Spatio-Temporal Analysis for Modeling High-Demand Events in European Private Aviation

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Abstract

Accurately predicting the demand for aviation is a complex problem that is essential for the success of private aviation providers. Factors such as seasonality and location affect the demand for private flights, but high-demand events and holidays introduce additional and often unexpected influences on these services. In European destinations, travel is heavily characterized by high-demand events and holidays. This research utilizes detailed characterization data centered in Europe containing over 1.1 million private flights between 2,016 locations from 2018 and 2019. Leveraging advanced data analysis techniques, this project constructs a spatio-temporal forecasting model to accurately predict the demand for private jet travel during high-demand events and holidays in European destinations. This research delivers valuable insights to providers of private aviation, enabling them to proactively respond to market fluctuations and optimize their operational strategies.

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1 Introduction

The private aviation industry plays a vital role in the transportation sector, catering to individuals and organizations seeking exclusive and efficient travel experiences. In recent years, the private aviation industry has witnessed significant growth worldwide, and demand for aviation services has further surged following the Covid-19 pandemic (Gollan, 2022). Accurately predicting the demand for private jet travel is crucial for the success and profitability of private aviation providers. However, this task is inherently complex, as it requires accounting for multiple factors that influence demand, including seasonality, location-specific dynamics, and the impact of high-demand events and holidays.

In European destinations, private jet travel is heavily characterized by high-demand events and holidays that attract a significant influx of travelers. Occasions such as international conferences, major sporting events, cultural festivals, and peak holiday periods, create unique travel patterns. Therefore, it is imperative for companies to accurately anticipate these fluctuations in demand to optimize revenue, flight scheduling, and resource allocation.

This paper aims to address the challenges faced by private aviation providers in forecasting demand, especially during high-demand events and holidays. By using a comprehensive dataset of over 1.1 million flights during the years 2018 and 2019, we leverage advanced data analysis techniques to examine predictive forecasting of demand. Our primary objective is to characterize the impact of high-demand events in the European private aviation market and implement these findings into an accurate spatio-temporal forecasting model. We seek to equip private aviation providers with the capability to manage uncertainties during high-demand events and holidays, thereby optimizing operational abilities. In this paper, we deliver three primary results: (1) characterization of aviation travel on a global scale, (2) high-demand event and holiday travel characterization in the European market, and (3) accurate forecasting of demand around these events.

The results of this paper contribute to the broader literature of predictive modeling. Forecasting demand and incorporating event characterization into models is necessary for any industry seeking to optimize operational strategies. This issue is at the forefront, addressed in consumer industries such as sales forecasting and prediction in fast fashion (Choi et al. 2014) and forecasting demand for emergency care (S.A. Jones et al. 2002), contributing to more accurate and efficient planning and resource allocation.

2 Context

Private aviation companies primarily rely on time series models to forecast fluctuations in flight demand (Zachariah et al. 2023, Xu et al., 2019). Although these models efficiently capture trends, they may be limited in predicting major spikes in demand, which are characteristic of high-demand events or holidays. Such events introduce unique dynamics that can significantly impact private aviation demand, and traditional time series models may not adequately account for them.

To address this gap, this project identifies the contributing factors of fluctuations in travel demand on a global scale, then characterizes several high-demand events in the European market. These events are subsequently implemented into the development of a statistical spatio-temporal model designed to predict flight demand in the private aviation industry. The model aims to incorporate coefficients for the those factors that influence fluctuations in private aviation demand.

By leveraging the spatio-temporal characteristics of the data, the proposed model captures the influential time and location elements of flight demand. This approach will facilitate a deeper understanding of the factors that impact demand, enabling private aviation companies to anticipate and effectively respond to increases in flight bookings during high-demand events and holidays.

3 Data

This project uses a comprehensive dataset comprising 1.1 million flights recorded during 2018 and 2019. These data encompass a network of 2,016 airports, including departure and arrival dates, airport specific information, and aircraft types. Recurring patterns in flight behaviors are observed. Among all airports cataloged in the dataset, 193 airports account for 80% of all recorded flights, and only eight airports handle 20% of the total flight volume. Table 1 displays these airports and their respective flight counts.

Figure 1 highlights distinctive travel patterns. The total number of flights gradually increases from the beginning of the year, peaks around mid-year, and then gradually decreases toward the year's end. This pattern suggests a non-linear relationship between the month of the year and the number of arrivals, with a peak occurring during the middle of the year. To further explore this relationship, we analyze the data by day of the week and month of the year.[1] Analyzing the average number of arrivals by month revealed that the months in the middle of the year, such as July and June, exhibited a higher number of arrivals per day compared to the months at the beginning and end of the year, such as December, January, and February.[2]

Table 2 presents the average number of arrivals per day and per month (January through December) based on the 2018 data. Analyzing the average number of arrivals by day of the week revealed that Thursdays and Fridays had the highest number of arrivals, while Saturdays showed significantly fewer.

[1]Several pre-processing steps were completed to ensure data quality and relevance. Incomplete observations were removed, specifically those related to airports with ICAO codes 'AFIL' (recorded when the flight was already in the air) or 'ZZZZ' (no ICAO code exists for the airport).

[2]Many arrival locations had less than ten flights per year, indicating a low volume of travel to these destinations. These locations were excluded from the analysis due to their limited data. As a result of this exclusion, the dataset was refined to 1,218 arrival locations.

The data support established aviation trends, revealing distinct variations across different months and days of the week. In Figure 2, we present heatmaps of flight density by day of the week and week of the year for 2018 and 2019. The x-axis represents the weeks of the year. The y-axis represents the days of the week, starting from Monday and ending with Sunday. Each cell in the heat map is color-coded to represent the intensity of arrivals, with darker red colors indicating a higher number of arrivals and darker blue colors indicating a lower number. Based on the heat maps, Thursdays and Fridays exhibit the highest intensity of arrivals, as shown by the red shades in these cells. Saturdays, on the other hand, show significantly fewer arrivals, represented by blue shades in the corresponding cells. [3] The summer months, specifically June, July, and August, see consistent increases across the days of week. Lower travel frequencies are evident in January and December across all weekdays and on Saturdays throughout the year.

The Paris Le-Bouget Airport (LFPB) is the highest flight density airport observed. In Figure 3, we graph the flight density for LFPB to confirm that trends hold on the airport level. We identify clear up-trends in flights during summer weeks and low demand on days of the week such as Saturday. The uniformity in trends across individual airports substantiates aggregate observed patterns, ensuring consistency at the airport level and in the aggregate dataset analysis.

Lastly, highlighting the spatial aspect of the data is crucial. Among the 2000+ airports documented, flights connect across five continents, including transatlantic flights depicted in Figure 4. For the scope of this project, we utilize airports with 500 or more flights per year, predominately located in Europe, as shown in Figure 5. The data include airports with one flight annually, to over 20,000, however, after restricting to airports with more than 500 flights annually, we utilize 203 airports for analysis. In Figure 5, we represent flight density by the size and color of the located point icon on the map. The red points are airports with more than 20,000 arrival flights in combined 2018 and 2019 years. Notably, we observe a high concentration of high-traffic airports in France, the United Kingdom, and Russia.

The data provide a rich source of information to analyze and model the demand for private aviation in Europe. We aim to develop a robust demand forecasting model specifically for European destinations. This involves exploring various factors that influence demand, such as seasonal patterns, event-driven fluctuations, and event locations, facilitating a comprehensive understanding of the dynamics and drivers of private aviation demand in Europe.

[3] On Tuesday, April 3, 2018 (week 14), there is a noticeably low number of arrivals compared to the surrounding days and weeks. Upon investigation we discovered a EUROCONTROL Network Manager systems outage on April 3, 2018 that caused delays and cancellations of flights in European airports. Thus, this day is removed from our analysis.

4 Methodology

4.1 Global Model

Using the 2018 arrival data, we develop a predictive global model accounting for variations based on the day of the week and month of the year. We identify 8 weeks that follow similar patterns of global travel demand, as illustrated in Figure 6. Baseline coefficients are developed based on these selected weeks that exhibit "regular" behavior.

To construct the model, we categorize the data by the day of the week and compute the average number of flights per day. Since Saturday has the lowest average number of flights, it is used as the baseline. The day-of-week coefficient, denoted as δ, is computed as:

$$\delta_i = \frac{\bar{F}_i}{\bar{F}_{\text{Sat}}}$$

where $\bar{F}_i$ represents the average number of flights for day i and $\bar{F}_{\text{Sat}}$ is the baseline value (1160.0). The day-of-week averages and resulting coefficients are shown in Table 3. For each day of the year, including "non-regular" weeks, the true number of flights per day is divided by the corresponding coefficient for that day of the week. This calculation removes the influence of the day of the week, resulting in a relative daily increase in value for flights.

We use a similar method to eliminate seasonal influence due to the month of the year. Using the flight count data adjusted to remove the day-of-the-week influence, the mean number of flights is computed for each month. Table 4 presents the average daily arrivals for each month (January through December) in 2018. December is used as the baseline, and the month coefficient, denoted as μ, is computed as:

$$\mu_j = \frac{\bar{F}_j}{\bar{F}_{\text{Dec}}}$$

where $\bar{F}_j$ represents the average number of flights for month j and $\bar{F}_{\text{Dec}}$ is the baseline value (834.8). For each day of the year, including "non-regular" weeks, the number of flights per day, after removing the influence of the day of the week, is divided by the corresponding coefficient for that month. This calculation effectively eliminates the influence of the month, resulting in a normalized value for the number of flights, as shown in Figure 7.[4] We define a baseline coefficient, β, as a normalized baseline value. In our implementation, we consider a normalized baseline value of 830, which represented a minimum on weeks that exhibit "regular" behavior, as shown in Figure 6.

The global model, as described, is computed as:

[4]The month coefficient for August is manually changed from 1.529 to 1.510 as the final model was more representative of the data and thus a better fit with this value.

$$\text{Global Arrivals}(\delta, \mu) = \beta \cdot \delta \cdot \mu$$

where β = the baseline number of flights, δ = day-of-the-week coefficient, capturing the proportion of daily arrivals relative to Saturday, and μ = month coefficient, capturing the proportion of monthly arrivals relative to December. The resulting model is graphed against the 2019 data in Figure 8.

4.2 Spatio-Temporal Model

A spatio-temporal predictive model is developed using the 2018 arrival data and incorporates variations related to the day of the week, month of the year, and location. The analysis focuses on the 203 airports that have over 500 annual arrivals in 2018 and 2019. The data are grouped by date and airport location. The normalization process starts by removing the day of the week influence similar to our strategy in section 4.1. Using coefficients from the global model for each day of the week, the number of arrivals for each day is divided by its corresponding day of the week coefficient. This step removes the weekly cyclical variation in private aviation, isolating other factors impactful to flight demand. Next, the day-removed arrivals are adjusted by dividing by the corresponding month coefficient, as used in the global model, to remove monthly fluctuations. The result is a value representing the number of arrivals for each airport, devoid of day and month influences.

To normalize these values further, each airport's day-month-removed value is divided by its corresponding average daily arrivals over the year. This final normalization step enables comparisons of arrival data across airports, as the data are compared on a relative scale.

The normalized arrivals used in the spatio-temporal model are computed using the following formula:

$$\text{Normalized Arrivals}(\delta, \mu, \alpha) = \left(\frac{\text{Actual Arrivals}}{\delta}\right) \times \frac{1}{\mu} \times \frac{1}{\alpha}$$

where: δ = day of the week coefficient, μ = month coefficient, and α = airport average

4.3 Event Identification

To identify significant events within these airports, we graph flight density using a heat map for normalized flight data that accounts for the day of the week, month, and airport-specific travel demand. By eliminating the impact of these factors, the analysis exclusively highlights the influence exerted by events on flight patterns. The entire flight density is graphed in Figure 9. From this heat map, we identify events that have a specific threshold increase in average flights.

Figure 10 shows days of the year for airports that saw an increase five times larger than their daily average. This analysis allows us to categorize multiple types of events. First are outlier events with a sudden spike in demand and no change before or after the event. Second, are events demonstrating a series of consecutive days with increased demand concurrently. Long-term demand increase may be evidence of seasonality. In this case, accurate categorization of events will increase the precision of overall event characterization.

5 Results

There are three major results of this project. First, the development of a global model. Second, the development of a predictive spatio-temporal model. Third, characterization and modeling of high-demand events and holidays.

5.1 Global Model

The results of the global model provide a foundation for the remaining results of this work. The model is graphed against the 2019 arrival data in Figure 8. Both lines exhibit a similar overall trend with slight variations. These variations may indicate dates that are influenced by global events or holidays, which could potentially impact travel demand. Additionally, the R-squared value produced by the model in comparison to the actual 2019 data is 0.76, indicating a strong correlation between the model's predictions and the observed values.

5.2 Spatio-Temporal Model

The spatio-temporal model expands upon the findings of the global model to incorporate location. We can produce a separate model for each of the 203 airport locations of interest. The baseline used to model each airport is its corresponding day-month-removed average. The final model equation for each day of the year and each airport is:

$$\text{Arrivals}(\text{Date}, \text{Location}) = \beta \cdot \delta \cdot \mu \cdot \gamma$$

where: β = baseline value (airport-specific normalized average), δ = day of the week, μ = month, γ = normalized arrival value.

The spatio-temporal model was calculated to predict 2019 data for each airport. When compared to the actual data, the weekly average produced by the model compared to the actual data had an R-squared value of over 0.5 for 29% of the airports.

5.3 Event Characterizations

Through our analysis, we identified four types of event characterizations based on their spatial and temporal impact on air travel demand. (1) Global events: These events, such as Easter and Christmas, exert influence across the entire market. They consistently trigger surges in demand across multiple regions, particularly in Europe, leading to increases ranging from 2 to 10 times the average number of flights per airport. (2) Seasonal events: Events such as ski season or summer travel contribute to prolonged elevations in demand. These events influence trends of heightened demand, persisting for multiple weeks or months. We identify eight airports that see consistent seasonal demand increases for the ski season, February to March. These airports see demand fluctuations between 2.2 to 21.7 times the average. (3) Local stationary events: These events impact smaller market segments and occur annually in a fixed location. They are often associated with festivals, localized celebrations, or region-specific holidays that create demand surges tied to specific dates. (4) Local dynamic events: This category includes events that impact localized market segments but change location annually, such as sporting championships or similar events with varying venues.[5]

The Cannes Film Festival in Cannes, France is an example of a local stationary event identified within our analysis. This event uniquely affects airports near Cannes and can be expected every year. We graph the flight counts for Cannes - Mandelieu Airport (LFMD) in Figure 11. The surge observed between days 50 and 100 in both the 2018 and 2019 graphs represents the influx of travel for the Cannes Film Festival. This event showcases calendar-specific consistency, clearly demonstrating its regular occurrence each year. Its impact remains localized, significantly influencing travel patterns exclusively at the Cannes airport without substantially affecting demand for neighboring airports and cities.

The Union of European Football Associations (UEFA) Champions League Final represents an example of a local dynamic event within the analysis. The location of the soccer league championship changes annually but impacts only the demand for nearby airports. In Figure 12, we graph 2018 demand for the Kyiv airport, which saw a dramatic spike up to 80 flights around day 150. In 2019, however, the demand remained relatively stable, peaking at around 17 flights. Examining the flight trends for Madrid in the second row of the graph reveals a consistent demand in 2018, with flight counts remaining under 45. In contrast, during the year Madrid hosted the Champions League final in 2019, there was a substantial spike in demand, to around 120 flights. This event aligns with the criteria defining a local dynamic event. Predominantly influencing nearby airports of the event location and exhibiting variability in demand from year to year based on the tournament's changing venue.

Through the characterization process, we located six expected high-demand events and an additional eleven which are

[5]The classification of events as either local or global is based on their observed influence on flight demand across multiple airports. While some events, such as the UEFA Champions League Final, receive widespread global attention, their direct impact on flight demand is typically concentrated around the host city and surrounding regions rather than across the entire market. In contrast, global events, like Christmas, cause significant and widespread travel increases across multiple countries, warranting a separate classification. This framework allows for distinguishing events based on their actual influence on travel patterns rather than their media visibility.

detailed in Table 5. We identify the estimated effect of each event through what we call a ”Factor of Change”. The factor of change represents the relative increase in flight arrivals due to the event, normalized against typical seasonal travel patterns for each airport. It quantifies how much higher the observed arrivals are compared to expected levels during regular travel periods. A factor of 2, for instance, indicates that arrivals on those days were 2 times the expected amount for that time of year.

5.3.1 Ski Season

Seven airports in Austria, France, and Switzerland experience the majority of recorded traffic during the winter months, attributed to the Ski Season. The affected dates are Fridays, Saturdays, and Sundays in February and March. The locations, dates and factor of change is found in Table 6. Additionally, we model 2019 data for these airports using the spatio-temporal model. The weekly average of arrivals is calculated for the modeled data and the actual 2019 data and compared. Figure 13 shows a comparison between the 2019 modeled weekly and daily average data and the actual weekly and daily average data for Chambéry Airport (LFLB). The spatio-temporal model used in this analysis demonstrates a strong fit, with an R-squared value of 0.92, indicating a high level of accuracy in predicting the weekly average data for the airport.

5.3.2 Easter

Easter, a globally recognized event, has a significant influence on flight demand across the airports analyzed. Specifically, the impact of Easter is observed from Thursday, March 29 to Monday, April 2, 2018. The locations and dates impacted, and the factor of change are recorded in Table 7.

5.3.3 Cannes Film Festival

The Cannes Film Festival, held annually in Cannes, France, has an impact on the flight demand at two airports, the Nice Côte d'Azur Airport and Cannes-Mandelieu Airport, located in southern France. Specifically, the weekends from May 8 to May 19, 2018, experience significant fluctuations in flight demand because of this event. These estimates are found in Table 8 and modeled data for 2019. Figure 14 shows a comparison between the 2019 modeled weekly average data and the actual weekly average data for Cannes-Mandelieu Airport (LFMD). The spatio-temporal model, as graphed against the actual 2019 data in Figure 14, demonstrates a strong fit, with an R-squared value of 0.87.

5.3.4 Monaco Grand Prix

The Monaco Grand Prix, held annually in Monte Carlo, Monaco, significantly impacts the two closest high-demand airports in southern France, the Nice Côte d'Azur Airport and Cannes-Mandelieu Airport, during the weekends from

May 8 to May 19, 2018, leading to notable fluctuations in flight demand. These estimates are found in Table 9. We also model the 2019 data for these airports using the spatio-temporal model. The weekly average of arrivals is calculated for the modeled data and the actual 2019 data and compared. Figure 15 shows a comparison between the 2019 modeled weekly average data and the actual weekly average data for Nice Côte d'Azur Airport (LFMN). The spatio-temporal model used in this analysis demonstrates a strong fit, with an R-squared value of 0.93.

5.3.5 Union of European Football Associations (UEFA) Campions League Final

The UEFA Champions League Final is a rotating event. As mentioned above, in 2018, it took place in Kyiv, Ukraine, on May 26, 2018, and had an impact on flight demand at three airports, the Boryspill International Airport, Sikorsky International Airport, and Pulkovo Airport, in Ukraine and Russia. In 2019, the game was held in Madrid, Spain, and affected one airport, the Adolofo Suárez Madrid–Barajas Airport. The 2019 data for Adolfo Suárez Madrid–Barajas Airport is modeled using the spatio-temporal model. Since the UEFA Chamipons League Final is a moving event, the model multiplies the affected days by 13.81, which represents the 2018 factor of change. The weekly average of arrivals is calculated for the modeled data and the actual 2019 data and compared. These estimates are found in Table 10. Figure 16 displays the comparison between the 2019 modeled and actual weekly average data for Adolfo Suárez Madrid–Barajas Airport (LEMD). The spatio-temporal model used in this analysis demonstrates a strong fit, with an R-squared value of 0.81.

5.3.6 Summer Travel

Twenty-one airports in Croatia, France, Greece, Germany, Italy, Montenegro, Spain, and Turkey primarily experience high travel volumes during the summer months, specifically on Fridays and Saturdays in July and August. The 2019 data for these airports is modeled using the spatio-temporal model. The weekly average of arrivals is calculated for the modeled data and the actual 2019 data and compared. These estimates are found in Table 11. Figure 17 shows a comparison between the 2019 modeled weekly average data and the actual weekly average data for Ibiza Airport (LEIB)[6]. The spatio-temporal model used in this analysis demonstrates a strong fit, with an R-squared value of 0.95.

5.3.7 Additional Events

The European Fine Art Fair, held annually in Maastricht, Netherlands, has an impact on the flight demand at one airport located in the city. Specifically, Maastricht Aachen Airport experiences a significant increase in private flights from March 7 to March 18, 2018 as a result of this event. In 2019, the European Fine Art Fair took place from March 16 to March 24, one week later in the year than in 2018. To account for this difference, we remove the factor of change

[6]The Ibiza Airport is one of the highest traffic summer airports in our sample while also a good representation of average summer airport trends. Thus it can be utilized to model the efficacy of summer characterization.

from the 2018 dates and apply them to the expected 2019 dates. We calculate the weekly average arrivals for both the modeled data and the actual 2019 data, allowing for a comparison. These estimates can be found in Table 12. Figure 18 displays the comparison between the 2019 modeled and actual weekly average data for Maastricht Aachen Airport (EHBK). The spatio-temporal model used in this analysis demonstrates a strong fit, with an R-squared value of 0.76, indicating high accuracy in predicting the airport's weekly average data.

The Hannover Messe, held annually in Hanover, Germany, has an impact on the flight demand at one airport located in the city. Specifically, Hannover Airport experiences a significant increase in private flights from April 23 to April 27, 2018 as a result of this event. In 2019, Hannover Messe was held from April 1 to April 5, 2019, which was three weeks earlier in the year than it was in 2018. Therefore, we remove the influence of the 2018 event from its dates and apply the factor of change to the 2019 dates. The weekly average of arrivals is calculated for the modeled data and the actual 2019 data and compared. These estimates are reported in Table 13.

The Union of European Football Associations (UEFA) Super Cup, held in Tallinn, Estonia, has an impact on the flight demand at one airport located in the city. Specifically, Tallinn Airport experiences a significant increase in private flights on August 15, 2018 as a result of this event. These estimates are reported in Table 14.

The Palermo Conference, held in Palermo, Italy, had an impact on the flight demand at one airport located in the city. Specifically, Palermo Airport experienced a significant increase in private flights on November 12 and 13, 2018 as a result of this event. These estimates are reported in Table 15.

The Fourth Conference on Advancement of Social Work in Post-Soviet Countries, held in Baku, Azerbaijan, had an impact on the flight demand at one airport located in the city. Specifically, Heydar Aliyev International Airport (UBBB) experienced a significant increase in private flights on April 26 and 27, 2018 as a result of this event. These estimates are reported in Table 16.

The 2018 Sochi GP3 Series, held in Sochi, Russia, had an impact on the flight demand at one airport located in the city. Specifically, Sochi International Airport experienced a significant increase in private flights on September 29 and 30, 2018 as a result of this event. These estimates are reported in Table 17.

5.3.8 Event Prediction Error Estimates

Table 18 shows the model's average estimation errors relative to the observed 2019 event data for location-specific events. The Prediction Error Estimate indicates the mean error in the number of flights calculated for each week of the event, encompassing all affected airports within the specified event. For events that changed locations from 2018 to 2019, such as the UEFA League Champions Final, the Prediction Error Estimate is based on the 2019 location and date.

6 Conclusion

Our demand analysis of private aviation in European destinations provides insights into various influencing factors. We explore seasonal patterns, event-related fluctuations, and the geographical aspects of these events to understand their collective impact on demand dynamics. Through this exploration, we uncovered significant trends and patterns, offering a deeper understanding of the European private aviation market.

We evaluated the performance of our developed spatio-temporal forecasting model based on its accuracy in predicting demand for private aviation in European destinations. By comparing model forecasts with actual demand data, we assessed its effectiveness in capturing demand fluctuations and providing reliable predictions. The results demonstrate the model's capability to support private aviation providers in making informed decisions and optimizing operational strategies.

Traditional time-series forecasting models such as SARIMA are well-suited for capturing seasonal patterns and temporal dependencies in structured time series data. SARIMA, for example, effectively models periodic fluctuations and trends, making it a powerful tool for forecasting air traffic when historical patterns remain stable. However, these models do not inherently incorporate spatial dependencies, which are crucial for capturing localized variations in air travel demand. In contrast, our spatio-temporal model integrates both temporal and spatial variations, allowing for a more granular understanding of arrival patterns across different airports. By normalizing arrivals based on day-of-week, month, and airport-specific factors, our approach effectively accounts for localized fluctuations. This approach enhances predictive accuracy in dynamic and geographically diverse events, where external influences may significantly impact travel patterns.

Additionally, our work characterized seventeen major events across European destinations. These event characterizations provide insights into the fluctuations of demand during these periods, highlighting their significant influence on private aviation demand. By accurately capturing the spatial and temporal relationships between these events and flight demand, our model has demonstrated improved accuracy in predicting demand during critical periods. This underscores the effectiveness of our approach in incorporating dynamic events into our forecasting model and the value it brings to private aviation providers in responding proactively to market fluctuations.

Accurately predicting events that are singular or move in location poses the greatest challenge for the spatio-temporal model. When the model's predictions are inaccurate, it often signifies the presence of events within the data that either changed their location or were one-time incidents. To address this challenge, future models can be enhanced by incorporating separate coefficients specifically designed for these events. This would enable annual adjustments to be made to their respective locations or time frames, thereby improving the overall accuracy of the predictions.

This paper aims to accurately characterize influential high-demand events and develop a robust demand forecasting model for European destinations in the private aviation industry. By analyzing the impact of significant events and holidays on demand and incorporating advanced data analysis techniques, we aim to create an accurate and tailored forecasting model. Ongoing monitoring, updating with real-time data, and enhancements to incorporate high-demand moving events are necessary for continued accuracy and relevance in the rapidly evolving private aviation industry.

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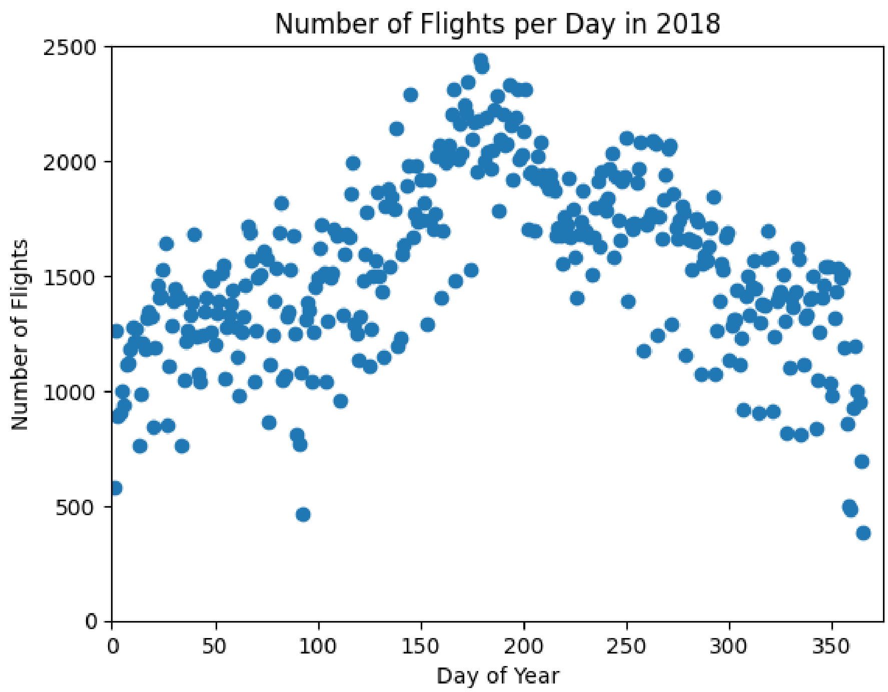
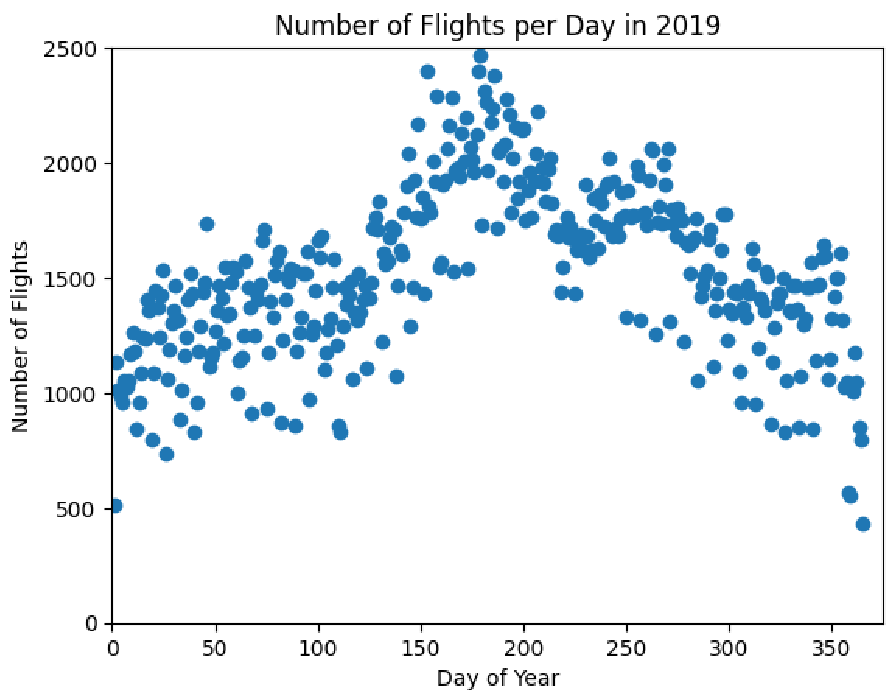
7 Figures

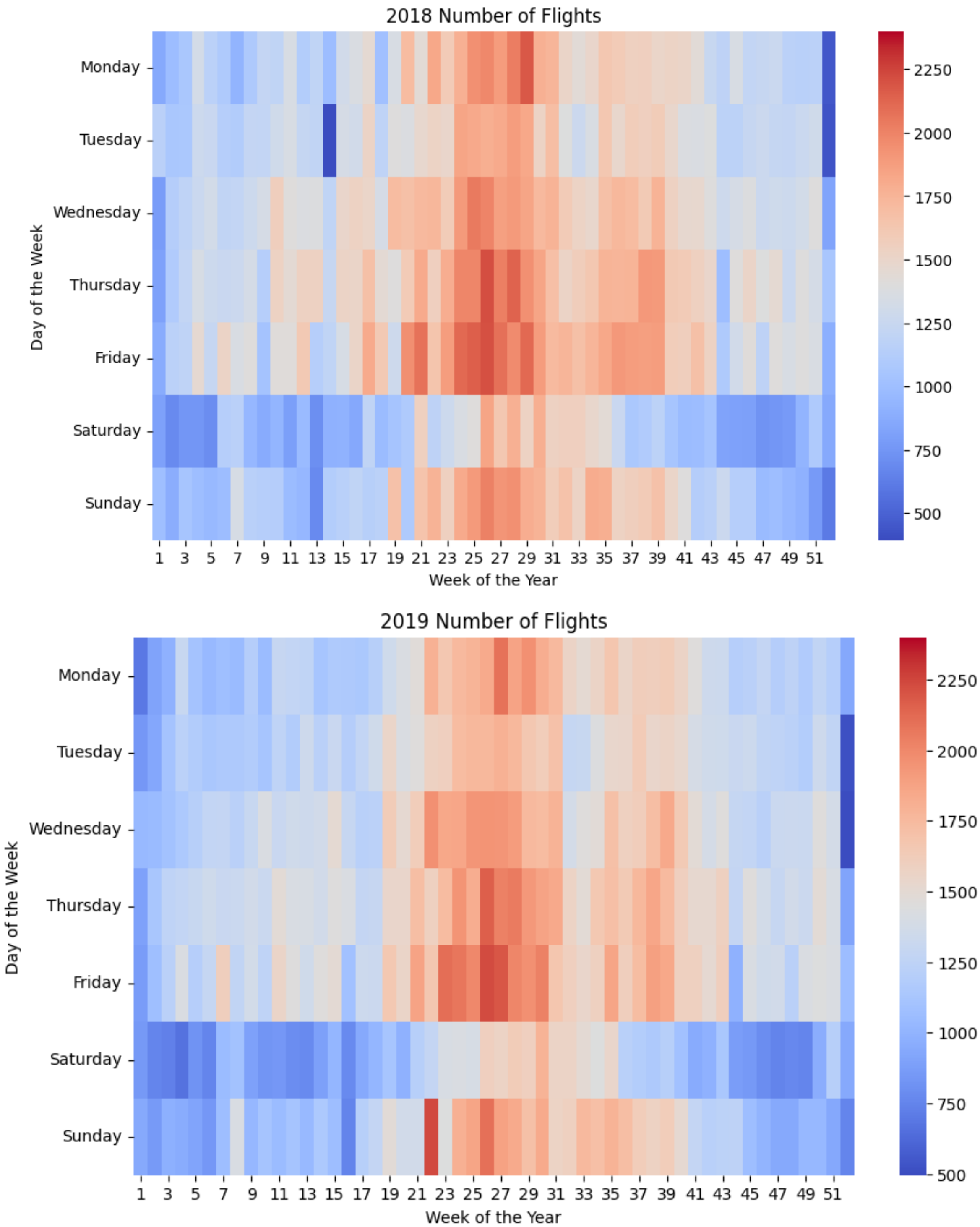
Figure 1: Number of Flights Per Day of Year





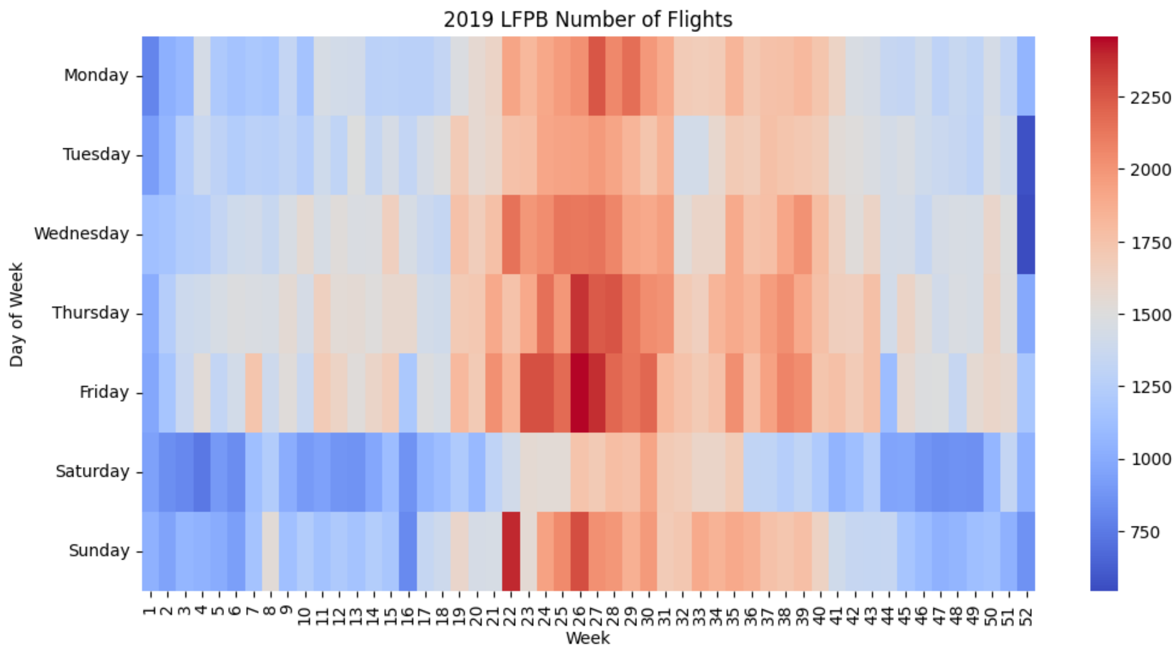
Notes: Daily flight counts from a dataset of 1.1 million flights recorded in 2018 and 2019. The plot highlights seasonal increases in flight activity across a network of 2,016 airports.

Figure 2: Flight Count Heat Map for 2018 and 2019.



Notes: The heat maps for 2018 and 2019 display flight density for each day of the week and week of the year. Darker red indicate higher flight counts while darker blue is indicative of low flight counts.

Figure 3: Heat Map of Flight Density of Paris-Le Bourget Airport (LFPB).



Notes: The heat map for the LFPB airport identifies key days of especially high or low travel days. Darker red areas represent especially high-count flight days while dark blue represents very low flight days.

Figure 4: Arrival Locations. Map of all arrival locations, 2018 and 2019.

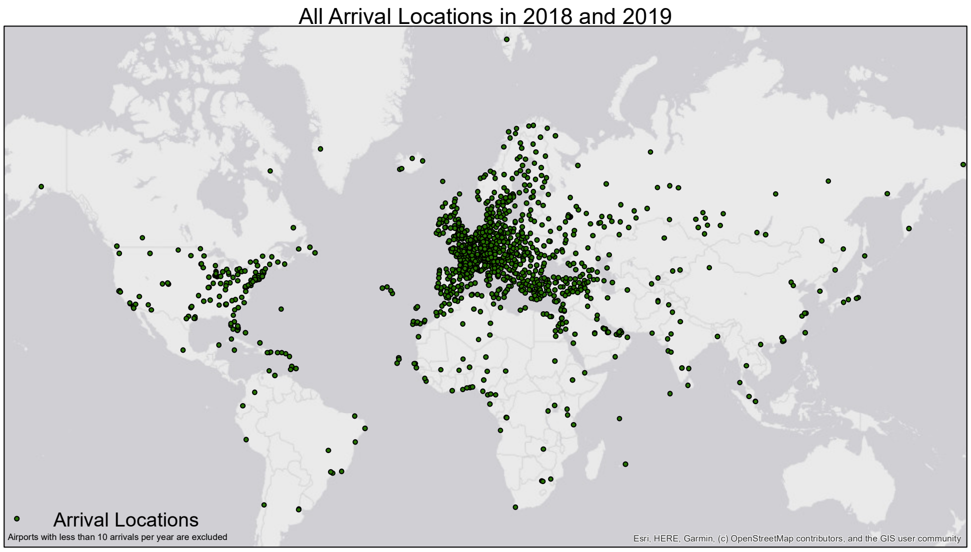
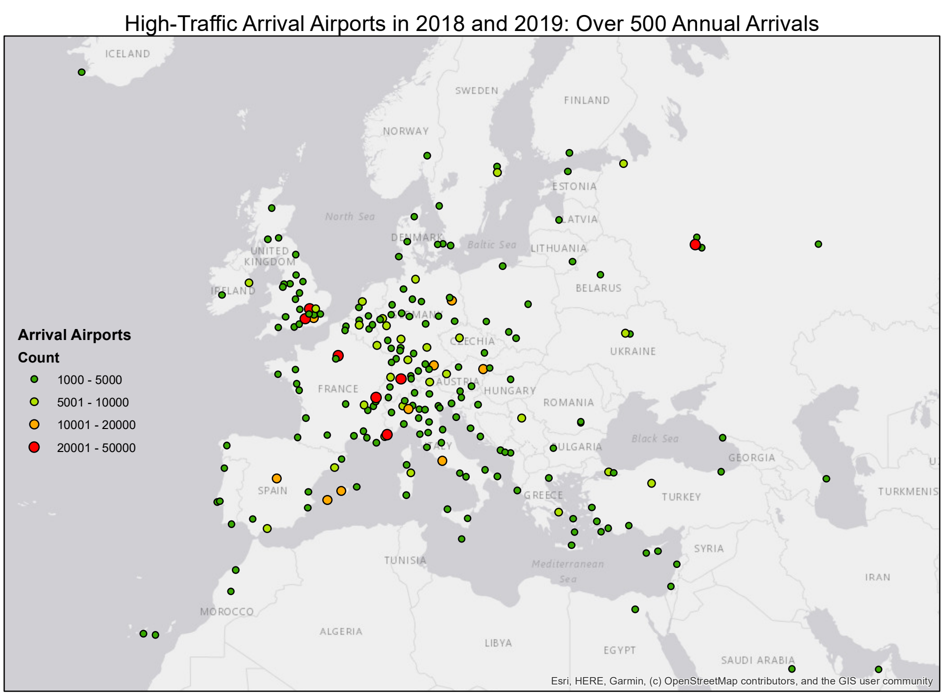
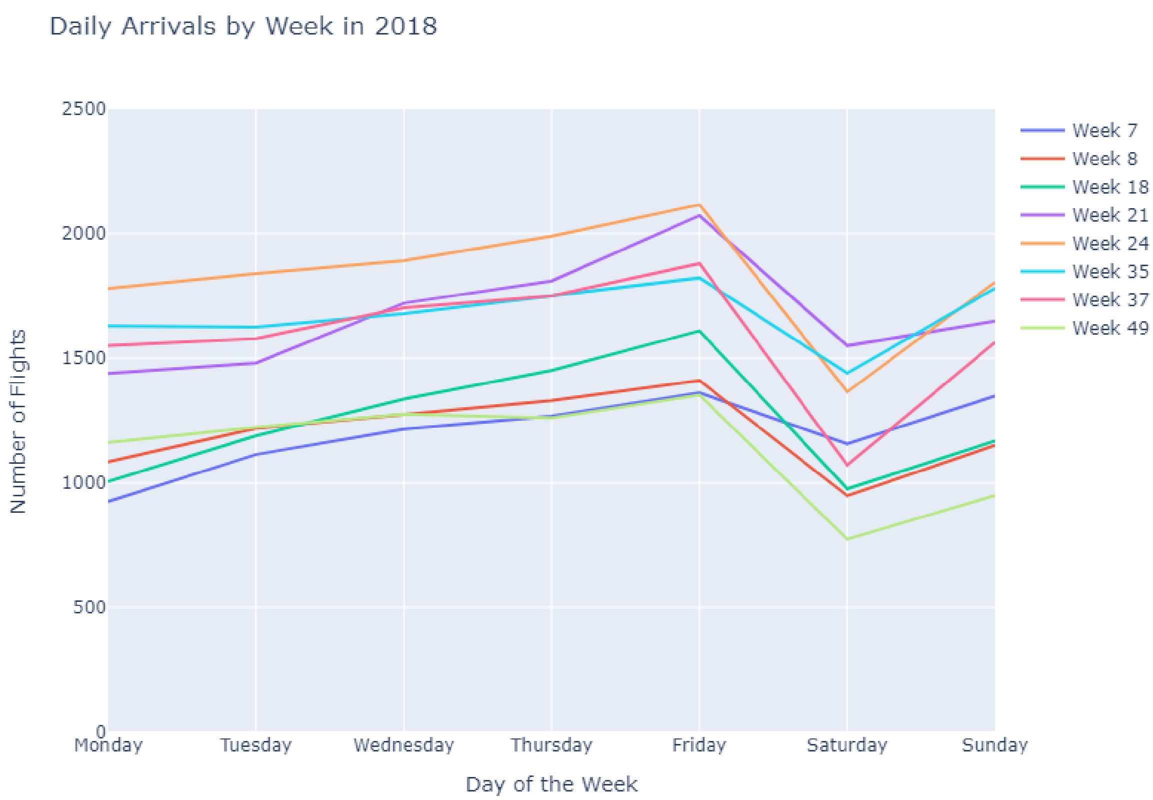


Figure 5: Top arrival locations. Map of Arrival Locations for Private Jet Travel with over 1000 arrivals (2018-2019)



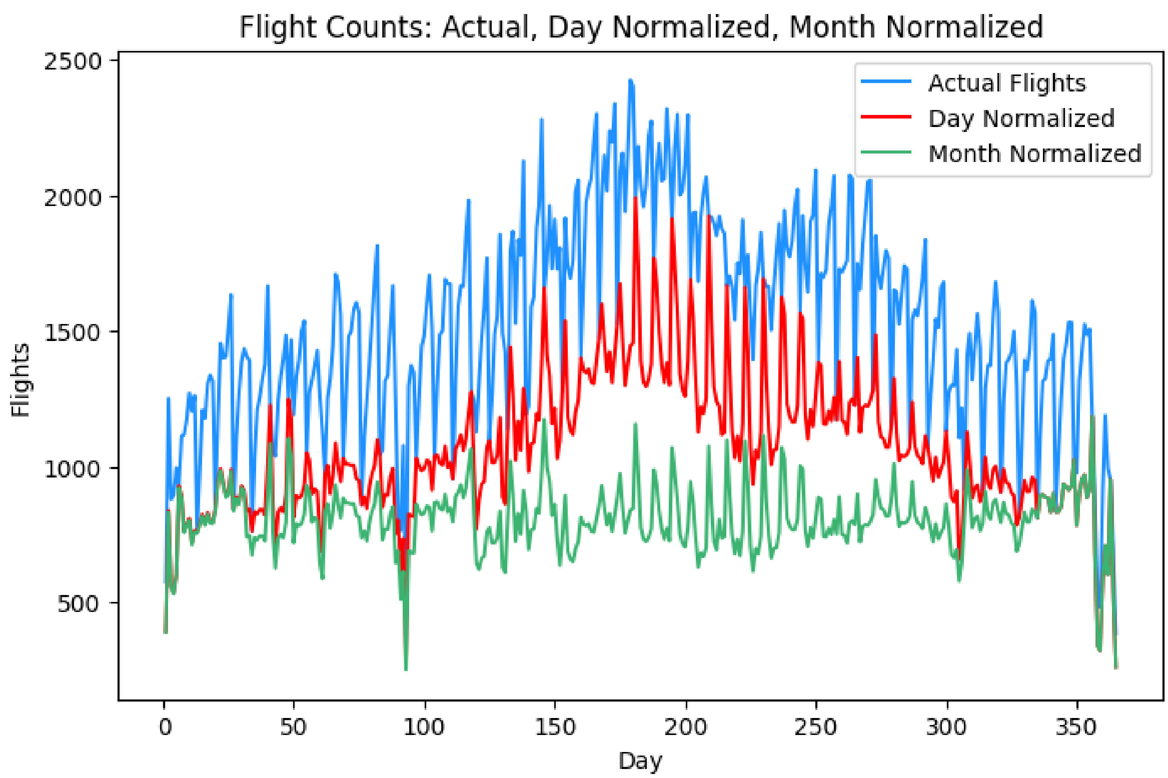
Notes: This figure presents two maps illustrating private jet arrival locations from 2018 to 2019. The first subfigure provides a comprehensive view of all recorded arrival locations. The second subfigure highlights top arrival locations, showing only destinations with over 1,000 recorded arrivals, offering insight into the concentration of private jet travel during this period.

Figure 6: Flights by Day of Week for Top Weeks



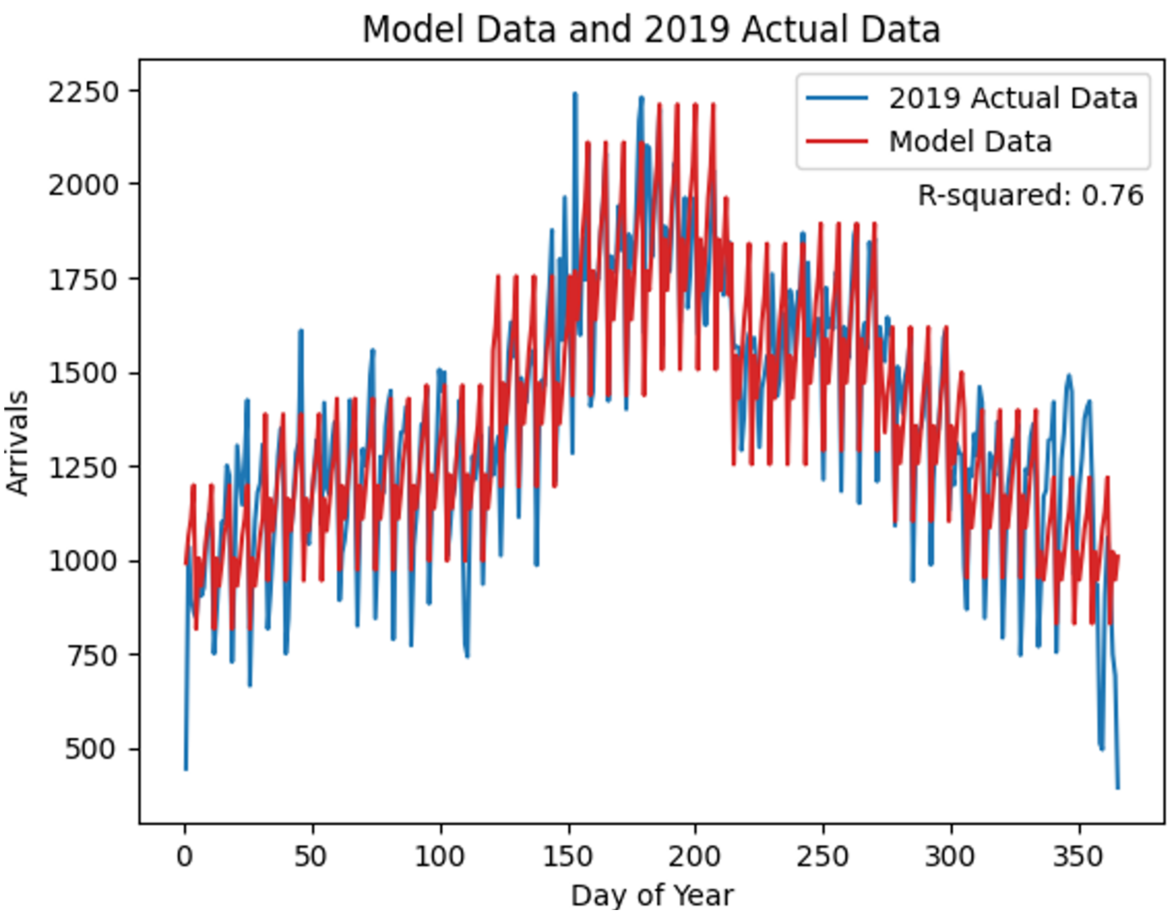
Notes: Average Number of Flights Per Weekday of Tracking Trends 2018. Identified weeks that behave similarly for average flight numbers per day of week in 2018.

Figure 7: Flight Counts Normalized by Day of Week and Month of Year



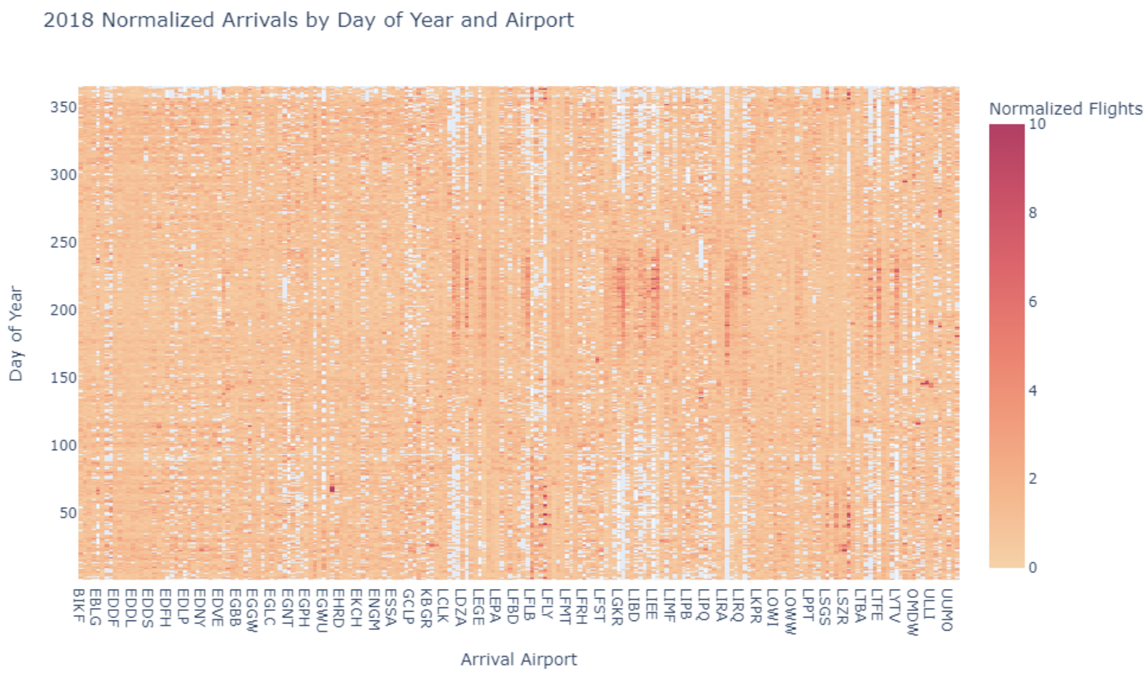
Notes: This figure presents daily flight counts normalized to account for systematic variations due to the day of the week and the month of the year. The normalization process adjusts for recurring seasonal and weekly trends, ensuring that fluctuations reflect underlying patterns rather than calendar effects. This approach allows for a clearer analysis of deviations from expected flight activity levels.

Figure 8: Global Model Predictions vs 2019 Actual Flights



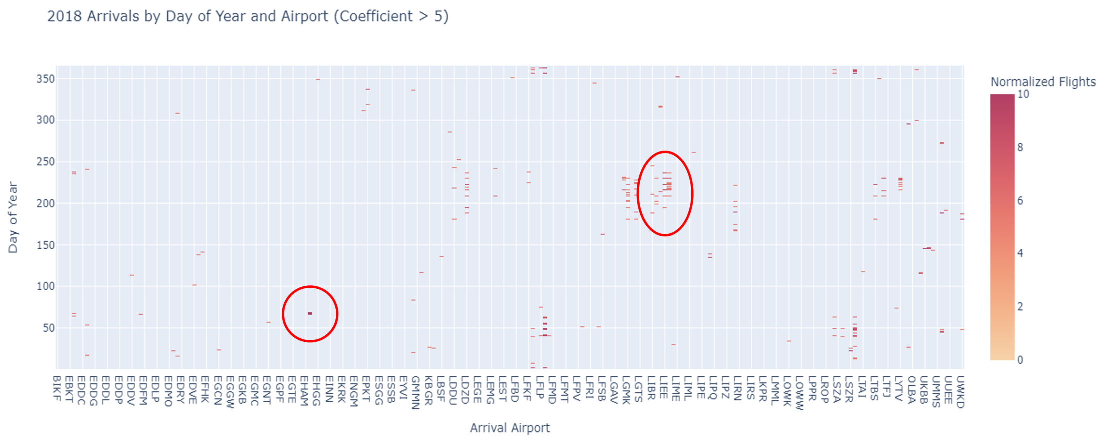
Notes: This figure compares the global model's predicted flight counts to actual 2019 flight data. The model demonstrates a strong fit, with an R-squared value of 0.76, indicating that 76% of the variation in actual flight counts is explained by the model. Deviations from the predicted values highlight areas where external factors or unmodeled dynamics may influence flight activity.

Figure 9: Heat map of Arrivals in 2018 for Each Airport (Scaled and Adjusted for Day of Week and Month)



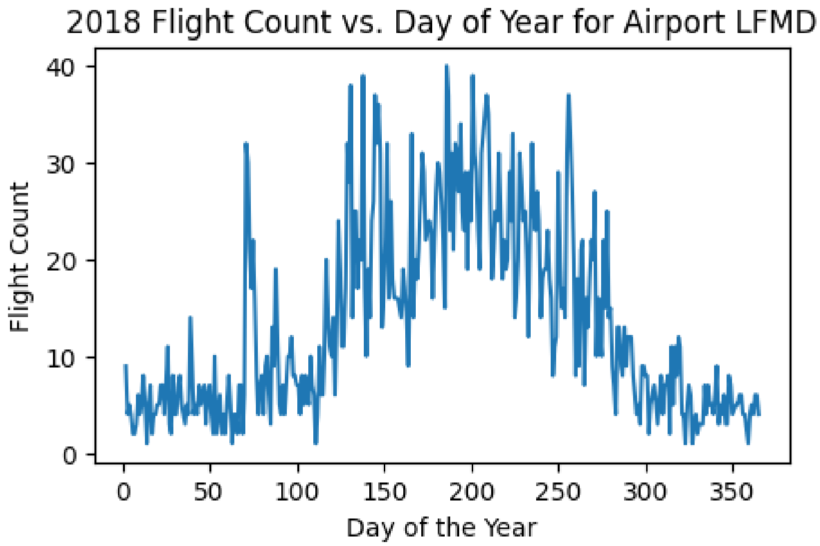
Notes: This figure visualizes daily arrival patterns across all recorded airports in 2018. The flight counts are normalized to remove systematic variations due to the day of the year and airport, allowing for a clearer comparison of within airport activity. The color scale highlights relative differences in flight volume, with darker shades indicating higher-than-average arrivals, scaled to a maximum of 10 times higher.

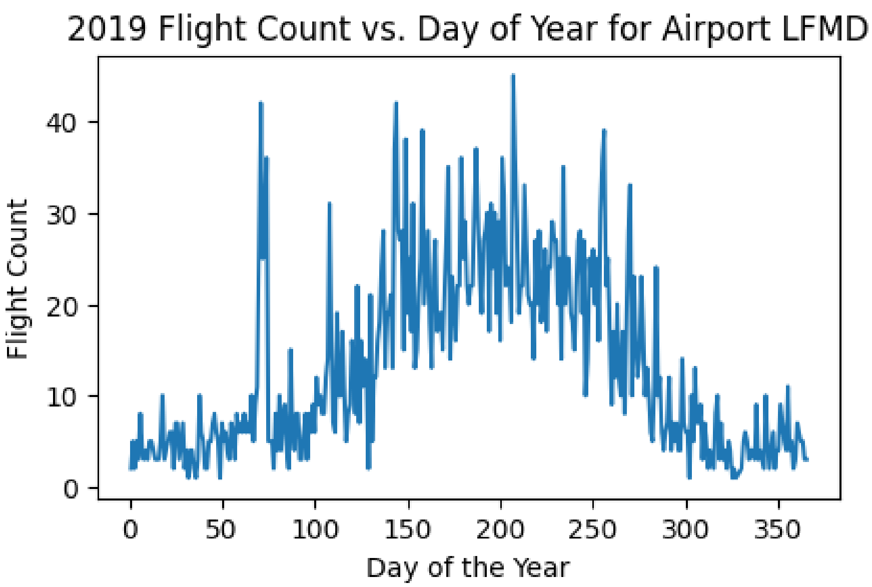
Figure 10: 2018 Airport Heatmap With Arrivals Exceeding Five Times the Normalized Baseline



Notes: This heatmap highlights significant surges in flight activity, where daily arrivals exceeded five times the expected volume after adjusting for seasonal and weekly trends. The intensity represents the magnitude of these deviations, with darker shades indicating larger spikes. This visualization helps identify unusual travel patterns across different airports and dates.

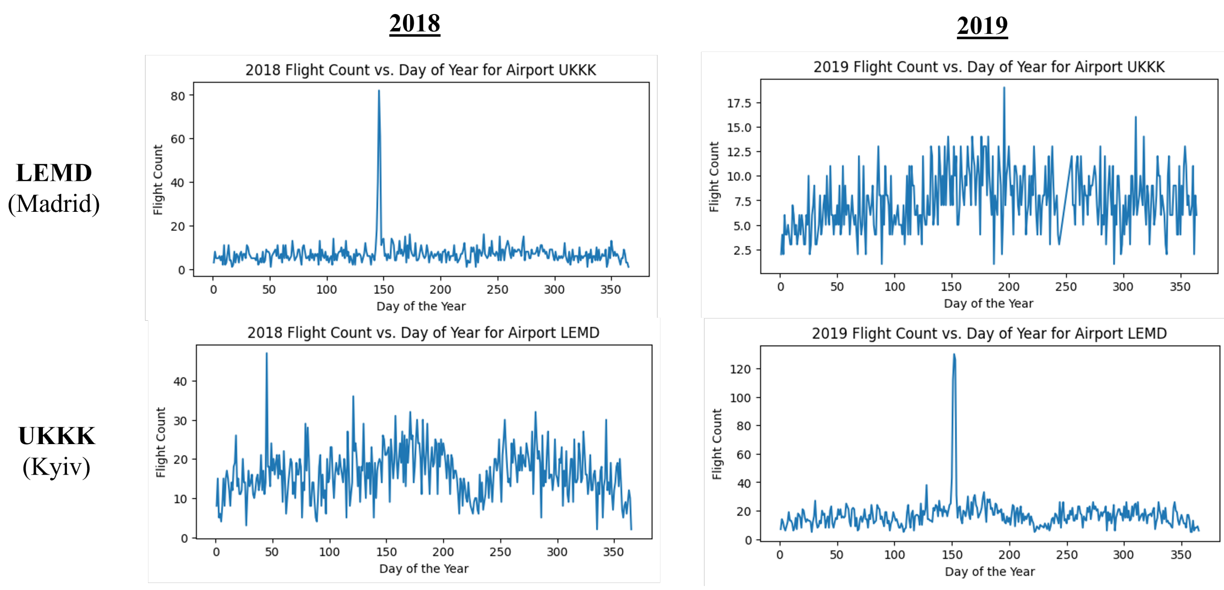
Figure 11: Local Stationary Example - Cannes Film Festival (Cannes, FR). 2018 and 2019 Flight Counts vs. Day of Year for Airport LFMD





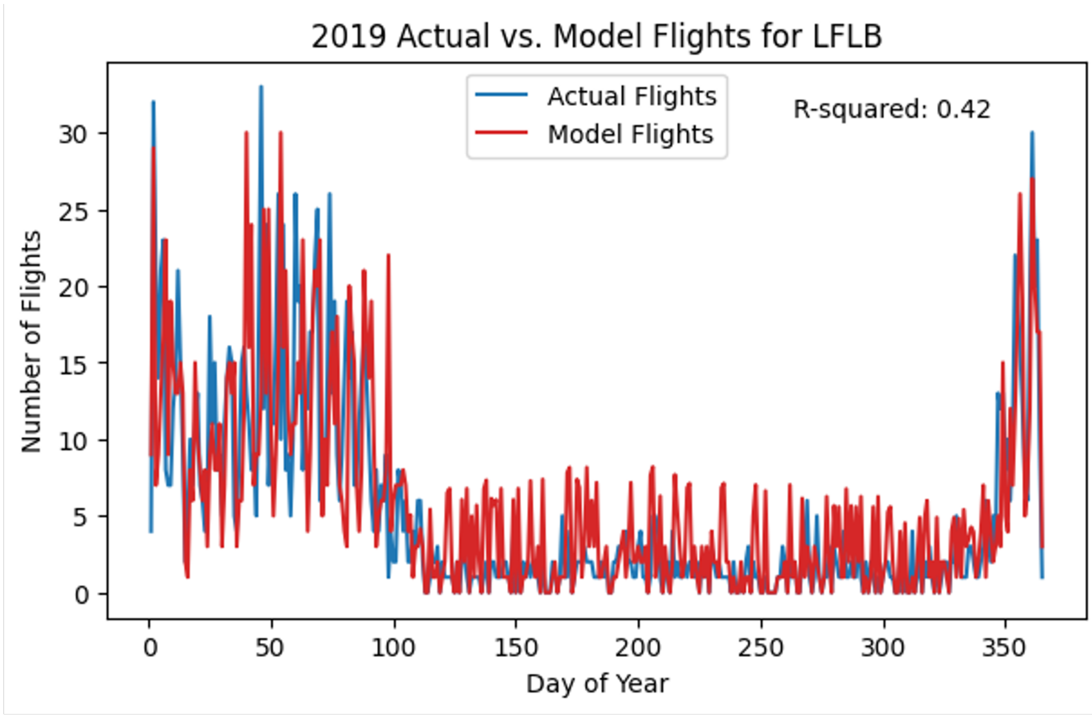
Notes: Both panels A and B show the daily flight counts for Airport LFMD in 2018 and 2019, respectively. A notable increase in flight traffic is observed in May of each year, coinciding with the timing of the Cannes Film Festival, showing one example of a local stationary event.

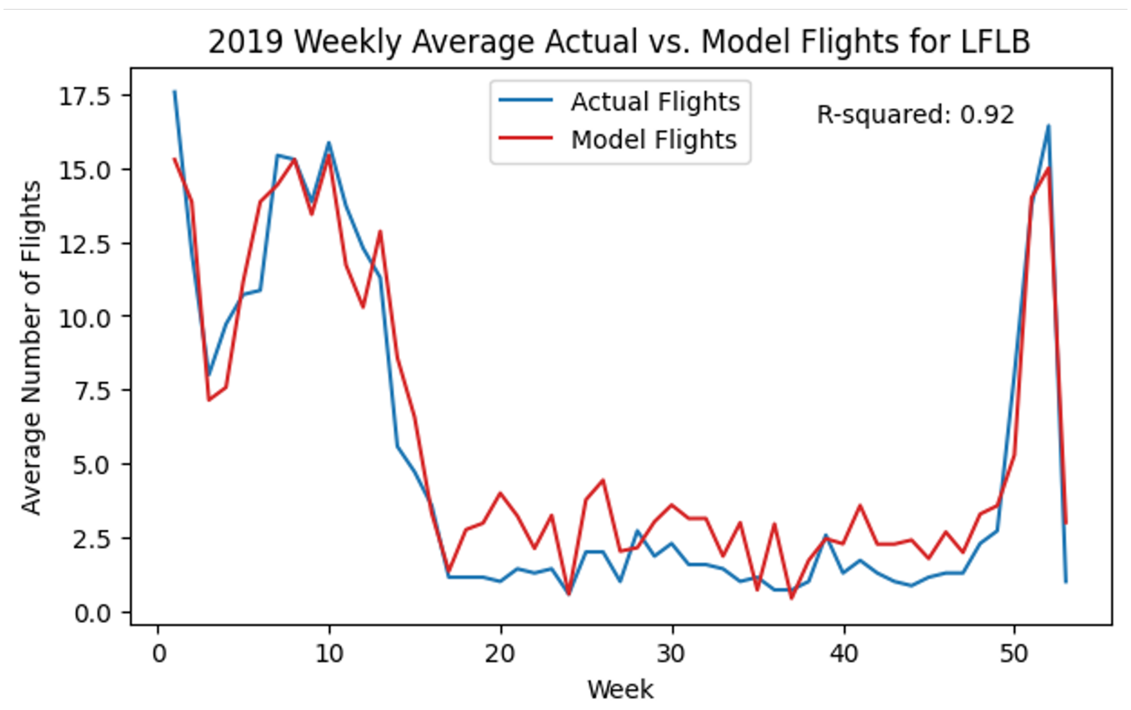
Figure 12: Local Dynamic Example - UEFA Champions League Final. 2018 and 2019 Flight Counts vs. Day of Year for Airports LEMD and UKKK



Notes: Flight counts plotted for Madrid airport and Kyiv airport in 2018 and 2019. Madrid hosted the UEFA finals in 2018 and Kyiv hosted the finals in 2019. The opposite years provide a reference for regular flights respectively.

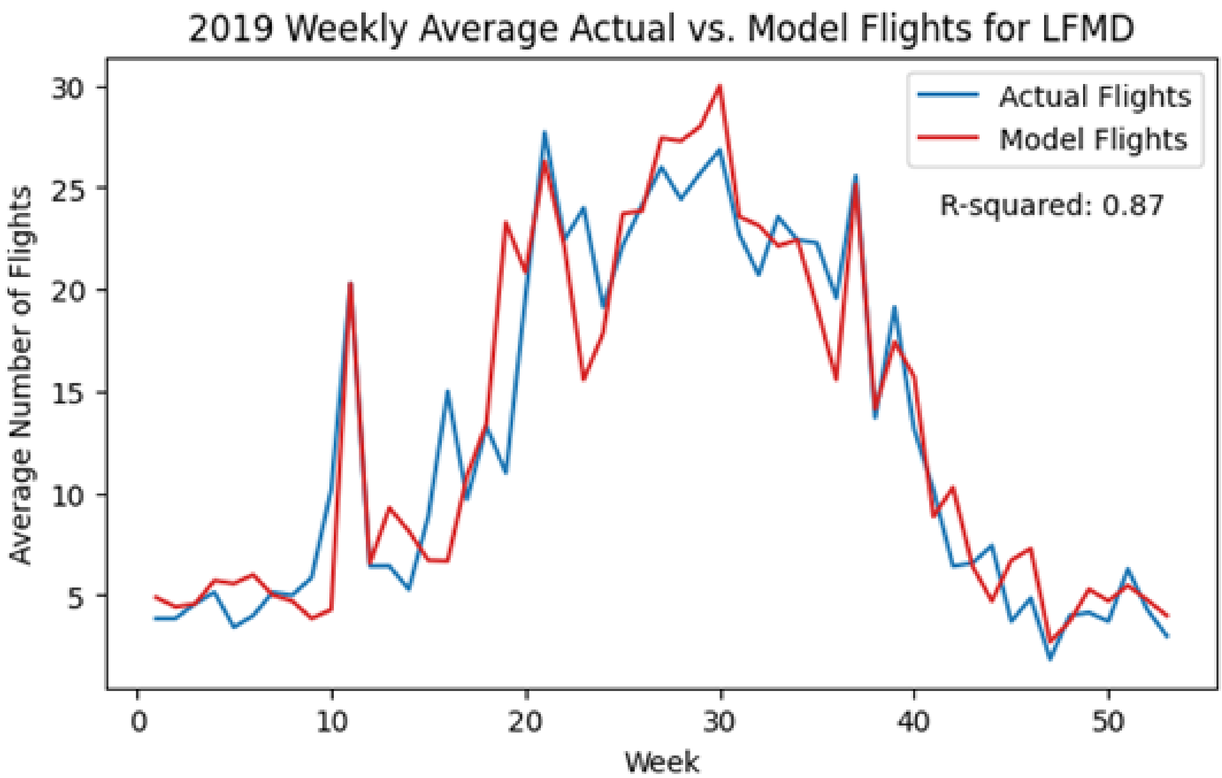
Figure 13: Ski Season Event Characterization Modeled Flights





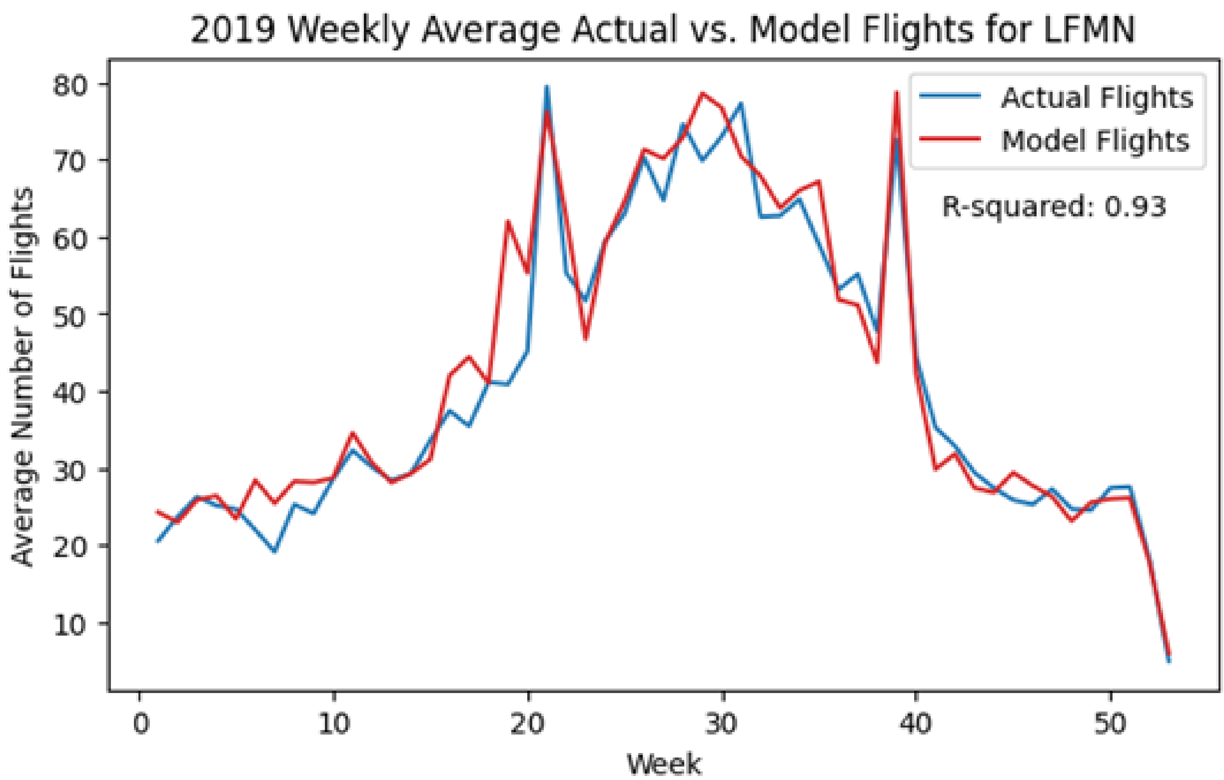
Notes: Modeled Data and Actual 2019 Data of Chambéry Airport (LFLB). A comparison between the 2019 modeled weekly and daily average data and the actual weekly and daily average data for Chambéry Airport (LFLB)

Figure 14: Cannes Film Festival Modeled Flights



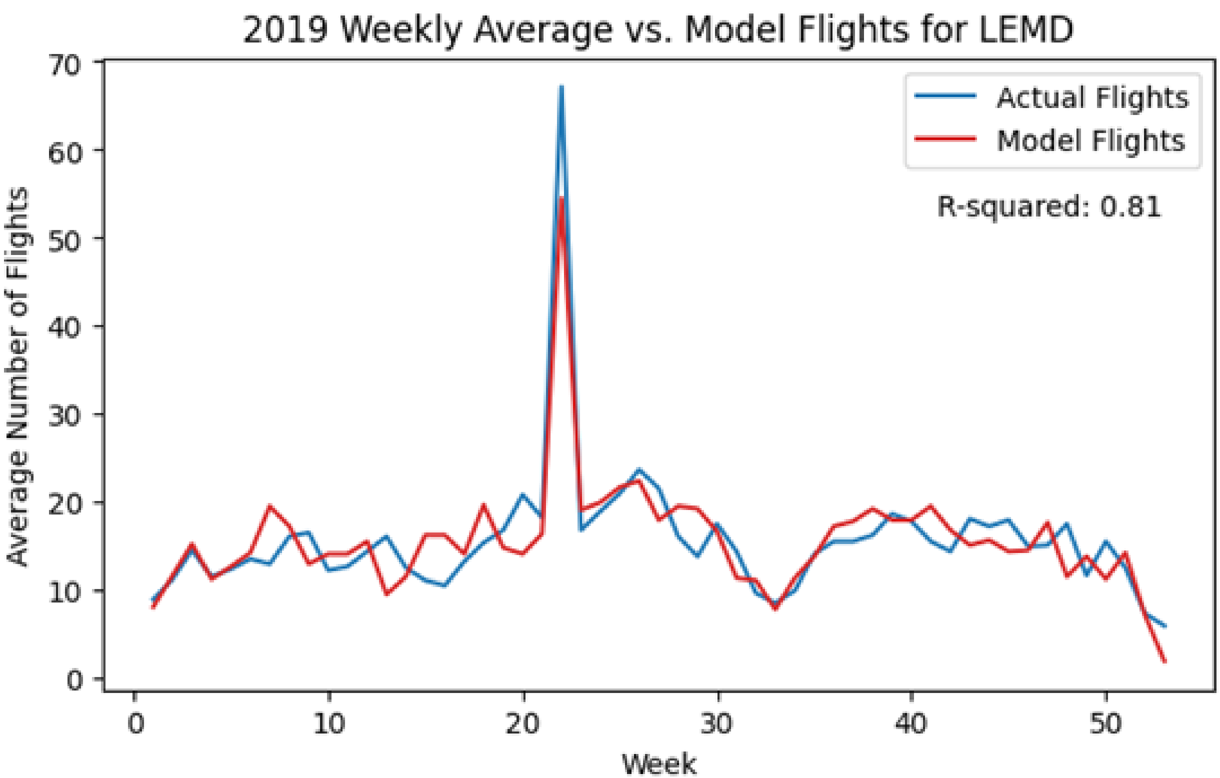
Notes: This figure shows a comparison between the 2019 modeled weekly average data and the actual weekly average data for Cannes-Mandelieu Airport (LFMD)

Figure 15: Monaco Grand Prix Modeled Flights



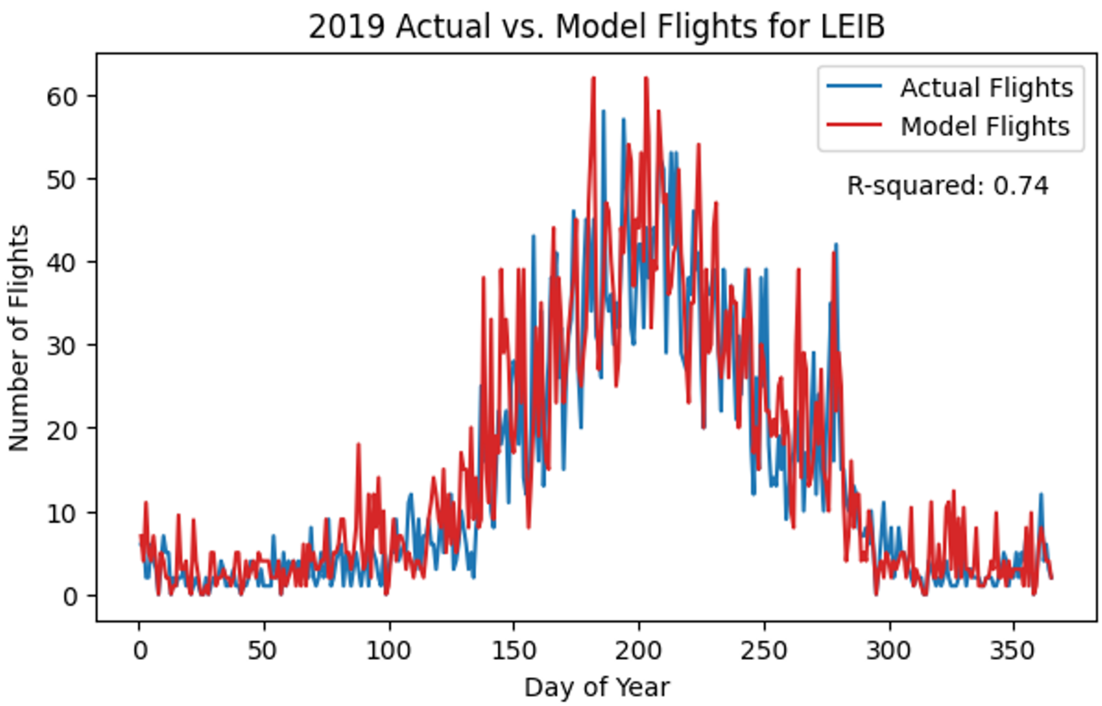
Notes: This figure shows a comparison between the 2019 modeled weekly average and the actual weekly average data for Nice Côte d'Azur Airport (LFMN).

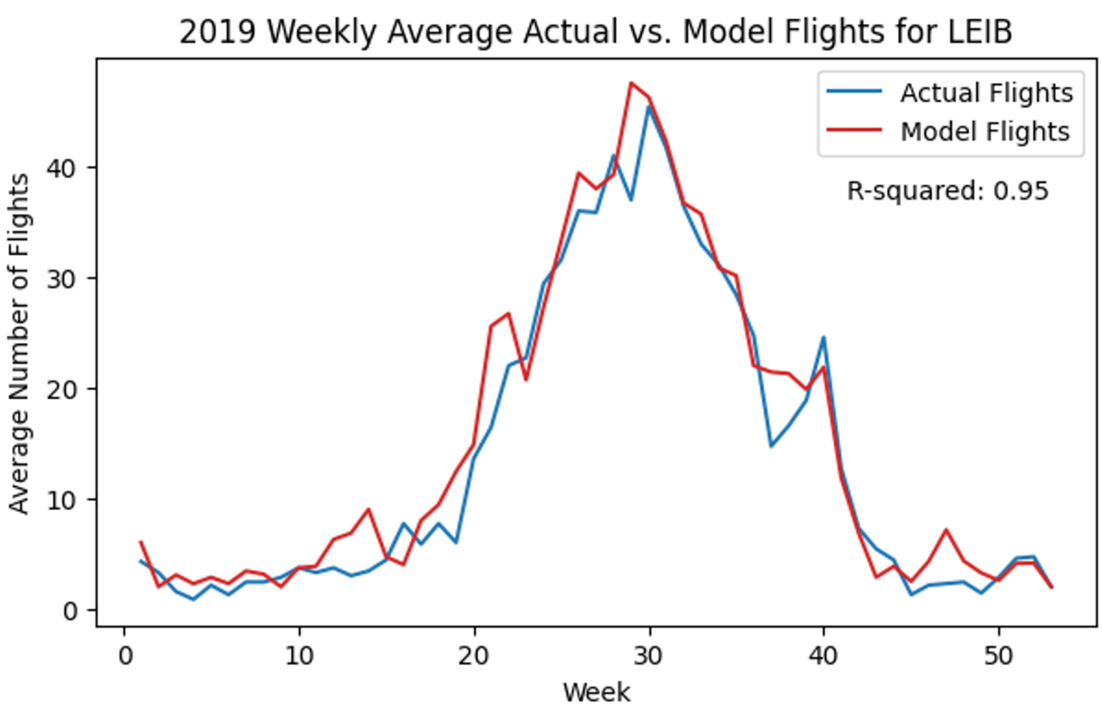
Figure 16: UEFA Champions League Finals Modeled Flights



Notes: This figure shows a comparison between the 2019 modeled and actual weekly average data for Adolfo Suárez Madrid–Barajas Airport (LEMD).

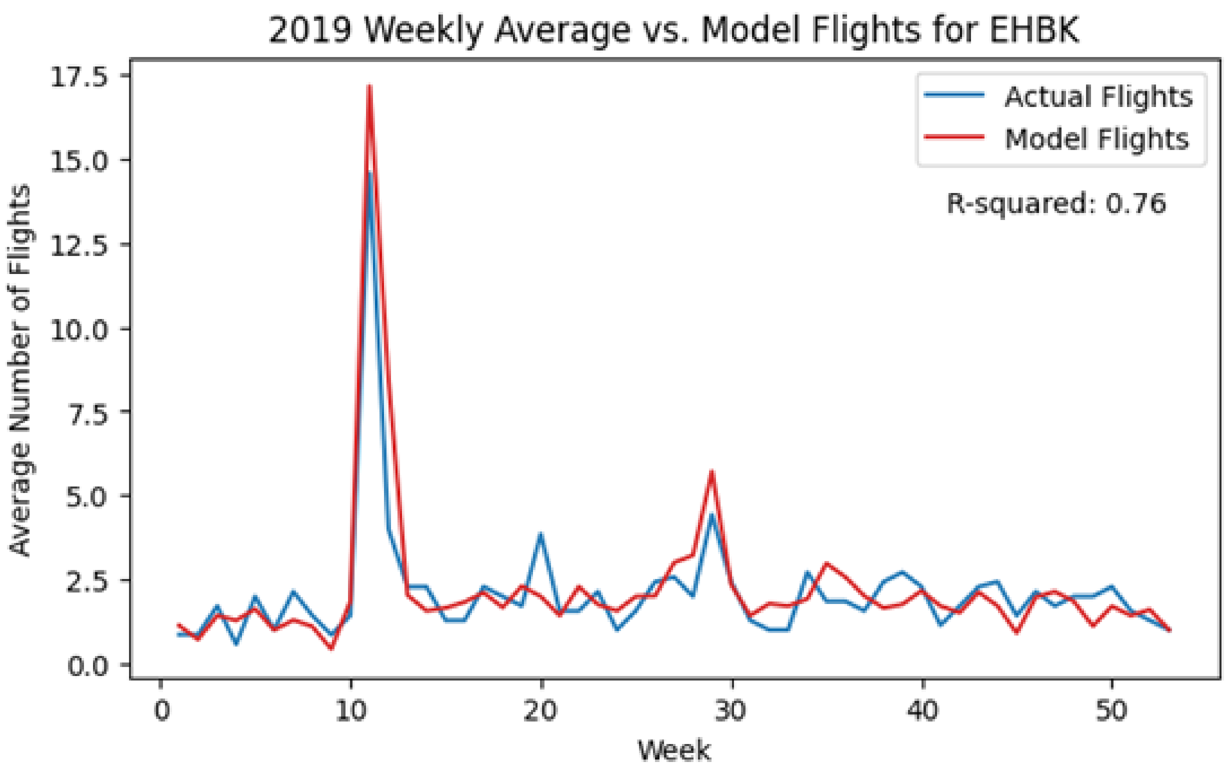
Figure 17: Summer characterization example. Modeled Data and Actual 2019 Data of Ibiza Airport (LEIB).





Notes: This figure shows a comparison between the 2019 modeled weekly average data and the actual weekly flight counts.

Figure 18: European Fine Arts Fair Modeled Flights



Notes: This figure displays the comparison between the 2019 modeled and actual weekly average data for Maastricht Aachen Airport (EHBK)

8 Tables

Table 1: Flights Counts for Top Eight Arrival Airports

			Flight Count	
Airport	Airport Code	Country	2018	2019
Paris-Le Bourget	LFPB	France	23004	21812
Nice-Cote d'Azur	LFMN	France	16183	15632
Geneva Cointrin International	LSGG	Switzerland	14852	14079
London Luton	EGGW	Great Britain	13143	13254
Farnborough	EGLF	Great Britain	12364	13254
Vnukovo International	UUWW	Russia	10551	10477
Zurich	LSZH	Switzerland	10267	9951
Linate	LIML	Italy	8846	6727

Table 2: Average Daily Arrivals by Month and Weekday (2018)

Month of Year	2018 Daily Average	Day of Week	2018 Daily Average
January	1167.8	Monday	1503.9
February	1297.2	Tuesday	1472.1
March	1353.3	Wednesday	1631.6
April	1378.5	Thursday	1692.8
May	1640.8	Friday	1729.4
June	1965.9	Saturday	1215.5
July	2030.5	Sunday	1433.6
August	1744.5		
September	1768.7		
October	1521.9		
November	1334.1		
December	1139.1		

Table 3: Average Daily Flights Per Day of the Week and Normalization Coefficient

Day of the Week	2018 Average Daily Arrivals	Coefficient
Monday	1322.0	1.140
Tuesday	1408.6	1.214
Wednesday	1512.0	1.303
Thursday	1576.4	1.359
Friday	1703.0	1.468
Saturday	1160.0	1.000
Sunday	1427.0	1.230

Table 4: Average Daily Flights Per Month and Normalization Coefficient

Month of Year	2018 Average Daily Arrivals	Coefficient
January	820.4	0.983
February	949.7	1.138
March	978.6	1.172
April	1025.0	1.228
May	1201.1	1.439
June	1444.7	1.731
July	1514.0	1.814
August	1276.1	1.510
September	1297.7	1.554
October	1108.3	1.328
November	957.6	1.147
December	834.8	1.000

Table 5: Major Event Characterizations

Panel A: Area Affected	
Local	Global
Ski Season	Easter
Cannes Fil Festival	
UEFA Champions League Final	
Summer Travel	
European Fine Art Fair*	
Hannover Messe*	
UEFA Super Cup*	
The Fourth Conference on Advancement of Social Work Post-Soviet Countries*	
Sochi GP3 Series*	
Panel B: Location Type	
Repetitive	Moving
Ski Season	UEFA Champions League Final
Easter	UEFA Super Cup*
Cannes Film Festival	The Fourth Conference on Advancement of Social Work Post-Soviet Countries*
Monaco Grand Prix	
Summer Travel	
European Fine Art Fair*	
Hannover Messe*	
Sochi GP3 Series*	
Panel C: Date Type	
Local	Global
Ski Season	Easter
Cannes Fil Festival	
UEFA Champions League Final	
Summer Travel	
European Fine Art Fair*	
Hannover Messe*	
UEFA Super Cup*	
The Fourth Conference on Advancement of Social Work Post-Soviet Countries*	
Sochi GP3 Series*	

Table 6: Ski Season Event Characterization

Locations	**Austria** Innsbruck Airport (LOWI) **France** Aéroport Chambéry Savoie Mont Blanc (LFLB) Grenoble Alpes Isère Airport (LFLS) **Switzerland** Sion Airport (LSGS) Bern Airport (LSZB) St. Gallen–Altenrhein Airport (LSZR) Samedan Airport (LSZS)
Date	February - March
Factor of Change	**Fridays** Average: 2.27 Maximum: 6.53 **Saturdays** Average: 3.74 Maximum: 21.29 (LFLS, day 41) **Sundays** Average: 3.09 Maximum: 13.6 (LSZS, day 42) **All Days** Average: 2.12 Maximum: 21.29 (LFLS, day 41)

Table 7: Easter Characterization

Locations	Worldwide
Date	Thursday March 29 - Monday April2, 2018
Factor of Change	**Thursday March 29** Average: 1.20 Maximum: 3.6 **Friday March 30** Average: 0.80 Maximum: 3.56 **Saturday March 31** Average: 0.74 Maximum: 3.63) **Sunday April 1 (Easter Sunday)** Average: 0.57 Maximum: 3.71 **Monday April 2** Average: 0.85 Maximum: 4.49

Table 8: Cannes Film Festival Event Characterization

Locations	**France** Nice Côte d'Azur Airport Cannes-Mandelieu Airport
Date	May 8-19, 2018 (weekends)
Factor of Change	**Fridays** Average: 1.91 Maximum: 2.40 **Saturdays** Average: 1.39 Maximum: 1.62 **Sundays** Average: 1.70 Maximum: 1.86 **All Days** Average: 1.57 Maximum: 2.40

Table 9: Monaco Grand Prix Event Characterization

Locations	**France** Cannes-Mandelieu Airport
Date	May 25-27, 2018
Factor of Change	**All Days** Average: 2.47 Maximum: 3.04

Table 10: UEFA Champions League Final Event Characterization

Locations	**2018: Ukraine and Russia** Boryspil International Airport Sikorsky International Airport Kyiv Pulkovo Airport **2019: Spain** Adolfo Suárez Madrid–Barajas Airport
Date	May 26, 2018 and June 1, 2019
Factor of Change	**Average** 2018: 13.81 2019: 6.90

Table 11: Summer Season Event Characterization

Locations	**Croatia** Dubrovnik Airport (LDDU) Split Airport (LDSP) Zadar Airport (LDZD) **France** Biarritz Airport (LFBZ) Figari-Sud Corse Airport (LFKF) Toulon Hyères Airport (LFTH) **Greece** Corfu International Airport (LGKR) Mykonos International Airport (LGMK) **Germany** Flughafen Sylt Airport (EDXW)	**Italy** Salento Airport (LIBR) Vincenzo Bellini Catania Airport (LICC) Palermo Airport (LICJ) Cagliari Elmas Airport (LIEE) Salerno Costa d'Amalfi Airport (LIRI) Naples International Airport (LIRN) Grosseto Airport (LIRS) **Montenegro** Tivat Airport (LYTV) **Spain** Girona–Costa Brava Airport (LEGE) Ibiza Airport (LEIB) **Turkey** Dalaman Airport (LTBS) Milas–Bodrum Airport (LTFE)
Date	July - August	
Factor of Change	**Fridays** Average: 2.30 Maximum: 6.83 **Saturdays** Average: 3.45 Maximum: 10.23 (LIEE, day 216) **All Days** Average: 2.48 Maximum: 10.23 (LIEE, day 216)	

Table 12: European Fine Art Fair

Locations	**Netherlands** Maastricht Aachen Airport
Date	March 7-18, 2018
Factor of Change	**All Days** Average: 10.85 Maximum: 20.29

Table 13: Hannover Messe

Locations	Hannover Airport, Germany
Date	April 23 - April 27, 2018
Factor of Change	**All Days** Average: 3.53 Maximum: 5.74

Table 14: UEFA Super Cup

Locations	Tallinn Airport, Estonia
Date	August 15, 2018
Factor of Change	5.09

Table 15: Palermo Conference

Locations	Palermo Airport, Italy
Date	November 12 and 13, 2018
Factor of Change	**All Days** Average: 5.17 Maximum: 5.26

Table 16: The Fourth Conference on Advancement of Social Work in Post-Soviet Countries

Locations	Heydar Aliyev International Airport, Azerbaijan
Date	April 26 and 27, 2018
Factor of Change	**All Days** Average: 7.24 Maximum: 9.17

Table 17: Sochi International

Locations	Sochi International Airport, Azerbaijan
Date	September 29 and 30, 2018
Factor of Change	**All Days** Average: 6.99 Maximum: 7.76

Table 18: Prediction Error Estimates

Event	**Date**	**Prediction Error Estimate**
Ski Season	February and March	1.72
Cannes Film Festival	May 8-19, 2018	11.21
Monaco Grand Prix	May 25-27, 2018	3.04
UEFA Champions League Final	June 1, 2019	1.86
Summer Travel	July and August	1.68