

Weather Data Analysis

Domain: Weather & Climate Analytics

Abstract

This project analyzes historical weather data to identify temperature trends, seasonal patterns, humidity behavior, and relationships between key meteorological variables. The goal is to derive climate insights and support weather-aware planning and decision-making.

Executive Summary

- Historical weather records were analyzed across multiple meteorological attributes.
- Temperature trends, humidity distribution, wind behavior, and seasonal patterns were explored using visual analytics.
- Correlation analysis was performed to identify relationships between variables.

Outcome: The analysis highlights clear seasonal variations and interdependencies between weather attributes, enabling better climate understanding and forecasting insights.

Introduction

Problem Statement

Weather patterns directly impact agriculture, transportation, energy consumption, and disaster preparedness. However, raw weather data alone does not provide clear insights without systematic analysis.

Objectives

- Analyze long-term temperature trends

- Identify seasonal weather patterns
- Study humidity and wind behavior
- Explore correlations between weather attributes
- Generate climate insights and recommendations

Dataset Description

- **Source:** weatherHistory.csv
- **Type:** Historical weather observations
- **Granularity:** Time-based records
- **Common Attributes:**
 - Temperature
 - Humidity
 - Wind Speed
 - Weather Summary
 - Date/Time

Methodology

1. Load and inspect the dataset
2. Validate schema and data quality
3. Perform feature engineering (date, season)
4. Conduct exploratory data analysis
5. Perform statistical and correlation analysis
6. Derive climate insights and recommendations

```
In [11]: import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

sns.set(style="whitegrid")
```

```
df = pd.read_csv("../datasets/weatherHistory.csv")
df.head()
```

Out[11]:

| | Formatted Date | Summary | Precip Type | Temperature (C) | Apparent Temperature (C) | Humidity | Wind Speed (km/h) | Wind Bearing (degrees) | Visibility (km) | Loud Cover | Pressure (millibars) | Sum |
|---|-------------------------------------|---------------|-------------|-----------------|--------------------------|----------|-------------------|------------------------|-----------------|------------|----------------------|---------------|
| 0 | 2006-04-01 00:00:00.000 +0200 | Partly Cloudy | rain | 9.472222 | 7.388889 | 0.89 | 14.1197 | 251.0 | 15.8263 | 0.0 | 1015.13 | c through the |
| 1 | 2006-04-01 01:00:00.000 +0200 | Partly Cloudy | rain | 9.355556 | 7.227778 | 0.86 | 14.2646 | 259.0 | 15.8263 | 0.0 | 1015.63 | c through the |
| 2 | 2006-04-01 02:00:00.000 +0200 | Mostly Cloudy | rain | 9.377778 | 9.377778 | 0.89 | 3.9284 | 204.0 | 14.9569 | 0.0 | 1015.94 | c through the |
| 3 | 2006-04-01 03:00:00.000 +0200 | Partly Cloudy | rain | 8.288889 | 5.944444 | 0.83 | 14.1036 | 269.0 | 15.8263 | 0.0 | 1016.41 | c through the |
| 4 | 2006-04-01 04:00:00.000 +0200 | Mostly Cloudy | rain | 8.755556 | 6.977778 | 0.83 | 11.0446 | 259.0 | 15.8263 | 0.0 | 1016.51 | c through the |

DATA VALIDATION & COLUMN INSPECTION

In [12]:

```
print("Dataset Shape:", df.shape)

print("\nColumns:")
for col in df.columns:
    print("-", col)
```

```
print("\nData Types:")
df.info()

print("\nMissing Values:")
df.isnull().sum()
```

Dataset Shape: (96453, 12)

Columns:

- Formatted Date
- Summary
- Precip Type
- Temperature (C)
- Apparent Temperature (C)
- Humidity
- Wind Speed (km/h)
- Wind Bearing (degrees)
- Visibility (km)
- Loud Cover
- Pressure (millibars)
- Daily Summary

Data Types:

<class 'pandas.core.frame.DataFrame'>

RangeIndex: 96453 entries, 0 to 96452

Data columns (total 12 columns):

| # | Column | Non-Null Count | Dtype |
|----|--------------------------|----------------|---------|
| 0 | Formatted Date | 96453 non-null | object |
| 1 | Summary | 96453 non-null | object |
| 2 | Precip Type | 95936 non-null | object |
| 3 | Temperature (C) | 96453 non-null | float64 |
| 4 | Apparent Temperature (C) | 96453 non-null | float64 |
| 5 | Humidity | 96453 non-null | float64 |
| 6 | Wind Speed (km/h) | 96453 non-null | float64 |
| 7 | Wind Bearing (degrees) | 96453 non-null | float64 |
| 8 | Visibility (km) | 96453 non-null | float64 |
| 9 | Loud Cover | 96453 non-null | float64 |
| 10 | Pressure (millibars) | 96453 non-null | float64 |
| 11 | Daily Summary | 96453 non-null | object |

dtypes: float64(8), object(4)

memory usage: 8.8+ MB

Missing Values:

```
Out[12]: Formatted Date      0  
Summary          0  
Precip Type     517  
Temperature (C)  0  
Apparent Temperature (C) 0  
Humidity         0  
Wind Speed (km/h) 0  
Wind Bearing (degrees) 0  
Visibility (km)   0  
Loud Cover       0  
Pressure (millibars) 0  
Daily Summary    0  
dtype: int64
```

FEATURE ENGINEERING

```
In [13]: # Convert date column to datetime  
import pandas as pd  
  
# ----- Robust datetime parsing for mixed timezones -----  
if "Formatted Date" in df.columns:  
    # Parse datetime with timezone handling  
    df["Formatted Date"] = pd.to_datetime(  
        df["Formatted Date"],  
        utc=True,           # REQUIRED for mixed timezones  
        errors="coerce"     # Invalid parsing → NaT  
    )  
  
    # Drop rows where datetime conversion failed  
    df = df.dropna(subset=["Formatted Date"])  
  
    # Convert timezone-aware datetime to timezone-naive  
    df["Formatted Date"] = df["Formatted Date"].dt.tz_convert(None)  
  
    # Feature engineering  
    df["Year"] = df["Formatted Date"].dt.year  
    df["Month"] = df["Formatted Date"].dt.month  
    df["Month_Name"] = df["Formatted Date"].dt.month_name()  
  
df.head()
```

Out[13]:

| | Formatted Date | Summary | Precip Type | Temperature (C) | Apparent Temperature (C) | Humidity | Wind Speed (km/h) | Wind Bearing (degrees) | Visibility (km) | Loud Cover | Pressure (millibars) | D | Summ |
|---|---------------------|---------------|-------------|-----------------|--------------------------|----------|-------------------|------------------------|-----------------|------------|----------------------|---|---------------------------|
| 0 | 2006-03-31 22:00:00 | Partly Cloudy | rain | 9.472222 | 7.388889 | 0.89 | 14.1197 | 251.0 | 15.8263 | 0.0 | 1015.13 | P | Partly cloudy through the |
| 1 | 2006-03-31 23:00:00 | Partly Cloudy | rain | 9.355556 | 7.227778 | 0.86 | 14.2646 | 259.0 | 15.8263 | 0.0 | 1015.63 | P | Partly cloudy through the |
| 2 | 2006-04-01 00:00:00 | Mostly Cloudy | rain | 9.377778 | 9.377778 | 0.89 | 3.9284 | 204.0 | 14.9569 | 0.0 | 1015.94 | P | Partly cloudy through the |
| 3 | 2006-04-01 01:00:00 | Partly Cloudy | rain | 8.288889 | 5.944444 | 0.83 | 14.1036 | 269.0 | 15.8263 | 0.0 | 1016.41 | P | Partly cloudy through the |
| 4 | 2006-04-01 02:00:00 | Mostly Cloudy | rain | 8.755556 | 6.977778 | 0.83 | 11.0446 | 259.0 | 15.8263 | 0.0 | 1016.51 | P | Partly cloudy through the |



