAV communication, location-deviation monitoring, event reporting, inter-UAV communication, and quality-of-service support for command-and-control links [110,111].

High-speed drone communication is particularly important when UAVs transmit 4K or thermal video, LiDAR point clouds, hyperspectral imagery, cooperative-navigation data, and real-time AI results. Communication performance should be measured through average and fifth-percentile user throughput, video-frame delivery rate (frames/s), data-age or age-of-information (ms), command-response time (ms), buffering time (s), and mission-data completeness. Although real-world performance depends on spectrum, antenna orientation, altitude, interference, network loading, and mobility, the IMT-2030 framework provides ambitious research benchmarks that illustrate the direction of future 6G-connected drone systems. These include possible peak rates of 50, 100, or 200 Gbit/s, user-experienced rates of 300 or 500 Mbit/s, area capacities of 30–50 Mbit/s/m², and connection densities between 10^6 and 10^8 devices/km². These values are research targets rather than guaranteed operational performance [112,113].

Low latency and high reliability are essential for remote piloting, collision avoidance, swarm coordination, emergency intervention, and safety-critical command transmission. Relevant metrics include radio-interface latency (ms), round-trip time (ms), packet error rate, control-loop update frequency (Hz), probability of successful packet delivery within a specified deadline, and loss-of-control-link events per 1,000 flight hours. The ITU IMT-2030 framework identifies research targets of approximately 0.1–1 ms radio-interface latency and reliability ranging from $1 - 10^{-5}$ to $1 - 10^{-7}$, corresponding to packet-success levels of approximately 99.999% to 99.99999% under the specified evaluation conditions. It also considers mobility support at 500–1,000 km/h, which is relevant to high-speed aerial platforms and seamless handovers between terrestrial, aerial, and satellite access networks [114,115].

Network slicing allows a shared communication infrastructure to provide separate logical networks for different drone services. A safety-critical command-and-control slice may prioritize reliability and bounded latency, while a broadband slice supports video streaming and a massive-connectivity slice serves telemetry, environmental sensors, and remote-identification devices. Slice performance should be assessed through service-level agreement satisfaction, slice-creation time (s), resource-utilization efficiency, inter-slice interference, latency violation rate, throughput isolation, and priority-packet delivery ratio. Dynamic slicing is particularly important during emergencies because communication resources can be reallocated to firefighting, medical delivery, police surveillance, or search-and-rescue drones. The IMT-2030 framework envisages radio-access-network slicing that configures logical resources according to the specific quality-of-service requirements of applications and operators [116,117].

UAV-assisted wireless networks use drones as aerial base stations, relays, repeaters, data collectors, or temporary edge-computing nodes. Their elevated position can improve line-of-sight connectivity and restore communication after earthquakes, floods, wildfires, power failures, or terrestrial-network congestion. Performance metrics include coverage-area increase, cell-edge throughput (Mbit/s), number of served users, signal-to-interference-plus-noise ratio (dB), spectral efficiency (bit/s/Hz), outage probability, deployment time (min), and energy efficiency (bit/J).

Optimization must jointly consider drone altitude, three-dimensional location, transmit power, user association, spectrum allocation, propulsion energy, and flight duration. A deployment that maximizes coverage but causes excessive interference or rapidly exhausts the UAV battery may therefore be less effective than a lower-altitude, energy-aware configuration [118,119].

Satellite–drone connectivity extends IoD services to oceans, deserts, mountains, border regions, and disaster zones where terrestrial 5G coverage is unavailable. Hybrid architectures may combine terrestrial networks, low-Earth-orbit satellites, geostationary satellites, and high-altitude platform stations to provide command-and-control redundancy and broadband payload communication. Relevant metrics include satellite-link availability, round-trip latency, received signal strength (dBm), link-margin availability, beam-handover interruption (ms), coverage continuity, antenna mass and power consumption, and data transmitted per unit of energy (Mbit/J). ESA has examined architectures in which high-altitude platforms relay communication between satellites and smaller drones that cannot carry conventional Ku-or Ka-band terminals because of size, weight, aerodynamic, and power constraints [120,121]. Such systems are intended to support high-throughput payload links, command-and-control communication, multi-UAV connectivity, and beyond-radio-line-of-sight operations.

Cooperative sensing enables connected drones to combine cameras, radar, LiDAR, radio-frequency measurements, and environmental sensors to create a shared representation of the operational environment. Instead of transmitting all raw data, drones may exchange detected objects, compressed features, local maps, trajectories, confidence scores, or hazard alerts. Cooperative-sensing performance should be measured through object-detection probability, false-alarm rate, localization RMSE (m), map-alignment error (m), track-continuity rate, sensor-update frequency (Hz), data-fusion latency (ms), and bandwidth consumed per cooperative track (kbit/s). The IMT-2030 framework explicitly includes integrated sensing and communication, covering range, velocity and angle estimation, object detection, localization, imaging, and mapping [122,123]. It also identifies a positioning research target of approximately 1–10 cm, although achievable drone positioning accuracy will depend on propagation conditions, geometry, bandwidth, sensor fusion, and system implementation.

Integrated air-traffic management is required when large numbers of connected drones operate simultaneously in urban and low-altitude airspace. Unmanned Aircraft System Traffic Management platforms support flight planning, authorization, surveillance, airspace-status exchange, strategic deconfliction, conformance monitoring, and management of beyond-visual-line-of-sight missions. Key metrics include flight-authorization response time, trajectory-conformance rate, position-update interval, track availability, predicted-conflict detection rate, false-conflict alert rate, conflict-resolution success, losses of minimum separation per flight hour, and airspace capacity measured in simultaneous operations/km² [124,125]. The FAA describes UTM as a distributed, highly automated ecosystem in which operators, service providers, and aviation authorities exchange real-time constraints and operational data primarily through application programming interfaces rather than conventional voice communication [126-129].

11. Cybersecurity, Privacy, Regulation, and Ethical Governance of Drone Systems

The rapid expansion of autonomous and connected drone operations creates a multidimensional risk environment involving cybersecurity, privacy, aviation safety, regulatory compliance, and ethical responsibility. Modern drones depend on global navigation satellite systems, wireless command-and-control links, onboard computers, cloud platforms, mobile applications, edge servers, and artificial intelligence. Compromise of any component may lead to navigation errors, unauthorized surveillance, disclosure of sensitive information, mission interruption, or loss of aircraft control. A comprehensive governance framework should therefore track attack-detection rate, false-alarm rate, mean time to detect, mean time to contain, system-recovery time, cyber incidents per 1,000 flight hours, and mission-completion rate under degraded or hostile conditions. CISA identifies the protection of UAS platforms, communications, stored information, and privacy as essential components of secure drone deployment, while NIST recommends integrating cybersecurity and AI risk management throughout the system lifecycle.

GNSS spoofing is one of the most serious navigation threats because counterfeit satellite signals can cause a drone to calculate an incorrect position, velocity, altitude, or time. A successful spoofing attack may redirect the aircraft, bypass geofencing controls, falsify flight records, or trigger an unsafe landing. Countermeasures include multi-constellation navigation, inertial measurement units, visual odometry, terrain matching, signal-authentication methods, and consistency checks among independent positioning sources. Spoofing resilience should be evaluated using probability of detection (%), false-positive rate, time to detection, maximum undetected position deviation (m), navigation RMSE under attack (m), and time required to activate backup navigation (s). For a safety-critical

mission, an illustrative engineering objective could be a detection rate above 99%, a false-alarm rate below 1%, and transition to an alternative navigation source within 1–2 seconds; however, these values are design targets rather than universal regulatory thresholds and must be adapted to the aircraft, environment, and operational risk.

Radio-frequency jamming can interrupt GNSS reception, command-and-control links, payload-data transmission, Remote ID broadcasts, and inter-drone communication. Jamming resilience requires spectrum monitoring, frequency diversity, directional antennas, adaptive modulation, multi-link communication, interference classification, and predefined lost-link procedures. Relevant metrics include jamming-to-signal ratio, packet-loss rate, command-link availability, communication outage duration, frequency-switching time, anti-jamming processing gain, and successful contingency-action rate. Operational targets may include command-link availability above 99.99%, critical-message delivery reliability above 99.999%, and successful return-to-home, holding, or emergency landing in nearly all tested loss-of-link scenarios. These targets should be validated through hardware-in-the-loop tests, controlled interference experiments, and field trials rather than inferred solely from simulation.

Drone hijacking may occur through stolen credentials, insecure wireless protocols, compromised mobile applications, malicious firmware, exposed cloud interfaces, or unauthorized command injection. Protection requires mutual authentication, encrypted command links, secure boot, signed firmware, hardware-protected cryptographic keys, least-privilege access, and continuous verification of command origin and integrity. Performance indicators should include unauthorized-command acceptance rate, authentication rejection accuracy, cryptographic verification latency, percentage of safety-critical commands authenticated, multifactor-authentication coverage, firmware-integrity verification rate, and credential-revocation time. The desired unauthorized-command acceptance rate should be zero, while all privileged access and flight-critical instructions should be authenticated, time-stamped, and recorded in tamper-resistant logs. NIST security guidance supports risk-based controls for identification, authentication, access management, communication protection, system integrity, and incident response.

