In [3]:
```
import pandas as pd

# Loading the dataset
file_path = "GlobalWeatherRepository.csv"
df = pd.read_csv(file_path)
```

In [5]:
```
# Printing dataset information
print("\n Displaying basic information about the dataset:\n")
df.info()

# Printing first few rows
print("\n Displaying the first 5 rows of the dataset:\n")
print(df.head())

# Printing dataset size
print("\n The dataset contains", df.shape[0], "rows and", df.shape[1], "colu

# Printing column names
print("\n Column names in the dataset:\n", df.columns.tolist(), "\n")

# Printing data types of columns
print("\n Data types of each column:\n")
print(df.dtypes)

# Checking missing values
print("\n Checking for missing values in the dataset:\n")
print(df.isnull().sum())

# Checking for duplicate rows
print("\n Number of duplicate rows in the dataset:", df.duplicated().sum(),
```

```
 Displaying basic information about the dataset:

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 56906 entries, 0 to 56905
Data columns (total 41 columns):
 #   Column                        Non-Null Count  Dtype  
---  ------                        --------------  -----  
 0   country                       56906 non-null  object 
 1   location_name                 56906 non-null  object 
 2   latitude                      56906 non-null  float64
 3   longitude                     56906 non-null  float64
 4   timezone                      56906 non-null  object 
 5   last_updated_epoch            56906 non-null  int64  
 6   last_updated                  56906 non-null  object 
 7   temperature_celsius           56906 non-null  float64
 8   temperature_fahrenheit        56906 non-null  float64
 9   condition_text                56906 non-null  object 
 10  wind_mph                      56906 non-null  float64
 11  wind_kph                      56906 non-null  float64
 12  wind_degree                   56906 non-null  int64  
 13  wind_direction                56906 non-null  object 
 14  pressure_mb                   56906 non-null  float64
 15  pressure_in                   56906 non-null  float64
 16  precip_mm                     56906 non-null  float64
 17  precip_in                     56906 non-null  float64
 18  humidity                      56906 non-null  int64  
 19  cloud                         56906 non-null  int64  
 20  feels_like_celsius            56906 non-null  float64
 21  feels_like_fahrenheit         56906 non-null  float64
 22  visibility_km                 56906 non-null  float64
 23  visibility_miles              56906 non-null  float64
 24  uv_index                      56906 non-null  float64
 25  gust_mph                      56906 non-null  float64
 26  gust_kph                      56906 non-null  float64
 27  air_quality_Carbon_Monoxide   56906 non-null  float64
 28  air_quality_Ozone             56906 non-null  float64
 29  air_quality_Nitrogen_dioxide  56906 non-null  float64
 30  air_quality_Sulphur_dioxide   56906 non-null  float64
 31  air_quality_PM2.5             56906 non-null  float64
 32  air_quality_PM10              56906 non-null  float64
 33  air_quality_us-epa-index      56906 non-null  int64  
 34  air_quality_gb-defra-index    56906 non-null  int64  
 35  sunrise                       56906 non-null  object 
 36  sunset                        56906 non-null  object 
 37  moonrise                      56906 non-null  object 
 38  moonset                       56906 non-null  object 
 39  moon_phase                    56906 non-null  object 
 40  moon_illumination             56906 non-null  int64  
dtypes: float64(23), int64(7), object(11)
memory usage: 17.8+ MB

 Displaying the first 5 rows of the dataset:

       country     location_name  latitude  longitude        timezone  \
0  Afghanistan             Kabul     34.52      69.18      Asia/Kabul   
1      Albania            Tirana     41.33      19.82   Europe/Tirane   
```

```
2      Algeria           Algiers     36.76       3.05  Africa/Algiers
3      Andorra  Andorra La Vella     42.50       1.52  Europe/Andorra
4       Angola            Luanda     -8.84      13.23   Africa/Luanda

   last_updated_epoch      last_updated  temperature_celsius  \
0          1715849100  2024-05-16 13:15                 26.6   
1          1715849100  2024-05-16 10:45                 19.0   
2          1715849100  2024-05-16 09:45                 23.0   
3          1715849100  2024-05-16 10:45                  6.3   
4          1715849100  2024-05-16 09:45                 26.0   

   temperature_fahrenheit condition_text  ...  air_quality_PM2.5  \
0                    79.8  Partly Cloudy  ...                8.4   
1                    66.2  Partly cloudy  ...                1.1   
2                    73.4          Sunny  ...               10.4   
3                    43.3  Light drizzle  ...                0.7   
4                    78.8  Partly cloudy  ...              183.4   

   air_quality_PM10  air_quality_us-epa-index air_quality_gb-defra-index  \
0              26.6                         1                          1   
1               2.0                         1                          1   
2              18.4                         1                          1   
3               0.9                         1                          1   
4             262.3                         5                         10   

    sunrise    sunset  moonrise   moonset      moon_phase  moon_illumination  
0  04:50 AM  06:50 PM  12:12 PM  01:11 AM  Waxing Gibbous                 55  
1  05:21 AM  07:54 PM  12:58 PM  02:14 AM  Waxing Gibbous                 55  
2  05:40 AM  07:50 PM  01:15 PM  02:14 AM  Waxing Gibbous                 55  
3  06:31 AM  09:11 PM  02:12 PM  03:31 AM  Waxing Gibbous                 55  
4  06:12 AM  05:55 PM  01:17 PM  12:38 AM  Waxing Gibbous                 55  

[5 rows x 41 columns]

 The dataset contains 56906 rows and 41 columns.


 Column names in the dataset:
 ['country', 'location_name', 'latitude', 'longitude', 'timezone', 'last_upd
ated_epoch', 'last_updated', 'temperature_celsius', 'temperature_fahrenhei
t', 'condition_text', 'wind_mph', 'wind_kph', 'wind_degree', 'wind_directio
n', 'pressure_mb', 'pressure_in', 'precip_mm', 'precip_in', 'humidity', 'clo
ud', 'feels_like_celsius', 'feels_like_fahrenheit', 'visibility_km', 'visibi
lity_miles', 'uv_index', 'gust_mph', 'gust_kph', 'air_quality_Carbon_Monoxid
e', 'air_quality_Ozone', 'air_quality_Nitrogen_dioxide', 'air_quality_Sulphu
r_dioxide', 'air_quality_PM2.5', 'air_quality_PM10', 'air_quality_us-epa-ind
ex', 'air_quality_gb-defra-index', 'sunrise', 'sunset', 'moonrise', 'moonse
t', 'moon_phase', 'moon_illumination']


 Data types of each column:

country                          object
location_name                    object
latitude                        float64
longitude                       float64
```

```
timezone                         object
last_updated_epoch                int64
last_updated                     object
temperature_celsius             float64
temperature_fahrenheit          float64
condition_text                   object
wind_mph                        float64
wind_kph                        float64
wind_degree                       int64
wind_direction                   object
pressure_mb                     float64
pressure_in                     float64
precip_mm                       float64
precip_in                       float64
humidity                          int64
cloud                             int64
feels_like_celsius              float64
feels_like_fahrenheit           float64
visibility_km                   float64
visibility_miles                float64
uv_index                        float64
gust_mph                        float64
gust_kph                        float64
air_quality_Carbon_Monoxide     float64
air_quality_Ozone               float64
air_quality_Nitrogen_dioxide    float64
air_quality_Sulphur_dioxide     float64
air_quality_PM2.5               float64
air_quality_PM10                float64
air_quality_us-epa-index          int64
air_quality_gb-defra-index        int64
sunrise                          object
sunset                           object
moonrise                         object
moonset                          object
moon_phase                       object
moon_illumination                 int64
dtype: object

 Checking for missing values in the dataset:

country                         0
location_name                   0
latitude                        0
longitude                       0
timezone                        0
last_updated_epoch              0
last_updated                    0
temperature_celsius             0
temperature_fahrenheit          0
condition_text                  0
wind_mph                        0
wind_kph                        0
wind_degree                     0
wind_direction                  0
pressure_mb                     0
```

```
pressure_in                    0
precip_mm                      0
precip_in                      0
humidity                       0
cloud                          0
feels_like_celsius             0
feels_like_fahrenheit          0
visibility_km                  0
visibility_miles               0
uv_index                       0
gust_mph                       0
gust_kph                       0
air_quality_Carbon_Monoxide    0
air_quality_Ozone              0
air_quality_Nitrogen_dioxide   0
air_quality_Sulphur_dioxide    0
air_quality_PM2.5              0
air_quality_PM10               0
air_quality_us-epa-index       0
air_quality_gb-defra-index     0
sunrise                        0
sunset                         0
moonrise                       0
moonset                        0
moon_phase                     0
moon_illumination              0
dtype: int64
```

```
Number of duplicate rows in the dataset: 0
```

Analysis from the above output

The dataset consists of **56,906 rows** and **41 columns**, containing **daily weather data** for various global locations. It includes a variety of meteorological and environmental parameters:

- **Temperature, Wind Speed, Pressure, Precipitation, Humidity, and Air Quality**
- **Astronomical Data** such as **sunrise, sunset, and moon phase**

Data Structure

- The dataset is **well-structured** with appropriate **data types**:
  - **Numerical features**: Stored as float or int64
  - **Categorical attributes**: Stored as object (e.g., weather conditions, wind direction)
  - **Timestamp column (last_updated)**: Currently in object format and needs conversion for **time series analysis**
- **No missing values** or **duplicate rows**, meaning **minimal preprocessing** is required.

Data Cleaning & Preprocessing

- **Redundant Columns**: Some features are duplicated in different units:
  - **Temperature** (Celsius & Fahrenheit)
  - **Wind Speed** (mph & kph)
  - These will be **dropped** to **avoid duplication**.
- **Categorical Feature Consistency**:
  - Weather condition descriptions and **wind direction** need to be checked for **uniformity**.

In [8]:
```
df['last_updated'] = pd.to_datetime(df['last_updated'])
print("Converted 'last_updated' to datetime format.")
```

```
Converted 'last_updated' to datetime format.
```

Data Cleaning: Removing Redundant Columns

To eliminate **duplicate information** and ensure **consistency** in the dataset, we removed **redundant columns** that provided the same data in different units. The following columns were dropped:

- **Temperature**: temperature_fahrenheit (retained temperature_celsius)
- **Pressure**: pressure_in (retained pressure_mb)
- **Precipitation**: precip_in (retained precip_mm)
- **Feels Like Temperature**: feels_like_fahrenheit (retained feels_like_celsius)
- **Visibility**: visibility_miles (retained visibility_km)
- **Wind Gust**: gust_mph (retained gust_kph)

Reasons for Removing These Columns

- **Ensured uniformity** by keeping only **metric units**.
- **Reduced memory usage**, making the dataset more efficient.
- **Prevented confusion** during analysis by maintaining **a single unit system**.

This step optimizes the dataset, making it **cleaner** and **more efficient** for **exploratory data analysis (EDA) and forecasting models**.

