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Resilient UAV Platforms for Remote Sensing: A Research Roadmap for UAV Impact Recovery

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***Abstract*—Unmanned Aerial Vehicles (UAVs) are integral to remote sensing yet remain critically vulnerable to impact events, including collisions and system failures. Despite expanding literature, research on UAV impact recovery lacks cohesive synthesis. To address this, we conducted a comprehensive bibliometric analysis of 1,855 publications from Scopus and Web of Science (1992–2024) using Biblioshiny, ScientoPy, and VOSviewer. This study maps publication trajectories, thematic structures, and collaboration patterns, illuminating the field's evolution across three distinct phases: a foundational epoch (1992–2003) establishing basic fault tolerance; a developmental stage (2004–2015) advancing reconfigurable control; and an era of exponential growth (2016–2024) driven by deep learning and holistic collision recovery systems. Global research output is heavily concentrated in China (31.8%) and the United States (27.5%). While fault-tolerant control, resilience, and adaptive control dominate this cross-disciplinary discourse, keyword co-occurrence analysis reveals substantial epistemological fragmentation. Specifically, perception-driven research operates in isolation from control-theoretic approaches, and individual platform recovery mechanisms remain disconnected from multi-agent swarm coordination. Furthermore, critical knowledge gaps persist, notably the absence of hardware-software co-design for sensor payloads, a scarcity of empirical validation within applied remote sensing environments, and the peripheral positioning of AI-based adaptive learning frameworks. Bridging these disciplinary silos and addressing these technological gaps is imperative for developing the resilient, autonomous UAV architectures required for complex, real-world remote sensing operations.**

***Index Terms*—Research trends, resilience, Scopus, thematic mapping, UAV impact recovery, Web of Science.**

I. INTRODUCTION

Unmanned Aerial Vehicles (UAVs) have revolutionised remote sensing applications, transforming how we approach large-scale environmental monitoring, precision agriculture and emergency response operations [1].

However, their growing deployment in complex and hazardous environments has revealed a critical challenge: ensuring operational continuity when these systems experience physical impacts [2]. When a UAV collides with obstacles or experiences aerodynamic disturbances, the resulting damage or destabilisation often leads to mission failures, financial losses and potential safety hazards. These challenges have become particularly critical in applications where continuous operation and safety-critical applications are essential, such as disaster response or time-sensitive surveillance missions in remote sensing operations that require failure-free operation [3].

Moreover, UAVs offer unique capabilities that impose unique demands on UAV systems that exacerbate these challenges [4]. Unlike other UAV operations, remote sensing often requires extended flight times over diverse terrains, airborne missions, operation in adverse weather conditions, and payload features [5]. Consequently, impact events, whether from bird strikes, wind gusts or object collisions, can not only terminate missions but also result in loss of valuable sensor data and expensive equipment. This impact can severely impact the stability and control of UAVs, leading to deviation from planned trajectories and potential mission failure [6][7]. Therefore, the ability to detect, respond to and recover from such impact autonomously has emerged as a critical capability for next-generation remote sensing UAVs.

In response to these challenges, recent advances in embedded electronics, coupled with evolutionary and adaptive algorithms, have opened new possibilities for developing truly autonomous recovery systems [8][9]. These systems integrate sophisticated sensor networks, intelligent signal processing and bio-inspired algorithms to detect impacts in real-time, assess damage and execute recovery manoeuvres without human intervention [9][10][11]. However, the development of such capabilities requires an interdisciplinary approach combining aerospace engineering, embedded systems design, evolutionary computations and machine learning expertise.

Despite the growing importance of UAV impact recovery systems, the research landscape suffers from significant fragmentation and a lack of comprehensive synthesis. Telli et al. [12] highlight this critical issue, noting that “due to the wide range of topics and subdomains within UAV research, newcomers may find themselves overwhelmed by the numerous options available”. This fragmentation is particularly pronounced in impact recovery research, where previous reviews have focused on narrow technical aspects such as UAV control systems [13], fault-tolerant control [14], or adaptive controllers [15], but no comprehensive analysis has examined the evolution and emerging trends across the entire domain.

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This fragmentation creates several critical issues that hinder progress in the fields.

First, the lack of research synthesis prevents researchers from identifying knowledge gaps and avoiding redundant efforts. Ahmed et al. [16] conducted a systematic literature survey of 254 UAV-related articles, revealing the scattered nature of current research efforts. Without a comprehensive understanding of the research landscapes, scientists may unknowingly duplicate existing work or fail to build upon previous findings, thereby slowing innovation in critical recovery technologies.

Second, current UAV recovery applications face operational challenges that remain poorly understood due to scattered research efforts. Shakhatreh et al. [17] identify that UAVs are susceptible to various disruptions arising from environmental elements such as weather, energy limitations, signal interference, and legislation, yet most research addresses only application-specific resiliency implementation rather than focusing on comprehensive system-wide inclusion of resilience mechanisms. These challenges include real-time impact detection limitations, inadequate damage assessment algorithms, and insufficient recovery manoeuvre capabilities in complex environments [18]. The absence of a systematic overview of these issues impedes the development of effective solutions.

Third, Mohsan et al. [5] emphasise that "UAVs face limitations in operability due to several critical concerns in terms of flight autonomy, path planning, battery endurance, flight time and limited payload carrying capabilities. However, the relationship between these operational constraints and impact recovery capabilities remains poorly understood, highlighting the urgent need for comprehensive analysis.

Consequently, there is an urgent need to identify emerging trends and research frontiers in UAV impact recovery systems to guide future research directions and technology development. Pal et al. [19] call for "comprehensive analysis of emerging trends" in UAV research, particularly as the field enters a period of exponential growth in artificial intelligence, requiring strategic guidance to maximise research impact and practical applications.

This bibliometric analysis addresses the critical gaps and provides substantial benefits to multiple stakeholders, particularly given the methodological advantage of combining multiple databases for comprehensive coverage [20]. Specifically, this study offers significant value to researchers that seeking to identify research gaps and opportunities in UAV impact recovery systems. Kotsemir [21] demonstrates how bibliometric analysis can effectively detect key countries in this field of research as well as the major centres of excellence in UAV research. By mapping the intellectual landscape, this analysis enables scientists to position their work strategically, identify unexplored areas and discover potential collaboration opportunities that can accelerate innovation [22].

Subsequently, government agencies are developing UAV policies and regulatory frameworks. Duque et al. [23] illustrate how systematic UAV research synthesis supports infrastructure inspection policies, noting that "a few departments of transportation have used UAVs to inspect bridges as a more economical and versatile tool". The insights from this study can inform evidence-based policy decisions regarding UAV safety standards, operational guidelines and investment priorities in recovery system technology, thereby enhancing public safety and regulatory effectiveness.

Thereafter, technology companies are developing cutting-edge UAV recovery solutions and conducting research. This analysis provides industry stakeholders with comprehensive market intelligence, emerging technology trends and competitive landscape insights that can guide product development strategies and investment decisions [24]. Furthermore, this study will be a foundation for researchers in this field to carry the research and propose new work in the context of existing solutions [25].

This study will provide a comprehensive bibliometric analysis of research publications related to UAV impact recovery systems throughout their entire historical development. Bibliometric analysis is the use of quantitative statistics to analyse information in books, papers and other publications [26]. A bibliometric study offers several benefits over typical literature evaluation and summarises the overall trend of the research in a field. First, bibliometric approaches analyse thousands of papers in a database to create a comprehensive picture of a study topic using professional software and high-performance computers. Second, citation analysis in bibliometric approaches allows for quantitative measurement of the effect of a study area, researchers and publications. Third, it is possible to rapidly identify research hotspots and classical literature on a certain topic. Bibliometric approaches offer quantitative insights into research patterns that cannot be gleaned from traditional reviews alone; it is possible to identify intellectual structures and evolution patterns that reveal both the current state and future trajectory of the field. We conducted a bibliometric review by using bibliometric visualisation techniques and statistical methods spanning the entire available publication history to summarise and evaluate articles, identifying trends and hotspots in the area of UAV impact recovery systems.

To address the identified problems and provide comprehensive insights, this study poses the following main research questions:

Main RQ: What are the main research trends, collaboration networks, and thematic clusters in UAV impact recovery systems as revealed through bibliometric analysis of Scopus and Web of Science-indexed publications?

This main question is operationalised through four specific sub-questions that directly address the fragmentation issues identified

RQ1: What has been the publication volume, and how has research activity evolved in UAV impact recovery over time?

RQ2: Which countries, authors, institutions and subject areas have produced the most scientific publications on UAV impact recovery?

RQ3: What are the dominant keywords, themes and research

clusters in UAV impact recovery systems?

RQ4: What research gaps and underexplored areas exist in UAV impact recovery systems, and what emerging frontiers can guide future research directions?

These questions directly address the problem of research fragmentation by systematically mapping the field's evolution, identifying key contributors and themes and revealing gaps that require attention [21]. Furthermore, they support the significance of this study by providing actionable insights for researchers, policymakers and industry stakeholders. The methodological approach follows established bibliometric practices for database integration as recommended by Echchakoui [27] for comprehensive literature analysis.

To comprehensively address these research questions, we employed a dual-database approach using Scopus and Web of Science, following best practices for bibliometric database integration [20]. This analysis is particularly relevant for the remote sensing community as we enter an era of increasingly autonomous and intelligent earth observation systems [28][29][30]. The insights generated can inform strategic decisions about technology developments, research collaboration and investment priorities in next-generation remote sensing platforms. The remainder of this article is structured as follows. Section II outlines our methodology, including data collection and analytical approaches following established bibliometric standards. Section III presents our findings addressing each research question through a comprehensive bibliometric analysis. Section IV discusses the research gaps, their implications and future research directions. Finally, Section V concludes with a synthesis of key contributions and recommendations for future research.

II. METHODOLOGY

A. Data Collection and Article Selection Strategy

The study was carried out using the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) statement in its 2020 update [31]. This statement is a tool whose fundamental purpose is to collect in a clear and transparent manner the objectives, procedures and results carried out by an author in a systematic review. In this sense, PRISMA contributes to the identification of the state of knowledge on a specific topic, which becomes a starting point for researchers who address these issues, to continue with the updating process or to contribute to the development of any of the lines of research evidenced [31].

This bibliometric analysis utilised data extracted from two premier scholarly databases, such as Web of Science (WoS) and Scopus. These databases were selected for their extensive coverage of literature relevant to "TITLE" and historical depth with Scopus indexing over 22,000 titles across science, technology, medicine, social science and humanities [32], while Web of Science provides access to over 33,000 journals across 250 science, social sciences and humanities disciplines [33].

The database selection was guided by several strategic considerations. First, both platforms offer comprehensive coverage of aerospace engineering, computer science, materials science and embedded electronics, all critical disciplines for UAV impact recovery research. Second, their advanced search capabilities, including sophisticated Boolean operators, filtering by document type, language, year range and more. Third, their robust citation indexing systems facilitate comprehensive citation analysis, mapping the citation networks and impact of this field over time [20].

To summarise, Scopus and Web of Science were selected for their disciplinary breadth, advanced search features, and robust citation tracking tools, all of which were essential in conducting a rigorous bibliometric analysis. The capabilities of these databases helped ensure a comprehensive literature review and analysis. The detailed search string applied in each database is presented in Table I.

The search strategy was designed to capture publications addressing three core conceptual areas: (1) Unmanned aerial vehicles and autonomous systems, (2) impact events and resilience and (3) recovery mechanisms and stabilisation. Multiple synonym variations were included to ensure comprehensive coverage across different terminologies used in the literature. To capture the complete historical evolution of UAV impact recovery systems, we imposed no temporal restriction on our search, retrieving documents spanning from 1992 to 2024. This approach allows us to trace the field's development from its theoretical origins through contemporary cutting-edge research.

