Predicting Geopolitical Instability through GNSS Anomalies and Air Traffic Data

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Abstract

This study examines whether GNSS anomalies in ADS-B data can serve as early indicators of geopolitical events, such as civil unrest or military conflict. Prior research suggests a link between air traffic volume and GNSS anomalies, particularly in regions with potential political instability. Using ADS-B data from the OpenSky Network and conflict data from the Armed Conflict Location & Event Data Project (ACLED), this study analyzes the relationship between GNSS anomalies and geopolitical tensions, including battles, violent protests, riots, explosions, and violence against civilians. GNSS anomalies are measured by the density of GNSS gaps and deviations, normalized by total traffic in a region. The findings suggest a connection between GNSS disruptions and political unrest, with anomalies often aligning with early conflict stages. The study indicates that GNSS interference patterns, combined with air traffic and other data, may offer insights into the timing and location of emerging geopolitical risks. This research enhances understanding of GNSS interference in aviation and proposes using open-source aviation data for geopolitical risk assessments, potentially enabling aviation stakeholders to mitigate risks in conflict-prone regions and supporting near real-time warnings for geopolitical instabilities.

Keywords: GNSS Anomalies, GNSS Jamming, GNSS Spoofing, Geopolitical Instability Prediction, ACLED

1 Introduction

Aviation cybersecurity is increasingly recognized as a critical concern by industry and regulatory bodies, primarily due to its potential impact on safety (Elmarady and Rahouma 2021; Lam et al. 2017; Ukwandu et al. 2022). Satellite-based navigation systems, particularly the Global Positioning System (GPS), are vital to the safety and efficiency of modern aviation. Recent increases in reported cases of intentional Global Navigation Satellite System (GNSS) interferences, including jamming and spoofing, have raised concerns about their impact on aviation safety (European Union Aviation Safety Agency 2024). Intentional use of GNSS jammers in conflict zones has been reported in recent news media articles (Shrama 2025; Cozzens 2025; Hirtenstein et al. 2025; Waterman 2024; Crisp 2025). These disruptions can affect critical aviation systems such as Automatic Dependent Surveillance-Broadcast (ADS-B), Controller-Pilot Data Link Communications (CPDLC), and Enhanced Ground Proximity Warning Systems (EGPWS). Ultimately, such events can reduce situational awareness and increase safety risks during critical phases of flight. Various studies have investigated GNSS anomalies from multiple perspectives, with prior research (Pik et al. 2024, 2025a) examining variables potentially linked to these anomalies and identifying issues in both high-traffic aircraft areas and low-traffic regions associated with potential conflicts. Areas with low traffic but a disproportionately high number of GNSS anomalies suggested an association with geopolitical instability and conflicts, prompting further investigation into the relationship.

The importance of ADS-B data and the availability of open flight traffic datasets has also been explored in the literature. Published research highlights the significant role of the OpenSky Network in advancing aviation research through crowdsourced ADS-B data, indicating that the initiative supported over 150 peer-reviewed studies (Strohmeier 2020). The authors also highlight the social impact of air traffic data research, particularly in enhancing understanding of air traffic trends during the COVID-19 pandemic. Some studies suggested that ADS-B data can help locate jamming sources (Schäfer et al. 2023; Liu et al. 2022), suggesting the associated data could help provide additional information to understand political instability and conflict dynamics.

2 Terminology

Several terms are commonly employed to address problems associated with missing aircraft position information in ADS-B messages, including "GNSS jamming," "GNSS gaps," "GNSS gaps in aircraft routes," "potential GNSS jamming" and "missing GNSS coordinates" (Pik et al. 2025a). These events are referenced in this research as "GNSS gaps." They describe an anomaly where consecutive ADS-B messages received from an aircraft do not carry GNSS position coordinate data for either the latitude or longitude fields, or both.

The second type of GNSS anomaly analyzed in this paper is referred to as "GNSS deviation." It occurs when ADS-B messages report sudden and unrealistic aircraft position displacement. These events may be referred to as "GNSS spoofing," "GNSS jumps," "GNSS deviations from routes," or "possible spoofing incidents." More discussion on these terminologies can be found in Pik et al. (2025a).

3 Current study

Initial explorations suggest heightened GNSS interference in regions experiencing political conflict or tensions, raising the possibility that GNSS disruptions could be used as early indicators of emerging conflict or unrest. This research evaluates whether GNSS anomalies in air traffic data collected in ADS-B messages can be reliable indicators of impending geopolitical events such as civil unrest, border tensions, or military engagements. To achieve this, ADS-B data is used to find patterns of GNSS "deviations" (unexpected shifts in reported aircraft position) and "gaps" (GNSS coordinates missing in ADS-B messages), geographic position, and air traffic volume. These data are then cross-referenced with information on conflict events worldwide. This approach enables a comparison of regions with known political violence against patterns of GNSS interference and air traffic activity, creating a model to support identifying the potential predictive relationship between aviation data and geopolitical instability.

By establishing a correlation between GNSS anomalies and geopolitical events, we aim to assess the extent to which these disruptions may serve as precursors or early warnings for future conflict. The analysis is subject to several challenges, primarily due to the inherent limitations of ADS-B data, which may not consistently capture the full extent of GNSS disruptions or reliably distinguish between naturally occurring anomalies and intentional interference. It is also expected that the unpredictable nature of political events complicates the development of predictive models based solely on air traffic data. However, despite these limitations, the research supported the analysis of the association between GNSS disruptions and regions experiencing political tension or unrest.

This research builds on previous work demonstrating the potential for geographic position data within ADS-B transmissions to detect GNSS jamming or spoofing activities (Pik et al. 2024, 2025a). Extending this analysis to geopolitical contexts, we contribute to the growing body of literature addressing the operational impacts of GNSS interference in aviation safety. We also offer new possibilities for using open-source aviation data to predict political instability.

This approach provides aviation stakeholders with an early warning mechanism to better anticipate disruptions in airspace and develop mitigation strategies in conflict-prone regions.

4 Materials and Method

4.1 Data sources

ADS-B data have been highly praised for its ability to support multifaceted approaches to aviation research. However, it is important to note potential challenges associated with the technology's limitations that could impact data reliability. Several factors can be involved, including equipment malfunction, precision of geographical position, and channel related interferences. Received messages may contain errors that, if not properly addressed, can distort results. In order to mitigate blatantly garbled messages, messages including latitudes and longitudes out of feasible ranges and aircraft ICAO code not meeting specification requirements were excluded. With regards to position data, even correctly received messages may still present inaccuracies. According to U.S. guidelines, ADS-B systems used in aviation must achieve an accuracy of 0.05 nautical miles and a maximum latency of 0.6 seconds if not compensated (for extrapolation compensation, up to two seconds) (Federal Aviation Administration 2025). Still, research on the accuracy of ADS-B broadcast position has found that the average error is under 60 ft laterally and 115 ft vertically (Dy and Mott 2022), suggesting sufficient precision to support the present study. The initial ADS-B data highlighting geographic positions for GNSS gaps and deviations supporting the present analysis was obtained from the dataset developed to support the research in Pik et al. (2024, 2025a) and available in Pik (2024).

Data on geopolitical conflict was sourced from the Armed Conflict Location and Event Data Project (ACLED). ACLED is one of the most prominent and comprehensive databases on geopolitical instabilities, including state-based and non-state-based political violence, conflict events, and demonstrations worldwide. Due to its granularity and spatiotemporal coverage, it is widely used in conflict scholarship and policy-making. ACLED data was deemed useful for the present study for proving detailed geo-referenced information on conflict events, which supported the possibility of merging conflict event data and the GNSS anomalies dataset. GNSS hourly records were further aggregated into daily metrics to reflect the granularity of ACLED data. The more consequential types of events such as those involving violence were included in the study were those with potential relevance to aviation activities, and were assumed to be the ones associated with direct or indirect conflict events. The event types considered in the analysis were *battles*, *protests* (excluding *peaceful protests*), *riots*, *explosions/remote violence*, and *violence against civilians*. All sub-event types were included in the analysis for the *battles* category. Likewise, all sub-event types under *riots* were considered relevant and therefore included. In the case of *protests*, the sub-event type *peaceful protest* was excluded, as these events, according to the ACLED codebook (ACLED 2024), do not involve force or intervention and are assumed not to impact GNSS disruptions. In the category of *explosions/remote violence*, sub-events such as *suicide bombings, remote explosives, landmines, IEDs (Improvised Explosive Devices)*, and *grenade attacks* were included. Although these events do not always involve direct clashes between armed groups, they were considered relevant due to their association with conflict zones, where disruptions to GNSS systems are expected to be more likely. Under *violence against civilians*, sub-events involving *sexual violence* and *abduction/forced disappearance* were excluded due to their unlikely association with air traffic activities or GNSS interference. *Abductions* were considered relevant only if they escalated into events involving further violence, such as *attacks*, which are coded separately in the ACLED dataset. Furthermore, all sub-event types under *strategic developments* were also excluded, as these events do not involve actual violence, which is expected to be a key factor for potential GNSS spoofing or jamming activities in conflict zones.

The resulting Geospatial Dataset of GNSS Anomalies and Political Violence Events dataset used to support the present analysis integrates aircraft flight information, GNSS anomalies, and political violence events. The final dataset is made available on Pik et al. (2025b). The dataset consists of three CSV files:

1. File `Daily_GNSS_Anomalies_and_ACLED-2023-V1.csv` contains all grids and dates with aircraft traffic during 2023, with 6,777,228 total records. This file provides a complete view of aircraft movements and associated data, including grids without any GNSS anomalies.
2. File `Daily_GNSS_Anomalies_and_ACLED-2023-V2.csv` is a filtered version of `V1` and focuses on areas and times with GNSS anomalies for targeted analysis. This second dataset includes only the grids where GNSS anomalies (deviations or gaps) were reported at least once during 2023. The total number of records in this file was 718,237.
3. File `Monthly_GNSS_Anomalies_and_ACLED-2023-V9.csv` contains aggregated monthly data for each grid cell, combining GNSS anomalies and ACLED political violence events. It summarizes aircraft traffic, anomaly counts, and conflict activity at a monthly resolution. The number of records is equal to 25,770.

The following figures visually illustrate the monthly statistics derived from these files.

4.2 Geographic analysis

The spatial analysis, maps, and graphs were created using ArcGIS Pro and Python. Point data was aggregated by time into 0.5-degree latitude and 0.5-degree longitude bins using a custom Python script and ArcGIS Pro's

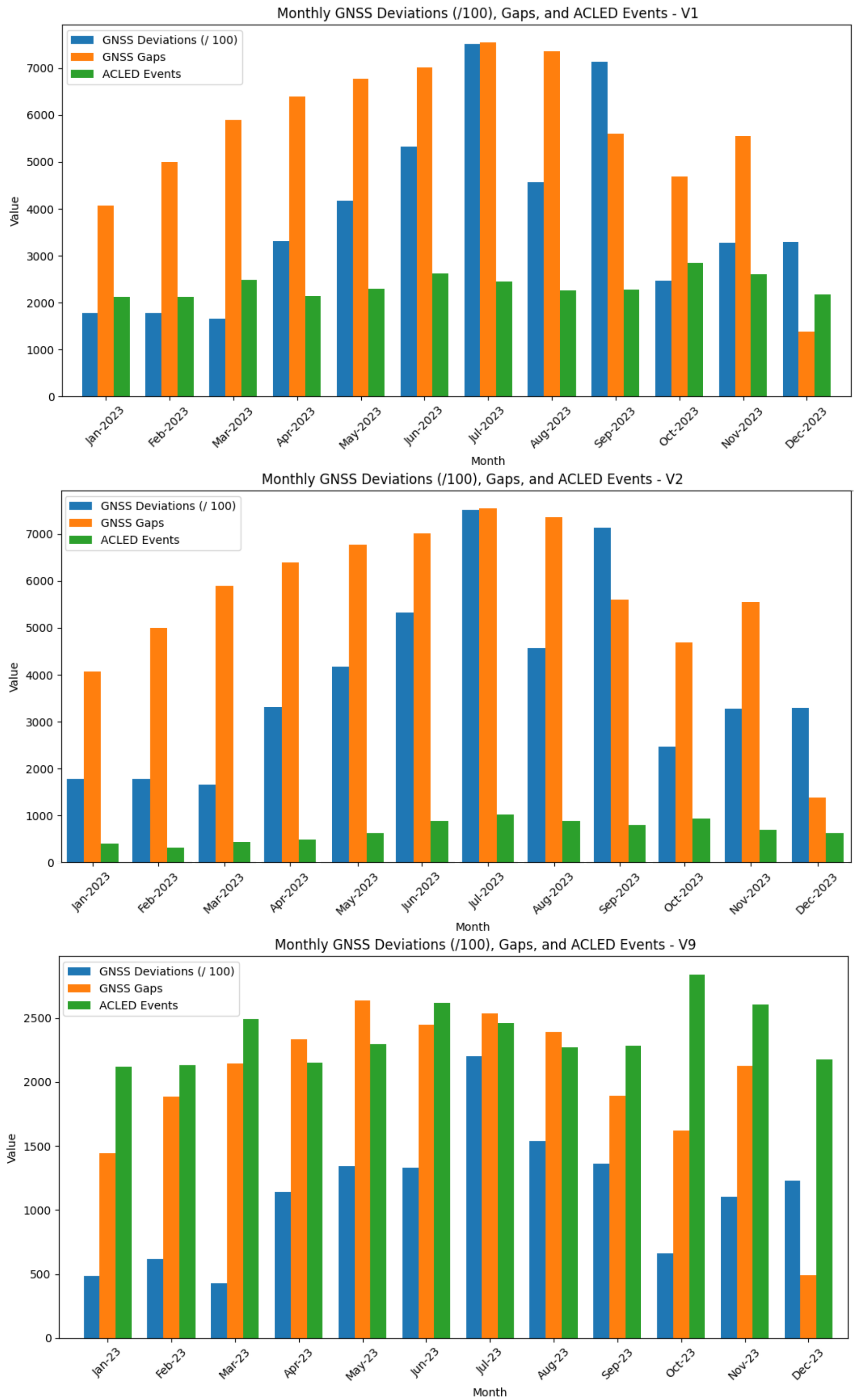

Fig. 1 Monthly statistics based on files 1, 2, and 3

Summarize Within tool. Data was further analyzed using ArcGIS Pro's Summary Statistics tool to calculate the mean values for density over time within each bin.

4.3 Design

A predictive design was employed to support the analysis, following the general definitions and limitations of observational approaches in non-experimental research (Edmonds and Kennedy 2017). Two pairs of variables were initially selected as predictors in the proposed models. The first was the total number of GNSS coordinate gaps and deviations in a particular geographic bin and time window. Subsequently, these variables were then normalized by the amount of air traffic in the same conditions to allow for better comparison among areas with distinct traffic levels, resulting in the "GNSS gap density" and "GNSS deviation density" variables. All variables were merged with data on the presence or absence of geopolitical conflict using the ACLED dataset, which served as the target variable in the analysis.

Model response to outliers, considered "one or more atypical data points that do not fit with the rest of the data" (Cohen et al. 2003, 391), was tested. The removal of outliers beyond three standard deviations from the hourly dataset did not impact results and the remaining analysis was done including the full dataset.

The initial approach selected to test the relationship was the development of a univariate logistic regression model, with a binary target variable reflecting whether ACLED indicated an event for the specific bin and time period, and a value of one if a relevant conflict event was present. The model was applied using either GNSS gap density or GNSS deviation density as the predictor variable. The logistic regression model is presented in Equation 1 below, with parameters β_0 and β_1 determined based on a training dataset using Matlab and its `glmfit` function.

$$p\left(x\right) = \frac{e^{\beta_0+\beta_1 x}}{1+e^{\beta_0+\beta_1 x}} \tag{1}$$

The main performance metric adopted to evaluate these models was the accuracy score calculated by

$$\frac{1}{n}\sum_{i=1}^{n} 1_A\left(\widehat{y}_i = y_i\right), \tag{2}$$

where $1_A(\cdot)$ is the indicator function, $\widehat{y}_i$ is the predicted probability for case i, and y_i the case i's actual observed status from a sample of n cases with known values of y_i (Lomuscio 2022; Hastie et al. 2009). A second approach was also investigated using a target variable reflecting the count of ACLED events for the specific bin and time period. Initially, a Poisson regression model was tested and failed to meet the equidispersion assumption leading to the evaluation of a negative binomial regression model. Different combinations of predictors supported the comparison of predictive performance among the negative binomial regression models using a Pseudo R^2 measure (Cohen et al. 2003, 502), calculated as

$$R_L^2 = \frac{D_{\text{null}} - D_{\text{fitted}}}{D_{\text{null}}}, \tag{3}$$

where D_{null} is the deviance of the null model (without predictors) and D_{fitted} is the deviance of the fitted model (with predictors). The deviance D is a measure of variation, analogous but not identical to the variance in linear regression. Thus, R_L^2 represents the proportional reduction in deviance between the null and fitted models.

5 Results

In some cases, GNSS anomalies coincide with the early stages of a conflict, offering an additional layer of insight for geopolitical risk assessments and aviation safety planning. The weekly incidence of conflict events in the ACLED dataset is presented in Figure 2. A visual distribution for the variables used in the current study is presented in Figure 3, with different images provided for (a) GNSS gap density, (b) GNSS deviation density, and (c) number of conflict events.

5.1 Predictive models

5.1.1 Binary target

An initial logistic regression model was created using daily data (ref. File 1) of GNSS deviations as the single predictor variable, which resulted in $\beta_0 = -4.5053$ and $\beta_1 = -0.0576$ if the complete data set was used (approximately six million cases) or $\beta_0 = -4.5730$ and $\beta_1 = -0.0469$, if just the first 70 percent of the data was used to build the

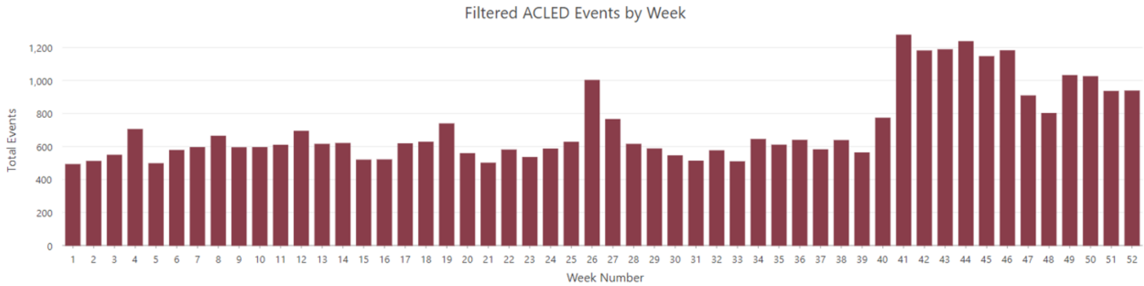

Fig. 2 ACLED Events by Week

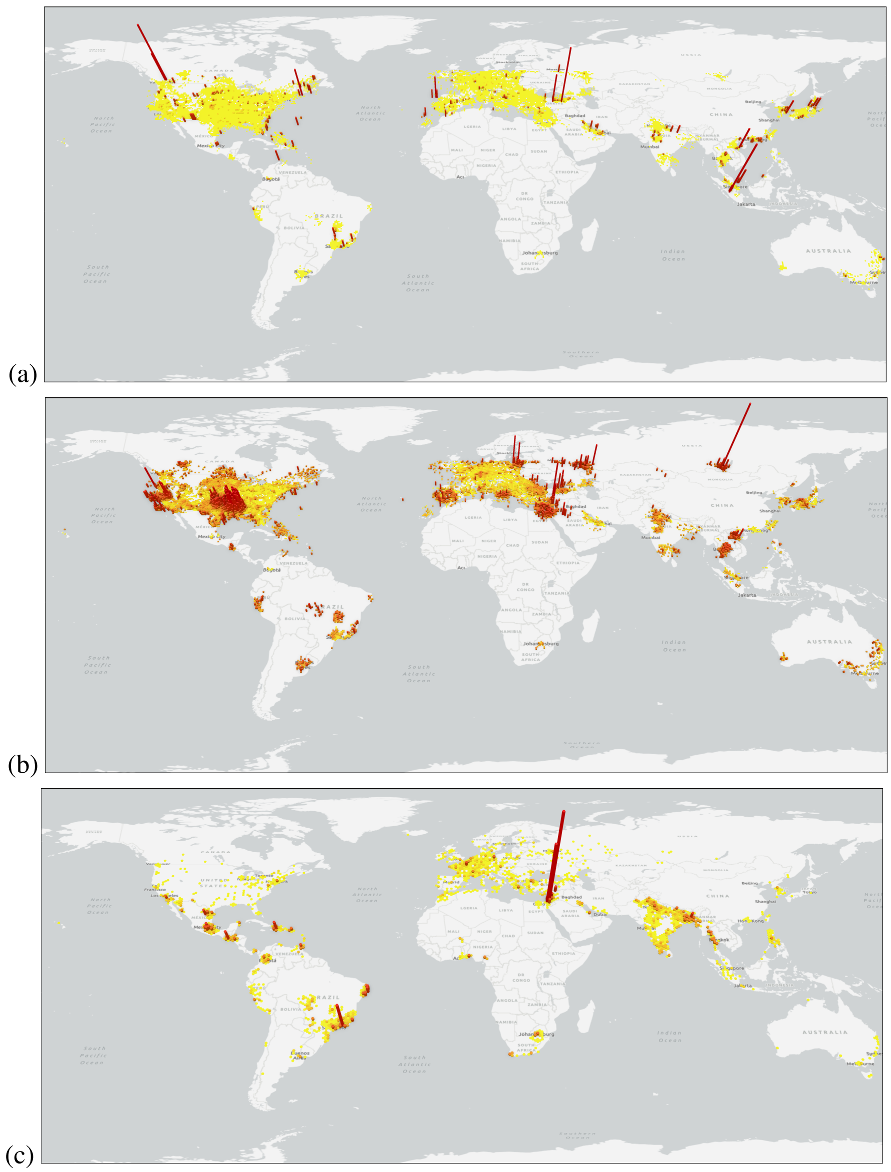

Fig. 3 Distribution of (a) GNSS gap density, (b) deviation density, and (c) number of conflict events.

model following a training-testing data split procedure. The high accuracy score of 0.9999 obtained was misleading due to significant class imbalance in the dataset.

To address this concern, a new dataset was created including only the grids and times where GNSS anomalies (deviations or gaps) were reported. This new data set (ref. File 2) contained a total of 718,237 rows of data entries, including the predictors "GNSS gaps density" and "GNSS deviation density" along with the binary target variable indicating whether a conflict occurred at the particular bin and time period. This procedure improved outcomes, but the data remained extremely imbalanced, with only 4017 instances where our dependent variable took the value of $y = 1$. Thus, a method of resampling was applied.

The resampling method started with 3,000 units of $y = 1$ cases selected for the training set. Ten distinct 3,000-unit samples of $y = 0$ cases were selected and combined with the $y = 1$ dataset using the code presented in the section Matlab code; these subsets were selected in a systematic way, as opposed to using a random subset creation, so that the results could be reproduced exactly. The coefficients β_0 and β_1 for the binomial regression were calculated for each of the ten datasets using GNSS deviation densities as the predictors and the average values obtained were $\beta_0 = 0.0201$ and $\beta_1 = -0.0548$. The results models' average likelihood ratio χ^2 test statistic was 42.334 ($p = 0.196$). Using GNSS gaps density as the predictor variable and the same procedure described above, resulting coefficients were $\beta_0 = 0.0200$ and $\beta_1 = -12.079$ and the average likelihood ratio χ^2 test statistic was 31.172 ($p = 0.1222$). Finally, the remaining 1072 cases of y_1 were combined with the same number of cases with $y = 0$ to create a balanced testing set.

The accuracy score from the model using GNSS gaps density as the predictor was 0.7038, slightly superior results compared to those obtained with the deviations model with an accuracy score of 0.6979. The models suggest a relationship between the predictors and response variables. One aspect worthy of mention is the fact that, contrary to initial expectation, the coefficients where negative, indicating that lower gap and deviations densities were associated with higher numbers of conflicts. Several reasons can explain this behavior. Issues associated with GNSS gaps and deviations densities may already be present in the days and weeks leading to conflict event, adding noise to the proposed relationship and the possibility of predicting precise location and timelines where a more violent outbreak on the conflict happened and was reported in ACLED. Still, when focusing only on items where the GNSS deviation density predictors were non-zero, the β_1 coefficient became positive, with a value of 0.567 and $\beta_0 = -3.427$. Further studies could explore the further aggregation of the time dimension, using weekly and monthly numbers to address such challenges. For instance, when the model was run on monthly data and logarithm applied to the predictor GNSS deviation density, only keeping nonzero entries, the model does have a positive slope. This model yielded the odds ratio of 1.132, suggesting that a one unit increase in the logged gaps density increases the odds of an ACLED event by approximately 13%.

5.1.2 Count target

In the previous section, the proposed model employed a binary response variable. Here, the analysis is further expanded by employing the count of ACLED events that occurred in a particular period and geographic area aggregated to the monthly level. The dataset supporting this step of the analysis is described in File 3.

In doing so, the model was expected to be able to capture a measure of intensity of ACLED events across particular geographic regions. The dataset employed in this analysis had 73% of observations with no ACLED event in the respective grid cell-month, 14.6% of our observations had only one ACLED event, and the remaining observations had multiple ACLED events, with observations having as high as 444 ACLED events.

For count outcome variables, a Poisson regression is commonly used but it comes with an underlying equidispersion assumption, requiring that the mean and the variance be the same (Cohen et al. 2003, 530). In our count data, the mean was found to be $\mu = 0.2684$ and the variance 5.5958. Application of Equation 4 confirmed an overdispersion in data (dispersion ratio = 5.87).

$$\frac{\text{deviance}(\text{model}_{\text{pois}})}{\text{df.residual}(\text{model}_{\text{pois}})} \tag{4}$$

As a result, negative binomial regression models were adopted instead. The models were initially run using the same predictors as in the last section, but additional variables were included by applying the log to the predictors and including time-lagged variables (West 2022).

An iterative approach was adopted for incrementally adding predictors to the more parsimonious models tested initially. Logged alternatives to deviation and gap densities were tested, along with lagged variants for these measures. Model 11, the more complete model prior to adding count history among the predictors showed potentially positive results, particularly for the GNSS logged deviation density predictor. The marginal effects for these predictors are indicated in Figures 4 and 5, respectively. While both predictors have positive and statistically significant marginal impact on the ACLED counts, we observe that the confidence interval of the impact of gaps density is much larger, with increasing values for larger values of the logged gaps density predictor, in contrast to the confidence interval for deviations density in Figure 5.

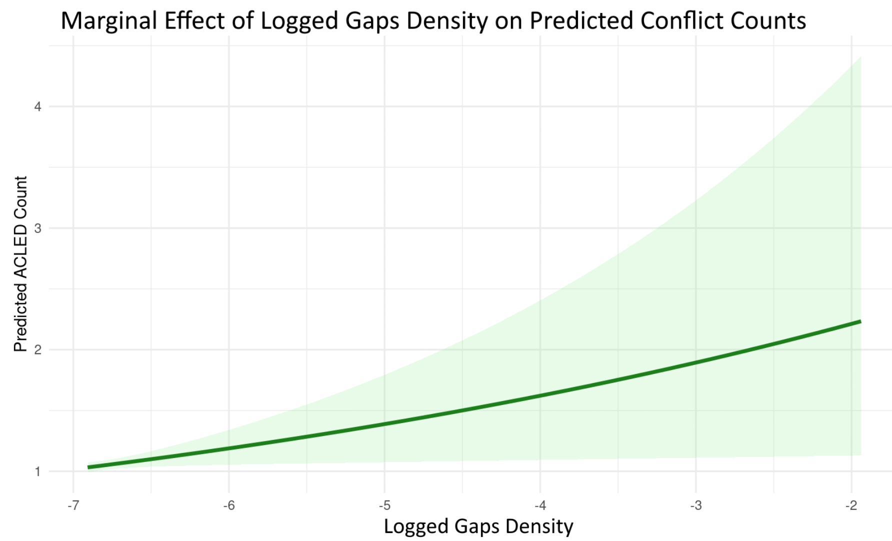

Fig. 4 Model 11 - Marginal effects of logged GNSS gaps density on predicted conflict counts.

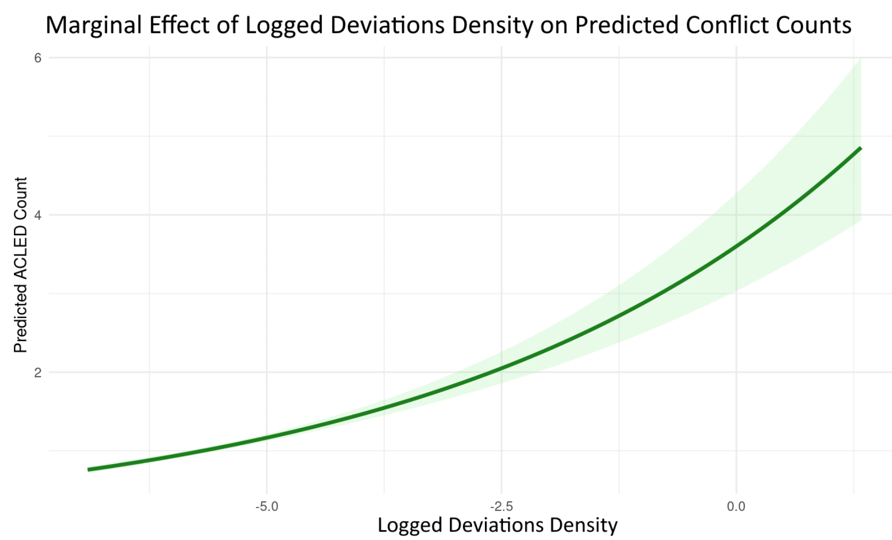

Fig. 5 Model 11 - Marginal effects of logged GNSS deviations density on predicted conflict counts.

Finally, as it is well established in conflict research, conflicts cluster in time and space (Buhaug and Gleditsch 2008; Black 2013; Hegre et al. 2013; Lane 2016; Williams 2016), lag of conflict counts was also added among predictors to provide a baseline for comparison. As expected, the Pseudo R^2 for all models including lagged ACLED counts were superior given the explanatory power of historic data for current conflict. In model 12, last month's ACLED Count, deviations density (logged), and last month's deviations density (logged) are statistically significant predictors. The slope for last month's ACLED count is 0.23 ($p < 0.001$) which indicates that it has a positive impact on ACLED count. Deviations density (logged) also has a positive slope of 0.12 ($p < 0.001$) which also indicates that it has a positive impact on ACLED count. The slope for last month's deviations density (logged) is -0.07 ($p < 0.001$), which suggests might have a decreasing effect on ACLED count. While this is somewhat surprising, it can be explained by the relatively high correlation ($r = 0.60$) between the deviations density values for the current and last month across the 23,665 observations in our sample. Gaps density for the current and previous months also have positive slopes while their effects are not statistically significant in model 12.

The general behavior of marginal effects for logged GNSS deviation density was maintained in model 12, as shown in Figure 6.

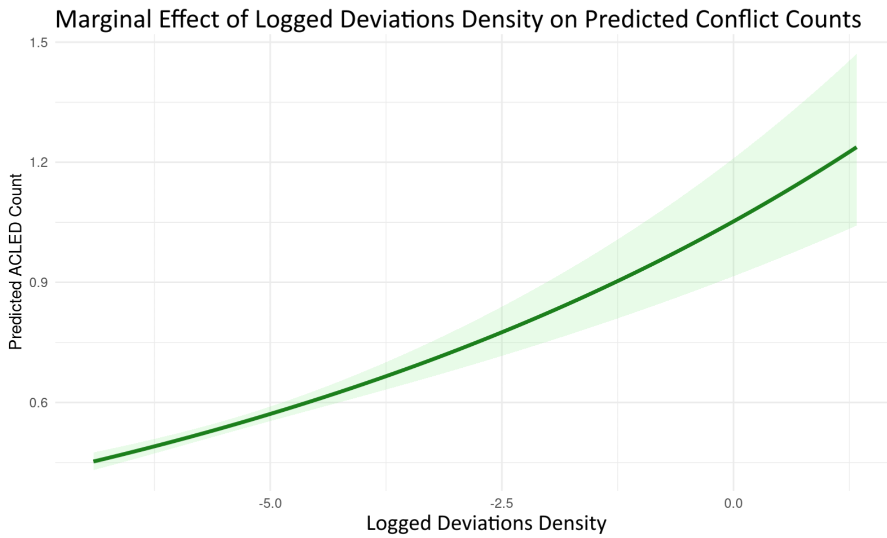

Fig. 6 Model 12 - Marginal effects of logged GNSS deviations density on predicted conflict counts.

While these general results suggest GNSS anomalies may serve as predictors to conflict, the results indicate that the explanatory power in the context of the proposed models is still limited. Future research could explore additional set of predictors relative to GNSS anomalies to potentially increase this performance. The results of all 12 model variants are presented in Tables 1 and 2, with the model performance results indicated in Table 3.

Table 1: Regression Results (Negative Binomial Regression Models 1–6)

Variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
(Intercept)	0.00	-0.90^{***}	1.99^{***}	-0.20	-0.16	-0.59^{***}
	(0.02)	(0.02)	(0.42)	(0.36)	(0.41)	(0.06)
Gaps Density	-11.71	-1.61				
	(12.48)	(9.92)				
Deviations Density	4.46^{***}	1.08^{***}				
	(0.25)	(0.19)				
ACLED Count Last Month		0.24^{***}		0.24^{***}	0.24^{***}	0.23^{***}
		(0.00)		(0.00)	(0.00)	(0.00)
Gaps Density Logged			0.12^{*}	0.04	0.00	
			(0.06)	(0.05)	(0.06)	
Deviations Density Logged			0.20^{***}	0.08^{***}		0.12^{***}
			(0.01)	(0.01)		(0.01)
Gaps Density Logged Last Month					0.10^{+}	
					(0.06)	
Deviations Density Logged Last Month						-0.07^{***}
						(0.01)
Number of Observations	23665.00	23665.00	23665.00	23665.00	23665.00	23665.00

Note: $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2: Regression Results (Negative Binomial Regression Models 7–12)

Variable	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
(Intercept)	1.41^{**}	-0.12	2.13^{***}	0.14	2.07^{***}	-0.02
	(0.43)	(0.35)	(0.51)	(0.41)	(0.51)	(0.41)
Gaps Density						
Deviations Density						
ACLED Count Last Month		0.24^{***}		0.24^{***}		0.23^{***}
		(0.00)		(0.00)		(0.00)
Gaps Density Logged			0.16^{*}	0.00	0.16^{*}	0.00
			(0.07)	(0.06)	(0.07)	(0.06)
Deviations Density Logged			0.21^{***}	0.08^{***}	0.23^{***}	0.12^{***}
			(0.01)	(0.01)	(0.02)	(0.01)
Gaps Density Logged Last Month	0.08	0.10^{*}	-0.02	0.09	-0.02	0.09
	(0.06)	(0.05)	(0.07)	(0.06)	(0.07)	(0.06)
Deviations Density Logged Last Month	0.15^{***}	0.01			-0.03	-0.07^{***}
	(0.01)	(0.01)			(0.02)	(0.01)
Number of Observations	23665.00	23665.00	23665.00	23665.00	23665.00	23665.00

Note: $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: Model Performance Comparison (Negative Binomial Regression Models)

Model	Null Deviance	Residual Deviance	AIC	BIC	Log Likelihood	RMSE	MAE	Pseudo R^2
model 1	14913.76	14788.26	56446.18	56478.80	−28219.09	124879.43	845.43	0.01
model 2	22743.20	14737.35	46594.81	46635.20	−23292.40	9.99e60	7.14e58	0.35
model 3	15146.79	14828.50	56257.82	56290.40	−28124.91	9.18	1.67	0.02
model 4	22814.40	14738.99	46557.38	46597.70	−23273.69	8.36e60	6.00e58	0.35
model 5	22735.21	14750.27	46612.12	46652.50	−23301.06	4.64e60	3.36e58	0.35
model 6	22865.61	14740.06	46530.45	46570.80	−23260.22	5.31e60	3.78e58	0.36
model 7	13820.13	13662.92	52042.74	52075.00	−26017.37	9.16	1.67	0.01
model 8	22733.45	14748.03	46610.85	46651.20	−23300.42	5.37e60	3.89e58	0.35
model 9	14005.02	13688.13	51889.20	51929.60	−25939.60	9.15	1.68	0.02
model 10	22819.71	14739.20	46556.68	46605.10	−23272.34	8.13e60	5.83e58	0.35
model 11	14005.90	13687.01	51889.23	51937.70	−25938.61	9.15	1.68	0.02
model 12	22872.80	14740.88	46531.35	46587.80	−23258.67	4.87e60	3.46e58	0.36

The negative binomial regression results and marginal effect graphs presented earlier are consistent with the results and marginal effect graph from our logistic regression model with which the probability of conflict was predicted. Collectively, these results suggest that GNSS anomalies (both GNSS gaps density and GNSS deviation density) are associated with higher likelihood and higher number of ACLED events. GNSS deviations density seems to be a more promising predictor as its impact is positive and statistically significant across all model specifications, but further model refinement is warranted.

6 Discussions and Conclusions

Our research attempts an innovative approach to predicting geopolitical instabilities by utilizing GNSS anomalies in air traffic data, particularly using GNSS gaps and deviations in ADS-B data. Several potential theoretical explanations exist for why GNSS anomalies might be associated with conflict events. Certain types of intentional and unintentional interferences might cause GNSS anomalies and, some of them may be associated with precursors to geopolitical instability. These include electronic warfare activities, cyber espionage or cyber attacks, irregular air traffic patterns, and intelligence-related flights. GNSS anomalies might be caused by electronic warfare activities such as GNSS jamming and spoofing by state or non-state actors, which, in turn, might serve as precursors to political violence.

Schäfer et al. (2023) offer GNSS jamming/spoofing as an explanation for GNSS irregularities. These electronic warfare activities might also indicate escalations toward conflict, particularly in conflict-prone areas or near military bases. State militaries or non-state actors (e.g., rebel groups and terrorist organizations) sometimes deploy GNSS jamming/spoofing equipment and engage in electronic warfare activities that lead to GNSS disruptions. Cyber espionage or cyberattacks by state and non-state actors might be another explanation. Cyber warfare against/sabotaging essential infrastructure has also been mentioned among preliminary steps in conflict escalation (Lam et al. 2017; Ukwandu et al. 2022). Cyberattacks on aviation infrastructure could directly indicate conflict escalation, as it is intuitive that actors would want to weaken adversary infrastructure.

Changes in air traffic characteristics can indicate logistical preparations for conflict, such as troop or equipment movements. These unexpected and rapid aerial deployments of troops and equipment cause non-standard flight paths or increased emergency flights, which may lead to GNSS anomalies. Therefore, there might be a potential association with GNSS irregularities and conflict preparations due to abnormal flight patterns.

Intelligence-gathering activities, particularly intelligence-related flights, may also be considered preliminary steps in conflict escalation. In fact, the utility of intelligence in preparing for conflict has been acknowledged since organized groups started fighting each other for the first time in history. Researchers, as far back as Sun Tzu, have consistently pointed out intelligence as essential to conflict (Handel 1990; Warner 2006; Gentry 2019). Since intelligence activities are important indicators of conflict preparation, intelligence-gathering activities, mainly flights related to electronic intelligence (ELINT) and signals intelligence (SIGINT) missions, may cause GNSS irregularities. Therefore, intelligence activities might serve as another link between GNSS anomalies and conflict events.

The results support our proposition that ADS-B data can be used as a predictor of political instability. Electronic and cyber-warfare activities and peculiarities in air traffic patterns due to intelligence and other logistics-related flights might be both associated with GNSS abnormalities and conflict preparations. Our findings and further studies on the link between GNSS anomalies in air traffic data and political instability may contribute to the scholarship regarding the spatial and temporal indicators of political violence. Our theoretical explanations provide a preliminary foundation for developing further hypotheses on the viability of GNSS anomalies in air traffic data as early indicators of political conflict. Future research may utilize our theoretical arguments to investigate whether different types of GNSS anomalies would be associated with different types of conflict events.

Among the several logistic regression models we ran to predict probability of conflict, the model using the predictor variable of GNSS deviation densities had the highest accuracy score. Notably, the binary logistic model showed that a one-unit increase in logged gap density increases the odds of an ACLED event by 13%. Among our second set of negative binomial regression models to predict conflict count, the model that included both the current and previous month's GNSS gaps and deviation density along with previous month's conflict count as predictors had the highest predictive performance (Pseudo $R^2 = 0.36$). While these results suggest the potential benefits of using ADS-B data in predicting conflict probability, several limitations are worth mentioning. One key limitation related to the fact that the initial exploratory logistic regression models were single-variate models. While our negative binomial models were multivariate, they had a limited set of predictors. These limitations restricted the amount of complexity they can explain, which is particularly relevant in predicting complex outcomes such as conflict. Still, our preliminary findings suggest that further research, potentially exploring more complex multivariate predictive models, can be worthwhile. Another limitation worth mentioning relates to the limited coverage of ADS-B receivers in parts of the world. The authors expect that such restrictions contribute to an underestimation of the proposed model predicted, as ADS-B receivers do not adequately cover areas with significant incidences of conflict events. As the OpenSky Network expands its receiver array to some of these locations over time, reevaluating the results and validating these assumptions may be relevant. One additional area for further exploration would be focusing on specific types of ACLED events and testing whether GNSS anomalies in ADS-B data can better predict specific types of conflict.

Acknowledgment

The authors thank the people and organizations responsible for the OpenSky Network and the Armed Conflict Location & Event Data Project (ACLED) for making these datasets available to support research.

Author contributions

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Funding statement

The authors declare that they have no relevant financial relationships with ineligible companies or personal relationships that could have appeared to influence the work reported in this paper. This research received no specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Open data statement

The dataset *2023 GPS Anomalies, NOTAMs, and Aircraft Traffic* Pik (2024) was collected and generated to support the study presented in Pik et al. (2024). The dataset provides the geospatial and temporal data on potential GNSS anomalies in aviation operations data for 2023. The dataset includes aircraft traffic and GNSS information calculated and extracted from the OpenSky Trino ADS-B database and NOTAM data provided by the FAA and ICAO. These data were augmented with the open Armed Conflict Location & Event Data Project (ACLED) data Raleigh et al. (2023) to support the present study. The final dataset supporting the present analysis is available in Pik et al. (2025b).

Reproducibility statement

Matlab code

Several software platforms and languages were employed in data preparation, analysis, and visualization, as presented in the Materials and Method section. The authors can provide further information to support reproducibility initiatives upon request. The Matlab code mentioned in 5.1.1 Binary target is listed below twice; the first code is for the GNSS gaps density predictor while the second code is for the GNSS deviations density predictor, and in both cases the numerical inputs to define the subset T within the 3rd command line should be manually updated as described in 5.1.1 Binary target.

```
% 1 - GNSS gaps predictor
% Load data from Excel file
num = xlsread("file path");

% Extract the first 3000 rows where the dependent variable is y = 1, only saving the
↪  columns that include the needed data of predictor variables
S = num(2:3001, 7:14);

% Extract a matching number of rows where y = 0
% Replace #1 and #2 with appropriate row indices (e.g., 4073:7072)
```

```
T = num(#1:#2, 7:14);

% Combine both subsets into a new dataset for balanced logistic regression
newDataset = [S; T];

% Select the predictor variable (e.g., GNSS gaps density)
col7 = newDataset(:, 7);

% Select the binary target variable (e.g., ACLED event: 1 or 0)
col14 = newDataset(:, 14);

% Perform logistic regression using the binomial distribution with logit link
[B, stats] = glmfit(col7, col14, 'binomial', 'link', 'logit');

% 2 - GNSS deviations predictor
% Load data from Excel file
num = xlsread("file path");

% Extract the first 3000 rows where the dependent variable y = 1, only saving the
↪  columns that include the needed data of predictor variables
S = num(2:3001, 8:14);

% Extract a matching number of rows where y = 0
% Replace #1 and #2 with appropriate row indices (e.g., 4073:7072)
T = num(#1:#2, 8:14);

% Combine both subsets into a new dataset for balanced logistic regression
newDataset = [S; T];

% Select the predictor variable (e.g., GNSS deviation density)
col8 = newDataset(:, 8);

% Select the binary target variable (e.g., ACLED event: 1 or 0)
col14 = newDataset(:, 14);

% Perform logistic regression using the binomial distribution with logit link
[B, stats] = glmfit(col8, col14, 'binomial', 'link', 'logit');
```

RStudio code

RStudio Code for Negative Binomial models (using acled_count as outcome variable) describes models used in the section 5.1.2 (Count target)

```
# Variables used:
# - acled_count: Number of conflict events (from ACLED dataset)
# - acled_count_lag1: Number of conflict events, prev. month
# - gaps_density: Density of GNSS gaps (from ADS-B data)
# - deviations_density: Density of GNSS deviations (from ADS-B data)
# - gaps_density_logged: Logarithm of gaps_density
# - deviations_density_logged: Logarithm of deviations_density
# - gaps_density_logged_lag1: Logarithm of gaps_density, prev. month
# - deviations_density_logged_lag1: Logarithm of deviations_density, prev. month

model_nb_1 <- glm.nb(acled_count ~ gaps_density + deviations_density, data = adsb_m)
```

```r
model_nb_2 <- glm.nb(acled_count ~ gaps_density + deviations_density +
↪  acled_count_lag1, data = adsb_m)

model_nb_3 <- glm.nb(acled_count ~ gaps_density_logged + deviations_density_logged,
↪  data = adsb_m)

model_nb_4 <- glm.nb(acled_count ~ gaps_density_logged + deviations_density_logged +
↪  acled_count_lag1, data = adsb_m)

model_nb_5 <- glm.nb(acled_count ~ gaps_density_logged + gaps_density_logged_lag1 +
↪  acled_count_lag1, data = adsb_m)

model_nb_6 <- glm.nb(acled_count ~ deviations_density_logged +
↪  deviations_density_logged_lag1 + acled_count_lag1, data = adsb_m)

model_nb_7 <- glm.nb(acled_count ~ gaps_density_logged_lag1 +
↪  deviations_density_logged_lag1, data = adsb_m)
summary(model_nb_7)

model_nb_8 <- glm.nb(acled_count ~ gaps_density_logged_lag1 +
↪  deviations_density_logged_lag1 + acled_count_lag1, data = adsb_m)

model_nb_9 <- glm.nb(acled_count ~ gaps_density_logged + gaps_density_logged_lag1 +
↪  deviations_density_logged, data = adsb_m)

model_nb_10 <- glm.nb(acled_count ~ gaps_density_logged + gaps_density_logged_lag1 +
↪  deviations_density_logged + acled_count_lag1, data = adsb_m)

model_nb_11 <- glm.nb(acled_count ~ gaps_density_logged + gaps_density_logged_lag1 +
↪  deviations_density_logged + deviations_density_logged_lag1, data = adsb_m)

model_nb_12 <- glm.nb(acled_count ~ gaps_density_logged + gaps_density_logged_lag1 +
↪  deviations_density_logged + deviations_density_logged_lag1 + acled_count_lag1,
↪  data = adsb_m)
```

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