In [11]:
```
# List of columns to drop (only the ones that exist)
columns_to_drop = ['temperature_fahrenheit', 'pressure_in', 'precip_in',
                   'feels_like_fahrenheit', 'visibility_miles', 'gust_mph']

# Drop only existing columns to avoid KeyError
df.drop(columns=columns_to_drop, inplace=True)

print(f"Dropped redundant columns: {columns_to_drop}\n")
```

```
Dropped redundant columns: ['temperature_fahrenheit', 'pressure_in', 'precip
_in', 'feels_like_fahrenheit', 'visibility_miles', 'gust_mph']
```

In [13]:
```
# Sort dataset by datetime column
df = df.sort_values(by='last_updated')
print("Sorted dataset by 'last_updated'.")
```

```
Sorted dataset by 'last_updated'.
```

In [15]:
```
# Check unique values in categorical columns
print("Unique values in 'condition_text':\n", df['condition_text'].unique())
print("Unique values in 'wind_direction':\n", df['wind_direction'].unique())
print("Unique values in 'moon_phase':\n", df['moon_phase'].unique())
```

```
Unique values in 'condition_text':
 ['Clear' 'Fog' 'Overcast' 'Moderate or heavy rain with thunder'
 'Patchy rain nearby' 'Mist' 'Partly cloudy' 'Partly Cloudy' 'Sunny'
 'Moderate or heavy rain shower' 'Light rain' 'Moderate rain'
 'Light drizzle' 'Thundery outbreaks in nearby'
 'Patchy light rain in area with thunder' 'Patchy light rain with thunder'
 'Moderate rain at times' 'Light rain shower' 'Cloudy'
 'Heavy rain at times' 'Patchy light rain' 'Patchy light drizzle'
 'Thundery outbreaks possible' 'Patchy rain possible'
 'Moderate or heavy rain in area with thunder' 'Heavy rain'
 'Torrential rain shower' 'Freezing fog' 'Moderate or heavy snow showers'
 'Light sleet' 'Blizzard' 'Moderate snow' 'Light snow'
 'Light sleet showers' 'Light freezing rain' 'Heavy snow' 'Blowing snow'
 'Patchy heavy snow' 'Light snow showers' 'Moderate or heavy sleet'
 'Patchy light snow' 'Patchy moderate snow' 'Freezing drizzle'
 'Moderate or heavy snow in area with thunder' 'Patchy snow nearby'
 'Patchy snow possible' 'Patchy light snow in area with thunder']
Unique values in 'wind_direction':
 ['SW' 'N' 'E' 'S' 'ESE' 'SSW' 'WSW' 'SE' 'ENE' 'SSE' 'NE' 'NNE' 'NNW'
 'WNW' 'W' 'NW']
Unique values in 'moon_phase':
 ['Waxing Gibbous' 'Full Moon' 'Waning Gibbous' 'Last Quarter'
 'Waning Crescent' 'New Moon' 'Waxing Crescent' 'First Quarter']
```

After Analyzing the Above Output

After reviewing the **unique values** in the categorical data, we identified minor inconsistencies in the `condition_text` (weather conditions) column. Some variations, such as **"Partly cloudy" vs. "Partly Cloudy"** and **"Patchy rain nearby" vs. "Patchy rain possible"**, indicate slight formatting differences or similar meanings. To ensure uniformity, we will **convert all weather condition values to lowercase**. The `wind_direction` column was found to be **consistent**, with all values using standardized **uppercase abbreviations** (e.g., N, NE, NW). Similarly, the `moon_phase` column had **no formatting issues**, with all values correctly structured. These steps help **maintain data integrity** and ensure **cleaner categorical data** for further analysis.

In [18]:
```
# Standardize weather condition text to lowercase
df['condition_text'] = df['condition_text'].str.lower()
print("Standardized 'condition_text' to lowercase for consistency.")
```

```
Standardized 'condition_text' to lowercase for consistency.
```

In [20]:
```
print(df['condition_text'].unique())
```

```
['clear' 'fog' 'overcast' 'moderate or heavy rain with thunder'
 'patchy rain nearby' 'mist' 'partly cloudy' 'sunny'
 'moderate or heavy rain shower' 'light rain' 'moderate rain'
 'light drizzle' 'thundery outbreaks in nearby'
 'patchy light rain in area with thunder' 'patchy light rain with thunder'
 'moderate rain at times' 'light rain shower' 'cloudy'
 'heavy rain at times' 'patchy light rain' 'patchy light drizzle'
 'thundery outbreaks possible' 'patchy rain possible'
 'moderate or heavy rain in area with thunder' 'heavy rain'
 'torrential rain shower' 'freezing fog' 'moderate or heavy snow showers'
 'light sleet' 'blizzard' 'moderate snow' 'light snow'
 'light sleet showers' 'light freezing rain' 'heavy snow' 'blowing snow'
 'patchy heavy snow' 'light snow showers' 'moderate or heavy sleet'
 'patchy light snow' 'patchy moderate snow' 'freezing drizzle'
 'moderate or heavy snow in area with thunder' 'patchy snow nearby'
 'patchy snow possible' 'patchy light snow in area with thunder']
```

Explanation of Data Cleaning & Preprocessing

We performed several **data cleaning steps** to prepare the dataset for analysis:

- **Converted** last_updated to **datetime** to enable **time-series analysis**.
- **Dropped redundant columns** that had duplicate information (e.g., **temperature in both Celsius & Fahrenheit**).
- **Sorted the dataset** by last_updated to ensure **chronological order**.
- **Standardized** condition_text to **lowercase** to eliminate **inconsistencies** in weather condition labels.

These steps ensure that the dataset is **clean, consistent, and optimized for analysis**. Now, we are ready to move to the **Exploratory Data Analysis (EDA) phase**!

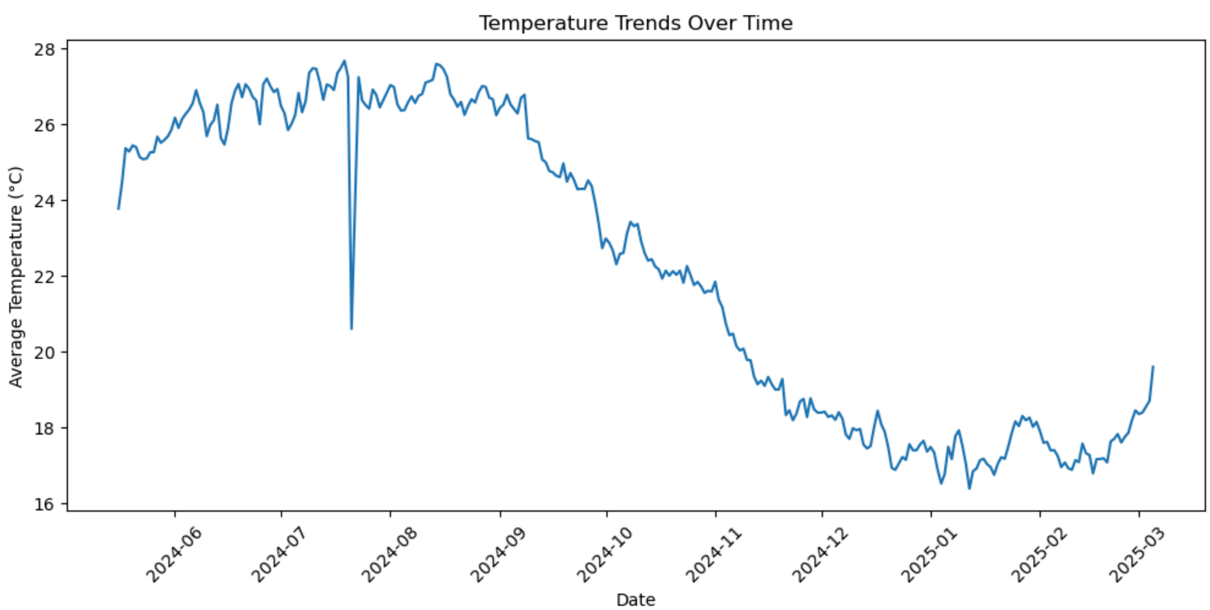
EDA

In [24]:
```
print(df.describe())
```

```
           latitude     longitude  last_updated_epoch  \
count  56906.000000  56906.000000        5.690600e+04   
mean      19.136988     22.187380        1.728530e+09   
min      -41.300000   -175.200000        1.715849e+09   
25%        3.750000     -6.836100        1.722255e+09   
50%       17.250000     23.320000        1.728554e+09   
75%       40.400000     50.580000        1.734862e+09   
max       64.150000    179.220000        1.741169e+09   
std       24.477303     65.808904        7.355847e+06   

                        last_updated  temperature_celsius      wind_mph  \
count                          56906         56906.000000  56906.000000   
mean   2024-10-10 05:31:21.892946176            22.278399      8.289013   
min              2024-05-16 01:45:00           -24.900000      2.200000   
25%              2024-07-29 15:15:00            17.100000      4.000000   
50%              2024-10-10 12:45:00            25.100000      6.900000   
75%              2024-12-22 15:45:00            28.500000     11.600000   
max              2025-03-05 23:00:00            49.200000   1841.200000   
std                              NaN             9.647370      9.398604   

           wind_kph   wind_degree   pressure_mb     precip_mm  ...  \
count  56906.000000  56906.000000  56906.000000  56906.000000  ...   
mean      13.343804    169.668857   1014.164341      0.140864  ...   
min        3.600000      1.000000    947.000000      0.000000  ...   
25%        6.500000     80.000000   1010.000000      0.000000  ...   
50%       11.200000    160.000000   1013.000000      0.000000  ...   
75%       18.700000    258.000000   1018.000000      0.030000  ...   
max     2963.200000    360.000000   3006.000000     42.240000  ...   
std       15.123937    103.767926     13.831804      0.605114  ...   

           gust_kph  air_quality_Carbon_Monoxide  air_quality_Ozone  \
count  56906.000000                  56906.00000       56906.000000   
mean      19.176788                    525.75107          63.465594   
min        3.600000                  -9999.00000           0.000000   
25%       10.800000                    223.60000          38.600000   
50%       16.600000                    323.75000          60.100000   
75%       25.600000                    500.70000          83.000000   
max     2970.400000                  38879.39800         480.700000   
std       16.949292                    954.16238          36.638077   

       air_quality_Nitrogen_dioxide  air_quality_Sulphur_dioxide  \
count                  56906.000000                 56906.000000   
mean                      14.831329                    11.301580   
min                        0.000000                 -9999.000000   
25%                        0.925000                     0.740000   
50%                        3.300000                     2.220000   
75%                       15.910000                     8.695000   
max                      427.700000                   521.330000   
std                       26.244844                    49.628464   

       air_quality_PM2.5  air_quality_PM10  air_quality_us-epa-index  \
count       56906.000000      56906.000000              56906.000000   
mean           25.130634         50.476481                  1.711015   
min             0.185000      -1848.150000                  1.000000   
25%             5.400000          8.510000                  1.000000   
50%            13.320000         20.300000                  1.000000   
```

```
75%            29.045000        44.770000                    2.000000
max          1614.100000      6037.290000                    6.000000
std            45.108696       157.568661                    0.988064

       air_quality_gb-defra-index  moon_illumination
count                56906.000000       56906.000000
mean                     2.667996          48.487717
min                      1.000000           0.000000
25%                      1.000000          13.000000
50%                      2.000000          48.000000
75%                      3.000000          83.000000
max                     10.000000         100.000000
std                      2.575774          35.021010

[8 rows x 25 columns]
```

In [26]:
```python
import matplotlib.pyplot as plt

# Plot temperature trends
plt.figure(figsize=(12, 5))
df.groupby(df['last_updated'].dt.date)['temperature_celsius'].mean().plot()
plt.xlabel("Date")
plt.ylabel("Average Temperature (°C)")
plt.title("Temperature Trends Over Time")
plt.xticks(rotation=45)
plt.show()
```



Analysis of the Temperature Trend Plot

The temperature trend over time exhibits **seasonal variations** with a **clear decline followed by an upward movement**. Initially, **temperature is high around mid-2024**, reaching a **peak** before **gradually decreasing** towards early 2025. By **March 2025**, the temperature **rises again**, suggesting a **seasonal cycle**.

A **notable anomaly** is observed around **July-August 2024**, where there is a **sharp drop in temperature**. This sudden decrease could be due to **data errors** or an **extreme weather event**. Overall, there is a **general downward trend from mid-2024 to early 2025**, likely reflecting the **transition from summer to winter** in various global locations.

