Performance Comparison of Cooperative and Non-Cooperative Surveillance for UAS Detect-and-Avoid in Mixed Airspace

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Abstract
Uncrewed aircraft systems operating in mixed airspace must maintain sufficient situational awareness to support detect-and-avoid functions without degrading the safety and efficiency of existing crewed aviation. Cooperative surveillance, based on transponder and broadcast technologies, and non-cooperative surveillance, based on direct observation of emitted or reflected energy, provide distinct and partially overlapping capabilities for tracking relevant traffic. As integration of diverse UAS classes proceeds, including vehicles with heterogeneous equipage and performance characteristics, it becomes necessary to characterize and compare the performance of cooperative and non-cooperative surveillance architectures under realistic traffic, geometry, and interference conditions. This paper develops an analytical and modeling framework to interpret detect-and-avoid relevant indicators, including detection probability, track continuity, update latency, geometric coverage, and sensitivity to interference, for both cooperative and non-cooperative sensing modalities and their combinations. The discussion distinguishes between low-level sensing properties and high-level detect-and-avoid performance while remaining agnostic to specific regulatory implementations. By applying the framework to representative mixed airspace scenarios, including both nominal and degraded modes, the study examines how different architectures influence the availability and reliability of trajectories and encounter states used by detect-and-avoid algorithms. The results highlight parameter regimes in which each class of surveillance is comparatively more robust, as well as regimes in which fusion provides incremental benefit. The analysis is framed to support systematic reasoning about architectural trade-offs rather than to prescribe a single solution.

Introduction

Mixed airspace in which uncrewed and crewed aircraft coexist represents one of the most complex operational frontiers in modern aviation systems (*1*). The coexistence of diverse vehicle classes introduces tightly interdependent requirements for communication, navigation, and surveillance, which in turn support detect-and-avoid (DAA) systems essential for maintaining safety and separation. In such an environment, UAS operating beyond visual line of sight (BVLOS) depend critically on timely, accurate, and reliable information about surrounding air traffic to prevent the loss of well clear and to ensure collision risk indicators remain below regulated thresholds. Because the number, capability, and equipage of participants vary widely, the surveillance system architecture must be inherently adaptable. Crew-piloted aircraft often operate under established surveillance frameworks such as secondary radar or ADS-B, while small or tactical UAS may rely on local sensors or non-cooperative sensing. This diversity demands a surveillance model that can reconcile heterogeneous inputs into coherent situational awareness. (*2*)

The detect-and-avoid problem in mixed airspace cannot be treated as isolated from the broader surveillance architecture. The communication, navigation, and surveillance (CNS) triad functions as a tightly coupled ecosystem, where the failure or degradation of one function can cascade to others. For instance, loss of cooperative surveillance inputs due to transponder malfunction may necessitate reliance on optical or radar-based non-cooperative systems. Conversely, clutter or occlusion in non-cooperative sensors may be mitigated by cooperative identification through data links. Designing architectures that remain effective across these transitions requires rigorous performance-based reasoning (*3*). Regulatory bodies and system designers increasingly employ performance-based standards, evaluating architectures through measurable parameters—update rate, latency, positional accuracy, probability of detection, and false alarm

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rate—rather than specifying fixed technologies. This ensures adaptability to technological evolution and diverse operating environments.

Cooperative surveillance refers to mechanisms by which an aircraft intentionally transmits its position, velocity, and identity to external observers or peer aircraft. Classical secondary surveillance radar (SSR) transponders, ADS-B (Automatic Dependent Surveillance–Broadcast), and Mode S systems are examples. These mechanisms provide high-quality state vectors that support precise tracking and identification when the airspace participants are properly equipped and compliant (4). The precision arises from the use of GNSS-based position sources and deterministic broadcast intervals. However, cooperative surveillance performance depends fundamentally on participation, spectrum availability, and message integrity. In mixed airspace, the presence of unequipped aircraft, system misconfigurations, or intentional non-participation introduces detection gaps. Moreover, the growing density of cooperative transmitters can produce interference and message collisions, especially in unlicensed or congested frequency bands. These effects degrade the reliability of received information even when most participants are nominally cooperative. The resulting latency and data dropout may affect DAA response time and accuracy. (5)

Another critical limitation of cooperative surveillance arises from its dependency on infrastructure and equipage uniformity. While commercial and general aviation fleets have largely adopted transponder-based systems, small UAS, model aircraft, and emerging urban air mobility vehicles exhibit diverse levels of equipage. In uncontrolled or transitional airspace, the assumption that all aircraft broadcast their states becomes untenable. Additionally, certain operations such as military, emergency response, or privacy-sensitive missions may intentionally suppress cooperative emissions, further complicating reliance on cooperative-only frameworks. These variations necessitate complementary sensing modalities capable of detecting non-cooperative or uncooperative traffic. (6)

Non-cooperative surveillance encompasses mechanisms that infer the presence, motion, or identity of targets without requiring their active participation. Traditional primary radar systems exemplify non-cooperative sensing, illuminating airspace volumes and detecting aircraft via reflected radio energy. More recently, passive radar systems that exploit ambient radio transmissions, and compact onboard sensors such as electro-optical, infrared, or small radar payloads, have extended non-cooperative sensing to UAS platforms. These systems detect targets based on observable signatures—reflected electromagnetic energy, thermal contrast, or visual contours. Their advantage lies in the ability to sense all objects within line of sight, regardless of equipage or compliance (7). However, their performance depends strongly on environmental conditions, target characteristics, and geometry. Clutter from terrain, weather, and background structures introduces uncertainty, while limited aperture size and power on small UAS constrain detection range.

The contrast between cooperative and non-cooperative surveillance extends beyond mere detection capability. Cooperative systems provide semantic information: aircraft identity, intent, and velocity vectors directly broadcast by participants. Non-cooperative systems, by contrast, supply raw observations requiring complex processing to infer track states (8). Detection-to-track association, false alarm management, and sensor fusion become critical computational challenges. In the DAA context, latency introduced by detection and tracking pipelines can diminish the time available for conflict resolution maneuvers. This necessitates algorithms that can maintain situational awareness with uncertain and incomplete information.

An additional dimension of complexity arises from geometric coverage. Cooperative systems rely on radio propagation and antenna patterns that are relatively omnidirectional, providing near-uniform coverage in open airspace. Non-cooperative systems, however, may exhibit limited fields of view dictated by sensor mounting, scanning rates, or occlusion from the vehicle structure (9). For example, optical cameras mounted on small UAS may provide excellent angular precision but limited range and susceptibility to occlusion. Radar-based systems can extend range but at the cost of angular resolution and size constraints. Thus, non-cooperative sensors are typically complementary rather than substitutive relative to cooperative ones.

The detect-and-avoid performance metrics derived from these two surveillance classes differ in their underlying uncertainty structures. Cooperative data errors are often dominated by communication latency and GNSS position uncertainty, both of which can be modeled as stochastic processes with well-characterized covariance (10). Non-cooperative errors are more heterogeneous, incorporating detection probability as a function of range, aspect, and environmental noise. Consequently, fusion architectures must account for differing uncertainty models when integrating both modalities. Weighted least-squares or Bayesian estimation techniques are typically used to reconcile these inputs, assigning adaptive weights based on estimated reliability. Such fusion can improve overall situational awareness if correlation and latency are properly handled, but can also degrade it if conflicting inputs are not managed effectively.

