Impact of Adverse Weather on Unmanned Aircraft Detect-and-Avoid Performance: Modeling, Simulation, and Operational Mitigations

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Abstract

Unmanned aircraft systems increasingly operate in airspace where reliable detect-and-avoid capabilities are required to maintain separation from cooperative and non-cooperative traffic. These systems are exposed to a wide spectrum of adverse weather phenomena that can alter both sensor performance and aircraft dynamics. Practical deployment scenarios in lower airspace, beyond-visual-line-of-sight corridors, and mixed-use terminal areas highlight the need to characterize how rain, fog, low clouds, snow, icing, turbulence, and convective activity affect detect-and-avoid decision quality, and how operational mitigations may be structured. This work develops a modeling and simulation framework that couples stochastic representations of adverse weather with parametric models of airborne and ground-based surveillance sensors, track filters, and conflict resolution logics. Weather is represented as a spatially and temporally correlated disturbance acting simultaneously on electromagnetic propagation, measurement quality, and vehicle motion. The detect-and-avoid system is represented at the level of detection probabilities, false alarm characteristics, state estimation error growth, and trajectory prediction uncertainty, all conditioned on weather intensity and structure. Monte Carlo simulations are used to explore conditions under which separation minima are approached or lost, with emphasis on parameter regimes that are plausible for small and medium unmanned aircraft operating in layered traffic. Results are interpreted in terms of performance envelopes and conservative triggers for operational mitigations, such as adaptive minima, route structure adjustments, or temporary restrictions. The study aims to provide a technically transparent basis for relating measurable weather products to detect-and-avoid performance margins without overstating capability.

1 Introduction

Detect-and-avoid functionality for unmanned aircraft is intended to provide an acceptable level of risk with respect to loss of separation or collision while enabling routine operations in airspace shared with crewed aircraft and other unmanned systems [1]. As detect-and-avoid concepts mature, attention has shifted from nominal performance demonstrations to systematic characterization under off-nominal and degraded conditions. Adverse weather is a central contributor to such degradations. It modifies underlying aircraft dynamics, influences pilot in the loop or supervisory control when present, and directly impacts the sensing and estimation elements that detect-and-avoid systems rely upon [2]. These elements include cooperative surveillance such as automatic dependent surveillance broadcast, non-cooperative primary radar, electro-optical and infrared sensors, acoustic sensing, and onboard or networked traffic information sources.

A range of atmospheric phenomena can modify detect-and-avoid performance along multiple channels. Precipitation attenuates and scatters radio-frequency and optical signals [3]. Fog and low clouds affect visual-band and infrared sensing, and can lead to persistent obscuration of traffic or terrain features. Turbulence and gust fronts introduce high-frequency perturbations in aircraft motion, affecting both the host unmanned aircraft and nearby traffic, thereby coupling weather into the relative state dynamics driving conflict detection algorithms. Icing alters aerodynamic characteristics, navigation system reliability, and achievable maneuvering capability, which in turn influences the feasibility of proposed resolution trajectories. Strong convection and embedded cells can create spatially heterogeneous regions in which detect-and-avoid performance varies significantly along a single flight path. [4]

Existing detect-and-avoid evaluations often assume standardized sensor characteristics and relatively benign atmospheric conditions, leading to performance estimates that may not generalize to operationally relevant weather regimes. At the same time, weather-aware guidance and operational constraints are typically specified at a relatively coarse granularity, often without explicit linkage to quantitative detect-and-avoid performance metrics. This creates a gap between regulatory or operational prescriptions and the underlying technical behavior of detect-and-avoid subsystems under realistic atmospheric disturbances [5]. A more direct coupling between measurable weather parameters, sensor and estimator behavior, and conflict resolution logic is needed to support robust operational envelopes.

This paper develops a technical framework to represent the interaction between adverse weather and detect-and-avoid performance for unmanned aircraft in a neutral manner. The approach is built around three elements: stochastic models of adverse weather fields and their impact on sensing and dynamics; analytical and semi-analytical models of detection, tracking, and conflict prediction under degraded conditions; and a Monte Carlo simulation architecture that samples weather, traffic, and system parameters to generate empirical distributions of key safety-related metrics. The focus is on representing mechanisms and sensitivities rather than prescribing specific quantitative minima [6]. The framework is then used to identify operational mitigations expressed as constraints or adaptations that are directly rooted in modeled relationships, such as dynamic limits on corridor usage, speed-altitude combinations, or detect-and-avoid alerting thresholds as functions of filtered weather inputs.

Table 1: Representative weather mechanisms and their primary modeled effects

Weather Effect	Impacted Element	Modeled Outcome
Attenuation	RF/optical sensing	Reduced P_D, higher noise variance
Visibility loss	EO/IR	Shorter effective range, missed intruders
Turbulence	Dynamics	Stochastic motion and covariance growth

Table 2: Key model blocks linking weather inputs to detect-and-avoid behavior

Model Block	Input from Weather	Output to DAA
Random fields	Intensity, correlation	Local attenuation and wind profiles
Sensor layer	Indices θ	$P_D(\theta)$, $\sigma^2(\theta)$
Dynamics	Wind, turbulence	Disturbed trajectories and envelopes

Table 3: Core elements of the Monte Carlo simulation framework

Simulation Element	Description	Purpose
Encounter set	Sampled host and intruders	Represent diverse traffic geometries
Weather samples	Realizations of fields	Capture variability across regimes
DAA policy	Fixed mapping	Evaluate alerts and maneuvers

2 Foundations of Weather-Sensitive Detect-and-Avoid Performance

Detect-and-avoid performance in unmanned aircraft operations can be framed as an emergent property of coupled subsystems acting under environmental uncertainty. Before constructing detailed stochastic models, it is useful to formalize how adverse weather feeds into safety-relevant metrics through sensing, estimation, control, and traffic encounter geometry [7]. The central objects of interest are the random processes describing host and intruder kinematics, the random fields describing weather, and the decision rules that map partial information into avoidance actions. In this context, performance is characterized not by isolated sensor probabilities or deterministic encounter outcomes, but by the induced distribution of minimum separation distances and associated alerting and maneuvering timelines, conditioned on weather-dependent information quality. This section develops a system-level formulation that links weather to detect-and-avoid behavior via abstract functional relationships and compact

Table 4: Primary performance metrics used to interpret weather impacts

Metric	Meaning	Use in Study
$P_{\mathrm{LOS}}(W)$	Loss-of-separation chance	Sensitivity of safety to weather class
Alert rate	Frequency of triggers	Balance between responsiveness and burden
Lead time	Margin before conflict	Feasibility under degraded performance

Table 5: Representative operational mitigations grounded in modeled sensitivities

Mitigation Type	Mechanism	Modeled Basis
Adaptive minima	Adjust $d_{\min}$ with θ	Reflects uncertainty growth and envelopes
Sensor conditions	Modality requirements	Triggered by degradation indicators
Traffic measures	Corridors, caps	Reduce encounter complexity in severe regions

mathematical structures [8]. The aim is to expose dependencies, rather than to assign fixed threshold values, and thus to provide a neutral foundation for subsequent modeling and simulation.