The search conducted in Scopus and Web of Science databases identified 2943 relevant papers on impact resilience and UAV impact recovery systems. After filtering out 370 records based on document type and language, 2573 papers remained. Of these, 1722 (66.94%) were retrieved from Scopus, while 851 (33.06%) originated from Web of Science, as shown in Table I. Duplication analysis using ScientoPy found 718 duplicated papers (27.90% of the total), with 6 from WoS and 712 from Scopus. After deduplication, 1855 papers remained, where 845 (45.60%) were from WoS and 1010 (54.50%) from Scopus (Fig. 1)

TABLE I. DATABASE AND QUERY

Databases	Query	Filters
Scopus (*n=1722*)	**TITLE-ABS-KEY**("Unmanned Aerial Vehicle*" **OR** "Unmanned Aircraft System*" **OR** "Remotely Piloted Aircraft*" **OR** "Remotely Piloted Aircraft System*" **OR** "Drone" **OR** "UAV" **OR** "UAS" **OR** "RPA" **OR** "RPAS") AND **TITLE-ABS-KEY** ("Impact" **OR** "Collision" **OR** "Crash" **OR** "Failure") **AND TITLE-ABS-KEY** ("Resilience" **OR** "Resilient" **OR** "Recovery" **OR** "Recov*" **OR** "Stabilization" **OR** "Stabilisation" **OR** "Mid-Air Recovery*" **OR** "Fault Tolerance" **OR** "Damage Tolerance" **OR** "System Recovery" **OR** "Adaptive Control" **OR** "Emergency Recovery"))	*Article; Conference Paper; English; No date restrictions*
Web of Science (*n=851*)	**TS**=("Unmanned Aerial Vehicle*" **OR** "Unmanned Aircraft System*" OR "Remotely Piloted Aircraft*" **OR** "Remotely Piloted Aircraft System*" **OR** "Drone" **OR** "UAV" **OR** "UAS" **OR** "RPA" **OR** "RPAS") **AND TS**=("Impact" **OR** "Collision" **OR** "Crash" **OR** "Failure") **AND TS**=("Resilience" **OR** "Resilient" **OR** "Recovery" **OR** "Recov*" **OR** "Stabilization" **OR** "Stabilisation" **OR** "Mid-Air Recovery*" **OR** "Fault Tolerance" **OR** "Damage Tolerance" **OR** "System Recovery" **OR** "Adaptive Control" **OR** "Emergency Recovery")	*Article; Proceeding Paper; English; No date restrictions*

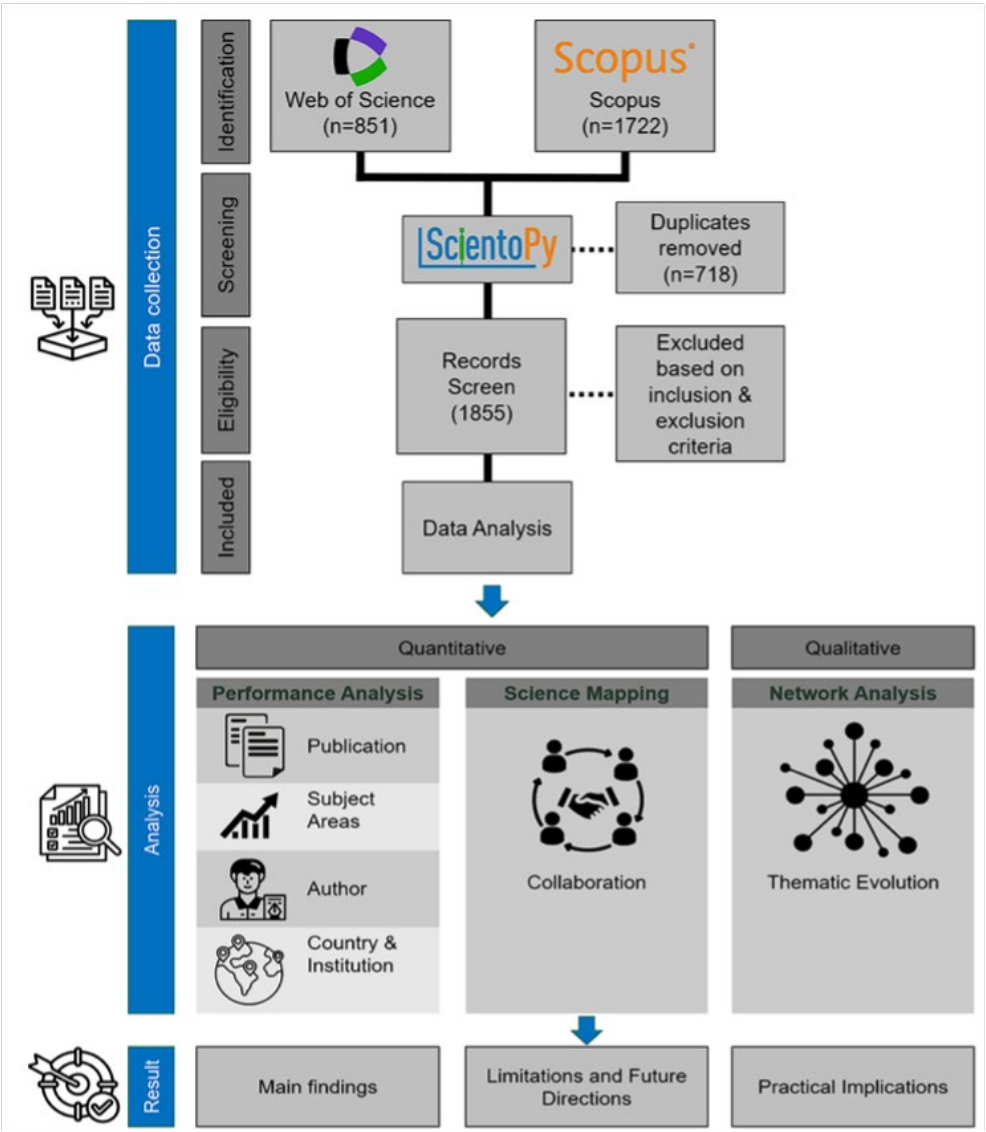


Fig. 1. The study flowchart.

B. Analytical Tool

Three primary tools were employed to conduct the bibliometric analysis: Biblioshiny, ScientoPy, and VOSviewer. These tools were selected based on their complementary strengths in data visualisation, temporal analysis and network mapping.

Biblioshiny 4.1, from RStudio, is an open-source bibliometric program that offers a comprehensive set of statistical techniques and visualisation that allow for performance analysis and conceptual mapping of the research topic [34]. Furthermore, Biblioshiny is released with an

intuitive web-based graphic user interface, where the user interface is straightforward and well-organised. The menu includes statistics and graphs for four levels of metric (source, author, document and clustering by Coupling), as well as the three types of knowledge structures (Conceptual Structure, Intellectual Structures and Social Structure). The analysis possibilities are extensive and classified into seven categories: 1) Introduction, 2) Sources, 3) Authors, 4) Documents, 5) Conceptual Structures, 6) Intellectual Structure, and 7) Social Structure. For this study, we employed Biblioshiny for thematic mapping using Multiple Correspondence Analysis (MCA) with automatic k-means clustering. Keyword co-occurrence networks were constructed with a minimum occurrence threshold of 5, and thematic maps were generated to identify motor themes, niche themes, emerging themes and basic themes based on centrality and density positioning.

ScientoPy, developed as a Python-based tool, was specifically utilised for deduplication analysis and advanced bibliometric processing. Unlike other bibliometric tools, ScientoPy offers specialised capabilities for detecting and resolving duplicate entries across multiple databases, which was essential for this analysis of publications from Web of Science and Scopus [35]. ScientoPy excels in temporal pattern detection and analysis of scientific evolution through time, enabling the identification of emerging research topics and trends in UAV impact recovery systems. The tool's strength lies in its ability to process large datasets efficiently and generate high-quality visualisations of subject areas, institutional contributions, and country-level scientific output.

For deduplicate detection, ScientoPy employed fuzzy matching algorithms comparing the title similarity, author overlap, and publication year to identify redundant records with a match threshold of 0.85. Additionally, the ScientoPy approach allows for reproducible bibliometric workflows, enabling systematic analysis of research trends and performance metrics that complement the visual analytics by VOSViewer and Biblioshiny.

Meanwhile, VOSviewer is a software application for creating and viewing bibliometric networks. These networks contain journals, research, or individual articles, and they may be built via citation, bibliographic coupling, co-citation, or co-authorship relationships [36]. VOSviewer also has text mining capabilities, which allow the creation and display of co-occurrence networks of key phrases taken from scientific literature. For this study, VOSviewer was used to generate keyword co-occurrence networks using association strength normalisation with a minimum keyword occurrence of 5 and a minimum cluster size of 10.

C. Data Quality Assurance

Several procedures ensured data quality and analytical rigour. Author name disambiguation was performed manually for the top 50 most productive authors, standardising name variations (e.g, "Zhang, Y." and "Zhang, Yi" from the same institution were merged). Institutional names were standardised using a reference list of official university names to address variations in institutional affiliations reporting (e.g., "Northwestern Polytechnic University" and "Northwestern Polytechnical University" were standardised to the official name).

Keyword normalisation followed systematic procedures to ensure consistency. Semantically equivalent terms were merged, including consolidation of platform terminology (UAV, unmanned aerial vehicles, drones, UAS) and methodological terms (machine learning and deep learning as a combined category).

D. Analytical Framework

The analytical framework addresses each research question through specific techniques:

RQ1 (Publication Trends): Time series analysis of annual publication volumes, calculation of average growth rates (AGR) and average documents per year (ADY) for specified periods, identification of temporal phases through visual inspection and growth rate changes.

RQ2 (Contributors): Frequency analysis of country affiliations, institutional affiliations and author productivity; citation analysis identifying most-cited papers and authors; subject area distribution analysis using database classification schemes.

RQ3: **(Keywords and Themes)**: Frequency analysis of author keywords and keywords plus; co-occurrence network analysis, identifying research clusters; thematic classification through narrative synthesis.

RQ4 (Research Gaps): Thematic mapping using centrality-density positioning; targeted searches within the dataset for specific keyword combinations to quantify integration gaps; comparative analysis between well-developed and underdeveloped themes.

III. Results and Discussion

A. What has been the publication volume and research activity evolved in UAV impact recovery over time (RQ1)?

The analysis of annual publication data from both Scopus and Web of Science databases reveals a remarkable growth trajectory in UAV impact recovery systems research over the past three decades. Fig. 2 illustrates the number of documents published annually from 1992 to 2024, demonstrating clear temporal patterns that reflect the field's evolution and maturity. The publication timeline can be characterised by three distinct phases, each representing different stages in the field development and reflecting broader trends in UAV technology adoption and autonomous systems research.

1) Phase 1: Foundation Period (1992-2003)

The initial phase shows minimal research activity with fewer than 5 publications per year across both databases. During this dormant period, only 20 publications were recorded, representing sporadic early investigations into UAV fault tolerance [37] and basic recovery mechanisms [38][39]. The research was primarily conceptual, focusing on theoretical frameworks adapted from manned aircraft systems. This limited activity reflects the nascent state of UAV technology during this period, when unmanned system was primarily

confined to military applications [40][41] with limited civilian research interest.

2) Phase 2: Development Period (2004-2015)

Beginning in 2004, a gradual but steady increase in publications is observed, rising from 5 to 15 papers annually. This phase produced 246 publications, indicating growing recognition of the importance of autonomous recovery capabilities. The research landscape during this period was dominated by three interconnected themes, such as fault-tolerant control architectures, autonomous operational capabilities and adaptive flight control systems. Early work established fundamental fault detection [42][43] and diagnosis frameworks for UAV systems [44][45][46][47], while parallel effort explored reconfigurable control strategies capable of compensating for actuator failures [48][49]. The emergence of neural network-based adaptive control marked a significant shift from traditional model-based approaches [50][51][52], enabling UAVs to maintain their stability despite impact or disturbance.

Concurrently, substantial research effort addressed recovery under adverse conditions [53][54], reflecting the defence sector demands for all-weather operation capabilities. The latter half of this period saw increased focus on multi-agent coordination and formation control [55][56], as researchers began exploring distributed decision-making architecture for collaborative UAV missions. This growth phase coincides with expanding commercial interest in UAV applications and the recognition that fault-tolerant autonomous capabilities would be essential for reliable civilian deployment beyond controlled military environments.

3) Phase 3: Exponential Growth Period (2015-2024)

The most dramatic change occurs after 2015, with both databases showing exponential growth in publication volume. Scopus publications increased from 20 in 2015 to 199 in 2024, while Web of Science grew from 15 in 2015 to 164 in 2024. This period accounts for 1460 publications, reflecting the field transformations into a major research field. The research paradigm shifted dramatically from incremental fault tolerance to complete failure recovery scenarios. Between 2016 and 2020, approximately 180 publications investigated complete rotor loss and total actuator failure [57][58][59], marking a departure from Phase 2. Researchers demonstrate that UAVs could maintain controlled flight despite catastrophic component losses [60][61], with this capability becoming a benchmark for system resilience evaluation. This escalation coincided with the integration of deep learning and reinforcement learning methods, with over 200 publications from 2020 to 2024 [62][63][64], enabling real-time adaptation to unprecedented failure modes that traditional model-based approaches could not anticipate. Simultaneously, the research focus expanded beyond controlled laboratory environments to address real-world operational challenges. Collision recovery systems emerged as a distinct research thread with approximately 150 publications [65][66][67], investigating how UAVs could detect and withstand impact, where this is a critical capability for dense urban operations. The proliferation of disaster response and emergency landing research after 2019 accounts for 300 publications [68][69][70], reflecting growing recognition of UAVs potential in humanitarian applications, where autonomous recovery capabilities are essential for operations in GPS-denied and communication-limited environments.

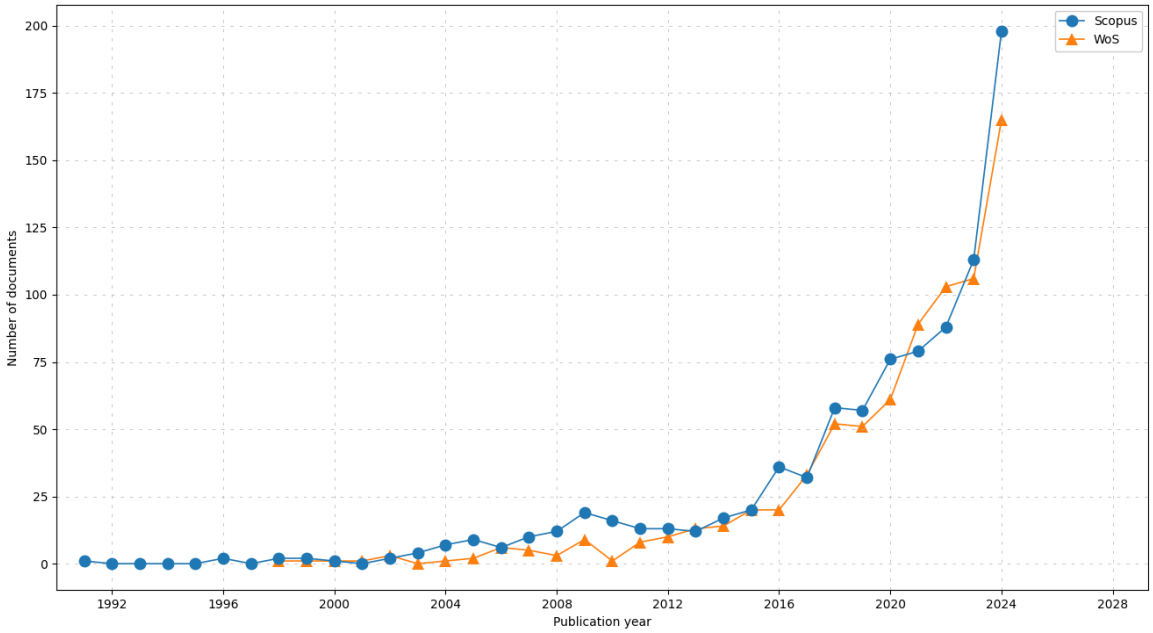


Fig. 2. The publication volume and growth. Source: ScientoPy.

The latter half of this period witnessed the convergence of swarm resilience and distributed fault tolerance, with approximately 250 publications from 2020 to 2024 [71][72][73] exploring how multi-UAV systems could collectively

compensate for individual unit failures through cooperative control strategies. This represented a fundamental shift from individual UAV survivability to system-level resilience, where it's a necessary evolution for large-scale commercial deployments in urban air mobility and logistics. This exponential expansion corresponds with widespread commercial UAV adoption, regulatory developments enabling broader civilian use and the technological maturation of embedded artificial intelligence processors and sensor fusion platforms necessary for real-time autonomous recovery UAV.

Within this broader growth trajectory, examining the actual content of the publication reveals important technological evolution specifically addressing remote sensing mission requirements. Table II presents a comparative analysis of multi-sensor fusion approaches for UAV state estimation, showing how researchers have progressively tackled the dual challenge of maintaining flight stability while preserving data collection accuracy during recovery manoeuvres. The progression of sensor configurations and fusion algorithms reflects increasing sophistication in meeting the practical demands of remote sensing operations, where impact recovery must preserve not only platform stability but also georeferencing accuracy and sensor calibration.

Early implementation exemplified by Valenti et al. [74] employed IMU configurations with complementary filtering, achieved high detection accuracy with real-time response, while maintaining low computational loads suitable for basic orientation and attitude estimation. These systems provide sufficient state information for fundamental flight control but lack the external position references necessary for georeferencing remote sensing data. The intermediate stage, represented by Arreola et al. [75], integrated IMU with GPS and optical flow sensors through Extended Kalman Filters, addressed positioning requirements for remote sensing operations, enabling hovering and trajectory tracking with enhanced precision that is suitable for navigation tasks with medium computational loads and vulnerability to GPS signal degradation in complex environments.

The approaches exemplified by Chen et al. [76] incorporate comprehensive sensor suites combining IMU, GPS, magnetometer and barometer measurements processed through Unscented Kalman Filters. These systems achieve improved accuracy over EKF implementation for complete state estimation, including position, speed and attitude with barometric and magnetic measurements providing critical redundancy during GPS outages.

This evolutionary progression reveals a fundamental trade-off constraining impact recovery systems for remote sensing applications. The computational load escalation from low through medium to high demonstrates that enhanced state estimation accuracy demands increasing processing resources that must compete with fault-tolerant control algorithms during impact events. This constraint intensifies for remote sensing platforms carrying expensive sensor payloads (hyperspectral cameras, lidar, SAR) that already consume significant payload capacity, leaving limited margins for computationally intensive fusion during recovery sequences. Furthermore, the GPS dependency across all approaches exposes vulnerability during impact scenarios where antenna damage or signal obstruction creates precisely the conditions requiring robust state estimation for continued georeferencing. Future research must develop adaptive fusion architectures that dynamically adjust computational complexity during recovery, hardware-accelerated sensor fusion offloading state estimation from flight control processors, and degraded-mode strategies maintaining minimum georeferencing accuracy using reduced sensor sets when comprehensive fusion becomes computationally infeasible.

The analysis of recent performance metrics for 2023-2024 reveals exceptional growth rates that underscore the field's current momentum. As shown in Table III, Scopus recorded 904 publications during these two-year periods with an average growth rate of 55.0% and an average of 155.5 documents per year. Web of Science showed 779 publications with an average growth rate of 31.0% and 135.5 documents per year. The h-index values of 48 (Scopus) and 53 (Web of Science) indicate substantial citation impact, suggesting that this rapidly expanding field is producing influential research rather than merely increasing publication volume without corresponding quality.

TABLE II. MULTI-SENSOR FUSION APPROACHES FOR UAVS STATE ESTIMATION

Ref	Author Year	Sensor Configuration	Fusion Algorithm	Application Focus	Detection Accuracy	Response Time	Computational Load
[74]	Valenti et al. (2015)	IMU	Complementary Filter	Orientation and attitude estimation	High	Real-time	Low
[75]	Arreola et al. (2018)	IMU + GPS + Optical Flow	Extended Kalman Filter	Hovering and trajectory tracking	Enhanced Precision	Real-time	Medium
[76]	Chen S et al. (2024)	IMU + GPS + Magnetometer + Barometer	Unscented Kalman Filter	Position estimation, speed and attitude	Improved over EKF	Real-time	High

TABLE III. GROWTH METRICS FOR UAV IMPACT RECOVERY RESEARCH (2023-2024 PERIOD)

Databases	Total	AGR	ADY	h-index
Scopus	904	55.0	*155.5*	*48*
Web of Science	*779*	31.0	*135.5*	*53*

Note: AGR= Average Growth Rate; ADY=Average Documents per Year

The substantial difference in growth rates between databases indicates varying coverage breadth, with Scopus capturing more conference proceedings and rapid-publication venues that characterise this fast-moving field. The total of 1683 papers processed across both databases represents unprecedented research volume for a single two-year period, exceeding the cumulative output of the first two decades of research in the field.

This exceptional growth pattern positions UAV impact recovery research as one of the most rapidly expanding areas within aerospace engineering and autonomous systems, with profound implications for remote sensing applications requiring reliable, autonomous operation in challenging environments. The acceleration appears driven by converging factors, including commercial deployment pressures, regulatory requirements for safety systems, technological maturation of enabling technologies and growing recognition that impact recovery capabilities represent critical enablers for autonomous operation in complex environments.

B. Which countries, authors, institutions and subject areas have produced the most scientific publications on UAV impact recovery (RQ2)?

1) Country-Level Scientific Production

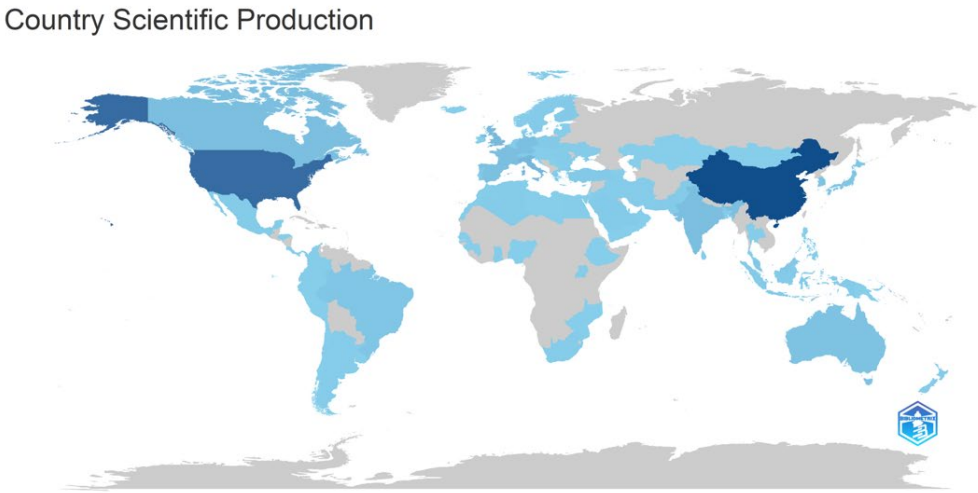
The analysis of country-level scientific production reveals a highly concentrated global research landscape in UAV impact recovery systems, characterised by pronounced bipolar dominance as shown in Fig. 3. China emerges as the undisputed leader with 977 publications, representing 31.8% of total global output, followed by the United States with 844 publications at 27.5%. This concentration pattern aligns with Kotsemir's [21] findings on UAV research distributions, where these two nations collectively account for 59.3% of all research publications in this critical domain. The substantial publication gap between the leading nations and subsequent contributor with the United Kingdom ranking third at only 159 publications, demonstrates the pronounced disparity in research investment and strategic prioritisation of UAV impact recovery capabilities.

The dominant positions of China and the United States reflect fundamentally different national approaches to technological development in this domain. China's remarkable output stems largely from centralised strategic initiatives, particularly the "Made in China 2025" industrial policy, which explicitly identifies aerospace equipment and unmanned systems as priority sectors [77]. This top-down approach operates through civil-military fusion policies that systematically eliminate barriers between defence and the civilian research ecosystem [78]. The strategy leverages state-owned enterprises like China Aerospace Science and Technology Corporation and defence-focused universities, including Northwestern Polytechnic University and Beihang University, creating coordinated networks, where research funding flow through government channels towards shared technological objectives [79]. As Van Oudenaren and Singer note, UAVs represent "the most representative products of military-civil fusion" due to their inherent dual-use nature and scalability [78].

In contrast, the United States exhibits a decentralised, industry-heavy approach where research emerges from diverse sources, including private aerospace companies, university laboratories, defence contractors and government research facilities. This fragmented landscape produces innovations through competition and market forces rather than centralised planning, with DARPA's program demonstrating collaborative efforts among companies like Anduril, RTX, Leidos, Northrop Grumman and SoarTech working as unified teams for common solutions [80]. The American institutional landscape reflects this diversity, with Georgia Institute of Technology, New York University and Texas A&M University contributing to this field, representing the distributed nature of US research efforts across multiple independent institutions rather than concentrated output from designated centres. The US model prioritises intellectual property protection and commercialisation pathways, resulting in delayed publication as companies protect competitive advantages, whereas the China model emphasises rapid knowledge dissemination to accelerate collective progress toward national technological goals. This structural difference manifests in publication patterns, with China producing concentrated output from designated institutions while US contributions span a broader institutional ecosystem, including startups, established defence prime and independent academic centres pursuing autonomous research agendas [81][82].

