Weather Impact Analysis for UAV-based Deforestation Monitoring Systems

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***Abstract*—Uncrewed Aerial Vehicles (UAVs) are increasingly employed for deforestation monitoring due to their flexibility, cost-effectiveness, and high-resolution sensing capabilities. However, their performance is highly susceptible to adverse weather conditions such as rainfall and wind, which significantly reduce flight endurance and detection accuracy. Among various adverse weather factors, rainfall intensity and wind speed emerge as the most influential contributors to heavy rainfall conditions, which represent one of the most critical external risks to UAV operations. This study presents an integrated methodology combining Failure Mode and Effects Analysis (FMEA) and Causal Loop Diagrams (CLDs) to identify weather-induced vulnerabilities and model their cascading impact on UAV-based monitoring systems. We extend an existing CLD model by incorporating rainfall intensity rate and wind speed. Based on the causal relationships identified, we develop a functional model to quantitatively evaluate UAV performance degradation. A numerical experiment is conducted to evaluate the impact of four representative weather scenarios: Clear, Light, Moderate, and Severe, on battery life, detection accuracy, and ultimately, the UAV's ability to reduce CO_2 emissions through timely deforestation detection. Results show that battery life declines from 120 minutes to 27.3 minutes, and accuracy drops from 95% to 78.8% as weather severity increases. Consequently, annual CO_2 emission reduction falls from 179.6 tons under clear conditions to just 32.9 tons under severe conditions. These findings illustrate how environmental risks propagate through system performance degradation, reducing environmental effectiveness. The proposed approach offers a valuable basis for resilience-oriented design and weather-aware mission planning in UAV-based environmental monitoring systems.**

***Index Terms*—CLD, Deforestation monitoring, FMEA, UAV, Weather impacts.**

I. Introduction

Deforestation represents a major environmental challenge, affecting ecosystems, biodiversity, and climate stability [1]. Effective monitoring is essential to quantify forest loss, assess its environmental impact, and identify high-risk areas. By tracking deforestation rates, we can identify areas at risk and take action to protect forests and wildlife habitats. Additionally, deforestation monitoring provides valuable information for policymakers to develop effective conservation policies and mitigate climate change.

Recently, Uncrewed Aerial Vehicles (UAVs) have been introduced for efficient deforestation monitoring. Conventional monitoring methods using satellite images often fall short in terms of coverage and real-time response capabilities [2]. In contrast, UAVs can rapidly collect data, survey large areas, and capture high-resolution imagery, enhancing deforestation detection and prevention efforts. Compared to conventional methods, UAVs are also cost-effective and safe [2].

Adverse weather conditions present significant challenges to UAV-based systems, yet they are often underestimated during system design. Factors such as heavy rainfall can compromise reliability, reduce operational efficiency, and impair sensing accuracy by increasing power consumption, diminishing lift, destabilizing flight, and obstructing sensors. Among the various external risks UAVs face, environmental hazards are particularly critical due to their unpredictability and widespread occurrence. [3]. A common question is why UAV operations are not simply limited to periods of favorable weather, allowing existing algorithms to function without modification. However, this approach is often impractical, especially in tropical or high-deforestation regions where adverse weather is both frequent and prolonged. Furthermore, deforestation activities tend to continue regardless of weather conditions, demanding uninterrupted monitoring to enable timely detection and intervention. These challenges emphasize the need to assess UAV performance in harsh environmental scenarios and to design systems capable of sustaining effective operation despite such disturbances. These challenges underscore the need to assess UAV performance under adverse environmental conditions and to design systems capable of maintaining operational effectiveness despite such disturbances.

This study investigates how adverse weather conditions impact the effectiveness of UAV-based deforestation monitoring systems. While previous research has explored UAV-based deforestation monitoring systems, most studies have been limited in scope [4] [5], addressing operational efficiency under standard conditions or focusing on isolated environmental challenges. Existing studies often lack consideration of the impacts of adverse weather conditions on UAV system performance and deforestation monitoring dynamics. To address this gap, we conduct a systematic impact analysis by leveraging a Causal Loop Diagram (CLD) [6] and Failure Mode and Effects Analysis (FMEA) [7]. First, FMEA is conducted to derive failure modes of system components affected by adverse weather conditions. For example, the UAV function of "Object

Detection" experiences the failure mode of "Sensor Malfunction," caused by obstructed vision due to rainfall intensity. This reduces detection accuracy, increasing the likelihood of missed deforestation events and compromising the effectiveness of monitoring activities. Next, we leverage CLDs to capture the causal relations between the system performance metrics, such as detection accuracy and battery life, and variables of adverse weather conditions, such as rainfall intensity and wind speed. The CLDs can illustrate the dynamic effects of adverse weather on UAV system performance and their cascading impact on the effectiveness of deforestation monitoring.

Building on this qualitative analysis, numerical experiments were conducted to quantify performance degradation under increasing weather severity. As rainfall and wind intensify, UAV battery life drops from 120 to 27.3 minutes, while detection accuracy falls from 95% to 78.8%. These reductions restrict flight duration and sensing reliability, directly limiting monitoring coverage and operational effectiveness. As a result, the potential annual CO_2 emission reduction achieved through UAV-based deforestation monitoring decreases from 179.6 to 32.9 tons. These findings demonstrate how adverse weather conditions propagate through system-level metrics, ultimately reducing the environmental benefits of UAV operations.

The rest of the paper is organized as follows. Section II introduces the concept of CLDs and reviews related work. Section III explains the motivation for analyzing the impact of weather on UAV-based monitoring systems. Section IV presents the case study, including the use of FMEA, CLD modeling, and a numerical experiment to assess the effects of adverse weather conditions. Section V concludes the paper.

II. Causal Loop Diagram

A. Definition

CLD is a systems mapping tool used to illustrate the dynamic interactions and feedback loops within a complex system. A CLD consists of variables and the causal relationships between them, represented by arrows. These relationships can be positive (+), indicating that an increase in one variable causes an increase in another, or negative (-), indicating an inverse relationship. Fig. 1 represents a CLD illustrating the interaction between the birth rate and population size.

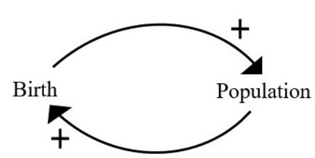

Fig. 1: Relationship between birth rate and population

An increase in population leads to a rise in the number of births, and more births, in turn, contribute to further growth in the population. The positive signs indicate a reinforcing relationship, meaning that changes in one variable positively influence the other, creating a continuous growth dynamic.

B. CLDs for Environmental Analysis

CLDs are often used in environmental, social, and technical domains to visualize and analyze systems' interdependencies and feedback mechanisms [6]. CLDs help visualize how different parts of a system interact over time. If one variable increases, it triggers a chain reaction that further increases that variable, creating a cycle of growth or decline. The cycle is often associated with exponential growth or collapse.

CLDs depict how different components interact, aiding in the understanding of complex systems [8]. For instance, in [6], the author demonstrated the use of CLDs in participatory system dynamics modeling by showing how they facilitate stakeholder engagement and provide insights for designing effective strategies in environmental monitoring and policy-making. CLDs have been utilized to map cascading climate change impacts on bioenergy supply systems, highlighting feedback mechanisms that intensify supply chain vulnerabilities under climate-induced stresses [9]. Similarly, CLDs have been applied in participatory design and performance assessment of Nature-Based Solutions (NBS) for water-related risks, effectively capturing stakeholder inputs to model co-benefits and trade-offs [10]. Additionally, they have been utilized to identify synergies and trade-offs within the Water-Energy-Food Nexus (WEFN), enabling targeted interventions to address resource scarcity [11]. Such studies highlight the adaptability of CLDs in tackling complex systemic challenges.

