Review Article

Drones Under Weather Pressure: Analyzing Environmental Impacts on Detection Accuracy in Disaster Response Using SUR and Traditional Models

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ABSTRACT

The use of unmanned aircraft systems (UAS) in disaster response within densely populated urban areas has continued to evolve. This study examines the deployment of drones in disaster management in Tokyo, with particular attention to the environmental factors of wind speed, temperature, and precipitation, using a filtered dataset of 44,569 entries obtained from Kaggle. Specifically, the study evaluates how these environmental variables affect the efficacy of drone missions in completing surveillance tasks, drawing on Tokyo's urban disaster response simulations as well as anthropological observations of drone flight practices using an array of regression models including a binary logit regression model, negative binomial model, and multiple linear models for individual variables affecting flight and ground detection. Finally, a joint model will be performed to determine any differences between the three individual models and determine any correlation between variables. By understanding the multi-factor influences on drone performance, disaster response teams can strengthen operational strategies for unmanned aerial vehicle (UAV) deployment in relief missions. The findings of this research can contribute to improving the strategic implementation of drones during both natural and human-made disasters in highly populated areas such as Tokyo.

Keywords: Unmanned Aircraft Systems; Unmanned Aerial Vehicle; Aerial Reconnaissance; Damage Assessment; Disaster Management

INTRODUCTION

In disaster scenarios where time is critical and access is limited, unmanned aerial vehicles (UAVs) have proven to be transformative tools in search and rescue (SAR) operations. Their ability to quickly survey hazardous areas, relay real-time imagery, and support geolocation efforts has significantly enhanced emergency response effectiveness across a range of terrains and disaster types, given appropriate safety measures are taken. Equipped with thermal imaging, LiDAR, and multi-lens high-resolution cameras, drones can identify victims, assess structural integrity, and assist in coordinating ground efforts—often without placing human responders in harm's way. Global case studies, such as those examined by Goodrich *et al.* (1), have demonstrated that UAVs can reduce response time and improve operational coordination during SAR missions. These technological advantages make drones especially relevant for urban megacities,

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where complexity, congestion, and infrastructural vulnerabilities present unique challenges for traditional response methods. However, a meta-analysis conducted by Syed Mohd Daud *et al*. suggested an insufficient amount of research done to definitively classify the benefit of drones in SAR operations. Therefore, expansion of analysis is necessary for further research of UAVs.

Given that Tokyo is one of the most populated cities in the world, and suffers from earthquakes, typhoons, and urban flooding, it offers a unique opportunity to study the performance of drones with different environmental conditions. Previous studies have focused on the use of drones in the disaster areas; however, other environmental factors that may affect the operation of drones have not received adequate attention. As disseminated by Semans (2), drones are now a core component of the disaster response mechanism, and their use is now part of the overall disaster management strategy in preparing and responding to disasters. This research further enhances the findings by studying the degree to which certain environmental conditions, or factors such as urban winds, thermal conditions, or urban canyons, affect the use of drones in actual disaster situations.

Despite growing adoption, there remains a significant gap in understanding the nuanced operational constraints of UAVs in real-world disaster contexts. Existing literature often focuses on technological capabilities in controlled or idealized conditions, leaving uncertainties about how drones perform when faced with simultaneous challenges such as high wind shear, fluctuating visibility, and electromagnetic interference from dense urban infrastructure. As an example, Kang *et al*. (3) looked at the 2020 wildfires in Oregon and described the uncrewed aircraft system's operational framework in understanding the given environmental constraints. Smoke, blockage, and airspace congestion add layers of complexity on top of basic UAV deployment. Moreover, most current studies emphasize technological performance metrics without sufficiently examining how environmental stressors directly influence mission success rates or decision-making processes in the field. As disaster events are inherently unpredictable and dynamic, there is a pressing need for empirical, data-driven analyses that bridge the gap between laboratory performance benchmarks and the unpredictable realities of urban disaster zones. Addressing this gap will not only clarify UAV limitations but also guide the development of adaptive flight strategies, sensor integration improvements, and policy frameworks tailored to complex metropolitan environments like Tokyo.

From a practical and policy perspective, these results indicate that disaster response organizations should give priority to training programs that replicate environmental stressors so that UAV operators can make adjustments in real time under difficult circumstances. To increase mission reliability, agencies may also need to update deployment procedures, such as establishing safe flight paths in urban areas with high wind turbulence or electromagnetic interference. Dynamic risk assessments could be incorporated into regulatory frameworks to allow for flexible UAV operations in emergency situations while maintaining public safety. By taking these steps, UAV fleets could be deployed more successfully, improving situational awareness, speeding up response times, and enhancing the results of disaster management in general.

METHODS AND MATERIALS

Published on Kaggle (4), The Autonomous Medical Aid Dataset includes 44,569 entries of drone-assisted disaster management operations, spanning from October 2019 to October 2024 in urban and suburban regions of Tokyo. The data is collected in varying visibility, humidity, and general weather conditions, which may impact detection efficiency. The excessive sample size satisfies the paper's main objective of determining the existence of a correlation between multiple variables during drone detection on a large scale. The datas*et al*so contains realistic contextual variables, which differ from lab-controlled datasets in its practicality.

However, there are certain limitations to the data set. Environmental factors may be correlated, which could dilute their singular contributions in regression models. This is attempted to be addressed using a joint model. Geographic limitations also arise due to its target location being a comparatively small point of interest. Nevertheless, any correlation or lack thereof can still reasonably be applied to urban areas of similar scale.

Data Description

Due to the large sample data and overall goal of the paper, multiple regression tools will be used to analyze effects of independently defined variables on dependent variables. A binary logit regression model will be performed for Injury_Detection, negative binomial model on Number_of_Individuals_Detected, and multiple linear model for Rescue_Priority_Score. Finally, an analysis of each model will be performed comprehensively in a Seemingly Unrelated Regression (SUR), estimated by GLS. This paper aims to determine any correlation between drone-related variables with human detection. Therefore, certain variables excluded from Table 1 such as Respiration_Rate, Recommend_Action, and Victim_Cooperation_Level in the full dataset were deemed irrelevant to the objective, allowing the models to focus on variables with stronger explanatory power and improving overall interpretability.

Binary Logit Regression

The binary logit model (binary logit regression) as listed by Hosmer (5) estimates the probability that the dependent variable equals one of the two categories, given the independent variables. It is appropriate for modeling binary outcome variables and allows

Table 1. List of Used Variables and Descriptive Statistics

Variables	Type	Definition	Descriptive Statistics
Dependent Variables:	-	-	-
Injury_Detection	Categorical	Binary label indicating detection of injury. 0 for not detected, 1 for one or more injuries detected.	0: 26,665 1:17,904
Number_of_Individuals_Detected	Numerical	Refers to an integer number of individuals detected.	Mean: 0.832 SD: 1.059 Min: 0 Max: 4
Rescue_Priority_Score	Continuous Quantitative Ratio	Range from 0 to 1 of mission priority.	Mean: 0.499 SD: 0.289 Min: $1.29 * 10^{-5}$ Max: 0.999
Independent Variables:	-	-	-
Weather_Condition	Categorical	Labeling of weather conditions at the time. 0 is clear, 1 is rainy, 2 is cloudy.	0: 26,571 1: 13,529 2: 4,469
Temperature_C	Numerical	Temperature measured at the time, in Celsius.	Mean: 30.006 SD: 5.769 Min: 20.000 Max: 39.998
Humidity_percent	Numerical	Environmental humidity during observation, in percent.	Mean: 49.909 SD: 22.986 Min: 10.000 Max: 89.998
Wind_Speed_kmph	Numerical	Wind speed, in kilometers/hour, at the time measured.	Mean: 9.991 SD: 5.793 Min: $4.960 * 10^{-4}$ Max: 19.999
Lighting_Condition	Categorical	Categorization of lighting conditions at the time. 0 is daylight, 1 is low light.	0: 35,641 1: 8,928
Visibility_km	Numerical	Visibility conditions during operation, in kilometers.	Mean: 5.064 SD: 2.857 Min: 0.101 Max: 10.000

estimation of the conditional probability of injury detection as a function of multiple predictor variables. The formula of the binary logit regression is expressed in Equation 1:

$$\ln(p / (1 - p)) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_p x_p \quad \text{(Equation 1)}$$

where P is the probability of injury detection, β_0 is the intercept, and the following Betas are the coefficients corresponding to predictor variables x_1, x_2, and so on.

The binary logit model, while widely employed for modeling dichotomous outcomes, is subject to several methodological limitations that warrant careful consideration. One notable constraint lies in its underlying assumption of a linear relationship between the independent variables and the log-odds of the dependent variable, which may not adequately capture complex, non-linear associations present in real-world phenomena. Additionally, the model is sensitive to issues of multicollinearity among predictors, which can inflate standard errors and compromise the reliability of parameter estimates.

Negative Binomial Model

The negative binomial regression model is employed to analyze the count of individuals detected in each drone observation. It generalizes the Poisson distribution by introducing a dispersion parameter α, which accounts for unobserved heterogeneity. The probability mass function for the negative binomial model is given by Hilbe (6):

$$\log(\mu) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_p x_p \quad \text{(Equation 2)}$$

where μ is the expected count of the outcome variable, β_0 is the intercept, x_1 is an independent variable.

Multiple Linear Regression

A multiple linear regression model is utilized to assess the relationship between Rescue_Priority_Score and a set of independent variables. The formula for the multiple linear regression by Kutner MH *et al*. (7) is as follows:

$$\hat{y} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_p x_p + \varepsilon \quad \text{(Equation 3)}$$

where $\hat{y}$ denotes the rescue priority score for observation, β_0 is the intercept, and x_j is the predictor variable.

This modeling framework allows for quantification of the marginal effect of each predictor on the rescue priority score, facilitating an understanding of how operational and environmental factors influence rescue urgency. However, multiple linear regression assumes independence of errors and absence of multicollinearity. Despite these limitations, multiple linear regression provides a transparent and interpretable approach for modeling continuous rescue prioritization metrics.

GLS Joint Model

A joint model between the three outcomes—Injury Detection (binary logit), Number of Individuals Detected (negative binomial), and Rescue Priority Score (multiple linear regression)—provides a framework to capture the interconnected nature of rescue operations. Rather than evaluating each outcome separately, the joint model acknowledges that these variables are not independent in real-world disaster response contexts. For example, the efficiency of injury detection directly influences how many individuals are identified. Modeling these relationships simultaneously allows for the estimation of shared latent structures, error dependencies, and cross-variable effects that would otherwise be lost in separate regressions.

The emphasis of this approach lies in its capacity to generate a more comprehensive understanding of UAV performance in evacuation scenarios. By accounting for dependencies with different variables, the joint model improves predictive accuracy and highlights whether certain environmental conditions or operational constraints exert consistent effects across all three measures of effectiveness.

The joint model from Greene WH (8) treats each variable as a vector of outcomes influenced by shared predictors and potentially correlated disturbances. The general form is expressed as:

$$Y_i = X_i\beta_i + \varepsilon_i,\ i = 1, 2, 3 \quad \text{(Equation 4)}$$

where Y_i is the dependent variable for equation i, X_i is the vector of explanatory variables, β_i is the vector of coefficients to be estimated, and ε_i is the associated error term.

RESULTS

Each of the mentioned methods are applied to provide a comprehensive analysis of the data entries.

Below are results for a binary logit regression, negative binomial regression, multiple linear regression, and a joint model comparing them, in order (Tables 2-4).

The logistic regression shows essentially no improvement over the intercept-only model. Pseudo-R squared = 1.54 * 10^{-5} and LLR p=0.9883. The log-likelihoods of the null and fitted models are virtually identical (both -30026), indicating that the included covariates do not explain variation in the probability of injury detection. Convergence was achieved, so the null finding is not due to numerical failure.

The intercept is negative and statistically significant, reflecting baseline log-odds of detection below zero. By contrast, all slope coefficients are very small in magnitude and statistically non-significant ($p \in [0.639, 0.786]$), with two-sided 95% intervals close to zero.

Given the very large sample (n=*44,569*), the analysis had power to detect even small effects. The combination

Table 2. Binary Logit Regression for Injury Detection

Variable	Coefficient	Std. Error	z-value	p-value	95% CI (Lower)	95% CI (Upper)
Intercept (const)	-0.3941	0.061	-6.469	0.000	-0.513	-0.275
Weather_Condition	-0.0039	0.014	-0.271	0.786	-0.032	0.024
Temperature_C	0.0007	0.002	0.421	0.674	-0.003	0.004
Humidity_percent	-0.0002	0.000	-0.381	0.703	-0.001	0.001
Wind_Speed_kmph	-0.0007	0.002	-0.434	0.664	-0.004	0.003
Lighting_Condition	-0.0113	0.024	-0.469	0.639	-0.059	0.036
Visibility_km	-0.0012	0.003	-0.348	0.728	-0.008	0.005

Table 3. Negative Binomial Regression for Number of Individuals Detected

Variable	Coefficient	Std. Error	z-value	p-value	95% CI (Lower)	95% CI (Upper)
Intercept (const)	-0.2380	0.044	-5.368	0.000	-0.325	-0.151
Weather_Condition	-0.0030	0.010	-0.289	0.772	-0.024	0.018
Temperature_C	0.0016	0.001	1.278	0.201	-0.001	0.004
Humidity_percent	0.0001	0.000	0.395	0.693	-0.000	0.001
Wind_Speed_kmph	-0.0004	0.001	-0.344	0.731	-0.003	0.002
Lighting_Condition	-0.0051	0.018	-0.289	0.773	-0.040	0.029
Visibility_km	0.0017	0.002	0.672	0.501	-0.003	0.006

Table 4. Multiple Linear Regression for Rescue Priority Score

Variable	Coefficient	Std. Error	t-value	p-value	95% CI (Lower)	95% CI (Upper)
Intercept (const)	0.4944	0.009	57.225	0.000	0.477	0.511
Weather_Condition	-0.0003	0.002	-0.136	0.892	-0.004	0.004
Temperature_C	0.0001	0.000	0.428	0.669	-0.000	0.001
Humidity_percent	0.0000455	0.0000596	0.764	0.445	-0.0000713	0.000
Wind_Speed_kmph	0.0002	0.000	0.885	0.376	-0.000	0.001
Lighting_Condition	-0.0005	0.003	-0.146	0.884	-0.007	0.006
Visibility_km	-0.0005	0.000	-1.007	0.314	-0.001	0.000

of tiny point estimates and wide CIs around OR≈1 suggests the true relationships between these environmental covariates and detection probability are weak to non-existent, or masked by other factors.

A negative binomial regression model was employed to account for overdispersion in the count-based dependent variable. The model's overall explanatory power was minimal, with a Pseudo-R squared value of $5.667 * 10^{-5}$ and a log-likelihood of −56,261. The deviance (37,498) and Pearson chi-square statistic ($3.27 * 10^{4}$) suggest that a substantial proportion of variability in the response variable remains unexplained by the set of predictors.

The intercept term ($\hat{B}$ = 0.0016), $p < 0.001$), was the only statistically significant coefficient, indicating a baseline expected count of $e^{-0.238} \approx 0.788$ individuals when all predictors are at their reference or mean values. All other variables exhibited coefficients close to zero and were not statistically significant ($p > 0.2$).

Similarly with the previous model, within the context of this dataset, the environmental conditions tested do not significantly predict the number of individuals detected. This could imply detection rates are largely affected by variations in weather, temperature, humidity, wind, lighting, or visibility.

The OLS model explains virtually none of the variability in Rescue_Priority_Score; the R-squared is essentially zero, and the F-test indicates that the predictors collectively do not improve fit over a model with only the intercept (p = 0.857). Durbin-Watson is close to 2, suggesting no major autocorrelation in residuals, but overall, the model does not provide meaningful explanatory power.

The joint model integrates the three dependent variables: Injury Detection, Number of Individuals Detected, and Rescue Priority Score, under a single generalized least squares (GLS) framework. The model attempts to identify any cross-equation correlations that would not have been found in independent models (Tables 5.1-5.3).

The results show, however, that the independent variables of temperature, humidity, wind speed, lighting, and visibility exhibit no statistically significant effects across any of the three outcomes. The R-squared value of the model was $6.65 * 10^{-5}$, suggesting that even when modeled jointly, the predictors explain none of

Table 5.1. GLS Estimation - Injury_Detection

Variable	Parameter	Std. Error	t-stat	p-value	95% CI (Lower)	95% CI (Upper)
Intercept (const)	0.403	0.015	27.535	0.000	0.374	0.431
Weather_Condition	-0.0009	0.004	-0.272	0.7860	-0.008	0.006
Temperature_C	0.0002	0.0004	0.421	0.6739	-0.0006	0.001
Humidity_percent	-3.848e-05	0.0001	-0.381	0.7030	-0.0002	0.0002
Wind_Speed_kmph	-0.0002	0.0004	-0.434	0.664	-0.001	0.0006
Lighting_Condition	-0.003	0.006	-0.469	0.639	-0.014	0.009
Visibility_km	-0.0003	0.001	-0.347	0.728	-0.002	0.001

Table 5.2. GLS Estimation - Number_of_Individuals_Detected

Variable	Parameter	Std. Error	t-stat	p-value	95% CI (Lower)	95% CI (Upper)
Intercept (const)	0.787	0.032	24.990	0.000	0.725	0.849
Weather_Condition	0.003	0.008	-0.335	0.738	-0.017	0.012
Temperature_C	0.001	0.001	1.492	0.136	-0.0004	0.003
Humidity_percent	0.0001	0.0002	0.463	0.643	-0.0003	0.0005
Wind_Speed_kmph	-0.0003	0.0009	-0.404	0.686	-0.002	0.001
Lighting_Condition	-0.0042	0.013	-0.340	0.734	-0.029	0.020
Visibility_km	0.0014	0.002	0.783	0.433	-0.002	0.005

Table 5.3. GLS Estimation - Rescue_Priority_Score

Variable	Parameter	Std. Error	t-stat	p-value	95% CI (Lower)	95% CI (Upper)
Intercept (const)	0.494	0.009	57.126	0.000	0.477	0.511
Weather_Condition	-0.0003	0.002	-0.137	0.891	-0.004	0.004
Temperature_C	0.0001	0.0002	0.428	0.669	-0.0004	0.0006
Humidity_percent	4.552e-05	5.97e-05	0.763	0.446	-7.148e-05	0.0002
Wind_Speed_kmph	0.0002	0.0002	0.883	0.377	-0.0003	0.0007
Lighting_Condition	-0.0005	0.003	-0.146	0.884	-0.007	0.006
Visibility_km	-0.0005	0.0005	-1.007	0.314	-0.001	0.0005

the variance.

When compared to the separate regression models, the joint specification provides the conclusion that the lack of universal explanatory power confirms the weak effects are not a result of isolated modeling.

Practically speaking, this means real-world disaster management drones are equipped in such a way where environmental factors minimally impact its detection efficiency, though the model highlights the need for more detailed data collection on UAV weather data in disaster scenarios.

CONCLUSION

The statistical analyses conducted in this study consistently revealed no significant associations between the examined environmental factors and the key outcome variables. Across individual models, coefficients were small in magnitude, confidence intervals consistently approached zero, and model fit indices indicated that the predictors explained little to none of the observed variance. Furthering this, the joint model produced similarly null results. While this reinforces the robustness of the finding that environmental variables did not meaningfully predict detection, injury identification, or rescue prioritization within this dataset, the outcome also highlights the limited explanatory power of weather and visibility conditions under the modeling approach employed.

Some real-world considerations might explain why the results from the analysis were not significant. To begin with, the hardware of the drone such as its camera resolution, altitude, and sensor configuration were disregarded, while weather and visibility data were not captured at the same level of detail as operational variables. Different drone models may produce different results such as flight stability and flight duration, which could affect detection efficiency. Furthermore, the collection and classification of the dataset may have overlooked critical relationships. For instance, the "Weather_Condition" variable may have generalized over specific conditions such as heavy rainfall or wind gusts that can further affect UAV detection capacity. It could be speculated that the many advances of modern UAV technology could also lead to minimal performance loss in different weather conditions.

Lastly, the absence of clear statistical relationships may also be specific to the context of Tokyo. The city benefits from a highly developed disaster management framework. This includes factors such as advanced early warning systems and coordinated multi-agency response strategies provided by the Japan Meteorological Agency (JMA) (9). These existing systems have the potential to seriously mitigate the direct influence of environmental factors on UAV operations, as drones function within an infrastructure designed to minimize risks and enhance efficiency. Tokyo's emphasis on centralized command structures can reduce uncertainty that UAVs would otherwise face in less well managed disaster scenes. The weak associations observed in both individual and joint models may instead reflect how Tokyo's disaster management practices shape the operational context of UAV deployment, rendering environmental stressors less influential than they might have been in less developed settings. Overall, more research should be conducted before establishing a correlation or lack thereof of drone performance and weather condition.

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CONFLICT OF INTEREST

The author declares no conflicts of interest related to this work.

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