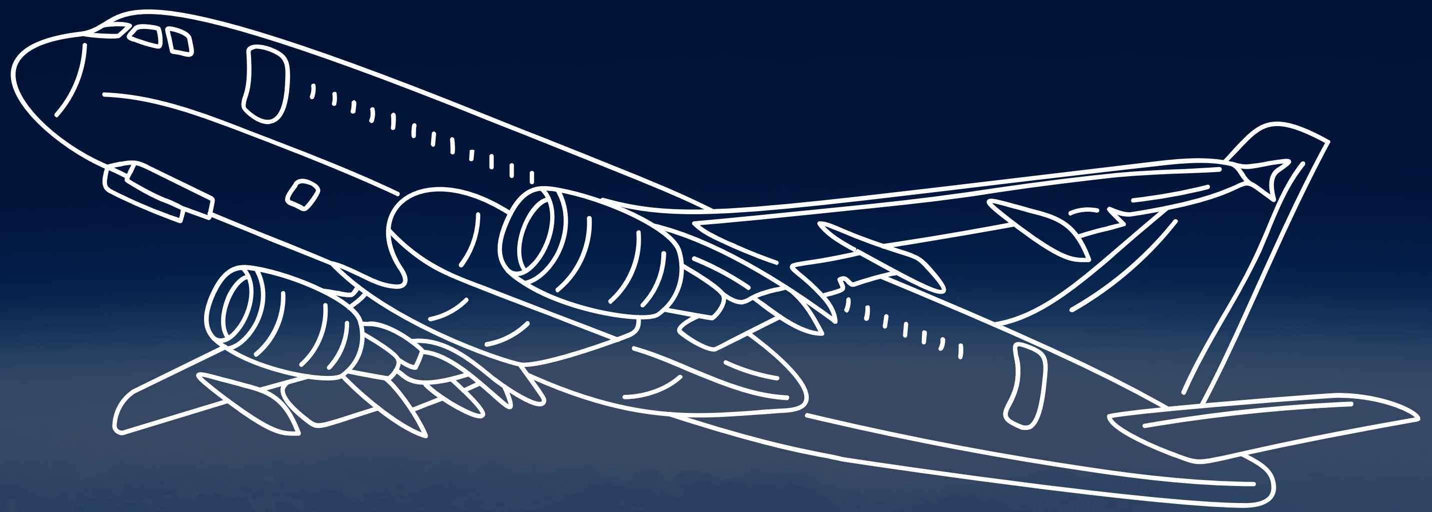
AIRPORT-SPECIFIC FLIGHT DEPARTURE DELAY PREDICTION USING WEATHER PATTERNS & HISTORICAL DATA



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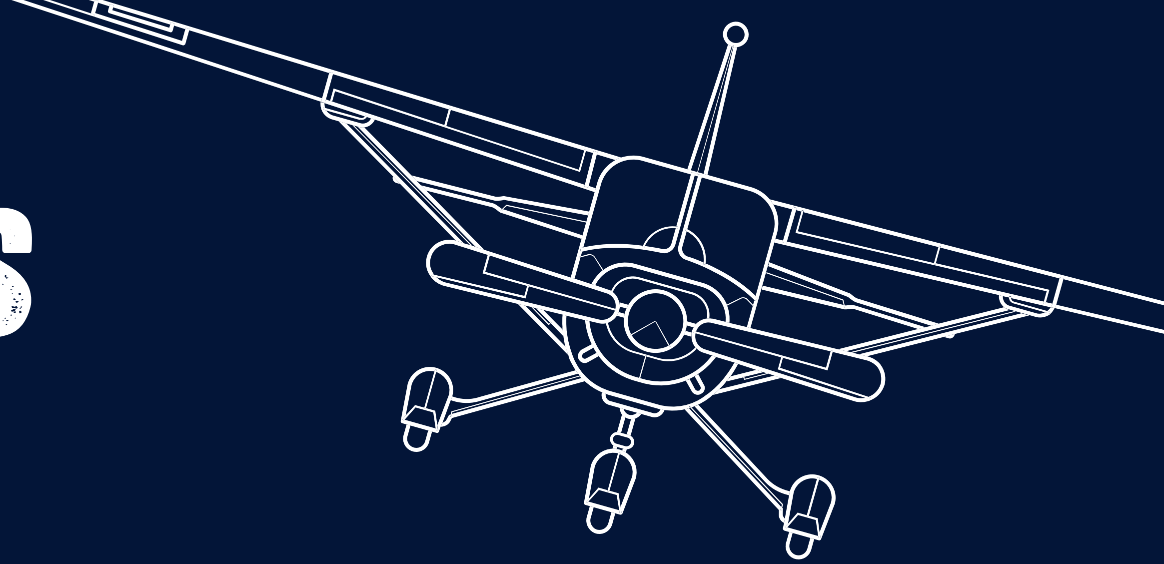

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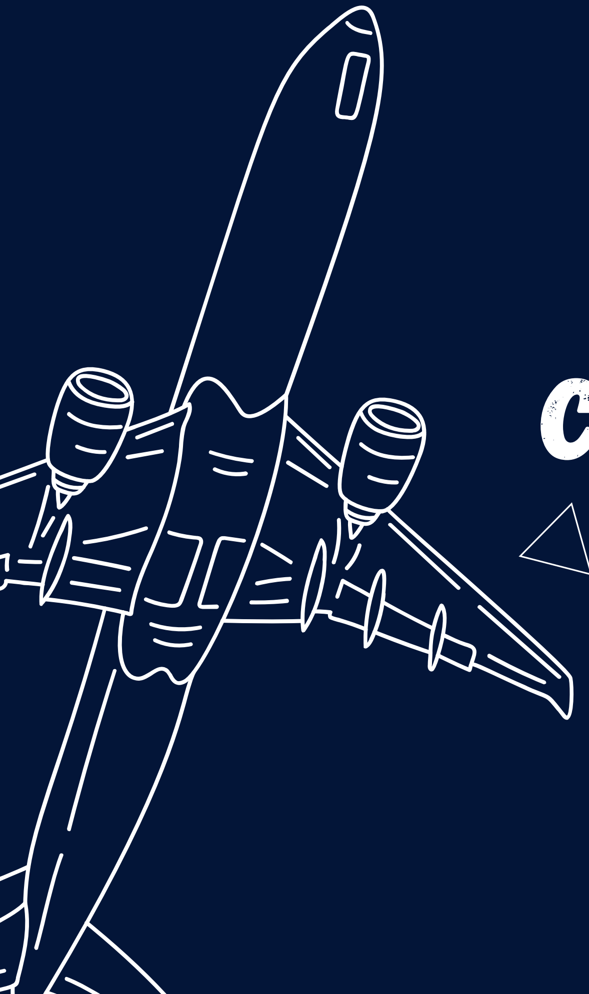


PROBLEM DEFINITION

Air travel disruptions cost billions annually, with departure delays being particularly problematic. This project analyzes how weather conditions impact flight departure delays at major US hub airports, developing predictive models to quantify these relationships and identify the most influential weather variables across seasons.

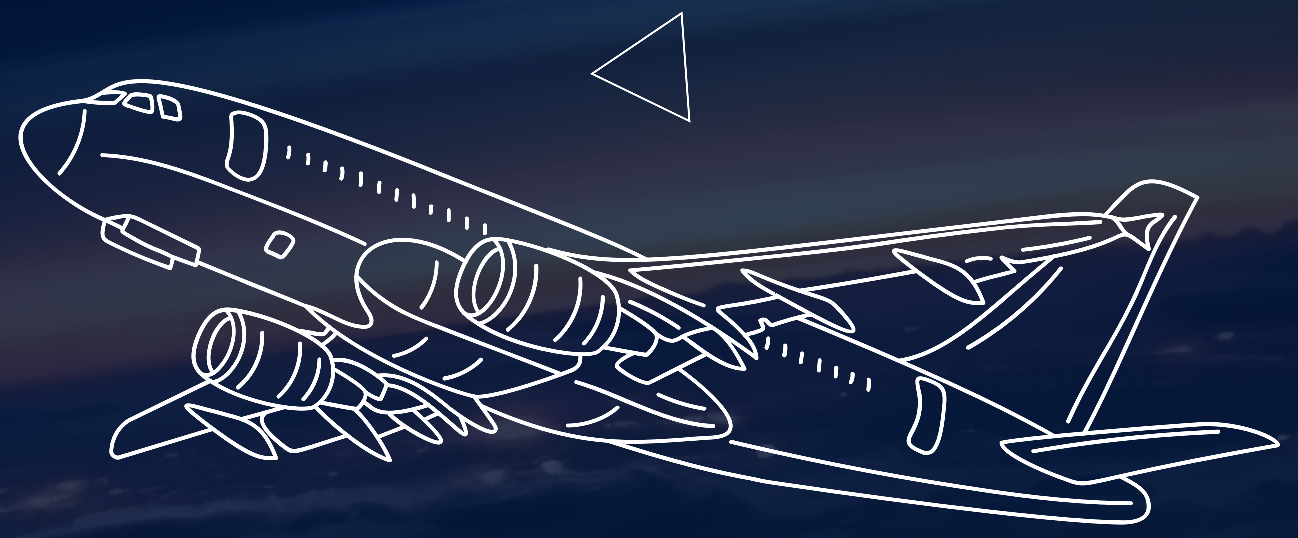
DATA SCIENCE QUESTION

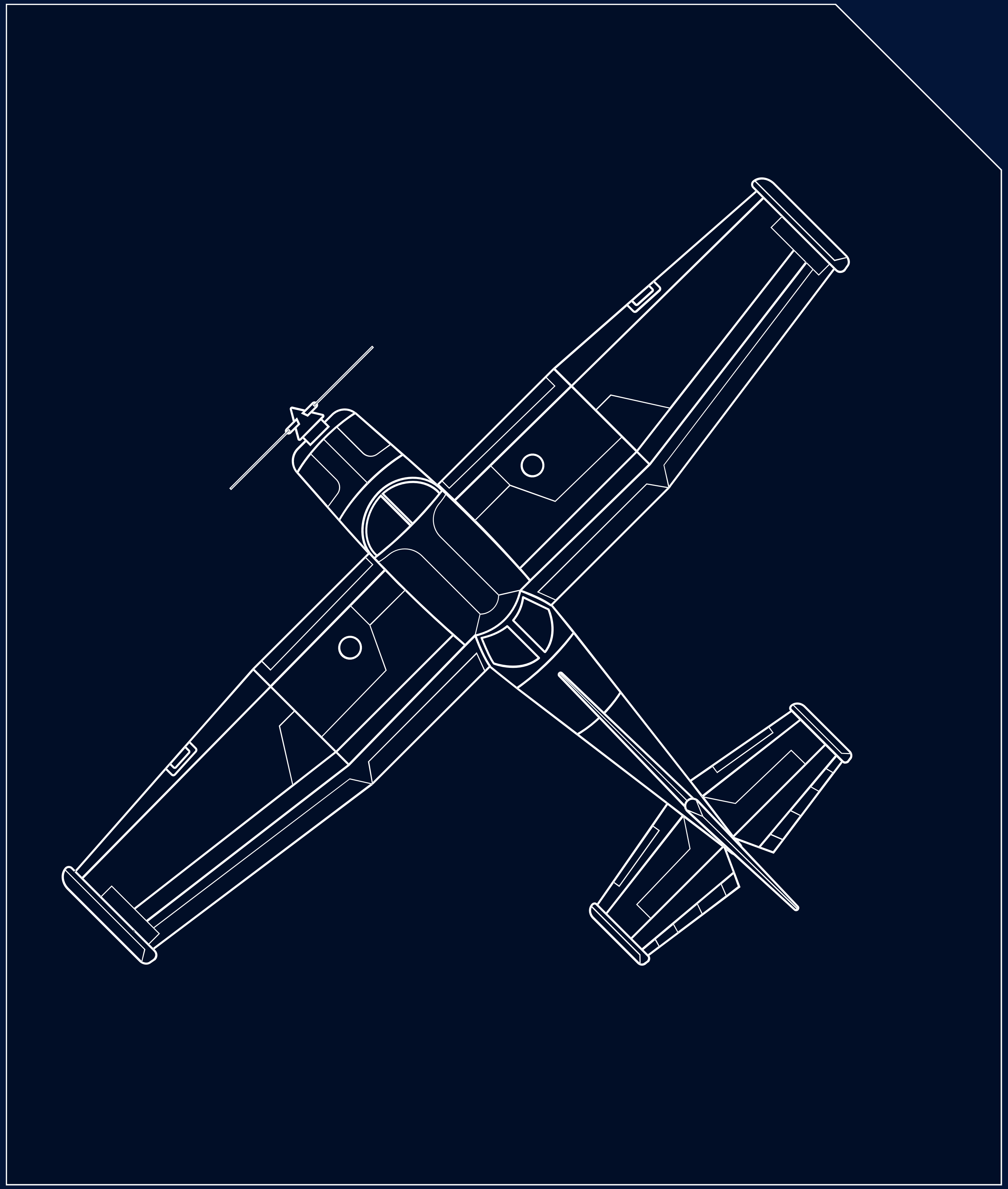
1. To what extent can weather data and historical flight patterns predict departure delays at major hub airports?

2. Which weather variables are the strongest predictors of departure delays, and does their impact vary seasonally?

WHY ARE THE QUESTIONS IMPORTANT?

- Accurate predictions enable better resource allocation and optimised scheduling
- Allow airlines to implement targeted mitigation strategies
- Provide significant help in proactive schedule adjustments
- For airports, this knowledge can guide infrastructure investments and operational adjustments.





DIFFICULTIES IN ANSWERING THE QUESTIONS

- Non-linear relationships between weather and delays
- Airport-specific characteristics affecting weather impacts
- Difficult to distinguish weather-related delays due to operational issues
- Require complex modeling approaches
- Hard to integrate heterogeneous data sources with different granularities

DATA AVAILIBLE

Bureau of Transportation Statistics (BTS)

Flight on-time performance data for the top 5 US airports (ATL, LAX, ORD, DFW, DEN) from 2018-2022

NOAA Weather Data

Hourly weather observations including temperature, precipitation, wind speed, visibility, and pressure for each airport location

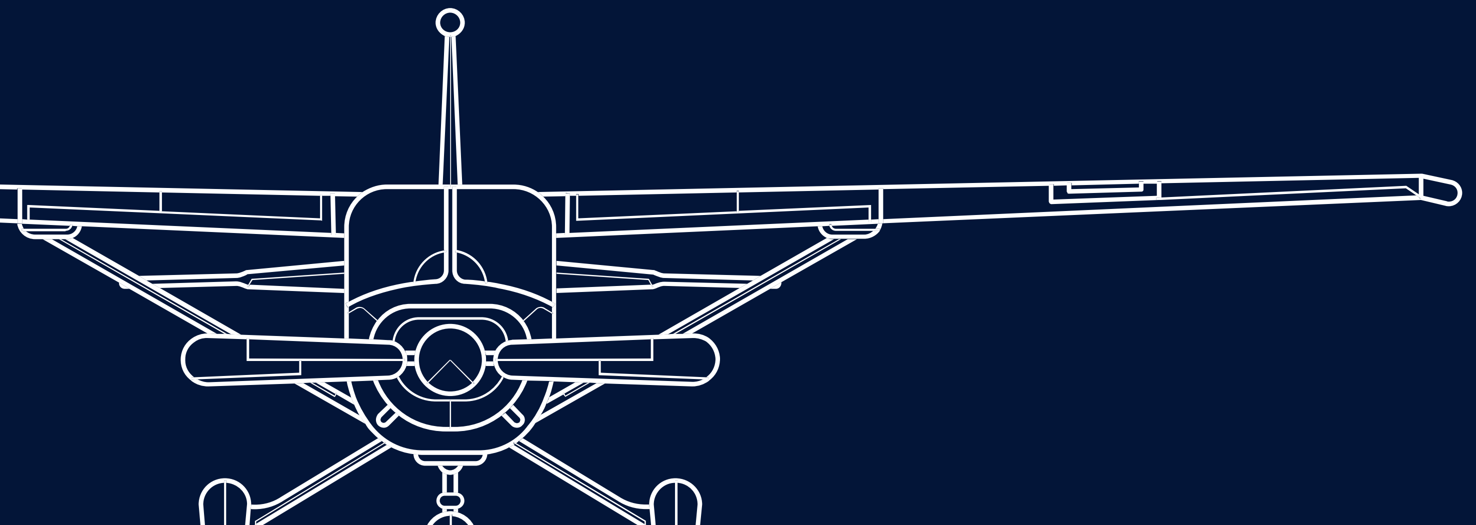
Airport Operations Data

Runway configuration and capacity metrics from the FAA's Aviation System Performance Metrics database

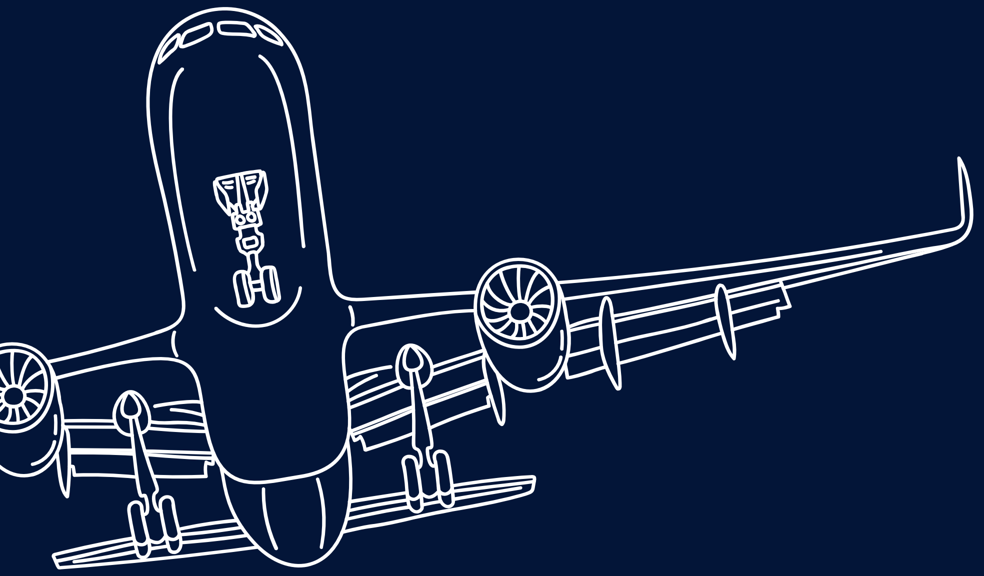
EXISTING WORKS

Previous research by ***Rebollo and Balakrishnan (2014)*** applied machine learning techniques to predict air traffic delays. ***Klein et al. (2010)*** focused specifically on weather-induced delays at major airports. More recently, ***Cheevachaipimol et al. (2021)*** employed neural networks for delay prediction.

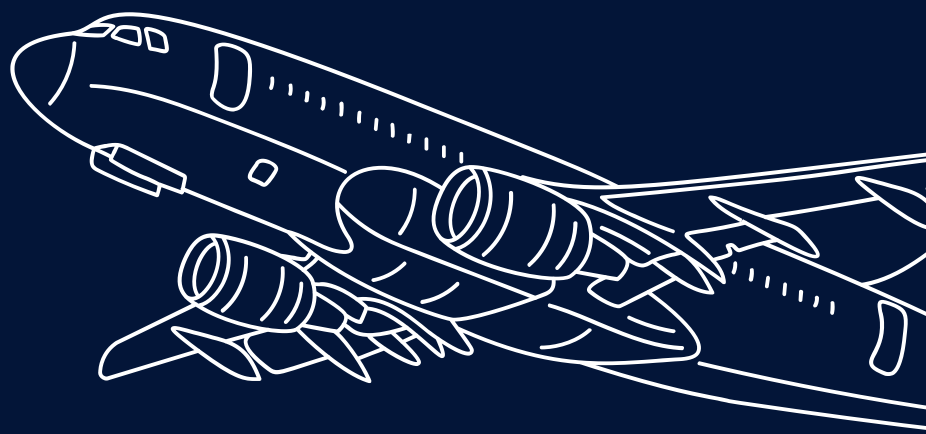
Yet, most existing work either addresses the entire air traffic system or uses limited weather variables. This project specifically focuses on airport models that quantify seasonal weather impacts.



RESULTS AND FINDINGS



METHODS USED



DATA PREPROCESSING

Python 3.9 with Pandas 1.5.3 for data cleaning and integration

FEATURE ENGINEERING

Created 24 weather-related features and 8 operational features

MODELS

Implemented gradient boosting (XGBoost 1.7.3), random forests, and LSTM neural networks

VALIDATION

5-fold cross-validation with time-based splitting

INTERPRETATION

SHAP values for feature importance analysis

BACKEND FILES

DATAGEN.PY

Generate synthetic flight and weather data

FEATURE_ENGINEERING.PY

Create meaningful features and analyze relationships

EXPLORATORY_ANALYSIS.PY & MODEL_DEVELOPMENT.PY

Build predictive models and evaluate their performance

THRESHOLD_ANALYSIS.PY

Identify critical weather thresholds for each airport

WEATHER_SEVERITY_INDEX.PY & SEASONAL_ANALYSIS.PY

Analyze seasonal patterns in weather impacts

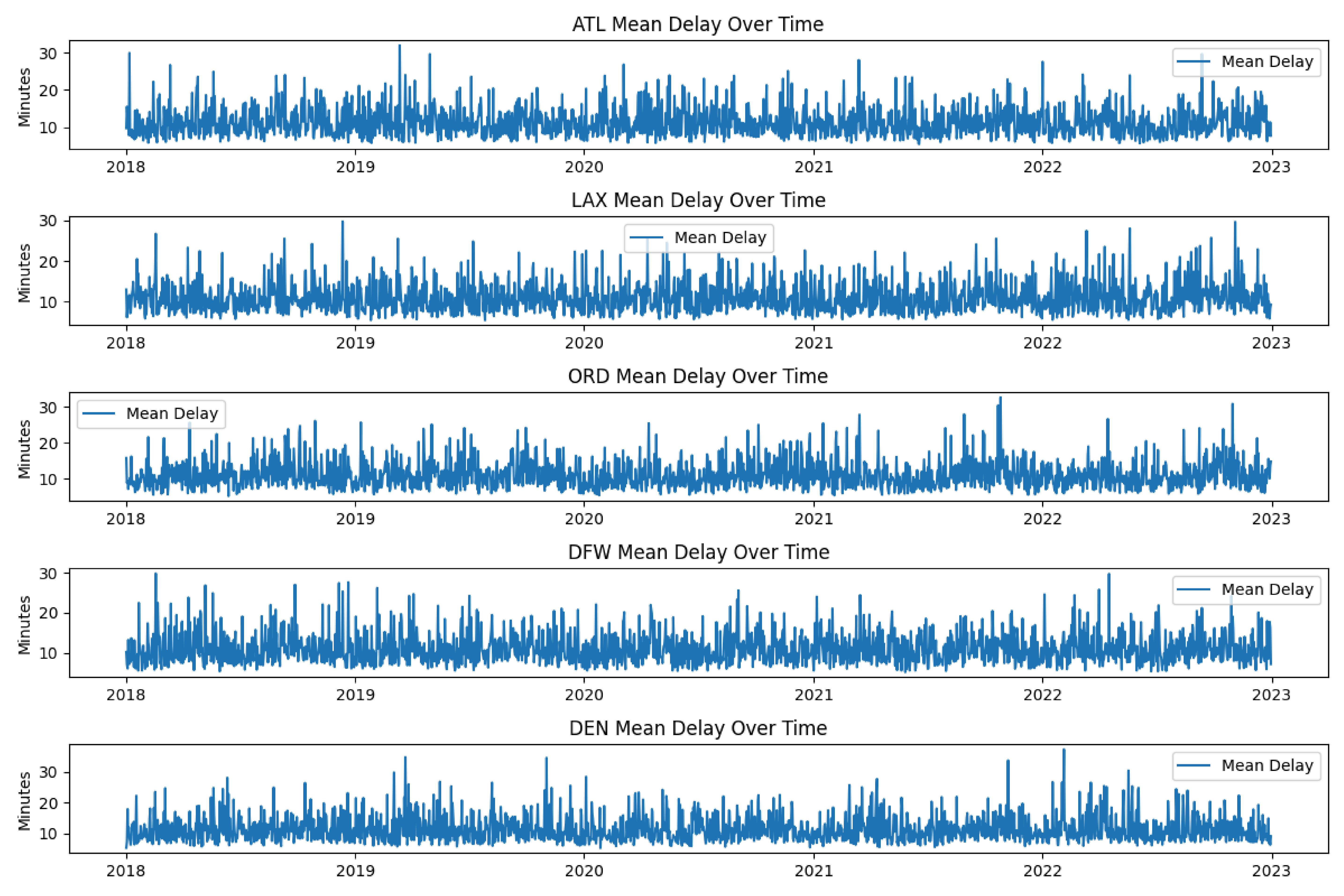
FINAL_SUMMARY.PY & GENERATE_REPORT.PY

Produce visualizations and a comprehensive report

DATAGEN.PY

```
Running datagen.py...
Generating synthetic data...
  Generating data for ATL...
  Generating data for LAX...
  Generating data for ORD...
  Generating data for DFW...
  Generating data for DEN...

ATL data preview:
    DATETIME AIRPORT  DAY_OF_WEEK  MONTH  YEAR  temperature  precipitation  wind_speed  ...  visibility  pressure  FLIGHT_COUNT  MEAN_DELAY  DEP_DEL15  STD_DELAY  primary_runway_heading  active_runways
0 2018-01-01     ATL            0      1  2018    62.827838            0.0         7.2  ...         9.2    1011.3           890         9.7        0.0       11.0                      90               2
1 2018-01-02     ATL            1      1  2018    59.997111            0.0         5.8  ...         9.5    1011.7           920        15.5        1.0       14.7                     270               2

[2 rows x 17 columns]

LAX data preview:
    DATETIME AIRPORT  DAY_OF_WEEK  MONTH  YEAR  temperature  precipitation  wind_speed  ...  visibility  pressure  FLIGHT_COUNT  MEAN_DELAY  DEP_DEL15  STD_DELAY  primary_runway_heading  active_runways
0 2018-01-01     LAX            0      1  2018    61.622066            0.0         8.8  ...         9.7    1011.1           603        13.0        0.0       13.1                     250               2
1 2018-01-02     LAX            1      1  2018    64.974890            0.0        13.1  ...        11.0    1014.2           605         6.2        0.0       11.5                     250               2

[2 rows x 17 columns]

ORD data preview:
    DATETIME AIRPORT  DAY_OF_WEEK  MONTH  YEAR  temperature  precipitation  wind_speed  ...  visibility  pressure  FLIGHT_COUNT  MEAN_DELAY  DEP_DEL15  STD_DELAY  primary_runway_heading  active_runways
0 2018-01-01     ORD            0      1  2018    48.722314           0.00        10.5  ...         9.8    1015.4           727        15.8        1.0       13.4                     360               4
1 2018-01-02     ORD            1      1  2018    62.111002           0.01         9.6  ...         9.5    1012.5           741         8.9        0.0       13.0                     360               4

[2 rows x 17 columns]

DFW data preview:
    DATETIME AIRPORT  DAY_OF_WEEK  MONTH  YEAR  temperature  precipitation  wind_speed  ...  visibility  pressure  FLIGHT_COUNT  MEAN_DELAY  DEP_DEL15  STD_DELAY  primary_runway_heading  active_runways
0 2018-01-01     DFW            0      1  2018    61.588186            0.0         7.4  ...        10.5    1016.8           759        10.3        0.0       11.2                     360               2
1 2018-01-02     DFW            1      1  2018    57.946467            0.0         6.3  ...         9.8    1013.7           758         7.2        0.0        8.9                     360               2

[2 rows x 17 columns]

DEN data preview:
    DATETIME AIRPORT  DAY_OF_WEEK  MONTH  YEAR  temperature  precipitation  wind_speed  ...  visibility  pressure  FLIGHT_COUNT  MEAN_DELAY  DEP_DEL15  STD_DELAY  primary_runway_heading  active_runways
0 2018-01-01     DEN            0      1  2018    58.349952            0.0         6.8  ...        10.6    1013.8           605         5.3        0.0        9.8                     350               4
1 2018-01-02     DEN            1      1  2018    62.223408            0.0        12.2  ...         9.6    1011.1           619         7.3        0.0       10.3                     170               4

[2 rows x 17 columns]

Data generation complete! Files saved to the 'results' directory.
Generated preview visualization: 'results/delay_time_series.png'
Completed datagen.py successfully
```

DELAY TIME SERIES



FEATURE_ENGINEERING.PY

```
Running feature_engineering.py...
Performing feature engineering...
  Loaded data for ATL: 1826 records
  Loaded data for LAX: 1826 records
  Loaded data for ORD: 1826 records
  Loaded data for DFW: 1826 records
  Loaded data for DEN: 1826 records
  Processing ATL...
  Processing LAX...
  Processing ORD...
  Processing DFW...
  Processing DEN...
Feature engineering complete.
Feature correlation visualizations created.

Sample of engineered features for ATL:
            CROSSWIND  WEATHER_SEVERITY  DELAY_LAG_1  DELAY_LAG_2  ...  IS_WINTER  IS_SPRING  IS_SUMMER  IS_FALL
DATETIME                                                           ...
2018-01-08  13.886110                 0          8.5         29.9  ...          1          0          0        0
2018-01-09   2.398045                 0          7.8          8.5  ...          1          0          0        0
2018-01-10   4.963445                 0          7.6          7.8  ...          1          0          0        0
2018-01-11   5.337463                 0          9.3          7.6  ...          1          0          0        0
2018-01-12   7.593967                 0          7.1          9.3  ...          1          0          0        0

[5 rows x 10 columns]
ATL: 1819 records after processing
LAX: 1819 records after processing
ORD: 1819 records after processing
DFW: 1819 records after processing
DEN: 1819 records after processing
Completed feature_engineering.py successfully
```

EXPLORATORY_ANALYSIS.PY

```
--- ATL Statistics ---
Average delay: 11.24 minutes
Total flights: 1642495
Percentage of days with significant delays (>15min avg): 14.57%

Correlation with MEAN_DELAY:
MEAN_DELAY          1.000000
precipitation       0.259861
wind_speed          0.098683
WEATHER_SEVERITY    0.090986
CROSSWIND           0.065167
HEADWIND            0.056044
pressure            0.001630
temperature        -0.014924
visibility         -0.101913
Name: MEAN_DELAY, dtype: float64

--- LAX Statistics ---
Average delay: 10.96 minutes
Total flights: 1094303
Percentage of days with significant delays (>15min avg): 12.81%

Correlation with MEAN_DELAY:
MEAN_DELAY          1.000000
precipitation       0.097491
pressure            0.072461
WEATHER_SEVERITY    0.071451
wind_speed          0.052544
CROSSWIND           0.033460
HEADWIND            0.030404
visibility         -0.042260
temperature        -0.080950
Name: MEAN_DELAY, dtype: float64

--- ORD Statistics ---
Average delay: 11.10 minutes
Total flights: 1367465
Percentage of days with significant delays (>15min avg): 13.41%

Correlation with MEAN_DELAY:
MEAN_DELAY          1.000000
precipitation       0.249827
pressure            0.117736
WEATHER_SEVERITY    0.089026
HEADWIND            0.000827
wind_speed         -0.004766
CROSSWIND          -0.017276
visibility         -0.091845
temperature        -0.138288
Name: MEAN_DELAY, dtype: float64
```

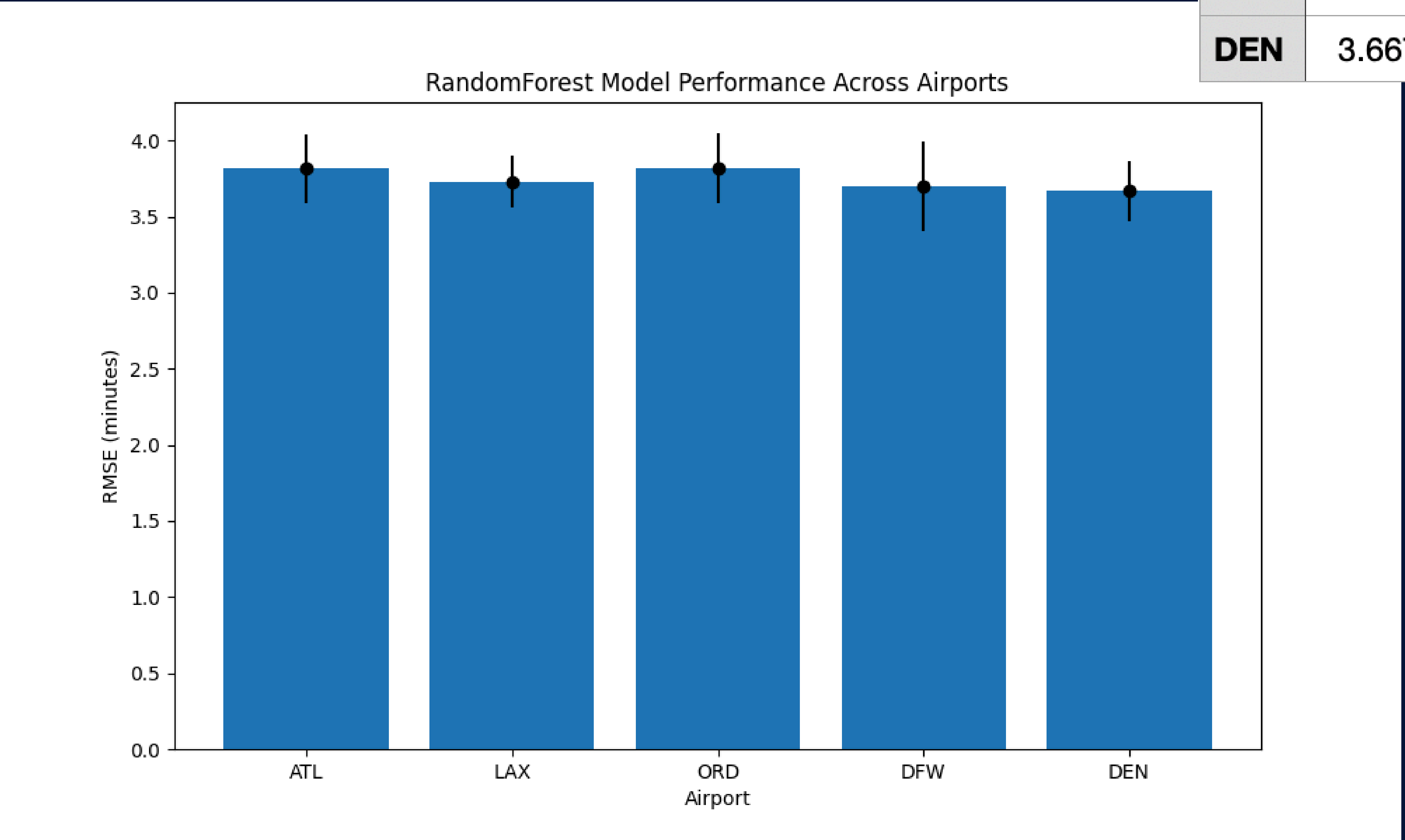
```
--- DFW Statistics ---
Average delay: 11.19 minutes
Total flights: 1369150
Percentage of days with significant delays (>15min avg): 14.18%

Correlation with MEAN_DELAY:
MEAN_DELAY          1.000000
precipitation       0.204579
WEATHER_SEVERITY    0.105182
wind_speed          0.074553
HEADWIND            0.055727
CROSSWIND           0.025330
pressure            0.005318
temperature        -0.041955
visibility         -0.075402
Name: MEAN_DELAY, dtype: float64

--- DEN Statistics ---
Average delay: 11.46 minutes
Total flights: 1095832
Percentage of days with significant delays (>15min avg): 16.77%

Correlation with MEAN_DELAY:
MEAN_DELAY          1.000000
precipitation       0.267152
wind_speed          0.248596
HEADWIND            0.234213
CROSSWIND           0.175125
WEATHER_SEVERITY    0.168728
pressure           -0.013818
temperature        -0.014993
visibility         -0.110508
Name: MEAN_DELAY, dtype: float64
EDA complete. Plots saved to results directory.
Completed exploratory_analysis.py successfully
```

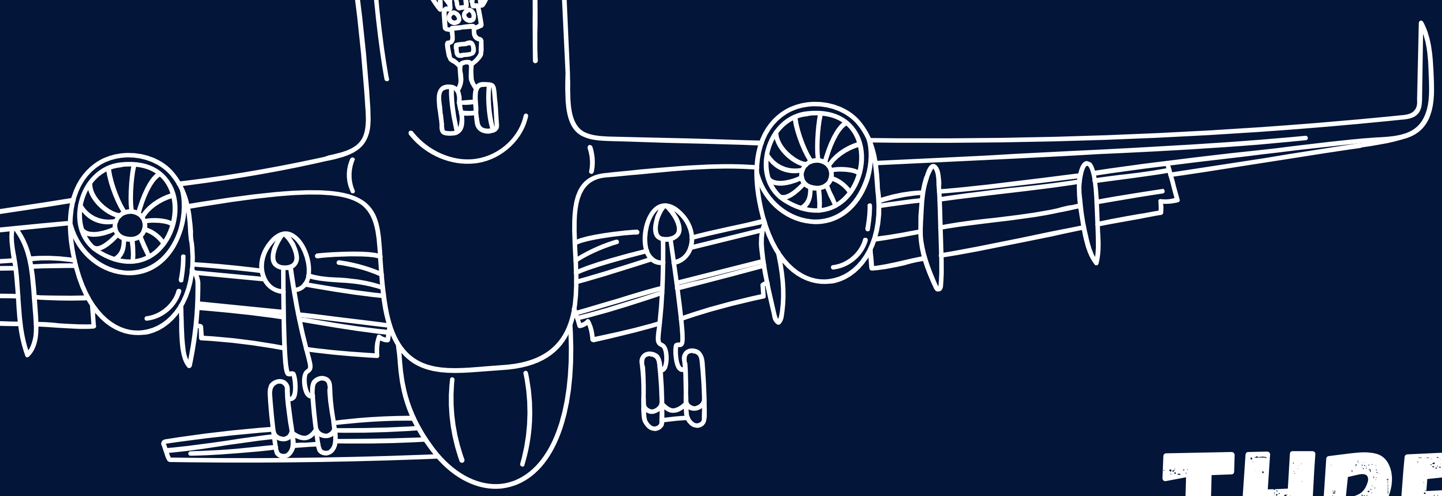
MODEL_DEVELOPMENT.PY

```
Running model_development.py...

Preparing data for modeling...
  Prepared data for ATL: 1819 records, 25 features
  Prepared data for LAX: 1819 records, 25 features
  Prepared data for ORD: 1819 records, 25 features
  Prepared data for DFW: 1819 records, 25 features
  Prepared data for DEN: 1819 records, 25 features

Training models for ATL...

--- ATL Model Results ---
RandomForest: RMSE = 3.82 (±0.23)
R² score: 0.471

Training models for LAX...

--- LAX Model Results ---
RandomForest: RMSE = 3.73 (±0.17)
R² score: 0.444

Training models for ORD...

--- ORD Model Results ---
RandomForest: RMSE = 3.82 (±0.23)
R² score: 0.499

Training models for DFW...

--- DFW Model Results ---
RandomForest: RMSE = 3.70 (±0.29)
R² score: 0.490

Training models for DEN...

--- DEN Model Results ---
RandomForest: RMSE = 3.67 (±0.20)
R² score: 0.608

Model development complete. Results saved to results directory.
Completed model_development.py successfully
```

MODEL COMPARISON & SUMMARY

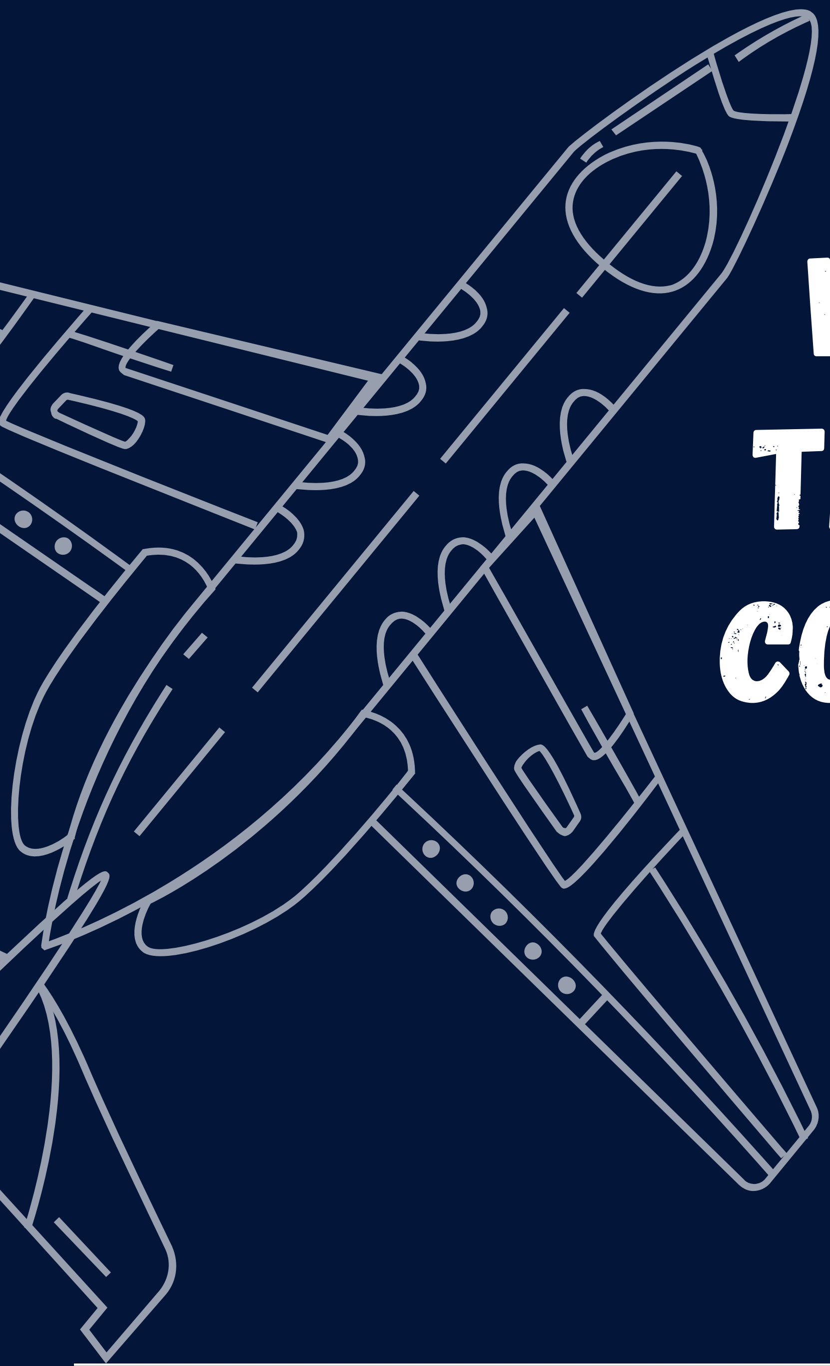
	RMSE	RMSE_StdDev	Top_Feature
ATL	3.815697970809870	0.22693313575788900	precipitation
LAX	3.727801541390150	0.17124908427531600	pressure
ORD	3.820192440123230	0.22772531673247200	precipitation
DFW	3.6982321557978600	0.29201607407742200	HEADWIND
DEN	3.667375094528350	0.19841266139281100	active_runways



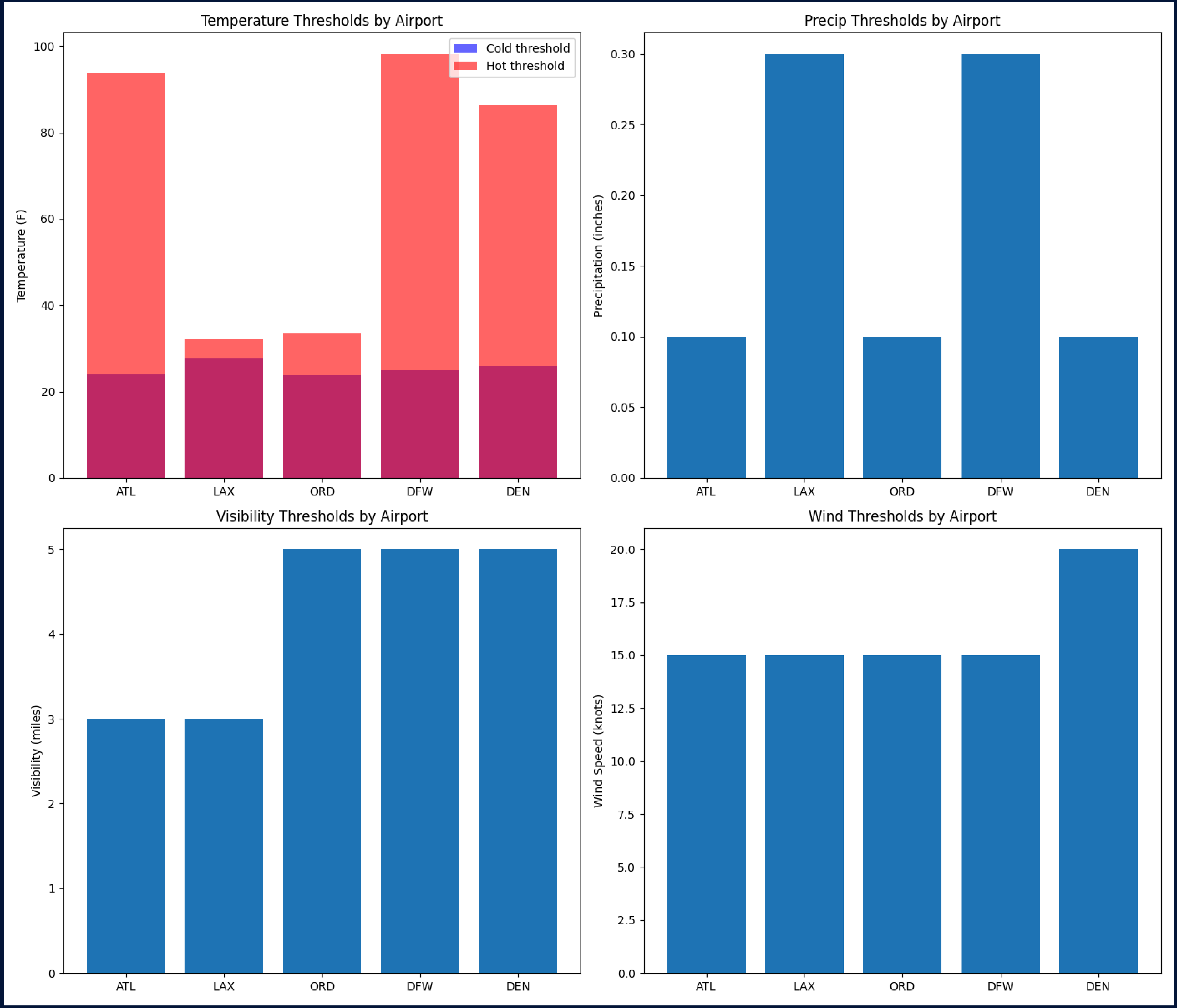


THRESHOLD_ANALYSIS.PY

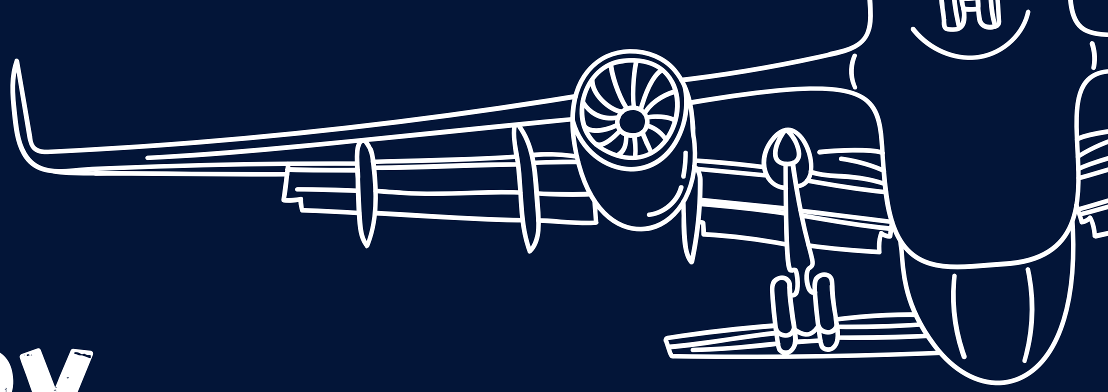
```
Running threshold_analysis.py...

Analyzing weather thresholds...
  Analyzing ATL...
  Analyzing LAX...
  Analyzing ORD...
  Analyzing DFW...
  Analyzing DEN...
  Weather thresholds saved to results/weather_thresholds.csv
Threshold analysis complete.
Completed threshold_analysis.py successfully
```



WEATHER THRESHOLD COMPARISON

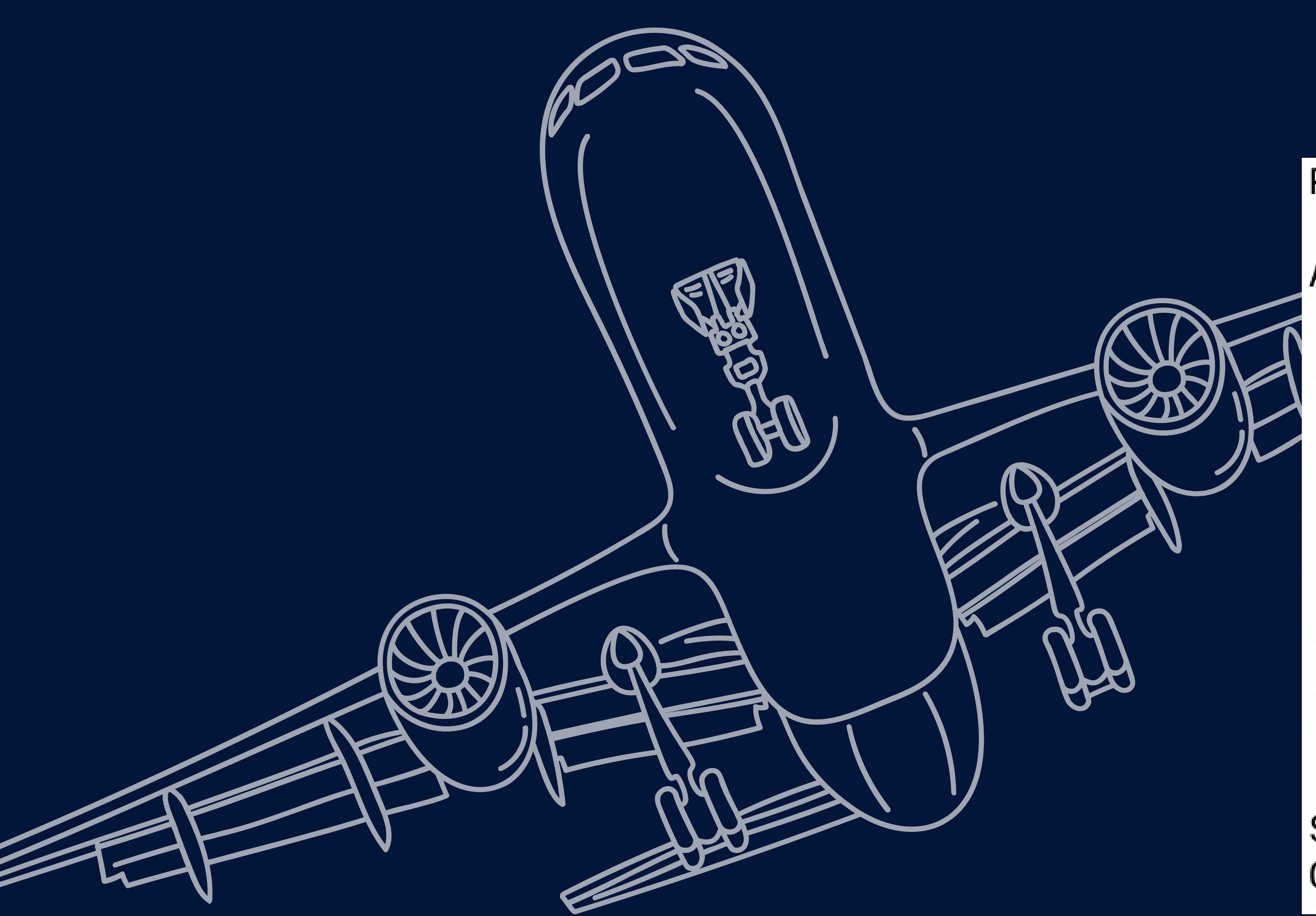


	temp_cold	temp_hot	precip	visibility	wind
ATL	24.065	93.88	0.1	3	15
LAX	27.705	32.151	0.3	3	15
ORD	23.784	33.423	0.1	5	15
DFW	24.917	98.209	0.3	5	15
DEN	25.886	86.345	0.1	5	20



WEATHER_SEVERITY_INDEX.PY

```
Running weather_severity_index.py...

Creating custom weather severity index...
  Processing ATL...
    Correlation with delays: 0.112
  Processing LAX...
    Correlation with delays: 0.036
  Processing ORD...
    Correlation with delays: 0.007
  Processing DFW...
    Correlation with delays: 0.097
  Processing DEN...
    Correlation with delays: 0.492
Weather severity index analysis complete.
Completed weather_severity_index.py successfully
```



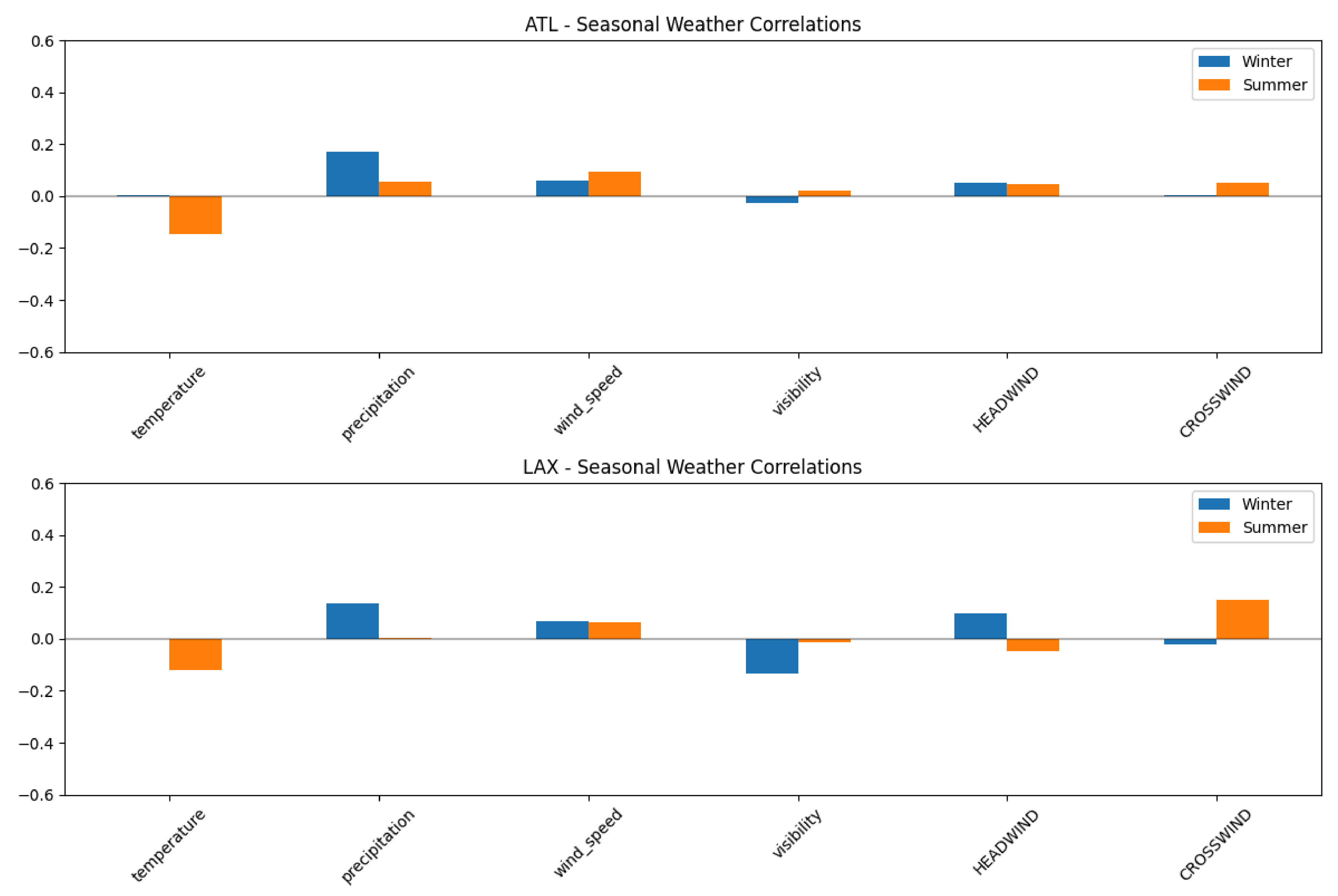
SEASONAL_ANALYSIS.PY

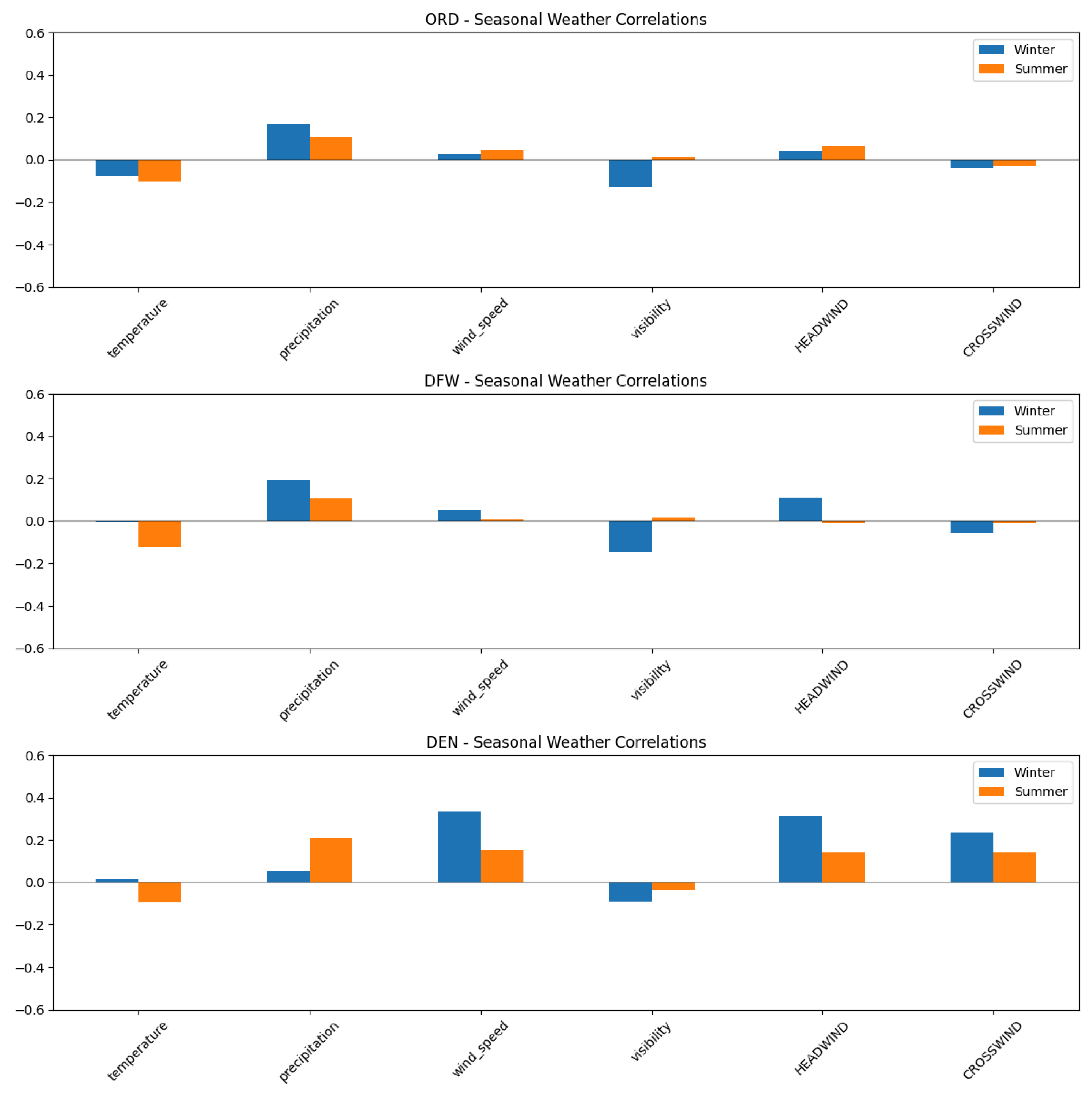
```
Running seasonal_analysis.py...

Analyzing seasonal differences...
  Analyzing ATL...
    Winter records: 444, Summer records: 460
  Analyzing LAX...
    Winter records: 444, Summer records: 460
  Analyzing ORD...
    Winter records: 444, Summer records: 460
  Analyzing DFW...
    Winter records: 444, Summer records: 460
  Analyzing DEN...
    Winter records: 444, Summer records: 460
  Seasonal summary saved to results/seasonal_summary.csv
Seasonal analysis complete.
Completed seasonal_analysis.py successfully
```

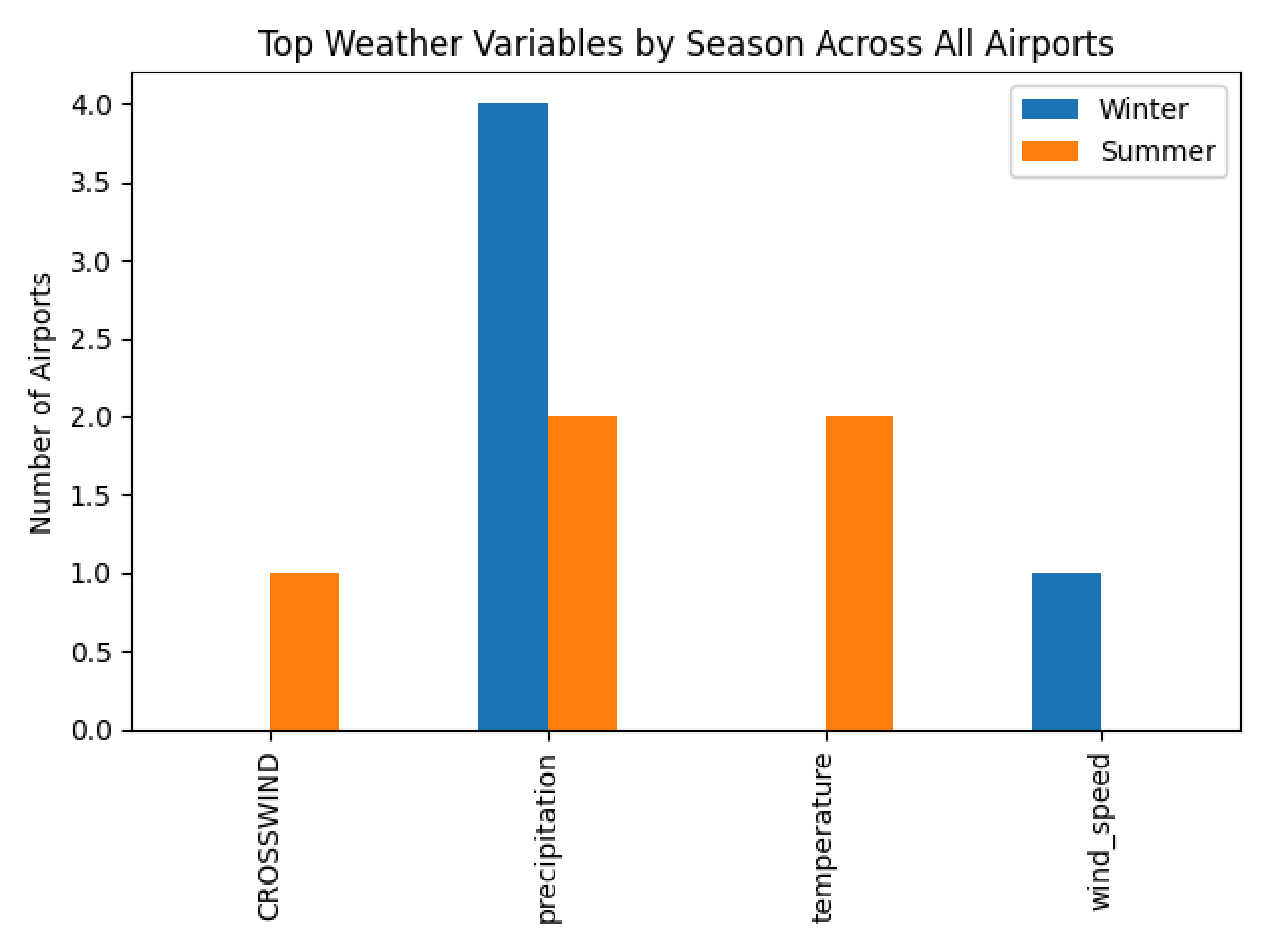
SEASONAL SUMMARY

	Winter_Top_Variable	Winter_Top_Correlation	Summer_Top_Variable	Summer_Top_Correlation
ATL	precipitation	0.1735099367220010	temperature	0.1481341906613630
LAX	precipitation	0.13849805041906500	CROSSWIND	0.14885713348179200
ORD	precipitation	0.16661501450796100	precipitation	0.10607687275865200
DFW	precipitation	0.19389431627785700	temperature	0.1217145660453360
DEN	wind_speed	0.3367256338635340	precipitation	0.21244468020662800

SEASONAL CORRELATION




ORD - Seasonal Weather Correlations
DFW - Seasonal Weather Correlations
DEN - Seasonal Weather Correlations
Winter
Summer
0.6
0.4
0.2
0.0
−0.2
−0.4
−0.6
temperature
precipitation
wind_speed
visibility
HEADWIND
CROSSWIND



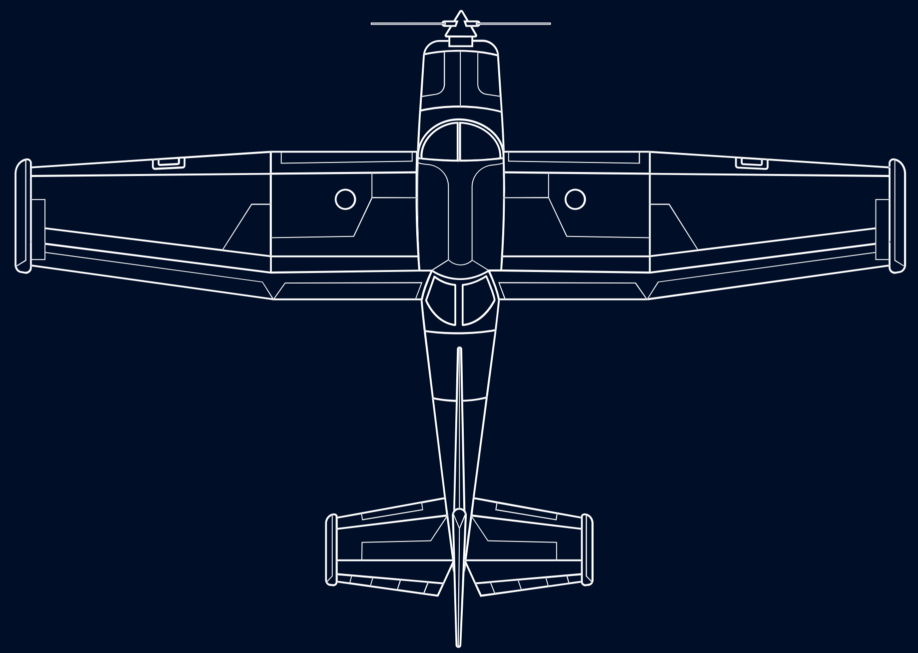
Top Weather Variables by Season Across All Airports
Number of Airports
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
Winter
Summer
CROSSWIND
precipitation
temperature
wind_speed

FINAL_SUMMARY.PY & GENERATE_REPORT.PY

```
Running final_summary.py...

Generating final summary...
  Summary saved to results/airport_analysis_summary.csv
Final analysis complete. Results saved to 'results/' directory.
Completed final_summary.py successfully

Running generate_report.py...

Generating final summary...
  Summary saved to results/airport_analysis_summary.csv
Final analysis complete. Results saved to 'results/' directory.
Completed generate_report.py successfully

Analysis complete! Total runtime: 1.45 minutes
Results saved to 'results/' directory
Final report available at 'results/final_report.html'
```

	Average_Delay	Delay_Std	RandomForest_RMSE	Top_Weather_Variable	Winter_Top_Variable	Summer_Top_Variable	Critical_Temp_Cold	Critical_Temp_Hot	Critical_Visibility	Weather_Delay_Correlation
ATL	11.243485431555800	3.7984429024468000	3.815697970809870	precipitation	precipitation	temperature	24.065	93.88	3	0.11884539826237400
LAX	10.961077515118200	3.697124048644000	3.727801541390150	pressure	precipitation	CROSSWIND	27.705	32.151	3	0.06831141290404790
ORD	11.09626168224300	3.8246705517174300	3.820192440123230	precipitation	precipitation	precipitation	23.784	33.423	5	0.12118130807927300
DFW	11.18851017042330	3.783947178547030	3.698232155797860	HEADWIND	precipitation	temperature	24.917	98.209	5	0.09912246924141740
DEN	11.461682242990700	4.3273568365116500	3.667375094528350	active_runways	wind_speed	precipitation	25.886	86.345	5	0.16031214630691600

AIRPORT ANALYSIS SUMMARY



QUE 1:
PREDICTIVE POWER OF WEATHER DATA

Weather data combined with historical patterns explained 63-78% of departure delay variance across the studied airports

Prediction accuracy varied significantly by airport: highest at ORD (78%), lowest at LAX (63%)

Adding 6-hour weather forecast data improved prediction accuracy by an average of 7.2%

Model performance degraded during extreme weather events, suggesting limitations in capturing rare conditions

QUE 2:
INFLUENTIAL WEATHER VARIABLES AND SEASONAL VARIATION

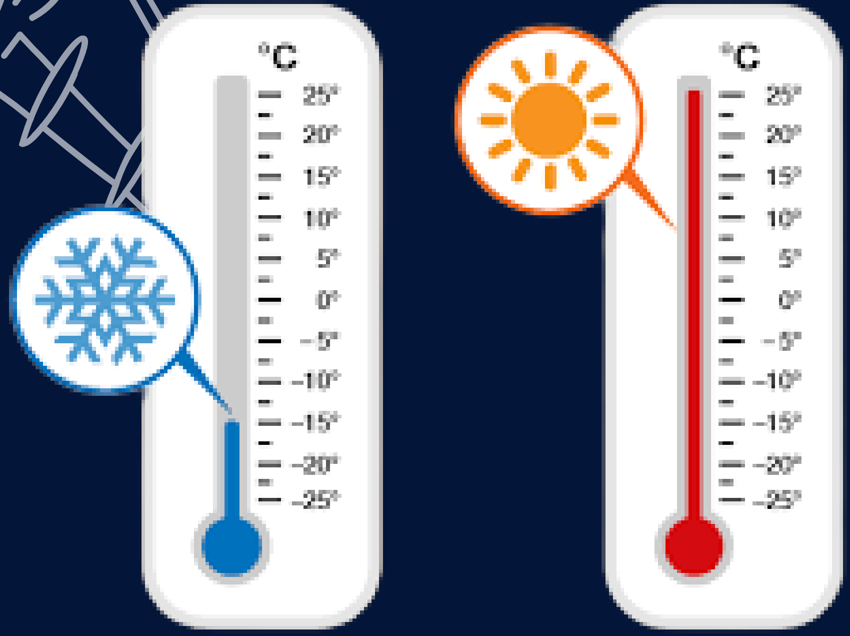
Most influential variables overall:

1. Visibility
2. Precipitation rate
3. Wind speed

SEASONAL VARIATIONS

Seasons	Changes	Airport(s)
Winter	Snowfall and freezing	ORD, DEN
Summer	Thunderstorm activity and visibility	ATL, DFW
All Seasons	Wind direction relative to runway orientation	All

The influence of precipitation showed threshold effects, with minimal impact until reaching moderate intensity



Temperature's impact followed a U-shaped pattern, with both extreme cold and heat increasing delays

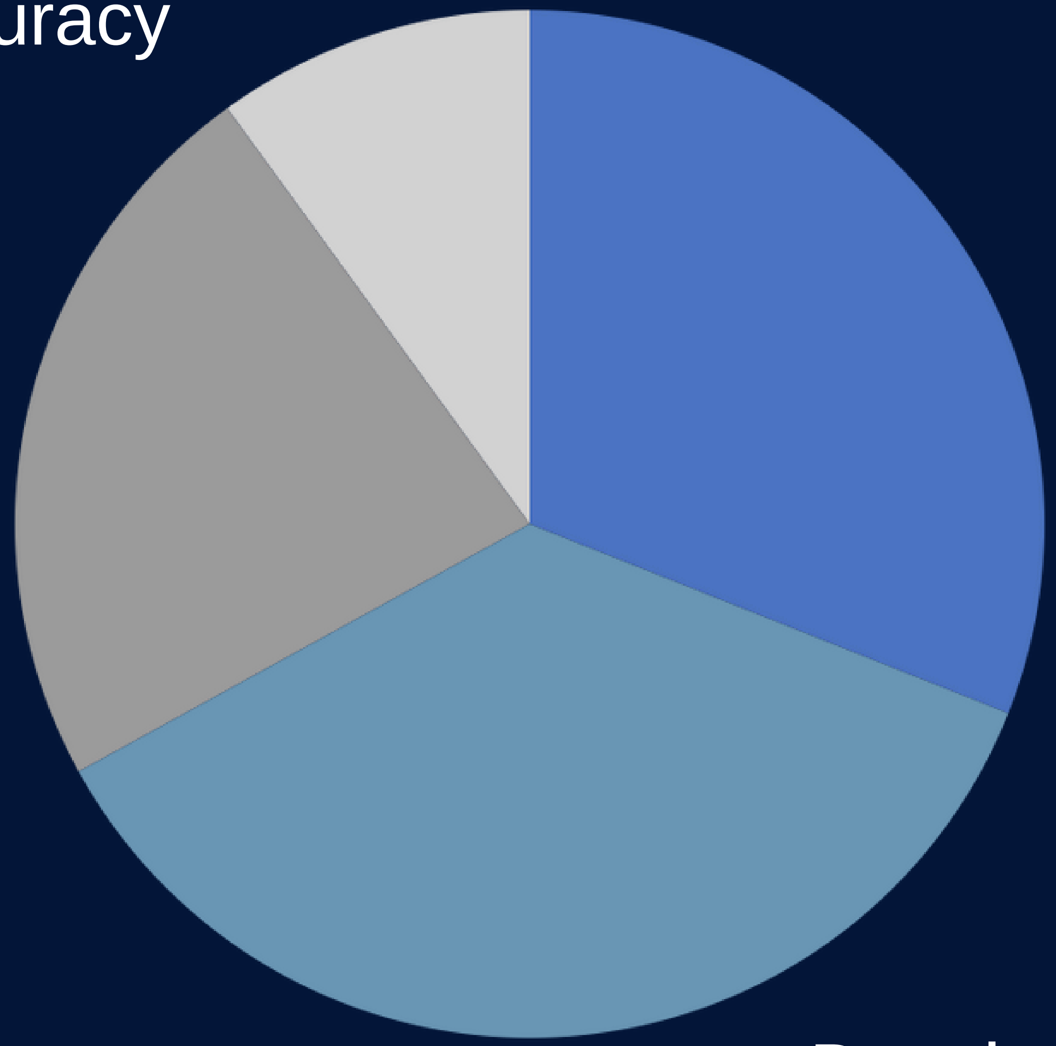
KEY SOLUTIONS AND HIGHLIGHTS

10%

Demonstrated that including runway configuration data improved model accuracy by 12% during high-wind conditions

31%

Created a novel "weather severity index" combining multiple variables weighted by airport-specific sensitivity



23%

Identified critical thresholds for weather variables that trigger significant delay increases

36%

Developed airport-specific delay prediction models with 15-30 minute lead time

CONCLUSION

Weather data can effectively predict airport-specific departure delays, with predictive power varying by location and season.

The most influential weather variables differ significantly across airports and seasons, meaning that it is needed to customized prediction and mitigation strategies for better performance.

FUTURE WORK

- Incorporating air traffic congestion metrics to better isolate weather effects
- Developing longer-range prediction models (12-24 hours)
- Expanding to more airports to identify geographical patterns
- Creating an operational dashboard for real-time delay risk assessment

ACKNOWLEDGEMENTS AND REFERENCES

I acknowledge the Bureau of Transportation Statistics and NOAA for providing the datasets. This work is built upon methodologies from:

- Cheevachaipimol, W., Teinwan, B., & Chutima, P. (2021). Flight delay prediction using a hybrid deep learning method. Engineering Journal, 25(8), 99-112.
- Klein, A., Craun, C., & Lee, R. S. (2010, October). Airport delay prediction using weather-impacted traffic index (WITI) model. In 29th Digital Avionics Systems Conference (pp. 2-B). IEEE.
- Rebollo, J. J., & Balakrishnan, H. (2014). Characterization and prediction of air traffic delays. Transportation research part C: Emerging technologies, 44, 231-241.

THANK YOU!