The remaining contributors form distinct tiers that reflect regional research capabilities and emerging technological priorities. European nations constitute a significant research block with the United Kingdom (159), Italy (133), France (125), Germany (100) and Spain (103) collectively contributing 620 publications, or approximately 20.2% of global output. This European engagement suggests coordinated regional interest in UAV recovery technologies, likely driven by both civilian applications and defence requirements, as noted by Ahmed et al. [16] in their comprehensive UAV review. Meanwhile, emerging research powers including India (125), Canada (116) and South Korea (107) demonstrate growing capabilities in this domain, reflecting the expanding global recognition of UAV impact recovery as a critical technological frontier for autonomous systems deployment in challenging environments. The geographical distribution reveals a clear

pattern where developed nations with advanced aerospace industries and substantial defence budgets dominate research output, while emerging economies are progressively establishing research capabilities in this strategically important field.



COUNTRIES	FREQ
CHINA	977
USA	844
UK	159
ITALY	133
FRANCE	125
INDIA	125
CANADA	116
SOUTH KOREA	107
SPAIN	103
GERMANY	100

Fig. 3. Country scientific production. Source: Biblioshiny.

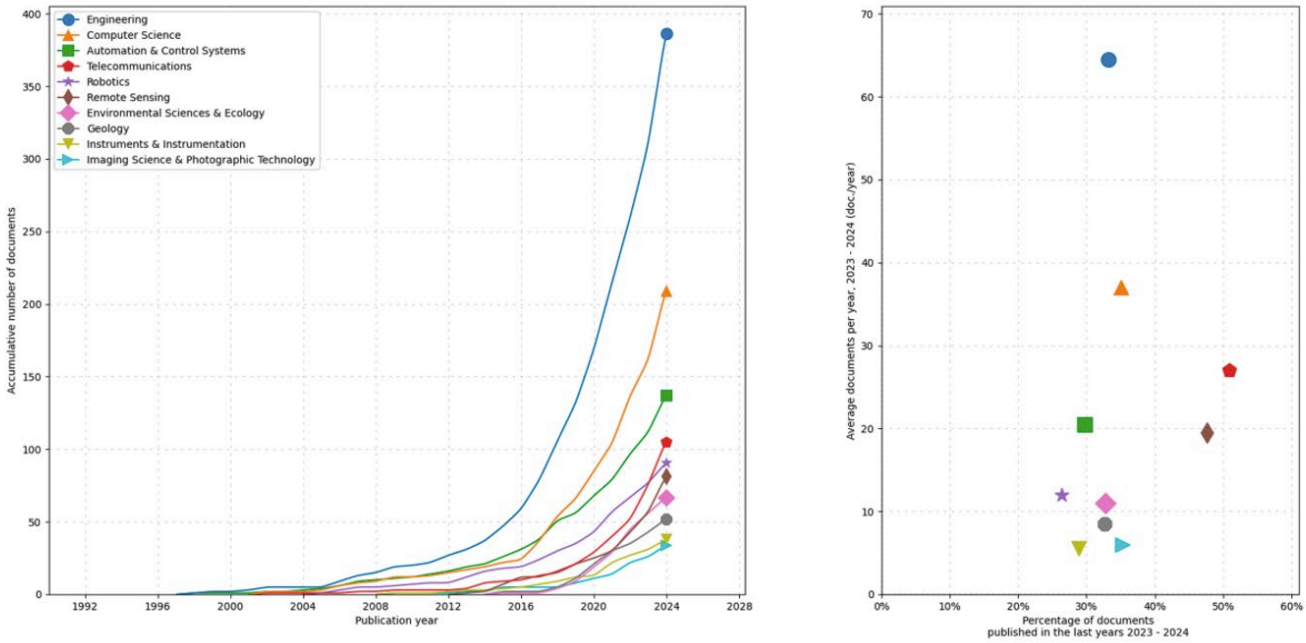


Fig. 4. The most common subject areas. Source: ScientoPy.

2) Subject Area Distribution and Evolution

The temporal analysis of subject area evolution reveals the interdisciplinary maturation of UAV impact recovery research from 1992 to 2024. As illustrated in Fig. 4, Engineering dominates the research landscape with exponential growth reaching approximately 389 accumulated documents by 2024, followed by Computer Science (211 documents). This engineering-centric approach reflects the fundamental aerospace and mechanical challenges inherent in developing a robust impact recovery mechanism [83][84][85][86]. The parallel growth in Computer Science publications underscores the increasing integration of artificial intelligence, machine learning, and embedded systems in recovery algorithms [87][88][89], with particular emphasis on neural network-based fault detection and reinforcement learning-driven control strategies that enable real-time adaptation to impact events.

Particularly noteworthy is the emergence and rapid growth of Automation & Control System research (140 documents), which demonstrates the field's evolution toward autonomous recovery capabilities [90][91][92]. The substantial contribution from Telecommunication (106 documents) reflects the critical need for resilient communication during emergency recovery operations [93][94], while Robotics (91 documents) indicates the growing complexity of UAV impact recovery systems that

require sophisticated sensor fusion, actuator coordination and adaptive control for effective recovery manoeuvres [95][96]. The presence of Remote Sensing (82 documents) as a distinct research area validates this study's focus where UAVs deployed for environmental monitoring, disaster assessment and infrastructure inspection operate in high-risk environments where collision events are more probable [97][98], this is further supported by environmental Sciences & Ecology (67 documents) that reflects the environmental monitoring applications driving using UAV deployment in challenging conditions where impact events are more likely to occur.

The interdisciplinary distribution pattern reveals a fundamental shift in research approach where early phase engineering-dominant publications focused on structural resilience and mechanical failure modes [99][100], whereas recent contributions increasingly emphasise the integration of multi-domain expertise combining control theory, machine learning, sensor technology and communication protocols into unified recovery frameworks [101][102]. This evolution from single-discipline solutions to integrated system approaches reflects the technological maturation necessary for deploying UAVs in complex, unstructured environments where impact recovery capabilities directly determine mission success and platform survivability.

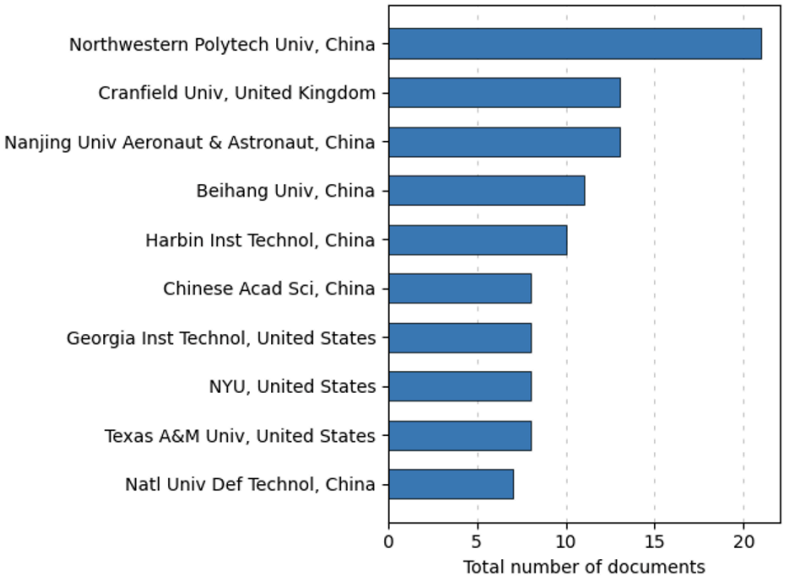


Fig. 5. The most active institutions. Source: ScientoPy.

3) Institutional Leadership and Expertise

The institutional analysis reveals pronounced concentration among Chinese aerospace universities, which occupy six of the top ten positions, as shown in Fig. 5. Northwestern Polytechnic University (China) leads with 22 publications, followed by Cranfield University (United Kingdom) with 14 publications. The Chinese institutional ecosystem demonstrates systematic national investment across diverse university type such as specialize aerospace institutions (Nanjing University of Aeronautics and Astronautics – 14 publications, Beihang – 12 publications), Comprehensive technology universities (Harbin Institute of Technology – 10 publications), and defence-oriented research centres (Chinese Academy of Sciences – 8 publications, National University of Defence Technology – 7 publications). This multi-institutional approach contrasts sharply with the Western research pattern, where output is more distributed across a broader range of universities.

Cranfield University's second-place ranking is particularly noteworthy, as it represents the only non-Chinese institution in the top three despite having significantly smaller total enrolment than its Chinese counterparts. This disproportionate output reflects Cranfield specialized focus on aerospace engineering and autonomous system research, demonstrating that institutional impact in UAV recovery research depends more on specialised expertise concentration than overall institutional size [103]. American institutions maintain a strategic presence through Georgia Institute of Technology, New York University, and Texas A&M University, where each is contributing to 8 publications, representing the USA decentralised research model, where UAV impact recovery capabilities are developed across geographically distributed rather than concentrated in national aerospace centres.

The institutional analysis reveals pronounced concentration in Chinese institutions, which occupy six of the top ten positions, as shown in Fig. 5. Northwestern Polytechnic University (China) leads with 22 publications, followed by Cranfield University (United Kingdom) with 14 publications. Notably, Chinese institutions demonstrate remarkable consistency across the top rankings, including Nanjing University of Aeronautics and Astronautics (14 publications), Beihang University (12 publications), Harbin Institute of Technology (10 publications), Chinese Academy of Sciences (8 publications) and National University of Defence Technology (7 publications). This institutional concentration directly correlates with China's position as the leading country in overall publication output, indicating a coordinated national research strategy in UAV impact recovery systems.

The institutional distribution pattern reveals two distinct

research models where China coordinated a national strategy leveraging multiple aerospace-specialised universities versus the West's distributed approach across general-purpose research universities. This divergence suggests fundamentally different pathways to technological development in UAV impact recovery systems with implications for knowledge transfer, innovation speed, and practical implementation in civilian and defence applications.

TABLE IV. MOST CITED AUTHORS AND PAPERS

Authors	Title	Year	Citations
Dydek, Z. T., Annaswamy, A. M., & Lavretsky, E	Adaptive control of quadrotor UAVs: A design trade study with flight evaluations [104]	2013	537
Bounemeur, A., Chemachema, M., & Essounbouli, N.	Indirect adaptive fuzzy fault-tolerant tracking control for MIMO nonlinear systems with actuator and sensor failures [105]	2018	316
Khan, A., Gupta, S., & Gupta, S. K.	Multi-hazard disaster studies: Monitoring, detection, recovery, and management, based on emerging technologies and optimal techniques [106]	2020	284
Bellingham, J. S., Tillerson, M., Alighanbari, M., & How, J. P.	Cooperative path planning for multiple UAVs in dynamic and uncertain environments [107]	2002	205
Song, Y., He, L., Zhang	Neuroadaptive Fault-Tolerant Control of Quadrotor UAVs: A More Affordable Solution [108]	2019	193
Hou, Z., Lu, P., & Tu, Z.	Nonsingular terminal sliding mode control for a quadrotor UAV with a total rotor failure [109]	2020	189
Shraim, H., Awada, A., & Youness, R.	A survey on quadrotors: Configurations, modeling and identification, control, collision avoidance, fault diagnosis and tolerant control [110]	2018	172
Hu, J., Niu, H., Carrasco, J., Lennox, B., & Arvin, F.	Fault-tolerant cooperative navigation of networked UAV swarms for forest fire monitoring [111]	2022	155
Yu, Z., Zhang, Y., Jiang, B., Fu, J., & Jin, Y.	A review on fault-tolerant cooperative control of multiple unmanned aerial vehicle [112]	2022	155
Valenti, M., Bethke, B., Fiore, G., How, J. P., & Feron, E.	Indoor multi-vehicle flight test bed for fault detection, isolation, and recovery [113]	2006	125

4) Most Influential Authors and Papers

In this section, we ascertained the most influential authors and papers that have shaped UAV impact recovery research through citation analysis. As shown in Table IV, the most cited work comes from Dydek et al.'s 2013 study on "Adaptive control of quadrotor UAVs: A design trade study with flight evaluations" [104], which has garnered 537 citations. This paper's enduring influence over more than a decade demonstrates that foundational work on adaptive control systems continues to guide current research directions, even as the field has evolved more sophisticated towards artificial intelligence approaches.

The second and third most-cited papers reveal the field's dual priorities. Adaptive control of quadrotor UAVs: A design trade study with flight evaluations et al.'s 2018 work on indirect adaptive fuzzy fault-tolerant control [105] received 316 citations, reflecting the research community's sustained interest in intelligent control systems that can handle both actuator and sensor failures simultaneously. Meanwhile, Khan et al.'s 2020 multi-hazard disaster studies paper [106] accumulated 284 citations, highlighting the growing recognition that UAV recovery capabilities are essential for real-world emergency response applications beyond controlled laboratory environments.

Interestingly, Bellingham et al.'s 2002 cooperative path planning [107] remains influential with 205 citations, suggesting that fundamental multi-UAV coordination principles established over two decades ago still provide essential theoretical foundations for current swarm resilience research. This citation longevity contrasts sharply with the rapid citation rates of recent papers, revealing how the field builds upon stable theoretical foundations while simultaneously experiencing rapid technological advancements.

Several highly cited papers specifically address complete failure scenarios where this theme emerged prominently in phase 3 of our temporal analysis. Song et al.'s 2019 neuroadaptive fault-tolerant control [108] received 193 citations, while Hou et al.'s 2020 paper on terminal sliding mode control for quadrotors with total rotor failure [109] achieved 189 citations. These citation counts confirm that the research community has increasingly prioritised catastrophic failure recovery rather than merely partial fault tolerance, validating our earlier observations about the paradigm shift from incremental improvements to complete system resilience.

The citation pattern also reveals disciplinary integration. Shraim et al.'s 2018 comprehensive survey [110] with 172 citations addresses configurations, modelling, control, collision avoidance, and fault diagnosis simultaneously, that reflecting the inherently multidisciplinary nature of UAV recovery systems. The strong citation performance of this survey paper validates our earlier finding that UAV impact recovery research has evolved from a narrow engineering speciality into an integrated research domain requiring expertise across control theory, computer science, robotics, and telecommunications.

The presence of two 2022 review papers, both with 155 citations, is particularly noteworthy [111][112]. Hu et al.'s work on fault-tolerant cooperative navigation for UAV swarms and Yu et al.'s comprehensive review on fault-tolerant

cooperative control demonstrate that the field has matured sufficiently to warrant a systematic synthesis of existing knowledge. The rapid citation accumulation for these recent reviews, with 155 citations in 2-3 years, indicates that researchers are actively seeking to understand the current state of knowledge before pushing new frontiers, a typical pattern in maturing research domains.

One notable observation is Valenti et al.'s 2006 paper on indoor multi-vehicle flight testbeds [113], which achieved 125 citations despite being published nearly two decades ago. This suggests that experimental validation methodologies established in the mid-2000s continue to influence how researchers design and test recovery systems today, emphasising the field's commitment to empirical validation rather than purely theoretical development.

The temporal distribution of these highly cited papers reveals a clear research evolution pattern. Early works (2002-2013) established fundamental control architectures and multi-UAV coordination frameworks. Mid-period papers (2018-2020) introduced intelligent, adaptive systems capable of handling sensor and actuator failures. Recent publications (2022 onwards) focus on complete system failures, swarm-level resilience, and real-world disaster applications. This progression directly mirrors the three-phase evolution identified in our temporal analysis, confirming that citation impact aligns with research paradigm shifts rather than merely reflecting publication volume increases.

C. What are the dominant keywords, themes and research clusters in UAV impact recovery systems (RQ3)?

The selection of keywords by authors for a publication has a pivotal role in shaping the communication among the articles within scientific communications [114]. Keyword analysis is a method to uncover overarching research patterns by aggregating the terms found in relevant papers within a particular paper [115]. We employed Biblioshiny to quantify the top twenty author keywords and keywords plus within this domain, as presented in Tables V and VI. To ensure consistency, semantically equivalent terms were merged, such as the consolidation of “uav”, “unmanned aerial vehicles”, “drones” and “quadrotor” as well as “machine learning” and “deep learning”.

1) Author Keyword Analysis

The analysis of author-selected keywords reveals four distinct research themes that define the conceptual landscape of UAV impact recovery systems, as shown in Table V. The top 20 author keywords collectively appear 546 times across the dataset with clear clustering around control methodologies, system resilience integration and practical application.

Control system dominates the keyword landscape with “fault-tolerant control” (70 occurrences) representing the most frequently selected keyword beyond general UAV terminology. This is complemented by “adaptive control” (40 occurrences) and “sliding mode control” (24 occurrences), collectively accounting for 134 occurrences, approximately 24.5% of all top 20 author keyword appearances. This concentration reveals that researchers prioritise control system robustness as the fundamental enabler of impact recovery. Notably, “fault-tolerant control” appears nearly five times more frequently than “fault-diagnosis” (15 occurrences), suggesting the research community focuses more heavily on developing systems that can continue operating despite failures rather than merely detecting when failures occur. This emphasis on tolerance over detection reflects the practical reality that remote sensing missions often cannot immediately land upon fault detection.

TABLE V. TOP 20 AUTHOR KEYWORDS AND THEIR OCCURRENCE

Author Keywords	Occurrences	Author Keywords	Occurrences
unmanned aerial vehicles	138	control allocation	15
fault-tolerant control	70	fault-diagnosis	15
resilience	46	obstacle avoidance	13
adaptive control	40	neural network	12
collision avoidance	33	safety	11
remote sensing	33	actuator failure	10
artificial intelligence	26	disaster management	9
sliding mode control	24	failure detection and recovery	9
machine learning	22	recovery	8
disturbance observer	17	stabilization	6

TABLE VI. TOP 20 KEYWORDS PLUS AND THEIR OCCURRENCE

Keyword Plus	Occurrences	Keyword Plus	Occurrences
unmanned aerial vehicles	926	collision avoidance	61
antennas	576	actuator failure	59
fault tolerance	291	disaster	55
adaptive control systems	249	decision making	51
aircraft accidents	121	failure analysis	51

fault detection	89	reinforcement learning	46
remote sensing	84	robustness	45
sliding mode control	83	external disturbances	43
recovery	70	stabilization	37
uncertainty analysis	65	resilience	34

Resilience and recovery mechanisms form the second major thematic cluster, encompassing "resilience" (46 occurrences), "collision avoidance" (33 occurrences), and specific recovery mechanisms including "failure detection and recovery" (9 occurrences) and "recovery" (8 occurrences). The substantial frequency of "resilience" as a standalone keyword indicates that researchers conceptualise impact recovery as extending beyond reactive fault tolerance to encompass proactive system adaptability. The presence of "collision avoidance" (33 occurrences) alongside recovery-focused terms reveals a dual research strategy: preventing impacts when possible while simultaneously ensuring graceful degradation when impacts are unavoidable. This balanced approach is essential for UAV operations in complex environments where obstacle-dense conditions like urban areas, forests, and disaster sites make collisions probabilistically inevitable.

Artificial intelligence (AI) integration represents an emerging but significant theme, featuring "artificial intelligence" (26 occurrences), "machine learning" (22 occurrences), and "neural network" (12 occurrences), totalling 60 occurrences or 11% of the top 20 keyword landscape. This AI-focused cluster demonstrates the field's evolution from rule-based recovery protocols to learning-based systems capable of adapting to novel failure modes. The keyword "disturbance observer" (17 occurrences) further supports this intelligent systems trend, as modern observers increasingly leverage machine learning for real-time state estimation under uncertain conditions. The relatively lower frequency of AI keywords compared to traditional control methods suggests the field is currently in transition, where AI approaches are gaining traction but haven't yet displaced established control-theoretic foundations.

Application-driven research context directly connects technical development to deployment scenarios, with "remote sensing" (33 occurrences), "safety" (11 occurrences), and "disaster management" (9 occurrences) representing key application domains. The equal frequency of "remote sensing" and "collision avoidance" (both 33 occurrences) validates our focus on impact recovery for sensing missions, where UAVs must operate in challenging environments such as post-disaster rubble, dense vegetation, and infrastructure inspection sites that significantly elevate collision risk. The presence of "disaster management" specifically indicates that impact recovery research is motivated by high-stakes scenarios where mission failure could delay emergency response or prevent critical data collection.

Two patterns warrant closer examination. First, "control allocation" (15 occurrences) and "actuator failure" (10 occurrences) appear with moderate frequency, suggesting researchers are developing recovery strategies that redistribute control authority among remaining functional actuators after partial system failures. This aligns with our Phase 3 finding that recent research increasingly addresses partial degradation scenarios like single rotor loss rather than assuming binary success or failure outcomes. Second, "obstacle avoidance" (13 occurrences) appearing separately from "collision avoidance" (33 occurrences) reveals potential terminological inconsistency in the field, where these terms are often used interchangeably but may represent subtly different research approaches that deserve clarification in future work.

2) Keywords Plus Analysis

Keyword Plus analysis reveals a substantially broader disciplinary scope compared to author-selected keywords, as shown in Table VI. While "unmanned aerial vehicles" dominates with 926 occurrences, it is 13 times higher than the top author keyword. This expanded terminology reflects how automated indexing captures interdisciplinary connections that authors don't explicitly tag. The top 20 Keyword Plus terms collectively appear 3,444 times, representing nearly 6.3 times the frequency of top author keywords, suggesting that impact recovery research intersects with far more disciplines than researchers explicitly acknowledge.

The high frequency of "antennas" (576 occurrences) initially appears anomalous but reveals an important research intersection. Analysis of representative papers shows these studies address UAV-based antenna measurement systems [116], coverage diagnostics in mobile networks [117], and adaptive beamwidth control for millimetre-wave communications [118]. While not directly focused on physical impact recovery, these works address resilience in UAV communication systems, particularly antenna steering mechanisms that maintain connectivity during flight instabilities, jitter, and positioning errors. This connection becomes especially relevant for multi-UAV recovery scenarios where maintaining communication links during and after impact events is critical for coordinated recovery operations. The presence of "actuator failure" (59 occurrences) and "external disturbances" (43 occurrences) provides more direct evidence of hardware-level recovery challenges, where physical component failures and environmental perturbations demand robust fault tolerance mechanisms.

Control system sophistication is evident through the convergence of multiple methodological approaches. "Fault tolerance" (291 occurrences) and "adaptive control systems" (249 occurrences) represent the most prominent technical frameworks, collectively accounting for 540 occurrences or 15.7% of the top 20 Keyword Plus landscape. The field's evolution toward intelligent systems appears through "reinforcement learning" (46 occurrences) and "decision making" (51 occurrences), though these AI-oriented terms

occur at significantly lower frequencies than traditional control methods. Notably, "uncertainty analysis" (65 occurrences) and "robustness" (45 occurrences) appear with moderate frequency. These terms indicate that researchers recognise that impact recovery systems must function effectively despite incomplete information about failure modes, environmental conditions, and system state. This capability represents a fundamental challenge for autonomous operations in unstructured environments where perfect information is rarely available.

Operational context keywords directly reveal the practical motivations driving impact recovery research. "Aircraft accidents" (121 occurrences), appearing as the fifth most frequent term, demonstrates that safety concerns heavily influence research priorities, likely driven by regulatory requirements for civilian UAV deployments. "Remote sensing" (84 occurrences) and "disaster" (55 occurrences) validate our study's application focus, confirming that impact recovery research is particularly motivated by high-value sensing missions. In these scenarios, platform loss would eliminate critical data collection capabilities during emergency response operations. The presence of "sliding mode control" (83 occurrences) and "recovery" (70 occurrences) at similar frequencies to "remote sensing" suggests that specific control methodologies have become deeply associated with recovery applications in the broader research literature.

Comparing author keywords to Keyword Plus reveals interesting differences in how researchers describe their work versus how algorithms categorise it. "Fault detection" appears 89 times in Keyword Plus but doesn't show up at all in the top 20 author keywords. Meanwhile, "fault-diagnosis" appears 15 times in author keywords but is absent from the top Keyword Plus terms. This suggests authors think about their work as diagnosing what type of fault occurred, while the algorithmic indexing emphasises simply detecting that something went wrong. Communication-related terms like "antennas" and "decision making" appear frequently in Keyword Plus, showing that impact recovery involves more than just flight control algorithms. The broader system includes communication links, sensors, and coordinated decision-making across multiple UAVs, even if authors don't always explicitly tag these aspects when describing their research.

3) Keywords Co-Occurrence Network

The keyword co-occurrence network visualised in Fig. 6 reveals how different research communities organise their work around five distinct thematic clusters. Unlike the simple frequency counts in Tables V and VI, this network analysis shows which concepts researchers use together in the same papers, revealing how ideas connect in practice rather than in isolation. Table VII groups the keywords by cluster, with colours corresponding to the network visualisation.