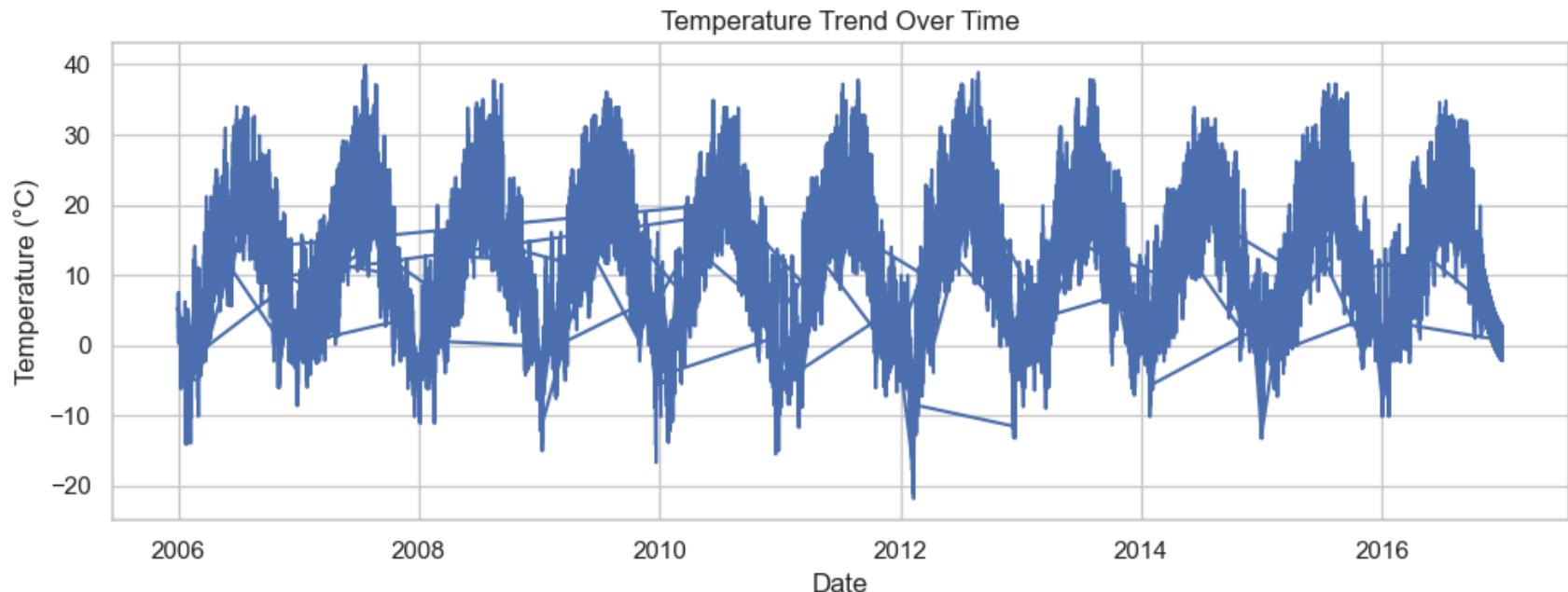
EXPLORATORY DATA ANALYSIS

Temperature Over Time

In [14]:

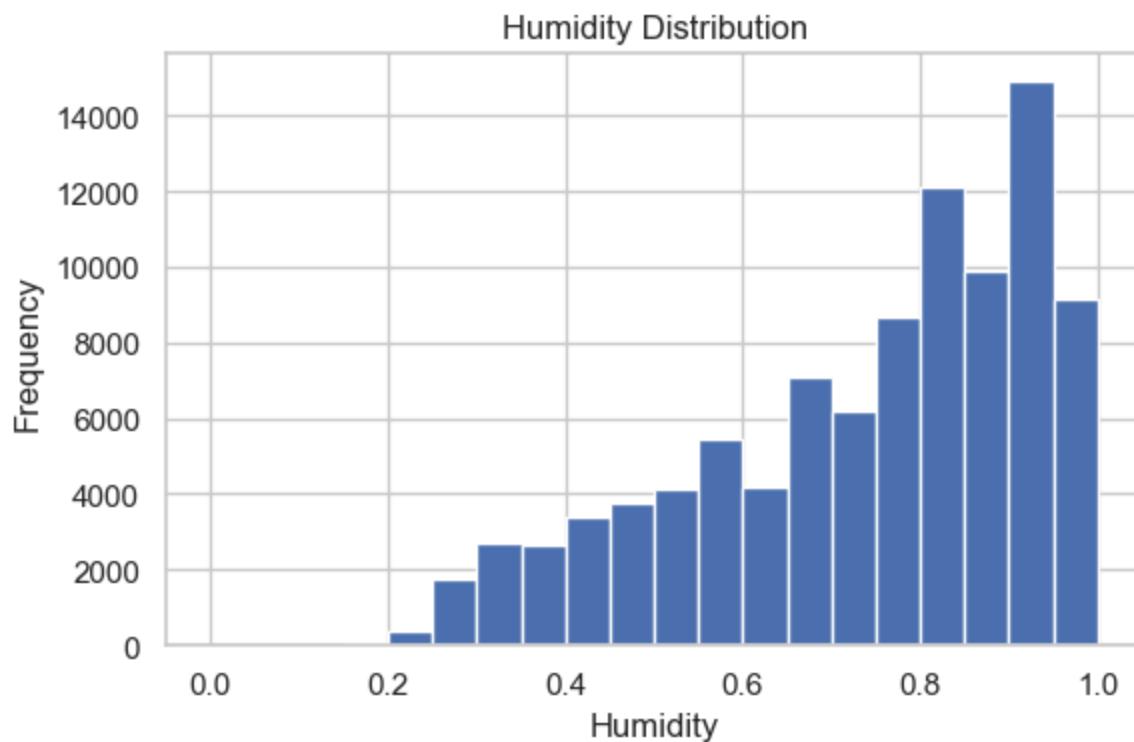
```
plt.figure(figsize=(10, 4))
plt.plot(df["Formatted Date"], df["Temperature (C)"])
plt.title("Temperature Trend Over Time")
plt.xlabel("Date")
plt.ylabel("Temperature (°C)")
plt.tight_layout()
```

```
plt.savefig("../visualizations/weather/temperature_trend.png")
plt.show()
```