Data-breach prevention must cover the entire information lifecycle, including sensor acquisition, onboard storage, wireless transmission, edge processing, cloud storage, analysis, sharing, archival, and deletion. Drone data may contain georeferenced imagery, facial information, vehicle registrations, infrastructure layouts, industrial measurements, medical information, or emergency-response records. Security performance can be measured using percentage of sensitive data encrypted at rest and in transit, unauthorized-access events per 1,000 missions, security-patch deployment time (days), vulnerability-remediation rate, audit-log completeness, backup-recovery success rate, and mean time to notify affected parties following a confirmed breach. Mature systems should pursue 100% encryption of sensitive data, authenticated privileged access, automated log monitoring, tested recovery procedures, and documented retention and deletion schedules.

Privacy preservation requires drone operators to collect only the information necessary for a defined and legitimate mission. Privacy-by-design mechanisms can include geofenced recording, camera masking, selective sensing, onboard anonymization, face and licence-plate blurring, short retention periods, role-based access, and restrictions on secondary data use. Recommended metrics include non-relevant imagery automatically removed, anonymization accuracy, residual re-identification risk, average retention duration (days), datasets with documented processing purposes, privacy-impact assessments completed, and privacy complaints per 1,000 operations. The NIST Privacy Framework promotes structured identification and management of privacy risks, while the GDPR establishes principles including lawfulness, transparency, purpose limitation, data minimization, storage limitation, and protection against unauthorized processing or accidental loss.

Operational safety must be integrated with cybersecurity because a technically secure system may still be unsafe if it cannot recognize degraded conditions, avoid collisions, or transition to a controlled state after failure. Safety performance should be measured using hazardous-event rate per flight hour, loss-of-control events per 1,000 missions, detect-and-avoid success rate, emergency-landing success rate, mean time between critical failures, software-recovery time, geofence-conformance rate, and percentage of flights completed within approved operating limits. Testing should include communication loss, GNSS disruption, sensor failure, malicious command injection, battery degradation, adverse weather, cloud-service outages, and incorrect AI decisions. Safety assurance should also document acceptable residual risk, contingency procedures, maintenance requirements, and the operator's ability to intervene.

Airspace regulation supports the identification, authorization, monitoring, and safe integration of drones with other airspace users. In the United States, FAA Remote ID requirements provide identification and location information for applicable drones and their control stations or takeoff locations, supporting safety, security, and accountability. Compliance metrics may include Remote ID

broadcast availability, message-update success rate, location error (m), authorization-response time (s), trajectory-conformance rate, and unauthorized-airspace entries per 1,000 flights. FAA discretionary enforcement concerning Remote ID ended on March 16, 2024, after which applicable registered-drone operations were expected to comply with the rule.

European U-space regulation similarly establishes a framework for digitally managed unmanned-aircraft operations and services. Its implementation supports functions such as flight authorization, network identification, geo-awareness, traffic information, and operational coordination. U-space and unmanned-traffic-management performance can be evaluated using flight-plan approval time (s), track availability, position-report latency (ms), strategic-conflict detection rate, false-conflict alert rate, conflict-resolution success rate, and losses of required separation per flight hour. EASA's consolidated U-space rules are based on Commission Implementing Regulation (EU) 2021/664 and associated compliance and guidance material.

Public acceptance is influenced by perceived safety, privacy, noise, transparency, fairness, environmental impact, and the social value of the mission. Acceptance should be measured through public-support rate, trust score, privacy-concern score, noise-annoyance rating, complaints per 1,000 flights, willingness to use drone services, and change in acceptance following consultation or demonstration projects. Results should be disaggregated by mission type because communities may evaluate emergency medical delivery, wildfire monitoring, commercial parcel delivery, and police surveillance differently. Operators should clearly communicate what information is collected, how it is processed, who can access it, how long it is retained, and how individuals may submit complaints or request corrective action.

Responsible AI governance is necessary when drones use machine learning for navigation, obstacle avoidance, facial or object recognition, target prioritization, route planning, risk assessment, or autonomous intervention. Model evaluation should extend beyond overall accuracy to include precision, recall, F1-score, calibration error, out-of-distribution detection rate, adversarial robustness, subgroup error differences, and performance under adverse weather or illumination conditions. Governance indicators should include AI decisions recorded in audit logs, human-override availability, override-command success rate, decision-explanation coverage, model-drift detection time, serious AI incidents per 1,000 operating hours, and models independently validated before deployment. NIST's AI Risk Management Framework organizes risk management around the functions Govern, Map, Measure, and Manage and identifies reliability, safety, security, resilience, transparency, explainability, privacy, and fairness as important characteristics of trustworthy AI.