TABLE VII. KEYWORD CO-OCCURRENCE GROUPED BY CLUSTER

Cluster 1 (Blue)	Cluster 2 (Green)	Cluster 3 (Red)	Cluster 4 (Yellow)	Cluster 5 (Purple)
Artificial intelligence	Actuator Failure	Unmanned aerial vehicle	Collision avoidance	Reinforcement learning
Deep learning	Adaptive Control	Deep reinforcement learning	Fault-tolerance control	Simulation
Remote sensing	Control Allocation	Fault-tolerance	Quadrotor	Quadcopter
UAV	Disturbance observer	Formation control		
Machine learning	Fault diagnosis	Obstacle avoidance		
Photogrammetry	Fault-tolerant control	Path Planning		
Lidar	Flight control	Resilience		
	Model reference adaptive	Safety		
	Neural network	Security		
	Quadrotor UAV	UAV swarm		
	Sliding mode control			

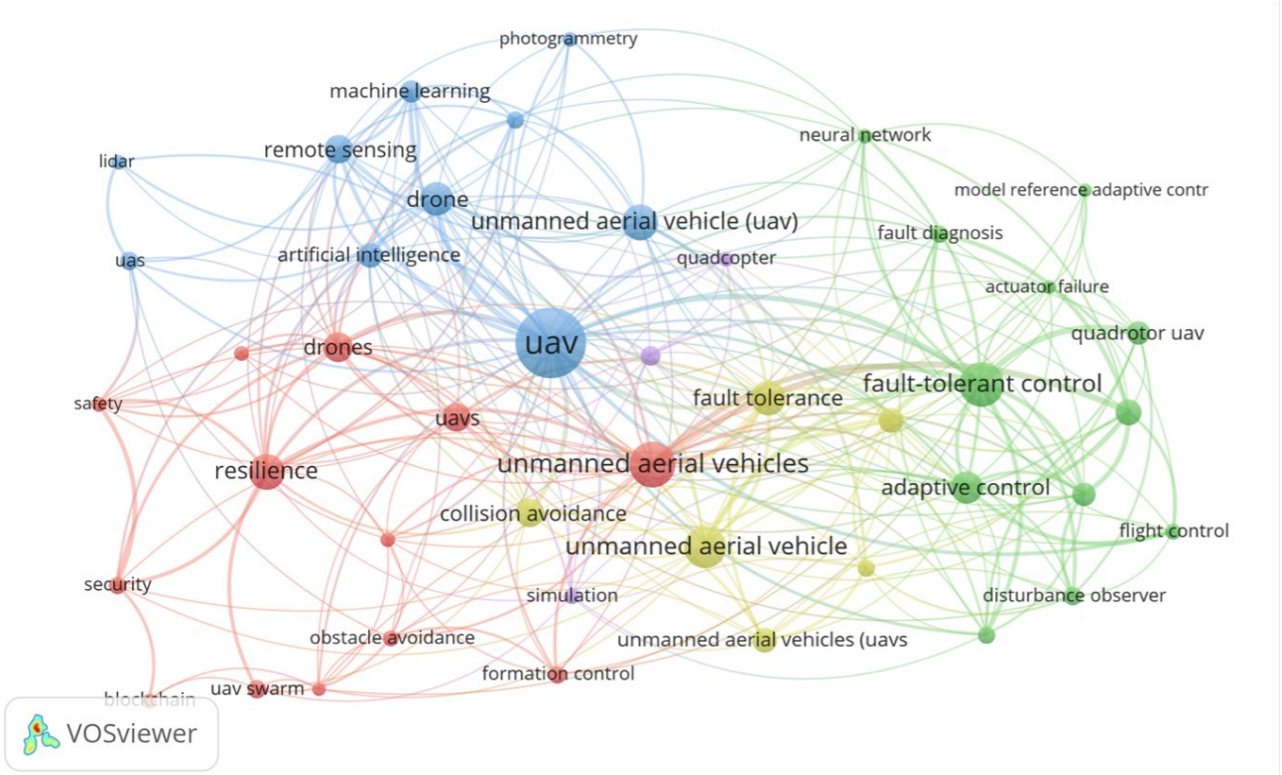


Fig. 6. Keyword co-occurrence network for UAV impact recovery. Source: VOSViewer.

The network structure tells an interesting story about how the field organises itself. The central position of "UAV" and "unmanned aerial vehicles" acts as a hub connecting all five clusters, but the clusters themselves show minimal cross-connections. This pattern suggests that different research communities work relatively independently, focusing on their specialised approaches to impact recovery rather than integrating across methodological boundaries. For instance, the AI-focused researchers in Cluster 1 (Blue) rarely collaborate directly with the traditional control theorists in Cluster 2 (Green), despite both addressing fundamentally similar problems of maintaining UAV stability after failures.

Cluster 1 (Blue) centres on intelligent sensing and perception, bringing together artificial intelligence, deep learning, remote sensing, machine learning, photogrammetry, and lidar. The tight clustering of these terms shows that researchers working on sensor-based recovery approaches consistently frame their work around AI methodologies. This makes practical sense because UAVs experiencing impact events often lose GPS signals and must rely on visual or lidar-based navigation to recover [119][120]. The inclusion of photogrammetry alongside recovery keywords indicates that researchers recognise the dual challenge of maintaining both platform stability and data collection quality during recovery manoeuvres, particularly relevant for remote sensing missions where losing position accuracy degrades the value of captured imagery.

Cluster 2 (Green) represents the traditional control systems community, densely connecting adaptive control, fault-tolerant control, flight control, sliding mode control, and neural networks. The presence of "quadrotor UAV" specifically in this cluster, rather than distributed across clusters, suggests that quadrotor platforms have become the standard testbed for control algorithm development [104][121]. This cluster's keywords reflect the evolution we identified in Phase 3, where neural network-based adaptive control [88][109] emerged to augment classical control methods like sliding mode approaches. The term "model reference adaptive" appearing here connects to the highly cited work by Dydek et al. [104], confirming that foundational adaptive control research continues to shape current methodologies.

Cluster 3 (Red) takes a systems-level view of operational safety, connecting fault tolerance, resilience, safety, security, UAV swarm, and formation control. Unlike Cluster 2's focus on individual platform control, this cluster addresses how multiple UAVs maintain coordinated operations despite individual failures. The presence of "obstacle avoidance" and "path planning" alongside "resilience" suggests this community conceptualises recovery as dynamic replanning rather than simply stabilising a damaged platform.

Cluster 4 (Yellow) forms a surprisingly small and isolated cluster focused exclusively on collision avoidance and fault-tolerance control for quadrotors. This isolation from other clusters is puzzling, given that collision avoidance logically connects to both the perception work in Cluster 1 and the control methods in Cluster 2. The separation suggests that collision avoidance research has developed its own specialised terminology and methods, possibly because it emphasises prediction and prevention rather than post-impact recovery. This finding validates our earlier observation that "collision avoidance" (33 occurrences in author keywords) represents a distinct research approach from fault-tolerant recovery systems.

Cluster 5 (Purple) captures the emerging reinforcement learning community, linking reinforcement learning, simulation, and quadcopter platforms. This cluster's small size but distinct separation from other clusters indicates that learning-based approaches remain relatively nascent compared to established control methods. The strong connection between "reinforcement learning" and "simulation" reflects the practical reality that training adaptive recovery behaviours requires extensive simulated crash scenarios before real-world deployment. This cluster's isolation from Cluster 1, which also includes AI methods, suggests that researchers using reinforcement learning versus supervised deep learning belong to different research communities with minimal overlap [122].

4) Key Findings from Dominant Keywords, Themes and Research Clusters

The keyword distribution patterns, as shown in Fig. 6, reveal the field's evolution from reactive fault tolerance toward proactive intelligent recovery systems. Traditional control terminology (Cluster 2: Green Cluster) maintains the densest internal connections, indicating a mature research community with well-established conventions. Meanwhile, AI-oriented clusters (1: Blue Cluster and 5: Purple Cluster) show looser internal structure, suggesting these approaches are still consolidating around standard methodologies. The presence of "stabilization" in both author keywords (6 occurrences) and Keyword Plus (37 occurrences) demonstrates that maintaining flight stability during and after impact remains the fundamental challenge regardless of whether researchers approach it through classical control theory or modern machine learning.

The network structure also explains patterns we observed in institutional and geographic analyses. The five distinct clusters align with different institutional strengths: Chinese aerospace universities dominate traditional control research (Cluster 2: Green Cluster), while Western institutions with strong AI programs contribute more to intelligent sensing approaches (Cluster 1: Blue Cluster). This specialisation explains why collaborative papers across geographic regions are relatively rare despite high overall publication volumes. Each research community has developed its own terminology, methods, and publication venues, creating parallel tracks rather than integrated approaches to UAV impact recovery.

Despite exponential growth over the past decade, the co-occurrence network analysis exposes a troubling fragmentation where distinct research communities pursue complementary objectives without meaningful integration. The field operates through isolated expertise silos where researchers working in parallel domains rarely cite each other or collaborate, creating gaps that fundamentally constrain the practical deployment of a comprehensive UAV impact recovery system. This fragmentation is primarily driven by two persistent divides that hinder the development of operationally viable recovery capabilities.

a) The Perception versus Control Silo: Cluster 1 and Cluster 2 Operating in Parallel

The most significant fragmentation occurs between the perception-focused research community (Cluster 1: Blue Cluster) and the control-focused research community (Cluster 2: Green Cluster), which function as parallel universes despite addressing inherently coupled problems requiring tight integration. Cluster 1 encompasses artificial intelligence, deep learning, remote sensing, machine learning, photogrammetry and lidar, focusing on environmental perception, obstacle detection and data-driven decision making. This community develops sophisticated algorithms for detecting failures, classifying environmental hazards and processing sensor information, treating the UAV primarily as a perception platform that must interpret complex visuals and sensor data. Research in this domain demonstrates impressive capabilities such as vision-based autonomous navigation, achieving high-speed obstacle avoidance through biologically inspired perception algorithms [123], yet these perception systems typically operate independently from the control systems that must execute recovery manoeuvres based on detected information.

Conversely, Cluster 2 encompasses actuator failure, adaptive control, fault diagnosis, fault-tolerant control, flight control, model reference adaptive control and sliding model control [124]. This community develops mathematical frameworks for maintaining flight stability, compensating for actuator failures and achieving tracking performance despite system degradation, treating the UAV primarily as a dynamical system requiring stabilisation through control-theoretic approaches. Research demonstrates advanced fault-tolerant control capabilities enabling quadrotors to maintain controlled flight despite complete rotor loss [125][126], yet these control methods critically depend on accurate state estimation from perception systems. The fundamental problem emerges because these communities work in isolation, with the perception group not considering the control mathematics required for recovery execution, while the control group does not adequately consider the AI-based perception data characteristics, including detecting latencies, classification uncertainties, and sensor degradation under failure conditions.

Evidence from actual implementation reveals this disconnect explicitly. State-of-the-art fault-tolerant flight controllers can stabilise a quadrotor subjected to complete rotor loss, yet these methods rely on external sensors such as GPS or motion capture systems for state estimation, with the achievement of autonomous flight with only onboard vision sensors representing a recent breakthrough that required explicit integration of fault-tolerant control with vision-based state estimation [125]. This dependency illustrates that sophisticated control algorithms typically assume perfect state information availability, while perception systems must operate under precisely the degraded conditions that necessitate fault-tolerant control, yet the two communities rarely collaborate to address this circular dependency. The development of integrated fault management systems that combine sensor failure detection with adaptive reconfigurable control [127] represents explicit recognition that perception and control must be co-designed rather than independently developed, yet such comprehensive approaches remain exceptional within the research landscape. The co-occurrence network positioning demonstrates this

isolation bibliometrically, where Cluster 1 and Cluster 2 show minimal interconnecting edges, indicating that researchers publishing in perception-focused venues rarely cite control-theoretic work and vice versa, perpetuating parallel development tracks that cannot address the integrated requirements of operational recovery systems.

b) The Swarm versus Individual Platform Silo: Collective Coordination Disconnected from Individual Recovery

The second critical fragmentation separates swarm coordination research (Cluster 3: Red Cluster) from individual platform recovery capabilities developed within Clusters 2: Green Cluster and 5: Purple Cluster. Cluster 3 encompasses formation control, obstacle avoidance, path planning, resilience, safety, and UAV swarm, focusing on multi-agent coordination, collective behaviours, and swarm-level optimisation for achieving mission objectives through distributed algorithms and cooperative control [128][129][130]. This community addresses how multiple UAVs coordinate formations, allocate tasks, and maintain collective capabilities, yet research in this domain treats individual platform failures primarily as discrete removal events. When one UAV fails, swarm algorithms redistribute tasks among surviving platforms and reconfigure formations to maintain collective performance, implicitly assuming that failed platforms either crash immediately or execute emergency landing procedures that effectively remove them from the swarm. Analysis of unmanned autonomous swarm failure considering cascading effects demonstrates how individual agent failures propagate through collective systems, affecting swarm-level resilience [131], yet the framework treats failures as binary states rather than scenarios where platforms might operate with degraded capabilities. The swarm silo does not know how to handle individual drone internal recovery mathematics when partial failures occur.