Consider a host unmanned aircraft H and one or more intruders I_j within a finite region of airspace. Let $x_h(t)$ and $x_j(t)$ denote their states, including position and velocity components. For a given intruder, define the joint state

$$z(t) = \begin{pmatrix} x_h(t) \\ x_j(t) \end{pmatrix}.$$

The relative state is $r(t) = r_j(t) = p_j(t) - p_h(t)$, with $p_h(t)$ and $p_j(t)$ the position vectors. Weather is represented by a random element W summarizing relevant atmospheric variables over the spatial-temporal domain of interest. In a reduced description, W is captured through indices such as attenuation level, turbulence intensity, icing potential, and visibility category, acknowledging that each index may itself be derived from an underlying random field [9]. The detect-and-avoid system observes $z(t)$ only through measurements whose distribution depends on both $z(t)$ and W, and issues resolution commands that must remain consistent with weather-modified vehicle capabilities.

From a system perspective, detect-and-avoid can be described as a mapping from the history of weather-conditioned observations to a sequence of binary or graded decisions regarding alerting and maneuver execution. Let $Y_{0:t}$ denote the measurement history up to time t, and let $U_{0:t}$ denote the control history for the host. The detect-and-avoid policy is an abstract function π such that [10]

$$U_{0:t} = \pi(Y_{0:t}, W^*)$$

where W^* represents the weather information available to the system or operator, which may be a filtered or coarsely classified version of the true W. Even when weather products are external, such as ground-based radar or numerical forecasts, they effectively enter into the decision logic and thus must be included in the information set. Under this construction, performance is evaluated over the joint distribution of $(z(t), W, Y_{0:t})$ induced by encounter models, weather models, and policy π. The presence of adverse weather alters this distribution through three channels: it modifies the dynamics of $z(t)$, it alters the measurement process that forms $Y_{0:t}$, and it changes the feasible set of controls contained in $U_{0:t}$.

A central safety-related quantity is the probability of loss of separation or collision over an encounter horizon. Let $D_{\min}$ be the minimum Euclidean distance between host and intruder during the considered interval. A generic loss-of-separation event is $\{D_{\min} \leq d_{\min}\}$, where $d_{\min}$ encodes the protected volume radius. For a given policy π, define

$$P_{\mathrm{LOS}}(W) = P\big(D_{\min} \leq d_{\min} \,\big|\, W\big).$$

This conditional probability expresses how likely a loss of separation is under a specific weather realization or weather class [11]. The marginal risk over a distribution of weather conditions with density $f_W(w)$ is

$$R = \int P_{\mathrm{LOS}}(w) f_W(w)\, dw.$$

In practice, neither $P_{\mathrm{LOS}}(w)$ nor $f_W(w)$ is exactly known, but this representation clarifies that detect-and-avoid performance in adverse weather cannot be decoupled from the statistics of environmental exposure. The modeling

Table 6: Synthesis of design insights emerging from the framework

Design Insight	Source	Implication
Weather as input	Stochastic modeling	DAA tuning tied to measurable indices
Model transparency	Structured relations	Supports cautious, revisable envelopes

task is to approximate $P_{\mathrm{LOS}}(w)$ through mechanistic descriptions of sensors, estimators, and maneuvers as functions of w, then to explore how operational mitigations may reshape R by modifying exposure, policy, or both.

Weather-sensitive detect-and-avoid assessment must also account for the balance between sufficient alerting and excessive alerting. Let $A(W)$ denote the rate or probability of unnecessary alerts (for example, alerts issued when $D_{\min} > d_{\min}$ would have been maintained without intervention). Similarly, let $T(W)$ characterize the distribution of alert lead times under weather condition W, relative to the earliest time at which feasible avoidance remains available given degraded maneuverability. A minimal performance representation involves the triplet $(P_{\mathrm{LOS}}(W), A(W), T(W))$. These functions depend on the detailed internal structure of π and the degradation of sensing and actuation with weather, but they provide a conceptually compact set of axes along which weather-induced changes can be understood [12]. Operational mitigations, when formulated analytically, can be viewed as controlled transformations of π or of the operating region in the space of W that alter these axes within specified bounds.

To establish a concrete link between weather and sensing, consider a generic measurement process for a single sensor modality. Let the ideal measurement of relative position be $h(r(t))$ [13]. Under adverse weather with index θ, the realized measurement at time t_k is

$$y_k = h(r(t_k)) + \epsilon_k(\theta)$$

with probability $P_D(\theta)$, and no measurement with probability $1-P_D(\theta)$. Here $\epsilon_k(\theta)$ is zero-mean noise with variance $\sigma^2(\theta)$. This stylized formulation isolates two effects: a reduction in observation frequency as detections are missed more often at higher θ, and a deterioration in the quality of available data. Both are monotone non-decreasing functions of adverse weather intensity in many physical scenarios. For example,

$$P_D(\theta) = \exp(-\beta\theta)[14]$$

and

$$\sigma^2(\theta) = \sigma_0^2(1 + \gamma\theta)$$

with $\beta, \gamma \geq 0$ provide an analytically manageable representation. While simple, these functions suffice to demonstrate how weather propagates into estimation error growth and thus into conservative conflict detection.

The estimation process forms an internal representation of relative state $\hat{r}(t)$ and associated uncertainty, which together drive conflict logic. In a linearized setting with state transition matrix F and process noise covariance Q, the error covariance $P(t)$ evolves through alternating prediction and update steps, with updates contingent on successful detections [15]. Adverse weather increases the expected prediction interval between updates and inflates measurement noise, both of which increase $\operatorname{tr} P(t)$. Under moderate conditions, this primarily leads to more conservative alerts as conflict logic reacts to enlarged uncertainty sets. Under more severe conditions where detections become sporadic and uncertainty grows substantially, conflict logic may oscillate between delayed alerts and extended periods without reliable tracks, potentially raising both $P_{\mathrm{LOS}}(W)$ and $A(W)$. The same weather realization thus influences safety risk and operational burden through a common mechanism: degradation of the internal state estimate.

Vehicle performance limits under weather introduce an additional coupling. Let the host lateral and vertical maneuver envelopes be described by bounds on achievable accelerations and climb or descent rates [16]. Under adverse conditions characterized by index θ, these bounds may be modeled as

$$a_{\max}(\theta) = a_0(1 - k_a\theta)$$

$$v_{\mathrm{climb}}(\theta) = v_0(1 - k_v\theta)$$

for non-negative coefficients k_a, k_v and θ constrained so that the right-hand sides remain positive. These expressions, while idealized, reflect reductions in margins due to turbulence, icing, and contaminated lifting surfaces. When conflict detection triggers an avoidance maneuver, the feasibility of maintaining separation depends on these degraded bounds [17]. For a given alert lead time Δt, the reachable set of relative states that can be steered away from the protected volume shrinks with increasing θ. Consequently, the same alerting logic may yield an acceptable $P_{\mathrm{LOS}}(W)$ in benign weather but become insufficient under more restrictive envelopes, illustrating why weather-conditioned performance cannot be inferred solely from fair-weather validation.

Encounter modeling interacts with weather in ways that can be structurally represented without imposing specific traffic densities. Let Ξ denote the set of encounter parameters, including initial positions, velocities, headings, and any intent structure. Assume a joint density $f_{\Xi,W}(\xi, w)$ describing how encounter geometries and weather co-occur. For example, certain adverse weather regimes may correlate with particular routing practices or with reduced densities in some regions and increased densities in others [18]. The probability of loss of separation under policy π can then be written abstractly as

$$P_{\mathrm{LOS}} = \int P\big(D_{\min} \leq d_{\min} \,\big|\, \xi, w, \pi\big) f_{\Xi,W}(\xi, w)\, d\xi\, dw.$$

This expression underscores that detect-and-avoid performance in adverse weather is a joint property of systems, environment, and operational patterns. Even when weather degrades sensing, changes in encounter distributions induced by conservative operational choices may reduce overall risk, while in other cases traffic compression or rerouting around weather may increase interaction densities and partially offset system-level gains. [19]

To guide operational mitigations without embedding prescriptive thresholds, a scalar performance index can be defined as a function of the key quantities associated with a given policy and weather class. One illustrative index is

$$J = \alpha R + \eta \bar{A} + \rho \bar{C}$$

where R is the overall loss-of-separation probability, $\bar{A}$ is a normalized measure of unnecessary alerts, $\bar{C}$ is a measure of control effort or deviation from nominal trajectories, and α, η, ρ are non-negative weighting coefficients reflecting neutral trade-offs between safety, operational stability, and efficiency. This index does not assert any particular acceptable value but serves as a compact representation for comparing alternative policies or mitigation strategies under varying distributions of W [20]. For instance, enabling weather-adaptive alert thresholds changes π, thereby modifying $(R, \bar{A}, \bar{C})$ and hence J. The modeling and simulation approach described in other sections can be interpreted as an attempt to approximate these components of J in a manner consistent with mechanistic understanding of weather impacts.

Crucially, the structure outlined here recognizes imperfect weather information. The detect-and-avoid policy in practice does not condition on the true W but on some observation or classification W^*. This leads to situations in which the system applies mitigation strategies tuned to an estimated weather class that may not fully match the local microphysical conditions affecting sensing and dynamics. The relationship between W and W^* can be represented probabilistically via a confusion matrix or conditional density, and this representation can be embedded into the performance integrals. The result is that even well-designed weather-adaptive strategies will exhibit residual mismatch-driven effects, which should be reflected in modeled distributions of $P_{\mathrm{LOS}}(W)$ and $A(W)$ rather than being neglected.

Within this foundational view, adverse weather does not appear merely as a binary constraint that either permits or prohibits unmanned aircraft operations [21]. Instead, it enters as a quantitative modifier of the information structure, maneuver envelope, and encounter statistics that together determine detect-and-avoid outcomes. A neutral technical treatment emphasizes the sensitivity of those outcomes to the chosen abstractions of weather, the fidelity of sensor and dynamics models, and the realism of encounter assumptions. The subsequent modeling choices, including simple parametric forms for detection probabilities and performance degradation, are selected for analytical tractability and interpretability, not as definitive characterizations of specific systems [22]. This structured perspective supports the later development of stochastic weather fields, sensor models, Monte Carlo simulations, and candidate operational mitigations that are explicitly traceable to identified mechanisms rather than to implicit or ad hoc assumptions.

3 Adverse Weather Phenomena and Detect-and-Avoid Architecture

Detect-and-avoid performance is conditioned by both the physical environment and the internal architecture of sensing, estimation, and decision subsystems. Adverse weather acts through several partially coupled mechanisms. First, it modifies electromagnetic propagation through attenuation, scattering, refraction, and depolarization [23]. Second, it perturbs platform motion through turbulence, wind shear, and convective updrafts or downdrafts. Third, it alters environmental clutter, including hydrometeors and background radiance, affecting detection of low-contrast or small targets. A technical description of these mechanisms provides the basis for subsequent mathematical modeling. [24]

For radio-frequency sensors, precipitation and cloud liquid water can be represented by an equivalent specific attenuation coefficient that depends on frequency, hydrometeor size distribution, and polarization. For optical systems, extinction due to aerosols, fog, or cloud droplets is described through visibility metrics that relate to the extinction coefficient governing contrast reduction. Infrared sensors are affected by both extinction and thermal emission from clouds and hydrometeors, which modify the apparent radiance contrast between target and background [25]. Acoustic sensing, when applicable for low-altitude unmanned aircraft, is influenced by wind, turbulence, and precipitation noise that may reduce signal-to-noise ratios for propeller or engine signatures. These mechanisms lead to reductions in effective detection range and increases in measurement noise variance for detected targets.

The detect-and-avoid architecture typically integrates multiple sensing modalities. Cooperative surveillance provides state information for appropriately equipped traffic using communication-based broadcast [26]. Non-cooperative detection relies on onboard radar or optical sensors. Data association and state estimation modules fuse measurements and propagate state estimates with associated covariance. Conflict detection logic evaluates predicted relative trajectories to generate alerts, while resolution logic selects maneuvers or guidance modifications consistent with aircraft performance and airspace constraints [27]. Adverse weather influences each of these blocks differently. Cooperative surveillance using data links may be less sensitive to visibility but can be affected by precipitation-induced attenuation or multipath. Primary radar is sensitive to attenuation and hydrometeor clutter. Optical systems degrade significantly with reduced visibility [28]. Estimation performance is sensitive to the frequency and quality of measurements, and conflict logic is sensitive to uncertainty growth driven by both sensing and dynamics.

A structured representation of the architecture in the presence of weather-induced perturbations recognizes that detect-and-avoid performance is not characterized by a single scalar metric but by a joint distribution of detection probabilities, false alarm rates, track continuity, and conflict resolution feasibility, conditioned on specific realizations of weather fields. The models developed in subsequent sections treat adverse weather as a random field that drives parametric modifications in the sensing and dynamic models, allowing detect-and-avoid performance to be represented quantitatively as a function of weather descriptors. [29]

4 Stochastic Modeling of Weather-Induced Disturbances

To capture spatially and temporally varying weather conditions, adverse weather is modeled as one or more stochastic fields defined over four-dimensional space-time. Let $x \in R^3$ denote position and t denote time. Consider a scalar field $w(x,t)$ representing a weather intensity variable, such as specific attenuation at a representative frequency or an extinction coefficient relevant to visibility. For analytic tractability, $w(x,t)$ can be decomposed as

$$w(x,t) = \mu_w + \tilde{w}(x,t)$$

where μ_w is a mean level associated with a broad weather regime and $\tilde{w}(x,t)$ is a zero-mean random fluctuation.

Assume $\tilde{w}(x,t)$ is second-order stationary within a localized region and admit a covariance function

$$C_w(\Delta x, \Delta t) = E[\tilde{w}(x,t)\tilde{w}(x+\Delta x, t+\Delta t)].$$

A practical choice for C_w in this context is an exponential or Matérn form with specified spatial and temporal correlation lengths, allowing the generation of weather realizations that vary smoothly over typical detect-and-avoid engagement scales. The intensity of adverse weather, such as convective cores or dense fog layers, is captured by the variance of $\tilde{w}$ and the chosen correlation parameters.

Wind and turbulence effects on aircraft dynamics are represented through a velocity disturbance field $v_w(x,t)$. For a host unmanned aircraft with nominal velocity $v_0(t)$, the actual velocity becomes

$$v(t) = v_0(t) + v_w(x(t), t)$$

where v_w is modeled using a spectral representation or shaping filter driven by white noise to match prescribed turbulence intensities and scales. A similar disturbance applies to intruder traffic when subject to the same or different weather realization [30]. This formulation leads to stochastic relative dynamics, with the relative position $r(t)$ between host and intruder influenced by correlated or uncorrelated wind fields, depending on separation distance and weather structure.

The coupling between weather fields and sensing is modeled via parametric mappings from $w(x,t)$ to sensor-level degradation factors. For instance, an attenuation field $a(x,t)$ along a line-of-sight segment between host and intruder of length L can be approximated by [31]

$$a(t) = \int_0^L \alpha(s,t)\, ds$$

with α derived from w. Under homogeneous conditions along the path, $a(t)$ reduces to $Lw(x^*, t)$ for some representative point x^*, remaining well within the width constraints for the mathematical expression. The resulting attenuation informs the effective signal-to-noise ratio of radio-frequency or optical measurements, which is subsequently mapped to detection probability and measurement noise variance. Through this construction, the stochastic weather field becomes an exogenous process driving both dynamics and sensing models within the detect-and-avoid system. [32]

5 Sensor, Estimation, and Conflict Modeling Under Degradation

The detect-and-avoid system is abstracted as a sequence of transformations from underlying relative state to measurements, to state estimates, and finally to conflict indicators and resolution trajectories. Under adverse weather, each transformation is parameterized by weather-dependent quantities. Let the true relative state between intruder and host be

$$z(t) = [33] \begin{pmatrix} r(t) \\ \dot{r}(t) \end{pmatrix}$$

where $r(t)$ is relative position and $\dot{r}(t)$ relative velocity in a chosen coordinate frame. Sensors produce measurements

$$y_k = h(z(t_k)) + \epsilon_k$$

where h is the observation function and ϵ_k represents measurement noise and missed detections. Adverse weather is modeled as modifying both the probability of receiving a measurement and the distribution of ϵ_k.

For a given sensor and weather intensity level θ derived from $w(x,t)$, define a detection probability function $P_D(\theta, R)$ where R is range, and a false alarm rate $\lambda_F(\theta)$. A simplified parametric form, restricted in width, is [34]

$$P_D(\theta, R) = \exp(-\beta_1 \theta R)$$

with β_1 a non-negative parameter. Measurement noise variance $\sigma^2(\theta)$ can be expressed as

$$\sigma^2(\theta) = \sigma_0^2(1 + \beta_2 \theta)$$

with σ_0^2 the nominal variance and β_2 a tuning parameter. These formulations maintain mathematically concise expressions while capturing monotone degradation with increasing adverse weather intensity.

State estimation is performed, for example, via a linearized Kalman filter or an equivalent Bayesian estimator. Let $\hat{z}(t)$ denote the estimate and $P(t)$ the estimation error covariance. Under intermittent observations with weather-dependent detection probabilities, the covariance evolves as

$$P_{k+1}^- = F P_k^+ F^\top + Q$$

$$P_{k+1}^+ = (I - K_{k+1} H) P_{k+1}^-$$

when a detection is present, with F the state transition matrix, Q the process noise covariance incorporating dynamic disturbances, and H the linearized observation matrix [35]. The gain K_{k+1} depends on $\sigma^2(\theta)$. When no detection occurs, the update step is skipped and the covariance remains P_{k+1}^-. Weather thus drives both an increase in effective process noise through turbulence and a reduction in update frequency and quality, leading to growth in $P(t)$ and increased uncertainty in relative state.

Conflict detection is based on predicting whether the relative state will enter a protected volume. For a deterministic prediction horizon τ, a simple closest point of approach evaluation uses the predicted relative position [36]

$$r_\tau = r(t) + \tau \dot{r}(t)$$

under constant relative velocity assumption for illustration. A conflict is declared when $\|r_\tau\|$ falls below a separation threshold. Under uncertainty, the relative state is a random vector with covariance derived from $P(t)$. A conservative probabilistic conflict indicator may be defined by requiring that [37]

$$P(\|r_\tau\| \leq d_{\min}) \geq \gamma$$

for some probability level γ. In practice, this probability is approximated using Gaussian assumptions on r_τ with covariance inflated due to adverse weather. Higher weather severity θ increases uncertainty and can lead to earlier or more frequent conflict alerts. Conversely, severe degradation may induce missed conflicts if detections are lost, illustrating the need to jointly characterize probabilities of late or missed alerts and probabilities of unnecessary alerts as functions of weather.

Resolution generation considers candidate maneuvers $u(t)$ constrained by host unmanned aircraft performance, which may be altered by icing or turbulence [38]. Let a simplified lateral acceleration bound under weather condition θ be

$$a_{\max}(\theta) = a_0(1 - \beta_3 \theta)$$

with a_0 nominal capability and $\beta_3 \theta < 1$. Reduced maneuverability shrinks the reachable set of trajectories that maintain separation once an alert is issued. Integrating sensor degradation and maneuver constraints provides a consistent view of detect-and-avoid performance under weather, relating detection opportunities, estimation error, and feasible conflict resolutions. [39]

6 Monte Carlo Simulation Framework and Performance Metrics

To explore detect-and-avoid behavior across weather regimes and operational geometries, a Monte Carlo simulation framework is constructed around the models introduced above. Each simulation trial draws a realization of the weather field, traffic configuration, and system parameter set, then propagates the coupled dynamics of host aircraft, intruders, sensors, estimators, and conflict logic. This produces empirical distributions of performance metrics without assuming a single deterministic outcome for any given condition.

For each trial, the host flight plan is specified as a nominal trajectory segment [40]. Intruder trajectories are sampled from distributions over initial positions, headings, speeds, and vertical profiles consistent with the relevant airspace. The stochastic weather field $w(x, t)$ is instantiated using a spectral or covariance-based generator, ensuring correlation lengths compatible with the scale of detect-and-avoid encounters. The wind disturbance $v_w(x, t)$ is jointly sampled such that its statistical properties match the adverse weather intensity class under consideration. These realizations determine the time-varying attenuation, visibility, and turbulence that act on sensing and dynamics. [41]

Sensor measurement processes are simulated by drawing random detections conditioned on $P_D(\theta, R)$ and superimposing noise with variance $\sigma^2(\theta)$ on range, bearing, or other measurement components. False alarms are generated according to a Poisson process with rate $\lambda_F(\theta)$. The resulting measurements are processed by the estimation algorithm, which updates $\hat{z}(t)$ and $P(t)$ over time. The conflict detection logic evaluates probabilistic conflict indicators at each decision step. When a threshold is exceeded, a resolution maneuver is synthesized within the bounds of $a_{\max}(\theta)$ and any additional operational constraints.

Performance metrics are defined to avoid overstatement while capturing essential aspects of detect-and-avoid behavior. One metric is the probability that the minimum separation between host and any intruder remains above the protected volume radius given the presence of adverse weather. Another metric is the conditional probability of issuing a timely alert, defined as an alert that occurs with sufficient lead time for at least one feasible maneuver within the degraded performance envelope [42]. A complementary metric is the rate of unnecessary alerts in which the protected volume would not have been penetrated even in the absence of a resolution, driven by uncertainty inflation or transient false tracks. Additional measures include track continuity statistics, such as average track life and gap duration under varying weather intensities.

The Monte Carlo construction supports systematic variation of weather parameters [43]. For example, one can define discrete weather classes indexed by θ_i associated with increasing attenuation or turbulence levels, and evaluate the empirical mapping from θ_i to loss-of-separation probability, alert lead time distributions, and alert frequency. It is also possible to vary sensor configurations to examine the effect of redundancy. When multiple sensors are present, joint detection probability models combine modality-specific P_D functions. The framework thereby exposes interactions where one sensor class maintains partial performance under conditions that strongly degrade another, as in the case of radio-frequency surveillance complementing impaired optical systems in low visibility.

By treating weather as a primary exogenous input, the simulation results can be organized as weather-conditioned performance envelopes [44]. For each weather class, and for each nominal operational scenario, empirical confidence bounds on key metrics are computed. These bounds are interpreted as technical inputs to operational mitigations rather than as definitive regulatory limits, acknowledging that underlying models and parameterizations are subject to uncertainty and that additional validation would be needed for specific systems.

7 Weather-Conditioned Operational Mitigation Strategies

Given quantitative relationships between weather intensity and detect-and-avoid performance, operational mitigations can be defined that adjust how unmanned aircraft are permitted or configured to operate in specific adverse conditions. Rather than treating weather exclusions as static binary constraints, the intent is to articulate structured adaptations whose logic follows from the underlying models without overstating robustness or risk reduction. [45]

One class of mitigations involves weather-conditioned separation buffers. Suppose simulation results indicate that estimation uncertainty and maneuverability degradation under a given θ increase the probability of loss of separation if nominal thresholds are maintained. An operational response is to increase minimum separation distances or alerting thresholds in proportion to weather-induced uncertainty growth [46]. In technical terms, a mapping from weather index θ to protected volume radius $d_{\min}(\theta)$ can be defined such that, for each class, the modeled probability of loss of separation remains within an agreed tolerance. This adaptation is implemented at the level of detect-and-avoid logic by adjusting its trigger criteria based on filtered weather inputs, provided such adjustments remain within system design constraints and are communicated to relevant stakeholders.

Another mitigation involves restrictions on reliance on particular sensing modalities when their performance is strongly weather-dependent. For example, in conditions with high extinction, onboard electro-optical sensing for non-cooperative detection may contribute minimally to effective detect-and-avoid performance. In such cases, operational policies may specify that beyond-visual-line-of-sight operations in certain volumes require the presence and integrity of less weather-sensitive surveillance sources, or impose altitude and route constraints that preserve separation given reduced detection range [47]. The modeling framework allows one to identify weather regimes in which single-modality detect-and-avoid becomes insufficient for maintaining the desired performance envelope, suggesting when redundancy is operationally necessary.

Traffic flow management measures constitute another category of mitigations. Under strongly heterogeneous weather fields, detect-and-avoid performance may vary markedly over short spatial scales [48]. Defining corridors that avoid regions of severe attenuation or turbulence, or temporarily limiting traffic density in affected sectors, directly reduces the number and complexity of potential encounters. In the modeling framework, such measures correspond to conditioning Monte Carlo experiments on constrained geometries or reduced encounter rates, and observing the resulting changes in performance metrics. Mapping these changes back to operationally meaningful triggers involves defining thresholds in weather products that, when exceeded, initiate corridor reconfiguration, altitude caps, or other traffic management actions. [49]

Mitigations can also target the detect-and-avoid algorithms themselves through configurable parameters. Alerting thresholds, conflict look-ahead times, and track confirmation rules can be made weather-aware within defined limits. For example, in moderate turbulence conditions where state estimation uncertainty grows more rapidly, extending look-ahead time and reducing the probability threshold for declaring potential conflict can counteract increased uncertainty, at the cost of higher alert rates. The modeling structure quantifies this trade, allowing an operator or certifying entity to select parameter schedules that maintain a balance between timely alerts and manageable false alarms for each weather class. [50]

These strategies remain conditional on the assumptions and abstractions of the models and simulations. They are not asserted as universally sufficient but as structurally aligned with the observed sensitivities of detect-and-avoid performance to adverse weather. Their usefulness depends on accurate and timely weather characterization, reliable integration of weather indicators into detect-and-avoid and operational decision-making processes, and continuous reassessment as more empirical data from real operations becomes available. [51]

8 Conclusion

This paper has presented a technical framework for examining the impact of adverse weather on unmanned aircraft detect-and-avoid performance through combined modeling, simulation, and operationally oriented interpretation. Adverse weather phenomena were treated as stochastic fields that influence both sensor performance and vehicle dynamics. Within this representation, detect-and-avoid systems were modeled in terms of detection probabilities, false alarm characteristics, state estimation processes, and conflict detection and resolution logic, all parameterized by weather intensity indicators. Concise mathematical expressions were used to connect weather variables to sensing degradation and maneuverability limits, enabling tractable propagation of weather effects into detect-and-avoid metrics. [52]

A Monte Carlo simulation architecture was outlined to generate empirical distributions of safety-relevant quantities under diverse weather and traffic conditions. By systematically varying weather parameters and system configurations, the framework supports the construction of weather-conditioned performance envelopes that identify parameter regimes in which detect-and-avoid capabilities are relatively robust and regimes in which they are significantly weakened. Emphasis was placed on maintaining a neutral interpretation of these envelopes, viewing them as tools for understanding sensitivities rather than as definitive certification standards. [53]

Based on the modeled relationships, several classes of operational mitigations were discussed, including weather-dependent separation buffers, modality-specific constraints, traffic flow adjustments, and limited algorithmic adaptations. These mitigations are framed as structurally consistent responses to quantified degradations rather than as comprehensive solutions. The overall approach underscores that integrating weather considerations into detect-and-avoid design and operation calls for explicit mappings from measurable atmospheric conditions to detect-and-avoid performance, supported by transparent models and simulations. Such mappings can assist in shaping cautious, evidence-informed operational envelopes for unmanned aircraft in the presence of adverse weather, while leaving room for refinement as more detailed system data and validation studies become available. [54]

References

[1] H. Ren, Y. Zhao, W. Xiao, and Z. Hu, "A review of uav monitoring in mining areas: Current status and future perspectives," *International Journal of Coal Science & Technology*, vol. 6, no. 3, pp. 320–333, Aug. 3, 2019. DOI: 10.1007/s40789-019-00264-5

[2] M. de Miguel Molina, V. S. Campos, M. Á. C. Montagud, and B. de Miguel Molina, "Ethics for civil indoor drones: A qualitative analysis:" *International Journal of Micro Air Vehicles*, vol. 10, no. 4, pp. 340–351, Aug. 8, 2018. DOI: 10.1177/1756829318794004

[3] T. Khamvilai, J. Dunham, E. Feron, and E. N. Johnson, "Avionics of aerial robots," *Current Robotics Reports*, vol. 2, no. 2, pp. 113–124, Apr. 19, 2021. DOI: 10.1007/s43154-021-00051-8

[4] Z. Zhang, J. Boubin, C. Stewart, and S. Khanal, "Whole-field reinforcement learning: A fully autonomous aerial scouting method for precision agriculture.," *Sensors (Basel, Switzerland)*, vol. 20, no. 22, pp. 6585–, Nov. 18, 2020. DOI: 10.3390/s20226585

[5] R. Campa, "De bello robotico. an ethical assessment of military robotics," *Studia Humana*, vol. 8, no. 1, pp. 19–48, Feb. 1, 2019. DOI: 10.2478/sh-2019-0002

[6] S. H. Derrouaoui, Y. Bouzid, and M. Guiatni, "Pso based optimal gain scheduling backstepping flight controller design for a transformable quadrotor," *Journal of Intelligent & Robotic Systems*, vol. 102, no. 3, pp. 1–25, Jun. 24, 2021. DOI: 10.1007/s10846-021-01422-1

[7] V. Rodríguez-Fernández, H. D. Menéndez, and D. Camacho, "A study on performance metrics and clustering methods for analyzing behavior in uav operations," *Journal of Intelligent & Fuzzy Systems*, vol. 32, no. 2, pp. 1307–1319, Dec. 23, 2016. DOI: 10.3233/jifs-169129

[8] A. Ahmad, J. Ordoñez, P. Cartujo, and V. Martos, "Remotely piloted aircraft (rpa) in agriculture: A pursuit of sustainability," *Agronomy*, vol. 11, no. 1, pp. 7–, Dec. 23, 2020. DOI: 10.3390/agronomy11010007

[9] J. Li, R. Kacimi, T. Liu, X. Ma, and R. Dhaou, "Non-terrestrial networks-enabled internet of things: Uav-centric architectures, applications, and open issues," *Drones*, vol. 6, no. 4, pp. 95–95, Apr. 10, 2022. DOI: 10.3390/drones6040095

[10] A. Tabassum and W. H. Semke, "Assessing the effect of ads-b message drop-out in detect and avoid of unmanned aircraft system using monte carlo simulation," *Safety*, vol. 4, no. 4, pp. 49–, Nov. 1, 2018. DOI: 10.3390/safety4040049

[11] F. Bonnin-Pascual, E. Garcia-Fidalgo, J. P. Company-Corcoles, and A. Ortiz, "Mussol: A micro-uas to survey ship cargo holds," *Remote Sensing*, vol. 13, no. 17, pp. 3419–, Aug. 28, 2021. DOI: 10.3390/rs13173419

[12] J.-M. Gilliot, J. Michelin, D. Hadjard, and S. Houot, "An accurate method for predicting spatial variability of maize yield from uav-based plant height estimation: A tool for monitoring agronomic field experiments," *Precision Agriculture*, vol. 22, no. 3, pp. 897–921, Oct. 20, 2020. DOI: 10.1007/s11119-020-09764-w

[13] D. E. Swihart et al., "Design, integration and flight test of an autonomous ground collision avoidance system," *Gyroscopy and Navigation*, vol. 2, no. 2, pp. 84–91, May 15, 2011. DOI: 10.1134/s2075108711020088

[14] Z. Lin, L. Castano, E. Mortimer, and H. Xu, "Fast 3d collision avoidance algorithm for fixed wing uas," *Journal of Intelligent & Robotic Systems*, vol. 97, no. 3, pp. 577–604, Jun. 29, 2019. DOI: 10.1007/s10846-019-01037-7

[15] H.-S. Shin, A. J. Garcia, and S. Alvarez, "Information-driven persistent sensing of a non-cooperative mobile target using uavs," *Journal of Intelligent & Robotic Systems*, vol. 92, no. 3, pp. 629–643, Oct. 13, 2017. DOI: 10.1007/s10846-017-0719-y

[16] A. M. Poncet, T. Knappenberger, C. J. Brodbeck, M. Fogle, J. N. Shaw, and B. V. Ortiz, "Multispectral uas data accuracy for different radiometric calibration methods," *Remote Sensing*, vol. 11, no. 16, pp. 1917–, Aug. 16, 2019. DOI: 10.3390/rs11161917

[17] J. R. Jover, A. Bermúdez, and R. Casado, "A tactical conflict resolution proposal for u-space zu airspace volumes," *Sensors (Basel, Switzerland)*, vol. 21, no. 16, pp. 5649–, Aug. 22, 2021. DOI: 10.3390/s21165649

[18] Y.-L. Park, K. Naharki, R. Karimzadeh, B. Y. Seo, and G.-S. Lee, "Rapid assessment of insect pest outbreak using drones: A case study with spodoptera exigua (hübner) (lepidoptera: Noctuidae) in soybean fields.," *Insects*, vol. 14, no. 6, pp. 555–555, Jun. 15, 2023. DOI: 10.3390/insects14060555

[19] Y. Zheng, C. Domier, M. Gonzalez, N. C. Luhmann, and D. Gamzina, "Underground imaging by sub-terahertz radiation," *Electronics*, vol. 10, no. 21, pp. 2694–, Nov. 4, 2021. DOI: 10.3390/electronics10212694

[20] B. K. Gullett, J. Aurell, W. J. Mitchell, and J. Richardson, "Use of an unmanned aircraft system to quantify no x emissions from a natural gas boiler," *Atmospheric measurement techniques*, vol. 14, no. 2, pp. 975–981, Feb. 9, 2021. DOI: 10.5194/amt-14-975-2021

[21] C. Zhang and J. M. Kovacs, "The application of small unmanned aerial systems for precision agriculture: A review," *Precision Agriculture*, vol. 13, no. 6, pp. 693–712, Jul. 31, 2012. DOI: 10.1007/s11119-012-9274-5

[22] F.-L. Chiper, A. Martian, C. Vladeanu, I. Marghescu, R. Craciunescu, and O. Fratu, "Drone detection and defense systems: Survey and a software-defined radio-based solution.," *Sensors (Basel, Switzerland)*, vol. 22, no. 4, pp. 1453–1453, Feb. 14, 2022. DOI: 10.3390/s22041453

[23] A. Barnas et al., "Evaluating behavioral responses of nesting lesser snow geese to unmanned aircraft surveys," *Ecology and evolution*, vol. 8, no. 2, pp. 1328–1338, Dec. 25, 2017. DOI: 10.1002/ece3.3731

[24] M. S. Adams, Y. Bühler, and R. Fromm, "Multitemporal accuracy and precision assessment of unmanned aerial system photogrammetry for slope-scale snow depth maps in alpine terrain," *Pure and Applied Geophysics*, vol. 175, no. 9, pp. 3303–3324, Dec. 14, 2017. DOI: 10.1007/s00024-017-1748-y

[25] J. K. Gillan, J. W. Karl, A. F. Elaksher, and M. C. Duniway, "Fine-resolution repeat topographic surveying of dryland landscapes using uas-based structure-from-motion photogrammetry: Assessing accuracy and precision against traditional ground-based erosion measurements," *Remote Sensing*, vol. 9, no. 5, pp. 437–, May 3, 2017. DOI: 10.3390/rs9050437

[26] P. Surový and K. Kuželka, "Acquisition of forest attributes for decision support at the forest enterprise level using remote-sensing techniques—a review," *Forests*, vol. 10, no. 3, pp. 273–, Mar. 19, 2019. DOI: 10.3390/f10030273

[27] M.-H. Kim, H. Baik, and S. Lee, "Response threshold model based uav search planning and task allocation," *Journal of Intelligent & Robotic Systems*, vol. 75, no. 3, pp. 625–640, Sep. 28, 2013. DOI: 10.1007/s10846-013-9887-6

[28] S. K. Mathanker, C. E. de Jensen, A. M. Pagán-López, and L. R. Pérez-Alegría, "Uav color images for determination of citrus plant parameters.," *The Journal of Agriculture of the University of Puerto Rico*, vol. 103, no. 2, pp. 141–153, Jan. 1, 2019. DOI: 10.46429/jaupr.v103i2.18226

[29] Q. Song, Y. Zeng, J. Xu, and S. Jin, "A survey of prototype and experiment for uav communications," *Science China Information Sciences*, vol. 64, no. 4, pp. 1–21, Feb. 26, 2021. DOI: 10.1007/s11432-020-3030-2

[30] J. A. Marshall, R. B. Anderson, W.-Y. Chien, E. N. Johnson, and A. L'Afflitto, "A guidance system for tactical autonomous unmanned aerial vehicles," *Journal of Intelligent & Robotic Systems*, vol. 103, no. 4, Nov. 25, 2021. DOI: 10.1007/s10846-021-01526-8

[31] J. Ortiz-Sanz, M. Gil-Docampo, M. Arza-García, and I. Cañas-Guerrero, "Ir thermography from uavs to monitor thermal anomalies in the envelopes of traditional wine cellars: Field test," *Remote Sensing*, vol. 11, no. 12, pp. 1424–, Jun. 14, 2019. DOI: 10.3390/rs11121424

[32] R. Guirado, J.-C. Padró, A. Zoroa, J. Olivert, A. Bukva, and P. Cavestany, "Stratotrans: Unmanned aerial system (uas) 4g communication framework applied on the monitoring of road traffic and linear infrastructure," *Drones*, vol. 5, no. 1, pp. 10–, Jan. 28, 2021. DOI: 10.3390/drones5010010

[33] A.-M. Bâldea and M. Garabet, "Information management in uas multiagent," *SCIENTIFIC RESEARCH AND EDUCATION IN THE AIR FORCE*, vol. 19, no. 1, pp. 49–54, Jul. 31, 2017. DOI: 10.19062/2247-3173.2017.19.1.4

[34] A. Canolla, M. B. Jamoom, and B. Pervan, "Interactive multiple model sensor analysis for unmanned aircraft systems (uas) detect and avoid (daa)," in *2018 IEEE/ION Position, Location and Navigation Symposium (PLANS)*, IEEE, 2018, pp. 757–766.

[35] G. Vachtsevanos, B. Lee, S. Oh, and M. Balchanos, "Resilient design and operation of cyber physical systems with emphasis on unmanned autonomous systems," *Journal of Intelligent & Robotic Systems*, vol. 91, no. 1, pp. 59–83, Jun. 14, 2018. DOI: 10.1007/s10846-018-0881-x

[36] S. Bhatti et al., "Toward automated irrigation management with integrated crop water stress index and spatial soil water balance," *Precision Agriculture*, vol. 24, no. 6, pp. 2223–2247, Jul. 3, 2023. DOI: 10.1007/s11119-023-10038-4

[37] S. Khanal, K. Kc, J. P. Fulton, S. A. Shearer, and E. Ozkan, "Remote sensing in agriculture—accomplishments, limitations, and opportunities," *Remote Sensing*, vol. 12, no. 22, pp. 3783–, Nov. 19, 2020. DOI: 10.3390/rs12223783

[38] 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*, 2017, p. 4384.

[39] D. Scherer et al., "Three-dimensional observation of atmospheric processes in cities," *Meteorologische Zeitschrift*, vol. 28, no. 2, pp. 121–138, Jun. 21, 2019. DOI: 10.1127/metz/2019/0911

[40] S. Seo, S. Han, and D. Kim, "D-cews: Devs-based cyber-electronic warfare m&s framework for enhanced communication effectiveness analysis in battlefield.," *Sensors (Basel, Switzerland)*, vol. 22, no. 9, pp. 3147–3147, Apr. 20, 2022. DOI: 10.3390/s22093147

[41] C. R. Ashokkumar and G. W. P. York, "Unmanned aerial vehicle flight control evaluations under sensor and actuator faults.," *Journal of Intelligent & Robotic Systems*, vol. 88, no. 2, pp. 437–447, Feb. 21, 2017. DOI: 10.1007/s10846-017-0514-9

[42] A. R. Segales et al., "The coptersonde: An insight into the development of a smart uas for atmospheric boundary layer research," pp. 1–21, Jan. 23, 2020. DOI: 10.5194/amt-2019-421

[43] H. Perez-Leon, J. J. Acevedo, I. Maza, and A. Ollero, "Integration of a 4d-trajectory follower to improve multi-uav conflict management within the u-space context," *Journal of Intelligent & Robotic Systems*, vol. 102, no. 3, pp. 1–13, Jun. 14, 2021. DOI: 10.1007/s10846-021-01415-0

[44] T. Langen, V. Nunavath, and O. H. Dahle, "A conceptual framework proposal for a noise modelling service for drones in u-space architecture.," *International journal of environmental research and public health*, vol. 19, no. 1, pp. 223–223, Dec. 25, 2021. DOI: 10.3390/ijerph19010223

[45] B. T. Fraser and R. G. Congalton, "A comparison of methods for determining forest composition from high-spatial-resolution remotely sensed imagery," *Forests*, vol. 12, no. 9, pp. 1290–, Sep. 21, 2021. DOI: 10.3390/f12091290

[46] N. Soulakellis et al., "Post-earthquake recovery phase monitoring and mapping based on uas data," *ISPRS International Journal of Geo-Information*, vol. 9, no. 7, pp. 447–, Jul. 17, 2020. DOI: 10.3390/ijgi9070447

[47] N. R. Turner, R. L. Perroy, and K. Hon, "Lava flow hazard prediction and monitoring with uas: A case study from the 2014–2015 pāhoa lava flow crisis, hawai'i," *Journal of Applied Volcanology*, vol. 6, no. 1, pp. 1–11, Nov. 2, 2017. DOI: 10.1186/s13617-017-0068-3

[48] M. Á. de Frutos Carro, F. C. LópezHernández, and J. J. R. Granados, "Real-time visual recognition of ramp hand signals for uas ground operations," *Journal of Intelligent & Robotic Systems*, vol. 107, no. 3, Mar. 20, 2023. DOI: 10.1007/s10846-023-01832-3

[49] A. K. Noor, "Potential of cognitive computing and cognitive systems," *Open Engineering*, vol. 5, no. 1, pp. 8–, Nov. 27, 2014. DOI: 10.1515/eng-2015-0008

[50] M. Jdiobe, K. Rouser, R. Paul, and A. Rouser, "Validation of a wind tunnel propeller dynamometer for group 2 unmanned aircraft," *Applied Sciences*, vol. 12, no. 17, pp. 8908–8908, Sep. 5, 2022. DOI: 10.3390/app12178908

[51] H. Baik and J. Valenzuela, "Unmanned aircraft system path planning for visually inspecting electric transmission towers," *Journal of Intelligent & Robotic Systems*, vol. 95, no. 3, pp. 1097–1111, Oct. 25, 2018. DOI: 10.1007/s10846-018-0947-9

[52] L. G. Poley and G. J. McDermid, "A systematic review of the factors influencing the estimation of vegetation aboveground biomass using unmanned aerial systems," *Remote Sensing*, vol. 12, no. 7, pp. 1052–, Mar. 25, 2020. DOI: 10.3390/rs12071052

[53] P. Moosbrugger, K. Y. Rozier, and J. Schumann, "R2u2: Monitoring and diagnosis of security threats for unmanned aerial systems," *Formal Methods in System Design*, vol. 51, no. 1, pp. 31–61, Apr. 12, 2017. DOI: 10.1007/s10703-017-0275-x

[54] A. V. Parshin, V. Morozov, N. Snegirev, E. Valkova, and F. Shikalenko, "Advantages of gamma-radiometric and spectrometric low-altitude geophysical surveys by unmanned aerial systems with small scintillation detectors," *Applied Sciences*, vol. 11, no. 5, pp. 2247–, Mar. 4, 2021. DOI: 10.3390/app11052247