Human oversight is particularly important in high-consequence operations. Authorized personnel should be able to understand system limitations, recognize abnormal behaviour, reject unsafe recommendations, and interrupt autonomous actions. Human–AI performance may be assessed through operator response time (s), percentage of missions with functional manual override, successful intervention rate, automation-surprise incidents, operator workload score, and time required to reconstruct an AI decision from system logs. The EU AI Act requires risk management, technical documentation, record-keeping, accuracy, robustness, cybersecurity, transparency, and proportionate human oversight for relevant high-risk AI systems. It also requires oversight mechanisms that enable responsible individuals to interpret system outputs and intervene when operation could threaten health, safety, or fundamental rights.

An effective governance framework should combine cybersecurity, privacy, aviation safety, regulatory compliance, ethical review, and continuous post-deployment monitoring. No single performance metric can establish trustworthiness; instead, drone operators should use a balanced scorecard covering security resilience, operational safety, data protection, AI reliability, regulatory conformance, transparency, and public acceptance. Future research should prioritize cyber-resilient navigation, anti-jamming communication, zero-trust fleet architectures, privacy-preserving edge analytics, secure federated learning, formal verification, standardized incident reporting, and auditable autonomous decision-making.

12. Conclusion

Drone technology is undergoing a fundamental transition from manually controlled aerial imaging platforms toward autonomous, intelligent, and networked systems capable of perception, reasoning, cooperation, and real-time decision-making. Advances in deep learning, computer vision, reinforcement learning, sensor fusion, simultaneous localization and mapping, and adaptive trajectory planning have substantially improved autonomous navigation in complex and partially unknown environments. These capabilities allow drones to detect obstacles, identify targets, construct environmental maps, optimize routes, and respond dynamically to changing mission conditions. However, the reliability of AI-enabled

navigation remains affected by limited onboard computing resources, environmental uncertainty, sensor degradation, model generalization, and the lack of universally accepted procedures for validating safety-critical autonomous decisions.

The development of drone swarms, multi-agent cooperation, edge intelligence, and cloud–edge computing has further expanded the operational capacity of unmanned aerial systems. Cooperative drones can distribute tasks, share sensing information, maintain formations, coordinate trajectories, and continue missions despite individual vehicle or communication failures. At the same time, lightweight AI models and embedded accelerators enable real-time onboard analytics, while edge and cloud platforms provide large-scale storage, fleet supervision, advanced processing, and long-term data analysis. These architectures support the transition from isolated drone missions to scalable service ecosystems, including Drone-as-a-Service platforms. Nevertheless, achieving reliable cooperation requires resilient communication, decentralized control, energy-aware task allocation, synchronized data exchange, interoperable software, and robust protection against cyberattacks.

The application landscape demonstrates the broad economic, environmental, and societal value of drone systems. In precision agriculture, drones support crop-health assessment, disease and pest detection, irrigation analysis, precision spraying, soil mapping, and yield prediction. In emergency response, wildfire management, and search-and-rescue operations, they provide rapid disaster mapping, victim localization, hazardous-area assessment, fire-front monitoring, and medical-supply delivery. Logistics applications include autonomous parcel transportation, humanitarian distribution, payload optimization, and beyond-visual-line-of-sight delivery networks. Environmental applications extend to forest and wildlife monitoring, pollution detection, air-quality measurement, coastal surveillance, flood mapping, biodiversity assessment, and ecological conservation. The integration of drones with 5G, emerging 6G networks, satellites, edge servers, and unmanned traffic-management systems is expected to improve connectivity, cooperative sensing, operational range, and airspace coordination.

Despite these advances, the future of drone technology will depend on resolving several interconnected technical and governance challenges. Limited battery endurance, payload constraints, adverse weather, communication outages, spectrum interference, GNSS spoofing, jamming, hijacking, and data breaches continue to restrict reliable deployment. Privacy preservation, public acceptance, airspace compliance, operational accountability, and responsible AI governance are equally important, particularly in applications involving surveillance, personal data, autonomous decisions, or densely populated environments. Future research should prioritize energy-efficient propulsion and computing, secure multi-link communication, autonomous charging, explainable and verifiable AI, privacy-preserving edge analytics, resilient swarm architectures, standardized performance assessment, and integrated air-traffic management. Progress in these areas will enable drones to evolve into trustworthy, interoperable, and sustainable components of next-generation smart cities, agricultural systems, logistics networks, emergency services, communication infrastructures, and environmental-management platforms.

Funding: Please add: This research received no external funding.

Acknowledgments: The authors would like to express their sincere appreciation to the Libyan Center for Sustainable Development Research, Al-Khums, Libya, for its valuable academic support and institutional facilitation that contributed to the completion and publication of this article.

Conflicts of Interest: The authors declare no conflicts of interest.

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