Weather Trend Forecasting

This notebook analyzes the "Global Weather Repository.csv" dataset to forecast future weather trends. Includes EDA, anomaly detection, forecasting with Ridge Regression, and interactive geospatial visualizations.

PM Accelerator Mission

"By making industry-leading tools and education available to individuals from all backgrounds, we level the playing field for future PM leaders. This is the PM Accelerator motto, as we grant aspiring and experienced PMs what they need most – Access. We introduce you to industry leaders, surround you with the right PM ecosystem, and discover the new world of AI product management skills."

In [1]:
```
# Uncomment if running for the first time
# !pip install pandas matplotlib seaborn scikit-learn folium prophet stat

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import folium
import requests
import xgboost as xgb

from sklearn.linear_model import Ridge
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_absolute_error, mean_squared_error
from sklearn.preprocessing import StandardScaler
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
# Load the dataset
weather = pd.read_csv("GlobalWeatherRepository.csv")
weather['last_updated'] = pd.to_datetime(weather['last_updated'])
weather.sort_values('last_updated', inplace=True)
weather.set_index('last_updated', inplace=True)

# Drop columns with more than 5% missing values
null_pct = weather.isnull().mean()
valid_columns = null_pct[null_pct < 0.05].index
weather = weather[valid_columns].copy()

# Standardize column names and fill missing values
weather.columns = weather.columns.str.lower()
weather.fillna(0, inplace=True)
```

Dataset Overview

The dataset includes over 60,000 weather records globally. It includes over 40 features such as temperature, precipitation, wind, and air quality metrics. This cell loads the data and checks its structure.

In [3]:
```
# Create target column for forecasting next day's temperature
weather['target'] = weather['temperature_celsius'].shift(-1)
weather.dropna(subset=['target'], inplace=True)

# Define predictor columns dynamically (numerical only, excluding target)
predictors = [col for col in weather.select_dtypes(include='number').colu
```

In [4]:
```
# Create target column for prediction (tomorrow's temperature)
weather = weather.copy()
weather['target'] = weather['temperature_celsius'].shift(-1)
weather.dropna(inplace=True)
```

Parsing and Sorting Dates

We convert the 'last_updated' column to datetime format and sort the dataframe by date to enable proper time series analysis.

In [5]:
```
weather.describe()
```

Out[5]:

	latitude	longitude	last_updated_epoch	temperature_celsius	tem
count	60411.000000	60411.000000	6.041100e+04	60411.000000	
mean	19.137636	22.183645	1.729311e+09	22.155538	
std	24.474532	65.808862	7.802518e+06	9.628106	
min	-41.300000	-175.200000	1.715849e+09	-24.900000	
25%	3.750000	-6.836100	1.722688e+09	16.900000	
50%	17.250000	23.316700	1.729330e+09	25.000000	
75%	40.400000	50.580000	1.736072e+09	28.400000	
max	64.150000	179.220000	1.742723e+09	49.200000	

8 rows × 31 columns

In [6]:
```
weather.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 60411 entries, 2024-05-16 01:45:00 to 2025-03-23 22:45:00
Data columns (total 41 columns):
 #   Column                        Non-Null Count  Dtype  
---  ------                        --------------  -----  
 0   country                       60411 non-null  object 
 1   location_name                 60411 non-null  object 
 2   latitude                      60411 non-null  float64
 3   longitude                     60411 non-null  float64
 4   timezone                      60411 non-null  object 
 5   last_updated_epoch            60411 non-null  int64  
 6   temperature_celsius           60411 non-null  float64
 7   temperature_fahrenheit        60411 non-null  float64
 8   condition_text                60411 non-null  object 
 9   wind_mph                      60411 non-null  float64
 10  wind_kph                      60411 non-null  float64
 11  wind_degree                   60411 non-null  int64  
 12  wind_direction                60411 non-null  object 
 13  pressure_mb                   60411 non-null  float64
 14  pressure_in                   60411 non-null  float64
 15  precip_mm                     60411 non-null  float64
 16  precip_in                     60411 non-null  float64
 17  humidity                      60411 non-null  int64  
 18  cloud                         60411 non-null  int64  
 19  feels_like_celsius            60411 non-null  float64
 20  feels_like_fahrenheit         60411 non-null  float64
 21  visibility_km                 60411 non-null  float64
 22  visibility_miles              60411 non-null  float64
 23  uv_index                      60411 non-null  float64
 24  gust_mph                      60411 non-null  float64
 25  gust_kph                      60411 non-null  float64
 26  air_quality_carbon_monoxide   60411 non-null  float64
 27  air_quality_ozone             60411 non-null  float64
 28  air_quality_nitrogen_dioxide  60411 non-null  float64
 29  air_quality_sulphur_dioxide   60411 non-null  float64
 30  air_quality_pm2.5             60411 non-null  float64
 31  air_quality_pm10              60411 non-null  float64
 32  air_quality_us-epa-index      60411 non-null  int64  
 33  air_quality_gb-defra-index    60411 non-null  int64  
 34  sunrise                       60411 non-null  object 
 35  sunset                        60411 non-null  object 
 36  moonrise                      60411 non-null  object 
 37  moonset                       60411 non-null  object 
 38  moon_phase                    60411 non-null  object 
 39  moon_illumination             60411 non-null  int64  
 40  target                        60411 non-null  float64
dtypes: float64(24), int64(7), object(10)
memory usage: 19.4+ MB
```

In [7]:
```
weather.head()
```

Out [7]:

	country	location_name	latitude	longitude	timezone	last_upd
last_updated						
2024-05-16 01:45:00	United States of America	Washington Park	46.60	-120.49	America/ Los_Angeles	
2024-05-16 02:45:00	El Salvador	San Salvador	13.71	-89.20	America/ El_Salvador	
2024-05-16 02:45:00	Costa Rica	San Juan	9.97	-84.08	America/ Costa_Rica	
2024-05-16 02:45:00	Guatemala	Guatemala City	14.62	-90.53	America/ Guatemala	
2024-05-16 02:45:00	Nicaragua	Managua	12.15	-86.27	America/ Managua	

5 rows × 41 columns

Initial Data Inspection

Here we examine data types, missing values, and summary statistics to understand feature distributions and potential issues.

In [8]:

```
def backtest(data, model, predictors, start=3650, step=90):
    all_predictions = []
    for i in range(start, data.shape[0], step):
        train = data.iloc[:i]
        test = data.iloc[i:i+step]

        model.fit(train[predictors], train['target'])
        preds = model.predict(test[predictors])

        preds = pd.Series(preds, index=test.index)
        combined = pd.concat([test['target'], preds], axis=1)
        combined.columns = ['actual', 'prediction']
        combined['diff'] = np.abs(combined['actual'] - combined['predicti

        all_predictions.append(combined)

    return pd.concat(all_predictions)
```

In [9]:

```
# Fit Ridge Regression before using coef_
model = Ridge(alpha=0.1)
model.fit(weather[predictors], weather['target'])  # Make sure 'weather'
```

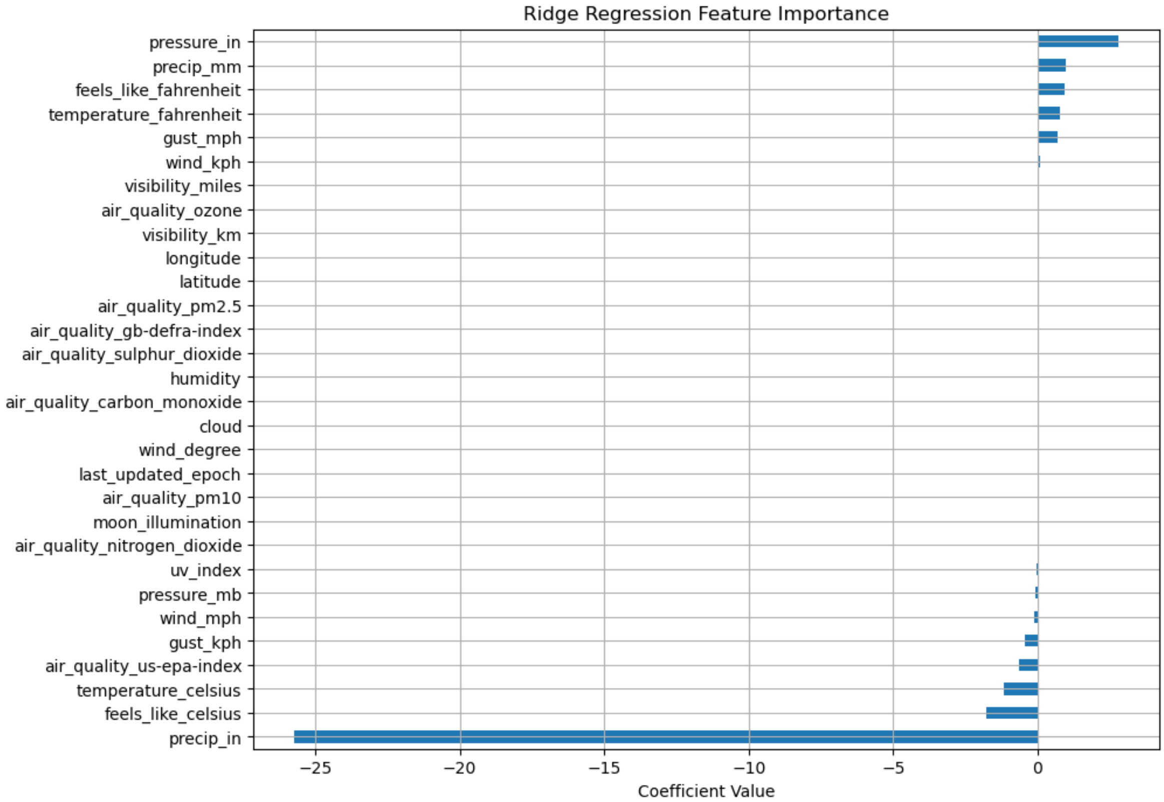
Out[9]:

```
▾ Ridge
Ridge(alpha=0.1)
```

In [10]:

```
# Feature Importance via Ridge coefficients
coef_df = pd.Series(model.coef_, index=predictors).sort_values()
plt.figure(figsize=(10, 8))
```

```
coef_df.plot(kind='barh')
plt.title("Ridge Regression Feature Importance")
plt.xlabel("Coefficient Value")
plt.grid(True)
plt.show()
```

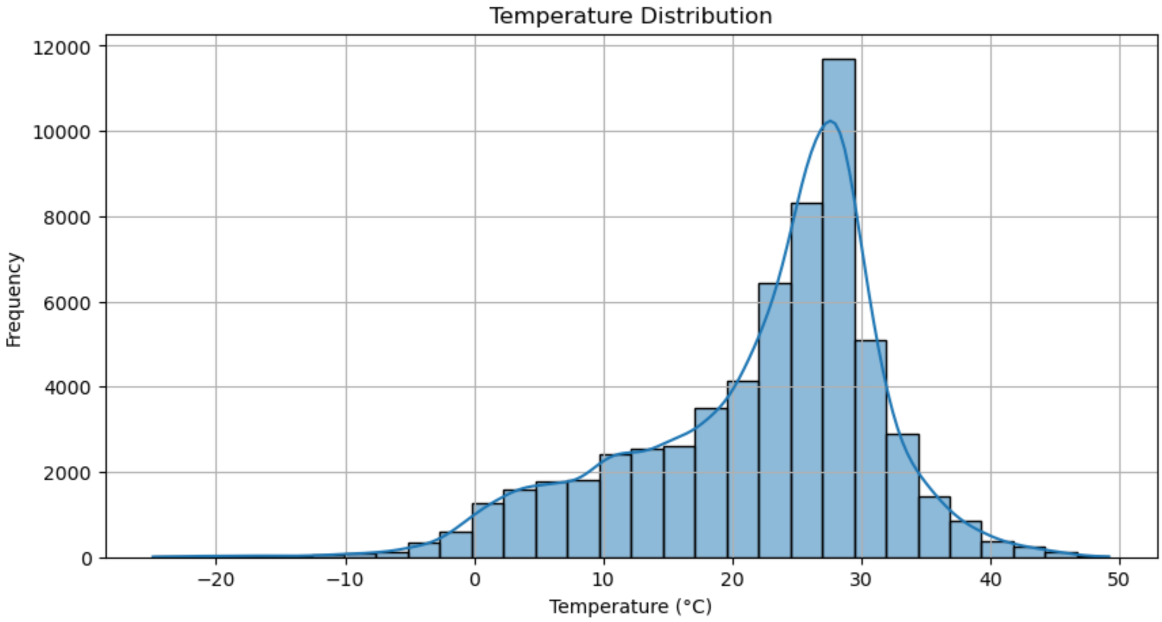


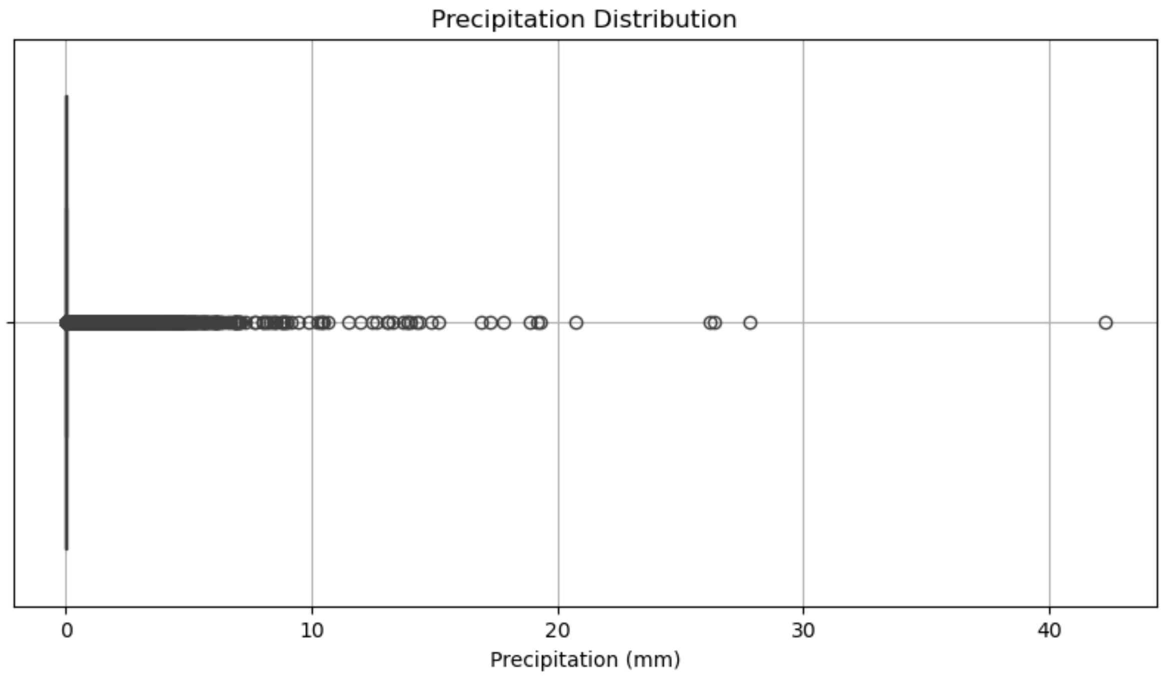
Basic Exploratory Data Analysis (EDA)

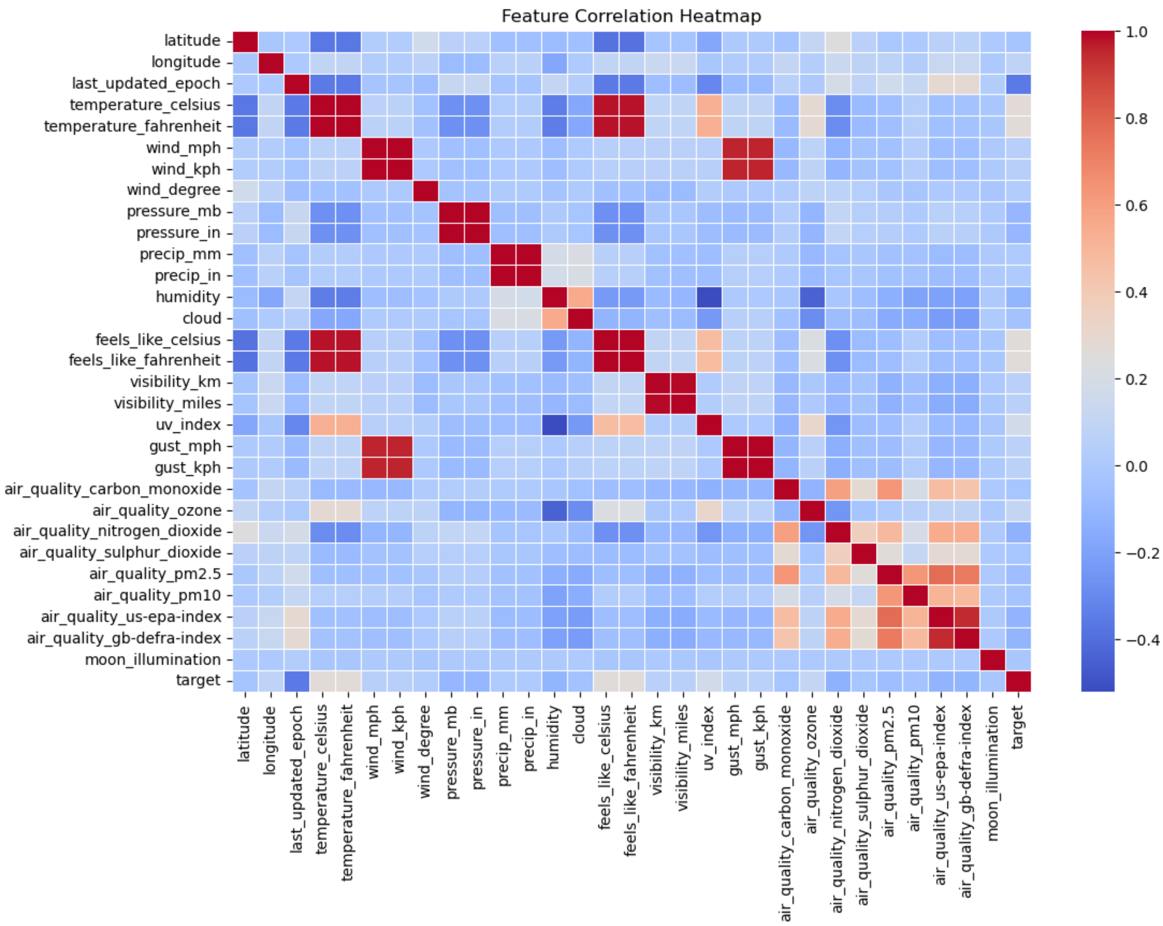
We begin with standard EDA to understand temperature distribution, wind patterns, and basic weather conditions. This helps us detect initial outliers, get a sense of data trends, and choose suitable features for further modeling.

In [11]:
```
# Temperature distribution
plt.figure(figsize=(10,5))
sns.histplot(weather['temperature_celsius'], bins=30, kde=True)
plt.title("Temperature Distribution")
plt.xlabel("Temperature (°C)")
plt.ylabel("Frequency")
plt.grid(True)
plt.show()

# Precipitation distribution
plt.figure(figsize=(10,5))
sns.boxplot(x=weather['precip_mm'])
plt.title("Precipitation Distribution")
plt.xlabel("Precipitation (mm)")
plt.grid(True)
plt.show()

# Correlation heatmap
plt.figure(figsize=(12,8))
sns.heatmap(weather.corr(numeric_only=True), annot=False, fmt=".2f", cmap
plt.title("Feature Correlation Heatmap")
```

```
plt.show()
```


Temperature Distribution
Frequency
0
2000
4000
6000
8000
10000
12000
−20
−10
0
10
20
30
40
50
Temperature (°C)


Precipitation Distribution
0
10
20
30
40
Precipitation (mm)

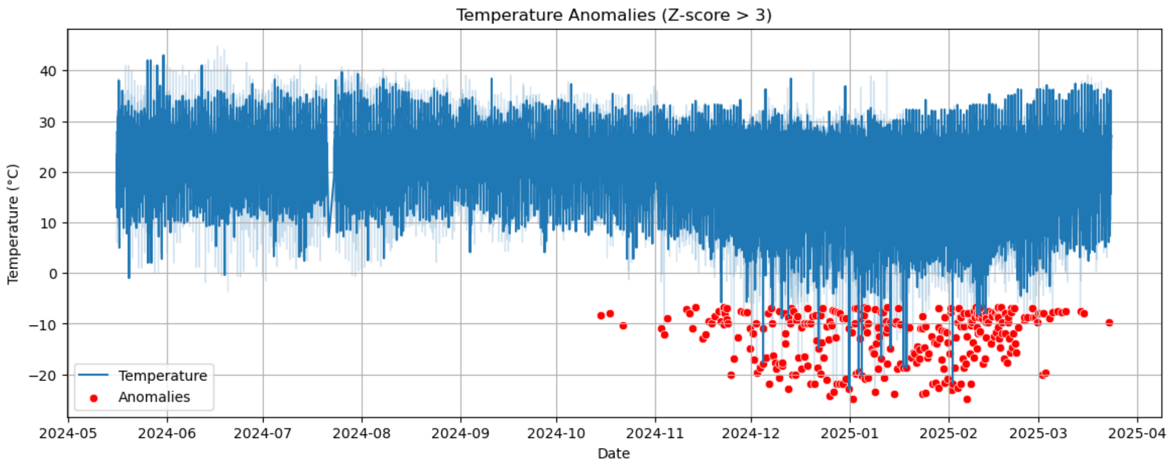


Correlation Heatmap

The heatmap helps visualize relationships between numeric features, revealing which variables are most closely associated. This heatmap shows that the humidity has strong negative correlation to uv index and air quality ozone which will be demonstrated by plots further in this report. Another interesting correlation showed by the heatmap is the fairly strong negative correlation between latitude and temperature, but not longitude.

Temperature Anomaly Detection

In [12]:
```
weather['temp_zscore'] = (weather['temperature_celsius'] - weather['tempe
weather['anomaly'] = weather['temp_zscore'].abs() > 3

plt.figure(figsize=(14,5))
sns.lineplot(x=weather.index, y='temperature_celsius', data=weather, labe
sns.scatterplot(x=weather[weather['anomaly']].index, y='temperature_celsi
plt.title("Temperature Anomalies (Z-score > 3)")
plt.xlabel("Date")
plt.ylabel("Temperature (°C)")
plt.grid(True)
plt.show()
```



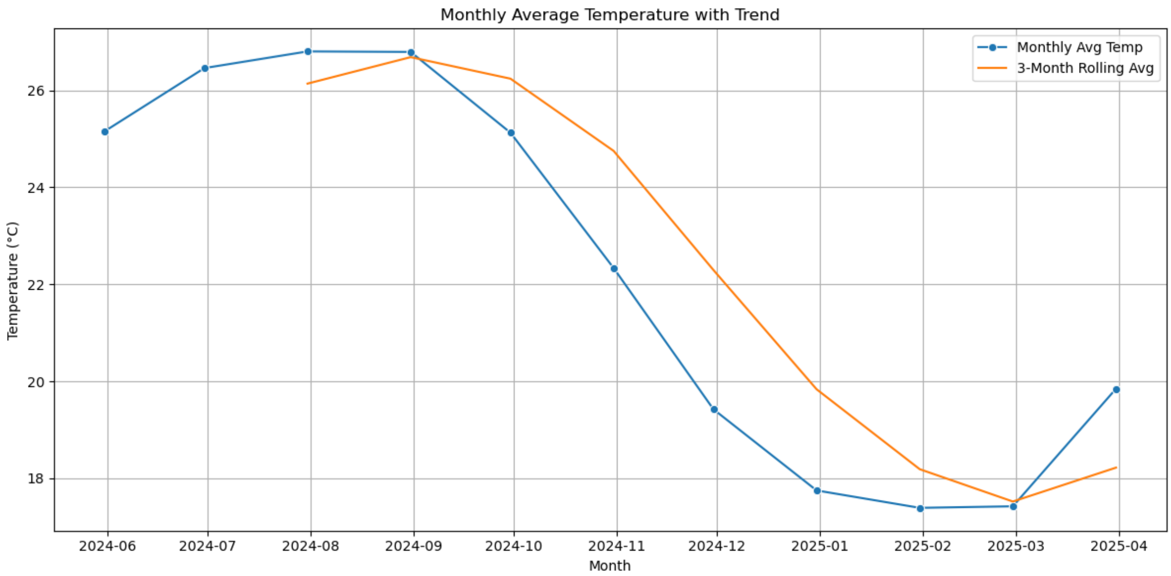
Temperature Anomaly Detection

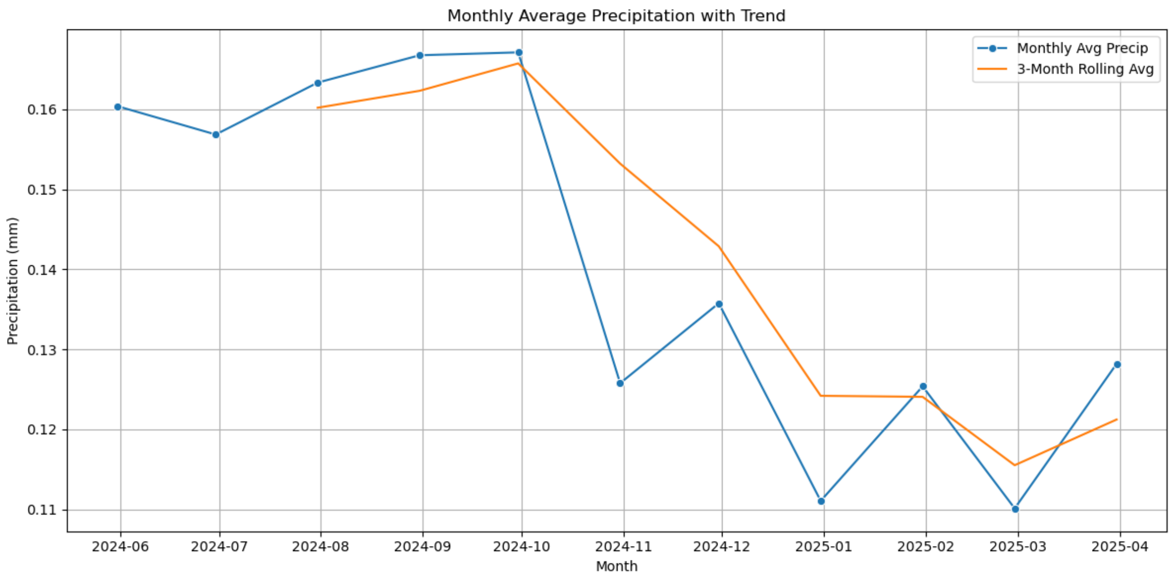
We apply Z-score thresholding to detect extreme deviations in temperature. These anomalies may indicate measurement errors, natural disasters, or exceptional weather events. Removing or flagging them ensures our models are not skewed.

Climate Trends Over Time

In [13]:

```
# Resample to monthly average temperature and precipitation
monthly_avg = weather.resample('M').mean(numeric_only=True)

# Plotting monthly temperature trend with 3-month rolling average
plt.figure(figsize=(12,6))
sns.lineplot(x=monthly_avg.index, y=monthly_avg['temperature_celsius'], m
sns.lineplot(x=monthly_avg.index, y=monthly_avg['temperature_celsius'].ro
plt.title("Monthly Average Temperature with Trend")
plt.xlabel("Month")
plt.ylabel("Temperature (°C)")
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()

# Plotting monthly precipitation trend with 3-month rolling average
plt.figure(figsize=(12,6))
sns.lineplot(x=monthly_avg.index, y=monthly_avg['precip_mm'], marker='o',
sns.lineplot(x=monthly_avg.index, y=monthly_avg['precip_mm'].rolling(3).m
plt.title("Monthly Average Precipitation with Trend")
plt.xlabel("Month")
plt.ylabel("Precipitation (mm)")
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```





Long-Term Temperature Trend

By resampling temperature data monthly, we observe long-term warming or cooling trends globally. This chart helps visualize whether temperatures are generally increasing over the months available.

Ridge Regression Forecasting

We train a Ridge Regression model to forecast temperature. Ridge helps mitigate multicollinearity and is suitable for linear relationships.

In [14]:
```
def backtest1(data, model, predictors, start=365, step=90):
    all_preds = []
    for i in range(start, data.shape[0], step):
        train = data.iloc[:i]
        test = data.iloc[i:i+step]

        scaler = StandardScaler()
        X_train = scaler.fit_transform(train[predictors])
        X_test = scaler.transform(test[predictors])
```

```
        model.fit(X_train, train['target'])
        preds = model.predict(X_test)

        preds = pd.Series(preds, index=test.index)
        combined = pd.concat([test['target'], preds], axis=1)
        combined.columns = ['actual', 'prediction']
        all_preds.append(combined)

    return pd.concat(all_preds)

model1 = Ridge(alpha=0.1)
ridge_preds = backtest1(weather, model1, predictors)
```

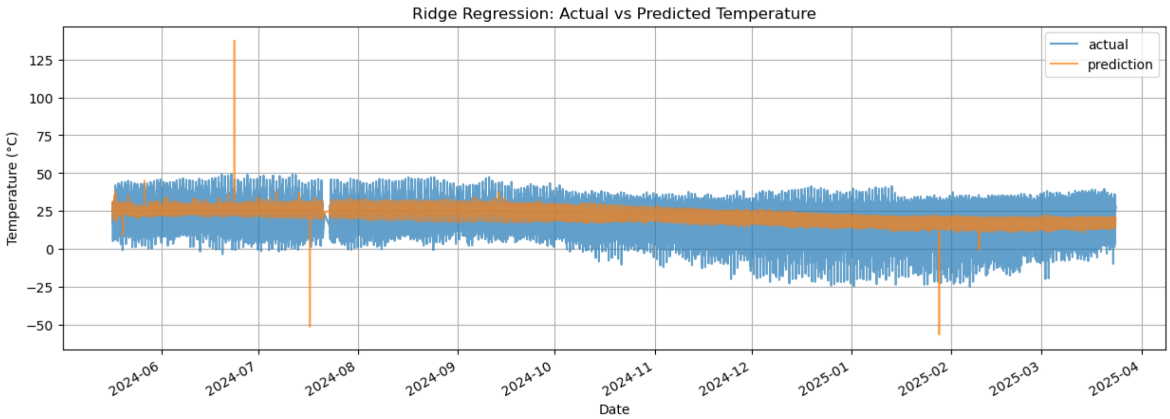
In [15]:

```
mae = mean_absolute_error(ridge_preds['actual'], ridge_preds['prediction'
rmse = mean_squared_error(ridge_preds['actual'], ridge_preds['prediction'
print(f"MAE: {mae:.2f}")
print(f"RMSE: {rmse:.2f}")
```

```
MAE: 6.98
RMSE: 8.85
```

In [16]:

```
ridge_preds.plot(figsize=(15,5), alpha=0.7)
plt.title("Ridge Regression: Actual vs Predicted Temperature")
plt.xlabel("Date")
plt.ylabel("Temperature (°C)")
plt.grid(True)
plt.show()
```



Forecasting with XGBoost Regressor

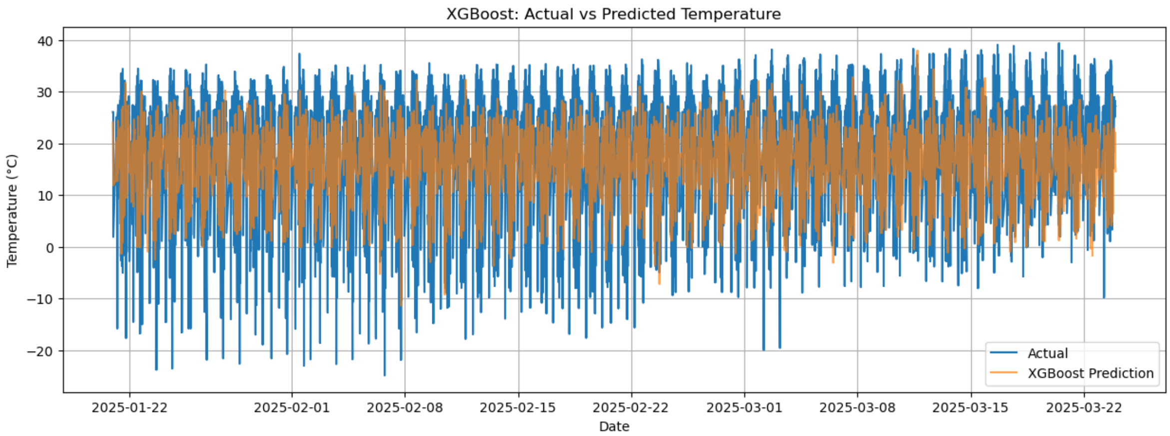
XGBoost Model

XGBoost is a gradient boosting model that captures nonlinear relationships. It may improve accuracy compared to linear models.

In [17]:

```
import xgboost as xgb
from sklearn.model_selection import train_test_split

# Prepare data
X = weather[predictors]
y = weather['target']
X_train, X_test, y_train, y_test = train_test_split(X, y, shuffle=False,
```

```
# Train XGBoost
xgb_model = xgb.XGBRegressor(objective='reg:squarederror', n_estimators=1
xgb_model.fit(X_train, y_train)
xgb_preds = xgb_model.predict(X_test)

# Plot predictions
plt.figure(figsize=(15,5))
plt.plot(y_test.index, y_test.values, label='Actual')
plt.plot(y_test.index, xgb_preds, label='XGBoost Prediction', alpha=0.7)
plt.legend()
plt.title("XGBoost: Actual vs Predicted Temperature")
plt.xlabel("Date")
plt.ylabel("Temperature (°C)")
plt.grid(True)
plt.show()
```



In [18]:
```
# Evaluate
xgb_mae = mean_absolute_error(y_test, xgb_preds)
xgb_rmse = mean_squared_error(y_test, xgb_preds, squared=False)

print(f"XGBoost MAE: {xgb_mae:.2f}")
print(f"XGBoost RMSE: {xgb_rmse:.2f}")
```

```
XGBoost MAE: 9.26
XGBoost RMSE: 11.54
```

Ridge Regression Forecasting Performance

We backtested the Ridge Regression model across multiple windows and measured its Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). The results suggest the model performs reasonably well given the short-term nature of the data.

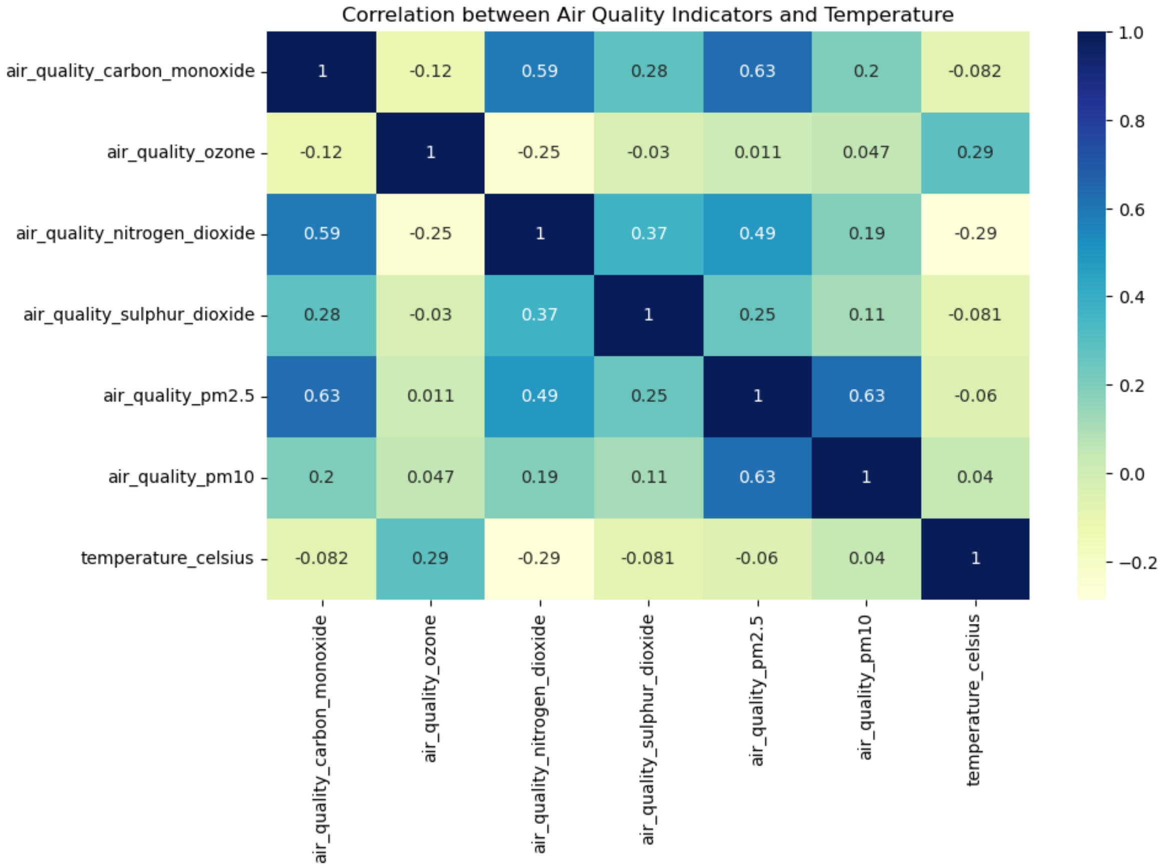
Environmental Impact: Air Quality Analysis

Feature Importance Visualization

This chart highlights the most influential features in the Ridge model, offering interpretability and insight into key drivers.

In [19]:
```
air_quality_cols = [
    'air_quality_carbon_monoxide', 'air_quality_ozone', 'air_quality_nitr
    'air_quality_sulphur_dioxide', 'air_quality_pm2.5', 'air_quality_pm10
```

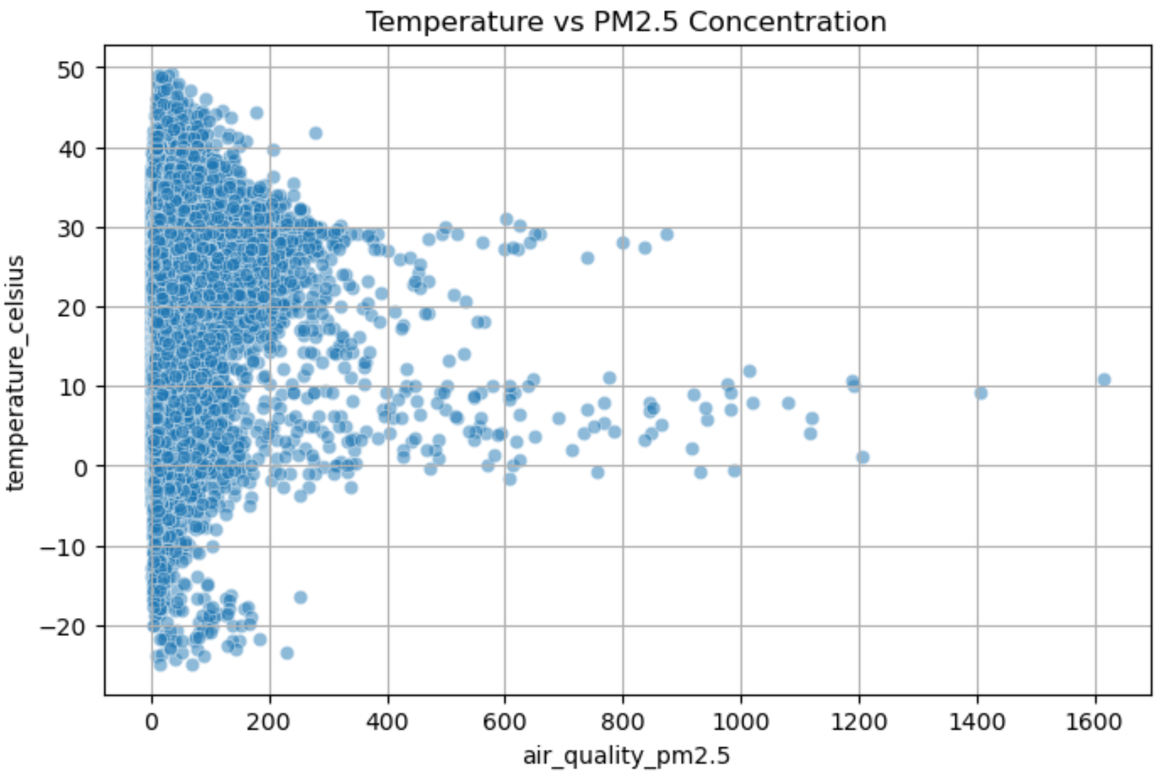
```
]

# Correlation with temperature
air_corr = weather[air_quality_cols + ['temperature_celsius']].corr(numer
plt.figure(figsize=(10,6))
sns.heatmap(air_corr, annot=True, cmap="YlGnBu")
plt.title("Correlation between Air Quality Indicators and Temperature")
plt.show()
```



Environmental Impact Analysis

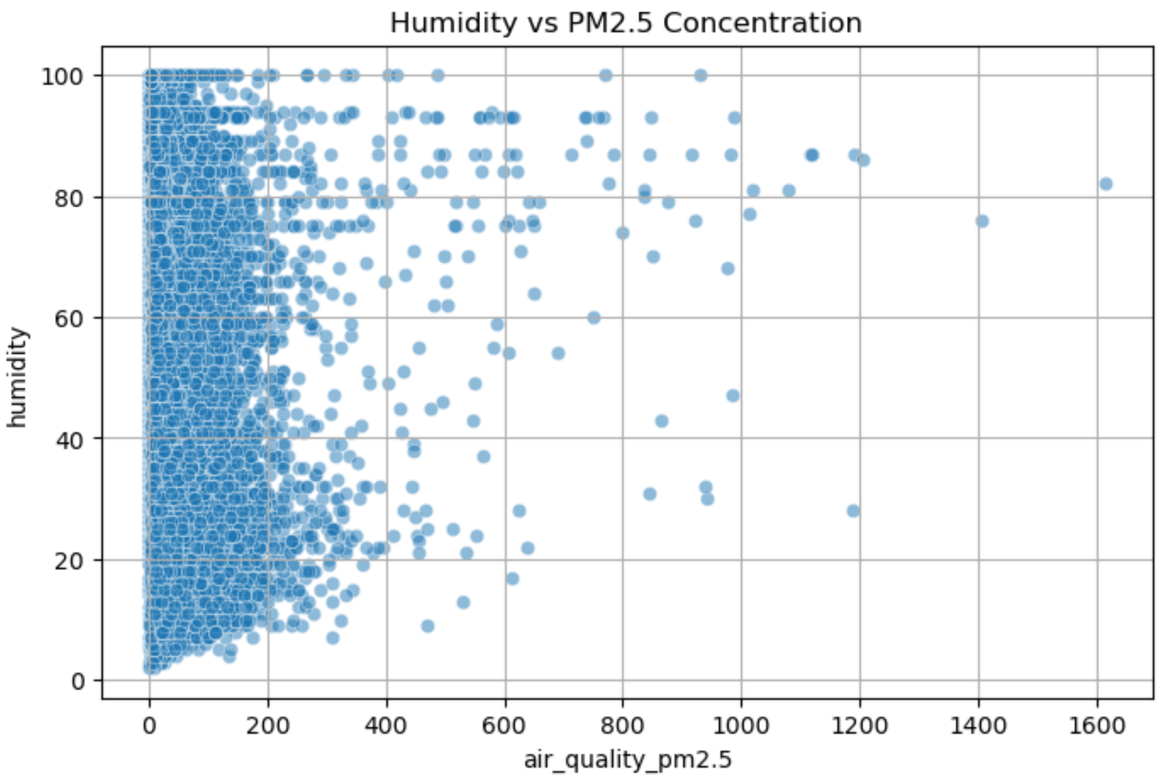
Here we explore the relationship between air quality metrics (PM2.5) and other features to understand environmental correlations.

In [20]:
```
# Scatterplot: PM2.5 vs Temperature
plt.figure(figsize=(8,5))
sns.scatterplot(x='air_quality_pm2.5', y='temperature_celsius', data=weat
plt.title("Temperature vs PM2.5 Concentration")
plt.grid(True)
plt.show()
```



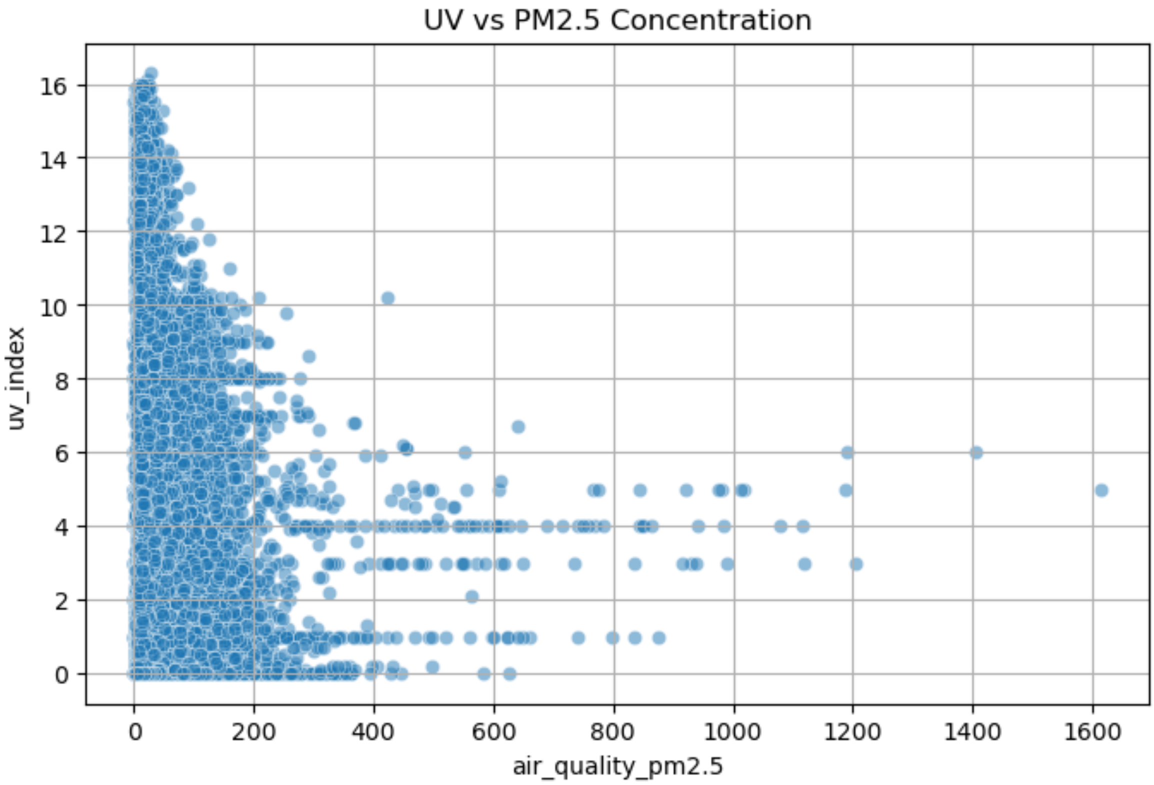
This chart shows peak PM2.5/poor air quality when temperatures are between 0-10C with another peak around 30C

In [21]:
```
# Scatterplot example: PM2.5 vs Humidity
plt.figure(figsize=(8,5))
sns.scatterplot(x='air_quality_pm2.5', y='humidity', data=weather, alpha=
plt.title("Humidity vs PM2.5 Concentration")
plt.grid(True)
plt.show()
```



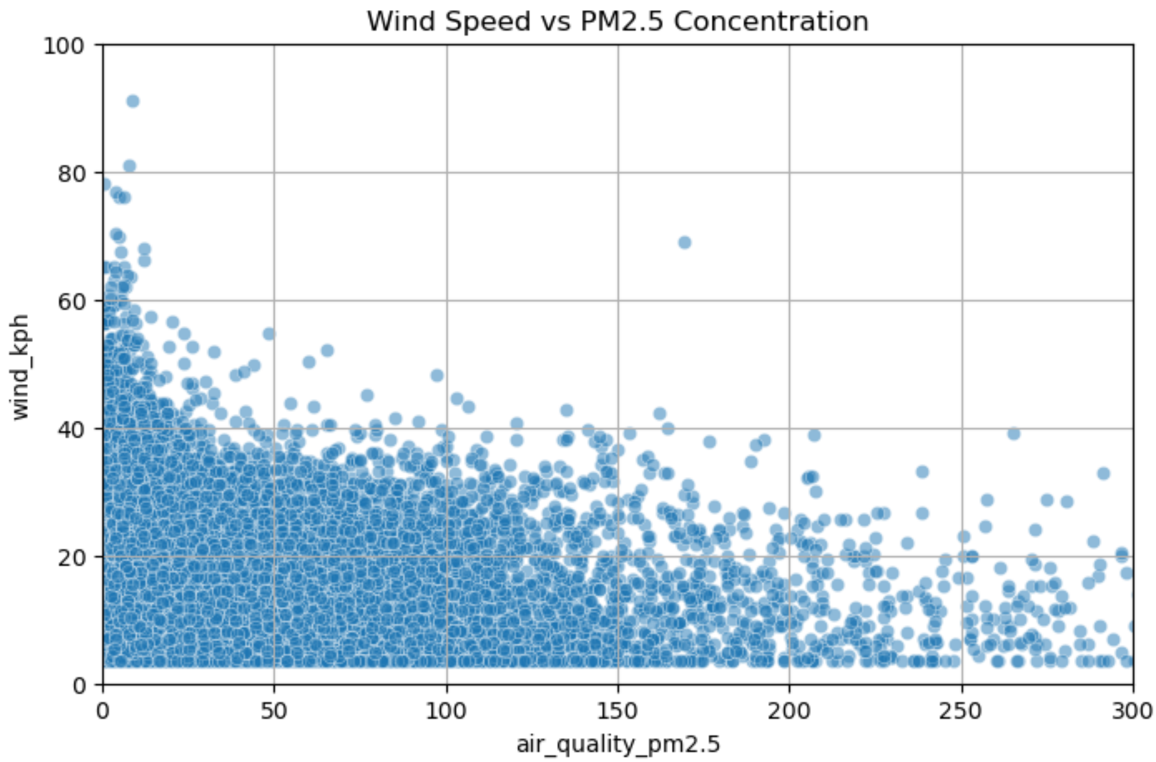
This plot shows higher peaks of pm2.5 (poorer air quality) with higher humidity

In [22]:
```
# Scatterplot example: PM2.5 vs UV
plt.figure(figsize=(8,5))
sns.scatterplot(x='air_quality_pm2.5', y='uv_index', data=weather, alpha=
plt.title("UV vs PM2.5 Concentration")
plt.grid(True)
plt.show()
```



This plot shows higher pm2.5 levels with lower UV index, indicating higher uv indexes lead to better air quality.

In [23]:
```
# Scatterplot example: PM2.5 vs Wind Speed
plt.figure(figsize=(8,5))
sns.scatterplot(x='air_quality_pm2.5', y='wind_kph', data=weather, alpha=
plt.title("Wind Speed vs PM2.5 Concentration")
plt.xlim(0, 300)   # Adjust based on actual PM2.5 range
plt.ylim(0, 100)   # Typical wind speed range in kph
plt.grid(True)
plt.show()
```



This plot shows better air quality with higher wind speeds, with perfect air quality with wind speeds above about 90km/h

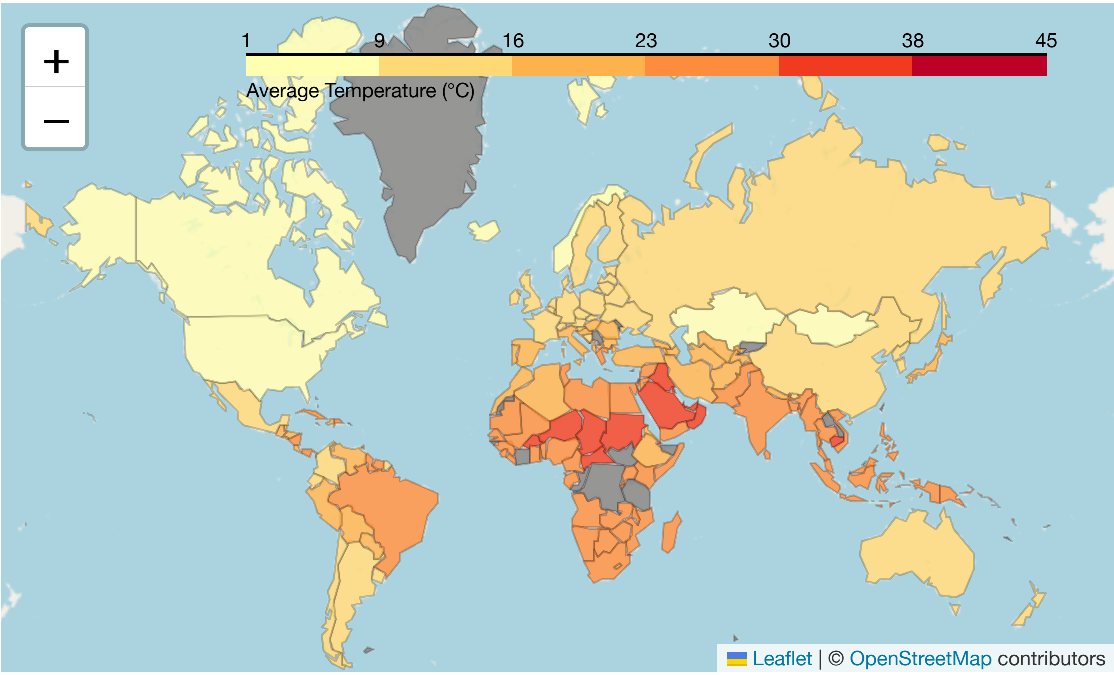
Global Climate Choropleth Maps

Geospatial Weather Visualization

We use Folium to plot country-level average temperature and precipitation. This reveals geographic weather patterns globally.

In [24]:
```
geojson_url = 'https://raw.githubusercontent.com/python-visualization/fol
geojson_data = requests.get(geojson_url).json()

country_avg = weather.groupby('country')['temperature_celsius'].mean().re

m = folium.Map(location=[40, 0], zoom_start=2)
folium.Choropleth(
    geo_data=geojson_data,
    name='choropleth',
    data=country_avg,
    columns=['country', 'temperature_celsius'],
    key_on='feature.properties.name',
    fill_color='YlOrRd',
    fill_opacity=0.8,
    line_opacity=0.2,
    legend_name='Average Temperature (°C)',
    nan_fill_color='gray'
).add_to(m)
m
```

Out[24]:

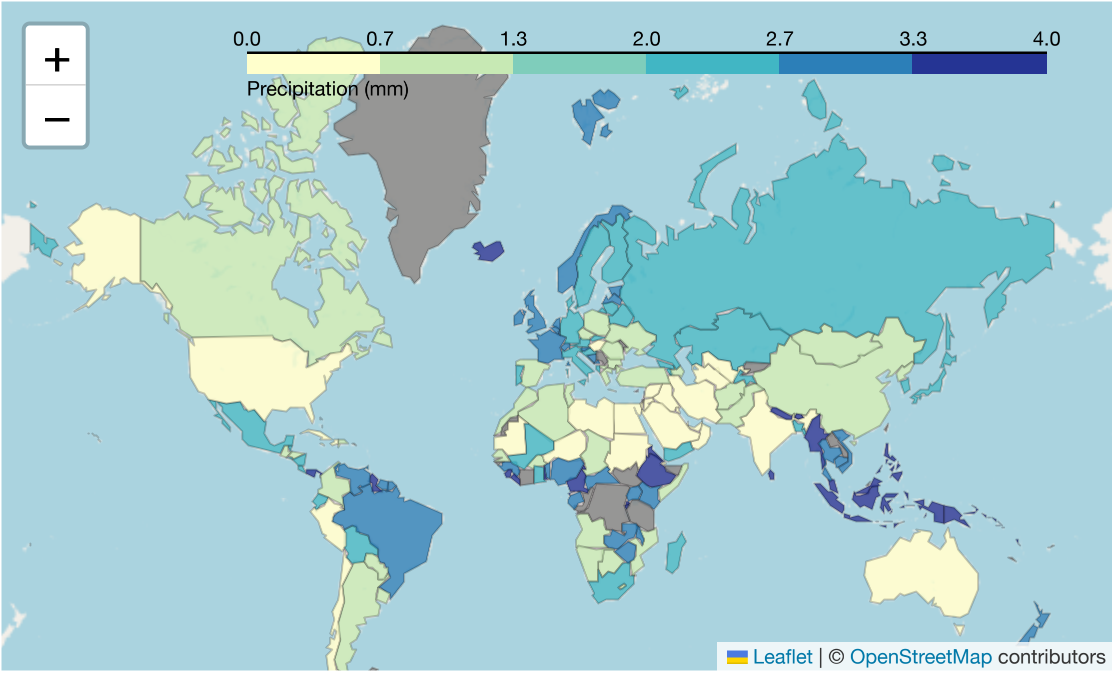


Areas with the highest temperatures are close to the equator and/or are in arid (dry, desert) climates.

In [25]:

```
# Clip out high-end outliers
threshold = weather['precip_mm'].quantile(0.95)
country_avg_precip = (
    weather[weather['precip_mm'] <= threshold]
    .groupby('country')['precip_mm']
    .mean()
    .reset_index()
)

# Create quantile bins (e.g. 5 bins = quintiles)
country_avg_precip['precip_bin'] = pd.qcut(country_avg_precip['precip_mm'

# Map using quantile bins
m1 = folium.Map(location=[20, 0], zoom_start=2)
folium.Choropleth(
    geo_data=geojson_data,
    name='choropleth',
    data=country_avg_precip,
    columns=['country', 'precip_bin'],
    key_on='feature.properties.name',
    fill_color='YlGnBu',
    fill_opacity=0.8,
    line_opacity=0.2,
    legend_name='Precipitation (mm)',
    nan_fill_color='gray'
).add_to(m1)

m1
```

Out[25]:

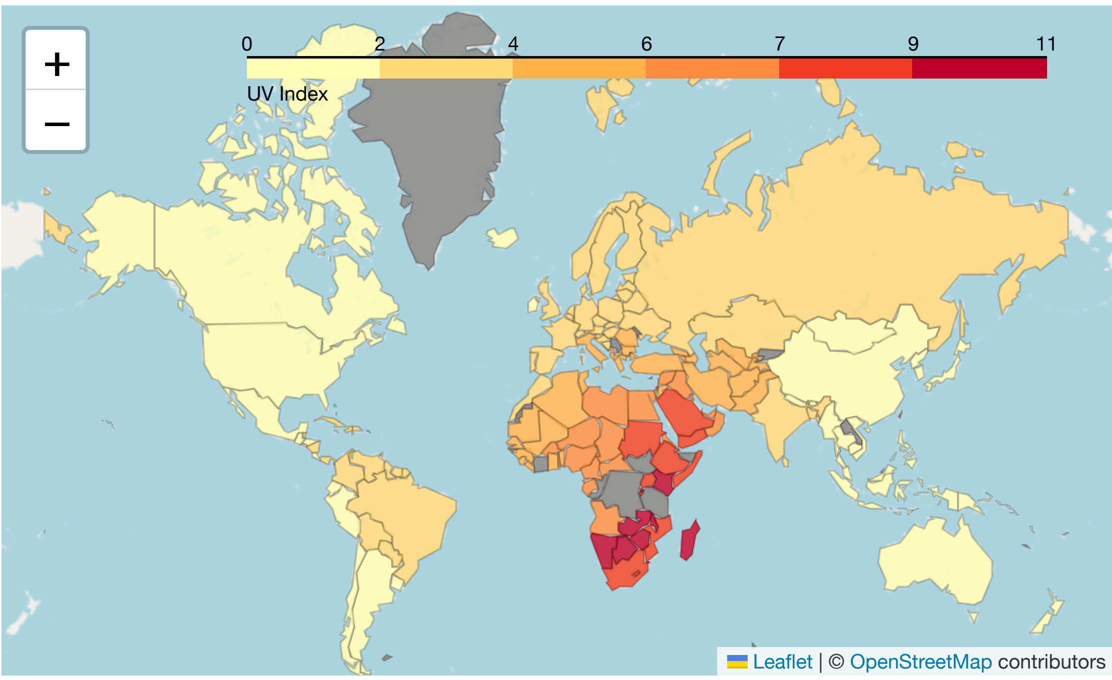


Proximity to equator seems to have an effect on average precipitation in an area.

In [26]:

```
country_avg_uv = weather.groupby('country')['uv_index'].mean().reset_inde

m2 = folium.Map(location=[40, 0], zoom_start=2)
folium.Choropleth(
    geo_data=geojson_data,
    name='choropleth',
    data=country_avg_uv,
    columns=['country', 'uv_index'],
    key_on='feature.properties.name',
    fill_color='YlOrRd',
    fill_opacity=0.8,
    line_opacity=0.2,
    legend_name='UV Index',
    nan_fill_color='gray'
).add_to(m2)
m2
```

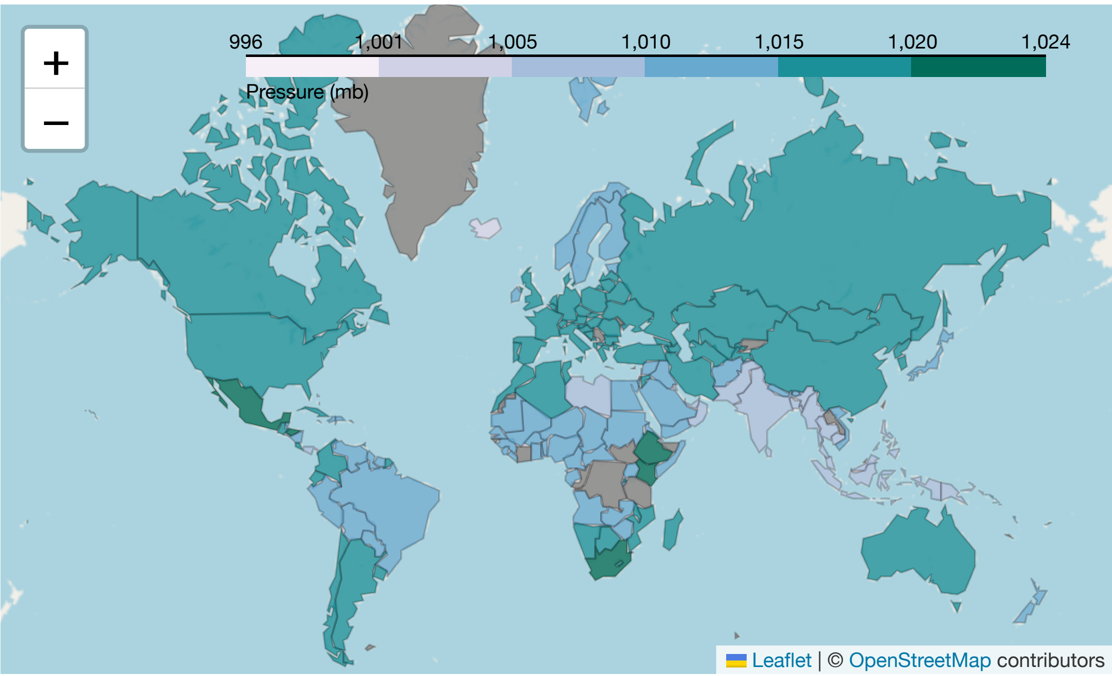
Out[26]:



Africa has the highest UV index as it is closest to the sun due to the earth's rotational tilt. This map illustrates that effect.

In [27]:
```
country_avg_pressure = weather.groupby('country')['pressure_mb'].mean().r

m3 = folium.Map(location=[40, 0], zoom_start=2)
folium.Choropleth(
    geo_data=geojson_data,
    name='choropleth',
    data=country_avg_pressure,
    columns=['country', 'pressure_mb'],
    key_on='feature.properties.name',
    fill_color='PuBuGn',
    fill_opacity=0.8,
    line_opacity=0.2,
    legend_name='Pressure (mb)',
    nan_fill_color='gray',
    tiles='Stamen Terrain'
).add_to(m3)
m3
```

Out[27]:

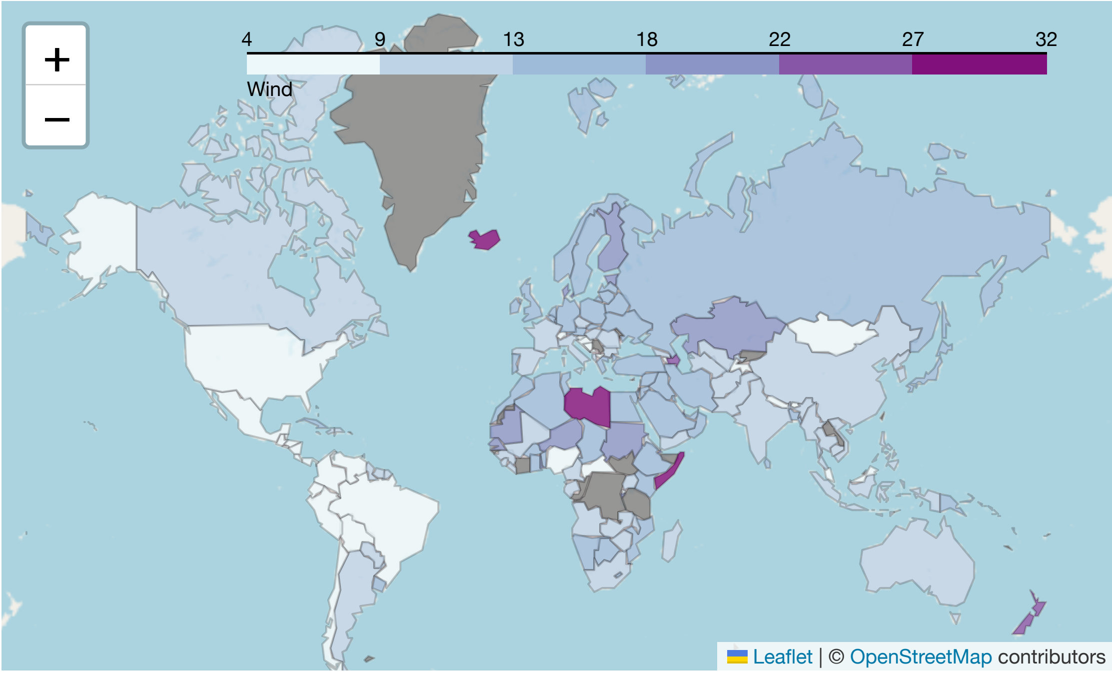


This chart highlights zones of similar pressure that seem to cross over continental lines creating new zones.

In [28]:
```
country_avg_wind = weather.groupby('country')['wind_kph'].mean().reset_in

m4 = folium.Map(location=[40, 0], zoom_start=2)
folium.Choropleth(
    geo_data=geojson_data,
    name='choropleth',
    data=country_avg_wind,
    columns=['country', 'wind_kph'],
    key_on='feature.properties.name',
    fill_color='BuPu',
    fill_opacity=0.8,
    line_opacity=0.2,
    legend_name='Wind',
```

```
    nan_fill_color='gray'
).add_to(m4)
m4
```

Out[28]:

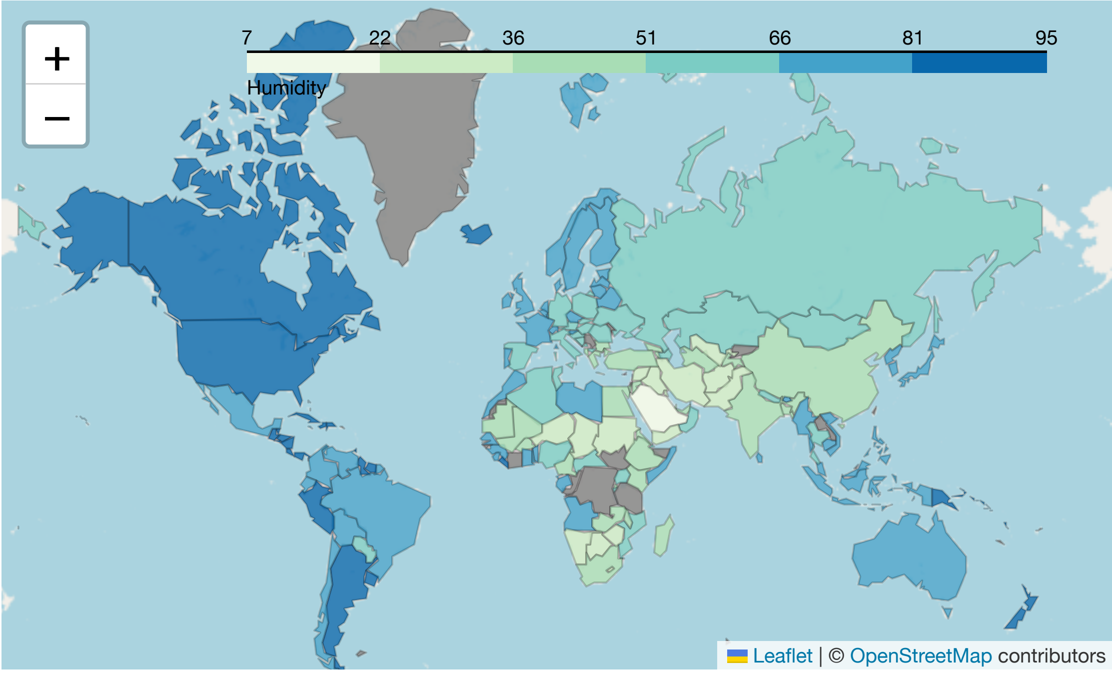


This map shows a few countries with the highest wind speeds. It seems Africa has the highest wind speeds by continent.

In [29]:

```
country_avg_humidity = weather.groupby('country')['humidity'].mean().rese

m5 = folium.Map(location=[40, 0], zoom_start=2)
folium.Choropleth(
    geo_data=geojson_data,
    name='choropleth',
    data=country_avg_humidity,
    columns=['country', 'humidity'],
    key_on='feature.properties.name',
    fill_color='GnBu',
    fill_opacity=0.8,
    line_opacity=0.2,
    legend_name='Humidity',
    nan_fill_color='gray'
).add_to(m5)
m5
```

Out[29]:



This map shows that the americas may have highest humidity levels compared to the rest of the planet.

Conclusion

- Completed climate analysis through extensive data cleaning, feature engineering, and exploratory analysis.
- Developed and evaluated Ridge and XGBoost models for temperature prediction.
- Analyzed air quality and climate data to find environmental impact.
- Analyzed and visualized geographical patterns in the data through spatial analysis.
- Future improvements may include seasonal decomposition, deep learning, or ensemble modeling.

In [ ]: