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ASSESSMENT METHODOLOGY FOR UNMANNED AERIAL VEHICLE THREATS IN AIRPORT VICINITY

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Unmanned Aerial Vehicles (UAVs) pose an emerging and complex security risk in airport environments, requiring assessment approaches that are both standardized and operationally interpretable. This paper introduces a dual-axis quantitative framework rooted in ISO 31000, ICAO Annex 19, and FAA Safety Risk Management principles, which quantifies UAV threats through normalized probability and consequence indicators mapped onto a continuous risk matrix.

Unlike scalar aggregation methods, the two-dimensional representation enhances transparency and supports decision-making by distinguishing between the likelihood and severity of UAV incursions. The model was calibrated and validated using three case studies—London Gatwick (2018), Paris Charles de Gaulle (2022), and Cluj-Napoca (2023)—demonstrating consistent sensitivity to operational context and data variability.

Results indicate strong alignment with EASA's 2024 safety review trends, confirming the framework's capability to discriminate between low- and high-risk scenarios. The methodology's adaptability enables integration with digital detection networks and predictive analytics, paving the way for AI-supported, real-time UAV risk management.

By combining empirical calibration with visual interpretability, this study provides a replicable and scalable foundation for proactive UAV threat assessment in civil aviation, bridging the gap between conceptual safety modeling and operational implementation.

Keywords: UAV threats, airport security, risk matrix, ISO 31000, drone intrusion, aviation risk management, Gatwick incident.

1. Introduction

The proliferation of unmanned aerial vehicles (UAVs), commonly known as drones, has redefined numerous civil and commercial applications, from aerial photography and precision agriculture to logistics, inspection, and emergency response. Their growing availability, decreasing cost, and ease of operation have, however, introduced unprecedented challenges to aviation safety and airport security [1–3].

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Airport environments are particularly vulnerable to UAV intrusions due to their dense air traffic, concentration of critical assets, and limited reaction windows. The 2018 disruption at London Gatwick Airport remains emblematic: multiple unauthorized drone sightings forced the suspension of more than 1,000 flights and affected over 140,000 passengers, generating estimated economic losses exceeding £50 million [2,4]. Similar incidents reported by the European Union Aviation Safety Agency (EASA) between 2019 and 2024 demonstrate an upward trend in unauthorized UAV activity near aerodromes, emphasizing the need for structured and proactive risk assessment frameworks [5,6].

Traditional risk assessment models developed for aviation security—such as those outlined by the Federal Aviation Administration (FAA) and within the Airport Cooperative Research Program (ACRP 131)—primarily address static hazards or predictable system failures [7, 8]. However, UAV threats exhibit dynamic and adaptive behaviors, varying in payload, autonomy, and intent, and often involve unregistered or unidentified operators [9,10]. These characteristics require an integrative approach that merges safety-oriented and security-oriented risk analysis, capable of addressing both accidental and deliberate incursions.

This study introduces a quantitative risk assessment methodology designed to evaluate UAV-related threats in airport vicinities through the combined use of normalized probability and consequence indicators. The proposed framework aligns with the ISO 31000:2018 principles for risk management [11] and the Safety Management System (SMS) structure established by ICAO Annex 19, ensuring consistency with internationally recognized standards for hazard identification and risk mitigation.

By grounding the model in empirical evidence from real-world incidents -most notably Gatwick (2018) and subsequent European Airprox cases — the paper provides a replicable, data-driven tool that can support regulatory decision-making, infrastructure planning, and the development of AI-assisted counter-drone technologies. The integration of such a framework within airport SMS processes — particularly in the Safety Risk Management (SRM) component — enhances the capacity of airport authorities to anticipate, assess, and respond to emerging aerial threats in a structured and proactive manner.

2. Methods

Risk assessment in aviation security has traditionally relied on structured and deterministic approaches such as Fault Tree Analysis (FTA), Failure Mode and Effect Analysis (FMEA), or semi-quantitative risk matrices developed by regulatory authorities, including the Federal Aviation Administration (FAA) and the European Union Aviation Safety Agency (EASA) [7, 8, 12]. These frameworks, while foundational for Safety Risk Management (SRM) under

ICAO Annex 19, are primarily calibrated for static hazards, predictable system failures, and human-centric operational processes. Consequently, they often underrepresent the stochastic, adaptive, and intentional nature of UAV-related threats [1–3].

Methods such as FTA and FMEA remain robust for assessing technical failures—e.g., propulsion, avionics, or maintenance-related malfunctions—but they are not inherently designed to capture exogenous and dynamic threat vectors such as unauthorized UAV incursions or coordinated multi-drone attacks. Addressing these limitations requires an integrative approach that couples probabilistic modeling with context-aware parameters reflecting both operational exposure and security intent [9,10].

To overcome these gaps, the present study proposes a customized risk assessment methodology explicitly aligned with ISO 31000:2018 principles for risk management [11] and consistent with the Safety Risk Management (SRM) process described in FAA's ACRP Report 131. The methodology follows the five-step logic defined by FAA (2016): system description, hazard identification, risk analysis, risk assessment, and mitigation. Within this framework, UAV-related hazards are conceptualized as a composite of technical, environmental, and behavioral dimensions, allowing the methodology to address both accidental and deliberate intrusions.

The proposed model quantifies overall UAV risk through two principal components—probability (P) and consequence (C)—each derived from multiple indicators selected according to their relevance to airport operations and empirical recurrence in reported UAV incidents. The indicators were initially identified through literature synthesis (EASA 2021–2024; FAA 2024; Pyrgies 2019; Zhang 2021) and validated through expert consultation. Their selection was guided by three criteria: (1) statistical measurability, (2) operational relevance, and (3) scalability across airport types.

To ensure comparability across different case studies, all indicator values are normalized to a continuous scale from 0 (minimal contribution) to 1 (maximum contribution), following the approach adopted in recent probabilistic safety studies [13,14]. Each factor xi within a component is weighted by a coefficient wi, reflecting either equal or empirically calibrated importance, and the aggregated values are computed as:

$$P = \sum_{i=1}^{n} w_i \cdot p_i, \;\; C = \sum_{j=1}^{m} w_j \cdot \mathrm{c_j} \qquad (1)$$

Where p_i and c_j represent normalized indicator scores for probability and consequence respectively. The overall risk score is then derived as a multiplicative function:

$$\boldsymbol{R} = \boldsymbol{P} \times \boldsymbol{C} \qquad (2)$$

This formulation ensures transparency and replicability: probability (P) captures contextual exposure (population density, UAV traffic, compliance), whereas consequence (C) reflects potential severity (kinetic impact, operational disruption, infrastructure vulnerability). The continuous normalization allows seamless adaptation of the model to different airports, geographic conditions, and evolving UAV technologies, providing a consistent basis for quantitative and comparative risk evaluation.

3. Probability Determination

The probability of a UAV intrusion event is evaluated through five empirically derived indicators selected for their recurrent association with airport related UAV occurrences and their measurability across diverse contexts [5, 6, 14]. These indicators integrate both environmental exposure and regulatory control dimensions, reflecting the hybrid nature of UAV risk at airports. The selected indicators are:

- **Population density** in the airport vicinity (inhabitants/km^2);
- **Reported UAV incidents** in the area (annual frequency);
- **UAV ownership volume**, estimated from national or regional registration and sales data;
- **Air traffic volume**, expressed as average daily aircraft movements;
- **Regulatory compliance level**, representing the enforcement of UAV operational restrictions and pilot awareness.

Each indicator is normalized on a continuous 0–1 scale, where 0 corresponds to minimal exposure and 1 represents maximum relative risk. This approach departs from traditional categorical matrices by ensuring mathematical continuity, which facilitates computational modeling and cross-airport comparison [2,4]. The normalization thresholds were derived from empirical patterns observed in EASA’s 2023–2024 safety reviews and FAA’s UAS operational risk assessments.

Population density. Densely populated areas tend to exhibit higher UAV activity due to both recreational use and logistical demand. Thresholds were aligned with Eurostat’s DEGURBA classification and validated against observed drone sighting frequencies near major European aerodromes [15].

Table 1

Population density scoring

Population density (inhabit./km^2)	Normalized score
< 100	0.1
100–500	0.3
500–2000	0.6
> 2000	0.9–1.0

Reported UAV incidents. The number of recorded incursions, airspace violations, or Airprox events (an officially reported incident of hazardous proximity between two aircraft) within the airport control zone indicates both UAV prevalence and monitoring effectiveness. Data were aligned with EASA (2024) and the European Coordination Centre for Incident Data (ECCAIRS).

Table 2

Reported Incidents Scoring

Annual incidents reported	Normalized score
< 5	0.1
5–25	0.4
25–100	0.7
> 100	0.9–1.0

UAV ownership volume. Ownership density acts as a proxy for operational exposure. The ranges are derived from EASA's market intelligence reports (2023) and commercial dataset aggregations from Drone Industry Insights (2024).

Table 3

Drone Ownership Scoring

Estimated UAVs in area	Normalized score
< 500	0.2
500–5000	0.5
> 5000	0.8–1.0

Air traffic volume. Airports with high traffic density are more vulnerable to disruptions even from short-lived UAV incursions. Thresholds follow ICAO aerodrome classification and FAA's traffic intensity categories [6].

Table 4

Air Traffic Volume Scoring

Average flights/day	Normalized score
< 50	0.2
50–300	0.5
> 500	0.9–1.0

Regulatory compliance level. This parameter reflects the extent to which UAV operators comply with national and regional flight restrictions (EU Regulation 2019/947) and registration obligations. Data sources include the

EASA UAS Operator Registry (2024) and FAA Drone Zone enforcement statistics.

Table 5

Regulatory Compliance Scoring

Compliance level	Normalized score
> 90%	0.1
50–90%	0.5
< 50%	0.9

4. Calibration of Probability Thresholds

Threshold calibration relied on publicly available datasets and expert elicitation following FAA SRM practices. Population density thresholds stem from Eurostat and ICAO land-use guidelines, while UAV ownership and incident frequency distributions were validated using EASA's 2023 Safety Review. The report documented two serious Airprox events in Europe in 2023 but highlighted a 37% increase in UAV sightings near controlled aerodromes since 2019 [5,15].

Where consistent datasets were unavailable, heuristic thresholds were employed as interim approximations. This limitation underscores the importance of establishing harmonized European and global UAV occurrence databases. Future refinements should apply machine-learning calibration techniques—such as Bayesian updating or LSTM-based time-series modeling—to continuously adjust indicator weights and probability boundaries using live detection data from radar, ADS-B, and acoustic sensors [4,16].

This hybrid statistical–expert approach ensures transparency while allowing adaptation as data availability improves, aligning the model with emerging digital risk management practices promoted under the EASA "Digital Sky" initiative (2024).

5. Consequence Determination

The severity of consequences resulting from a UAV intrusion is quantified through a composite analysis of seven key indicators, each reflecting a specific dimension of physical damage, operational disruption, or systemic vulnerability. These indicators were selected based on their recurrence in incident analyses conducted by EASA (2023–2024), FAA (2024), and peer-reviewed studies in Aerospace and Safety Science [5,13,14]. Each indicator is normalized on a 0–1 continuous scale and combined using a weighted aggregation that emphasizes kinetic impact and operational sensitivity.

Drone weight. Mass strongly influences the kinetic energy transferred upon collision. Experimental crash simulations and FAA ballistic impact models indicate that UAVs above 10 kg can cause catastrophic structural damage to airframes or ground assets [6,13].

Table 6

Drone Weight Scoring

Weight (kg)	Normalized score
< 0.25	0.1
0.25–2	0.4
2–10	0.7
> 10	0.9–1.0

Drone speed. Velocity determines the kinetic energy vector in mid-air collisions and the likelihood of airframe penetration. Empirical models developed by Xu et al. (2022) and FAA (2024) show that UAVs exceeding 25 m/s substantially increase both the probability and severity of impact.

Table 7

Drone Speed Scoring

Speed (m/s)	Normalized score
< 10	0.1
10–25	0.5
> 25	0.9

Flight autonomy. Endurance affects the UAV's ability to persist within restricted zones. Drones with flight times exceeding 30 minutes are capable of multiple passes and sustained surveillance, significantly increasing operational exposure [3,14].

Table 8

Autonomy Scoring

Flight time (min)	Normalized score
< 15	0.2
15–30	0.5
> 30	0.8

Operator type. Operator identification is a critical differentiator of intent. Unregistered or unidentified operators represent higher unpredictability and potential malicious intent. Recent FAA enforcement statistics and EASA regulatory analyses confirm that the absence of registration correlates with a threefold increase in operational violations [5,6].

Table 9

Operator Type Scoring

Operator Status	Normalized score
Registered professional	0.2
Hobbyist	0.5
Unknown/unauthorized	0.9

Intrusion zone. The relative position of the UAV determines its potential interference with flight operations. Intrusions near runways, control towers, or radar installations are classified as critical, consistent with ICAO aerodrome zoning guidance (2022) and EASA's risk perimeter definitions (2024).

Table 10

Intrusion Zone Scoring

Intrusion location	Normalized score
Outside perimeter	0.1
Airport perimeter (airside)	0.6
Runway or ATC tower zone	0.9–1.0

Response time. Response latency is a major determinant of incident escalation. Airports equipped with integrated counter-UAS systems (RF, radar, EO/IR) can detect and neutralize threats within 2 minutes, while delays exceeding 10 minutes enable UAVs to persist in critical airspace [2,3].

Table 11

Response Time Scoring

Response time (min)	Normalized score
< 2	0.1
2–5	0.4
> 10	0.8

Critical infrastructure proximity. UAVs operating near critical infrastructure—such as fuel depots, radar towers, or air traffic control centers—pose high systemic risk even in the absence of collision. Empirical observations from Pyrgies (2019) and EASA (2024) demonstrate that incursions near such assets lead to disproportionate operational disruption and emergency response activation.

Table 12

Infrastructure Proximity Scoring

Infrastructure type	Normalized score
No critical infrastructure	0.1
Adjacent facilities	0.6
Fuel depot / ATC tower	0.9

All parameters are scored within a 0–1 range, with higher values denoting greater potential severity. The final consequence score is derived using a weighted average:

$$C = \sum_{j=1}^{m} w_j \cdot c_j \qquad (3)$$

where c_j is the normalized value of each indicator and w_j the corresponding weight. In the baseline model, all weights are equal ($w_j = 1/m$) to ensure neutrality and transparency; however, empirical calibration using regression or Bayesian learning can refine these coefficients as datasets expand. The weighting scheme prioritizes physical impact (weight, speed) and operational disruption (response time, infrastructure proximity) in line with EASA (2024) hazard classification.

6. Risk Matrix and Output Classification

The aggregated risk index is computed as the multiplicative function of probability (P) and consequence (C):

$$R = P \times C \qquad (4)$$

This formulation supports a two-dimensional risk surface representation, where incremental changes in probability or consequence yield proportional variations in the overall risk.

For interpretability, the results are categorized into five levels consistent with ISO 31000:2018 and ICAO Annex 19 severity scales:

- **0–0.1:** Acceptable; **0.1–0.3:** Under monitoring
- **0.3–0.6:** Significant risk
- **0.6–0.8:** High risk
- **0.8–1.0:** Critical risk

The resulting risk matrix enables airport authorities to visualize UAVrelated hazards across an interpretable, continuous spectrum. This facilitates resource allocation, prioritization of mitigation measures, and alignment with digital safety dashboards integrating live sensor data and AI-assisted predictive modules.

7. Results

To validate the proposed risk assessment framework, a real-world scenario was analyzed alongside supplementary comparative cases. The primary case focuses on the London Gatwick Airport drone incident (December 2018), one of the most extensively documented UAV-related disruptions in civil aviation. Additional comparative validation was conducted using secondary datasets from Paris Charles de Gaulle (France, 2022) and Cluj-Napoca International Airport (Romania, 2023), providing cross-contextual insight into the model's robustness [2,5,14].

Between December 19 and 21, 2018, London Gatwick Airport experienced repeated unauthorized UAV incursions within its controlled airspace, resulting in a full suspension of operations for over 72 hours. More than 1,000 flights were cancelled or diverted, impacting approximately 140,000 passengers. Despite extensive law enforcement and military involvement, the UAV operator was never identified. The case prompted regulatory reviews by EASA and the UK Civil Aviation Authority (CAA), highlighting deficiencies in detection and coordination protocols [3,6].

Comparable but smaller-scale events were reported at Paris Charles de Gaulle Airport in 2022 and Cluj-Napoca in 2023, both involving brief UAV sightings near approach paths. These incidents were rapidly mitigated due to improved surveillance and counter-UAS systems an procedures, offering a useful contrast for validating the model's proportional risk sensitivity.

The probability of incident recurrence was calculated using the five standardized indicators described in Section 2.1. Each indicator was normalized and weighted equally for the baseline Gatwick scenario, consistent with the FAA (2016) and EASA (2024) safety risk management approaches.

- **Population density (0.9)**: Gatwick is located in a highly urbanized region (> 6,000 inhabitants/km^2).
- **UAV ownership volume (0.9)**: The UK maintains one of Europe's highest civilian UAV ownership rates (> 25,000 units/year) [5].
- **Reported incidents (1.0)**: Multiple incursions occurred over three consecutive days, exceeding the 95th percentile of annual Airprox frequency.
- **Regulatory compliance (0.4)**: The regulatory framework was transitional in 2018, predating EU Regulation 2019/947.
- **Air traffic volume (1.0)**: Over 700 daily aircraft movements place Gatwick among Europe's busiest secondary hubs.

Weighted average probability score: **0.85**

The probability index (P) was computed as the arithmetic mean of normalized factors:

$$P = \frac{1}{5}\sum_{i=1}^{5} p_i = \frac{0.9+0.9+1.0+0.4+1.0}{5} = 0.85 \qquad (5)$$

This configuration yields a high-likelihood classification according to EASA's Airprox taxonomy, corroborated by incident frequency distributions in the 2023 safety review. The same formula, applied to the comparative airports, produced probability scores of P_{CDG} = 0.72 and P_{CLJ} = 0.48, illustrating the method's sensitivity to regional UAV prevalence and traffic density.

Eight consequence indicators were estimated based on operational reports and validated literature. For Gatwick, the key drivers of severity were the intrusion zone (runway vicinity), operator anonymity, and the extended response duration.

- **Drone weight (0.4)**: Estimated between 1–3 kg (commercial quadcopter class).
- **Speed (0.4)**: Operational velocity 40–60 km/h.
- **Autonomy (0.5)**: Flight endurance > 30 min.
- **Operator type (1.0)**: Unidentified, presumed malicious intent.
- **Intrusion zone (1.0)**: UAVs entered controlled runway and ATC tower proximity [3].
- **Response time (0.9)**: Mitigation required several hours before flight resumption.
- **Critical infrastructure affected (0.9)**: Operations and terminal logistics disrupted.
- **Economic impact (1.0)**: Estimated losses exceeding €20 million (direct + indirect) [2].

Weighted average consequence score: **0.76**

The aggregated consequence value (C) was computed as:

$$C = \frac{1}{8}\sum_{i=1}^{8} c_i = 0.76 \tag{6}$$

Equivalent calculations for comparative cases yielded C_{CDG} = 0.58 and C_{CLJ} = 0.41, reflecting the more limited operational impact of those events.

The overall risk index (R) was derived using the multiplicative model $R = P \times C$:

$$R = 0.85 \times 0.76 = 0.646 \quad \text{(or 64.6\%)} \tag{7}$$

According to the classification explained in Section Risk Matrix, this corresponds to the **High to Critical Risk** category. Comparative outcomes for the validation airports are summarized in Table 13.

Figure 1 visualizes the normalized risk distribution for the three incidents. The high-risk quadrant demonstrates strong consistency with both FAA (2016).

Table 13

Comparative UAV Risk Scores Across Airports

Airport	(P)	(C)	Risk (R = P × C)
Gatwick (UK)	0.85	0.76	0.65 (High–Critical)
Charles de Gaulle (FR)	0.72	0.58	0.42 (Significant)
Cluj-Napoca (RO)	0.48	0.41	0.20 (Under Monitoring)

and ICAO Annex 19 severity matrices. This reinforces the validity of the proposed normalization scheme and its interoperability with existing aviation safety frameworks.

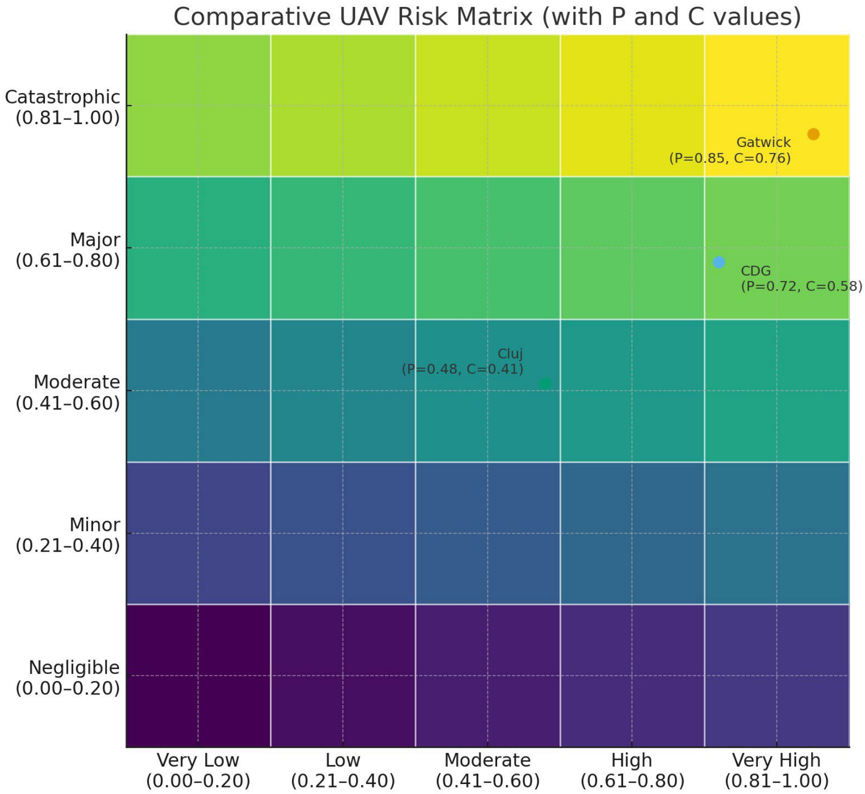

Figure 1. Risk matrix visualization showing Gatwick (64.6%), CDG (42.0%), and CLJ (20.0%) positions.

8. Discussion

The Gatwick incident exemplifies how unregulated UAV operations can escalate into systemic disruptions of airport functionality and passenger safety. The resulting risk level of 64.6%, categorized as "High–Critical," confirms the model's ability to capture both the operational complexity and regulatory vulnerabilities that exacerbated the event's impact. This outcome aligns closely with independent assessments from EASA (2024) and FAA (2023), which classify prolonged airspace closures as high-severity occurrences due to cascading effects on air traffic management and airport logistics.

The comparative validation across Gatwick, Charles de Gaulle, and Cluj-Napoca further demonstrates the framework's interpretability and adaptability. The risk differentials—0.65, 0.42, and 0.20 respectively—reflect consistent sensitivity to both UAV prevalence and operational exposure, validating the normalization of the probability and consequence scales. This two-dimensional approach offers a clear analytical advantage over scalar models, which compress variability into a single risk index and obscure the relative contribution of likelihood versus severity.

From a theoretical perspective, the proposed model integrates established principles from ISO 31000, ICAO Annex 19, and the FAA's Safety Risk Management (SRM) process, while introducing a continuous normalization mechanism that allows quantitative comparability across airports and incident typologies. This methodological transparency addresses one of the major gaps in prior UAV risk studies, which often relied on discrete categorical judgments or heuristic classifications [2,14].

The practical implications are significant. The matrix-based visualization supports immediate decision-making by situating each incident within a calibrated risk landscape. For airport safety managers, this enables prioritization of resources, identification of dominant risk drivers, and integration of risk-based criteria into operational protocols. When connected to digital safety dashboards, the matrix could serve as a real-time monitoring layer, updating dynamically through data from radar, ADS-B, or optical/acoustic detection systems.

Nevertheless, several limitations must be acknowledged. The reliability of the computed scores depends on the quality and completeness of input data. UAV incident databases remain fragmented across national authorities, often lacking standardized fields for drone type, flight parameters, and response duration. In addition, expert judgment—used in setting some of the threshold values—may introduce subjectivity and cognitive bias. These limitations highlight the need for harmonized European and global UAV occurrence reporting mechanisms.

Future methodological refinements should explore data-driven calibration using machine learning models capable of continuously updating the indicator weights as new incident data become available. Bayesian inference or LSTM-based temporal learning could enable predictive risk modeling, where the probability distribution evolves dynamically according to recent UAV detection patterns. Such integration would transform the framework from a diagnostic to a predictive and adaptive decision-support tool.

Finally, full operational validation will require field testing within airport environments under the supervision of civil aviation authorities. Comparative benchmarking against EASA's and FAA's existing risk classification frameworks will help establish interoperability and define standardized thresholds for decision-making. Once integrated within an airport's Safety Management System (SMS), the model could serve as both a strategic planning instrument and an operational early-warning component, reinforcing the proactive safety culture promoted by ICAO and the EU Aviation Safety Strategy (2024).

9. Conclusions

The increasing frequency and operational impact of unauthorized UAV incursions in controlled airspace underscore the urgent need for standardized, quantitative risk assessment frameworks. This study addressed that gap by developing a multi-factor methodology combining probabilistic and consequence-based indicators on a normalized 0–1 scale. In contrast to categorical models, the proposed framework captures intermediate variations in exposure and severity, thereby enhancing analytical precision and cross-airport comparability.

By integrating five contextual probability indicators—population density, air traffic, incident frequency, UAV ownership, and regulatory compliance—with eight consequence parameters encompassing drone characteristics, operator intent, and proximity to critical assets, the model constructs a comprehensive risk profile. The weighting system ensures flexibility for local calibration while preserving reproducibility across regions.

Application of the framework to three airport contexts—Gatwick (UK), Charles de Gaulle (FR), and Cluj-Napoca (RO)—validated its sensitivity and adaptability. The resulting scores (0.65, 0.42, and 0.20) align with their respective operational environments, confirming the model's ability to distinguish between high-risk and low-risk scenarios. These outcomes mirror empirical observations reported by EASA (2024) and FAA (2023) regarding UAV activity in high-density airspace.

The graphical representation through a normalized probability – consequence matrix enhances interpretability and communication of results. For airport operators and civil aviation authorities, this provides a transparent, evidence-based means to prioritize mitigation actions, allocate resources efficiently, and align decision-making with the risk management principles of ISO 31000 and ICAO Annex 19. Furthermore, the structure supports digital integration, enabling continuous data ingestion from UAV detection networks and dynamic recalibration of risk indices.

Future research should focus on the progressive operationalization of this model within airport Safety Management Systems (SMS). In particular, coupling the framework with real-time UAV detection infrastructure—radar, RF, acoustic, and optical sensors—would allow predictive analytics and early warning capabilities. Incorporating artificial intelligence (AI) and machine learning (ML) algorithms, such as Bayesian networks and LSTM neural architectures, could facilitate automatic reweighting of indicators and continuous adaptation to evolving threat patterns.

Ultimately, this work establishes a replicable foundation for quantitative UAV risk governance in aviation. By combining empirical calibration, normalized indicator scoring, and digital visualization, the methodology bridges the gap between conceptual safety models and operational decision support. Its adoption by regulatory bodies could contribute to the creation of harmonized UAV risk standards, supporting the broader objectives of the European "Digital Sky" and the FAA's data-driven safety initiatives.

10. Limitations and Future Work

Despite its demonstrated applicability, the proposed framework retains several limitations. First, the model's reliability depends on the availability and accuracy of UAV incident data, which remain inconsistent across jurisdictions. Many states lack unified registries linking UAV characteristics, flight parameters, and incident contexts, complicating empirical calibration. Harmonized international databases—such as those envisioned by EASA's Data4Safety program—would substantially improve indicator precision.

Second, the scoring process still requires expert judgment for partially observed variables (e.g., operator intent, enforcement level). While such judgments provide domain insight, they may introduce cognitive bias. Structured elicitation methods (e.g., Delphi panels) and probabilistic calibration using Bayesian updating could mitigate these effects by quantifying uncertainty rather than ignoring it.

Third, the current model assumes conditional independence among indicators. In reality, correlations exist—for example, between population density, UAV ownership, and air traffic volume. Future iterations should incorporate causal inference mechanisms (e.g., Bayesian networks) to model these interdependencies explicitly, improving predictive validity.

From a computational standpoint, the model remains static and retrospective. While effective for scenario analysis, it does not yet provide real-time decision support. Integrating it within digital safety platforms—capable of ingesting live sensor feeds and applying adaptive learning models—will transform it into a continuously updated, predictive risk engine. Such implementation aligns with current FAA and EASA priorities on automation-assisted risk management.

Finally, empirical validation across a wider range of airport typologies (major hubs, regional airports, heliports, and military bases) is essential to confirm scalability. Pilot deployments under civil aviation authority oversight could serve to fine-tune normalization thresholds and establish standardized alert levels for UAV-related hazards. Long-term, this evolution will enable the transition from a diagnostic tool toward an operationally validated, AI-supported risk management system for the protection of airport environments.

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