C. CLDs for deforestation monitoring

A study on deforestation drivers in Colombia used CLDs to map both legal and illegal drivers of deforestation and their socio-economic effects [12]. The feedback loops identified in the system revealed how economic incentives could reinforce deforestation, while governance and community-driven conservation could create balancing loops to slow down the process. This systemic perspective provided actionable insights for designing tailored environmental strategies. Similarly, in Malaysia, CLDs highlighted the relationship between population growth, infrastructure demands, and deforestation, revealing feedback loops where deforestation exacerbates climate change risks, such as heavy rainfall and rising sea levels [13]. Besides CLDs were employed within a socio-ICT (Information and Communication Technology) model for UAV-based deforestation monitoring to model relationships between system metrics (e.g., detection accuracy, service availability) and key performance indicators like deforestation rates and CO_2 emissions [14]. The model illustrates the system dynamics of a UAV-based deforestation monitoring system, highlighting key variables such as detection accuracy, monitoring area, and preventive actions. This model provides a systemic view of deforestation monitoring, emphasizing the interdependencies among UAV operational metrics and environmental outcomes. Although primarily focused on essential dynamics, this study emphasized the potential for incorporating external risk factors, such as environmental risks, to enhance the model's applicability.

Unlike previous studies, which primarily focused on system dynamics under standard conditions, our research fills this gap by analyzing the impact of adverse weather conditions as a key external risk factor to UAV-based deforestation monitoring.

III. Impact of adverse weather conditions

In real-world forest environments, the performance of UAVs is frequently affected by adverse weather conditions, including rainfall, wind, fog, and extreme heat. For instance, heavy rain can obscure camera vision, while strong winds may destabilize flight, reducing detection accuracy, and shortening battery life. These disruptions can result in missed detections of illegal logging or delayed intervention. Despite these critical risks, many UAV systems are developed without sufficiently considering environmental factors. A structured and systematic approach is therefore essential to evaluate and mitigate the effects of such conditions, ensuring more dependable and effective deforestation monitoring.

To address this gap, this study leverages the CLD from [14] to make a comprehensive analysis of adverse weather impacts on UAV-based deforestation monitoring. While existing work modeled the essential system dynamics of UAV-based deforestation monitoring systems, the influence of external environmental risks have not yet been accounted for. By extending the CLD to include heavy rainfall as a representative risk factor, this study aims to explore how weather conditions propagate through the system and affect key variables such as detection accuracy, service availability, and preventive actions. This inclusion not only enhances the realism of the model but also provides actionable insights into designing UAV systems capable of maintaining operational effectiveness under adverse conditions.

IV. Impact analysis

A. Rainfall parameters impacting UAV systems

Several quantitative parameters of heavy rainfall have been discussed in [15], which collectively characterize the dynamics of heavy rainfall events. Among these, we have selected rainfall intensity rate and wind speed as variables that might have a significant impact on UAV-based deforestation monitoring systems.

1) **Rainfall intensity rate :** Rainfall intensity rate quantifies the instantaneous rate of precipitation, serving as an indicator of operational challenges during heavy rainfall events.
2) **Wind speed:** Wind speed represents the intensity of atmospheric movement during heavy rainfall, which directly impacts UAV stability and energy consumption.

B. FMEA for critical failure modes

FMEA [7] is a structured methodology used to identify potential failure modes within a system, assess their effects, and prioritize them based on their severity, occurrence, and detectability. In this study, FMEA was applied to identify the failure modes resulting from rainfall intensity rate and wind speed on UAV-based deforestation monitoring systems.

Table I summarizes how rainfall intensity rate and wind speed affect UAV performance through specific failure modes associated with five key functions: flight stabilization, object detection, navigation, service operations, and equipment integrity. For flight stabilization, heavy rainfall increases power demands, causing energy drain and reduced battery life. Object detection suffers from sensor malfunction and data inaccuracy due to obstructed vision, lowering detection accuracy. Navigation is impacted by positional deviation as wind disrupts stability and causes flight drift, reducing monitoring precision. Service operations are delayed by water accumulation and unsafe wind conditions, limiting UAV availability. Equipment integrity is compromised through structural damage from prolonged exposure to rain and wind. In total, six major failure modes are identified as direct consequences of heavy rainfall. These disruptions illustrate how multiple subsystems are simultaneously affected by environmental factors. Through the FMEA result analysis, we identified the rainfall intensity rate and wind speed affecting key UAV functions and incorporated these parameters into the extended CLD to model their dynamic impacts.

C. CLD for weather impact analysis

Heavy rainfalls significantly degrade the performance of UAV-based monitoring systems by adversely affecting battery life and detection accuracy. Considering the failure modes derived from the FMEA in Table I, we extend the CLD from [14] with two new variables, rainfall intensity and wind speed as shown in Fig. 2.

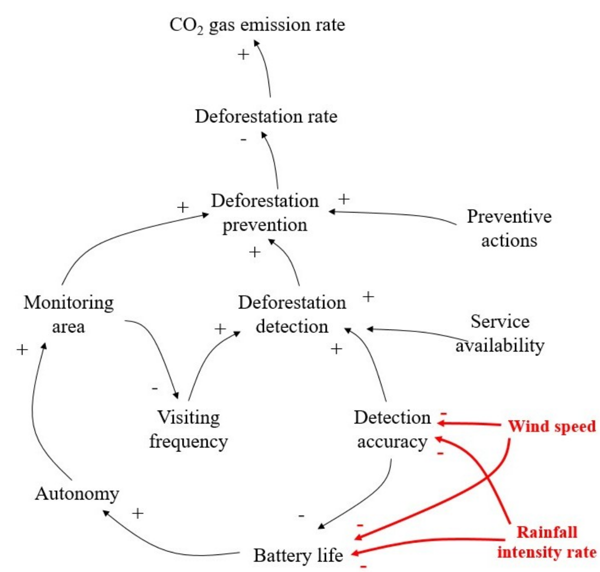

Fig. 2: Extended CLD for deforestation monitoring solution in Brazilian Amazon

Fig. 2. represents a causal view of how adverse weather conditions, specifically rainfall intensity rate and wind speed, disrupt the functioning of UAV-based deforestation monitoring systems. These environmental stressors directly reduce battery

TABLE I: FMEA of heavy rainfall impact on UAV systems

Function	Failure Mode	Cause	Effect
Flight Stabilization	Energy drain	Increased power demands for stabilization	Reduced battery life, decreased flight autonomy.
Object Detection	Sensor malfunction	Rainfall intensity obstructs vision sensors (camera lenses)	Impaired detection accuracy, missed deforestation events
	Data inaccuracy	Reduced visibility due to Rainfall intensity	Reduced precision in deforestation detection
Navigation	Positional deviation	Erratic movements due to wind speed	Navigation errors and compromised monitoring coverage
Service Operations	Delayed takeoff/landing	Groundwater accumulation and wind speeds hindering UAV operation	Reduced service availability
Equipment Integrity	Structural damage	Prolonged exposure to water droplets and wind	Reduced system lifespan

life by increasing power demands for flight stabilization and sensor operation, and they degrade detection accuracy by causing sensor obstruction and image distortion. As these core capabilities decline, UAV autonomy is reduced. In this context, autonomy refers to the total flight duration under operational conditions. This reduction limits the monitoring area, which refers to the geographic range the UAV can cover, and lowers the visiting frequency, meaning how often a specific location is revisited. Together, these reductions impair deforestation detection, which is the UAV system's ability to identify illegal forest clearing. In turn, this affects the initiation of preventive actions and overall deforestation prevention, which reflects the system's effectiveness in halting forest loss. A drop in prevention capacity leads to a higher deforestation rate, contributing to an increased CO_2 gas emission rate due to diminished carbon absorption.

D. Function definitions

To quantify the effects of adverse weather, we conduct a numerical experiment where rainfall intensity (R) and wind speed (W) are modeled as constant external inputs influencing battery life and detection accuracy. This complements the CLD by translating qualitative relationships into functional forms for system-level analysis.

In this study, we focus on two key performance metrics that determine UAV efficiency and reliability in adverse weather conditions: Battery life (B) and Detection accuracy (A). Battery life is defined as the maximum duration (in minutes) the UAV can operate under given environmental conditions. We express the UAV's battery life as a function of rainfall and windspeed. Adverse weather forces the UAV to expend more energy to counteract strong winds or overcome raindrop impact, which significantly reduces the UAV's battery life. To capture this effect, we propose a reciprocal formula for battery life:

$$\mathrm{B}(R, W) = \frac{C_0}{1 + \alpha R + \beta W} \tag{1}$$

Where:

- C_0: Ideal battery life in clear weather ($R = 0$, $W = 0$) assumed to be 120 minutes [16].
- α, β: Nonnegative sensitivity coefficients representing increased energy consumption due to rainfall and wind speed.

We modeled battery life as a reciprocal function of rainfall intensity (R) and wind speed (W) to capture the nonlinear relationship between environmental stressors and energy consumption. As R and W increase, UAVs require increasingly more power to maintain stability and control, leading to a sharp reduction in operational duration.

Detection accuracy reflects how reliable the UAV is in identifying targets under weather interference. Under clear weather, the UAV's onboard sensors and algorithms can achieve a maximum accuracy of 90-99%. However, rainfall and wind degrade the reliability. Rain can obscure the drone's sensors and cameras, making it difficult to collect data effectively. Winds have the potential to destabilize the UAV, causing misalignment or image distortion. We capture these effects with a linear decrement model (with a floor at 0% to avoid negative accuracy):

$$\mathrm{A}(R, W) = \max\left(0, A_0 - (\gamma R + \delta W)\right) \tag{2}$$

Where:

- A_{max}: Maximum detection accuracy in clear weather (approximately 99%)
- γ, δ: Degradation coefficients for rainfall and wind speed.

We modeled detection accuracy using a linearly decreasing function, as environmental interference, such as sensor obstruction and flight instability, generally degrades sensing performance in an approximately proportional manner.

In accordance with the causal relationships illustrated in the system's CLD in Fig. 2, UAV autonomy is conceptually and operationally driven by battery life. Specifically, rainfall intensity and wind speed contribute to increased energy consumption, thereby reducing the available battery life, and, consequently, the effective flight autonomy. To reflect this relationship, we define UAV battery life $B(R, W)$ as a function of weather parameters in Exp (1). This battery life function quantifies how adverse weather variables reduce operational endurance. Following the directional logic of the CLD, autonomy t_{flt} is modeled as a direct function of battery life:

$$t_{\text{flt}} = k \cdot B(R, W) \tag{3}$$

Where:

- k: A proportionality constant that maps available battery life to operational flight time. In most configurations, k can be assumed as unity (i.e., 1 minute of battery life enables 1 minute of autonomy), though it may be adjusted to reflect payload weight or other mission-specific constraints.

E. Numerical Experiment

Using the formulated static model, we conducted a numerical experiment to evaluate the UAV performance across a spectrum of constant weather conditions. We sampled rainfall intensity R from 0 to 100 mm/h and wind speed W from 0 to 200 m/s, covering the full range of interest. For each (R, W) pair, we computed the battery life and detection accuracy. We analyzed four representative weather conditions, increasing in severity: clear, light, moderate, and severe, as shown in Table II.

TABLE II: Weather conditions used in the numerical analysis

Scenario	Rainfall (R)	Wind Speed (W)	Description
Clear	0 mm/h	0 m/s	Ideal, calm weather
Light	10 mm/h	10 m/s	Slightly breezy & wet
Moderate	50 mm/h	100 m/s	Storm-like conditions
Severe	80 mm/h	180 m/s	Near-failure, extreme

The parameters used in evaluating UAV performance, including environmental sensitivity coefficients and system constants, are summarized in Table III. The minimum acceptable thresholds used in this study are defined in Table IV.

TABLE III: Parameters used in UAV performance evaluation

Parameter	Symbol	Value	Description
Battery capacity	C_0	120 min	Nominal UAV battery life under clear conditions
Rain sensitivity factor	α	0.02	Battery drain rate per mm/h of rainfall
Wind sensitivity factor	β	0.01	Battery drain rate per m/s of wind speed
Battery-to-autonomy ratio	k	1.0	Conversion constant from battery life to flight autonomy
Scan probability [14]	p_{sca}	0.60	Probability UAV can scan the area during available time
Service availability [14]	p_{sav}	0.90	Proportion of time the UAV is operational
Prevention success rate [14]	p_{def}	0.70	Likelihood of stopping deforestation after detection
Emission factor [14]	E_f	10 tons CO_2/ha	Total CO_2 released per hectare of deforestation

The numerical experiment evaluates the impact of varying weather conditions on UAV operational performance, specifically focusing on how rainfall and wind affect battery life and detection accuracy. Four representative weather scenarios are analyzed to quantify performance degradation and its cascading effects.

TABLE IV: The minimum acceptable threshold

Metric	Threshold	Description
Battery Life	20 minutes	Minimum flight time required for mission success
Detection Accuracy	85%	Minimum acceptable accuracy for reliable detection or classification tasks

Fig. 3 illustrates the UAV battery life as a function of rainfall and wind. The function assumes battery capacity decreases with increasing rainfall and wind speed due to higher aerodynamic drag and sensor processing load. The maximum endurance under ideal conditions (clear) is set at 120 minutes. As the environmental severity increases, the flight duration degrades significantly. Notably, the Moderate condition yields only 40 minutes, while Severe condition reduces endurance to 27.3 minutes, approaching the critical mission failure threshold of 20 minutes (shown in a transparent red plane in Fig. 3). This threshold demarcates the operational boundary below which UAVs cannot sustain a standard half-hour reconnaissance mission. The graph clearly shows that combinations of even moderate weather intensity can drastically reduce UAV viability.

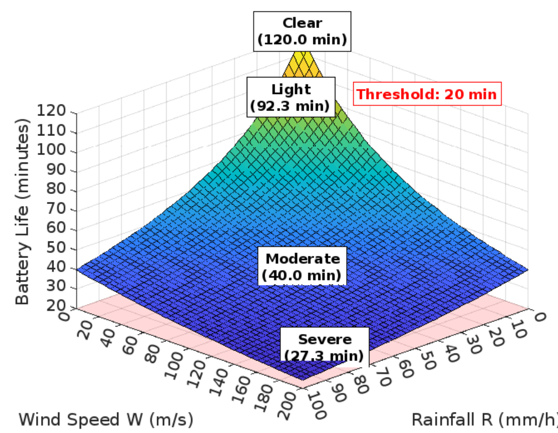

Fig. 3: Battery life degradation under four weather conditions

In contrast, Fig. 4 presents the impact of environmental conditions on detection accuracy. The accuracy function linearly decreases from a maximum of 95% under Clear weather to 78.8% in Severe conditions. The Moderate scenario barely meets the 85% minimum accuracy threshold, while the Severe case falls below it, indicating substantial risk to reliable target recognition. The accuracy degradation is more gradual than the battery drop, yet it still demonstrates the UAV's diminishing sensing capability in challenging weather. Even when flight duration remains viable, the UAV may fail to deliver mission-relevant outputs due to poor sensing performance. These findings emphasize the importance of treating sensor reliability as a first-class constraint in UAV mission design, particularly for

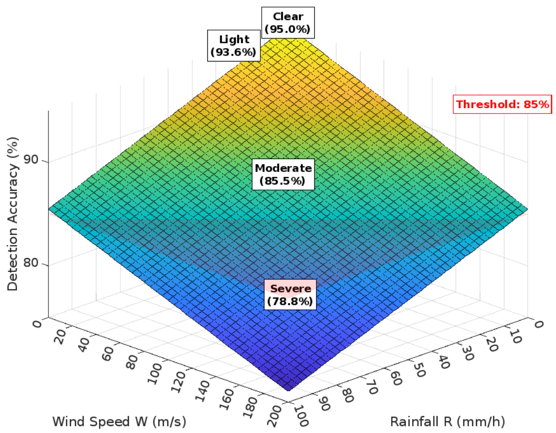

Fig. 4: Detection accuracy degradation under four weather conditions

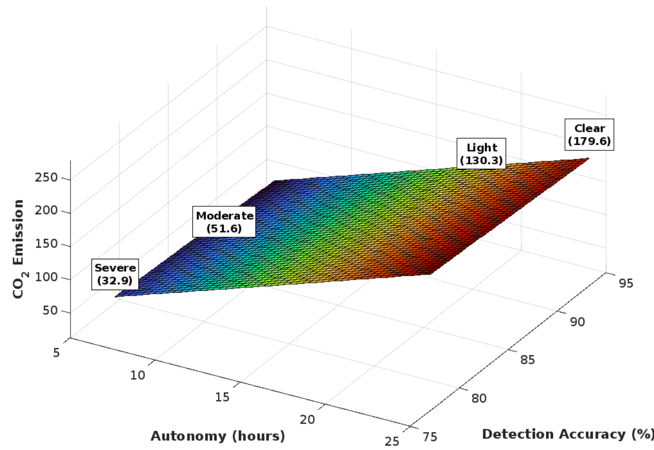

Fig. 5: CO_2 emission reduction decreases with lower autonomy and detection accuracy

surveillance, disaster response, or reconnaissance applications where decision-making depends on accurate data acquisition. Following the analysis of battery life and detection accuracy degradation due to adverse weather conditions, we now evaluate the system-level impact using the CLD for the UAV-based deforestation monitoring system [14]. While [14] does not provide a single consolidated equation for estimating CO_2 impact, it outlines a causal sequence that links UAV autonomy, scan probability, service availability, detection accuracy, and intervention success. Autonomy affected by battery life serves as a key factor in determining flight duration and, consequently, the area that can be effectively monitored. In this study, we adopt the same computational steps proposed in [14], using UAV performance metrics, particularly autonomy and detection accuracy, as inputs to quantify the system's capacity for deforestation prevention and corresponding CO_2 emission mitigation under different environmental conditions.

Fig. 5 presents a surface plot of CO_2 emission reduction (tons) as a function of UAV autonomy (hours) and detection accuracy (%), using four weather conditions: clear, light, moderate, and severe. The clear condition, representing ideal weather, supports a high autonomy of 24 hours and a detection accuracy of 95%, yielding a potential CO_2 emission reduction of 179.6 tons per year. In contrast, under severe conditions, with reduced autonomy (5.45 hours) and degraded accuracy (78.8%), the potential drops to only 32.9 tons, reflecting an over 80% reduction in system impact. The plot demonstrates a clear nonlinear relationship: while the CO_2 emission reduction is stable and high in the upper-right region (high autonomy and accuracy), it rapidly declines in the lower-left zone (poor autonomy and accuracy). The four scenario points are highlighted on the surface, clearly illustrating how increasingly adverse weather conditions shift the UAV system toward a lower-performance and less effective state.

Overall, this evaluation confirms the system's strong sensitivity to weatherdriven performance degradation and highlights the importance of maintaining both high autonomy and detection accuracy to achieve meaningful environmental outcomes. These findings are crucial for weather-aware mission planning, battery design, and sensor optimization in UAV-based monitoring systems.

V. Conclusion

This study used a CLD to conceptually model the influence of adverse weather variables, specifically rainfall intensity and wind speed, on the performance of UAV-based deforestation monitoring systems. Building on this, we develop static functional models to quantify the impact of these weather variables on two UAV performance metrics: battery life and detection accuracy. Numerical analysis revealed that even moderate weather conditions can significantly degrade UAV endurance and sensing capability, with clear thresholds identified for mission failure. For example, battery life dropped below the critical 30-minute threshold in severe weather, and detection accuracy fell below 85% under high rainfall intensity and high wind speed. These results illustrate the effects described in the CLD, where weather impacts propagate through the system, reducing both autonomy and monitoring effectiveness. By formalizing these relationships and visualizing them through interpretable surface plots, the study provides a practical foundation for risk-aware mission planning and design optimization of resilient UAV operations in adverse weather.

Acknowledgment

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