Conversely, individual platform recovery research within Clusters 2 and 5 demonstrates that UAVs can continue operating with reduced rotor count, degraded sensors, or structural damage by adapting control strategies through fault-tolerant control and reinforcement learning-based recovery approaches [101][125][132]. These capabilities enable platforms to maintain flight with performance limitations rather than complete failure, yet swarm coordination algorithms remain unaware of these individual recovery possibilities because the research communities operate independently. If one drone in a swarm experiences rotor failure but executes a successful individual recovery, maintaining limited flight capability, current swarm coordination frameworks cannot accommodate this partially functional state. The swarm treats the platform as failed and removes it from collective operations, discarding potential contributions to sensing, communication relay [133], or reduced-capability tasks that the recovered platform could still provide. This disconnect becomes operationally significant during multi-UAV remote sensing missions where partially recovered platforms could continue contributing to mission objectives if swarm algorithms were adapted to accommodate degraded individual capabilities, yet the research silo prevents development of such integrated approaches. The perception-shared swarm trajectory optimisation demonstrates coordination among functional platforms [134] yet does not address how swarm coordination adapts when individual platforms transition through partial failure and recovery states with time-varying capabilities [107].

The bibliometric evidence confirms this silo through co-occurrence network topology, where Cluster 3 shows weak connections to both Cluster 2 (traditional control and fault tolerance) and Cluster 5 (reinforcement learning recovery), indicating that swarm researchers rarely cite individual platform recovery work despite the operational necessity for integration. Citation patterns reveal that swarm optimisation papers focus on collective algorithms assuming binary platform states, while individual recovery papers demonstrate advanced fault tolerance without addressing swarm-level coordination implications. This structural separation persists across publication venues, institutional affiliations, and funding streams, creating parallel research tracks where swarm coordination advances without incorporating individual recovery capabilities, while individual platform recovery progresses without considering swarm-level coordination requirements. The practical consequence emerges during operational deployment, where system integrators must manually combine technologies from disconnected research streams, discovering incompatibilities only during field testing when swarm algorithms prove unable to accommodate the partially functional states that individual recovery systems enable.

D. What research gaps and underexplored areas exist in UAV impact recovery systems, and what emerging frontiers can guide future research directions (RQ4)?

The thematic map of author keywords, generated through Biblioshiny analysis (Fig. 7), reveals the strategic positioning of research themes across four distinct quadrants defined by developmental degree (maturity) and relevance degree (centrality). This visualisation identifies which research areas are well-established versus emerging, and which are central versus peripheral to the field's core focus. The quadrant positioning provides critical insights into research gaps, opportunities, and future directions for UAV impact recovery systems.

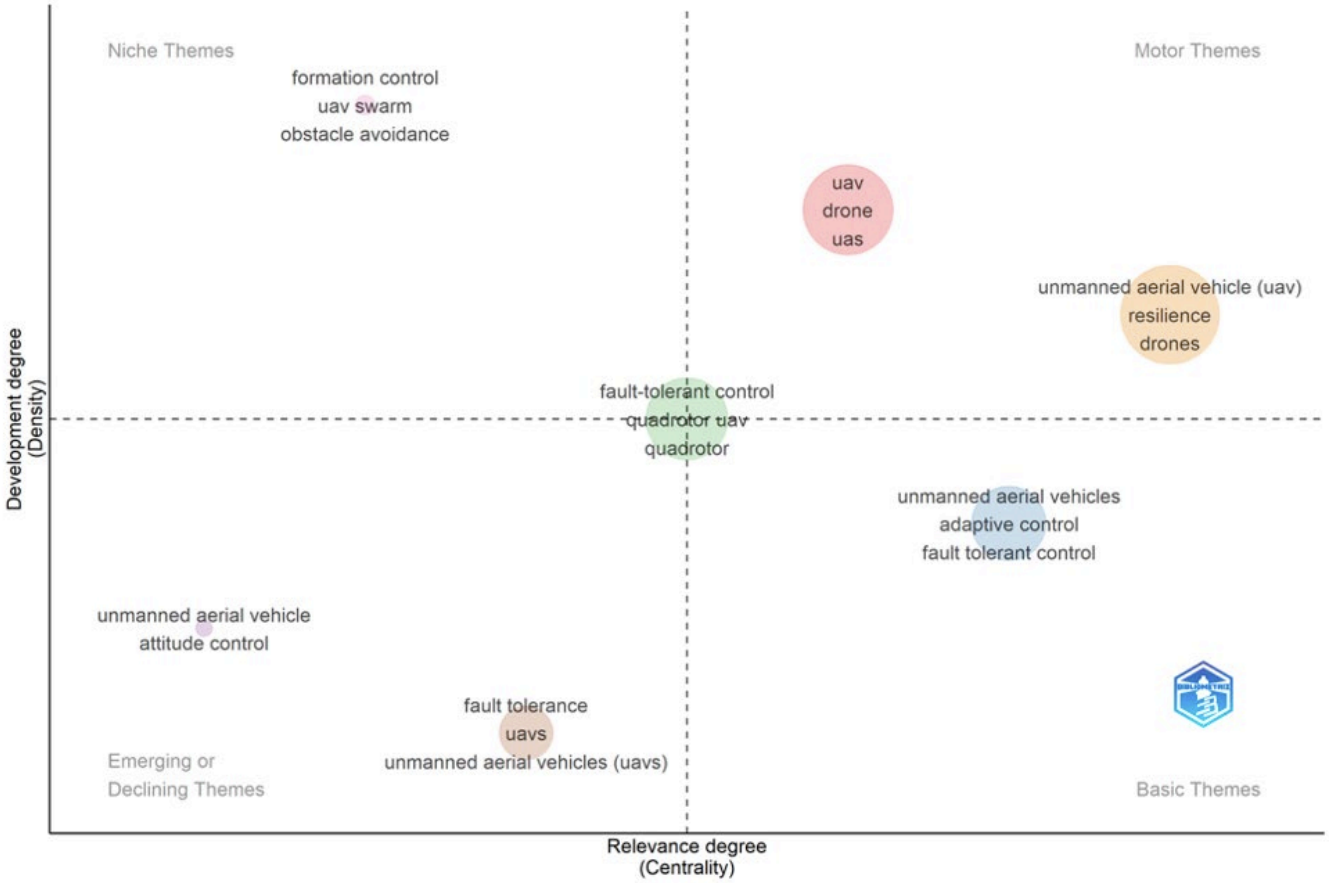


Fig. 7. Thematic map of the author's keywords. Source: Biblioshiny.

1) Motor Themes (High Centrality, High Development)

The upper-right quadrant accommodates motor themes representing the field's mature, core research domains. This quadrant contains "UAV," "drone," "UAS," "unmanned aerial vehicle (UAV)," "resilience," and "drones," indicating that general UAV terminology and resilience concepts are well-developed and central to the research discourse. The clustering of platform terminology (UAV, drone, UAS) in this quadrant confirms that the field has established a standardised vocabulary around aerial platforms. However, the presence of only "resilience" as a substantive technical concept in this quadrant reveals a critical insight: the field lacks mature, central research themes beyond platform definitions and general resilience discussions. This suggests that specific technical approaches to impact recovery have not yet achieved simultaneous high development and high centrality, indicating fragmentation across methodological approaches rather than convergence around dominant paradigms.

2) Basic Themes (High Centrality, Low Development)

The lower-right quadrant represents important but underdeveloped research areas. This quadrant features "unmanned aerial vehicles," "adaptive control," and "fault-tolerant control," revealing a paradox that, despite being central to the field's identity, these fundamental control approaches remain relatively immature in their development [92][104]. This positioning suggests that while researchers widely recognise adaptive and fault-tolerant control as essential for impact recovery, the research has not yet converged on standardised methodologies or achieved comprehensive theoretical frameworks. The presence of "quadrotor" in this quadrant indicates that, despite quadrotors serving as the dominant experimental platform [108][110], research specific to quadrotor recovery mechanisms remains underdeveloped relative to their prevalence in the literature. This gap presents a significant opportunity: developing standardised control architectures specifically optimised for quadrotor impact recovery could accelerate practical deployments.

3) Niche Themes (Low Centrality, High Development)

The upper-left quadrant represents specialised, mature research areas that operate at the periphery of mainstream impact recovery research. This quadrant contains "formation control," "UAV swarm," and "obstacle avoidance," indicating these topics have achieved internal maturity through dedicated research communities but remain disconnected from core recovery system development [72][102]. The isolation of swarm-related keywords is particularly noteworthy given the growing importance of multi-UAV systems for large-scale remote sensing missions [71]. This positioning reveals a critical research gap: swarm-level recovery strategies have not been integrated with individual platform recovery mechanisms, despite the operational reality that remote sensing missions increasingly deploy multiple coordinated UAVs where

individual failures must be managed without compromising fleet-level mission objectives.

4) Emerging or Declining Themes (Low Centrality, Low Development)

The lower-left quadrant represents either nascent research directions or topics losing research momentum. This quadrant contains "unmanned aerial vehicle," "attitude control," "fault tolerance," and "UAVs," with positioning that requires careful interpretation. The presence of fundamental concepts like "fault tolerance" and "attitude control" in this quadrant appears counterintuitive, given their obvious importance to impact recovery. This positioning likely reflects terminological fragmentation, where researchers use varied terminology for similar concepts, preventing any single term from achieving high centrality or development scores. Alternatively, these terms may represent declining themes being superseded by more specific technical vocabulary as the field matures.

IV. Research Gaps and Future Directions

A. Critical Research Gap Identified

The thematic map reveals significant research gaps that constrain the practical deployment of UAV impact recovery systems for remote sensing applications. The observed separation between swarm coordination (niche theme) and individual platform control (basic theme) indicates researchers' address recovery at either the platform or fleet level, but rarely integrate both perspectives [72]. Remote sensing missions requiring coordinated multi-UAV operations need recovery strategies that simultaneously address individual platform failures while maintaining fleet-level mission integrity. Current research fragmentation prevents the development of hierarchical recovery architectures where platform-level fault tolerance enables graceful fleet-level degradation.

Furthermore, the analysis points to an insufficient emphasis on hardware-software co-design. The absence of hardware-related keywords within the motor and basic themes suggests a prevailing focus on control algorithms without addressing physical platform design optimised for impact tolerance. Although prior studies have examined crashworthiness [84], protective structures [86] and impact absorbing mechanisms, these efforts remain marginal despite their potential to complement software-based recovery approaches. This limitation is especially consequential for remote sensing platforms carrying high-value sensor payloads where structural mitigation could prevent minor impacts from escalating into catastrophic system failures.

The thematic positioning also reveals real-world validation within remote sensing contexts, where "remote sensing" terminology outside the motor themes quadrant indicates that impact recovery research remains largely disconnected from actual remote sensing mission requirements. Most studies validate recovery algorithms in controlled laboratory environments or generic flight scenarios rather than addressing specific challenges of maintaining sensing mission objectives during and after impact events [97][135]. This validation gap creates uncertainty about whether a developed recovery system can maintain data collection quality, georeferencing accuracy and mission timeline adherence when recovering from impacts during operational remote sensing flights.

Finally, the analysis highlights the absence of learning-enabled long-term adaptation as a mainstream research focus. While reinforcement learning appears in the network analysis (Cluster 5, purple), the thematic map lacks AI and machine learning terminology in motor or basic themes, indicating these approaches remain peripheral to mainstream recovery research. This gap is significant because operational UAV systems' accumulation of flight hours will encounter diverse impact scenarios that pre-programmed recovery protocols cannot anticipate [136]. The field lacks systematic research on how recovery systems can learn from accumulated impact experiences to improve performance over time, a capability essential for autonomous long-duration remote sensing missions in unstructured environments.

B. Implications of Impact Recovery on Sensing Data Quality

The thematic analysis reveals a critical disconnect between impact recovery system development and remote sensing mission requirements. While "remote sensing" appears in the co-occurrence network (Cluster 1), its positioning outside motor themes and basic themes quadrantes indicates that recovery research has not adequately addressed how impact events and subsequent recovery manoeuvres affect sensor data quality, georeferencing accuracy and measurement continuity essential for operational remote sensing applications.