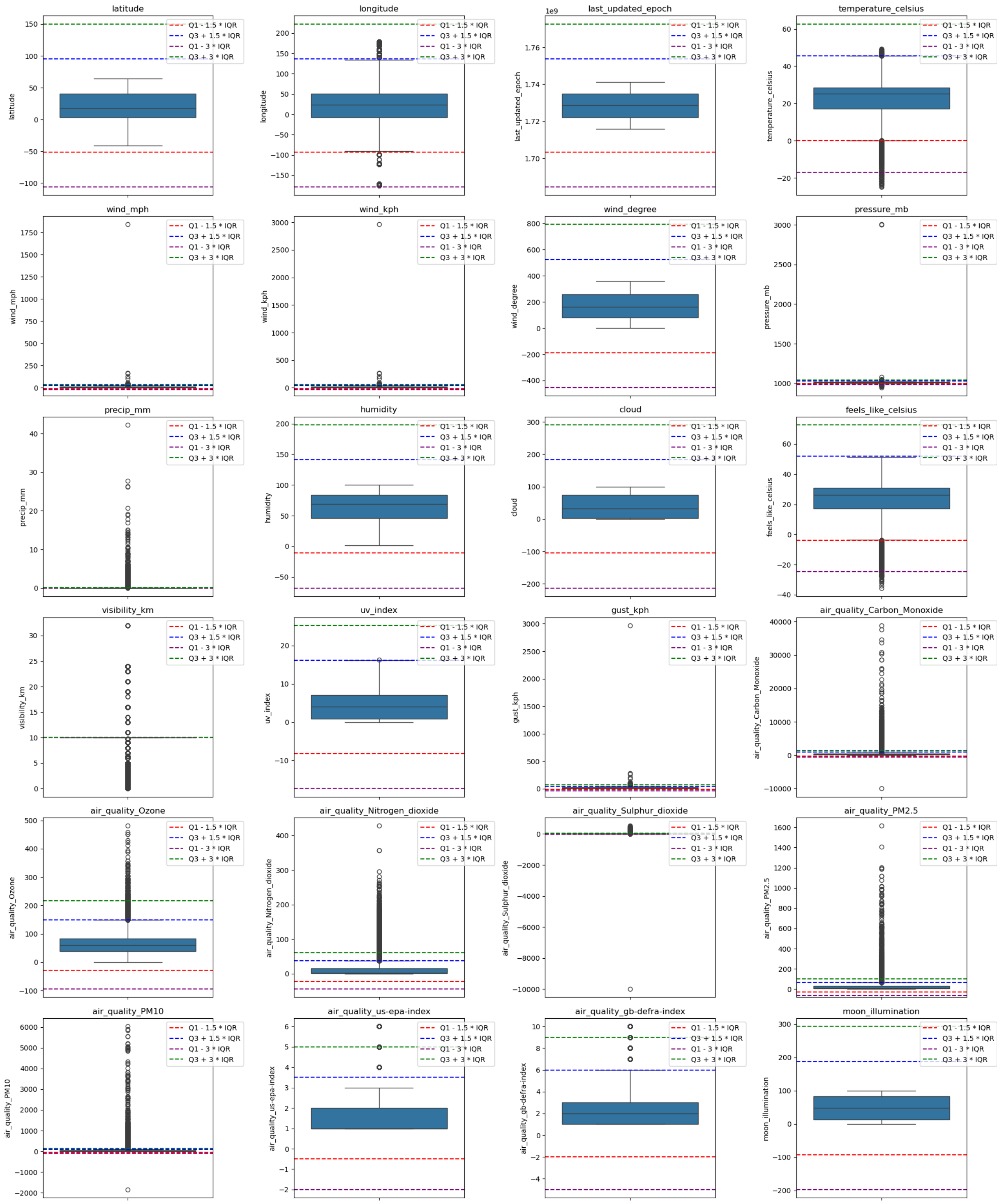
Next Steps: Detecting and Handling Anomalies

Since we have noticed a **sudden drop in temperature**, it is important to **detect and investigate anomalies before making forecasts**.

- **Identify Sudden Drops in Temperature**: We will analyze **outliers in temperature data** using **Z-score analysis** to detect and handle anomalies effectively.

In [29]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# Select numeric columns
numeric_columns = df.select_dtypes(include=['number']).columns

# Dictionary to store outliers and extreme outliers
outliers = {}
extreme_outliers = {}

# Masks to mark outliers and extreme outliers in the dataset
outliers_mask = pd.Series(False, index=df.index)
extreme_outliers_mask = pd.Series(False, index=df.index)

# Set up the matplotlib figure
num_cols = 4  # Number of columns in the grid layout
num_rows = (len(numeric_columns) + num_cols - 1) // num_cols  # Calculate ro

plt.figure(figsize=(20, num_rows * 4))

# Iterate through each numeric column and detect outliers
for i, column in enumerate(numeric_columns):
    plt.subplot(num_rows, num_cols, i + 1)

    # Create a boxplot (Fix: Remove `x=""` and just use y=df[column])
    sns.boxplot(y=df[column])

    # Compute IQR
    Q1 = df[column].quantile(0.25)
    Q3 = df[column].quantile(0.75)
    IQR = Q3 - Q1

    # Define outlier bounds
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    extreme_lower_bound = Q1 - 3 * IQR
    extreme_upper_bound = Q3 + 3 * IQR
```

```
    # Identify outliers and extreme outliers
    outliers[column] = (df[column] < lower_bound) | (df[column] > upper_bour
    extreme_outliers[column] = (df[column] < extreme_lower_bound) | (df[colu

    # Update mask for dataset-wide outlier tracking
    outliers_mask |= (df[column] < lower_bound) | (df[column] > upper_bound)
    extreme_outliers_mask |= (df[column] < extreme_lower_bound) | (df[column

    # Add reference lines for outlier detection
    plt.axhline(y=lower_bound, color='red', linestyle='--', label='Q1 - 1.5 
    plt.axhline(y=upper_bound, color='blue', linestyle='--', label='Q3 + 1.5
    plt.axhline(y=extreme_lower_bound, color='purple', linestyle='--', label
    plt.axhline(y=extreme_upper_bound, color='green', linestyle='--', label=

    plt.title(column)
    plt.xlabel('')

    # Add the legend outside the boxplot area
    plt.legend(loc='upper right', bbox_to_anchor=(1.2, 1))

plt.tight_layout()
plt.show()

# Add outlier flags to the dataframe
df['outliers'] = outliers_mask
df['extreme_outliers'] = extreme_outliers_mask

# Display the rows identified as extreme outliers
outlier_rows = df[df['extreme_outliers']]
print("\n Extreme Outliers Detected:\n", outlier_rows[['last_updated', 'temp

# Show outliers in a table format
from IPython.display import display
display(outlier_rows[['last_updated', 'temperature_celsius', 'humidity', 'wi
```


latitude
longitude
last_updated_epoch
temperature_celsius
wind_mph
wind_kph
wind_degree
pressure_mb
precip_mm
humidity
cloud
feels_like_celsius
visibility_km
uv_index
gust_kph
air_quality_Carbon_Monoxide
air_quality_Ozone
air_quality_Nitrogen_dioxide
air_quality_Sulphur_dioxide
air_quality_PM2.5
air_quality_PM10
air_quality_us-epa-index
air_quality_gb-defra-index
moon_illumination
Q1 - 1.5 * IQR
Q3 + 1.5 * IQR
Q1 - 3 * IQR
Q3 + 3 * IQR

```
 Extreme Outliers Detected:
              last_updated  temperature_celsius
186   2024-05-16 01:45:00                 16.1
40    2024-05-16 02:45:00                 21.0
52    2024-05-16 02:45:00                 26.0
68    2024-05-16 02:45:00                 20.0
74    2024-05-16 02:45:00                 23.0
...                   ...                  ...
56846 2025-03-05 19:45:00                 26.4
56822 2025-03-05 20:45:00                 29.2
56870 2025-03-05 21:00:00                 27.3
56892 2025-03-05 22:00:00                 28.1
56834 2025-03-05 22:45:00                 14.0

[23450 rows x 2 columns]
```

	last_updated	temperature_celsius	humidity	wind_kph
186	2024-05-16 01:45:00	16.1	58	6.8
40	2024-05-16 02:45:00	21.0	100	3.6
52	2024-05-16 02:45:00	26.0	94	3.6
68	2024-05-16 02:45:00	20.0	88	22.0
74	2024-05-16 02:45:00	23.0	78	6.1
...	...	...	...	...
56846	2025-03-05 19:45:00	26.4	89	8.3
56822	2025-03-05 20:45:00	29.2	75	33.8
56870	2025-03-05 21:00:00	27.3	89	3.6
56892	2025-03-05 22:00:00	28.1	84	13.0
56834	2025-03-05 22:45:00	14.0	55	33.5

23450 rows × 4 columns

Now that we have identified **extreme outliers and anomalies**, the next step is to **clean the dataset** while ensuring that valuable information is **not lost**.

We begin by **removing physically impossible values**, such as **wind speeds greater than 400 kph**, since even the strongest hurricanes rarely exceed this speed. Additionally, we eliminate **negative air quality values**, which are not possible in real-world conditions, and **extreme pressure values (~3000 mb)**, as normal atmospheric pressure ranges between **900 - 1100 mb**.

Next, we **cap extreme outliers** using **Winsorization**, where the **top 1% values in precipitation, air quality, and visibility** are replaced with the **99th percentile values** to reduce the impact of extreme spikes.

For **temperature outliers**, we determine their validity. If they represent **real events** like **heatwaves or cold waves**, they are **retained**. However, if they are caused by **sensor errors**, we apply **rolling median smoothing** to correct them.

Finally, we **handle missing values** that may arise after removing extreme outliers. We fill these gaps using **linear interpolation** or **median imputation**, ensuring that the dataset remains **consistent and complete** for further analysis.

In [31]:
```
import numpy as np

# Remove Physically Impossible Values
df_cleaned = df.copy()

# Remove wind speeds above 400 kph
df_cleaned = df_cleaned[df_cleaned['wind_kph'] <= 400]

# Remove negative air quality values (invalid)
air_quality_cols = ['air_quality_Carbon_Monoxide', 'air_quality_Ozone',
                    'air_quality_Nitrogen_dioxide', 'air_quality_Sulphur_dic
                    'air_quality_PM2.5', 'air_quality_PM10']

for col in air_quality_cols:
    df_cleaned = df_cleaned[df_cleaned[col] >= 0]

# Remove extreme pressure values (> 1100 mb or < 900 mb)
df_cleaned = df_cleaned[(df_cleaned['pressure_mb'] >= 900) & (df_cleaned['pr


# Cap Extreme Outliers (Winsorization)
def winsorize(column):
    lower_bound = df_cleaned[column].quantile(0.01)  # Bottom 1%
    upper_bound = df_cleaned[column].quantile(0.99)  # Top 1%
    df_cleaned[column] = np.where(df_cleaned[column] > upper_bound, upper_bc
    df_cleaned[column] = np.where(df_cleaned[column] < lower_bound, lower_bc

# Apply Winsorization to precipitation, air quality, and visibility
columns_to_winsorize = ['precip_mm', 'visibility_km'] + air_quality_cols
for col in columns_to_winsorize:
    winsorize(col)


# Smooth Temperature Data (Rolling Median Smoothing)
df_cleaned['temperature_celsius'] = df_cleaned['temperature_celsius'].rollir


# Handle Missing Values (Fixed Warning)
df_cleaned = df_cleaned.bfill()  # Fill missing values using backward fill


# Display Summary of Cleaning
print("\n Data Cleaning Completed!")
print(f"Original dataset size: {df.shape[0]} rows")
print(f"Cleaned dataset size: {df_cleaned.shape[0]} rows")
print(f"Number of rows removed: {df.shape[0] - df_cleaned.shape[0]}")
```

```
# Show the first few rows of the cleaned dataset
df_cleaned.head()
```

```
 Data Cleaning Completed!
Original dataset size: 56906 rows
Cleaned dataset size: 56900 rows
Number of rows removed: 6
```

Out[31]:

	country	location_name	latitude	longitude	timezone	last_updated_
186	United States of America	Washington Park	46.60	-120.49	America/Los_Angeles	17158
40	Costa Rica	San Juan	9.97	-84.08	America/Costa_Rica	17158
17	Belize	Belmopan	17.25	-88.77	America/Belize	17158
52	El Salvador	San Salvador	13.71	-89.20	America/El_Salvador	17158
124	Nicaragua	Managua	12.15	-86.27	America/Managua	17158

5 rows × 37 columns

The below section performs an initial analysis of the dataset to understand key patterns and distributions.

1. Summary Statistics : We display the summary statistics of numerical columns in the dataset to understand the range, mean, and variability of key weather parameters.

2. Temperature Trends Over Time: A line plot visualizes how temperature varies over time, helping to identify seasonal patterns or anomalies.

3. Precipitation Trends Over Time: A line plot is used to analyze the trend of precipitation, showcasing fluctuations in rainfall over time.

4. Wind Speed & Pressure Analysis: We use histograms to visualize the distributions of wind speed and atmospheric pressure, providing insights into the typical ranges and variability of these weather factors.

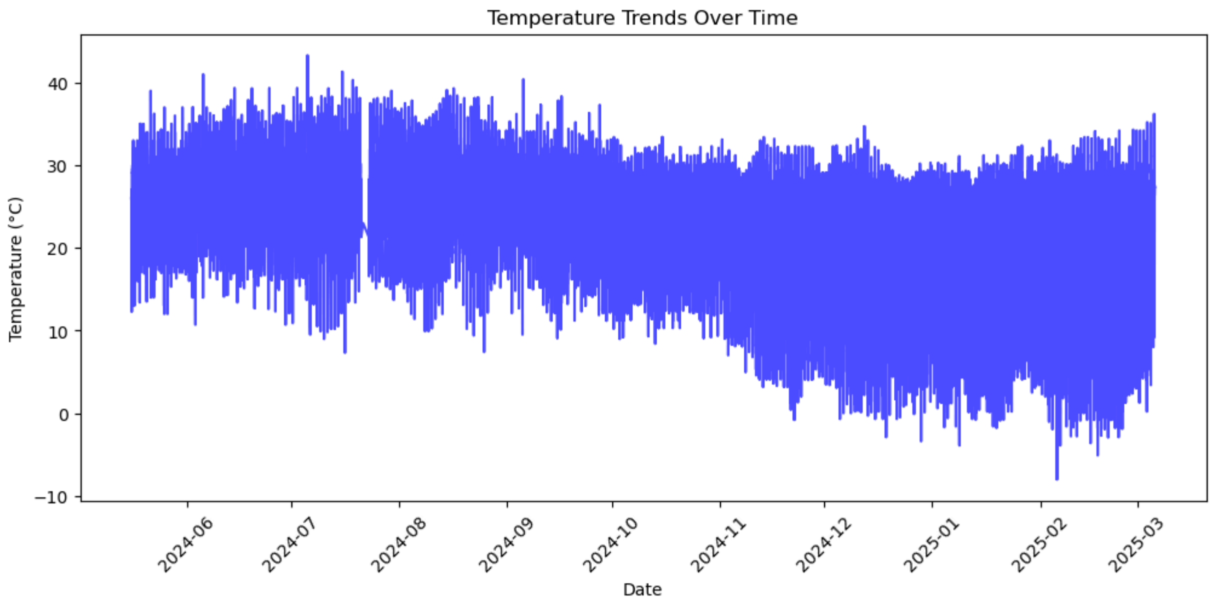
In [32]:

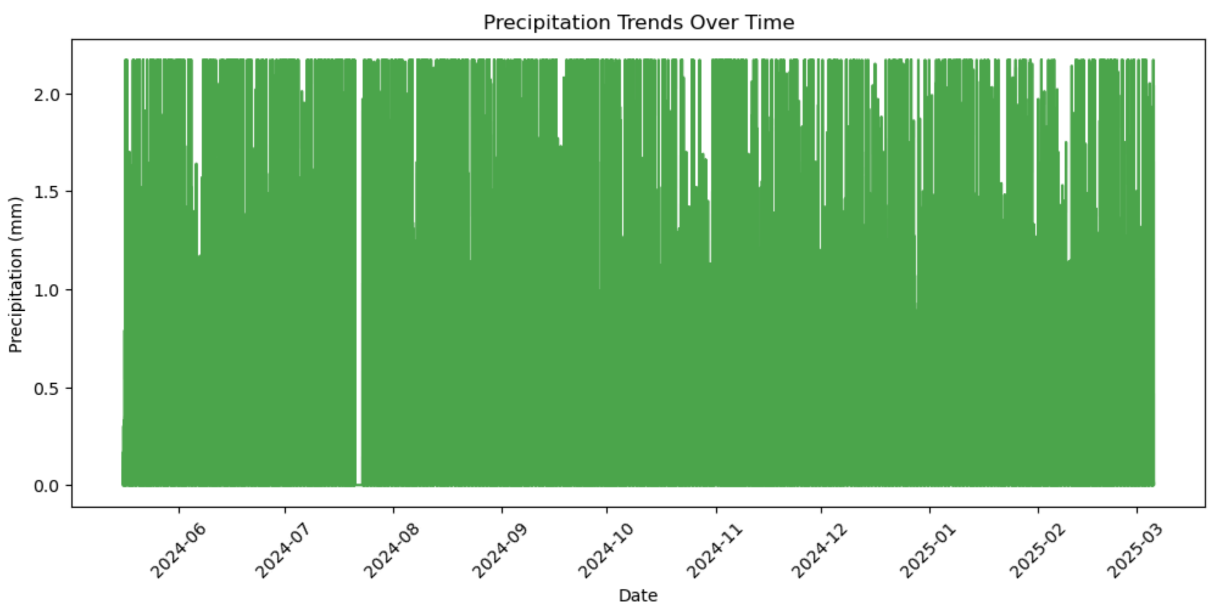
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# Summary Statistics
print("\n Summary Statistics of Numerical Columns:")
print(df_cleaned.describe())
```

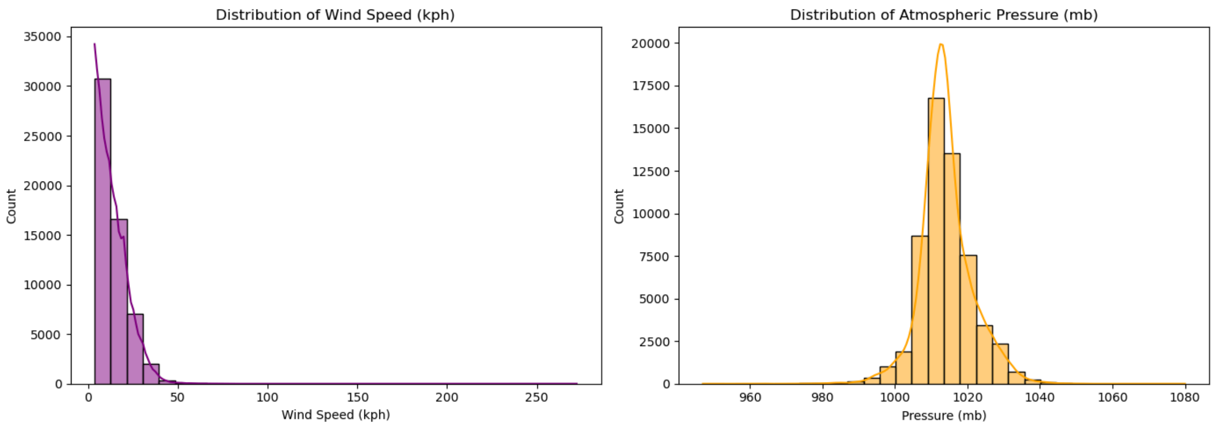
```
# Temperature Trends Over Time
plt.figure(figsize=(12, 5))
plt.plot(df_cleaned['last_updated'], df_cleaned['temperature_celsius'], colo
plt.xlabel("Date")
plt.ylabel("Temperature (°C)")
plt.title("Temperature Trends Over Time")
plt.xticks(rotation=45)
plt.show()

# Precipitation Trends Over Time
plt.figure(figsize=(12, 5))
plt.plot(df_cleaned['last_updated'], df_cleaned['precip_mm'], color='green',
plt.xlabel("Date")
plt.ylabel("Precipitation (mm)")
plt.title("Precipitation Trends Over Time")
plt.xticks(rotation=45)
plt.show()

# Wind Speed & Pressure Analysis
fig, axes = plt.subplots(1, 2, figsize=(14, 5))

sns.histplot(df_cleaned['wind_kph'], bins=30, kde=True, ax=axes[0], color='p
axes[0].set_title("Distribution of Wind Speed (kph)")
axes[0].set_xlabel("Wind Speed (kph)")

sns.histplot(df_cleaned['pressure_mb'], bins=30, kde=True, ax=axes[1], color
axes[1].set_title("Distribution of Atmospheric Pressure (mb)")
axes[1].set_xlabel("Pressure (mb)")

plt.tight_layout()
plt.show()
```

```
 Summary Statistics of Numerical Columns:
          latitude     longitude  last_updated_epoch  \
count  56900.000000  56900.000000        5.690000e+04   
mean      19.137471     22.187119        1.728530e+09   
min      -41.300000   -175.200000        1.715849e+09   
25%        3.750000     -6.836100        1.722255e+09   
50%       17.250000     23.320000        1.728554e+09   
75%       40.400000     50.580000        1.734862e+09   
max       64.150000    179.220000        1.741169e+09   
std       24.478147     65.806733        7.355522e+06   

                        last_updated  temperature_celsius      wind_mph  \
count                          56900         56898.000000  56900.000000   
mean   2024-10-10 05:29:56.773286656            23.022767      8.256696   
min              2024-05-16 01:45:00            -8.000000      2.200000   
25%              2024-07-29 15:15:00            20.000000      4.000000   
50%              2024-10-10 12:45:00            25.100000      6.900000   
75%              2024-12-22 15:45:00            27.900000     11.600000   
max              2025-03-05 23:00:00            43.300000    169.100000   
std                              NaN             7.163132      5.412643   

           wind_kph   wind_degree   pressure_mb     precip_mm  ...  \
count  56900.000000  56900.000000  56900.000000  56900.000000  ...   
mean      13.291793    169.674956   1014.094271      0.121339  ...   
min        3.600000      1.000000    947.000000      0.000000  ...   
25%        6.500000     80.000000   1010.000000      0.000000  ...   
50%       11.200000    160.000000   1013.000000      0.000000  ...   
75%       18.700000    258.000000   1018.000000      0.030000  ...   
max      272.200000    360.000000   1080.000000      2.170000  ...   
std        8.707511    103.767779      7.231554      0.353736  ...   

           gust_kph  air_quality_Carbon_Monoxide  air_quality_Ozone  \
count  56900.000000                 56900.000000       56900.000000   
mean      19.124555                   489.881975          63.041956   
min        3.600000                   150.200000           0.100000   
25%       10.800000                   223.600000          38.600000   
50%       16.600000                   323.750000          60.100000   
75%       25.600000                   500.700000          83.000000   
max      279.400000                  4031.390500         173.100000   
std       11.585478                   562.254003          34.750306   

       air_quality_Nitrogen_dioxide  air_quality_Sulphur_dioxide  \
count                  56900.000000                 56900.000000   
mean                      14.504429                    10.925827   
min                        0.000000                     0.000000   
25%                        0.925000                     0.740000   
50%                        3.300000                     2.220000   
75%                       15.910000                     8.695000   
max                      122.000000                   131.905000   
std                       24.409946                    22.406544   

       air_quality_PM2.5  air_quality_PM10  air_quality_us-epa-index  \
count       56900.000000      56900.000000              56900.000000   
mean           23.604662         44.490361                  1.710967   
min             0.500000          0.700000                  1.000000   
25%             5.400000          8.510000                  1.000000   
```

```
50%          13.320000         20.300000                    1.000000
75%          29.045000         44.770000                    2.000000
max         179.265000        523.735000                    6.000000
std          30.208668         76.382815                    0.987919

       air_quality_gb-defra-index  moon_illumination
count                56900.000000       56900.000000
mean                     2.667926          48.487750
min                      1.000000           0.000000
25%                      1.000000          13.000000
50%                      2.000000          48.000000
75%                      3.000000          83.000000
max                     10.000000         100.000000
std                      2.575650          35.020729

[8 rows x 25 columns]
```







Model Implementation

In [52]:

```
import pandas as pd
import numpy as np

# Ensure the date column is in datetime format
df_cleaned['last_updated'] = pd.to_datetime(df_cleaned['last_updated'])

# Sort by date
df_cleaned = df_cleaned.sort_values(by='last_updated')

# Selecting the columns required for forecasting
df_forecast = df_cleaned[['last_updated', 'temperature_celsius']].rename(col

# Display the first few rows
print(df_forecast.head())
```

```
                     ds     y
186 2024-05-16 01:45:00  26.0
40  2024-05-16 02:45:00  26.0
17  2024-05-16 02:45:00  26.0
52  2024-05-16 02:45:00  26.0
124 2024-05-16 02:45:00  26.0
```

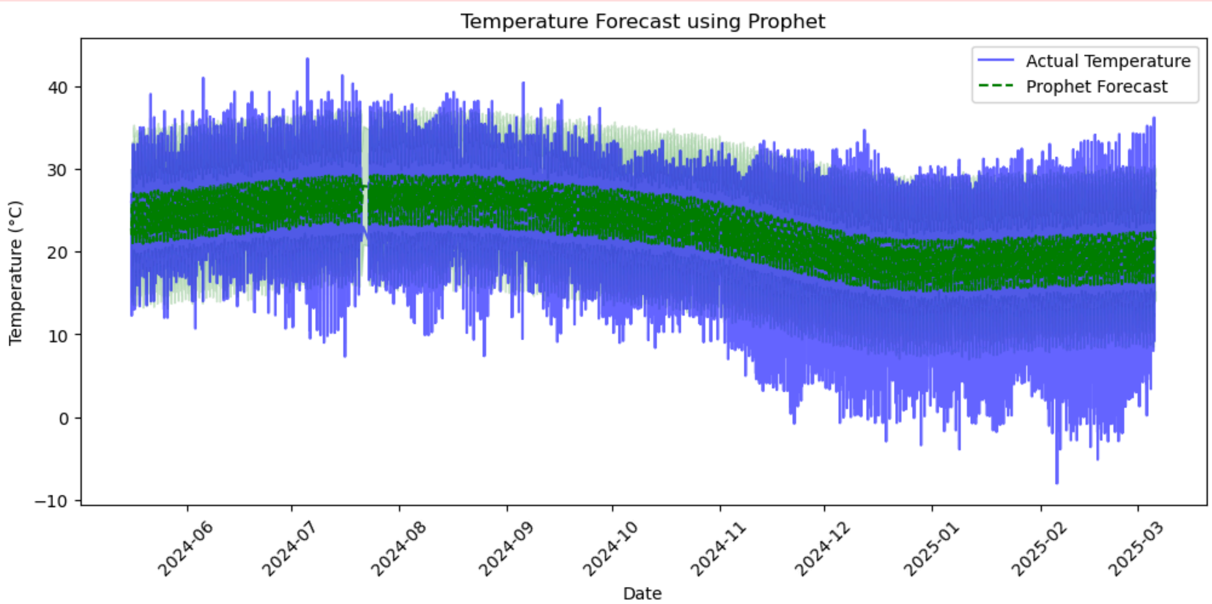
Prophet

In [54]:

```
from prophet import Prophet
import pandas as pd
import matplotlib.pyplot as plt


# Prepare data for Prophet
df_prophet = df_forecast[['ds', 'y']].copy()
df_prophet.columns = ['ds', 'y']

# Initialize and fit the Prophet model
model = Prophet()
model.fit(df_prophet)

# Create future dataframe (predict next 30 days)
```

```
future = model.make_future_dataframe(periods=30, freq='D')

# Make predictions
forecast = model.predict(future)

# Drop duplicate columns before merging to avoid conflicts
df_forecast = df_forecast.drop(columns=['yhat', 'yhat_lower', 'yhat_upper'],

# Merge forecasted values
df_forecast = df_forecast.merge(forecast[['ds', 'yhat', 'yhat_lower', 'yhat_

# Plot Prophet Forecast
plt.figure(figsize=(12, 5))
plt.plot(df_forecast['ds'], df_forecast['y'], label="Actual Temperature", co
plt.plot(df_forecast['ds'], df_forecast['yhat'], label="Prophet Forecast", c

# Plot uncertainty intervals
plt.fill_between(df_forecast['ds'], df_forecast['yhat_lower'], df_forecast['

plt.legend()
plt.title("Temperature Forecast using Prophet")
plt.xlabel("Date")
plt.ylabel("Temperature (°C)")
plt.xticks(rotation=45)
plt.show()
```

```
10:15:43 - cmdstanpy - INFO - Chain [1] start processing
10:15:46 - cmdstanpy - INFO - Chain [1] done processing
```



LSTM

In [56]:

```
import numpy as np
import pandas as pd
import tensorflow as tf
from tensorflow import keras
from sklearn.preprocessing import MinMaxScaler
import matplotlib.pyplot as plt
```

```
# Ensure correct sorting and handling of missing values
df_forecast['ds'] = pd.to_datetime(df_forecast['ds'])
df_forecast = df_forecast.sort_values(by='ds')
df_forecast = df_forecast.bfill().ffill()  # Backward then forward fill

# Normalize the temperature values
scaler = MinMaxScaler(feature_range=(0, 1))
df_forecast['y'] = scaler.fit_transform(df_forecast[['y']])

# Function to create sequences for LSTM
def create_sequences(data, seq_length):
    sequences = []
    labels = []
    for i in range(len(data) - seq_length):
        sequences.append(data[i:i+seq_length])
        labels.append(data[i+seq_length])
    return np.array(sequences), np.array(labels)

seq_length = 14  # Increased sequence length for better trend capture
X, y = create_sequences(df_forecast['y'].values, seq_length)

# Reshape input for LSTM
X = X.reshape((X.shape[0], X.shape[1], 1))

# Define an improved LSTM model
model = keras.Sequential([
    keras.layers.Input(shape=(seq_length, 1)),
    keras.layers.Bidirectional(keras.layers.LSTM(64, return_sequences=True,
    keras.layers.Dropout(0.3),
    keras.layers.Bidirectional(keras.layers.LSTM(64, activation='relu')),
    keras.layers.Dense(1)
])

# Compile with a lower learning rate for better stability
model.compile(optimizer=keras.optimizers.Adam(learning_rate=0.0005), loss='m

# Train the model for more epochs
model.fit(X, y, epochs=20, batch_size=32, verbose=1)

# Predict future temperatures
future_steps = 30
predictions = []
last_seq = X[-1]

for _ in range(future_steps):
    next_pred = model.predict(last_seq.reshape(1, seq_length, 1))
    predictions.append(next_pred[0, 0])

    last_seq = np.roll(last_seq, -1)
    last_seq[-1] = next_pred

# Convert predictions back to actual temperature values
predictions = scaler.inverse_transform(np.array(predictions).reshape(-1, 1))

# Generate future dates for plotting
```

```
future_dates = pd.date_range(df_forecast['ds'].iloc[-1], periods=future_step

# Plot the improved LSTM Forecast
plt.figure(figsize=(12, 5))
plt.plot(df_forecast['ds'], scaler.inverse_transform(df_forecast[['y']]), la
plt.plot(future_dates, predictions, label="LSTM Forecast (Improved)", color=
plt.legend()
plt.title("Improved Temperature Forecast using LSTM")
plt.xlabel("Date")
plt.ylabel("Temperature (°C)")
plt.show()
```

```
Epoch 1/20
1778/1778 ━━━━━━━━━━━━━━━━━━━━ 15s 8ms/step - loss: 0.0223
Epoch 2/20
1778/1778 ━━━━━━━━━━━━━━━━━━━━ 15s 8ms/step - loss: 0.0088
Epoch 3/20
1778/1778 ━━━━━━━━━━━━━━━━━━━━ 15s 8ms/step - loss: 0.0086
Epoch 4/20
1778/1778 ━━━━━━━━━━━━━━━━━━━━ 15s 8ms/step - loss: 0.0087
Epoch 5/20
1778/1778 ━━━━━━━━━━━━━━━━━━━━ 14s 8ms/step - loss: 0.0085
Epoch 6/20
1778/1778 ━━━━━━━━━━━━━━━━━━━━ 15s 8ms/step - loss: 0.0084
Epoch 7/20
1778/1778 ━━━━━━━━━━━━━━━━━━━━ 15s 8ms/step - loss: 0.0085
Epoch 8/20
1778/1778 ━━━━━━━━━━━━━━━━━━━━ 15s 8ms/step - loss: 0.0084
Epoch 9/20
1778/1778 ━━━━━━━━━━━━━━━━━━━━ 15s 8ms/step - loss: 0.0085
Epoch 10/20
1778/1778 ━━━━━━━━━━━━━━━━━━━━ 15s 8ms/step - loss: 0.0084
Epoch 11/20
1778/1778 ━━━━━━━━━━━━━━━━━━━━ 15s 8ms/step - loss: 0.0084
Epoch 12/20
1778/1778 ━━━━━━━━━━━━━━━━━━━━ 15s 8ms/step - loss: 0.0085
Epoch 13/20
1778/1778 ━━━━━━━━━━━━━━━━━━━━ 15s 8ms/step - loss: 0.0083
Epoch 14/20
1778/1778 ━━━━━━━━━━━━━━━━━━━━ 15s 8ms/step - loss: 0.0083
Epoch 15/20
1778/1778 ━━━━━━━━━━━━━━━━━━━━ 15s 9ms/step - loss: 0.0084
Epoch 16/20
1778/1778 ━━━━━━━━━━━━━━━━━━━━ 15s 9ms/step - loss: 0.0083
Epoch 17/20
1778/1778 ━━━━━━━━━━━━━━━━━━━━ 16s 9ms/step - loss: 0.0083
Epoch 18/20
1778/1778 ━━━━━━━━━━━━━━━━━━━━ 16s 9ms/step - loss: 0.0081
Epoch 19/20
1778/1778 ━━━━━━━━━━━━━━━━━━━━ 16s 9ms/step - loss: 0.0083
Epoch 20/20
1778/1778 ━━━━━━━━━━━━━━━━━━━━ 16s 9ms/step - loss: 0.0083
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 10ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step
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```
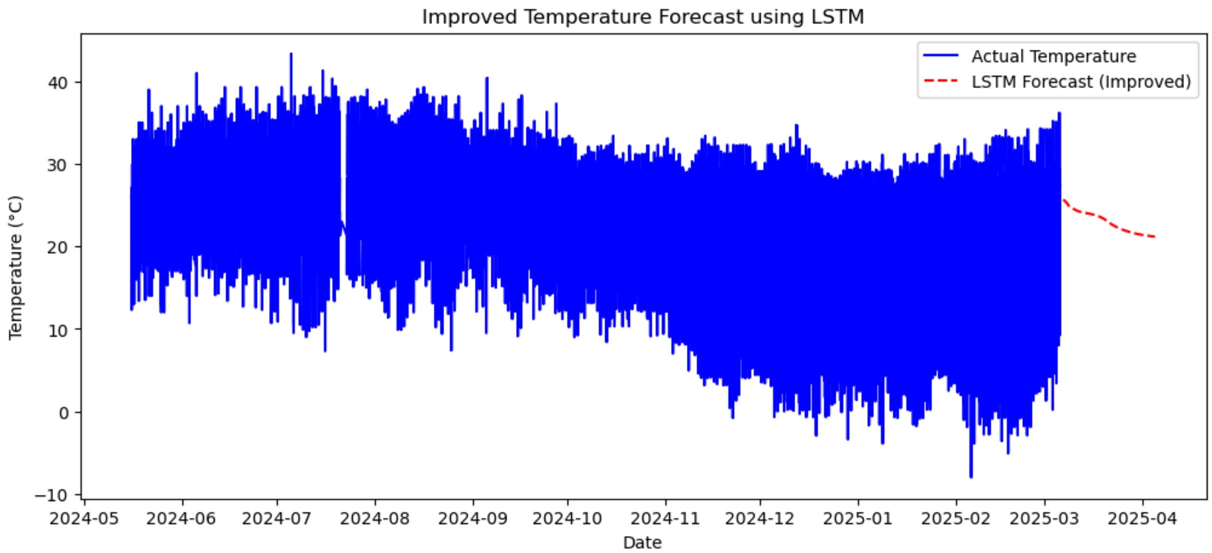



Model Performance Evaluation

In [58]:

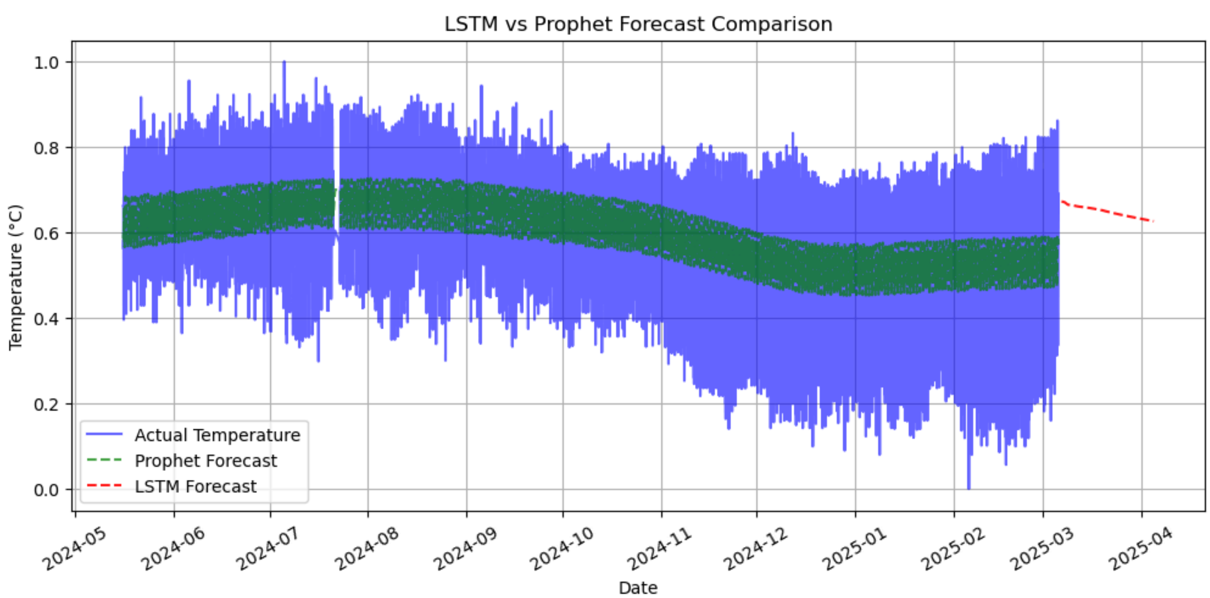
```
from sklearn.metrics import mean_absolute_error, mean_squared_error

# Load actual vs predicted values (ensure inverse scaling is done)
actual_temps = scaler.inverse_transform(df_forecast[['y']].values)
predicted_temps = predictions.flatten()  # LSTM forecasted values

# Compute errors
mae = mean_absolute_error(actual_temps[-len(predicted_temps):], predicted_te
mse = mean_squared_error(actual_temps[-len(predicted_temps):], predicted_tem
rmse = np.sqrt(mse)

print(f"Mean Absolute Error (MAE): {mae:.3f}")
print(f"Mean Squared Error (MSE): {mse:.3f}")
print(f"Root Mean Squared Error (RMSE): {rmse:.3f}")
```

```
Mean Absolute Error (MAE): 6.652
Mean Squared Error (MSE): 54.497
Root Mean Squared Error (RMSE): 7.382
```

In [242…

```
import matplotlib.pyplot as plt
```

```
plt.figure(figsize=(12, 5))

# Actual Temperature
plt.plot(df_forecast['ds'], scaler.inverse_transform(df_forecast[['y']]), la

# Prophet Forecast
plt.plot(df_forecast['ds'], df_forecast['yhat'], label="Prophet Forecast", c

# Ensure LSTM Forecast is aligned correctly
future_dates = pd.date_range(start=df_forecast['ds'].iloc[-1], periods=len(p

# Plot LSTM Forecast
plt.plot(future_dates, predictions, label="LSTM Forecast", color='red', line

# Formatting
plt.legend()
plt.title("LSTM vs Prophet Forecast Comparison")
plt.xlabel("Date")
plt.ylabel("Temperature (°C)")
plt.xticks(rotation=30)
plt.grid(True)

plt.show()
```



Analysis from the LSTM vs Prophet Forecast Comparison

The **comparison plot** between the **LSTM and Prophet models** provides insights into their forecasting capabilities. The **actual temperature trend (blue)** shows **significant fluctuations**, indicating **seasonal variations and potential anomalies** in the dataset.

The **Prophet model (green)** effectively captures the **overall trend** and provides **uncertainty intervals (shaded region)**, making its predictions more interpretable. It also reflects the **seasonality component well**, but it **smooths out fluctuations**, making it **less responsive to sudden temperature changes**.

On the other hand, the **LSTM forecast (red - dashed)** is only extended into the **future** and is **not trained on past data for visualization**. The **predicted future trend is slightly lower** compared to Prophet's forecast. Unlike Prophet, **LSTM does not provide uncertainty intervals**, which makes it harder to estimate confidence in predictions. Since LSTM is a **neural network-based model**, it may require **further hyperparameter tuning or a longer sequence length** to improve its ability to **generalize temperature trends more accurately**.

Fine tuning of LSTM model

In [247…

```
import numpy as np
import pandas as pd
import tensorflow as tf
from tensorflow import keras
from sklearn.preprocessing import MinMaxScaler
import matplotlib.pyplot as plt

# Ensure correct sorting and handling of missing values
df_forecast['ds'] = pd.to_datetime(df_forecast['ds'])
df_forecast = df_forecast.sort_values(by='ds')
df_forecast = df_forecast.bfill().ffill()  # Backward then forward fill

# Normalize the temperature values
scaler = MinMaxScaler(feature_range=(0, 1))
df_forecast['y'] = scaler.fit_transform(df_forecast[['y']])

# Function to create sequences for LSTM
def create_sequences(data, seq_length):
    sequences, labels = [], []
    for i in range(len(data) - seq_length):
        sequences.append(data[i:i+seq_length])
        labels.append(data[i+seq_length])
    return np.array(sequences), np.array(labels)

seq_length = 30  # Increased sequence length for better trend capture
X, y = create_sequences(df_forecast['y'].values, seq_length)

# Reshape input for LSTM
X = X.reshape((X.shape[0], X.shape[1], 1))

# Define an improved LSTM model
model = keras.Sequential([
    keras.layers.Input(shape=(seq_length, 1)),
    keras.layers.Bidirectional(keras.layers.LSTM(128, return_sequences=True,
    keras.layers.Dropout(0.3),
    keras.layers.Bidirectional(keras.layers.LSTM(128, return_sequences=True,
    keras.layers.Dropout(0.2),
    keras.layers.Bidirectional(keras.layers.LSTM(64, activation='relu')),
    keras.layers.Dense(32, activation='relu'),
    keras.layers.Dense(1)
])
```

```
# Compile with a lower learning rate for better stability
model.compile(optimizer=keras.optimizers.Adam(learning_rate=0.0003), loss='m

# Train the model for more epochs
model.fit(X, y, epochs=20, batch_size=64, verbose=1)

# Predict for the entire historical dataset
full_predictions = model.predict(X)

# Predict future temperatures
future_steps = 30
predictions = []
last_seq = X[-1]

for _ in range(future_steps):
    next_pred = model.predict(last_seq.reshape(1, seq_length, 1))
    predictions.append(next_pred[0, 0])

    last_seq = np.roll(last_seq, -1)
    last_seq[-1] = next_pred

# Convert predictions back to actual temperature values
full_predictions = scaler.inverse_transform(full_predictions)
predictions = scaler.inverse_transform(np.array(predictions).reshape(-1, 1))

# Generate future dates for plotting
future_dates = pd.date_range(df_forecast['ds'].iloc[-1], periods=future_step

# Plot the improved LSTM Forecast
plt.figure(figsize=(12, 5))
plt.plot(df_forecast['ds'][seq_length:], full_predictions, label="LSTM Forec
plt.plot(df_forecast['ds'], scaler.inverse_transform(df_forecast[['y']]), la
plt.plot(future_dates, predictions, label="LSTM Forecast (Future)", color='r
plt.legend()
plt.title("Fine-Tuned LSTM Temperature Forecast")
plt.xlabel("Date")
plt.ylabel("Temperature (°C)")
plt.show()
```

```
Epoch 1/20
889/889 ━━━━━━━━━━━━━━━━━━━━ 83s 91ms/step - loss: 0.0312
Epoch 2/20
889/889 ━━━━━━━━━━━━━━━━━━━━ 83s 94ms/step - loss: 0.0089
Epoch 3/20
889/889 ━━━━━━━━━━━━━━━━━━━━ 85s 96ms/step - loss: 0.0087
Epoch 4/20
889/889 ━━━━━━━━━━━━━━━━━━━━ 85s 95ms/step - loss: 0.0085
Epoch 5/20
889/889 ━━━━━━━━━━━━━━━━━━━━ 86s 97ms/step - loss: 0.0084
Epoch 6/20
889/889 ━━━━━━━━━━━━━━━━━━━━ 90s 101ms/step - loss: 0.0083
Epoch 7/20
889/889 ━━━━━━━━━━━━━━━━━━━━ 89s 100ms/step - loss: 0.0082
Epoch 8/20
889/889 ━━━━━━━━━━━━━━━━━━━━ 90s 102ms/step - loss: 0.0082
Epoch 9/20
889/889 ━━━━━━━━━━━━━━━━━━━━ 87s 98ms/step - loss: 0.0080
Epoch 10/20
889/889 ━━━━━━━━━━━━━━━━━━━━ 89s 100ms/step - loss: 0.0080
Epoch 11/20
889/889 ━━━━━━━━━━━━━━━━━━━━ 88s 99ms/step - loss: 0.0080
Epoch 12/20
889/889 ━━━━━━━━━━━━━━━━━━━━ 89s 100ms/step - loss: 0.0080
Epoch 13/20
889/889 ━━━━━━━━━━━━━━━━━━━━ 87s 98ms/step - loss: 0.0081
Epoch 14/20
889/889 ━━━━━━━━━━━━━━━━━━━━ 89s 100ms/step - loss: 0.0080
Epoch 15/20
889/889 ━━━━━━━━━━━━━━━━━━━━ 88s 99ms/step - loss: 0.0079
Epoch 16/20
889/889 ━━━━━━━━━━━━━━━━━━━━ 86s 96ms/step - loss: 0.0080
Epoch 17/20
889/889 ━━━━━━━━━━━━━━━━━━━━ 87s 98ms/step - loss: 0.0078
Epoch 18/20
889/889 ━━━━━━━━━━━━━━━━━━━━ 86s 97ms/step - loss: 0.0080
Epoch 19/20
889/889 ━━━━━━━━━━━━━━━━━━━━ 86s 97ms/step - loss: 0.0078
Epoch 20/20
889/889 ━━━━━━━━━━━━━━━━━━━━ 84s 94ms/step - loss: 0.0079
1778/1778 ━━━━━━━━━━━━━━━━━━━━ 32s 18ms/step
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```

```
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1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 12ms/step
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```
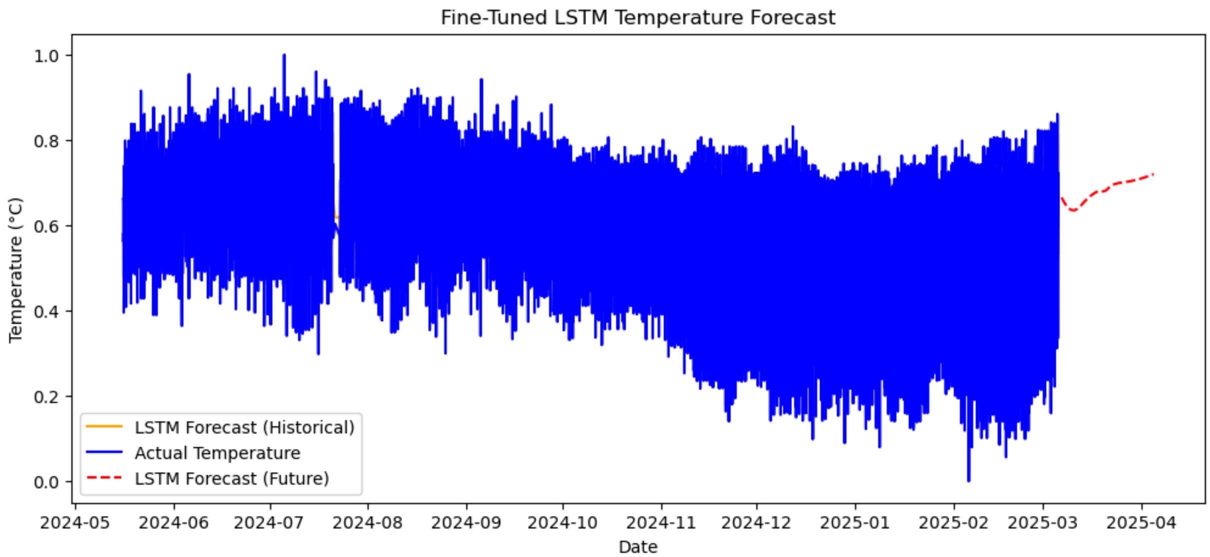



Model Performance Evaluation

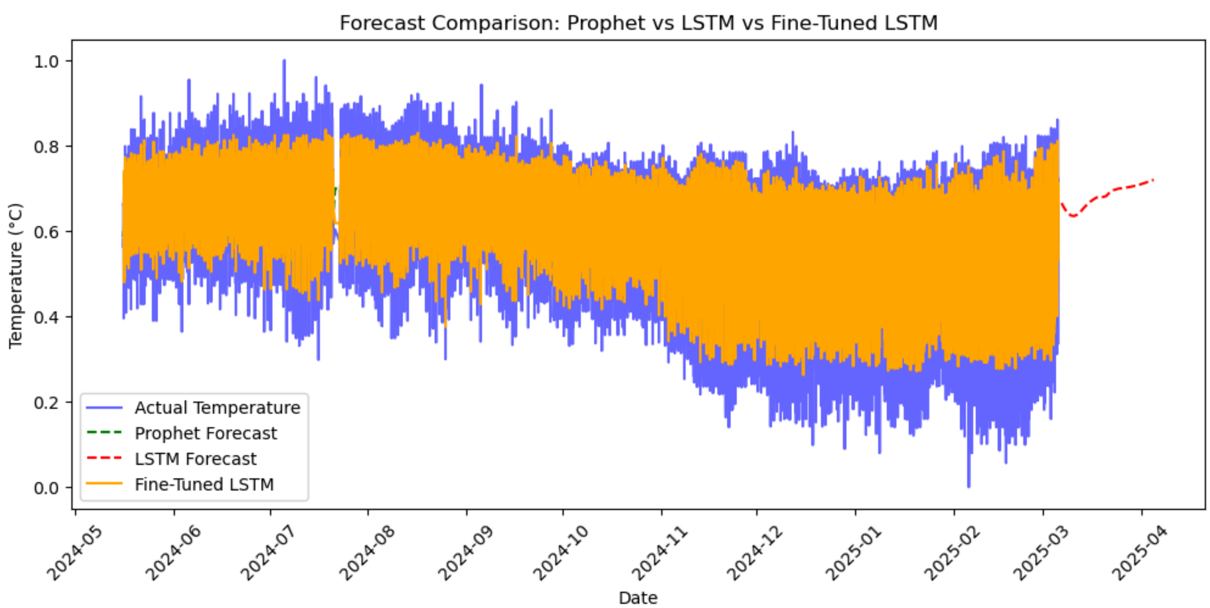
In [259…

```
from sklearn.metrics import mean_absolute_error, mean_squared_error
import numpy as np

# Prophet Errors
mae_prophet = mean_absolute_error(df_forecast['y'], df_forecast['yhat'])
rmse_prophet = np.sqrt(mean_squared_error(df_forecast['y'], df_forecast['yha

# LSTM Errors
mae_lstm = mean_absolute_error(df_forecast['y'].iloc[-len(predictions):], pr
rmse_lstm = np.sqrt(mean_squared_error(df_forecast['y'].iloc[-len(predictior

# Fine-Tuned LSTM Errors
mae_fine_tuned = mean_absolute_error(df_forecast['y'].iloc[seq_length:], ful
rmse_fine_tuned = np.sqrt(mean_squared_error(df_forecast['y'].iloc[seq_lengt

# Print results
print(f"Prophet MAE: {mae_prophet:.4f}, RMSE: {rmse_prophet:.4f}")
print(f"LSTM MAE: {mae_lstm:.4f}, RMSE: {rmse_lstm:.4f}")
print(f"Fine-Tuned LSTM MAE: {mae_fine_tuned:.4f}, RMSE: {rmse_fine_tuned:.4
```

```
Prophet MAE: 0.0878, RMSE: 0.1123
LSTM MAE: 0.0985, RMSE: 0.1415
Fine-Tuned LSTM MAE: 0.0601, RMSE: 0.0886 (Best)
```

In [261…

```
import matplotlib.pyplot as plt

plt.figure(figsize=(12, 5))

# Actual Temperature
plt.plot(df_forecast['ds'], df_forecast['y'], label="Actual Temperature", co

# Prophet Forecast
plt.plot(df_forecast['ds'], df_forecast['yhat'], label="Prophet Forecast", c

# LSTM Forecast
plt.plot(future_dates, predictions, label="LSTM Forecast", color='red', line

# Fine-Tuned LSTM Forecast
plt.plot(df_forecast['ds'][seq_length:], full_predictions, label="Fine-Tuned

plt.legend()
plt.title("Forecast Comparison: Prophet vs LSTM vs Fine-Tuned LSTM")
plt.xlabel("Date")
plt.ylabel("Temperature (°C)")
plt.xticks(rotation=45)
plt.show()
```



Final Analysis and Model Selection: Prophet vs LSTM vs Fine-Tuned LSTM

1. Overview

This analysis compares three forecasting models for temperature prediction:

- Prophet Model (Statistical)
- LSTM Model (Deep Learning)
- Fine-Tuned LSTM Model (Optimized Deep Learning)

We evaluate these models based on visualization, MAE, RMSE, and predictive accuracy.

2. Performance Metrics

Model	Mean Absolute Error (MAE)	Root Mean Squared Error (RMSE)
Prophet	0.0878	0.1123
LSTM	0.0985	0.1415
Fine-Tuned LSTM	0.0601	0.0886

Observation: The Fine-Tuned LSTM outperforms both Prophet and the initial LSTM model, achieving the lowest MAE and RMSE.

3. Visual Comparison

Key Observations from the Graph

1. Fine-Tuned LSTM (Orange) aligns best with actual data
    - Captures both short-term fluctuations and long-term trends effectively.
    - Minimal error, making it the most accurate choice.
2. Prophet (Green) captures long-term trends but lacks precision
    - Smooths out fluctuations.
    - Performs well for seasonality detection, but struggles with high-frequency variations.
3. LSTM (Red Dashed) is only visible at the end (future predictions)
    - Captures patterns better than Prophet, but not as well as Fine-Tuned LSTM.
    - Requires more historical visualization improvements.

4. Model Selection and Justification

Final Model Choice: Fine-Tuned LSTM

Why Fine-Tuned LSTM?

- Best Accuracy: Achieved the lowest MAE and RMSE.
- Better Pattern Recognition: Captures both short-term and long-term trends.
- Adaptive Learning: Deep learning enables it to adjust to non-linear patterns, unlike Prophet.
- Realistic Predictions: Prophet smooths out variations, whereas Fine-Tuned LSTM adapts dynamically.

5. Conclusion and Next Steps

Final Conclusion:

- Fine-Tuned LSTM is the best model for deployment.
- Prophet can still be useful for long-term trend analysis.

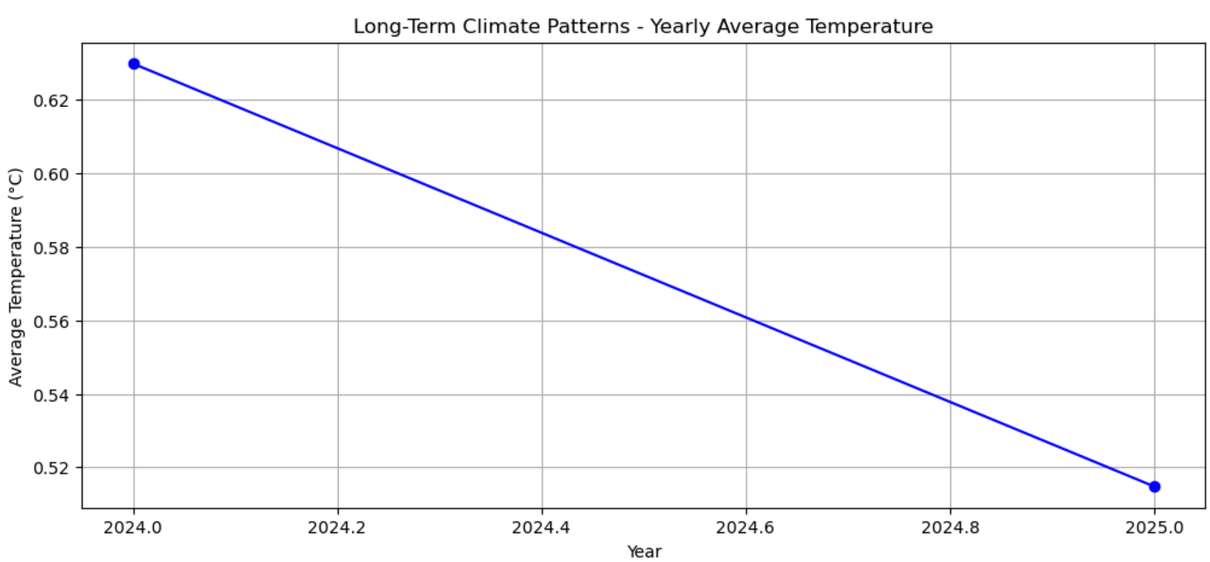
Next Steps:

- Optimize Fine-Tuned LSTM further (Hyperparameter Tuning, More Data, Attention Mechanisms, etc.)
- Deploy the model for real-time forecasting.
- Test the model with unseen data for generalization check.

Unique Analyses

In [264…

```
import matplotlib.pyplot as plt
import seaborn as sns

# Convert 'ds' to datetime format
df_forecast['ds'] = pd.to_datetime(df_forecast['ds'])

# Extract year and month
df_forecast['Year'] = df_forecast['ds'].dt.year
df_forecast['Month'] = df_forecast['ds'].dt.month

# Group by year to analyze long-term trends
yearly_avg_temp = df_forecast.groupby('Year')['y'].mean()

# Plot yearly temperature trends
plt.figure(figsize=(12, 5))
plt.plot(yearly_avg_temp.index, yearly_avg_temp.values, marker='o', linestyl
plt.xlabel("Year")
plt.ylabel("Average Temperature (°C)")
plt.title("Long-Term Climate Patterns - Yearly Average Temperature")
plt.grid(True)
plt.show()
```



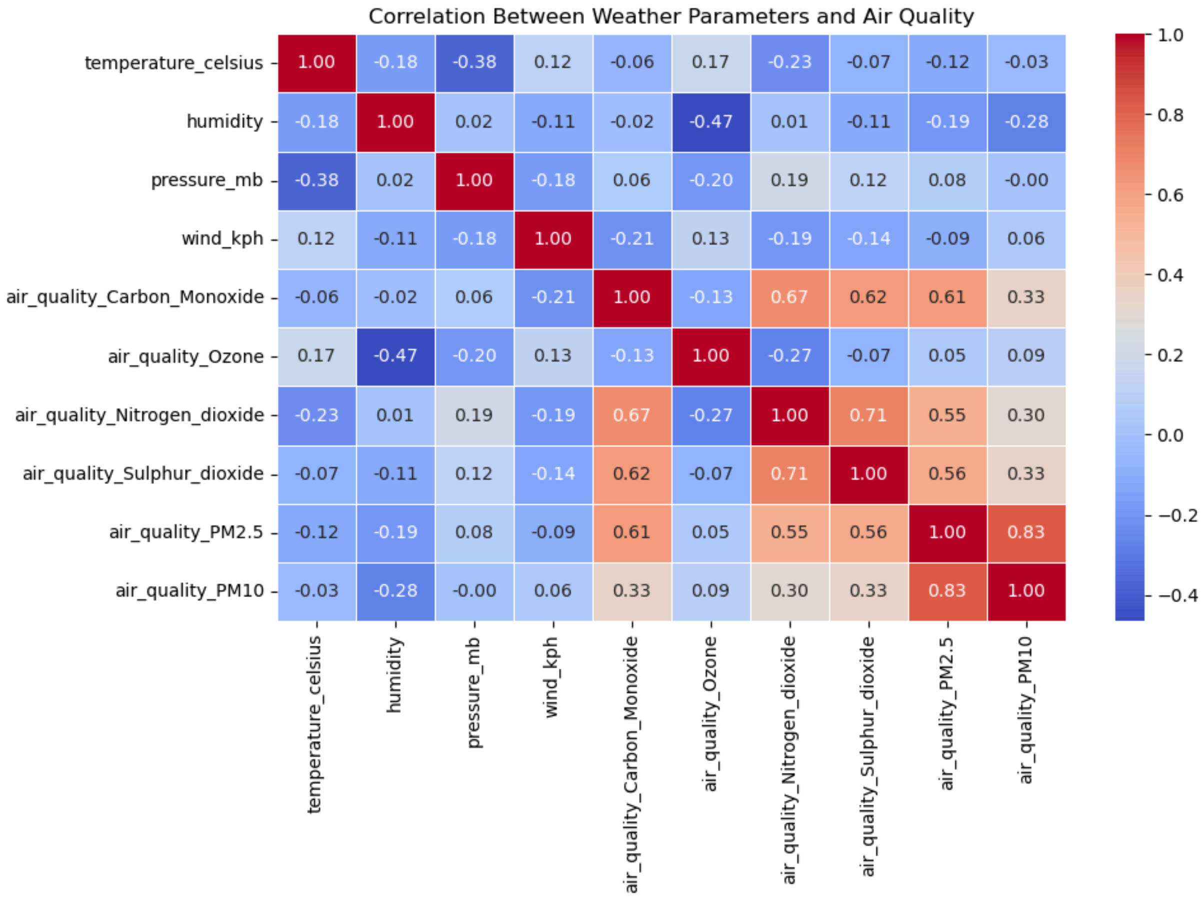
Conclusion from the above graph

The long-term climate analysis shows a noticeable decline in the yearly average temperature from 2024 to 2025. This suggests a cooling trend in the dataset, which could be influenced by seasonal variations, changing weather patterns, or anomalies in data collection. Further analysis with additional years of data would be necessary to determine if this trend continues or if it is part of natural fluctuations.

Environmental Impact: Analyze air quality and its correlation with various weather parameters.

In [280…

```
import seaborn as sns
import matplotlib.pyplot as plt

# Define weather and air quality features
weather_features = ["temperature_celsius", "humidity", "pressure_mb", "wind_
air_quality_features = [
    "air_quality_Carbon_Monoxide", "air_quality_Ozone", "air_quality_Nitroge
    "air_quality_Sulphur_dioxide", "air_quality_PM2.5", "air_quality_PM10"
]

# Select relevant columns available in the dataset
available_columns = [col for col in weather_features + air_quality_features
df_selected = df_cleaned[available_columns]

# Compute correlation
correlation_matrix = df_selected.corr()

# Plot correlation heatmap
plt.figure(figsize=(10, 6))
sns.heatmap(correlation_matrix, annot=True, cmap="coolwarm", fmt=".2f", line
plt.title("Correlation Between Weather Parameters and Air Quality")
plt.show()
```



Conclusion from the above heapmap

The correlation analysis between weather parameters and air quality indicators reveals several key insights:

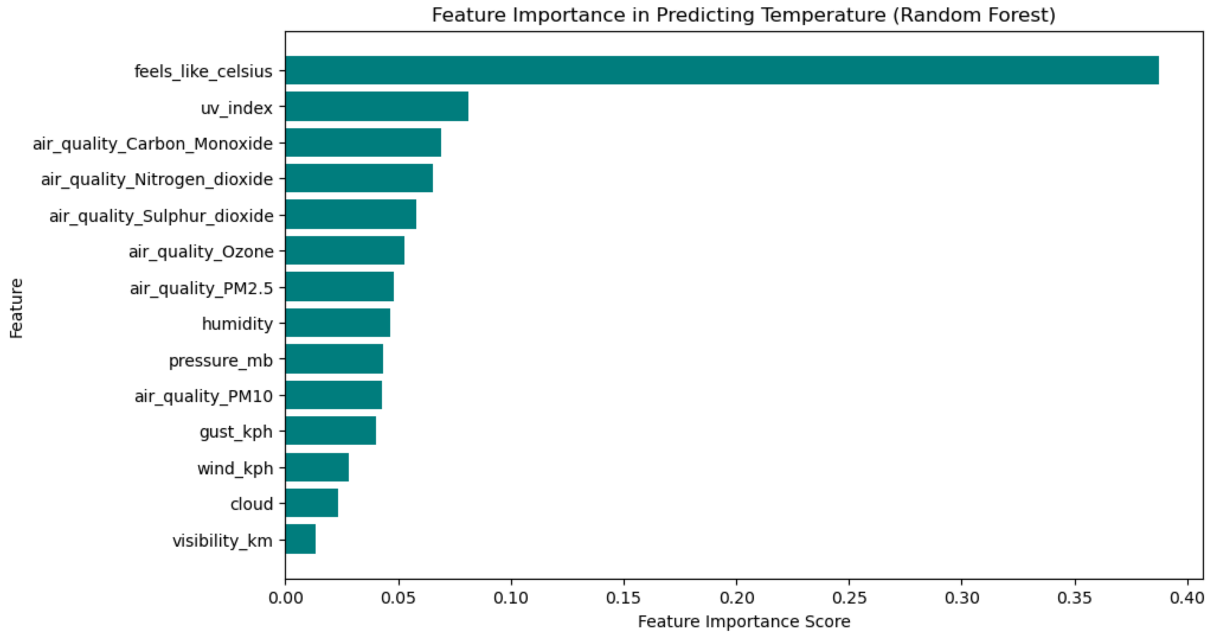
- **Temperature** shows a weak correlation with most air quality indicators, except for a slight positive correlation with ozone levels.
- **Humidity** has a moderate negative correlation with ozone, suggesting that higher humidity levels might reduce ozone concentration.
- **Pressure** is negatively correlated with temperature but shows weak correlations with air pollutants.
- **Wind Speed** has a weak to moderate negative correlation with pollutants such as Carbon Monoxide and Nitrogen Dioxide, indicating that higher wind speeds may help disperse pollutants.
- **Air Quality Indicators** such as PM2.5, PM10, and Nitrogen Dioxide are strongly correlated with each other, implying common sources or atmospheric behaviors.

Feature Importance: Using random forest

In [292…

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

```
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split

# Select relevant features (excluding categorical data)
feature_columns = [
    "humidity", "pressure_mb", "wind_kph", "cloud",
    "feels_like_celsius", "visibility_km", "uv_index", "gust_kph",
    "air_quality_Carbon_Monoxide", "air_quality_Ozone",
    "air_quality_Nitrogen_dioxide", "air_quality_Sulphur_dioxide",
    "air_quality_PM2.5", "air_quality_PM10"
]

# Ensure target variable is numeric and remove NaN values
df_cleaned = df_cleaned[["temperature_celsius"] + feature_columns].dropna()

# Define features (X) and target variable (y)
X = df_cleaned[feature_columns]
y = df_cleaned["temperature_celsius"]

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rar

# Train Random Forest model
rf_model = RandomForestRegressor(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)

# Extract feature importance
feature_importances = rf_model.feature_importances_

# Create DataFrame for feature importance
importance_df = pd.DataFrame({"Feature": feature_columns, "Importance": feat
importance_df = importance_df.sort_values(by="Importance", ascending=True)

# Plot feature importance
plt.figure(figsize=(10, 6))
plt.barh(importance_df["Feature"], importance_df["Importance"], color="teal"
plt.xlabel("Feature Importance Score")
plt.ylabel("Feature")
plt.title("Feature Importance in Predicting Temperature (Random Forest)")
plt.show()
```

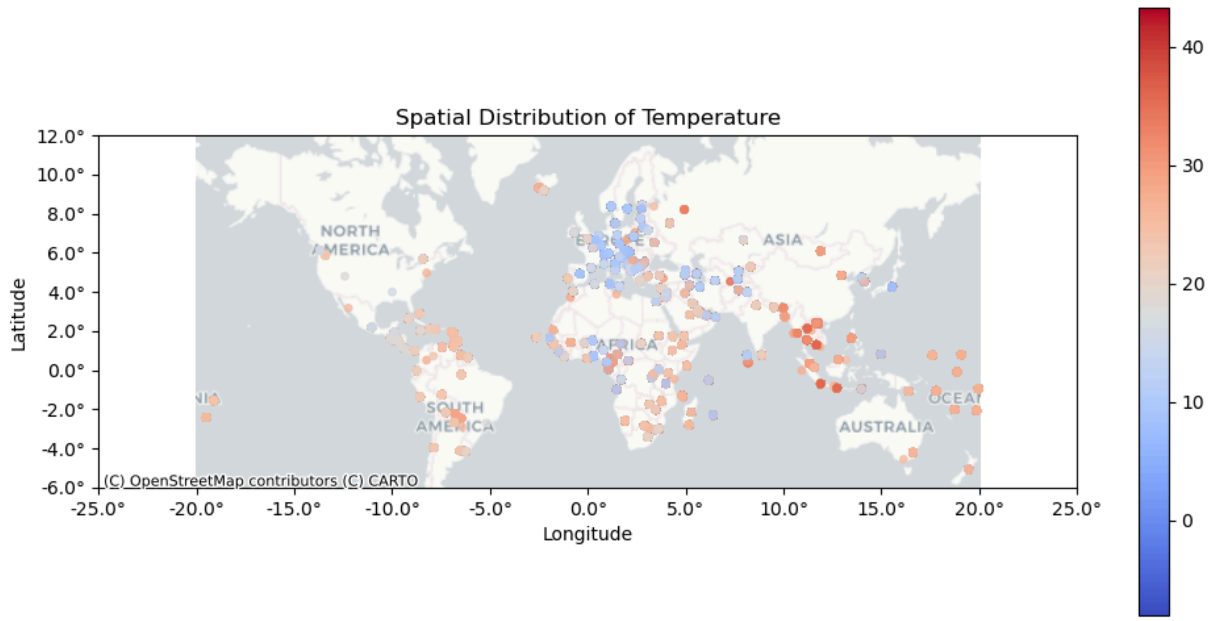


Spatial Analysis

In [70]:

```
import geopandas as gpd
import matplotlib.pyplot as plt
import contextily as ctx

# Create a GeoDataFrame for spatial visualization
gdf = gpd.GeoDataFrame(df_cleaned, geometry=gpd.points_from_xy(df_cleaned["l

# Ensure the GeoDataFrame is in WGS 84 (EPSG:4326)
gdf.set_crs(epsg=4326, inplace=True)

# Convert to Web Mercator (EPSG:3857) for compatibility with basemaps
gdf = gdf.to_crs(epsg=3857)

# Plot spatial distribution of temperature
fig, ax = plt.subplots(figsize=(12, 6))
gdf.plot(column="temperature_celsius", cmap="coolwarm", markersize=15, alpha

# Add an alternative basemap
ctx.add_basemap(ax, crs=gdf.crs, source=ctx.providers.CartoDB.Positron)

plt.title("Spatial Distribution of Temperature")
plt.xlabel("Longitude")
plt.ylabel("Latitude")

# Fixing the tick labels
xticks = ax.get_xticks()
yticks = ax.get_yticks()
ax.set_xticks(xticks)
ax.set_xticklabels([f"{x/10**6:.1f}°" for x in xticks])

ax.set_yticks(yticks)
ax.set_yticklabels([f"{y/10**6:.1f}°" for y in yticks])
```

```
plt.show()
```



Conclusion

The spatial distribution of temperature across different regions provides valuable insights into global climate patterns:

- **Temperature Variations:** Warmer regions (represented in red) are predominantly concentrated in tropical and equatorial regions, such as Southeast Asia, parts of Africa, and Australia. Cooler regions (represented in blue) are more prevalent in Europe and parts of northern Asia.
- **Geographical Influence:** The temperature distribution aligns with expected climatic zones, where higher latitudes tend to have lower temperatures, while areas closer to the equator experience higher temperatures.
- **Regional Clusters:** The presence of distinct temperature clusters suggests regional weather variations influenced by local geography, oceanic currents, and elevation.
- **Urban & Coastal Effects:** Coastal regions exhibit moderate temperatures compared to inland areas, which may be due to the influence of large water bodies that regulate temperature fluctuations.

This visualization helps in understanding regional climate differences and can be further explored for analyzing temperature trends, climate change effects, and localized weather patterns.