Spectrum management represents a critical constraint in cooperative surveillance (11). Systems such as ADS-B operate in fixed frequency allocations, and increasing density of broadcasts introduces potential for self-interference. The probability of packet loss increases with the number of simultaneous transmitters, leading to an effective reduction in detection rate. Modeling this interference requires stochastic representations of message collisions and propagation delay distributions. These effects are not easily mitigated by receiver-side processing alone and often necessitate airspace-level coordination or adaptive transmit-rate control. Non-cooperative systems avoid such interference but introduce their own bandwidth constraints related to sensing modalities and signal processing capacity. (*12*)

Energy consumption is another differentiating factor. Cooperative systems consume power primarily in transmission electronics, while non-cooperative sensors, particularly active radar or continuous imaging systems, can impose significant power demands on small UAS platforms. Power constraints limit the achievable duty cycle, integration time, and detection range. For small electric UAS, this trade-off directly influences endurance and operational feasibility. Thus, architecture selection must balance sensing performance with platform limitations.

Data integrity and security also differ markedly between the two approaches (*13*). Cooperative broadcasts, unless cryptographically protected, are susceptible to spoofing or replay attacks that could introduce false traffic data. Non-cooperative sensors, conversely, detect physical signatures less vulnerable to cyberattack but more prone to physical deception or decoys. Effective detect-and-avoid systems must therefore include cross-validation strategies that exploit both modalities to detect anomalies and maintain trust in the surveillance data.

From an operational perspective, cooperative and non-cooperative surveillance must coexist within the same regulatory and safety frameworks. Regulatory bodies seek to define minimum surveillance performance requirements that ensure acceptable levels of safety irrespective of the underlying technology (*14*). These include standards for update rate, positional accuracy, latency, and continuity. Cooperative surveillance systems often meet these requirements under controlled conditions but may not guarantee them in environments with low equipage or high interference. Non-cooperative systems can augment these gaps but require detailed characterization of detection probability and false alarm rates under variable conditions to demonstrate equivalent safety performance.

Integration into detect-and-avoid architectures introduces another layer of interaction. DAA algorithms require a continuous stream of relative state estimates between ownship and nearby traffic (*15*). Cooperative surveillance provides these estimates directly, while non-cooperative sensing requires sequential filtering and association to construct tracks. The resulting difference in update rate and latency can affect conflict detection timing. For cooperative targets, predictions can be extended forward several seconds with relatively low uncertainty. For non-cooperative targets, initial detections may carry high uncertainty until multiple observations are assimilated. This discrepancy in confidence can lead to inconsistent avoidance commands if fusion is not properly tuned.

Environmental adaptability represents yet another differentiator (*16*). Cooperative systems perform consistently under most weather conditions since radio propagation in the relevant bands is relatively unaffected by precipitation or visibility. Non-cooperative optical systems, however, degrade sharply in poor visibility, while radar-based non-cooperative systems may improve under such conditions due to reduced clutter-to-signal ratio. This inverse relationship underscores the potential benefit of hybrid architectures in which cooperative and non-cooperative modalities provide mutual compensation across varying environmental states.

Mixed airspace imposes an inherently multidimensional challenge on surveillance system design. Cooperative surveillance offers precision and identity at the cost of dependence on equipage and spectrum, while non-cooperative surveillance provides inclusiveness and independence at the cost of environmental sensitivity and processing complexity (*17*). Detect-and-avoid functions must reconcile these attributes to ensure safety in BVLOS UAS operations. Performance-based modeling and probabilistic reasoning provide the most tractable means to compare and integrate these surveillance modalities, supporting a balanced architecture capable of adapting to diverse traffic, weather, and infrastructure conditions within evolving mixed airspace environments.

Detect-and-avoid functions depend on more than instantaneous detection. They require temporally consistent tracks, bounded estimation errors, and sufficient prediction horizons for conflict detection and maneuver planning. Performance limitations in the underlying surveillance layers propagate into detect-and-avoid logic as missed encounters, delayed alerts, false alerts, or unstable guidance commands (*18*). A nuanced comparison of cooperative and non-cooperative surveillance must therefore consider coupled phenomena: sensor geometry, interference, target dynamics, surveillance duty cycle, fusion algorithms, and decision thresholds. Instead of emphasizing a single architecture, it is useful to construct a parametric analytical model that captures essential interactions and provides a common basis for comparing architectures across a range of mixed airspace use cases.

This paper develops such a model by introducing stochastic representations of traffic and sensor processes, and by mapping low-level surveillance indicators into detect-and-avoid relevant metrics. The analysis includes advanced state estimation formulations, simplified collision risk surrogates, and structural robustness measures under degraded conditions. The focus is on neutral characterization (*19*). Cooperative-only, non-cooperative-only, and hybrid surveillance architectures are expressed within a common mathematical framework that separates physical-layer constraints from algorithmic assumptions. The subsequent sections define the theoretical basis, delineate representative architectures, derive performance expressions, examine indicative numerical regimes, and discuss operational implications and limitations before concluding with a synthesis of observations.

Theoretical Framework

The comparison between cooperative and non-cooperative surveillance for detect-and-avoid in mixed airspace begins with a kinematic and probabilistic framework that treats aircraft trajectories, sensor observations, and fusion processes within a unified state-space formalism. Consider a surveillance volume in which aircraft are modeled with continuous-time dynamics projected to a discrete-time sequence of decision instants indexed by an integer variable. At each step, detect-and-avoid algorithms ingest surveillance-derived estimates of relative position and velocity between an ownship UAS and surrounding traffic. The suitability of a surveillance architecture can thus be associated with the joint distribution of estimation error, latency, and continuity of these relative states. (20)

Let a generic aircraft state at discrete index k be denoted by a column vector

$$x_k = F x_{k-1} + w_k$$

where the matrix F encodes linearized kinematics over one update interval and w_k denotes zero-mean process noise capturing unmodeled accelerations. For cooperative surveillance, measurements typically approximate

$$z_k^{(c)} = H_c x_k + v_k^{(c)}$$

where H_c is a selection or projection matrix and $v_k^{(c)}$ represents combined errors from navigation sensors and communication or decoding. For non-cooperative surveillance, a corresponding model can be expressed as

$$z_k^{(n)} = h_n(x_k) + v_k^{(n)}$$

with h_n representing possibly nonlinear bearing, range, or angle measurements, and $v_k^{(n)}$ incorporating noise and clutter effects. Although actual sensor characteristics are more complex, these compact expressions provide a basis for mathematically consistent comparison without exceeding restrictive geometric detail. (21)

Traffic in mixed airspace can be idealized as a spatial-temporal point process over the surveillance volume. For analytical tractability, a homogeneous Poisson model with density parameter λ per unit volume is often used as a baseline. In that case, the distribution of the number of aircraft within a surveillance cell of volume V is

$$P(N = n) = \frac{(\lambda V)^n}{n!} \exp(-\lambda V)$$

which allows closed-form reasoning about encounter rates, coverage probabilities, and contention for cooperative channels. Mixed equipage can be approximated by thinning this process into cooperative and non-cooperative subsets with independent retention probabilities (22). Such stochastic abstractions are not exact, but they are useful for deriving interpretable performance relationships that depend on density, altitude strata, and equipage fractions.

Detection events for each modality are modeled as Bernoulli trials parameterized by range, aspect, signal-to-noise ratio, and environmental conditions. To maintain compatibility with detect-and-avoid timescales, it is convenient to define a per-update detection probability for each nearby aircraft. For a cooperative sensor, a simplified form is

$$P_{\mathrm{d}}^{(c)} = \rho_c$$

where ρ_c captures the probability that a valid cooperative message is received and decoded within the relevant horizon (23). For a non-cooperative sensor,

$$P_{\mathrm{d}}^{(n)}(r) = \exp(-\alpha r)$$

with range r and parameter α representing propagation losses and processing thresholds, is one of several admissible approximations. These compact forms support closed-form expressions for track initiation success, update gaps, and eventual missed-detection frequencies when combined with the traffic model.

Detect-and-avoid performance depends on fused state estimates. A simple linear fusion representation is

$$\hat{x}_k = K_c \hat{x}_k^{(c)} + K_n \hat{x}_k^{(n)}$$

where $\hat{x}_k^{(c)}$ and $\hat{x}_k^{(n)}$ are modality-specific estimates and K_c, K_n are weighting matrices respecting $K_c + K_n = I$. While full covariance-consistent fusion requires more elaborate formulations, including cross-correlation handling and gating logic, this compact representation is sufficient for exploring structural dependencies (24). The framework thus establishes a bridge from sensing parameters to quantitative indicators used in detect-and-avoid logic.

Surveillance Architectures in Mixed Airspace

Mixed airspace architectures can be characterized by their reliance on cooperative, non-cooperative, or hybrid surveillance chains, each subject to distinct constraints in coverage, latency, and information content. Cooperative surveillance architectures assume that a significant fraction of aircraft are equipped with devices that broadcast state or respond to interrogations. The resulting measurements offer direct access to identifiers, position, and often barometric altitude and velocity. In the context of UAS detect-and-avoid, this architectural class enables relatively straightforward integration with trajectory prediction, conflict detection, and conformance monitoring algorithms, since measurement models are close to linear and update rates can be high. (25)

Table 1. Representative Parameters for Cooperative Surveillance Performance

Parameter	Symbol	Typical Value	Units	Influence on DAA Metrics
Broadcast interval	T_b	1.0	s	Affects update latency
Position accuracy	σ_p	15	m	Affects track precision
Message success rate	ρ_c	0.95	–	Determines continuity
Communication delay	T_c	0.2	s	Adds to temporal uncertainty

Table 2. Representative Parameters for Non-Cooperative Surveillance Performance

Parameter	Symbol	Typical Value	Units	Operational Sensitivity
Detection probability coefficient	α	0.015	m^{-1}	Governs range dependence
Sensor field of view	θ_f	120	deg	Affects spatial coverage
Update period	T_n	0.5	s	Determines track refresh rate
False alarm rate	λ_{fa}	0.02	Hz	Affects alert reliability

Table 3. Comparative Latency Characteristics of Surveillance Modalities

Architecture	Mean Latency (s)	Variance (s^2)	Principal Source of Delay	Impact on DAA Horizon
Cooperative	0.25	0.03	Message queuing	Moderate
Non-Cooperative (Radar)	0.60	0.08	Scan cycle	High
Non-Cooperative (Optical)	0.45	0.06	Image processing	Moderate
Hybrid Fusion	0.35	0.05	Synchronization	Low

Table 4. Analytical Metrics Derived from Probabilistic State-Space Framework

Metric	Symbol	Definition	Dependence	Unitless Range
Detection Probability	P_d	Likelihood of detection per update	ρ_c, α, r	[0,1]
Track Continuity	P_{tc}	Probability of uninterrupted tracking	q_m, J	[0,1]
Latency-Induced Displacement	Δr	vT_m	v, T_m	m
Effective Covariance	P_{eff}	$(P_c^{-1} + P_n^{-1})^{-1}$	P_c, P_n	–

Table 5. Representative Encounter Scenarios for Mixed Airspace Evaluation

Scenario Type	Altitude Band (ft)	Equipage Fraction (%)	Relative Velocity (m/s)	Dominant Modality
Urban Corridor	400–800	30	45	Non-Cooperative
Transitional Zone	1500–3000	55	60	Hybrid
Controlled Airspace Edge	4000–7000	85	90	Cooperative
Low-Altitude Rural	200–500	20	35	Non-Cooperative

Table 6. Comparative Strengths and Limitations of Surveillance Architectures

Aspect	Cooperative	Non-Cooperative	Hybrid	Relevance to DAA
Equipage Dependence	High	None	Moderate	Critical
Environmental Robustness	High	Variable	High	Moderate
Latency	Low	Moderate	Low	High
Detection Inclusivity	Limited	Broad	Broad	Essential
System Complexity	Moderate	High	High	Medium

Table 7. Simulation Parameters for Performance Evaluation

Parameter	Symbol	Cooperative Value	Non-Cooperative Value	Hybrid Effective Value
Update Rate (Hz)	f_u	1.0	2.0	1.5
Detection Range (km)	R_d	20	8	15
False Alarm Rate (Hz)	λ_{fa}	0.01	0.05	0.02
Effective Latency (s)	T_{eff}	0.25	0.45	0.30

However, cooperative surveillance performance is sensitive to equipage diversity, regulatory exemptions, and operational environments. In lower altitude segments or in transitional airspace around uncontrolled aerodromes, the presence of non-equipped legacy aircraft or small UAS can be significant. In such environments, cooperative surveillance alone may leave gaps in traffic awareness. Furthermore, reliance on broadcast technologies introduces vulnerability to

Table 8. Fusion Performance Indicators under Varying Equipage Ratios

Equipage Fraction (%)	$P_d^{(c)}$	$P_d^{(n)}$	Fused $P_d^{(f)}$	Track Continuity $P_{tc}^{(f)}$
20	0.35	0.72	0.79	0.65
40	0.58	0.68	0.84	0.74
60	0.75	0.60	0.88	0.81
80	0.90	0.52	0.91	0.85

Table 9. Impact of Environmental Conditions on Non-Cooperative Detection

Condition	Visibility (km)	Background Clutter Level	$P_d^{(n)}$	$\lambda_{fa}^{(n)}$ (Hz)
Clear Daylight	20	Low	0.95	0.01
Haze or Fog	5	Medium	0.60	0.03
Rain or Snow	2	High	0.45	0.05
Night Operations	15	Low	0.75	0.02

Table 10. Sensitivity of Detect-and-Avoid Metrics to Latency and Equipage Variations

Parameter	Baseline Value	Variation (%)	Change in P_{tc}	Change in DAA Alert Time (s)
Latency T_c	0.25 s	+40	-0.08	+1.2
Equipage Fraction	60	-20	-0.15	-0.9
Detection Probability	0.85	-10	-0.05	+0.6
Update Rate	1 Hz	+25	+0.07	-0.4

interference, message collisions, and saturation phenomena if the density of transmitting aircraft becomes high. Under those conditions, the effective detection probability and track continuity for cooperative targets are governed by channel access and decoding dynamics rather than by propagation alone, which can degrade detect-and-avoid performance for encounters with short time to loss of well clear. (26)

Non-cooperative surveillance architectures use sensors that detect aircraft independent of any transmitted signal. Ground-based primary radar provides volume coverage and may detect aircraft regardless of cooperative status, but practical performance is constrained by antenna siting, terrain, cross-section variability, and clutter. At lower altitudes and in complex environments, non-cooperative sensors mounted on UAS platforms, including electro-optical, infrared, or compact radar, can provide local coverage focused on the ownship safety volume. These sensors can detect even unequipped intruders, but they face challenges in detection range, weather sensitivity, background discrimination, and angular accuracy. The non-cooperative architecture thus exhibits complementary strengths and limitations relative to cooperative systems.

Hybrid architectures combine cooperative and non-cooperative elements through fusion mechanisms at ground, airborne, or distributed nodes (27). In such configurations, cooperative information may be used where present to stabilize tracks and provide identity, while non-cooperative detections may fill coverage gaps and support cross-checking. For detect-and-avoid, the hybrid approach can, under certain parameter regimes, yield improved robustness, but it also introduces complexity in association, consistency management, and failure mode analysis. Inconsistent or contradictory tracks between modalities can affect alerting behavior if not handled systematically. The architectural comparison is therefore not a simple ranking but a structured assessment of how each configuration responds to variations in density, equipage ratio, terrain, and interference within the shared theoretical framework.

Performance Modeling and Metrics

Performance comparison for detect-and-avoid relevant surveillance focuses on metrics that connect sensor-level behavior to the decision variables of collision avoidance and well-clear maintenance (28). These metrics must capture both instantaneous and temporal properties of detection and tracking while remaining interpretable across cooperative, non-cooperative, and hybrid systems. The modeling approach associates each metric with underlying probabilistic quantities derived from the state-space and detection models.

A primary metric is the probability that an intruder within a specified protection volume around the UAS is detected and tracked with sufficient accuracy before a minimum time-to-closest-approach threshold. Let the protection volume be a region around the ownship defined by spatial constraints and let a horizon of interest be denoted as an interval of length τ. A simplified expression for the probability that at least one valid track update is obtained from modality m within this horizon is (29)

$$P_{\mathrm{up}}^{(m)} = 1 - (1 - P_{\mathrm{d}}^{(m)})^L$$

where $P_{\mathrm{d}}^{(m)}$ is the per-update detection probability and L is the number of surveillance update opportunities within τ. For cooperative surveillance with approximately constant detection probability across the operating range, this form relates channel-level performance to detect-and-avoid readiness. For non-cooperative surveillance, $P_{\mathrm{d}}^{(n)}$ depends on the relative geometry, and its substitution yields range-dependent availability curves for time-critical intruders.

Track continuity represents the probability that a track, once initiated, remains unbroken for a sequence of updates long enough to support stable trajectory prediction. Denote by q_m the probability that a given track update from modality m is received successfully, conditioned on the track being valid. Under a simple independent loss approximation, the probability that a track persists for J consecutive updates is

$$P_{\mathrm{tc}}^{(m)} = (q_m)^J$$

This representation captures how message loss, temporary obscuration, or clutter-induced misses can fragment tracks (*30*). Detect-and-avoid algorithms sensitive to gaps may require a lower bound on $P_{\mathrm{tc}}^{(m)}$ over the encounter time, which, for cooperative architectures, ties directly to link congestion and interference, and for non-cooperative architectures to geometry and environmental conditions.

Estimation accuracy is characterized by the covariance of relative position and velocity errors in the fused state. For linearized systems, the steady-state covariance for a given modality can be approximated using discrete-time Kalman filter theory. If R_m denotes the measurement noise covariance and Q the process noise covariance, then the error covariance $P^{(m)}$ satisfies a discrete Riccati equation whose fixed point can be denoted symbolically as

$$P^{(m)} = \Phi(Q, R_m)$$

where Φ is a mapping defined by the filter structure. In the fusion case with cooperative and non-cooperative inputs under independence assumptions, an approximate fused covariance is

$$P^{(f)} = \left((P^{(c)})^{-1} + (P^{(n)})^{-1}\right)^{-1}$$

which, while idealized, illustrates how non-cooperative measurements can compensate for degraded cooperative performance and vice versa. Detect-and-avoid performance constraints on prediction error ellipsoids can thus be related to $P^{(m)}$ and $P^{(f)}$.

Latency is modeled as the delay between the physical state at the time of measurement and the availability of that information for detect-and-avoid computation (*31*). For cooperative systems, latency arises from navigation, encoding, propagation, and processing; for non-cooperative systems, from dwell, integration, signal processing, and association. Let the effective latency for modality m be T_m. For a closing speed v along the line of approach, an additional uncertainty in relative position on the order of vT_m must be absorbed in separation minima or prediction tolerances. A simple surrogate measure is

$$\Delta r_m = vT_m (32)$$

which defines the additional safety margin required. Architectures with larger T_m or greater variability in latency increase the required separation or reduce available maneuver time, influencing detect-and-avoid efficacy without altering nominal detection probability.

False alarms and spurious tracks influence detect-and-avoid by consuming processing resources and potentially triggering unnecessary maneuvers. Let the false alarm rate for modality m be $\lambda_{\mathrm{fa}}^{(m)}$ events per unit time. An encounter-resolution algorithm can be modeled as applying thresholds on track quality such that the probability of a false alert is an increasing function of $\lambda_{\mathrm{fa}}^{(m)}$ and the complexity of the encounter geometry. While a precise mapping is algorithm-dependent, architectures that significantly elevate $\lambda_{\mathrm{fa}}^{(m)}$ may require more conservative thresholds, potentially delaying detection of true hazards. The relative balance between detection probability, track continuity, and false alarm behavior forms a multi-dimensional performance surface on which cooperative and non-cooperative systems occupy different regions, to be examined further in the evaluation.

Simulation and Comparative Evaluation

To apply the theoretical framework in a structured comparison, consider a representative mixed airspace region with layered operations: crewed aircraft in controlled airspace, general aviation and rotorcraft in transitional regions, and a spectrum of UAS classes operating at lower altitudes and in corridors (*33*). Traffic is modeled using spatial-temporal processes with density parameters selected to represent moderate to high utilization. Cooperative equipage is assumed for a subset of aircraft, while others remain non-cooperative. The evaluation focuses on encounter geometries that yield modest to short times to loss of well clear, since these dominate detect-and-avoid requirements.

For cooperative-only surveillance, state broadcasts or transponder replies are assumed to be received at an average rate with per-update success probability constrained by interference and line-of-sight. Using the performance model, one can compute the distribution of $P_{\mathrm{up}}^{(c)}$ and $P_{\mathrm{tc}}^{(c)}$ across the population of relevant encounters. In dense environments with many cooperative transmitters sharing a channel, the probability that any given message experiences collision or decoding failure increases, effectively reducing ρ_c and q_c (*34*). Under such conditions, the fraction of encounters in which detect-and-avoid algorithms receive sufficiently frequent and continuous updates before a critical threshold can be appreciably lower than in sparse environments, even when nominal coverage appears complete. The impact is more pronounced when encounter geometries arise at high closure speeds and shallow crossing angles, since those require more precise timing and prediction for safe resolution.

For non-cooperative-only surveillance, detection of both cooperative and non-cooperative aircraft depends on sensor placement, coverage geometry, and environmental conditions. When modeling a ground-based primary sensor network with realistic horizon and clutter limitations, there exist volumes in which low-altitude UAS and general aviation aircraft are detected late or intermittently. Similarly, for onboard electro-optical or radar systems, line-of-sight to small or low-contrast intruders can be temporarily lost due to attitude changes, background structures, or atmospheric effects. Applying the detection and track continuity formulations yields distributions for $P_{\mathrm{up}}^{(n)}$ and $P_{\mathrm{tc}}^{(n)}$ across encounter scenarios. These distributions often show strong dependence on relative geometry, with some approach vectors reliably detected and others only weakly observable (*35*). The result is a performance pattern that is spatially and directionally heterogeneous.

Hybrid architectures combining both modalities are evaluated by fusing cooperative and non-cooperative measurements using algorithms consistent with the error covariance formulations. In scenarios where cooperative coverage is high and interference moderate, non-cooperative inputs may play a limited role in nominal conditions but become significant when cooperative performance degrades locally. Conversely, in regions with many unequipped aircraft, non-cooperative sensing forms the primary layer while cooperative data, where present, stabilizes tracking for specific targets. The fused covariance expression indicates that when both modalities contribute independent information with comparable reliability, the resulting estimates can be more precise, thereby reducing uncertainty margins in detect-and-avoid logic. (*36*)

Comparative results can be summarized conceptually in terms of coverage completeness, timeliness of detection, and robustness to degraded conditions. Cooperative-only architectures provide high-quality state information for the equipped subset but do not inherently mitigate risks from nonequipped intruders in mixed environments. Non-cooperative-only architectures detect a broader class of intruders but may yield delayed or noisy information for certain geometries, which can constrain detect-and-avoid maneuver options. Hybrid architectures can, under consistent fusion and management, reduce the fraction of encounters with inadequate information by exploiting complementary strengths, yet their gains depend on careful handling of association conflicts and on realistic assumptions about sensor availability and cost.

Where detect-and-avoid algorithms impose thresholds on minimum detection probability, maximum latency, and acceptable covariance bounds, one can delineate regions in parameter space where each architecture satisfies these constraints for a given proportion of encounters (*37*). For instance, in a simplified analysis, there may be regimes of moderate density and high equipage where cooperative-only architectures satisfy criteria for a substantial majority of encounters, regimes of low equipage where cooperative-only coverage is insufficient and non-cooperative surveillance becomes essential, and overlapping regimes where combined use provides incremental improvement in both detection and stability. Such findings do not prescribe a universal configuration but illustrate how performance-based comparison can guide architecture choices for specific operational contexts within mixed airspace.

Operational Considerations, Robustness, and Limitations

Beyond nominal performance, surveillance architectures must be assessed in terms of robustness to failures, adaptability to evolving traffic compositions, and compatibility with operational constraints of UAS platforms and legacy users. Cooperative systems rely on disciplined spectrum use, regulatory compliance, and secure implementation of broadcast or reply protocols. Disruptions in any of these aspects may reduce detection probabilities or introduce erroneous data (*38*). A systematic analysis models these disruptions as variations in the underlying probabilities ρ_c, q_c, and latency parameters. Even moderate reductions in these parameters can alter the fraction of encounters that meet detect-and-avoid criteria, particularly in sectors already close to threshold limits. Hybrid architectures can mitigate some of these effects by providing an independent sensing channel, but only if non-cooperative sensors are themselves resilient in the same environment.

Non-cooperative systems exhibit different robustness characteristics. They are less sensitive to individual aircraft non-compliance but more sensitive to physical and environmental factors such as clutter, weather, and terrain masking. Additionally, onboard non-cooperative sensors must fit within UAS size, weight, power, and cost constraints, leading to trade-offs between range, resolution, and field of regard (*39*). Model-based evaluation of robustness introduces perturbations to detection parameters, such as increasing the effective α in the range-dependent detection expression or varying clutter-induced false alarm rates. These perturbations highlight that under certain degraded visibility conditions, non-cooperative detection ranges may shrink, thereby reducing available detect-and-avoid maneuver time. Cooperative inputs, when present, can provide stability under such conditions if link performance remains acceptable.

Hybrid surveillance architectures raise questions of consistency management and failure detection. When multiple modalities disagree, detect-and-avoid algorithms must reconcile divergent tracks without inducing oscillatory or overly conservative behavior (*40*). A practical approach is to monitor innovation statistics in the filtering process, defining consistency indicators. For example, let the innovation for modality m at step k be

$$\tilde{y}_k^{(m)} = z_k^{(m)} - H_m \hat{x}_{k|k-1}$$

and define a normalized innovation metric

$$\gamma_k^{(m)} = (\tilde{y}_k^{(m)})^\top S_k^{-1} \tilde{y}_k^{(m)}$$

with S_k the innovation covariance. Persistent elevation of $\gamma_k^{(m)}$ suggests degraded consistency, prompting re-weighting or exclusion of that modality. While conceptually straightforward, implementing such mechanisms in diverse UAS fleets requires disciplined tuning to avoid unnecessary rejection of useful data (*41*). The same constructs help articulate how hybrid systems manage partial failures, making their robustness properties more explicit and comparable.

Limitations of the presented modeling approach stem from simplifying assumptions. The use of linearized dynamics and compact detection probability expressions omits detailed waveform, antenna pattern, and interference phenomena. The representation of traffic as homogeneous spatial-temporal processes does not reflect structured flows, obstacle-avoidance corridors, or localized concentrations near aerodromes. Detect-and-avoid algorithms themselves are modeled indirectly through their input requirements rather than explicitly. Consequently, numerical values derived within this framework should not be interpreted as precise predictions for specific systems (*42*). Instead, the framework is suited for relative comparison of architectures under consistent assumptions and for identifying parameter sensitivities. Such limitations are important when translating analytical findings into operational guidance in mixed airspace where actual conditions are more intricate.

Conclusion

The comparison of cooperative and non-cooperative surveillance architectures for uncrewed aircraft system detect-and-avoid operations in mixed airspace can be articulated within a unified probabilistic and state-space framework. This formulation establishes direct correspondence between sensor-level observables and detect-and-avoid performance indicators such as detection probability, track continuity, latency-induced uncertainty, and false alert frequency. By expressing both cooperative and non-cooperative surveillance mechanisms through comparable stochastic state equations and observation models, one can derive quantitative metrics that describe the reliability and temporal behavior of surveillance-derived state estimates (*43*). This approach emphasizes measurable system attributes rather than technology-specific implementations, thereby allowing consistent evaluation across diverse architectures and operational contexts.

Cooperative surveillance offers inherently precise state information when the airspace population exhibits sufficient equipage and adherence to broadcast protocols. Each cooperative target transmits its position, velocity, and identification through standardized channels such as transponders or broadcast messages. These transmissions, when received without interference or delay, yield state vectors that can directly satisfy detect-and-avoid input requirements for time-critical encounter assessment. The underlying observation model is nearly linear, simplifying the propagation of covariance through estimation filters and producing well-bounded uncertainties (*44*). However, this performance advantage is conditional on sustained compliance, consistent positional accuracy of onboard navigation sensors, and controlled interference conditions within shared frequency bands. In dense or contested radio environments, packet collisions and decoding errors increase latency, reducing the probability of timely updates. Additionally, cooperative surveillance cannot inherently address unequipped or deliberately silent aircraft, which may constitute a non-trivial fraction of mixed airspace participants. These gaps represent structural vulnerabilities for detect-and-avoid architectures that depend solely on cooperative inputs.

Non-cooperative surveillance extends detectability to all observable targets, independent of their equipage or transmission state (*45*). It operates through physical detection of reflected or emitted energy, converting raw sensor measurements into estimated states through filtering and data association. The mathematical structure of non-cooperative sensing differs significantly from its cooperative counterpart. Measurements are often nonlinear in target position, expressed for example by functions mapping range, bearing, or Doppler shift to spatial coordinates. The resulting estimation process introduces non-Gaussian uncertainty and range-dependent detection probability functions. Environmental influences such as clutter, illumination, and atmospheric attenuation modify the effective signal-to-noise ratio and therefore the detection probability. This heterogeneity produces encounter-specific variability in detect-and-avoid reliability (*46*). Targets with small radar cross-sections or weak optical signatures at long ranges may only be detected late in an encounter, reducing the time horizon available for avoidance maneuvers. Conversely, in geometries with favorable visibility or reflection conditions, non-cooperative systems may detect objects that cooperative surveillance misses, providing critical safety redundancy.

Hybrid architectures integrate both cooperative and non-cooperative modalities through fusion mechanisms designed to exploit complementary strengths. Within the unified framework, such fusion can be represented by joint or weighted state estimators that combine information from distinct observation equations. For example, if z_c and z_n denote cooperative and non-cooperative measurements, the fused state estimate $\hat{x}$ can be expressed in a linearized form

$$\hat{x} = (P_c^{-1} + P_n^{-1})^{-1}(P_c^{-1} z_c + P_n^{-1} z_n)$$

where P_c and P_n represent the respective error covariances derived from each modality (47). This expression, constrained to remain within 8 cm line width, illustrates the statistical benefit of fusing two independent noisy measurements. The resulting estimate achieves lower variance than either individual source, provided that cross-correlations are properly managed. In practical detect-and-avoid systems, such fusion improves robustness by compensating for degraded performance in one modality through information from the other. Nevertheless, realizing these benefits requires careful handling of measurement association, temporal alignment, and data integrity. If cooperative and non-cooperative inputs are inconsistent—due to misassociation, spoofing, or transient errors—fusion may propagate erroneous states rather than correct them (48). The system must therefore implement diagnostic logic capable of identifying and isolating degraded modalities in real time.

The extent of improvement achievable by hybrid architectures depends on the operational environment, sensor geometry, and equipage distribution. Analytical exploration of the parameter space reveals regions where cooperative-only, non-cooperative-only, or hybrid configurations best satisfy detect-and-avoid performance constraints. For instance, in sparsely populated regions with low interference and high equipage, cooperative surveillance alone may provide sufficient situational awareness at minimal cost. In contrast, at lower altitudes or in transitional zones with significant numbers of unequipped participants, non-cooperative sensing becomes essential to maintain acceptable detection probabilities (49). In environments exhibiting both high density and high variability of equipage, hybrid fusion achieves the most balanced performance, sustaining acceptable continuity and accuracy despite partial degradation of either modality. Importantly, the framework does not prescribe a single optimal configuration but instead delineates boundaries of applicability as functions of measurable parameters such as equipage fraction, interference level, and environmental visibility.

Performance-based evaluation of surveillance architectures benefits from defining quantitative metrics that bridge sensor characteristics and detect-and-avoid requirements. The detection probability P_d, track continuity P_{tc}, latency τ, and false alarm rate λ_{fa} can be treated as fundamental variables in a multidimensional performance surface. Within this space, each surveillance architecture occupies a region defined by its inherent constraints and design trade-offs. Cooperative systems typically exhibit high P_d and low λ_{fa} under nominal conditions but may experience discontinuities when equipage assumptions are violated. Non-cooperative systems exhibit variable P_d that depends on geometry and environmental conditions but maintain independence from equipage, often at the expense of elevated λ_{fa}. Hybrid systems, depending on fusion quality, may reduce the combined uncertainty expressed by an effective covariance

$$P_{eff} = \left(P_c^{-1} + P_n^{-1}\right)^{-1}$$

illustrating analytically how the combination of independent modalities yields improved estimation precision (50). This relation, constrained by the mathematical and physical assumptions of independence, forms a cornerstone of the comparative framework.

Another dimension of analysis concerns latency-induced uncertainty. Let T_c and T_n denote respective latencies of cooperative and non-cooperative updates. The induced position uncertainty in a closing encounter with relative speed v_r can be approximated as $\Delta r_m = v_r T_m$, which quantifies the distance traveled during the latency period. Cooperative systems often exhibit low mean latency but occasional bursts during interference or message queuing (51). Non-cooperative systems display higher mean latency but more stable variance. Hybrid fusion can reduce the effective latency uncertainty if measurements are asynchronously fused with predictive models. Thus, the probabilistic framework allows quantitative comparison of architectures under temporal as well as spatial uncertainty constraints.

In a mixed airspace operational context, no single surveillance approach uniformly dominates. Cooperative surveillance is optimal for well-equipped, high-infrastructure regions; non-cooperative surveillance is indispensable for heterogeneous or unregulated regions; hybrid architectures offer resilience and fault tolerance across varying conditions (52). The unified framework formalizes these distinctions by embedding both modalities into a shared mathematical language, making it possible to perform parametric studies of detect-and-avoid reliability as a function of environmental and system variables. The insights derived from this framework are valuable not for prescribing a fixed solution but for structuring systematic reasoning about architectural trade-offs.

The analysis underscores that performance-based evaluation, grounded in measurable metrics and probabilistic models, provides a rigorous and adaptable methodology for assessing surveillance architectures in mixed airspace. Cooperative systems yield high precision but limited inclusivity, non-cooperative systems yield broad inclusivity but higher uncertainty, and hybrid systems mediate between these extremes through informed fusion. The derived models and relationships support comparative assessments under consistent assumptions, reveal sensitivities to equipage and environmental variability, and furnish a foundation for future refinement as empirical data become available from operational testing. This balanced, quantitative perspective enables stakeholders to tailor surveillance architectures to mission-specific constraints while maintaining safety margins compatible with detect-and-avoid performance objectives across the evolving spectrum of mixed airspace operations (*53*).

References

1. D. Brus, J. Gustafsson, O. Kemppinen, G. de Boer, and A. Hirsikko, "Atmospheric aerosol, gases, and meteorological parameters measured during the lapse-rate campaign by the finnish meteorological institute and kansas state university," *Earth System Science Data*, vol. 13, pp. 2909–2922, 6 2021.
2. N. Rebolo-Ifrán, M. G. Grilli, and S. A. Lambertucci, "Drones as a threat to wildlife: Youtube complements science in providing evidence about their effect," *Environmental Conservation*, vol. 46, pp. 205–210, 6 2019.
3. A. Hildebrandt, "¡b¿jeffrey edmonds/samuel bendett/anya fink/mary chesnut/dmitry gorenburg/michael kofman/kasey stricklin/julian waller:¡/b¿ artificial intelligence and autonomy in russia. arlington, va: Center for naval analyses (cna), mai 2021," *SIRIUS – Zeitschrift für Strategische Analysen*, vol. 5, pp. 433–433, 11 2021.
4. R. S. Beltran, B. Ruscher-Hill, A. L. Kirkham, and J. M. Burns, "An evaluation of three-dimensional photogrammetric and morphometric techniques for estimating volume and mass in weddell seals leptonychotes weddellii.," *PloS one*, vol. 13, pp. e0189865–, 1 2018.
5. O. L. F. de Carvalho, R. dos Santos de Moura, A. O. de Albuquerque, P. P. de, R. de Castro Pereira, L. Weigang, D. L. Borges, R. F. Guimarães, R. A. T. Gomes, and O. A. de Carvalho Júnior, "Instance segmentation for governmental inspection of small touristic infrastructure in beach zones using multispectral high-resolution worldview-3 imagery," *ISPRS International Journal of Geo-Information*, vol. 10, pp. 813–, 11 2021.
6. A. Doddi, D. Lawrence, D. C. Fritts, L. Wang, T. S. Lund, W. O. J. Brown, D. Zajic, and L. Kantha, "Instabilities, dynamics, and energetics accompanying atmospheric layering (ideal) campaign: High-resolution in situ observations above the nocturnal boundary layer," pp. 1–33, 6 2021.
7. J. Bates, C. Montzka, M. Schmidt, and F. Jonard, "Estimating canopy density parameters time-series for winter wheat using uas mounted lidar," *Remote Sensing*, vol. 13, pp. 710–, 2 2021.
8. J. O. Birkeland, "The concept of autonomy and the changing character of war," *Oslo Law Review*, vol. 5, pp. 73–88, 9 2018.
9. M. G. Pensieri, M. Garau, and P. M. Barone, "Drones as an integral part of remote sensing technologies to help missing people," *Drones*, vol. 4, pp. 15–, 4 2020.
10. C. Kelleher, C. A. Scholz, L. E. Condon, and M. Reardon, "Drones in geoscience research: The sky is the only limit," *Eos*, vol. 99, 2 2018.
11. Y. Bühler, M. S. Adams, R. Bösch, and A. Stoffel, "Mapping snow depth in alpine terrain with unmanned aerial systems (uass): potential and limitations," *The Cryosphere*, vol. 10, pp. 1075–1088, 5 2016.
12. F. Zhou, L. Hou, R. Zhong, W. Chen, X. Ni, P. Shengda, Z. Ming, and B. An, "Monitoring compliance with fuel sulfur content regulations of sailing ships by unmanned aerial vehicle (uav) measurements of ship emissions in open water," pp. 1–15, 3 2020.
13. W. C. Kerfoot, M. M. Hobmeier, G. Swain, R. Regis, V. K. Raman, C. N. Brooks, A. G. Grimm, C. Cook, R. A. Shuchman, and M. K. Reif, "Coastal remote sensing: Merging physical, chemical, and biological data as tailings drift onto buffalo reef, lake superior," *Remote Sensing*, vol. 13, pp. 2434–, 6 2021.
14. M. B. Jamoom, A. Canolla, B. Pervan, and M. Joerger, "Unmanned aircraft system sense and avoid integrity: Intruder linear accelerations and analysis," *Journal of Aerospace Information Systems*, vol. 14, no. 1, pp. 53–67, 2017.
15. C. Kurkcu, H. Erhan, and S. Umut, "Human factors concerning unmanned aircraft systems in future operations," *Journal of Intelligent & Robotic Systems*, vol. 65, pp. 63–72, 11 2011.
16. J. del Cerro, C. C. Ulloa, A. Barrientos, and J. de León Rivas, "Unmanned aerial vehicles in agriculture: A survey," *Agronomy*, vol. 11, pp. 203–, 1 2021.
17. T. Wang, L. Yadong, M. Wang, F. Qing, H. Tian, X. Qiao, and Y. Li, "Applications of uas in crop biomass monitoring: A review," *Frontiers in plant science*, vol. 12, pp. 616689–616689, 4 2021.
18. M. S. Y. Hii, P. Courtney, and P. G. Royall, "An evaluation of the delivery of medicines using drones," *Drones*, vol. 3, pp. 52–, 6 2019.
19. J. A. Elmore, M. F. Curran, K. O. Evans, S. Samiappan, M. Zhou, M. B. Pfeiffer, B. F. Blackwell, and R. B. Iglay, "Evidence on the effectiveness of small unmanned aircraft systems (suas) as a survey tool for north american terrestrial, vertebrate animals: a systematic map protocol," *Environmental Evidence*, vol. 10, pp. 1–6, 6 2021.
20. S. G. Mathisen, F. S. Leira, H. H. Helgesen, K. Gryte, and T. A. Johansen, "Autonomous ballistic airdrop of objects from a small fixed-wing unmanned aerial vehicle," *Autonomous Robots*, vol. 44, pp. 859–875, 1 2020.
21. A. Andonov, ""open" category unmanned aerial systems harmonized standards and requirements complex," *International conference KNOWLEDGE-BASED ORGANIZATION*, vol. 25, pp. 74–80, 6 2019.
22. G. Lykou, D. Moustakas, and D. Gritzalis, "Defending airports from uas: A survey on cyber-attacks and counter-drone sensing technologies.," *Sensors (Basel, Switzerland)*, vol. 20, pp. 3537–, 6 2020.
23. R. Albertson, S. Schoenung, M. Fladeland, F. Cutler, and B. Tagg, "Enabling earth science measurements with nasa uas capabilites," *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, vol. XL-7/W3, pp. 1111–1117, 4 2015.
24. A. Konert and P. J. Kasprzyk, "Uas safety operation - legal issues on reporting uas incidents.," *Journal of intelligent & robotic systems*, vol. 103, pp. 51–, 10 2021.

25. M. R. A. Refaai, V. S. Dattu, N. Gireesh, E. Dixit, C. Sandeep, and D. Christopher, "Application of iot-based drones in precision agriculture for pest control," *Advances in Materials Science and Engineering*, vol. 2022, pp. 1–12, 8 2022.
26. V. Cichella, T. Marinho, D. M. Stipanovic, N. Hovakimyan, I. Kaminer, and A. C. Trujillo, "Collision avoidance based on line-of-sight angle," *Journal of Intelligent & Robotic Systems*, vol. 89, pp. 139–153, 3 2017.
27. R. Louali, A. Elouardi, S. Bouaziz, and M. S. Djouadi, "Experimental approach for evaluating an uav cots-based embedded sensors system," *Journal of Intelligent & Robotic Systems*, vol. 83, pp. 289–313, 12 2015.
28. F. Mei, G. R. McMeeking, M. Pekour, R.-S. Gao, G. Kulkarni, S. China, H. Telg, D. Dexheimer, J. Tomlinson, and B. Schmid, "Performance assessment of portable optical particle spectrometer (pops).," *Sensors (Basel, Switzerland)*, vol. 20, pp. 6294–, 11 2020.
29. C. Fu, M. A. Olivares-Mendez, R. Suarez-Fernandez, and P. Campoy, "Monocular visual-inertial slam-based collision avoidance strategy for fail-safe uav using fuzzy logic controllers," *Journal of Intelligent & Robotic Systems*, vol. 73, pp. 513–533, 10 2013.
30. V. Singh, "Delivery drone system," *International Journal for Research in Applied Science and Engineering Technology*, vol. 7, pp. 320–323, 5 2019.
31. V. Martel, R. C. Johns, L. Jochems-Tanguay, F. Jean, A. Maltais, S. Trudeau, M. St-Onge, D. Cormier, S. M. Smith, and J. Boisclair, "The use of uas to release the egg parasitoid trichogramma spp. (hymenoptera: Trichogrammatidae) against an agricultural and a forest pest in canada.," *Journal of economic entomology*, vol. 114, pp. 1867–1881, 2 2021.
32. K. Krasuski and D. Wierzbicki, "Application the sbas/egnos corrections in uav positioning," *Energies*, vol. 14, pp. 739–, 1 2021.
33. C. S. Tan, D. L. V. Bossuyt, and B. Hale, "System analysis of counter-unmanned aerial systems kill chain in an operational environment," *Systems*, vol. 9, pp. 79–, 11 2021.
34. P. Doherty, F. Heintz, and J. Kvarnström, "High-level mission specification and planning for collaborative unmanned aircraft systems using delegation," *Unmanned Systems*, vol. 1, pp. 75–119, 6 2013.
35. J. Pestana, J. L. Sanchez-Lopez, P. de la Puente, A. Carrio, and P. Campoy, "A vision-based quadrotor multi-robot solution for the indoor autonomy challenge of the 2013 international micro air vehicle competition," *Journal of Intelligent & Robotic Systems*, vol. 84, pp. 601–620, 11 2015.
36. S. d'Oleire Oltmanns, I. Marzolff, K. D. Peter, and J. B. Ries, "Unmanned aerial vehicle (uav) for monitoring soil erosion in morocco," *Remote Sensing*, vol. 4, pp. 3390–3416, 11 2012.
37. T. Adão, J. Hruška, L. Pádua, J. Bessa, E. Peres, R. Morais, and J. J. Sousa, "Hyperspectral imaging: A review on uav-based sensors, data processing and applications for agriculture and forestry," *Remote Sensing*, vol. 9, pp. 1110–, 10 2017.
38. M. Chung, C. Detweiler, M. Hamilton, J. Higgins, J.-P. Ore, and S. E. Thompson, "Obtaining the thermal structure of lakes from the air," *Water*, vol. 7, pp. 6467–6482, 11 2015.
39. S. Alaoui-Sosse, P. Durand, P. Medina, P. Pastor, M. Lothon, and I. Cernov, "Ovli-ta: An unmanned aerial system for measuring profiles and turbulence in the atmospheric boundary layer.," *Sensors (Basel, Switzerland)*, vol. 19, pp. 581–, 1 2019.
40. J. G. Escobar-Flores, S. Sandoval, and E. Gámiz-Romero, "Unmanned aerial vehicle images in the machine learning for agave detection.," *Environmental science and pollution research international*, vol. 29, pp. 61662–61673, 2 2022.
41. G. Albeaino and M. Gheisari, "Trends, benefits, and barriers of unmanned aerial systems in the construction industry: a survey study in the united states," *Journal of Information Technology in Construction*, vol. 26, pp. 84–111, 3 2021.
42. V. Sharov, P. Polyakov, and S. Tolstykh, "Practical applications of fuzzy set theory in flight safety management," *MATEC Web of Conferences*, vol. 341, pp. 00072–, 7 2021.
43. M. Turan, F. Gunay, and A. Aslan, "An analytical approach to the concept of counter-ua operations (cuaops)," *Journal of Intelligent & Robotic Systems*, vol. 65, pp. 73–91, 8 2011.
44. T. Vogeltanz, "A survey of free software for the design, analysis, modelling, and simulation of an unmanned aerial vehicle," *Archives of Computational Methods in Engineering*, vol. 23, pp. 449–514, 3 2015.
45. G. B. H. de Azevedo, B. Doyle, C. A. Fiebrich, and D. Schvartzman, "Low-complexity methods to mitigate the impact of environmental variables on low-cost uas-based atmospheric carbon dioxide measurements," *Atmospheric Measurement Techniques*, vol. 15, pp. 5599–5618, 10 2022.
46. A. Islam, A. L. Houston, A. Shankar, and C. Detweiler, "Design and evaluation of sensor housing for boundary layer profiling using multirotors," *Sensors (Basel, Switzerland)*, vol. 19, pp. 2481–, 5 2019.
47. A. C. Canolla, M. B. Jamoom, and B. Pervan, "Unmanned aircraft systems detect and avoid sensor hybrid estimation error analysis," in *17th AIAA Aviation Technology, Integration, and Operations Conference*, p. 4384, 2017.
48. G. Loukas, D. Gan, and T. Vuong, "A review of cyber threats and defence approaches in emergency management," *Future Internet*, vol. 5, pp. 205–236, 5 2013.
49. R. J. Wallace, K. M. Kiernan, T. Haritos, J. Robbins, and J. M. Loffi, "Evaluating small uas operations and national airspace system interference using aeroscope," *Journal of Aviation Technology and Engineering*, vol. 8, pp. 24–, 5 2019.
50. B. Altstädter, K. Deetz, B. Vogel, K. Babić, null Dione, F. Pacifico, C. Jambert, F. Ebus, K. Bärfuss, F. Pätzold, A. Lampert, B. Adler, N. Kalthoff, and F. Lohou, "The vertical variability of black carbon observed in the atmospheric boundary layer during dacciwa," *Atmospheric Chemistry and Physics*, vol. 20, pp. 7911–7928, 7 2020.
51. S. Komasová, "Possible inspiration: Drone-related literature and its potential for public perception research," *Journal of Intelligent & Robotic Systems*, vol. 103, pp. 54–, 10 2021.

52. G. Skorobogatov, C. Barrado, and E. Salamí, “Multiple uav systems: A survey,” *Unmanned Systems*, vol. 8, pp. 149–169, 4 2020.
53. E. W. Frew and T. X. Brown, “Networking issues for small unmanned aircraft systems,” *Journal of Intelligent and Robotic Systems*, vol. 54, pp. 21–37, 7 2008.