1) Platform Instability and Measurement Accuracy

The physical instability of the UAV platform directly impacts the accuracy of remote sensing measurements. Research by comparison of tools and techniques for stabilising unmanned aerial system (UAS) imagery for surface flow observations demonstrates that platform-induced motion significantly affects camera-based measurement accuracy [137]. Digital image stabilisation methods must compensate for this motion to maintain measurement quality, with stabilisation accuracy varying substantially depending on flight conditions and the robustness of feature tracking algorithms [137]. This relationship between platform stability and data quality becomes critical during impact recovery scenarios where the platform experiences destabilisation far exceeding normal flight conditions. The study quantifies measurement uncertainty induced by platform motion using root mean squared differences of inter-frame pixel intensities, providing a metric framework that could be adapted to assess data quality degradation during recovery manoeuvres; however, current recovery research does not incorporate such sensor-centric performance metrics.

2) State Estimation Dependencies and Sensor Requirements

Recovery systems demonstrate fundamental dependencies on accurate state estimation that directly affect the utility of remote sensing data. Study on Autonomous Quadrotor Flight despite rotor failure with onboard vision Sensors: Frames vs Events shows that recovery following complete rotor failure requires vision-based state estimation to replace GPS in

degraded environments [125]. However, the high-speed yaw rotation during single-rotor failure (exceeding 20 rad/s) causes motion blur detrimental to visual odometry algorithms, navigation and data collection. The primary challenge stems from inevitable platform motion during fault-tolerant control, where aggressive recovery manoeuvres introduce motion blur, attitude oscillation and sensor instabilities that compromise measurement quality. This trade-off between achieving flight stability and maintaining sensor data quality remains unaddressed in current recovery frameworks, which prioritise platform survivability without quantifying impacts on remote sensing mission objectives.

3) Operational Remote Sensing During Emergency Response

Emergency response applications reveal the operational importance of maintaining data quality throughout mission execution. UAV strategies validation and remote sensing data for damage assessment in post-disaster scenarios demonstrate that UAV photogrammetry for post-disaster damage assessment requires careful attention to georeferencing strategies, block orientation and multitemporal co-registration to produce reliable 3D metrics products [97]. These workflows demand stable platform dynamics and reliable positioning information throughout data collection. When UAVs experience mid-mission impacts during disaster response operations, current recovery approaches focus mainly on regaining flight control without considering whether the recovered platform can continue collecting usable remote sensing data. The research validates UAV strategies specifically for damage assessment in post-disaster scenarios. This validation assumes nominal flight conditions without addressing how impact events and recovery manoeuvres degrade the georeferencing accuracy and 3D reconstruction quality essential for rapid mapping applications.

4) Disaster Monitoring Applications

Disaster monitoring applications using remote sensing techniques face compounded challenges when platforms experience failures during critical data collection phases. A Study on Multi-hazard disaster studies: Monitoring, detection, recovery, and management, based on emerging technologies and optimal techniques, shows that multi-hazard disaster studies encompassing monitoring, detection, recovery, and management rely on continuous data streams from UAV platforms equipped with various sensors [106]. The loss of data continuity during impact and recovery sequences creates temporal gaps in monitoring critical for early warning systems, particularly for rapidly evolving scenarios such as forest fires, landslides, or earthquake aftermath, where timing determines response effectiveness. Fault-tolerant cooperative navigation of networked UAV swarms for forest fire monitoring demonstrates that fault-tolerant navigation must maintain both formation control and sensing capability [110]. The decentralised task reassignment algorithms address operational platform reassignment without explicitly preserving data collection quality or measurement continuity across the swarm during individual platform recovery sequences.

C. Future Research Opportunities

Future research should develop recovery control strategies explicitly optimised for maintaining remote sensing data quality rather than merely preserving platform flight capability. This encompasses recovery manoeuvres minimising attitude disturbance affecting photogrammetric accuracy [97][120], rapid re-acquisition of GPS lock for georeferencing [103][119][138], and perseveration of sensor calibration notwithstanding impact-induced structural flexure. Such research would address the operational reality for remote sensing missions; successful recovery necessitates preserving data collection capabilities, not solely achieving stable flight.

At the fleet level, recovery research must also extend toward coordinated multi-UAV architectures in which task reallocation, formation reconfiguration and cooperative sensing [107][128]. This research direction becomes imperative as remote sensing mission scales to fleets of dozens or hundreds of UAVs, wherein individuals' failure should degrade mission performance gracefully rather than trigger cascade failure or mission aborts.

In parallel, research should develop AI-based recovery systems that integrate advanced control strategies addressing the complex dynamics of UAV operations under failure conditions [101]. This approach proves essential for developing autonomous recovery systems capable of handling diverse failure scenarios encountered during civilian remote sensing operations within challenging environments, rather than opaque responses, addressing regulatory and operational requirements for understanding why autonomous systems execute specific recovery actions. This transparency proves essential for certifying autonomous recovery systems for civilian remote sensing operations within regulated airspace [139]

Lastly, future work should explore how recovery strategies developed for specific UAV platforms or mission scenarios can transfer to different configurations through meta-learning approaches [140]. This research would accelerate the deployment of recovery capabilities across the diverse UAV platforms employed in remote sensing without requiring exhaustive retraining or testing for each platform variant.

D. Implications to the Remote Sensing Community

The identified research gaps and future research directions bear direct implications for remote sensing researchers and practitioners deploying UAV systems in operational environments.

Current UAV impact recovery systems cannot guarantee mission completion within challenging environments wherein obstacles, adverse meteorological conditions or equipment failures increase the likelihood of impact events, thereby constraining high-reliability applications such as disaster response, infrastructure inspection, and environmental monitoring in complex terrain [68][69].

These limitations are further amplified in large-scale multi-UAV sensing missions where the absence of integrated swarm-level recovery frameworks necessitates conservative flight planning with substantial safety margins, reducing operational efficiency and limiting the scalability of coordinated sensing

operations. Advancing swarm-level recovery frameworks could enable mission design that tolerates higher individual platform failure rates while preserving overall mission objectives through collective adaptation [71].

Moreover, the lack of hardware-software co-design within recovery research places additional responsibility on remote sensing system developers, who cannot rely solely on algorithmic solutions to protect high-value sensor payloads such as hyperspectral cameras, lidar systems and SAR antennas. Effective mitigation of impact-induced damage requires deliberate structural design choices that enhance crashworthiness alongside recovery control capabilities, influencing platform selection and system integration strategies [100].

Finally, limited real-world validation of recovery systems introduces uncertainty into regulatory approval pathways for autonomous UAV operations, as the absence of standardised testing and evaluation frameworks restricts the ability of regulatory bodies to assess recovery performance across diverse failure scenarios. This ambiguity complicates the certification process and delays broader adoption of autonomous UAV-based remote sensing within civilian airspace [138]

V. Conclusion

This bibliometric analysis mapped the research landscape of UAV impact recovery systems from 1992 to 2024, analysing 1,855 publications from Scopus and Web of Science databases to understand how this field evolved and identify critical gaps constraining practical deployment for remote sensing applications.

The temporal analysis revealed three developmental phases showing the field's maturation trajectory. Phase 1, from 1992 to 2003, established theoretical foundations with only 20 publications adapting fault tolerance concepts from manned aircraft. Phase 2, from 2004 to 2015, produced 246 publications developing fundamental fault detection frameworks, reconfigurable control strategies, and autonomous capabilities. Phase 3, from 2016 to 2024, demonstrated exponential growth with 1,460 publications, shifting from incremental fault tolerance toward complete failure recovery scenarios, deep learning integration, and collision recovery systems.

Geographic patterns showed China and the United States dominating with 59.3% of global output, while subject area analysis confirmed interdisciplinary maturation spanning Engineering, Computer Science, Automation, and Telecommunications. Northwestern Polytechnic University leads institutionally with 22 publications, though Cranfield University's second-place ranking with 14 publications, despite its smaller size, demonstrates that specialised expertise generates disproportionate impact. The citation analysis revealed that foundational work on adaptive control systems continues to guide current research directions, with Dydek et al.'s 2013 study garnering 537 citations over more than a decade. The presence of multiple 2022 review papers with 155 citations each demonstrates that the field has matured sufficiently to warrant a systematic synthesis of existing knowledge.

The thematic map analysis revealed critical insights about the field's current state. The absence of mature, central research themes beyond platform terminology indicates a lack of convergence around dominant paradigms. Fundamental approaches like adaptive control and fault-tolerant control remain in the basic themes quadrant with high centrality but low development, suggesting widespread recognition without methodological standardisation. Swarm coordination occupies the niche themes quadrant, revealing that multi-UAV recovery strategies remain disconnected from individual platform mechanisms despite operational importance for large-scale missions.

Beyond these thematic patterns, the co-occurrence network analysis exposes troubling fragmentation where the field operates through isolated expertise silos. Distinct research communities pursue complementary objectives without meaningful integration, manifesting through two persistent divides. The perception versus control silo separates artificial intelligence-focused research (Cluster 1) from control-theoretic approaches (Cluster 2) despite addressing inherently coupled problems requiring tight integration, with minimal cross-cluster citations indicating researchers in perception-focused venues rarely cite control-theoretic work and vice versa. The swarm versus individual platform silo disconnects multi-UAV coordination (Cluster 3) from individual recovery capabilities (Clusters 2 and 5), where swarm algorithms treat failures as binary removal events, unable to accommodate the partially functional states that individual recovery systems enable. These research silos perpetuate parallel development tracks that system integrators must manually combine during operational deployment.

These patterns expose four critical research gaps. First, the separation of swarm coordination from individual platform control prevents the development of hierarchical recovery architectures where platform-level fault tolerance enables fleet-level graceful degradation. Second, the absence of hardware-related terminology in motor themes indicates research focuses on algorithms while neglecting physical platform design for impact tolerance, critical for protecting expensive sensor payloads. Third, remote sensing terminology positioned outside motor themes shows that validation occurs in laboratory environments rather than addressing actual mission requirements for maintaining data quality and georeferencing accuracy. Fourth, artificial intelligence approaches remain peripheral despite operational systems encountering diverse scenarios that pre-programmed protocols cannot anticipate.

These gaps simultaneously represent opportunities for accelerating practical deployment. Developing sensor-centric recovery control optimised for maintaining data quality rather than just stable flight addresses the operational definition of successful recovery for sensing missions. Investigating coordinated recovery where multiple UAVs collectively compensate through dynamic task reallocation becomes imperative as missions scale to fleets requiring graceful degradation rather than cascade failures. Creating AI-based systems that integrate advanced control strategies proves essential for handling diverse failure scenarios.

For the remote sensing community, current recovery capabilities remain insufficient for high-reliability missions in challenging environments, forcing conservative flight planning that reduces operational efficiency. The hardware-software co-design gap indicates platform selection must prioritise demonstrated crashworthiness alongside algorithmic capabilities. The validation gap creates uncertainty for operational deployment, as controlled laboratory demonstrations do not address actual mission environments where diverse failure scenarios occur. However, the exponential growth trajectory suggests continued momentum, with publications likely exceeding 200 annually by 2025-2026 if trends persist.

This study acknowledges methodological limitations. The focus on peer-reviewed publications may exclude proprietary industrial research, while keyword-based searching may miss research using alternative terminology. Bibliometric analysis reveals patterns but cannot assess practical applicability or technological readiness. The analysis aggregates diverse platforms and failure modes, potentially obscuring technical distinctions, and does not distinguish simulation studies from field-validated systems. The January 2025 cutoff means recent publications may not reflect ultimate influence.

Future research should prioritise integrated multi-level frameworks addressing simultaneous platform and fleet-level adaptation, sensor-centric control maintaining data quality, hardware-software co-design combining structural protection with algorithmic recovery, and standardised testing protocols enabling regulatory frameworks. Lastly, future work should explore how recovery strategies developed for specific UAV platforms or mission scenarios can transfer to different configurations through meta-learning approaches. This research would accelerate the deployment of recovery capabilities across the diverse UAV platforms employed in remote sensing without requiring exhaustive retraining or testing for each platform variant. Advancing these directions requires shifting emphasis from algorithmic novelty toward systematic validation, standardisation, and integration with operational workflows addressing real mission requirements. The field's evolution from reactive fault tolerance toward proactive intelligent recovery positions these systems as essential components of next-generation autonomous platforms capable of reliable operation in complex environments where remote sensing generates the greatest societal value for disaster response, environmental monitoring, and infrastructure management.

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of the paper.

AUTHOR CONTRIBUTION

The authors confirm their contribution to the paper as follows: ***Writing–Original Draft:*** *LAJ;* ***Conceptualization:*** *AHAR;* ***Formal Analysis:*** *LAJ, AHAR and MFMI;* ***Investigation:*** *LAJ and AKH;* ***Writing–Review & Editing:*** *AHAR, MFMI and AKH. All authors reviewed and approved the final version of the manuscript.*

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