Humidity Distribution

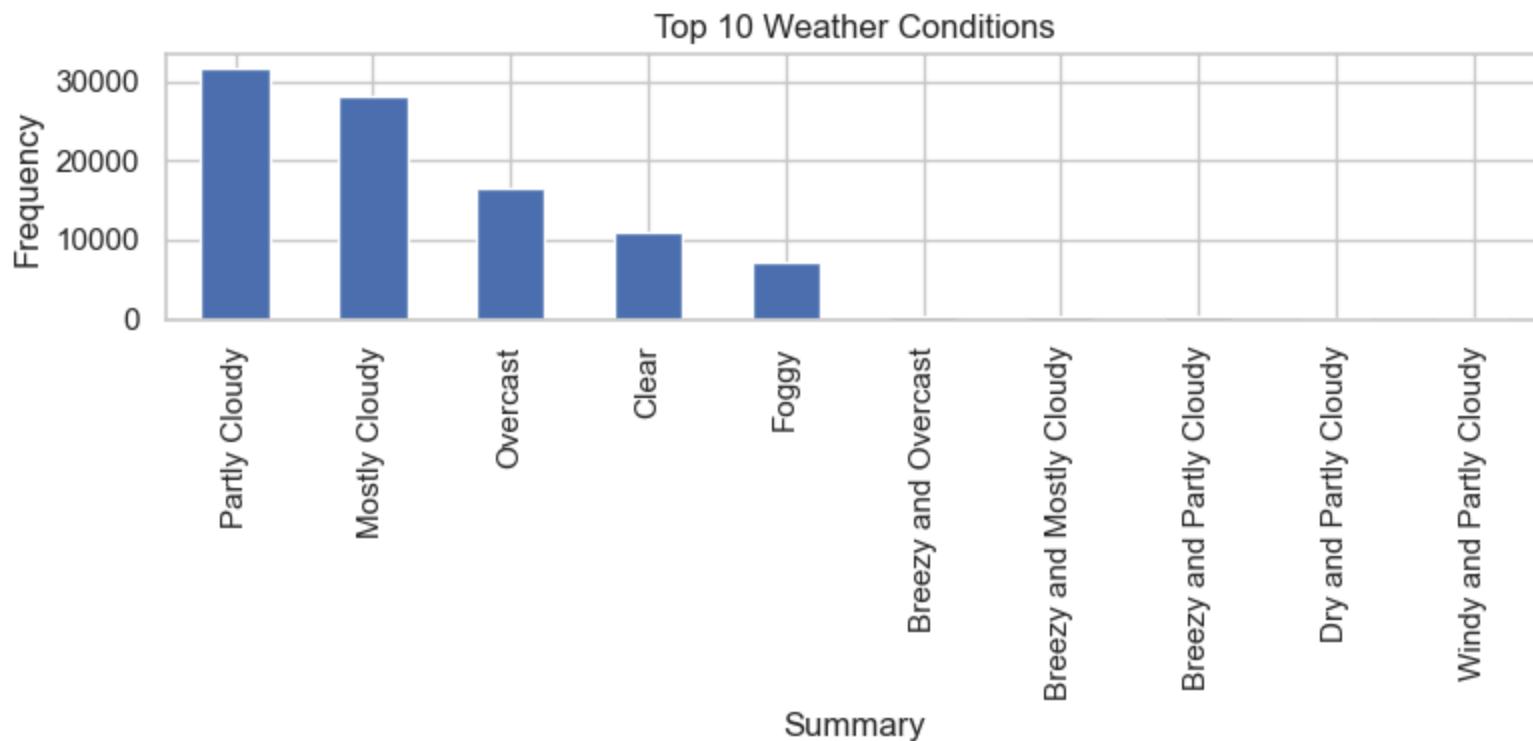
```
In [15]: plt.figure(figsize=(6, 4))
plt.hist(df["Humidity"], bins=20)
plt.title("Humidity Distribution")
plt.xlabel("Humidity")
plt.ylabel("Frequency")
plt.tight_layout()
plt.savefig("../visualizations/weather/humidity_distribution.png")
plt.show()
```



Weather Condition Frequency

```
In [16]: weather_counts = df["Summary"].value_counts().head(10)

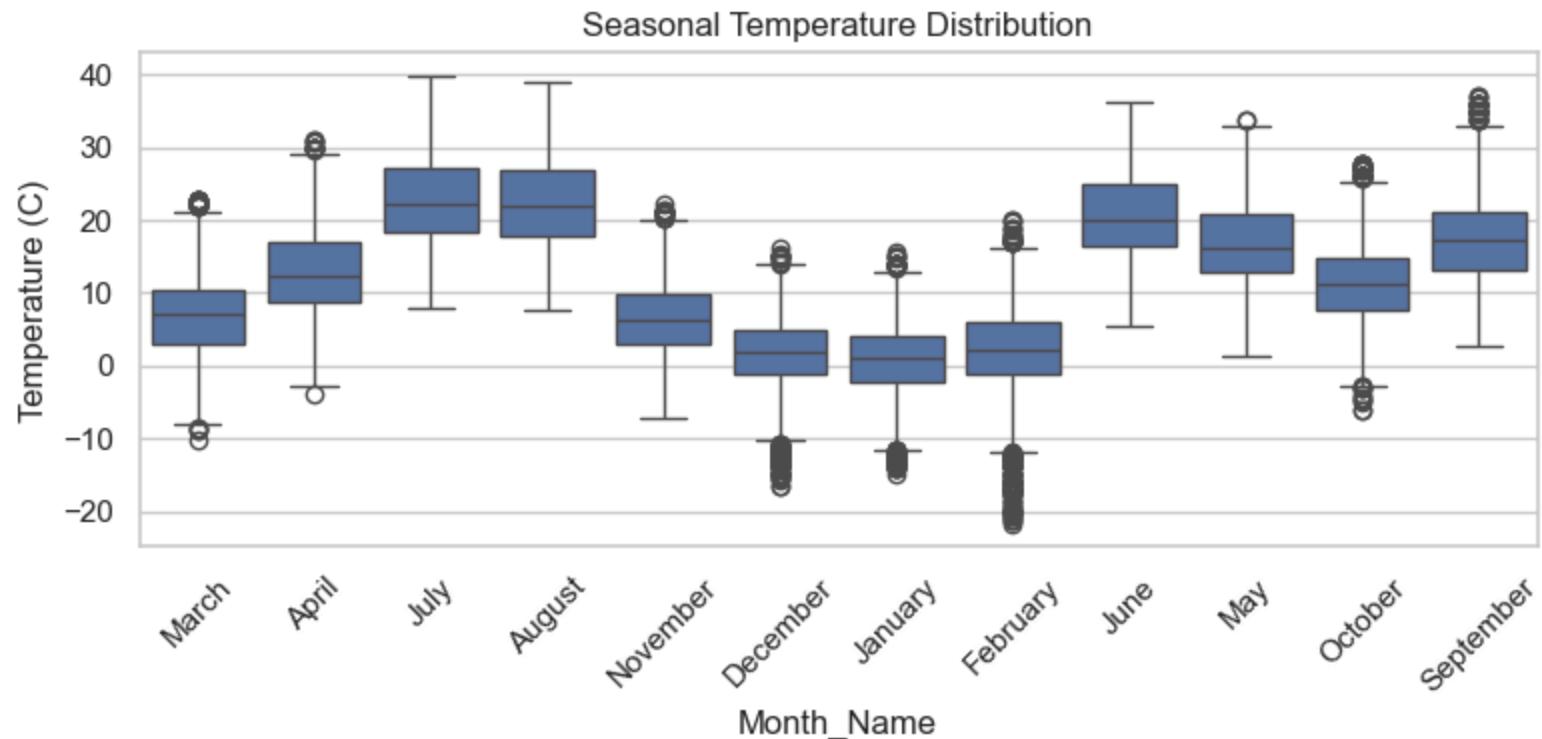
plt.figure(figsize=(8, 4))
weather_counts.plot(kind="bar")
plt.title("Top 10 Weather Conditions")
plt.ylabel("Frequency")
plt.tight_layout()
plt.savefig("../visualizations/weather/weather_condition_frequency.png")
plt.show()
```



ADVANCED WEATHER ANALYSIS

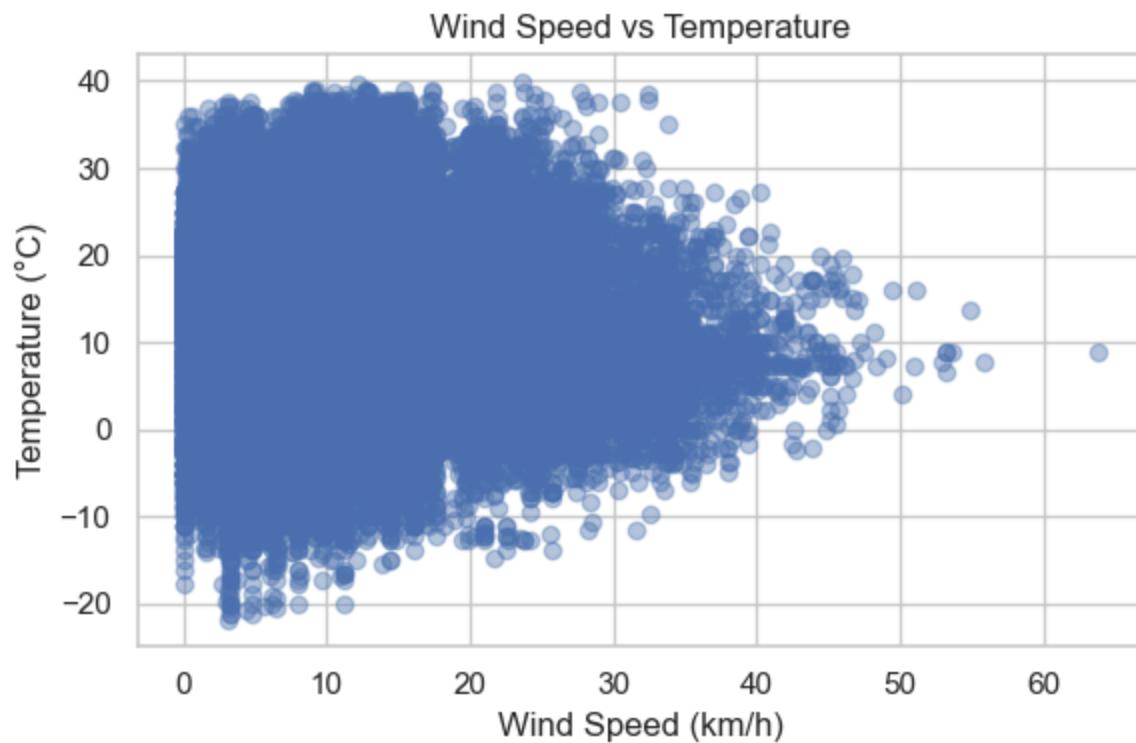
Seasonal Temperature Trends

```
In [17]: plt.figure(figsize=(8, 4))
sns.boxplot(x="Month_Name", y="Temperature (C)", data=df)
plt.xticks(rotation=45)
plt.title("Seasonal Temperature Distribution")
plt.tight_layout()
plt.savefig("../visualizations/weather/seasonal_temperature.png")
plt.show()
```



Wind Speed vs Temperature

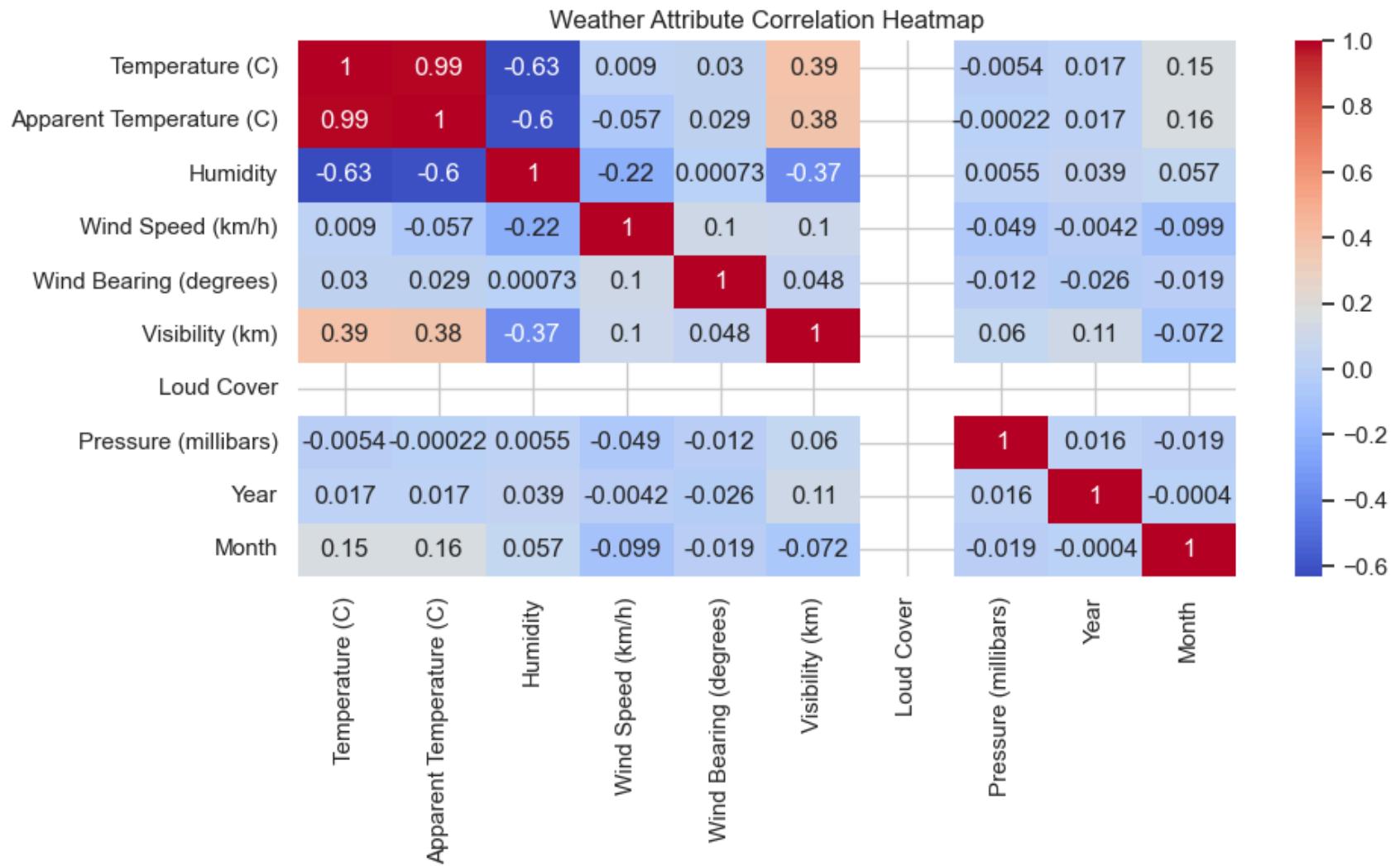
```
In [18]: plt.figure(figsize=(6, 4))
plt.scatter(df["Wind Speed (km/h)"], df["Temperature (C)"], alpha=0.4)
plt.title("Wind Speed vs Temperature")
plt.xlabel("Wind Speed (km/h)")
plt.ylabel("Temperature (°C)")
plt.tight_layout()
plt.savefig("../visualizations/weather/wind_vs_temperature.png")
plt.show()
```



Correlation Heatmap

```
In [19]: numeric_df = df.select_dtypes(include="number")

plt.figure(figsize=(10, 6))
sns.heatmap(numeric_df.corr(), cmap="coolwarm", annot=True)
plt.title("Weather Attribute Correlation Heatmap")
plt.tight_layout()
plt.savefig("../visualizations/weather/correlation_heatmap.png")
plt.show()
```



STATISTICAL ANALYSIS

```
In [20]: df[['Temperature (C)', "Humidity", "Wind Speed (km/h)']].describe()
```

Out[20]:

| | Temperature (C) | Humidity | Wind Speed (km/h) |
|--------------|-----------------|--------------|-------------------|
| count | 96453.000000 | 96453.000000 | 96453.000000 |
| mean | 11.932678 | 0.734899 | 10.810640 |
| std | 9.551546 | 0.195473 | 6.913571 |
| min | -21.822222 | 0.000000 | 0.000000 |
| 25% | 4.688889 | 0.600000 | 5.828200 |
| 50% | 12.000000 | 0.780000 | 9.965900 |
| 75% | 18.838889 | 0.890000 | 14.135800 |
| max | 39.905556 | 1.000000 | 63.852600 |

Key Findings

- Temperature exhibits clear seasonal variation.
- Humidity levels are skewed towards moderate values.
- Wind speed shows weak to moderate correlation with temperature.

Climate Insights & Recommendations

Insights

- Seasonal patterns significantly influence temperature behavior.
- Certain weather conditions dominate the dataset.

Recommendations

1. Use seasonal trends for weather forecasting models.
2. Prepare infrastructure planning based on historical extremes.
3. Monitor wind and humidity interactions for climate studies.

Conclusion & Future Scope

This analysis demonstrates how historical weather data can uncover meaningful climate patterns and trends.

Future Scope

- Extreme weather detection
- Predictive climate modeling
- Regional climate comparison studies

In [20]: