GPS Anomalies in Aviation: Preliminary Insights from ADS-B data

Eugene Pik*
Mevocopter Aerospace, Vaughan, ON L4J7C8, Canada

Matthew Berra†
Loxodrome Labs, Fairfax, VA, 22032, USA

Dr. Jeff Yearwood‡ and Dr. Joao S. D. Garcia§
Embry-Riddle Aeronautical University, Daytona Beach, FL 32114, USA

This paper presents an exploratory investigation of GPS anomalies in aviation, focusing on gaps and deviations in Automatic Dependent Surveillance–Broadcast (ADS-B) data. The study evaluates the association between these events and distinct factors, including navigation-related Notices to Air Missions (NOTAMs). The study is supported by 376.9 billion ADS-B messages from the OpenSky database, where 53,232 GPS gaps were identified in 37,546 distinct aircraft flights and 5,878,275 GPS deviations were identified in messages from 101,681 aircraft. The analysis included 455,385 US and 30,160 global NOTAMs. Results indicate a higher relative incidence of GPS anomalies in areas with high aircraft traffic and a spatiotemporal association between the incidence of NOTAM warnings and GPS gaps. GPS gaps in ADS-B data also present longer average duration in areas with effective navigation-related NOTAM warnings. An association between GPS deviations, suggestive of potential spoofing, and NOTAM warnings related to navigation interference. These results support the role of NOTAMs as an effective risk control strategy by providing relevant information to crews regarding potential GPS anomalies. Finally, an assessment of the Navigation Integrity Category (NIC) values associated with GPS gaps indicated a significant portion of messages with NIC above seven.

I. Introduction

The integrity and reliability of the Global Positioning System (GPS) are critical to modern aviation [1]. GPS, integrated with Automatic Dependent Surveillance-Broadcast (ADS-B), provides precise aircraft location data for navigation, air traffic control, and collision avoidance [2]. However, GPS signals are vulnerable to interference, such as jamming and spoofing, disrupting the accuracy of aircraft positioning information. International Civil Aviation Organization (ICAO), International Air Transport Association (IATA), European Union Aviation Safety Agency (EASA), Federal Aviation Administration (FAA), and other relevant international organizations have identified GPS spoofing and jamming as a critical threat to the civil aviation infrastructure [3]. These disruptions pose significant risks to aviation safety, making it crucial to detect and analyze the causes and effects of GPS anomalies [4–11]. This paper employs ADS-B data to detect GPS anomalies and correlates GPS gaps and deviations with Notices to Air

* CEO, Mevocopter Aerospace, eugene.pik@mevocopter.com, https://orcid.org/0000-0001-6296-919X
† Founder and Technical Lead, Loxodrome Labs.
‡ Adjunct Faculty, Department of Graduate Studies, College of Aviation.
§ Assistant Professor, DB-School of Graduate Studies, https://orcid.org/0000-0001-6802-6889

Missions (NOTAM) navigation-related warnings [12]. These anomalies, characterized by missing or unrealistic GPS coordinates, disrupt aircraft navigation, and can pose safety concerns.

By taking an exploratory approach to the problem, this study proposed to address the following research question: *What factors are commonly associated with GPS anomalies in aviation?* The study then moves on to explore the various potentially relevant factors to these gap and deviation anomalies, including the volume of flight traffic within a geographic area, the incidence of NOTAM warnings, seasonal changes in solar activities, and measures of data integrity in position data. The results were expected to support the identification of patterns and trends that could predict and mitigate these disruptions. Several hypotheses were tested and are presented in more detail in the Results section. To address these hypotheses, the study employed distinct statistical, geospatial, and temporal analyses, evaluating different aspects of the association between GPS gaps and deviations with several other factors. One of the main objectives was to test correlations and provide insights into the effectiveness of NOTAMs as indicators of GPS interference.

Our findings aim to contribute to the development of more robust GPS anomaly detection systems and improving aviation safety. Identifying regions and times with higher frequencies of GPS anomalies can help aviation authorities issue more precise NOTAMs, enhancing situational awareness and preparedness. Understanding the patterns and causes of GPS disruptions can inform the design of more resilient navigation systems and strategies to counteract jamming and spoofing. This paper proposes a process for using ADS-B data to the analysis of GPS anomalies, ultimately contributing to a safer global air transportation system.

II. Literature Review

ADS-B is an airspace surveillance system, which can eventually replace secondary surveillance radar as the main surveillance method for controlling aircraft worldwide [13]. ADS-B enhances safety by making an aircraft real-time visible to air traffic control (ATC) and to other ADS-B In equipped aircraft with position and velocity data transmitted every second. Other uses of ADS-B data include post-flight analysis, inexpensive flight tracking, planning, and dispatch. The use of keywords including ADS-B Data, ADS-B Coordinates, Airplane GPS, GPS Anomalies, GPS Interference, GPS Jamming and Spoofing Detection, and NOTAMs supported the identification of relevant datasets and literature supporting the analyses. NOTAM and ADS-B data were provided by FAA and OpenSky Network [14]. Due to the extensive volume of the OpenSky database, the download of the complete dataset of ADS-B messages was not possible. This led to the creation of SQL scripts for searching the OpenSky Trino database directly, and only the first-level results that supported the analyses were downloaded [15]. For example, some of the results, such as the hourly traffic numbers, contain tens of millions of records. The first level results were used to support testing of the hypotheses, leading to second-level results. Relevant literature was used to support the understanding of the inner workings of GPS systems, and the causes and implications of issues including GPS spoofing, GPS jamming, GPS gaps in aircraft routes and many others.

As much research is ongoing using ADS-B as an airborne surveillance system, it is important to ensure the quality of the data being collected [16]. Per the article written by Tabassum and Semke [16], they go on to state how the data parsing and algorithms were adopted to decode the archived raw data streams. The FAA identified and investigated missing GPS mappings, which they defined as 'worm holes' in the aircraft data [1]. Darabseh et al. [17] argued for the importance of accurate position data while acknowledging that GPS jamming can adversely affect the precision of received GPS signals. The FAA has extensively addressed the issue in guidance material and regulatory documents such as the Advisory Circular 90-114A [2]. This issue can be traced back to the early stages of technology development, raising concerns about data quality degradation in these systems. Studies from the 1980s already presented concerns with the issue [18].

Grant et al. [4] support initiatives to combat the use of GPS jamming for malicious attacks, which could carry profound effects on GPS denial. Westbrook contends that the reporting systems for aviation risks presume that threats are geographically static, which does not accurately reflect the nature of the risk [19]. This further supports the need to protect and monitor the use of ADS-B systems as described by ICAO in [20], where ICAO addresses the monitoring of ADS-B to allow for a better understanding of the data being sent and received.

Kacem et al. [21] explore the impact of security requirements on user interactions with ADS-B systems and proposes a methodology leveraging semantic technologies for defining security requirements from a systemic perspective. Specifically, it employs knowledge engineering focused on misuse scenarios to develop resilient, customized software-defined radar applications and to classify cyber-attack severity using measurable security metrics. The authors apply these concepts to an ADS-B scenario to evaluate their research, enhancing the understanding of optimal ADS-B utilization.

While substantial literature is available on the issues of blocking and mishandling of ADS-B data, there is broad consensus on the need to further expand such studies. Detecting GPS anomalies in aviation using ADS-B can enhance the aviation cybersecurity body of knowledge. It provides relevant insights into the factors associated with gaps and deviations in GPS positions reported in ADS-B data and demonstrates the use of NOTAM as a risk mitigation strategy. In the following section, the terminology used to address the types of GPS anomalies of interest to the present study are further described.

III. Terminology

Several terms are commonly employed to address problems indicating missing aircraft position information, including "GPS jamming", "GPS gaps," "GPS gaps in aircraft routes," "potential GPS jamming," "missing GPS coordinates," and similar expressions. These events are referenced in this research as "*GPS gaps*" and describe a GPS anomaly where consecutive ADS-B messages received from an aircraft stops carrying GPS coordinate data in either the latitude or longitude field, or both. Such anomalies may indicate intentional or unintentional jamming incidents, occurring due to overloaded radio frequency by multiple radio transmitters, hardware malfunction, or natural events [22].

The second type of GPS anomaly analyzed in this paper is referred to as "*GPS deviation*" and occurs when ADS-B messages report sudden and unrealistic aircraft position displacement. These events may be referred to as "GPS spoofing", "GPS jumps," "GPS deviations from routes," or "possible spoofing incidents." The observational aspect of research supported by ADS-B data restricts inferences concerning the intentionality and causal links associated with GPS spoofing.

IV. Methodology

The data sources for this study include FAA domestic and ICAO NOTAMs received via email from the FAA, and ADS-B data obtained from the OpenSky Network. Additionally, our team created custom datasets, SQL and Python scripts, which are made openly available to support open research and replication [15,23,24]. Data collection was conducted throughout 2023 to ensure comprehensive and recent data coverage. Upon reviewing the messages received through the ADS-B system, it became evident that some data was not accurately represented, leading to data integrity issues. The researchers employed several approaches to improve the reliability of analysis data. To mitigate the impact of equipment malfunctions, analysis ensured that GPS coordinates were updated at least 2 seconds before and after each anomaly. Additionally, we filtered out brief events that might occur as 'noise' or 'glitches' in the system. More detail on the data processing steps are presented in the Appendix.

A. GPS Anomalies – GPS Gaps, Possible Jamming Incidents

To support the study, flights with gaps in either latitude or longitude information were classified as "GPS gaps," indicating possible data transmission issues in the ADS-B or GPS systems. The research focused on gaps that lasted at least 60 seconds to ensure they were significant. The study also utilized the Navigation Integrity Category (NIC) in the transmitted ADS-B messages [20] as a potential measure of the quality of navigational data. NIC values ranged from zero to 11, with higher numbers indicating superior reliability, or can be reported as NULL. Accuracy of position data was supported by ensuring the time difference between the time recorded in the ADS-B message and the last position GPS update remained below 2 seconds. Additionally, icao24 aircraft identifier was validated as a hexadecimal number to avoid potentially malformed ADS-B messages.

For the analysis of ADS-B messages stored in the OpenSky Trino database, researchers developed an SQL script and the corresponding Python code that executed this script, generating output files and logs [23].

The SQL script initializes a named prepared statement called flight_analysis for optimal repeated executions. This SQL script structures its query using multiple Common Table Expressions (CTEs) to perform detailed analysis of aircraft tracking data, specifically focusing on identifying and handling gaps in positional data. The first CTE filters data to include only airborne aircraft at specific points in time and ensures data integrity by validating aircraft identifiers. Subsequent CTEs use window functions to identify data continuity or gaps, marking potential starts of missing data segments and validating geographic data points based on their proximity to the last known position updates. Contiguous null data records are aggregated into sessions, focusing on significant data losses by filtering out gaps shorter than 60 seconds.

The final step involves attempting to measure data quality by extracting NIC values during identified null periods and validating coordinates before and after these gaps. The output includes validated coordinates, null period durations, and NIC values for further analysis or monitoring. This structured approach allowed for precise and efficient handling of large volumes of ADS-B data, ensuring the analysis focused on more reliable data anomalies, which is crucial for aviation safety and operational monitoring. The geographic distribution of identified GPS gap events is shown in Fig. 1. All figures in the Methodology section were created using the open-source geographic information system software QGIS [25].

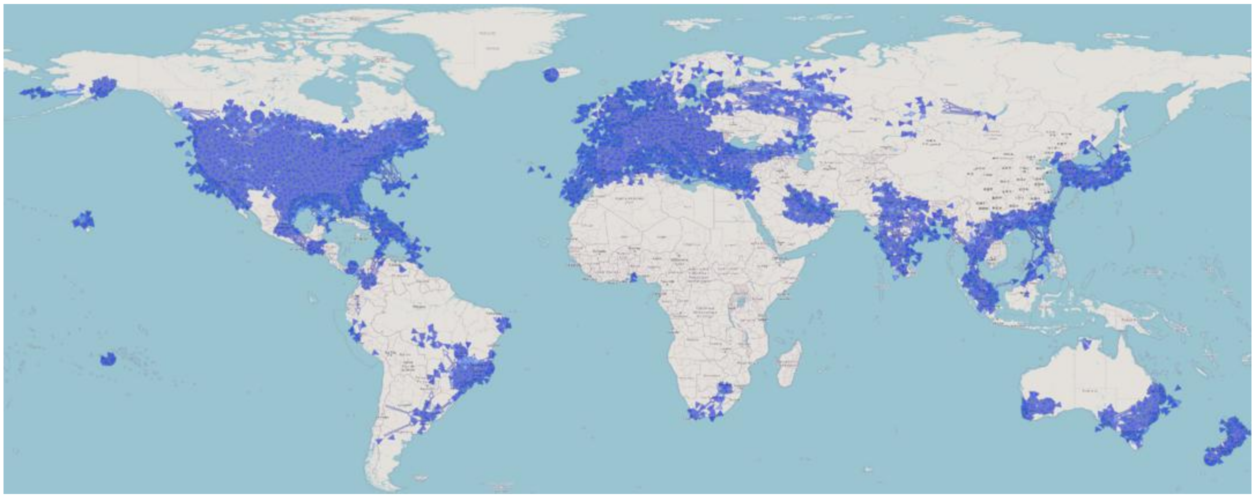

Fig. 1 GPS gap events in aircraft routes - possible GPS jamming incidents, year 2023

B. GPS Anomalies – GPS Deviations - Possible Spoofing Incidents

To support the analysis of GPS deviations, an SQL script was used to identify GPS deviations by analyzing ADS-B messages for unusually large distances traveled between consecutive data points relative to the time elapsed [23]. The analysis assumed a maximum speed of 600 m/s for civilian aircraft and flagged discrepancies suggesting positional anomalies caused by a possible GPS spoofing. The script focused on aircraft in flight, ensuring data precision and relevance by confirming that the GPS coordinates in the ADS-B messages were recorded within the last two seconds from the time of reported position and the aircraft identifiers are valid hexadecimal numbers. The analysis also considers only messages where the aircraft is airborne.

The SQL script, named spoofing_analysis, is structured using multiple CTEs to enhance readability and organize the logic. The first CTE, FilteredData, extracts ADS-B data, focusing on records within a specified hour range and ensuring the aircraft is airborne. It filters messages based on several criteria, including valid hexadecimal ICAO 24-bit addresses and properly formatted and timely latitude and longitude data. Latitudes outside -90 and 90 degrees, and longitude beyond -180 and 180 degrees are purged from the analysis. The script also ensures the time difference between the last position update and ADS-B broadcast is below 2 seconds. A DistanceCalculations CTE utilizes Trino's geospatial functions to calculate the spherical distance between consecutive positions logged in the ADS-B messages and computes the time differences to establish if the recorded distances exceed the 600 m/s threshold.

The final part of the analysis involves anomaly detection, where the script flags incidents where the distance traveled between two consecutive points significantly exceeds the expected maximum, based on the aircraft's speed. Incidents are flagged if the distance surpasses both the speed threshold and a minimum distance of 2000 meters. A final SELECT statement generates a report listing all detected GPS deviations, including aircraft identifiers, callsigns, timestamps, and coordinates before and at the point of detection, and the calculated distance and time difference. This use of SQL script to support data preparation enabled the efficient handling of high-volume ADS-B data, providing essential insights into potential security threats like GPS spoofing and maintaining the integrity of positional data critical for air traffic management and safety. The geographic distribution of identified GPS deviation cases is presented in Fig. 2. The yellow lines represent a hypothetical path connecting the GPS coordinates from two consecutive ADS-B messages. Each line represents one deviation, therefore all lines represent the total deviation picture over the year 2023

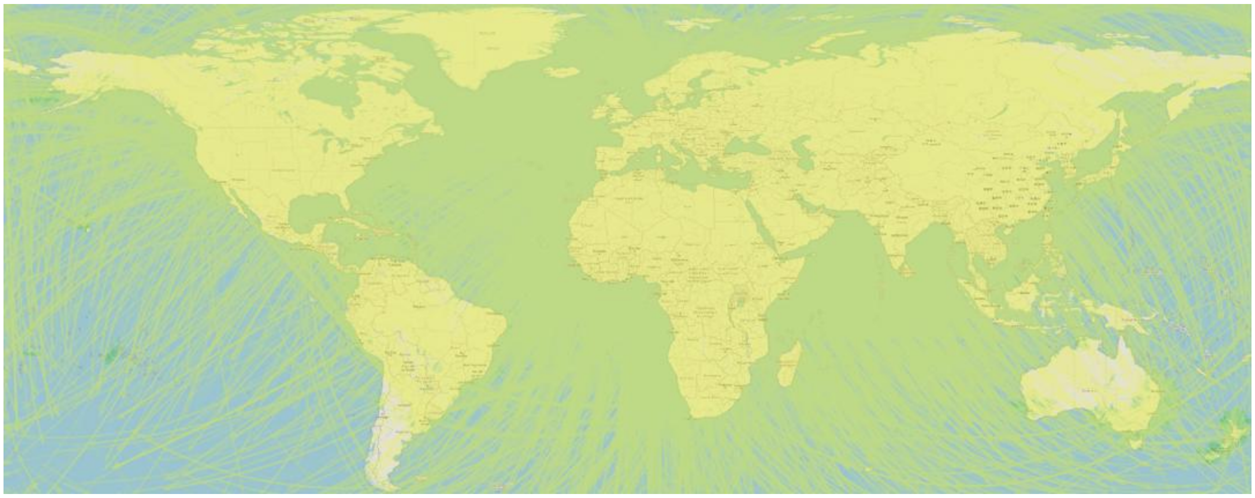

Fig. 2 GPS Deviations - possible GPS spoofing incidents, year 2023

C. GPS Anomalies - Python Script

A Python script automated data extraction and analysis from the OpenSky Network Trino database, focusing on identifying gaps in aircraft ADS-B transmission data [23]. It constructs a complex SQL query using multiple CTEs to process aircraft state vectors and identify missing ADS-B transmissions. Operating within a specified date range, the script iterates through each day, executing the SQL query, and processing the fetched data into pandas DataFrames.

Each DataFrame is used to calculate geodesic distances between pairs of valid positional coordinates that flank detected gaps, quantifying the movements of aircraft between recorded positions. We calculated the geodesic (great-circle) distance between two latitude/longitude coordinates using the following SQL function: ST_Distance(to_spherical_geography(ST_Point(x, y)), to_spherical_geography(ST_Point(a, b)))

The results are systematically exported to dynamically named Excel files based on the processed date range, ensuring organized and accessible output. Extensive logging and error handling mechanisms are included to the code to ensure stable execution and facilitate troubleshooting for database connectivity, data processing, or file I/O issues. This methodical approach provides detailed analysis of positional integrity and data continuity in aircraft tracking systems.

The Python script was used to execute the SQL described in "GPS Anomalies – GPS Gaps, Possible Jamming Incidents." A similar script, focusing on the GPS deviations, was employed for "GPS Anomalies – GPS Deviations - Possible Spoofing Incidents." The script's structured design ensured precise handling of large volumes of ADS-B data, focusing on relevant and significant data anomalies crucial for aviation safety and operational monitoring.

D. GPS Related FAA Domestic NOTAM Messages

A total of 455,385 domestic NOTAM messages issued by the FAA during the years 2022-2023 were obtained to support the analysis. These messages had start, end, and cancellation dates and times extracted and stored. All messages with dates outside the year 2023 were discarded. The text of the remaining NOTAMs was parsed to extract the location and category information. The locations in the NOTAM body were encoded as names of Military Operations Areas (MOA), Restricted Areas, Warning Areas, FAA location codes of airports and NavAids, or as GPS coordinates of a central point and a radius. We used geographic data from public documents and websites created by the FAA and US DoD to assign coordinates to every domestic NOTAM [26–38]. We then parsed their locations and saved them as Well-Known Text (WKT) polygons [39].

The map in Fig. 3 graphically represents the locations used to assign NOTAM messages with GPS coordinates, resulting in the map depicted in Fig. 4. The prevalence of locations in the USA, compared to the relative scarcity in regions such as South America or Asia, is due to the need to populate GPS coordinates for NOTAMs that lacked them. Most ICAO NOTAMs already include coordinates, obviating the need for additional information. Conversely, many FAA NOTAMs use location IDs instead of GPS coordinates, necessitating the use of these locations to complete the NOTAMs.

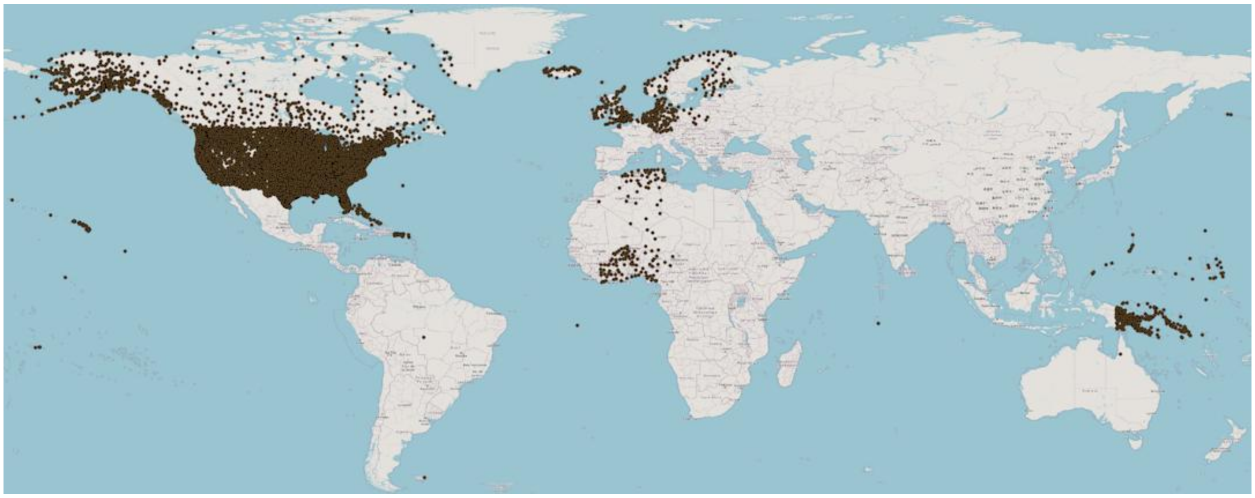

Fig. 3 FAA and ICAO locations used to complete NOTAM messages

Fig. 4 FAA domestic NOTAM messages, year 2023

USA domestic NOTAMs indicated 179 distinct categories [40]. To simplify the analysis, seven broader groups were defined, as indicated in Table 1. Only NOTAMs in the "Navigation and Communication" category were kept in the analysis, as being potentially relevant to the GPS anomaly analyses.

Table 1. Categories of FAA domestic NOTAMs.

New Category	Original Categories
Navigation and Communication	ADS-B, 5G C-band interference, Altimeter unrel, APP clsd, APP u/s, ATC services, Freq outage, GPS, Nav VOR u/s, TIS-B
Aerial Activities	Aerial spraying, Aerobatic, Agricultural acft, Air show, Airdrop, Balloon, Banner towing, Blasting, Burning man, Firefighting, Flare drop, FLTCK acft ops, Glider, Gnd proximity testing, Hel ops, High angle descent maneuvers, High speed aircraft, Kite, Low flying acft, Low flying helicopters, Model acft, Numerous acft, Numerous helicopters, Parachute jumping, Paragliding, Paramotor, Parasail, Payload falling, PJE, Pyrotechnic demonstration, Rocket launch, Spraying, UAS, Ultralight, Unmanned acft
Environmental and Geophysical Events	Avalanche control, Controlled burn, Crane, Demonstration, Geothermal storm, Glacial flooding, Hurricane, Natural gas release, Smoke and fire, Solar flare, Wind turbine
Lighting and Visibility	Search light, Tower lgt, LGT out, OBST, Pole lgt

New Category	Original Categories
Operational Restrictions	Alt reservation, Security, Special event, TFR, TWR clsd, MOA active, Restricted area active
Military Activities	EROP, Laser lgt, Mil ops, Military acft, Naval acoustics exer, Ordinance disposal, Refueling, ROPS
Miscellaneous	Cancelled, Experimental acft, Race, Kentucky derby, TFC pattern

E. International NOTAM Messages

Among the ICAO NOTAMs issued in 2023, a total of 30,160 referred to GPS issues. Each NOTAM was parsed, assigned a geographic position, and had a WKT polygon created. These results are shown in Fig. 5, with overlaps of multiple NOTAMs showing a darker coloration.

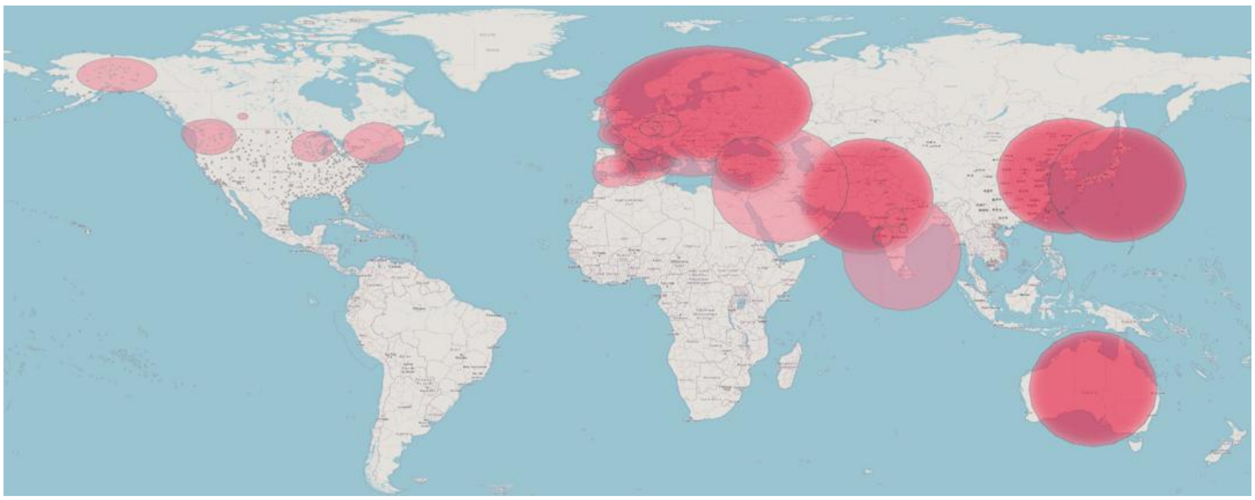

Fig. 5 GPS related ICAO NOTAM messages, year 2023

F. Number of Unique Aircraft per Hour per Grid

The process of receiving data from the OpenSky Trino database and saving it into a file is designed to handle and accumulate data about aircraft movements. The script processes data starting from January 1, 2023, over a full year, focusing on hourly intervals. Python and SQL scripts were used to extract data representing the number of unique aircraft per hour per grid, capturing significant aircraft movements over the specified period. This data served as an estimate of traffic density to support relativization of anomaly analysis. For each hour within the specified date range, data is fetched and processed to assign grid IDs based on latitude and longitude, grouping coordinates into 0.5° x 0.5° grids. The script counts the number of unique aircraft within each grid for each hour, summarizing aircraft movements. This processed data is accumulated into a daily dataset, which contains the number of unique aircraft per hour per grid. Fig. 6 presents a visualization of this distribution.

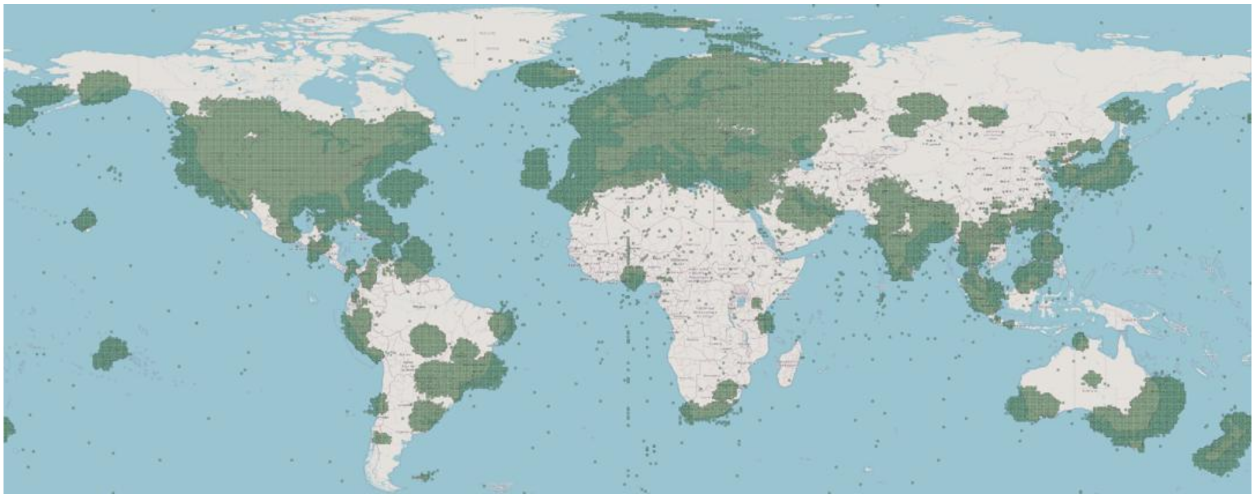

Fig. 6 OpenSky Network - number of unique aircraft per hour per grid, year 2023

G. Geospatial Data Analysis

We employed a MySQL database and Python scripts supplemented by manual searches, to clean, sort, and populate data. The final table sizes were ICAO NOTAM (30,160 rows), domestic NOTAM (234,205 rows), "GPS gaps" (53,232 rows), and "GPS jumps" (5,878,275 rows). We also created a table "Flights per Hour per Grid" (74,219,036 rows). The tables were ported to a PostgreSQL server with the PostGIS extension to support the geospatial analysis. The open-source geographic information system software QGIS and commercial ArcGIS software for geospatial analysis were used to analyze the datasets [25,41]. Finally, we utilized ArcGIS and python scripts for the statistical testing of the hypotheses.

V. Results

We analyzed 376.9 billion ADS-B messages, collected into OpenSky Network database between January 01, 2023 and January 01, 2024 and identified 53,232 GPS gaps involving 37,546 aircraft, indicative of potential jamming incidents. We also detected 5,878,275 GPS deviations from routes involving 101,681 aircraft, which can be associated with spoofing incidents. The next sections address the hypotheses indicating an association between GPS anomalies and other relevant factors.

A. Number of GPS Anomalies and Traffic Density

Hypothesis 1: There is an association between GPS gaps and air traffic density.

Hypothesis 2: There is an association between GPS deviations and air traffic density.

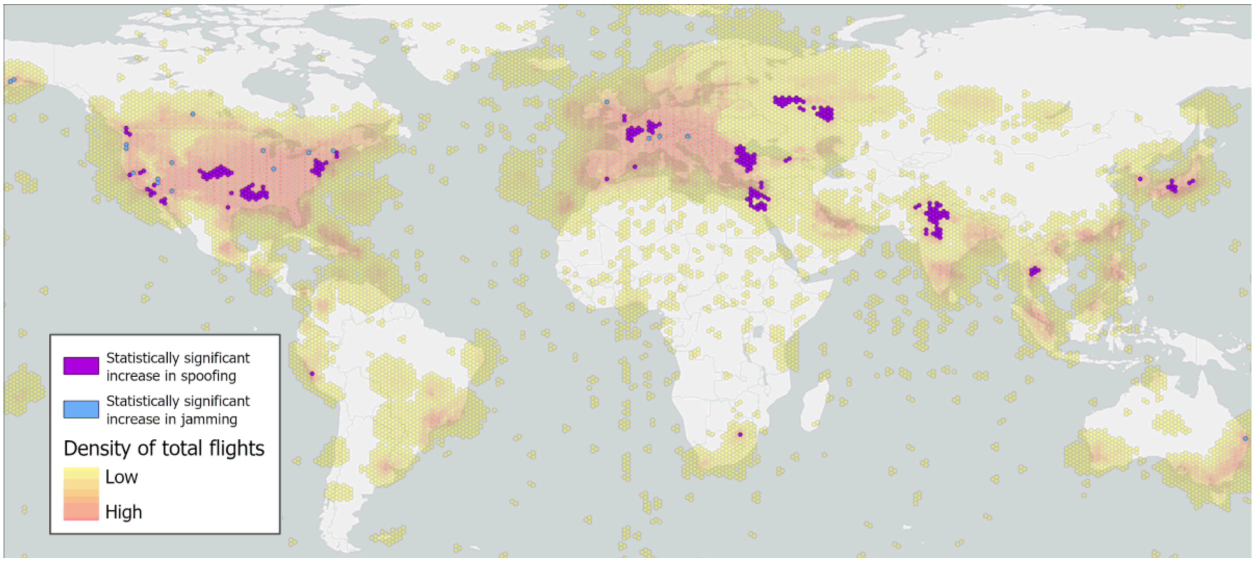

Fig. 7 Map of GPS anomalies and density of flights

Figure 7 shows a map created using ArcGIS software. We divided the globe into hexbins, each with an average area of 385 square kilometers. Once the hexbin grid was established, data from the GPS gaps, GPS deviations, and Traffic Density datasets were used to populate these hexbins with relevant information. On average, each hexbin has around 23,478 flights passing through it. However, there is significant variability in these numbers, as indicated by the standard deviation of 72,477 flights. The minimum number of flights recorded in a hexbin is one, and the maximum reaches up to 1,722,939. Similarly, the number of gap and deviation incidents varies greatly. On average, each hexbin experiences about 9.7 GPS gap incidents and 848 GPS deviation incidents. The standard deviations for gap and deviation incidents are 112.1 and 3,648.7, respectively. Some hexbins had no GPS anomalies, while the most affected areas report up to 8,238 gap incidents and 114,289 deviation incidents. The median values show that 50% of the hexbin areas have fewer than 523 flights, no gap incidents, and 7 or fewer deviation incidents. In addition, 75% of the hexbins have 12,291 or fewer flights, two or fewer gap incidents, and 261 or fewer deviation incidents.

To determine whether a significant linear association exists between these metrics, a Spearman's rank-order correlation was calculated. Visual inspection of the scatterplot showed the relationship to be monotonic. The Spearman correlation coefficients were computed using the spearmanr function from the scipy.stats Python module. Data on GPS anomalies and flight density for a total of 14,118 hexbins supported the analysis. The dataset is made openly available to support replicability studies [24]. A significant relationship was suggested, with a strong positive correlation between GPS gaps and density of flights. A significant Spearman correlation was also identified for GPS deviations and density of flights $r_s(14,116) = 0.699$, $p < 0.001$, indicating a moderate positive relationship, $r_s(14,116) = 0.699$, $p < 0.001$.

When examining the threshold analysis, it becomes clear that high traffic areas (defined as the top 25% of flight counts) experience a disproportionate number of GPS anomalies. High traffic areas account for 10,484,704 GPS deviations, compared to 1,487,929 in low traffic areas. Similarly, high traffic areas report 125,721 GPS gaps, whereas low traffic areas report 10,665.

The statistical analysis supports the hypothesis that there is an association between GPS gaps and air traffic density. Similarly, *the hypothesis that there is an association between GPS deviations and air traffic density is also supported*, although the relationship is weaker compared to GPS gaps.

Fig. 7 also presents clusters of concentrated GPS deviations in areas of low flight traffic. These areas are located primarily in Turkey, Israel, Egypt, Russia, India, and Thailand. At first look, clusters of GPS anomalies in low traffic areas seem to be associated with areas with or close to relevant geopolitical events, but further studies would be necessary to establish said association.

B. Numbers of GPS Gaps in Aircraft Routes and the NOTAM Warnings.

Hypothesis 3: There is a difference in the incidence of GPS gaps in active and inactive spatiotemporal windows of navigation-related NOTAM.

An initial attempt to address Hypothesis 3 started with the inspection of GPS gaps positions and the identification of whether they started in geographic position and time with an active or inactive navigation-related NOTAM. Table

2 shows the results produced by the spatiotemporal analysis using ArcGIS software. The results indicated that 43,566 out of 65,959 (66%) GPS gap events occurred in conditions with active navigation NOTAMs, compared to 22,393 (34%) in areas with inactive NOTAMs. If contrasted with the average time duration of individual NOTAMs effectiveness (M = 5.68 days*), these results could indicate that a difference exists in the spatiotemporal occurrence of GPS gaps based on whether NOTAM warnings are active or not*. Additional detailed analysis would be warranted to support the further determination of these conditions.

Table 2. GPS gaps in active and inactive spatiotemporal windows of navigation-related NOTAM

Metric	Value
GPS gaps that spatially intersected NOTAMs	65,959
GPS gaps that spatially intersected active NOTAM area	43,566 (66%)
GPS gaps that spatially intersected inactive NOTAM area	22,393 (34%)
Average NOTAM duration	5.68 days

C. Percentage of NOTAM Messages and a Percentage of GPS Anomalies in Geographic Areas

Hypothesis 4: There is an association in geographic locations for GPS gaps and navigation-related NOTAMs.

Hypothesis 5: There is an association in geographic locations for GPS deviations and navigation-related NOTAMs.

The top 10% hexbins in terms of GPS gaps and navigation-related NOTAMs were selected for analysis. Figure 8 shows a geospatial visualization generated using ArcGIS software, where yellow hexagons mark the top 10% concentrations of global GPS Jamming events and red hexagons mark the top 10% concentrations of global NOTAM events. *Visual inspections of the plot suggest an association in geographic location for the top GPS gap and navigation-related NOTAMS, with 19% of intersections among associated hexbins. No intersections were identified outside of North America.*

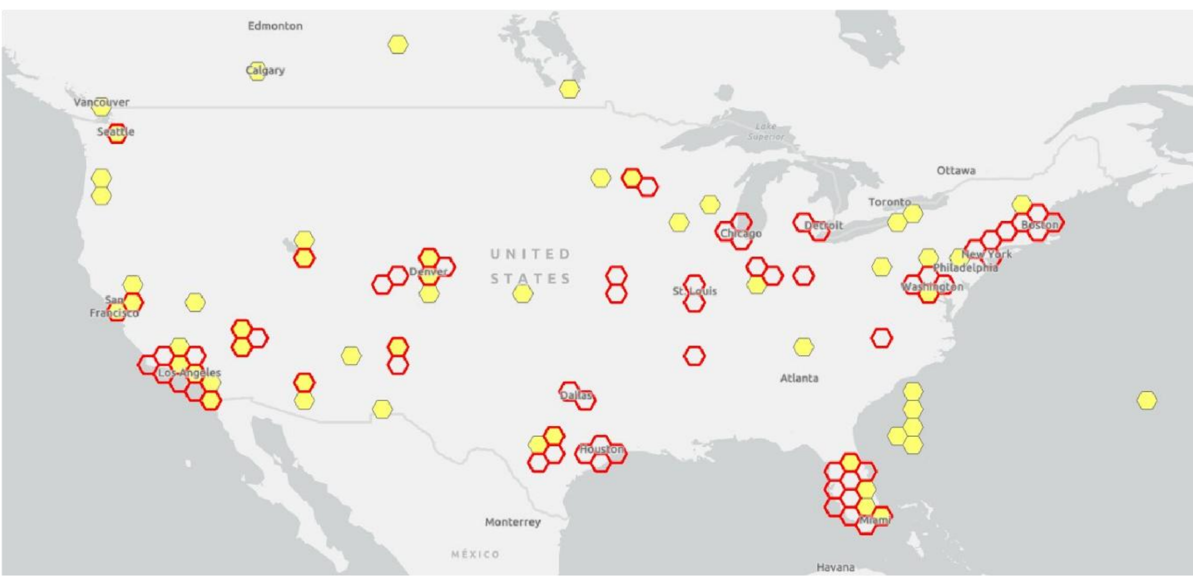

Fig. 8 Top 10% of GPS gaps and NOTAM hexbin intersections

A similar analysis was performed for GPS deviation events, considering the initial position of the deviation as the reference position. The top 10% of hexbins from both GPS deviations and NOTAM were selected. Figure 9 shows the geospatial visualization generated using ArcGIS software, where yellow hexagons mark the top 10% concentrations of global GPS deviation events and red hexagons mark the top 10% concentrations of global NOTAM events. *Visual inspections of the plot suggest an association in geographic locations for the top GPS deviation and navigation-related NOTAMs. No intersections were identified outside of North America.*

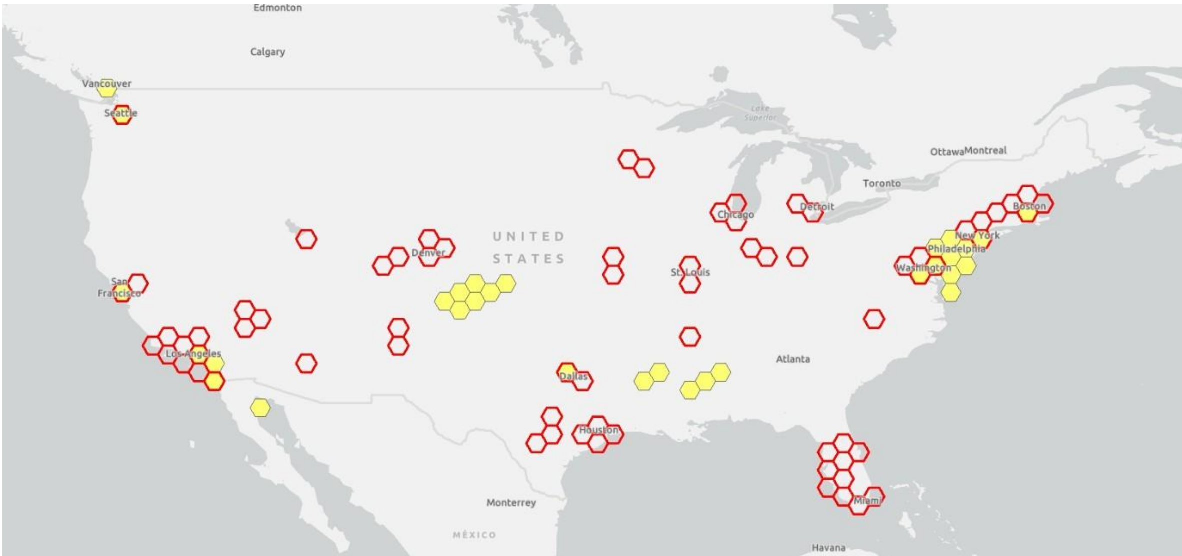

Fig. 9 Top 10% of GPS deviations and NOTAM hexbin intersections

D. Duration of GPS Gaps among Areas with Active and Inactive Navigation Related NOTAMS

Hypothesis 6: There is a difference in the duration of GPS gaps among areas with active and inactive NOTAMs.

Table 3 shows the results produced by the statistical analysis using ArcGIS software. The mean duration of GPS gaps in ADS-B data intersecting active NOTAM areas (1,911 s) is higher compared to not intersected data (1,654 s). This suggests that, on average, areas with NOTAM warnings issued for GPS interference experience longer GPS gaps. The standard deviation is slightly lower in intersected data (1,177) compared to not intersected data (1,246), indicating less variability in GPS gap durations where NOTAM warnings are present. The total count of GPS gaps is significantly lower in intersected data (12,612) compared to not intersected data (40,116). This could be due to a more focused analysis in specific areas with NOTAM warnings, the fact that most NOTAM as permanent or are active a significant proportion of the time, or it could indicate that GPS gaps occur more often in areas with active NOTAMs. An initial inspection of the descriptive statistics for the analysis indicates that areas with active navigation-related NOTAMs have 15.5% longer gaps than areas with inactive NOTAMs. Figure 10 displays histogram of the intersected results for the duration of GPS gaps in ADS-B data and the number of NOTAM warnings issued for GPS interference in the same geographic area. Figure 11 displays the histogram of the not intersected results for the duration of GPS gaps in ADS-B data and the number of NOTAM warnings issued for GPS interference in the same geographic area.

The results of the descriptive statistics for GPS gap durations among active and inactive NOTAM areas suggest that areas with active navigation-related NOTAMs have on average 257 s longer GPS gaps.

Table 3. Statistical data generated using ArcGIS software for hypothesis 6

Metric	Intersected Data	Not Intersected Data
Mean	1,911	1,654
Standard Deviation	1,177	1,246
Total Count	12,612	40,116
Mode	95	103
Outliers	0	0

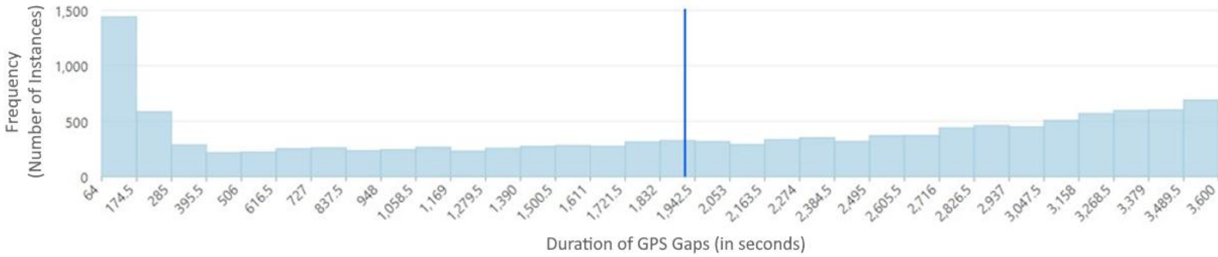

Fig. 10 GPS gaps and NOTAM warnings - intersected results

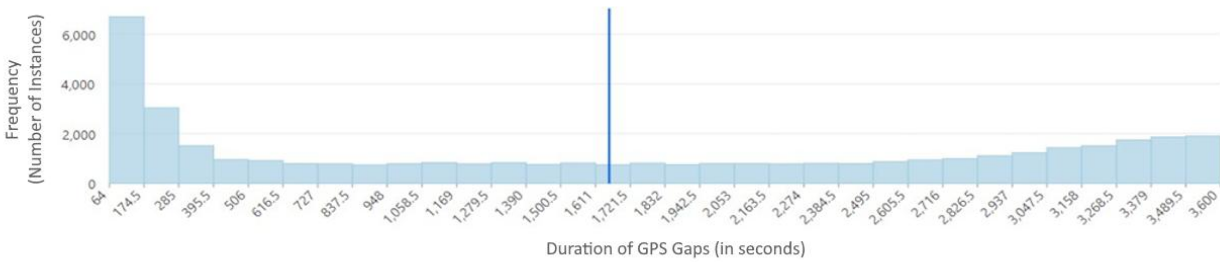

Fig. 11 GPS gaps and NOTAM warnings – not-intersected results

E. Frequency of GPS Deviation Incidents among Areas with Active and Inactive Navigation Related NOTAMS

Hypothesis 7: There is a difference in the incidence of GPS deviations in active and inactive spatiotemporal windows of navigation-related NOTAMs.

Researchers sought to test Hypothesis 7 by exploring the frequency of GPS deviation incidents relative to whether they started during an active or inactive navigation-related NOTAM applicability time and geographic area. Table 4 shows variables calculated with support of geospatial analysis conducted with ArcGIS software. Whereas 41% (n = 1,239,144) of deviation events occurred in conditions where a navigation-related NOTAM was active, the remaining 59% (n = 1,750,153) occurred when NOTAMs were not active. *While more detailed analysis can further support the establishment of stronger assertions about the relationship, these results provide initial support to the consideration that there is a difference in GPS deviation events among NOTAM active and inactive conditions.*

Table 4. GPS deviations in active and inactive spatiotemporal windows of navigation-related NOTAMs

Metric	Value
GPS deviations that spatially intersected active NOTAM area	1,239,144 (41%)
GPS deviations that spatially intersected inactive NOTAM area	1,750,153 (59%)

F. Temporal Patterns (Hourly, Daily or Monthly) of GPS Anomalies and Number of Active NOTAM Warnings.

Hypothesis 8: There is a correlation between GPS gap incidents and navigation-related NOTAMs in effects among the hours of the day (UTC time).

Hypothesis 9: There is a correlation between GPS deviation incidents and navigation-related NOTAMs in effects among the hours of the day (UTC time).

A visual inspection of the bar chart in Fig. 12 for variables GPS Gaps, GPS deviation and active NOTAMS indicated significant variations among the hours of the day. Standard deviation for the three variables were 51895, 648, and 982, and the coefficient of variation 1.07, 1.14, and 0.81, respectively. While attempting to determine the significance of a potential correlation between GPS gaps and the number of active NOTAMs among the hours of the day, the assumptions for a linear regression were not met and, thus, the use of the statistics was dismissed. Potential alternatives for supporting the test of such association in future research would include the use of more complex non-parametric correlation methods or time-series models.

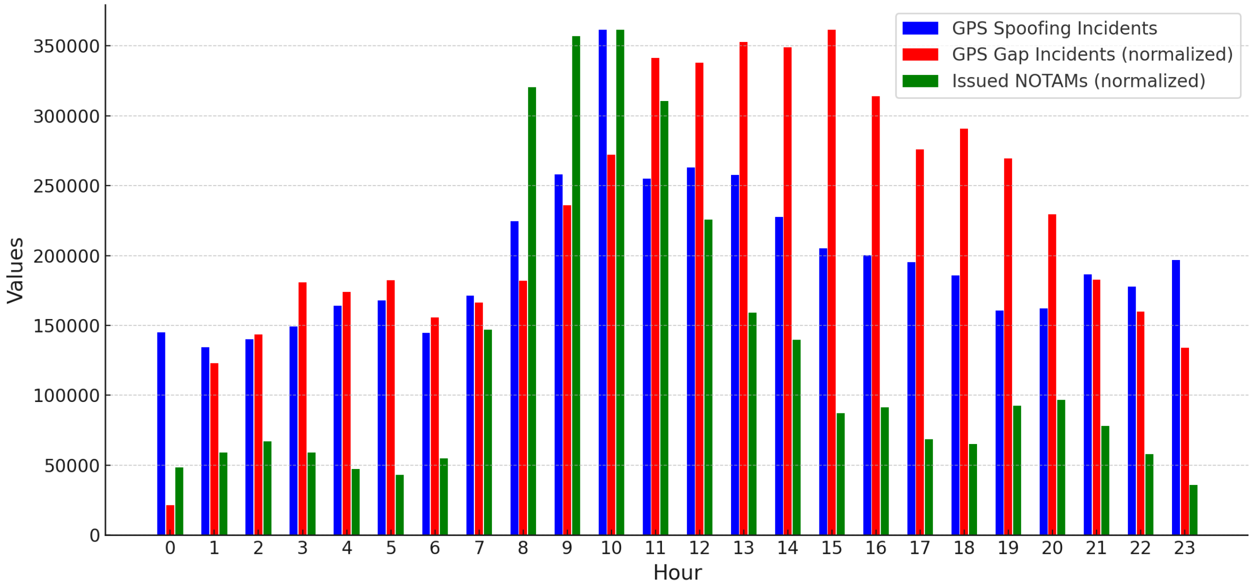

Fig. 12 GPS gap incidents and issued NOTAMs normalized to GPS spoofing incidents, by hour

Hypothesis 10: There is a difference in the number of GPS anomalies and navigation-related NOTAMs in effect among the days of the week.

In comparison to hourly variations, daily changes seemed less significant based on inspection of the bar plot for the three variables shown in Fig. 13. The standard deviation for GPS gaps, GPS deviations, and Active NOTAMS was 351, 75243, and 1911, and the coefficient of variation 0.047, 0.112, and 0.410, respectively. Table 5 shows the results produced by the statistical analysis created by ArcGIS software. *The variance seemed significant, especially when comparing the observed proportions of GPS deviation and gap incidents to the expected proportions if there were no correlation, calculated based on the issuance timings of NOTAMs.* While future research can strengthen the establishment of said association, these results provide initial support to the consideration that there is a difference in GPS gap and deviation events among the days of the week.

Table 5. GPS anomaly incidents, GPS gap incidents, and issued NOTAMs by day of week, for year 2023

Day of the Week	GPS Gaps	NOTAMs	GPS Spoofing
Mon	7,501	4,115	816,773
Tue	7,343	6,064	631,208
Wed	7,860	6,974	713,063
Thu	7,896	5,970	628,292
Fri	7,960	3,573	671,828
Sat	7,052	1,285	583,808
Sun	7,116	1,270	690,138

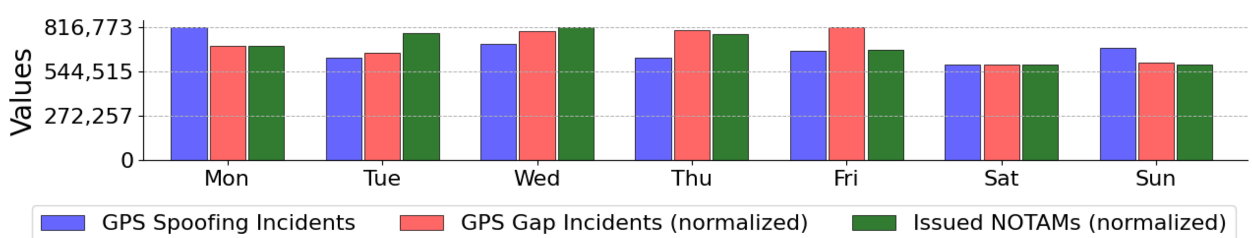

Fig. 13 GPS gap incidents and issued NOTAMs normalized to GPS spoofing incidents range, by day of week

The analysis shows that the distribution of GPS anomalies during NOTAM issuance timings is significantly different from the expected distribution, supporting the hypothesis indicating a difference in the daily numbers of GPS anomalies and NOTAM warnings.

Hypothesis 11: There is a difference in the number of GPS anomalies and navigation-related NOTAMs in effect among the months of the year.

Inspection of the bar charts in Fig. 14 for the numbers of GPS gaps, deviations, and active NOTAM throughout the months of the year indicate a significant variation, with coefficients of variation of 0.47, 0.30, and 0.29, respectively. Table 6 shows the results produced by the statistical analysis created by ArcGIS software. Further analysis can provide a more rigorous assessment of the initial impressions indicating support for the significant differences in GPS gap and deviation events among the distinct months of the year.

Table 6. GPS spoofing incidents, GPS gap incidents, and issued NOTAMs, by month, for year 2023

Month	GPS Spoofing Incidents	GPS Gap Incidents	NOTAMs
Jan	242027	3302	2379
Feb	226087	3996	2772
Mar	188545	4477	2895
Apr	294753	4916	2458
May	344626	5346	2521
Jun	538783	5386	2541
Jul	741162	5838	2643
Aug	478805	5568	3587
Sep	712255	4741	1984
Oct	253886	3581	2617
Nov	350549	4467	2334
Dec	363632	1110	520

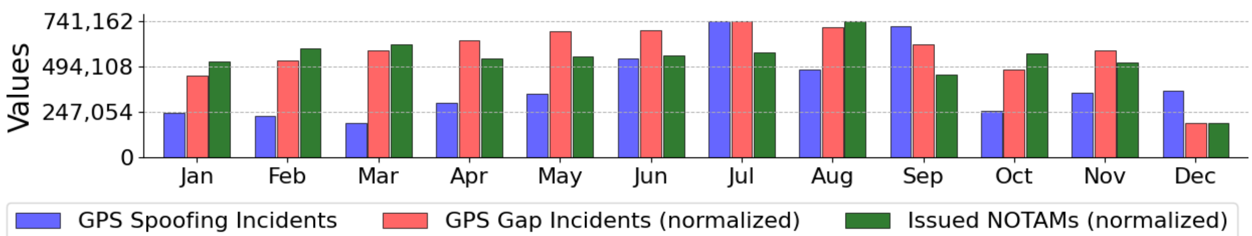

Fig. 14 GPS gap incidents and issued NOTAMs normalized to GPS spoofing incidents range, by month

G. Monthly Number of GPS Gaps and Solar Activity (Flux).

Hypothesis 12: There is a correlation between the number of GPS gaps and solar flux among the months of 2023.

To support the analysis, solar activity was obtained from NOAA [42]. Descriptive statistics for these variables calculated by the ArcGIS software are presented in Table 7 with the solar activity obtained from NOAA and GPS anomalies during the year 2023 shown in Fig. 15. StatCrunch statistical software was used to calculate the Pearson's correlation [43]. The normality assumption was assessed by a Shapiro-Wilk's test ($p > 0.05$). The results did not show a 0.933) significant relationship ($p = 0.933$). This suggests that there is almost no linear relationship between solar flux and GPS anomalies. The p-value of 0.933 is much higher than the conventional significance level of 0.05, indicating that the correlation is not statistically significant.

Table 7. GPS gaps and Solar Activity (Flux)

Metric	Solar Flux	GPS gaps
Count	12	12
Mean	159.90	4394.00
Standard Deviation	12.11	1298.79
Minimum	141.59	1110.00
Median	156.79	4609.00

Metric	Solar Flux	GPS gaps
Maximum	182.47	5838.00

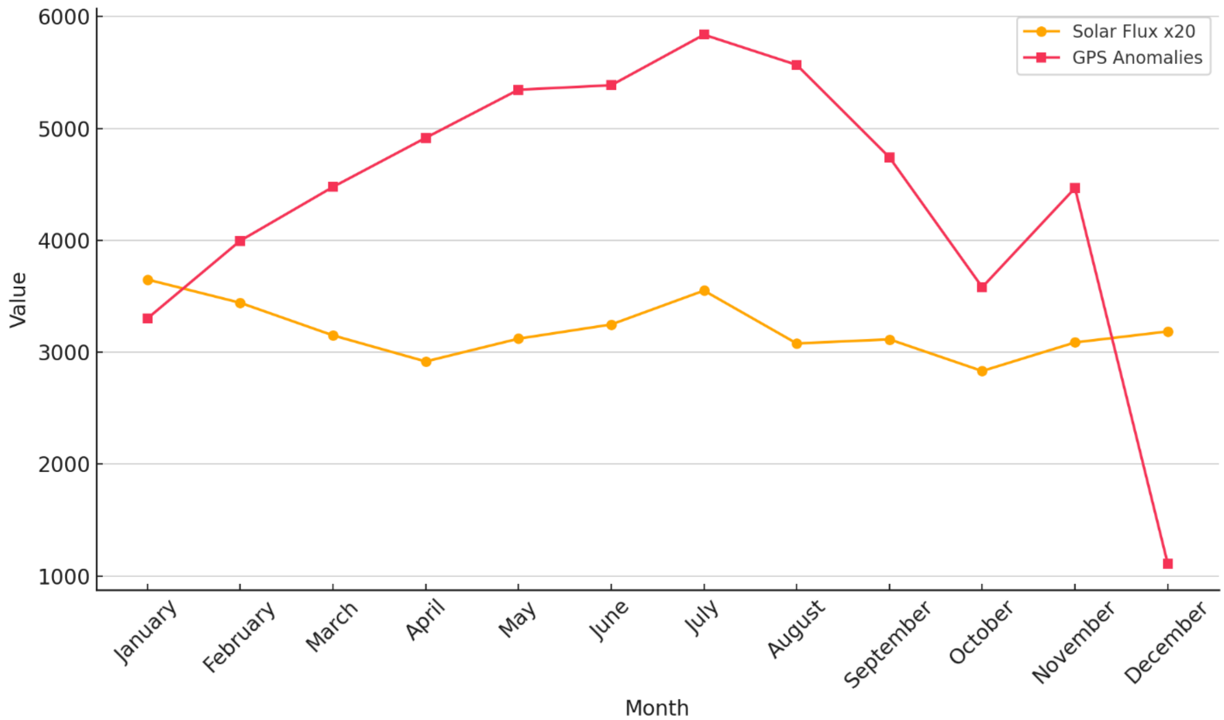

Fig. 15 Solar flux (x20) and GPS gaps per month in 2023.

The statistical analysis does not support the hypothesis that there is an association between the number of GPS gaps detected in ADS-B data with the level of monthly solar activity. *The weak correlation and high p-value suggest that there is no significant relationship between solar activity and GPS anomalies for the given data.*

H. Navigation Integrity Category (NIC) Values and GPS Gaps

We analyzed NIC values during all GPS gap incidents that occurred in 2023. For each gap, NIC values were recorded from the beginning to the end of the gap. These values fluctuated, ranging from minimal to maximal NIC, with the average NIC representing the mean of all NICs observed during the gap.

Fig. 16 shows a Kernel Density diagram to visualize the density of minimum, maximum, and average NIC values during GPS gap incidents. This analysis underscores the variability of NIC values during GPS gaps, which is critical for assessing the integrity and reliability of navigation systems. Understanding NIC behavior during GPS gap incidents is crucial for improving the robustness of navigation systems in aviation.

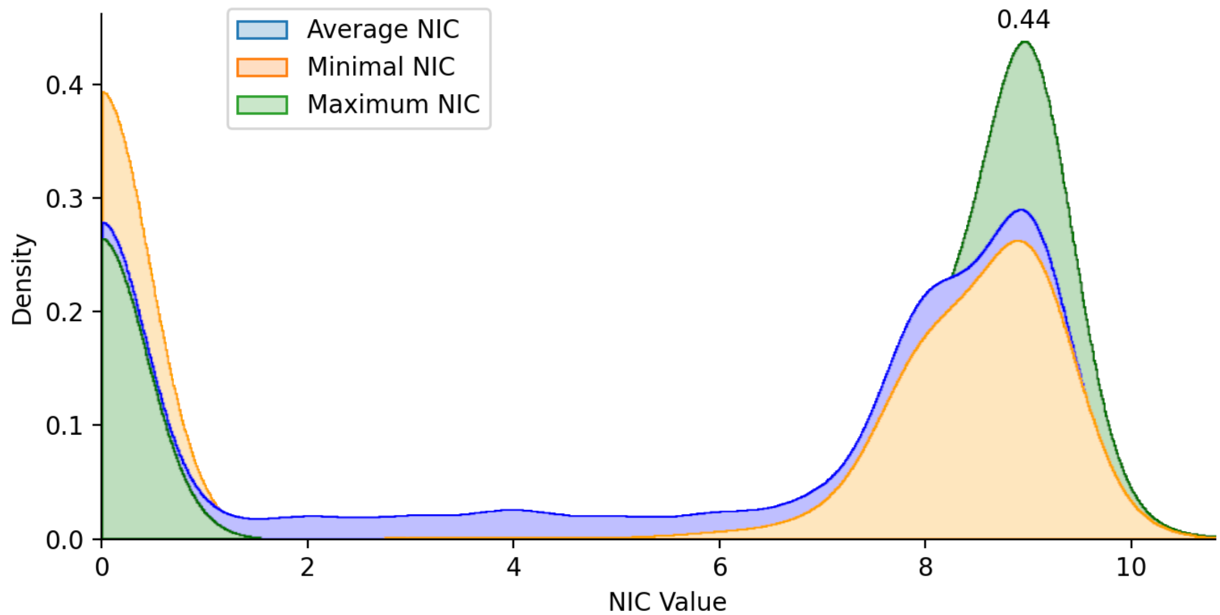

Fig. 16 Kernel density estimation of NIC values during GPS anomalies

VI. Limitations of this Study

These preliminary results share some challenges associated with the data sources of the process for calculating associated metrics. As such, it is important to consider some of these shortcomings when interpreting these results. The primary challenges identified by the researchers are presented below.

ADS-B Coverage. The geographic coverage of ADS-B varies significantly, with some areas having dense coverage and others sparse. This uneven distribution can bias the results, as anomalies are more likely to be detected in well-covered regions, potentially underrepresenting issues in areas with sparse coverage [14,44,45].

ADS-B Data Accuracy. Erroneous GPS readings or malfunctioning ADS-B equipment can result in inaccurate positional data, leading to false positives in GPS anomaly detection [46]. For instance, an incorrect sudden position change might be mistakenly classified as a spoofing incident.

ADS-B Data Completeness. Missing or incomplete ADS-B messages can create gaps in tracking aircraft positions, potentially resulting in the misidentification of GPS anomalies. Inconsistent transmission of ADS-B signals by aircraft may cause the analysis to either overlook real anomalies or falsely detect nonexistent ones.

Environmental Factors. Natural phenomena such as solar flares, lightning, and atmospheric conditions can disrupt GPS signals and ADS-B transmissions, making it challenging to distinguish between intentional jamming or spoofing and these natural interferences [47,48].

Validation and Filtering. Although efforts were made to filter out noise, glitches, and equipment malfunctions, some detected anomalies may still be attributed to these factors rather than intentional interference. Rigorous validation and filtering are crucial for maintaining data integrity, but complete accuracy cannot be guaranteed.

External Data Sources for NOTAM Locations. Parsing FAA domestic NOTAM locations involved using PDF files from additional sources, which may contain errors. These inaccuracies can impact the precision of the location data used in the analysis.

VII. Conclusion

The statistical analysis of the geospatial information reveals the following key findings:

A. Number of GPS Anomalies and Traffic Density

H1: There is an association between GPS gaps and air traffic density.

H2: There is an association between GPS deviations and air traffic density.

Result: There is an association between GPS gaps and air traffic density. Similarly, the hypothesis that there is an association between GPS deviations and air traffic density is also supported, although the relationship is weaker compared to GPS gaps.

B. Numbers of GPS Gaps in Aircraft Routes and the NOTAM Warnings.

H3: There is a difference in the incidence of GPS gaps in active and inactive spatiotemporal windows of navigation-related NOTAM.

Result: A difference exists in the spatiotemporal occurrence of GPS gaps based on whether NOTAM warnings are active or not. Additional detailed analysis would be warranted to support the further determination of these conditions.

C. Percentage of NOTAM Messages and a Percentage of GPS Anomalies in Geographic Areas

H4: There is an association in geographic locations for GPS gaps and navigation-related NOTAMs.

H5: There is an association in geographic locations for GPS deviations and navigation-related NOTAMs.

Result: Visual inspections of the plot suggest an association in geographic location for the top GPS gap and navigation-related NOTAMS, with 19% of intersections among associated hexbins. No intersections were identified outside of North America. Visual inspections of the plot suggest an association in geographic locations for the top GPS deviation and navigation-related NOTAMs. No intersections were identified outside of North America.

D. Duration of GPS Gaps among Areas with Active and Inactive Navigation Related NOTAMS

H6: There is a difference in the duration of GPS gaps among areas with active and inactive NOTAMs.

Result: The results of the descriptive statistics for GPS gap durations among active and inactive NOTAM areas suggest that areas with active navigation-related NOTAMs have on average 257 s longer GPS gaps.

E. Frequency of GPS Deviation Incidents among Areas with Active and Inactive Navigation Related NOTAMS

H7: There is a difference in the incidence of GPS deviations in active and inactive spatiotemporal windows of navigation-related NOTAMs.

Result: There is an initial support to the consideration of a difference in GPS deviation events among NOTAM active and inactive conditions.

F. Temporal Patterns (Hourly, Daily or Monthly) of GPS Anomalies and Number of Active NOTAM Warnings.

H8: There is a correlation between GPS gap incidents and navigation-related NOTAMs in effects among the hours of the day (UTC time).

H9: There is a correlation between GPS deviation incidents and navigation-related NOTAMs in effects among the hours of the day (UTC time).

Result: While attempting to determine the significance of a potential correlation between GPS gaps and the number of active NOTAMs among the hours of the day, the assumptions for a linear regression were not met and, thus, the use of the statistics was dismissed. Potential alternatives for supporting the test of such association in future research would include the use of more complex non-parametric correlation methods or time-series models.

H10: There is a difference in the number of GPS anomalies and navigation-related NOTAMs in effect among the days of the week.

Result: The variance seemed significant, especially when comparing the observed proportions of GPS deviation and gap incidents to the expected proportions if there were no correlation, calculated based on the issuance timings of NOTAMs.

H11: There is a difference in the number of GPS anomalies and navigation-related NOTAMs in effect among the months of the year.

Result: Inspection of the bar charts for the numbers of GPS gaps, deviations, and active NOTAM throughout the months of the year indicate a significant variation.

G. Monthly Number of GPS Gaps and Solar Activity (Flux).

H12: There is a correlation between the number of GPS gaps and solar flux among the months of 2023.

Result: The weak correlation and high p-value suggest that there is no significant relationship between solar activity and GPS anomalies for the given data.

H. Navigation Integrity Category (NIC) Values and GPS Gaps

Result: In order to understand how NIC values behaved in GPS gap incidents, researchers created a Kernel Density diagram to visualize the density of minimum, maximum, and average NIC values during GPS gap incidents. FAA references address NIC below 7 as indicating low position precision [49]. However, the research found that a significant portion of messages with NIC above 7 had missing coordinate information.

Future Research

To build upon the findings and address the limitations of this study, future research should explore several key areas to enhance the understanding and mitigation of GPS anomalies in aviation. One question that could be explored relates to the integration of additional data sources, such as radar, satellite systems, and other Global Navigation Satellite Systems (GNSS), to cross-validate GPS anomalies. This multi-source approach can improve the accuracy of identifying disruptions and provide a more comprehensive understanding of factors associated with GPS anomalies.

Expanding ADS-B coverage in regions with sparse data is another essential avenue for research. Enhanced coverage can offer a more complete understanding of GPS anomalies across diverse geographic areas and reduce biases in anomaly detection, particularly in regions with low infrastructure density. Developing advanced filtering techniques is also crucial. More sophisticated algorithms are needed to differentiate between natural interferences, such as solar flares, lightning, and atmospheric conditions, and intentional disruptions like jamming or spoofing. Enhanced machine learning models can significantly improve the accuracy of filtering false positives in ADS-B data, ensuring more reliable detection systems. Another area requiring attention is the impact of equipment malfunctions on the detection of GPS anomalies. Detailed investigations into the reliability and failure modes of ADS-B equipment can lead to the development of more robust mechanisms for identifying and mitigating anomalies caused by hardware issues. Research should also explore the correlation between GPS anomalies and flight operational data, such as deviations from planned routes, delays, and fuel consumption. Analyzing these impacts can provide valuable insights into the practical implications of GPS disruptions on aviation safety, efficiency, and cost-effectiveness. Additional exploration of temporal factors associated with anomaly incidence could also provide further insights into the problem.

A deeper geopolitical analysis is necessary to investigate the relationship between geopolitical events and the frequency of GPS anomalies, particularly in regions with low flight traffic but high incidence rates, such as Turkey, Israel, Egypt, Russia, India, and Thailand. Understanding these patterns could shed light on intentional interference and its underlying causes. Finally, future studies should examine the impact of emerging technologies, including the deployment of 5G networks, on GPS signal integrity. Assessing the interactions between new technologies and GPS systems will be critical for developing proactive strategies to mitigate potential disruptions. By addressing these areas, future research can contribute to the creation of more robust GPS anomaly detection systems, enhance aviation safety, and reduce the risks posed by GPS interference in aviation operations.

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Appendix

GPS gaps workflow

(1) **FilteredData**
- Exclude rows with onground = false (only flying).
- Ensure icao24 is valid (not NULL, length=6, hex).
- Use LAG/LEAD SQL functions to add previous/next coordinates & times.

(2) **Sessionized**
- For each aircraft in time order, if the previous row had lat/lon and the current row is NULL, set is_start_of_null=1.

(3) **ValidPrevious**
- Check if the previous coordinates are “fresh”:

– ABS(previous_time - previous_lastposupdate) <= 2 sec
- If so, is_valid_previous=TRUE; otherwise FALSE.
- This ensures a trustworthy anchor point before any gap.

(4) **ValidNext**
- Similarly, check if the next coordinates are “fresh”:

– ABS(next_time - next_lastposupdate) <= 2 sec
- If so, is_valid_next=TRUE; otherwise FALSE.
- This ensures a trustworthy anchor point after a gap.

(5) **CollapsedNulls**
• Take rows from step (4) where current_lat or current_lon is NULL.
• Use is_start_of_null to group these NULL rows into "sessions" (blocks of consecutive missing-data rows for one aircraft).
• For each session, record:
– The earliest and latest times of the NULL rows (null_start_time, null_end_time).
– The valid_previous_lat/lon/time only if is_valid_previous=TRUE.
– The valid_next_lat/lon/time only if is_valid_next=TRUE.
• Keep only sessions that last at least 60 seconds: (MAX(time) - MIN(time)) >= 60 sec.

(6) **NICData**
• Gather NIC (Navigation Integrity Category) from another table for each gap's time range.
• Filter NIC to [0..11] and not NULL, then compute average, min, and max NIC.

(7) **ValidCoords**
• Join **CollapsedNulls** and **NICData**.
• Keep only gaps with valid anchors on both ends (is_valid_previous=TRUE and is_valid_next=TRUE).

(8) **Final SELECT**
• For each missing-data session, output:
– Plane ID (icao24) and callsign.
– Timestamps for when the gap starts/ends.
– Reliable previous/next coords/times.
– Duration of the gap.
– Average, min, and max NIC values in that time.
• Sort by aircraft and gap start time.

GPS deviations workflow

(1) FilteredData
• Keep only records where:
– onground = false (plane is airborne)
– icao24 is 6 chars, valid hex
– lat and lon are not NULL and are within normal Earth bounds
– ABS(time - lastposupdate) < 2 seconds (fresh data)
• Use LAG SQL function to attach previous coordinates and time.

(2) DistanceCalculations
• Check that the previous coordinates are also fresh:

• Calculate the distance between consecutive points:
– ST_Distance([current coords], [previous coords])
• Convert to meters, round, and call that result distance.
• Compute time_difference = (time - prev_time).
• Compute max_allowed_distance = time_difference * 600 (assuming a speed limit of 600 m/s).

(3) Final SELECT
• Flag potential GPS deviation if both:
– distance > max_allowed_distance
– distance > 2000 meters
• Output details:
– icao24, callsign
– time_before_deviation / time_of_deviation

– lat/lon before and at the deviation point
– distance, time_difference