data collection from Api

```
import requests
import pandas as pd

# Define a list of cities with their respective latitudes and
longitudes
cities = {
    "Lahore": {"latitude": 31.5204, "longitude": 74.3587},
    "Quetta": {"latitude": 30.1798, "longitude": 66.9750},
    "Karachi": {"latitude": 24.8607, "longitude": 67.0011},
    "Islamabad": {"latitude": 33.6844, "longitude": 73.0479}
}

# Define the API endpoint
url = "https://archive-api.open-meteo.com/v1/archive"

# Function to fetch weather data for a city
def fetch_weather_data(city, lat, lon, start_date, end_date):
    params = {
        "latitude": lat,
        "longitude": lon,
        "start_date": start_date,
        "end_date": end_date,
        "daily":
"temperature_2m_max,temperature_2m_min,temperature_2m_mean,precipitati
on_sum,wind_speed_10m_max,wind_gusts_10m_max,shortwave_radiation_sum,e
t0_fao_evapotranspiration",
        "timezone": "auto"
    }
    response = requests.get(url, params=params)
    if response.status_code == 200:
        data = response.json()
        if 'daily' in data:
            df = pd.DataFrame(data['daily'])
            df['city'] = city
            return df
        else:
            print(f"No daily data found for {city}.")
            return pd.DataFrame()
    else:
        print(f"Failed to fetch weather data for {city}. Status code:
{response.status_code}")
        return pd.DataFrame()

# Define the date range for data collection
start_date = "2020-01-01"
end_date = "2024-05-26"
```

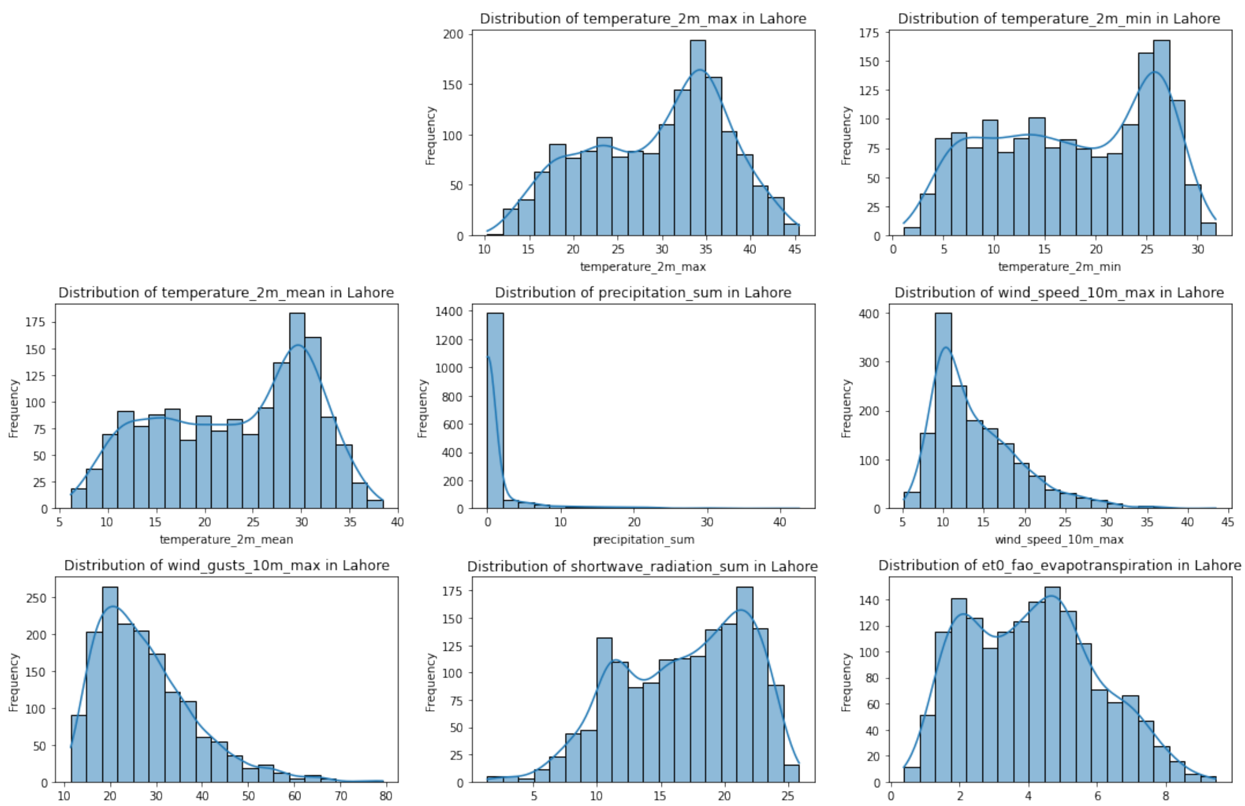
```
# Initialize an empty DataFrame to hold all cities' data
all_weather_data = pd.DataFrame()

# Loop through each city and fetch weather data
for city, coords in cities.items():
    lat = coords["latitude"]
    lon = coords["longitude"]
    city_weather_data = fetch_weather_data(city, lat, lon, start_date,
end_date)
    all_weather_data = pd.concat([all_weather_data,
city_weather_data], ignore_index=True)

# Save the collected data to a CSV file
all_weather_data.to_csv('weather_data_all_cities.csv', index=False)

print("Weather data for all cities saved to
'weather_data_all_cities.csv'.")
```

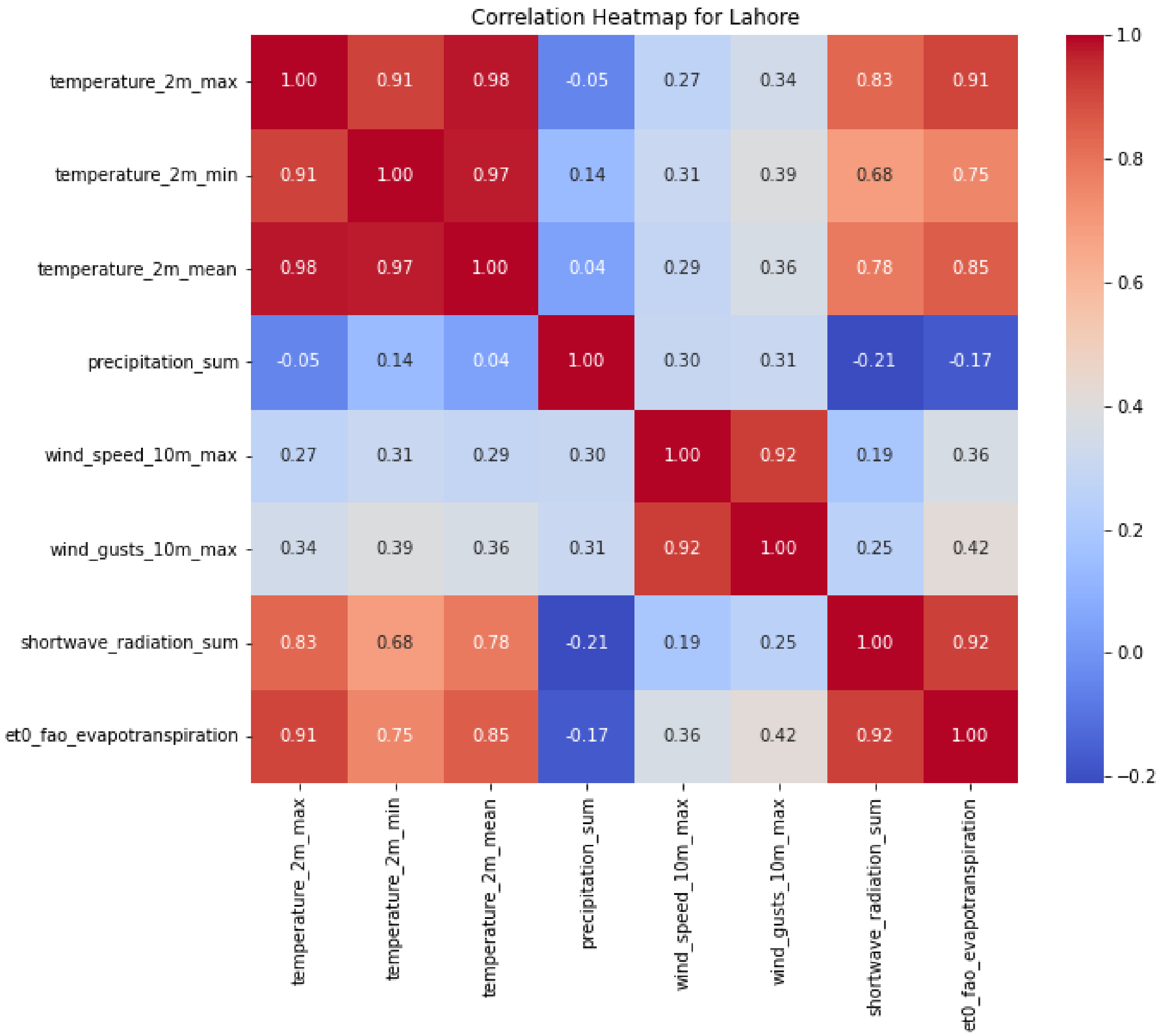
```
Weather data for all cities saved to 'weather_data_all_cities.csv'.
```

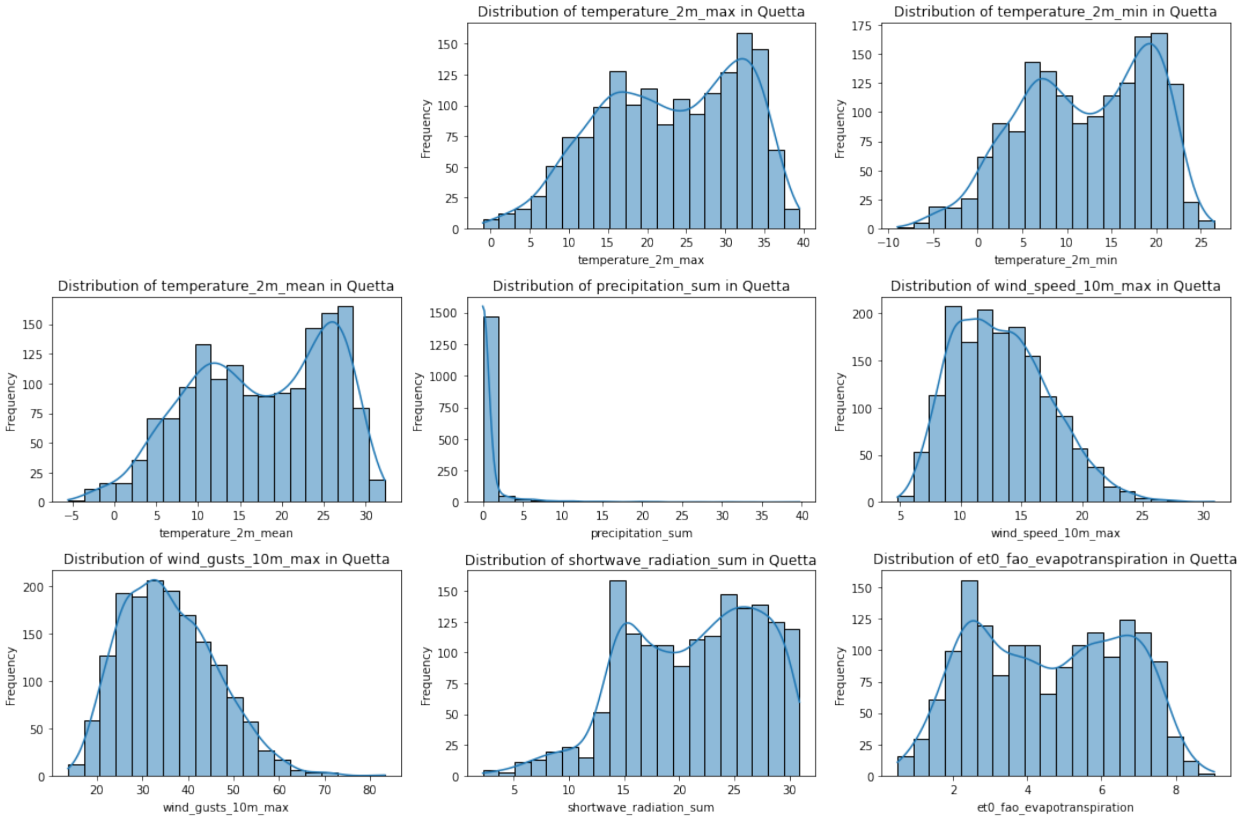
data preprocessing

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

# Load the collected weather data
weather_data = pd.read_csv('weather_data_all_cities.csv')

# Data Preprocessing and Exploration for each city
for city in cities.keys():
    city_data = weather_data[weather_data['city'] == city].copy()  #
Create a copy of the DataFrame

    # Handling missing values
    city_data.dropna(inplace=True)

    # Explore data distributions and handle outliers
    plt.figure(figsize=(15, 10))
    for i, column in enumerate(city_data.columns):
        if city_data[column].dtype != 'object':  # Exclude non-numeric
columns
            plt.subplot(3, 3, i + 1)
            sns.histplot(city_data[column], bins=20, kde=True)
            plt.title(f'Distribution of {column} in {city}')
            plt.xlabel(column)
            plt.ylabel('Frequency')
```

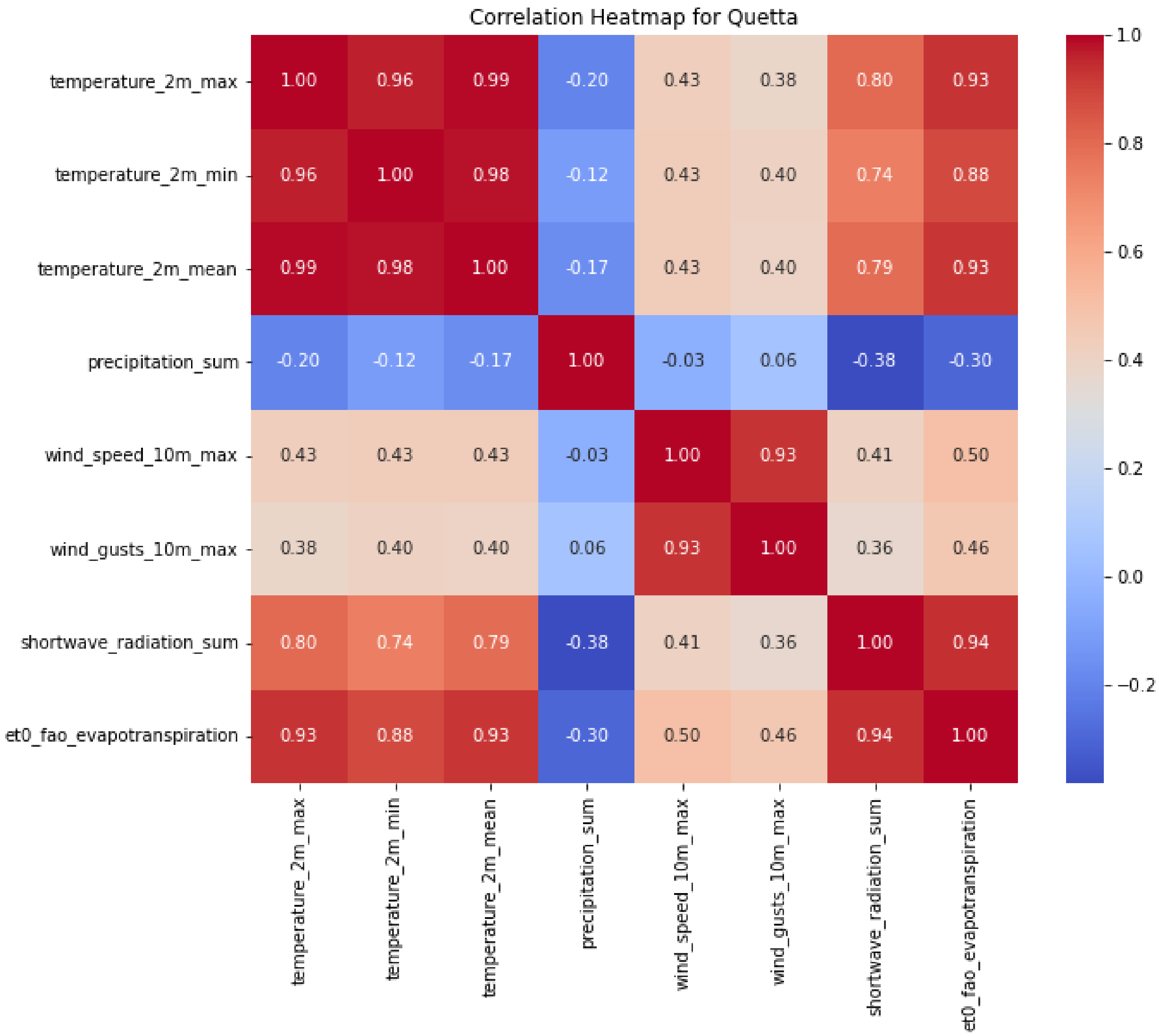
```
    plt.tight_layout()
    plt.show()

    # Convert categorical variables to numerical representations
    # One-hot encoding for city names
    city_data = pd.get_dummies(city_data, columns=['city'],
drop_first=True)

    # Visualize correlations using a heatmap
    plt.figure(figsize=(10, 8))
    correlation_matrix = city_data.corr()
    sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm',
fmt=".2f")
    plt.title(f'Correlation Heatmap for {city}')
    plt.show()


/opt/anaconda3/lib/python3.9/site-packages/scipy/__init__.py:146:
UserWarning: A NumPy version >=1.16.5 and <1.23.0 is required for this
version of SciPy (detected version 1.26.4
  warnings.warn(f"A NumPy version >={np_minversion} and
<{np_maxversion}"
```

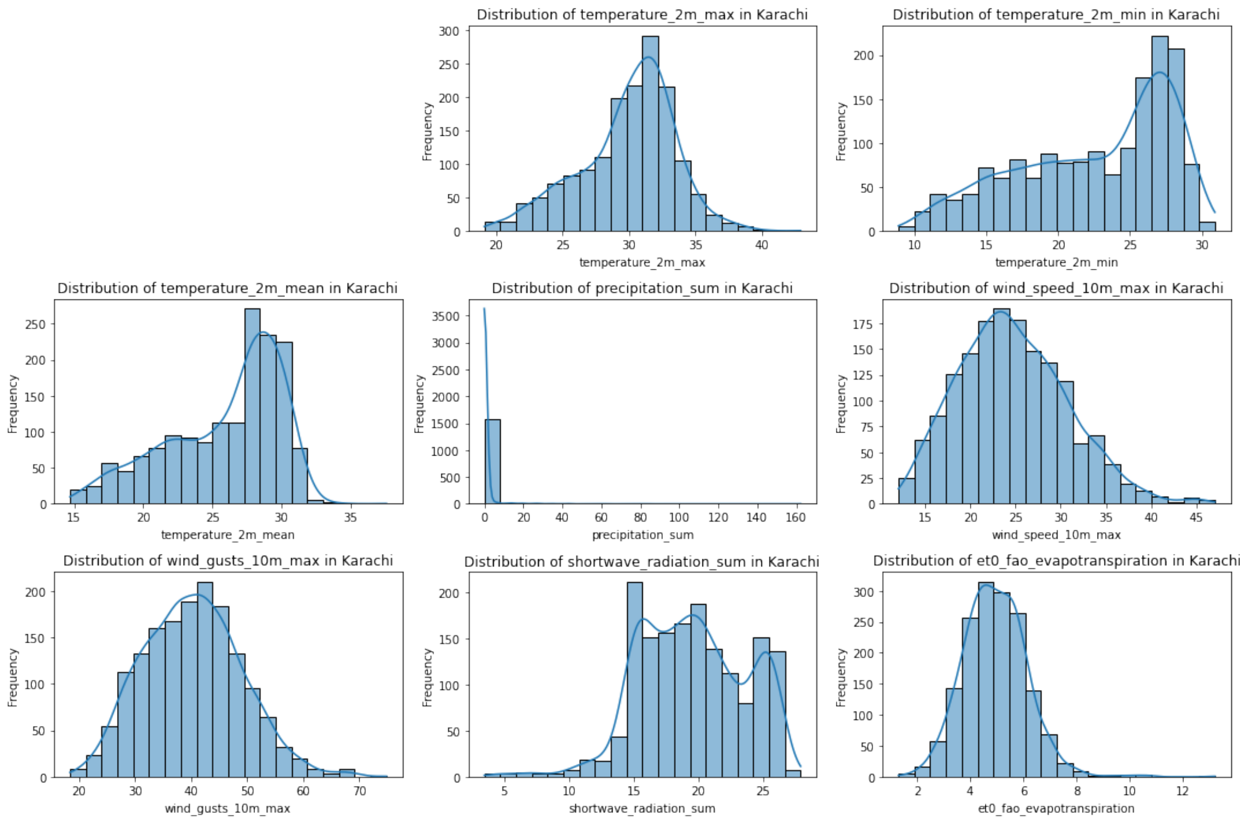


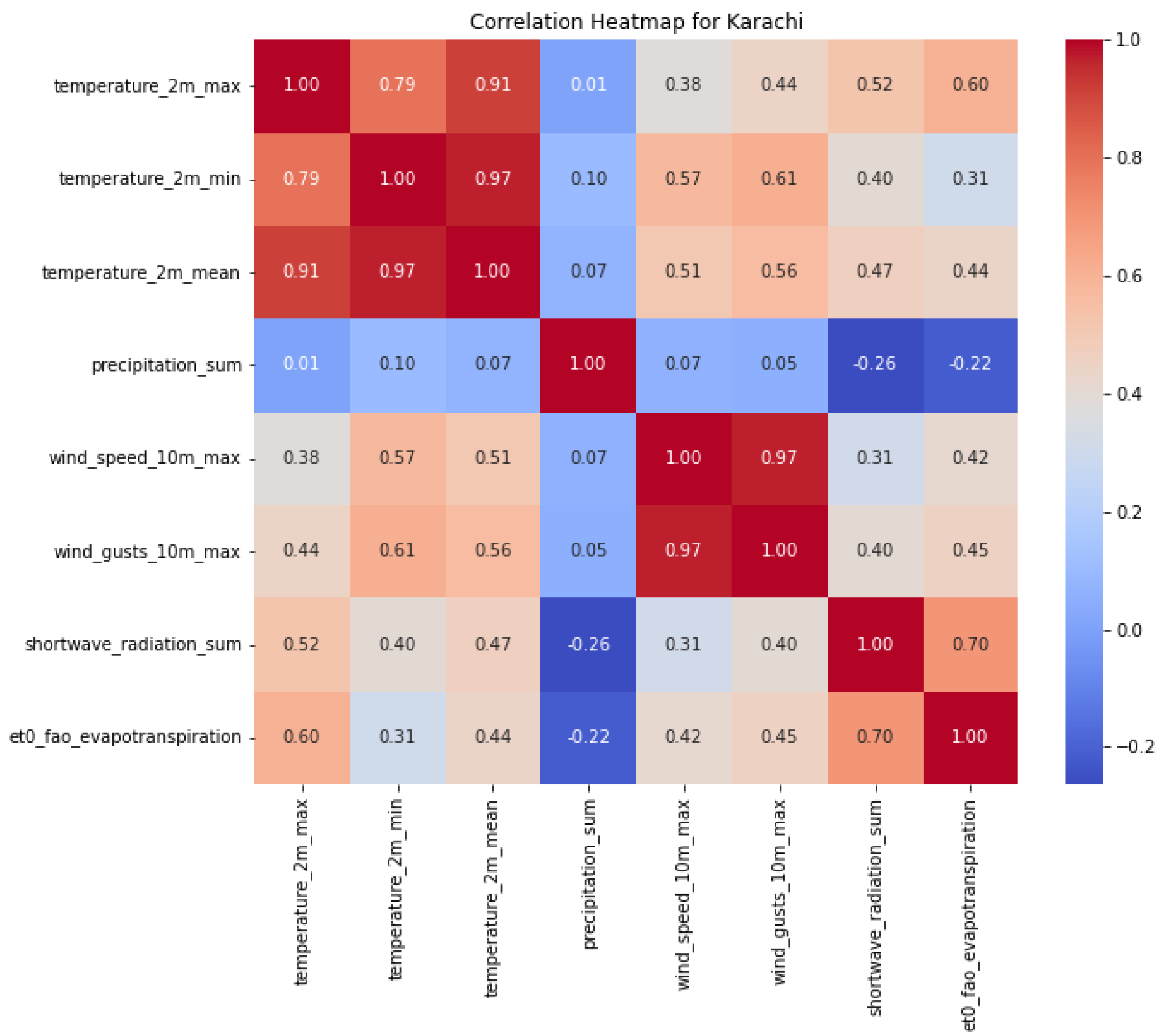

Correlation Heatmap for Lahore
temperature_2m_max
temperature_2m_min
temperature_2m_mean
precipitation_sum
wind_speed_10m_max
wind_gusts_10m_max
shortwave_radiation_sum
et0_fao_evapotranspiration
1.00 0.91 0.98 -0.05 0.27 0.34 0.83 0.91
0.91 1.00 0.97 0.14 0.31 0.39 0.68 0.75
0.98 0.97 1.00 0.04 0.29 0.36 0.78 0.85
-0.05 0.14 0.04 1.00 0.30 0.31 -0.21 -0.17
0.27 0.31 0.29 0.30 1.00 0.92 0.19 0.36
0.34 0.39 0.36 0.31 0.92 1.00 0.25 0.42
0.83 0.68 0.78 -0.21 0.19 0.25 1.00 0.92
0.91 0.75 0.85 -0.17 0.36 0.42 0.92 1.00
1.0
0.8
0.6
0.4
0.2
0.0
−0.2

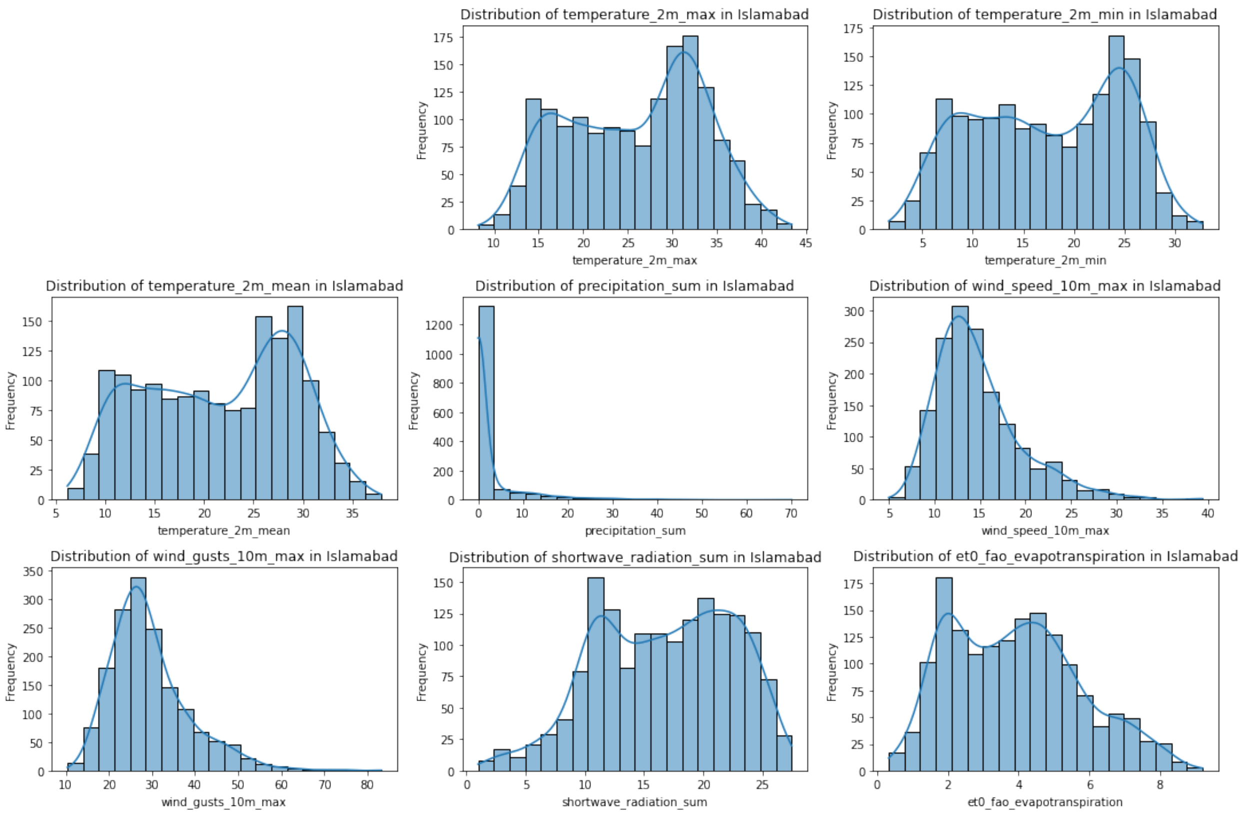


Distribution of temperature_2m_max in Quetta
Frequency
temperature_2m_max
Distribution of temperature_2m_min in Quetta
Frequency
temperature_2m_min
Distribution of temperature_2m_mean in Quetta
Frequency
temperature_2m_mean
Distribution of precipitation_sum in Quetta
Frequency
precipitation_sum
Distribution of wind_speed_10m_max in Quetta
Frequency
wind_speed_10m_max
Distribution of wind_gusts_10m_max in Quetta
Frequency
wind_gusts_10m_max
Distribution of shortwave_radiation_sum in Quetta
Frequency
shortwave_radiation_sum
Distribution of et0_fao_evapotranspiration in Quetta
Frequency
et0_fao_evapotranspiration

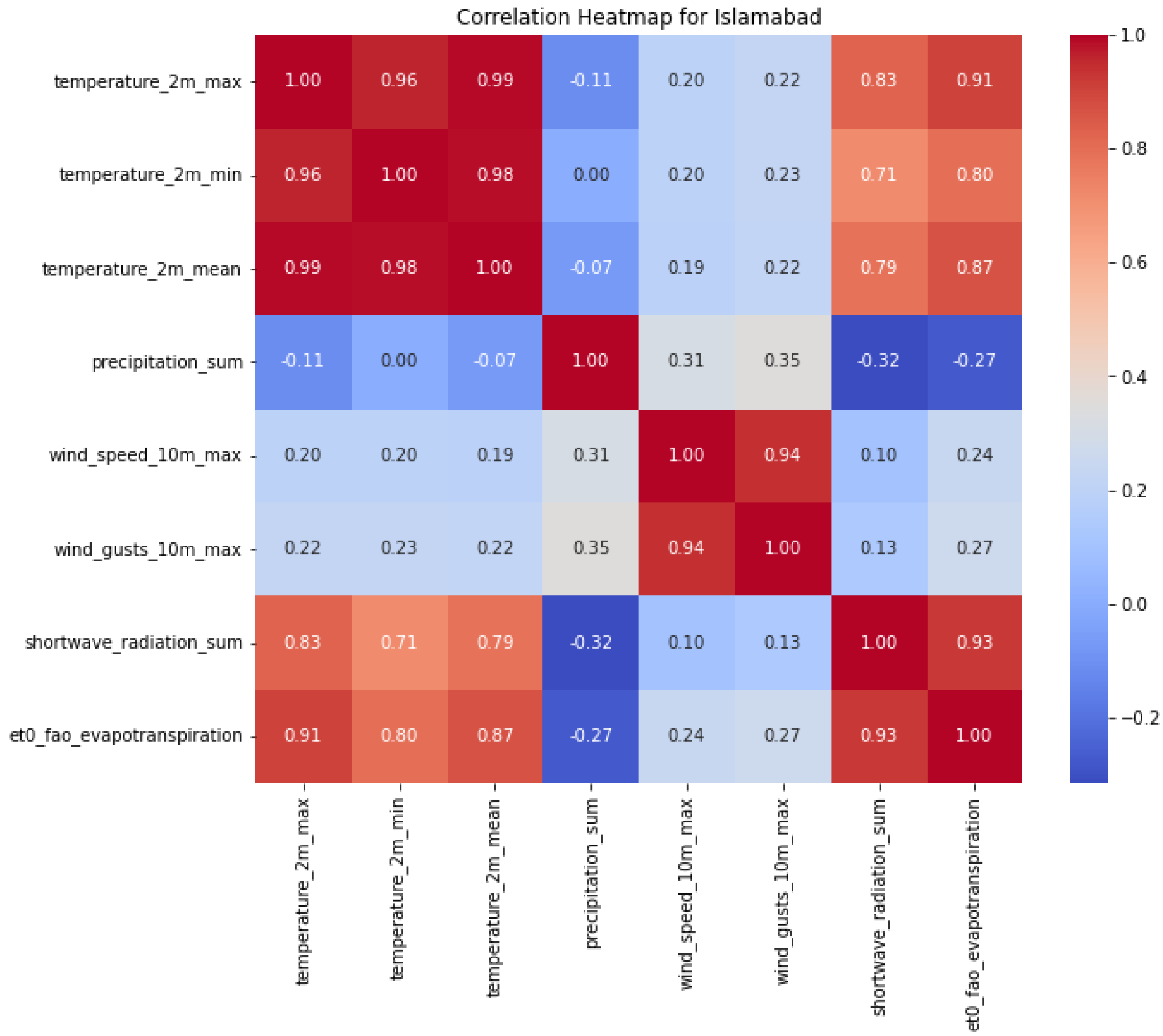

Correlation Heatmap for Quetta
temperature_2m_max
temperature_2m_min
temperature_2m_mean
precipitation_sum
wind_speed_10m_max
wind_gusts_10m_max
shortwave_radiation_sum
et0_fao_evapotranspiration
1.00 0.96 0.99 -0.20 0.43 0.38 0.80 0.93
0.96 1.00 0.98 -0.12 0.43 0.40 0.74 0.88
0.99 0.98 1.00 -0.17 0.43 0.40 0.79 0.93
-0.20 -0.12 -0.17 1.00 -0.03 0.06 -0.38 -0.30
0.43 0.43 0.43 -0.03 1.00 0.93 0.41 0.50
0.38 0.40 0.40 0.06 0.93 1.00 0.36 0.46
0.80 0.74 0.79 -0.38 0.41 0.36 1.00 0.94
0.93 0.88 0.93 -0.30 0.50 0.46 0.94 1.00
1.0
0.8
0.6
0.4
0.2
0.0
−0.2


Distribution of temperature_2m_max in Karachi
Frequency
temperature_2m_max
Distribution of temperature_2m_min in Karachi
Frequency
temperature_2m_min
Distribution of temperature_2m_mean in Karachi
Frequency
temperature_2m_mean
Distribution of precipitation_sum in Karachi
Frequency
precipitation_sum
Distribution of wind_speed_10m_max in Karachi
Frequency
wind_speed_10m_max
Distribution of wind_gusts_10m_max in Karachi
Frequency
wind_gusts_10m_max
Distribution of shortwave_radiation_sum in Karachi
Frequency
shortwave_radiation_sum
Distribution of et0_fao_evapotranspiration in Karachi
Frequency
et0_fao_evapotranspiration


Correlation Heatmap for Karachi
temperature_2m_max
temperature_2m_min
temperature_2m_mean
precipitation_sum
wind_speed_10m_max
wind_gusts_10m_max
shortwave_radiation_sum
et0_fao_evapotranspiration
1.00 0.79 0.91 0.01 0.38 0.44 0.52 0.60
0.79 1.00 0.97 0.10 0.57 0.61 0.40 0.31
0.91 0.97 1.00 0.07 0.51 0.56 0.47 0.44
0.01 0.10 0.07 1.00 0.07 0.05 -0.26 -0.22
0.38 0.57 0.51 0.07 1.00 0.97 0.31 0.42
0.44 0.61 0.56 0.05 0.97 1.00 0.40 0.45
0.52 0.40 0.47 -0.26 0.31 0.40 1.00 0.70
0.60 0.31 0.44 -0.22 0.42 0.45 0.70 1.00
1.0
0.8
0.6
0.4
0.2
0.0
−0.2



Distribution of temperature_2m_max in Islamabad
Frequency
temperature_2m_max
Distribution of temperature_2m_min in Islamabad
Frequency
temperature_2m_min
Distribution of temperature_2m_mean in Islamabad
Frequency
temperature_2m_mean
Distribution of precipitation_sum in Islamabad
Frequency
precipitation_sum
Distribution of wind_speed_10m_max in Islamabad
Frequency
wind_speed_10m_max
Distribution of wind_gusts_10m_max in Islamabad
Frequency
wind_gusts_10m_max
Distribution of shortwave_radiation_sum in Islamabad
Frequency
shortwave_radiation_sum
Distribution of et0_fao_evapotranspiration in Islamabad
Frequency
et0_fao_evapotranspiration



feature engineering

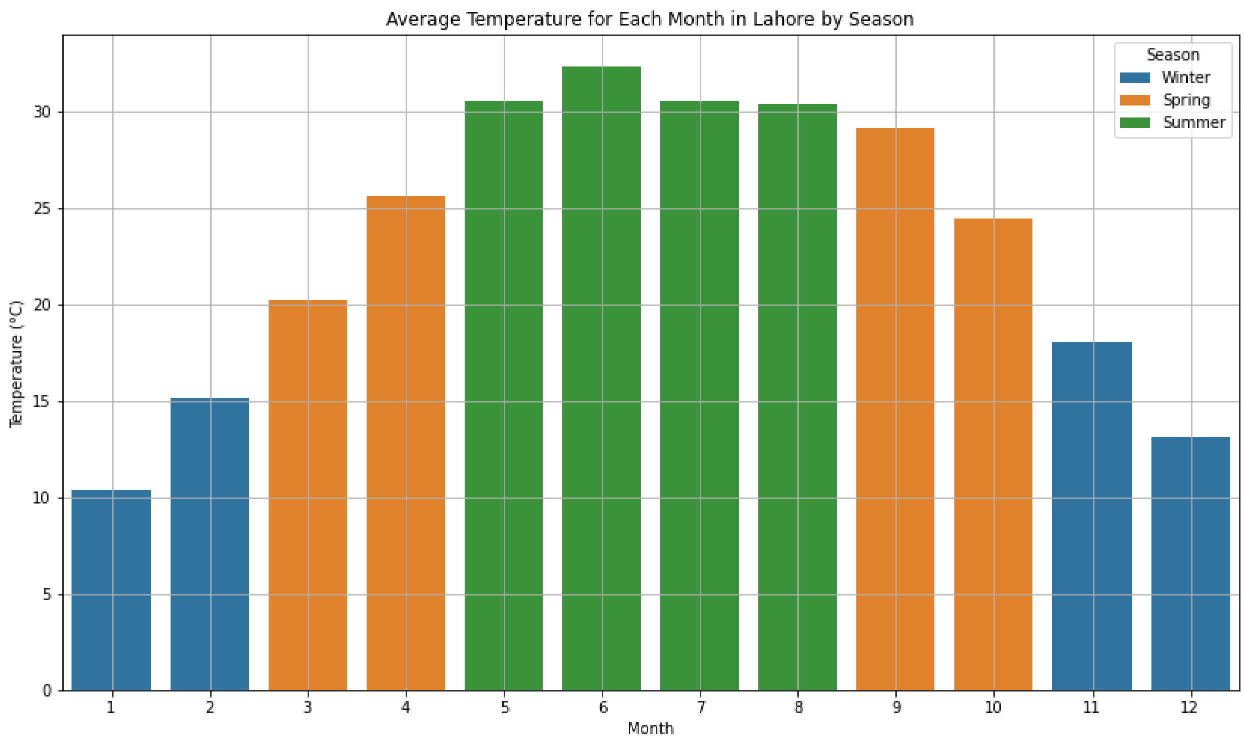
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Load the preprocessed weather data
weather_data = pd.read_csv('weather_data_all_cities.csv')

# Feature Engineering
# Extracting temporal features
weather_data['date'] = pd.to_datetime(weather_data['time'])  # Convert
'time' column to datetime
weather_data['day_of_week'] = weather_data['date'].dt.dayofweek  #
Extract day of the week (Monday=0, Sunday=6)
```

```
weather_data['month'] = weather_data['date'].dt.month  # Extract month

# Lagged variables (previous day's temperature)
weather_data['prev_day_temp_mean'] = weather_data.groupby('city')
['temperature_2m_mean'].shift(1)

# Drop unnecessary columns after feature engineering
weather_data.drop(columns=['time', 'date'], inplace=True)  # Drop
'time' and 'date' columns as we have extracted temporal features

# Create a binary column for rain occurrence (1 if precipitation_sum >
0, else 0)
weather_data['rain'] = weather_data['precipitation_sum'] > 0

# Define seasons based on temperature
def determine_season(temp):
    if temp < 20:
        return 'Winter'
    elif 20 <= temp <= 30:
        return 'Spring'
    else:
        return 'Summer'

weather_data['season'] =
weather_data['temperature_2m_mean'].apply(determine_season)

# Display the updated DataFrame with engineered features
print(weather_data.head())

# Group by city and month, then calculate the average temperature
monthly_avg_temp = weather_data.groupby(['city', 'month'])
['temperature_2m_mean'].mean().reset_index()

# Add season information to the monthly average temperatures
monthly_avg_temp['season'] =
monthly_avg_temp['temperature_2m_mean'].apply(determine_season)

# Visualization for each city - Highest Average Temperature
for city in weather_data['city'].unique():
    city_monthly_avg_temp = monthly_avg_temp[monthly_avg_temp['city']
== city]

    plt.figure(figsize=(14, 8))
    sns.barplot(data=city_monthly_avg_temp, x='month',
y='temperature_2m_mean', hue='season', dodge=False, palette='tab10')
    plt.title(f'Average Temperature for Each Month in {city} by
Season')
    plt.xlabel('Month')
    plt.ylabel('Temperature (°C)')
    plt.legend(title='Season')
```

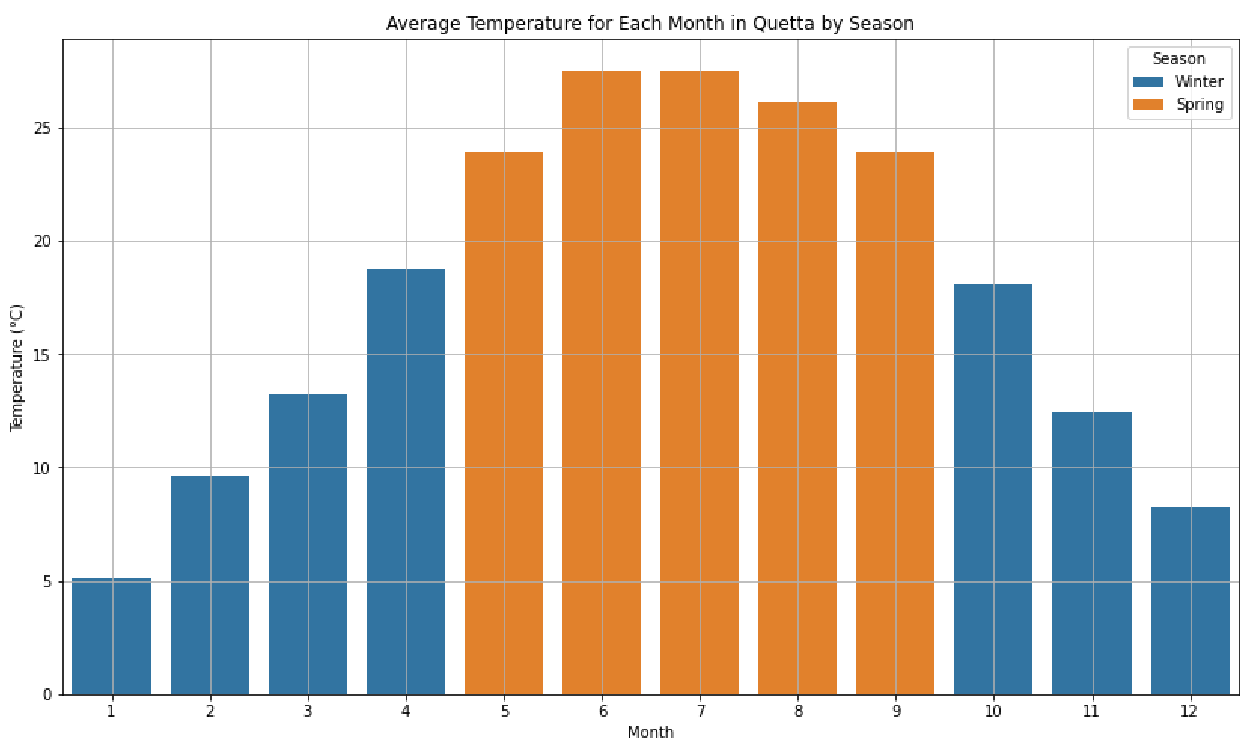
```
    plt.grid(True)
    plt.show()

# Visualization for each city - Seasons
for city in weather_data['city'].unique():
    city_data = weather_data[weather_data['city'] == city]

    plt.figure(figsize=(14, 8))
    sns.barplot(data=city_data, x='month', y='temperature_2m_mean',
hue='season', dodge=False, palette='tab10')
    plt.title(f'Seasonal Temperature Variation for Each Month in
{city}')
    plt.xlabel('Month')
    plt.ylabel('Temperature (°C)')
    plt.legend(title='Season')
    plt.grid(True)
    plt.show()

# Group by city and month, then calculate the probability of rain
monthly_rain_chances = weather_data.groupby(['city', 'month'])
['rain'].mean().reset_index()

# Visualization for each city - Chances of Rain
for city in weather_data['city'].unique():
    city_monthly_rain_chances =
monthly_rain_chances[monthly_rain_chances['city'] == city]

    plt.figure(figsize=(14, 8))
    sns.barplot(data=city_monthly_rain_chances, x='month', y='rain',
palette='tab10')
    plt.title(f'Chances of Rain for Each Month in {city}')
    plt.xlabel('Month')
    plt.ylabel('Chance of Rain')
    plt.grid(True)
    plt.show()

# Combined visualization comparing all cities month and season-wise
plt.figure(figsize=(18, 10))
sns.barplot(data=monthly_avg_temp, x='month', y='temperature_2m_mean',
hue='city', dodge=True, palette='tab10')
plt.title('Comparison of Average Monthly Temperatures by City and
Season')
plt.xlabel('Month')
plt.ylabel('Average Temperature (°C)')
plt.legend(title='City', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.grid(True)
plt.show()
```

```
   temperature_2m_max  temperature_2m_min  temperature_2m_mean  \
0                13.4                 2.0                  6.2
```

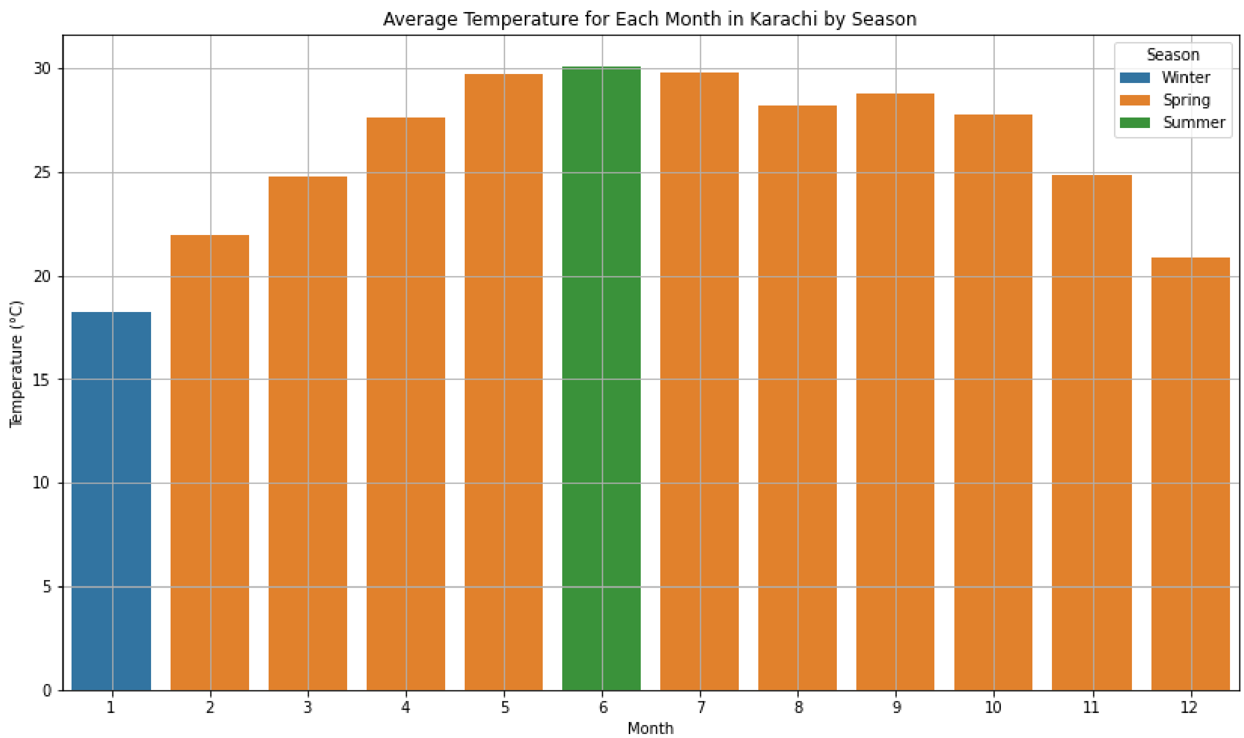
```
1                 18.0                 3.9                  9.5
2                 18.0                 4.2                 11.3
3                 16.4                 5.3                 10.6
4                 15.9                 5.1                 10.4

   precipitation_sum  wind_speed_10m_max  wind_gusts_10m_max  \
0                0.0                10.1                15.8
1                0.0                10.4                21.2
2                0.0                 9.6                17.3
3                0.2                10.2                21.2
4                1.0                 8.6                15.1

   shortwave_radiation_sum  et0_fao_evapotranspiration    city
day_of_week  \
0                     9.36                        1.23  Lahore
2
1                    10.17                        1.61  Lahore
3
2                    11.63                        1.78  Lahore
4
3                     8.84                        1.45  Lahore
5
4                     7.32                        1.21  Lahore
6

   month  prev_day_temp_mean   rain  season
0      1                 NaN  False  Winter
1      1                 6.2  False  Winter
2      1                 9.5  False  Winter
3      1                11.3   True  Winter
4      1                10.6   True  Winter
```

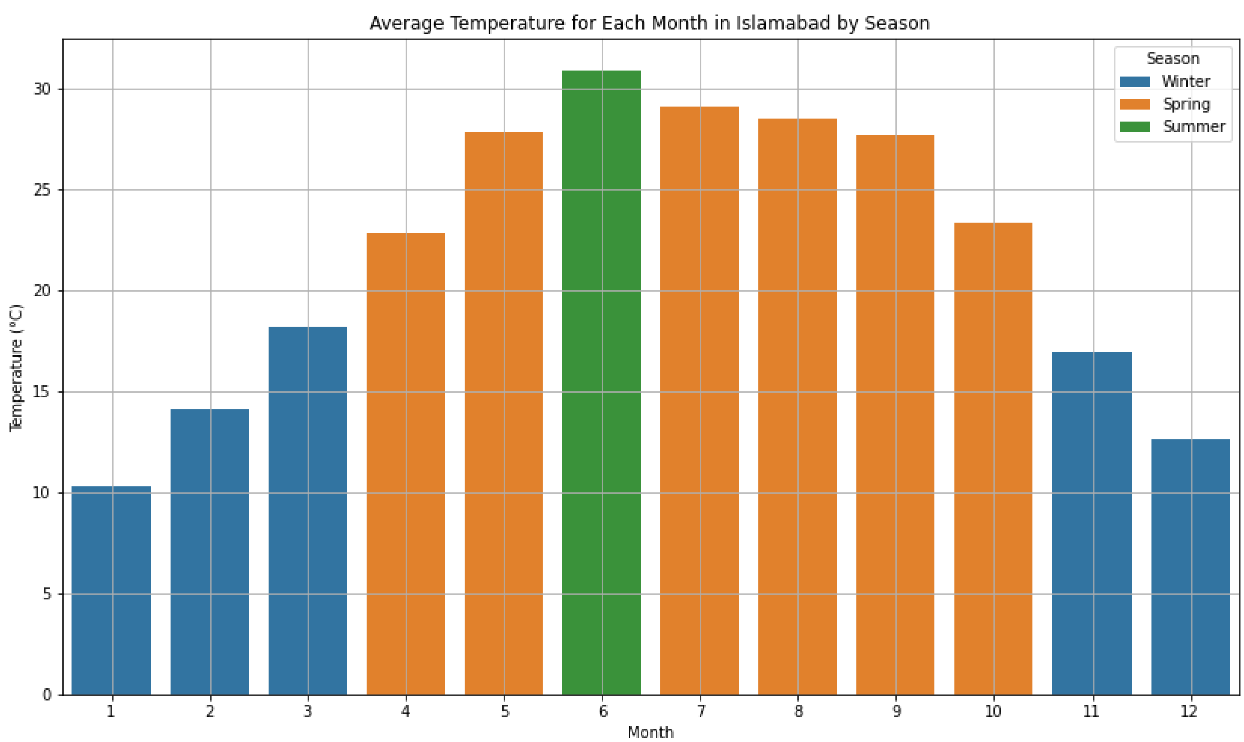


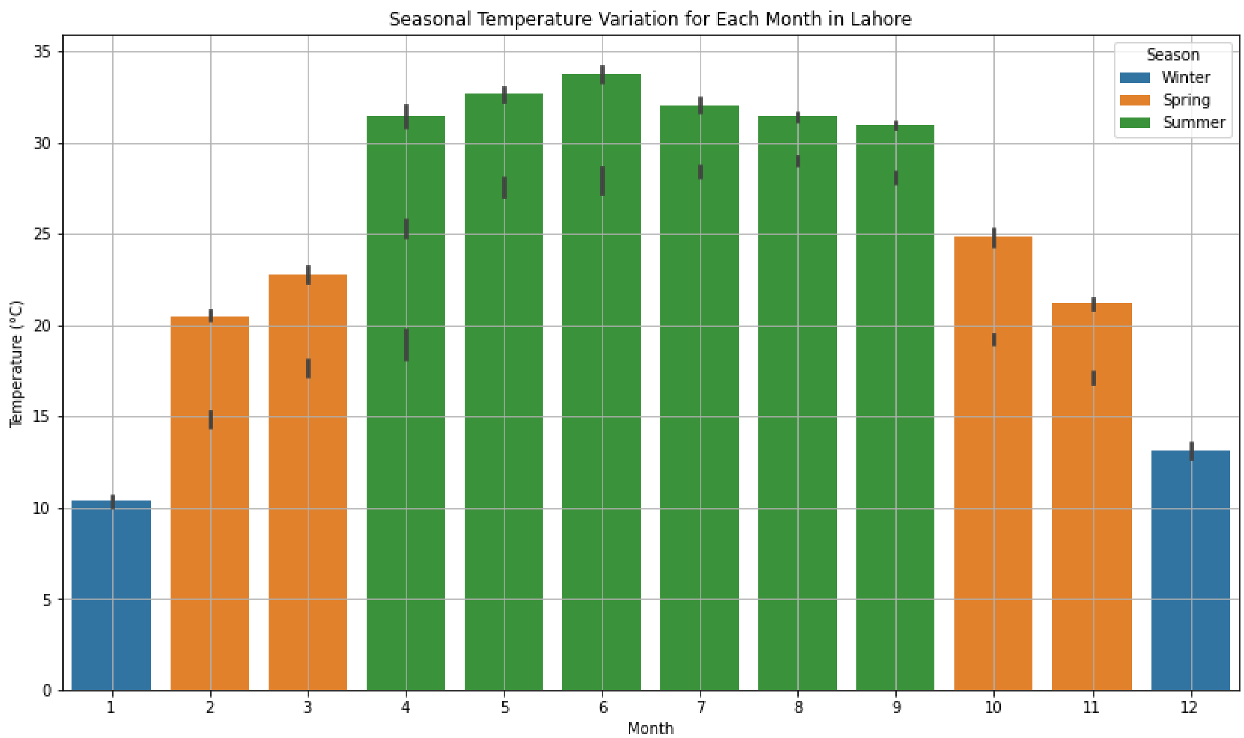
Average Temperature for Each Month in Lahore by Season
Season
Winter
Spring
Summer
Temperature (°C)
0
5
10
15
20
25
30
1
2
3
4
5
6
7
8
9
10
11
12
Month

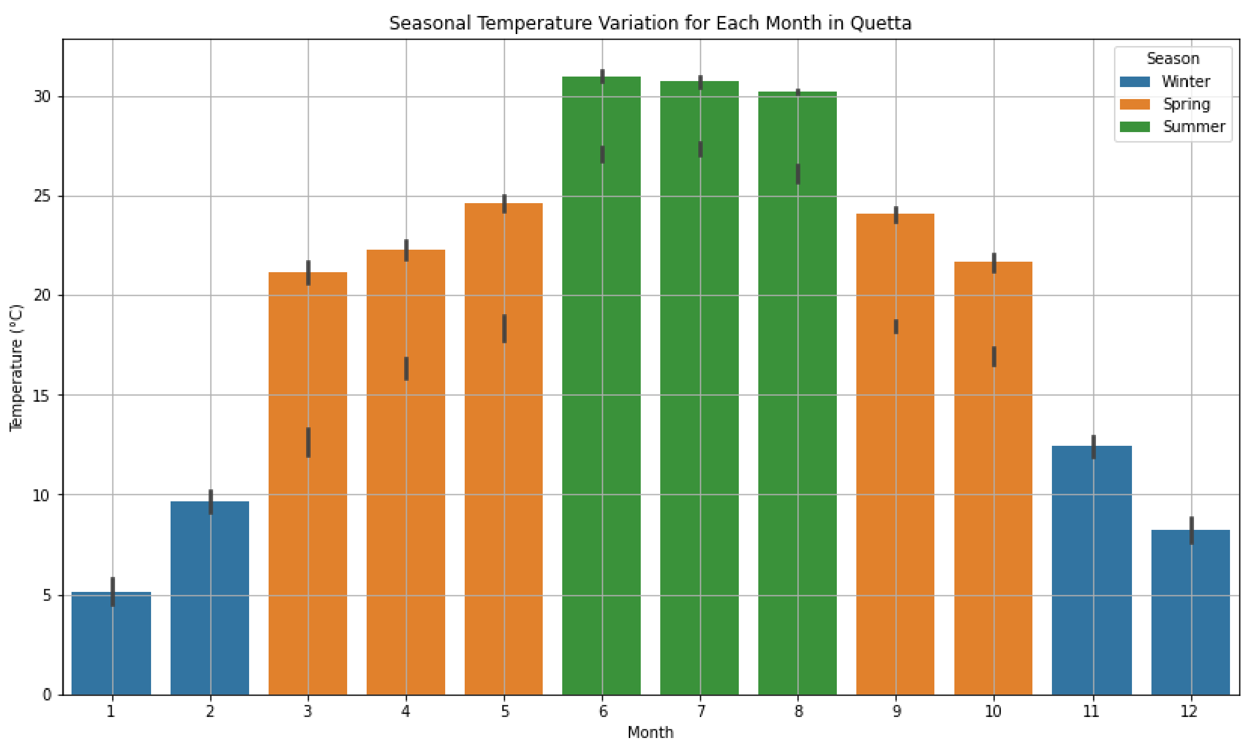


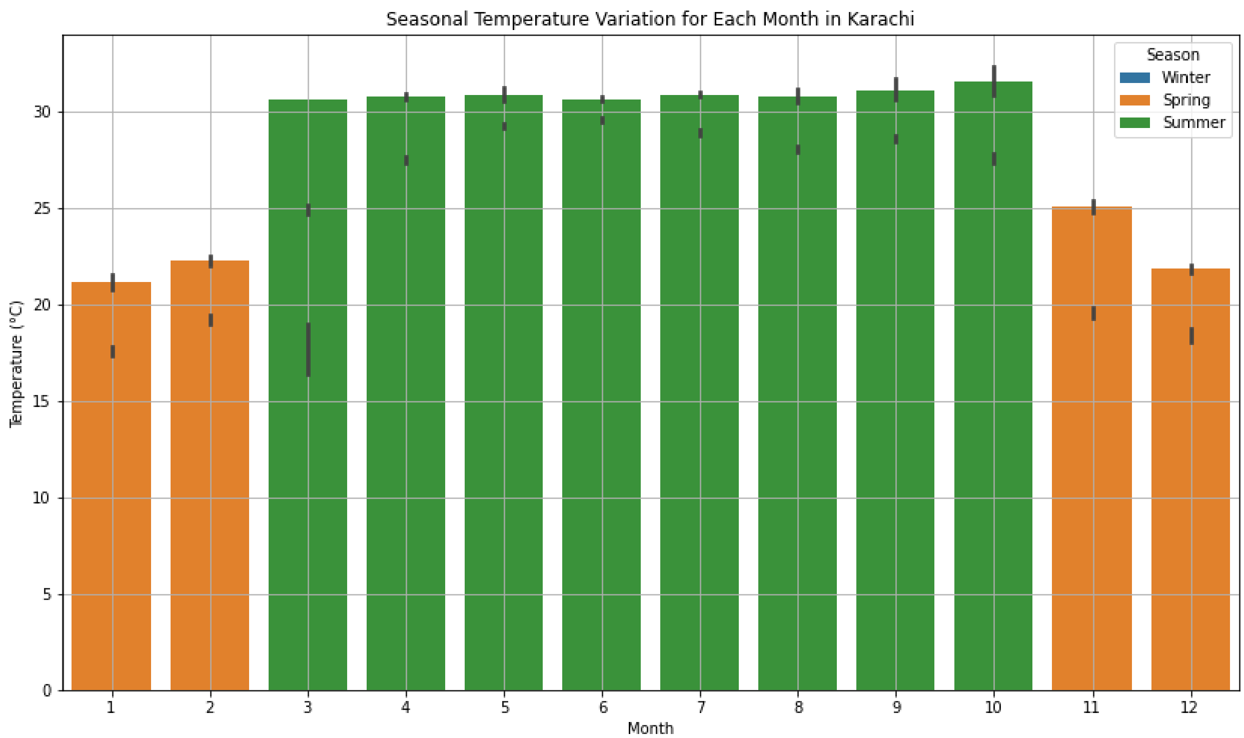
Average Temperature for Each Month in Quetta by Season
Season
Winter
Spring
Temperature (°C)
0
5
10
15
20
25
1
2
3
4
5
6
7
8
9
10
11
12
Month

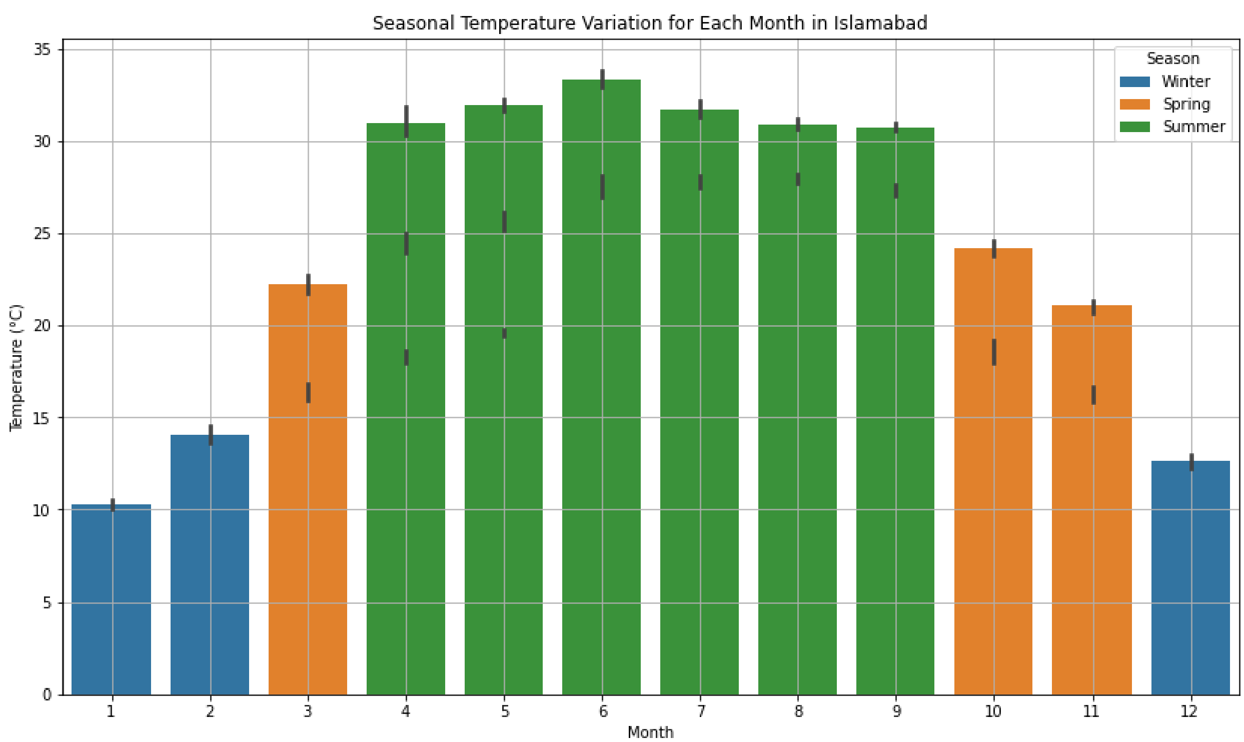

Average Temperature for Each Month in Karachi by Season
Season
Winter
Spring
Summer
Temperature (°C)
0
5
10
15
20
25
30
1
2
3
4
5
6
7
8
9
10
11
12
Month

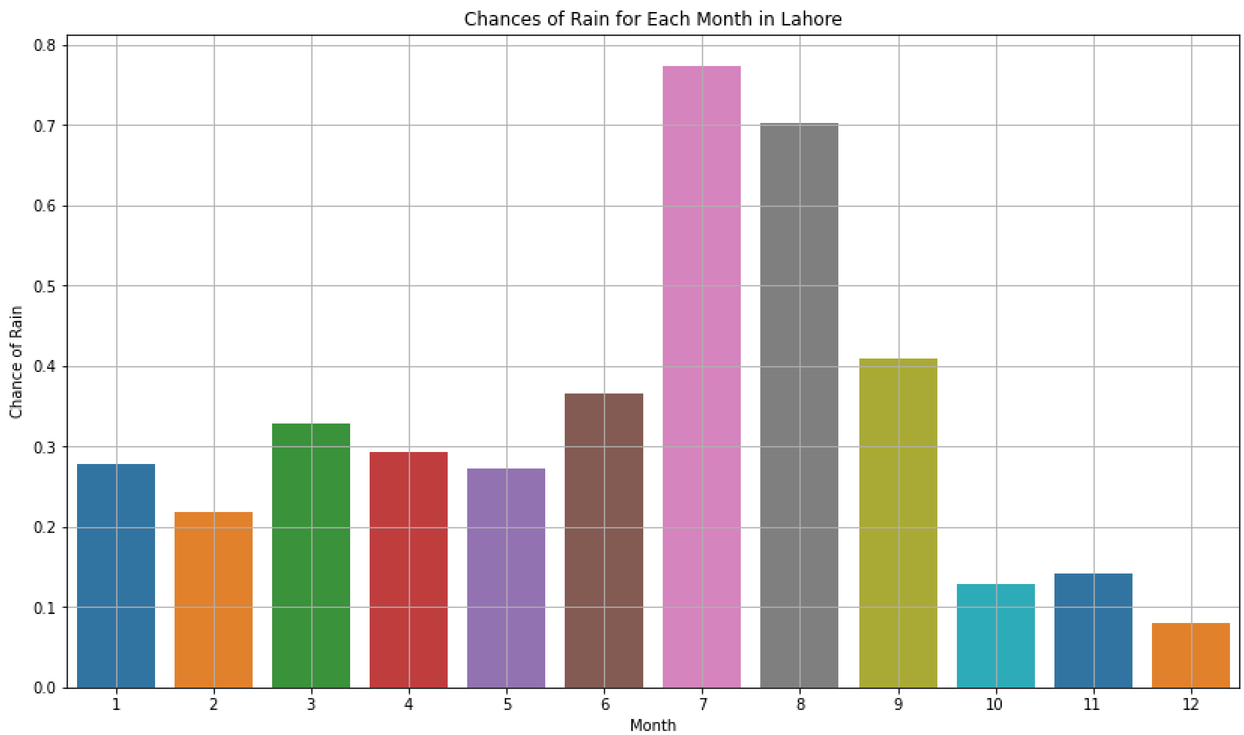

Average Temperature for Each Month in Islamabad by Season
Season
Winter
Spring
Summer
Temperature (°C)
0
5
10
15
20
25
30
1
2
3
4
5
6
7
8
9
10
11
12
Month

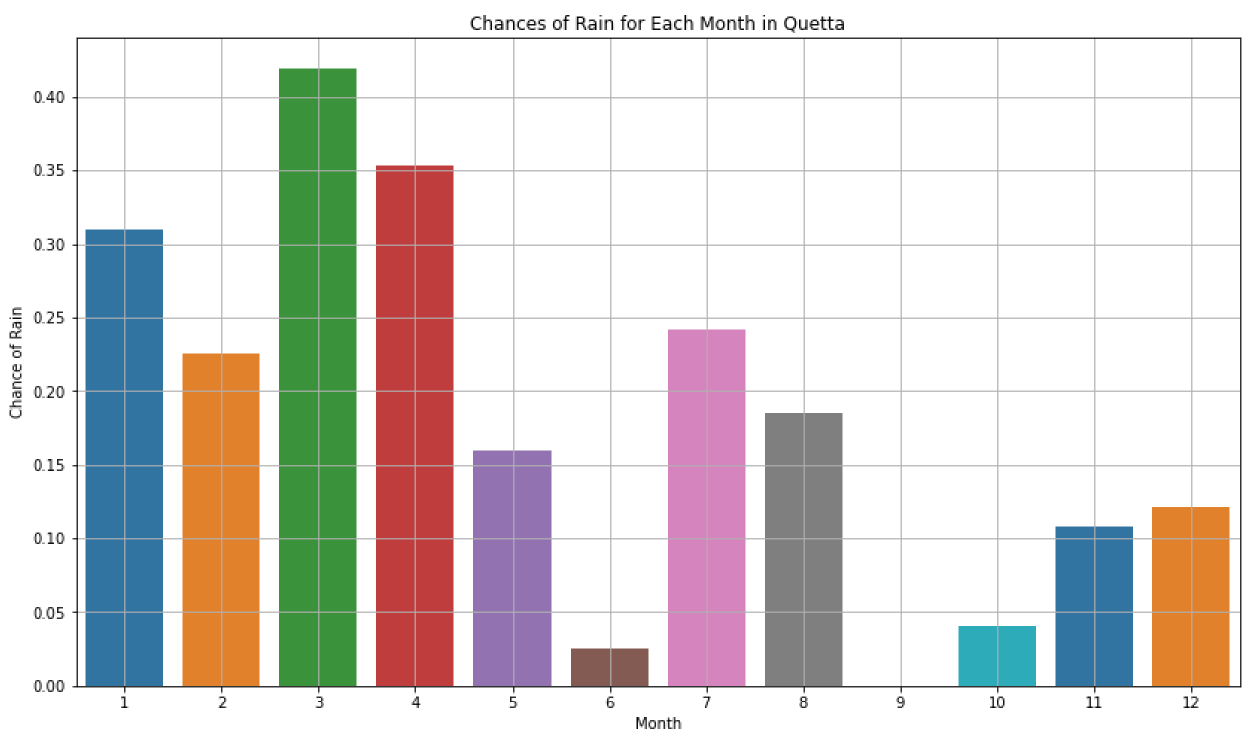

Seasonal Temperature Variation for Each Month in Lahore
Season
Winter
Spring
Summer
Temperature (°C)
Month
0
5
10
15
20
25
30
35
1
2
3
4
5
6
7
8
9
10
11
12

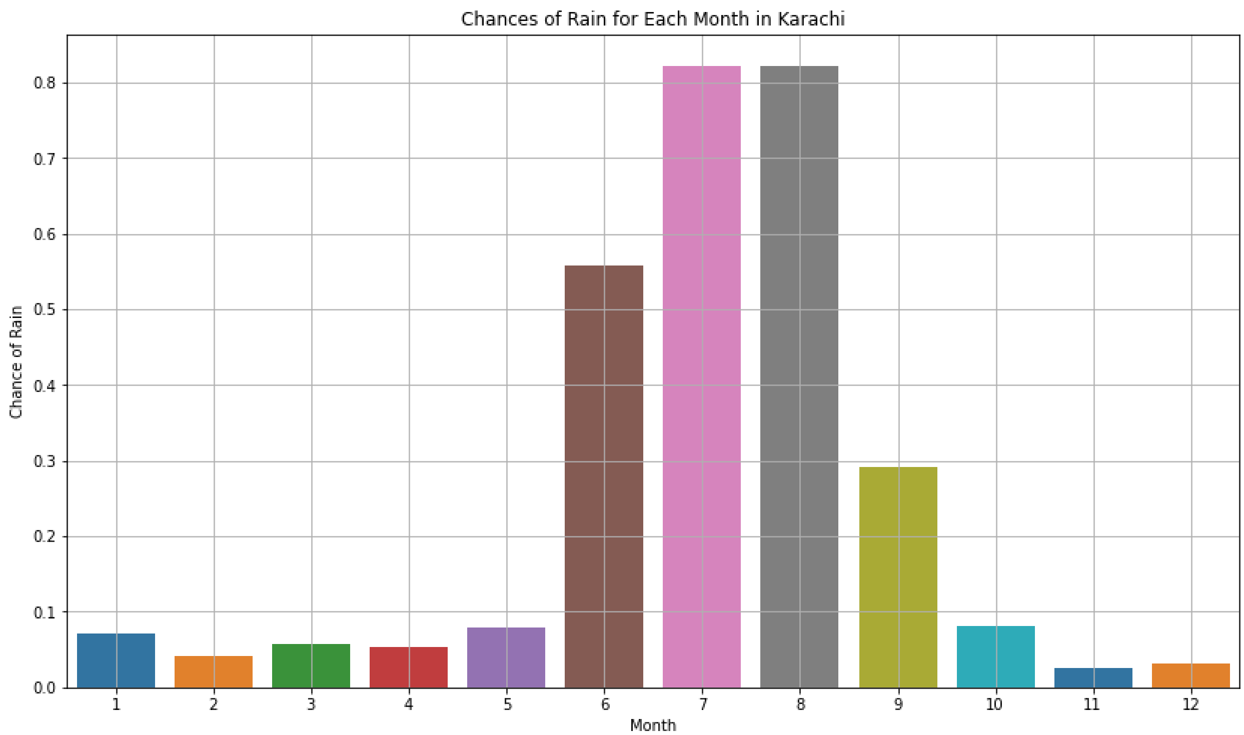

Seasonal Temperature Variation for Each Month in Quetta
Season
Winter
Spring
Summer
Temperature (°C)
Month
0
5
10
15
20
25
30
1
2
3
4
5
6
7
8
9
10
11
12

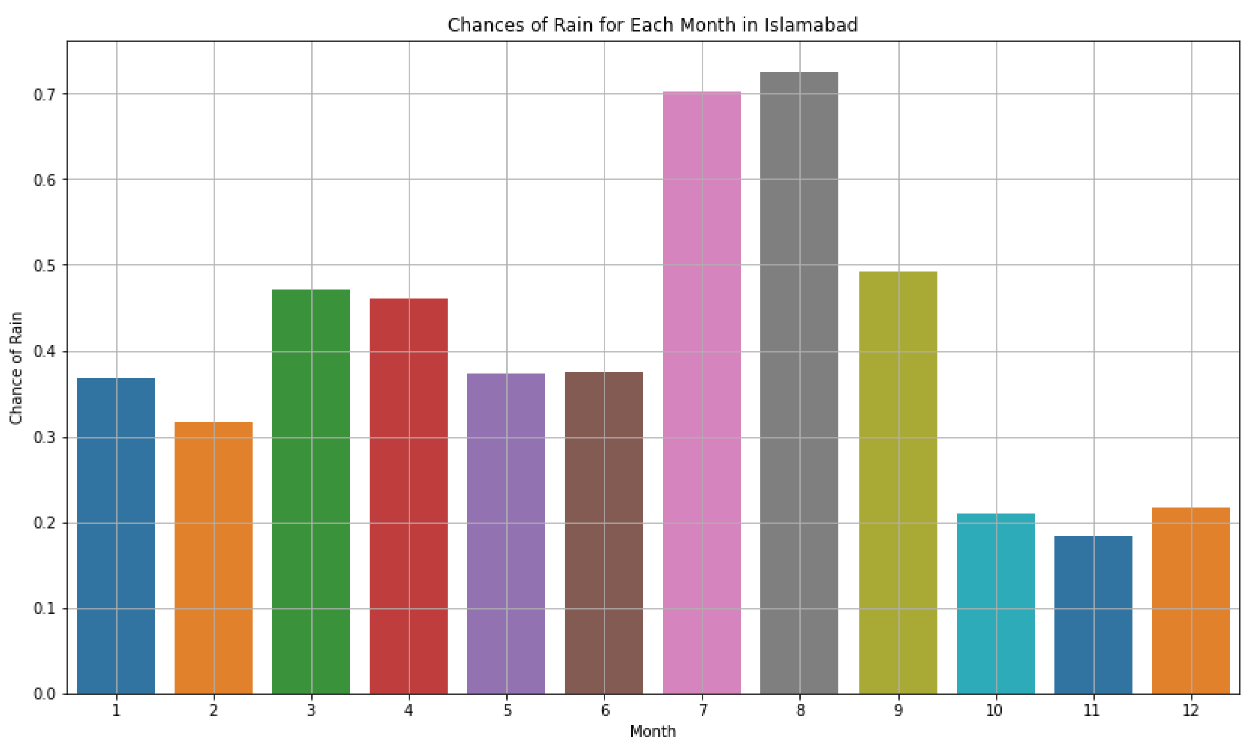

Seasonal Temperature Variation for Each Month in Karachi
Season
Winter
Spring
Summer
Temperature (°C)
Month
0
5
10
15
20
25
30
1
2
3
4
5
6
7
8
9
10
11
12

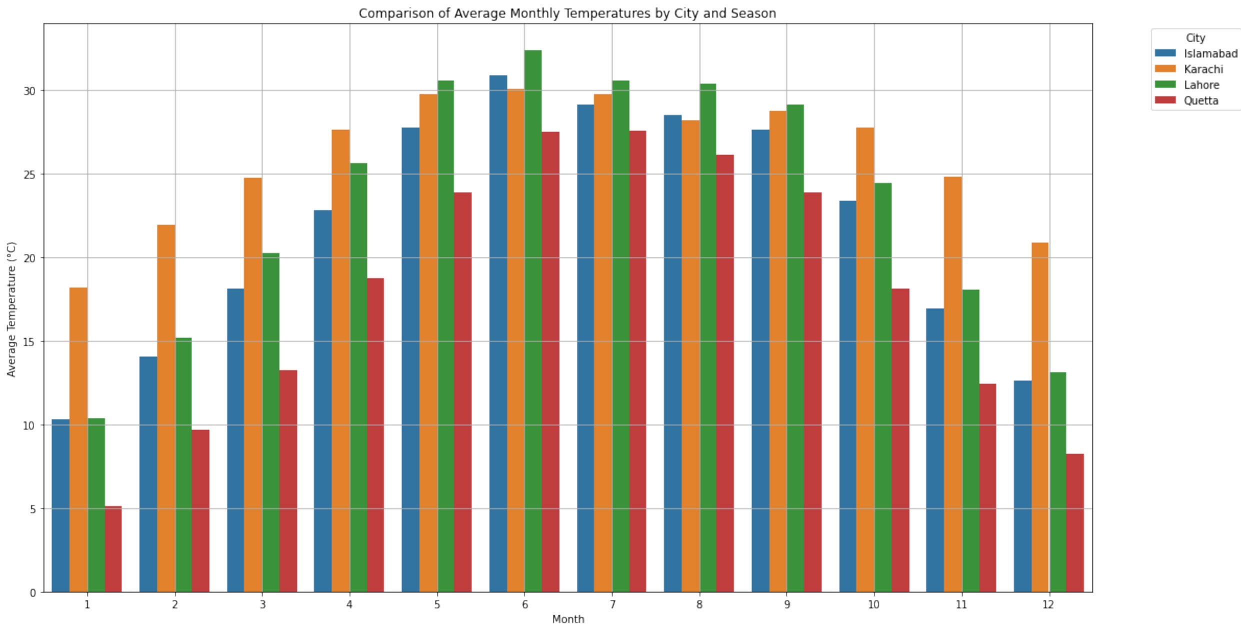

Seasonal Temperature Variation for Each Month in Islamabad
Season
Winter
Spring
Summer
Temperature (°C)
Month
0
5
10
15
20
25
30
35
1
2
3
4
5
6
7
8
9
10
11
12


Chances of Rain for Each Month in Lahore
Chance of Rain
Month
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
1
2
3
4
5
6
7
8
9
10
11
12


Chances of Rain for Each Month in Quetta
Chance of Rain
Month
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0.35
0.40
1
2
3
4
5
6
7
8
9
10
11
12


Chances of Rain for Each Month in Karachi
Chance of Rain
Month
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
1
2
3
4
5
6
7
8
9
10
11
12


Chances of Rain for Each Month in Islamabad
Chance of Rain
Month
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
1
2
3
4
5
6
7
8
9
10
11
12



check data columns

```
print(weather_data.columns)

Index(['temperature_2m_max', 'temperature_2m_min',
'temperature_2m_mean',
       'precipitation_sum', 'wind_speed_10m_max',
'wind_gusts_10m_max',
       'shortwave_radiation_sum', 'et0_fao_evapotranspiration',
'city',
       'day_of_week', 'month', 'prev_day_temp_mean', 'rain',
'season'],
      dtype='object')
```

data spliting

```
from sklearn.model_selection import train_test_split

# Define the features (X) and target variable (y)
X = weather_data.drop(columns=['temperature_2m_mean', 'city'])  #
Features excluding target variable and city
y = weather_data['temperature_2m_mean']  # Target variable (mean
temperature)

# Define indices for training and testing sets
train_indices = weather_data.sample(frac=0.8, random_state=42).index
test_indices = weather_data.drop(train_indices).index
```

```
# Split the data into training and testing sets using specific indices
X_train = X.loc[train_indices]
X_test = X.loc[test_indices]
y_train = y.loc[train_indices]
y_test = y.loc[test_indices]

# Display the shape of the training and testing sets
print("Shape of X_train:", X_train.shape)
print("Shape of X_test:", X_test.shape)
print("Shape of y_train:", y_train.shape)
print("Shape of y_test:", y_test.shape)
```

```
Shape of X_train: (5146, 12)
Shape of X_test: (1286, 12)
Shape of y_train: (5146,)
Shape of y_test: (1286,)
```

```
weather_data.dropna(inplace=True)
```

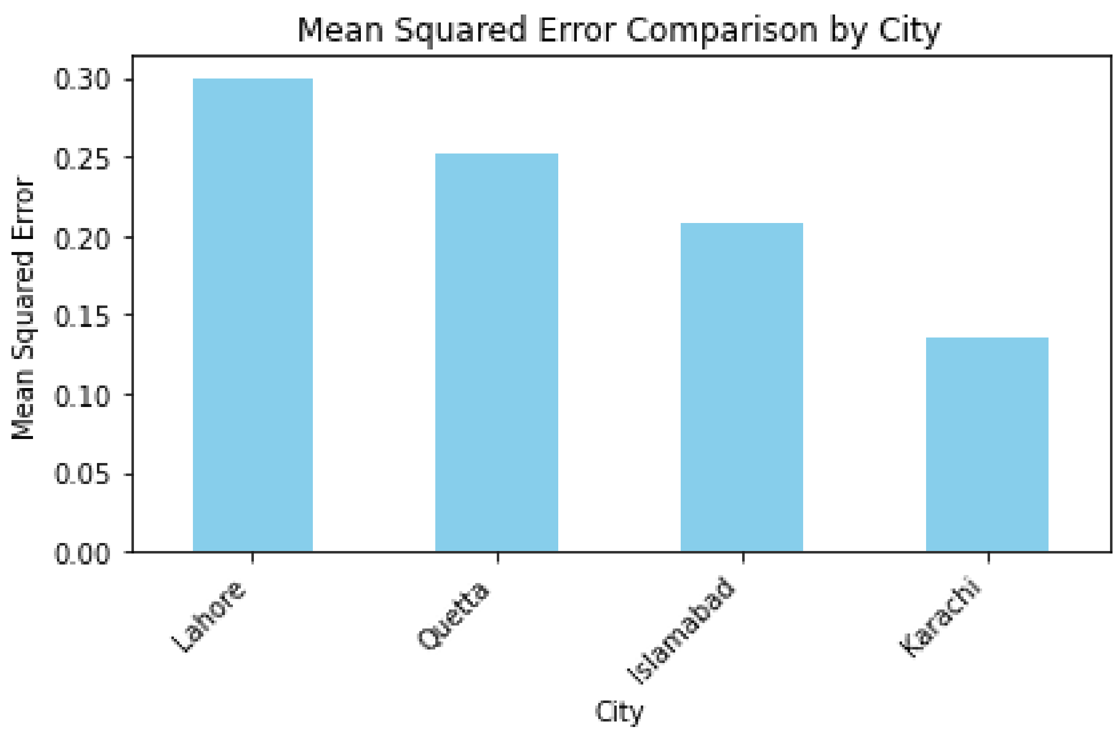
model training

```
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error

# Load the preprocessed weather data
weather_data = pd.read_csv('weather_data_all_cities.csv')

# Feature Engineering
# Extracting temporal features
weather_data['date'] = pd.to_datetime(weather_data['time'])  # Convert
'time' column to datetime
weather_data['day_of_week'] = weather_data['date'].dt.dayofweek  #
Extract day of the week (Monday=0, Sunday=6)
weather_data['month'] = weather_data['date'].dt.month  # Extract month

# Lagged variables (previous day's temperature)
weather_data['prev_day_temp_mean'] = weather_data.groupby('city')
['temperature_2m_mean'].shift(1)

# Drop unnecessary columns after feature engineering
weather_data.drop(columns=['time', 'date'], inplace=True)  # Drop
'time' and 'date' columns as we have extracted temporal features

# Remove rows with missing values
```

```
weather_data.dropna(inplace=True)

# Initialize an empty dictionary to store MSE values for each city
mse_per_city = {}

# Iterate over unique cities in the dataset
for city in weather_data['city'].unique():
    # Filter data for the current city
    city_data = weather_data[weather_data['city'] == city]

    # Define the features (X) and target variable (y) for the current
city
    X_city = city_data.drop(columns=['temperature_2m_mean', 'city'])
# Features excluding target variable and city
    y_city = city_data['temperature_2m_mean']  # Target variable (mean
temperature)

    # Define indices for training and testing sets for the current
city
    city_indices = city_data.index
    train_indices = city_data.sample(frac=0.8, random_state=42).index
    test_indices = city_data.drop(train_indices).index

    # Split the data into training and testing sets for the current
city using specific indices
    X_train_city = X_city.loc[train_indices]
    X_test_city = X_city.loc[test_indices]
    y_train_city = y_city.loc[train_indices]
    y_test_city = y_city.loc[test_indices]

    # Initialize the Random Forest Regression model for the current
city
    rf_model_city = RandomForestRegressor(random_state=42)

    # Train the model on the training data for the current city
    rf_model_city.fit(X_train_city, y_train_city)

    # Evaluate the model on the testing set for the current city
    y_pred_city = rf_model_city.predict(X_test_city)
    mse_city = mean_squared_error(y_test_city, y_pred_city)

    # Store the MSE value for the current city
    mse_per_city[city] = mse_city

# Convert the MSE dictionary to a pandas DataFrame
mse_df = pd.DataFrame.from_dict(mse_per_city, orient='index',
columns=['MSE'])

# Print the MSE for each city
print("Mean Squared Error (MSE) for Each City:")
```

```
print(mse_df)

# Plot the MSE comparison for each city
plt.figure(figsize=(10, 6))
mse_df.sort_values(by='MSE', ascending=False).plot(kind='bar',
color='skyblue', legend=None)
plt.title('Mean Squared Error Comparison by City')
plt.xlabel('City')
plt.ylabel('Mean Squared Error')
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.show()
```

```
Mean Squared Error (MSE) for Each City:
                MSE
Lahore     0.298915
Quetta     0.252637
Karachi    0.135979
Islamabad  0.207889

<Figure size 720x432 with 0 Axes>
```

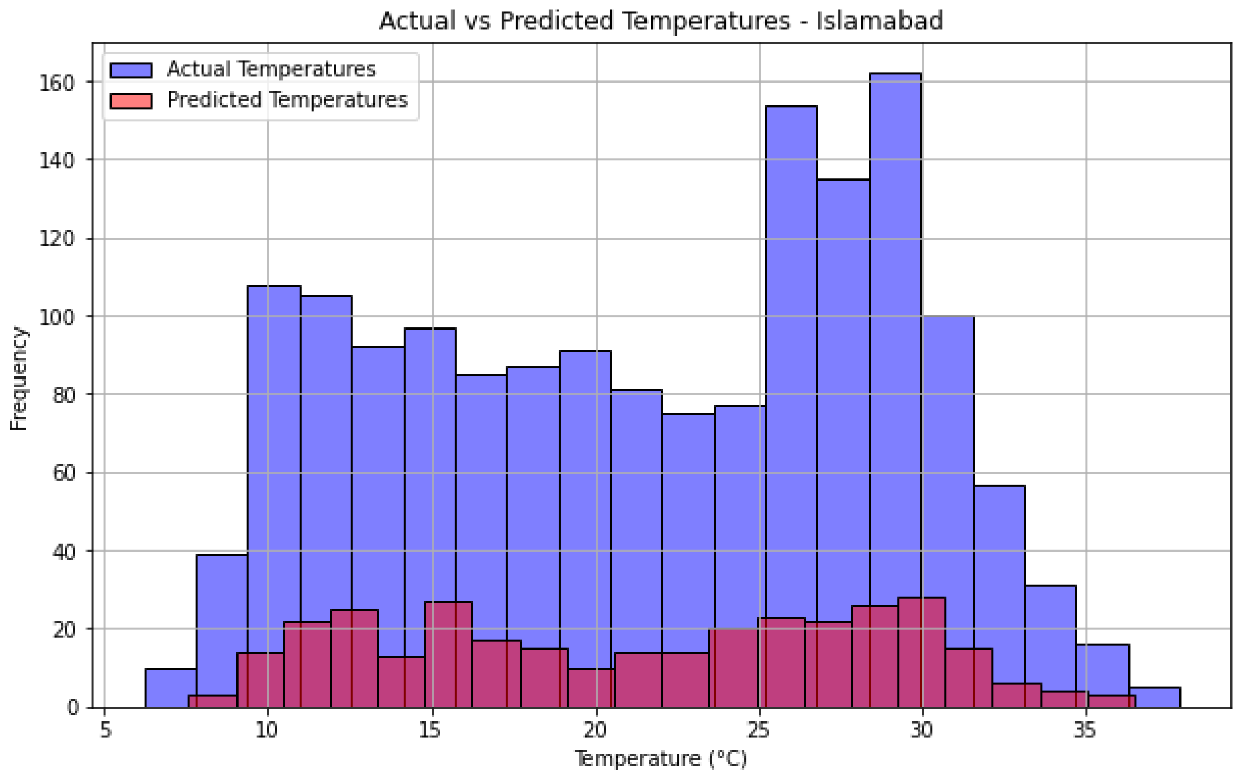


model evaluation

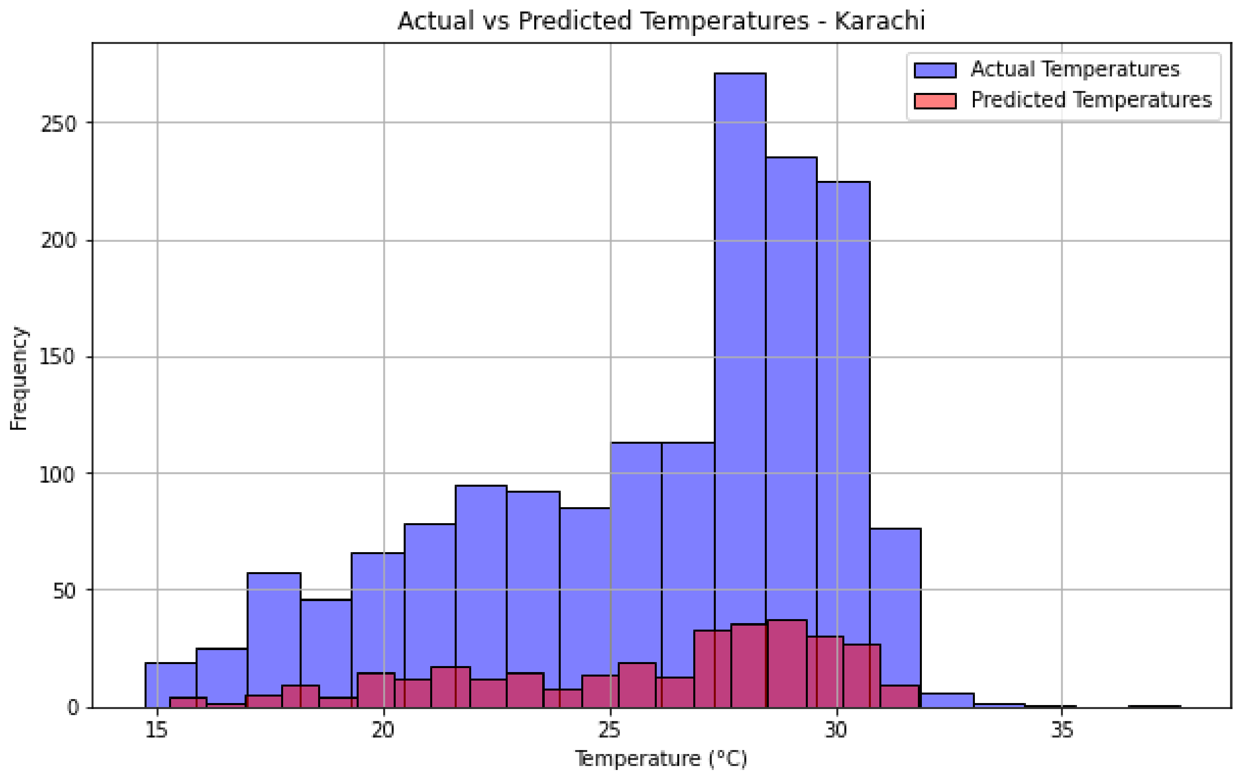
```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_absolute_error, mean_squared_error
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# Load the preprocessed weather data
weather_data = pd.read_csv('weather_data_all_cities.csv')

# Feature Engineering
# Extracting temporal features
weather_data['date'] = pd.to_datetime(weather_data['time'])  # Convert
'time' column to datetime
weather_data['day_of_week'] = weather_data['date'].dt.dayofweek  #
Extract day of the week (Monday=0, Sunday=6)
weather_data['month'] = weather_data['date'].dt.month  # Extract month

# Lagged variables (previous day's temperature)
weather_data['prev_day_temp_mean'] = weather_data.groupby('city')
['temperature_2m_mean'].shift(1)

# Drop unnecessary columns after feature engineering
weather_data.drop(columns=['time', 'date'], inplace=True)  # Drop
'time' and 'date' columns as we have extracted temporal features

# Remove rows with missing values
weather_data.dropna(inplace=True)

# Define a function to train and evaluate the model for each city
def train_evaluate_model(city_data, train_indices, test_indices):
    X = city_data.drop(columns=['temperature_2m_mean', 'city'])  #
Features excluding target variable and city
    y = city_data['temperature_2m_mean']  # Target variable (mean
temperature)

    # Split the data into training and testing sets using specific
indices
    X_train, X_test = X.loc[train_indices], X.loc[test_indices]
    y_train, y_test = y.loc[train_indices], y.loc[test_indices]

    # Initialize the Random Forest Regression model
    rf_model = RandomForestRegressor(random_state=42)

    # Train the model on the training data
    rf_model.fit(X_train, y_train)
```

```python
    # Evaluate the model on the testing set
    y_pred = rf_model.predict(X_test)

    # Calculate evaluation metrics
    mae = mean_absolute_error(y_test, y_pred)
    mse = mean_squared_error(y_test, y_pred)
    rmse = np.sqrt(mse)

    return mae, mse, rmse, y_pred, y_test

# Iterate over each city, train and evaluate the model, and print the
evaluation metrics
for city_name, city_data in weather_data.groupby('city'):
    print(f"City: {city_name}")

    # Define indices for training and testing sets for the current
city
    city_indices = city_data.index
    train_indices = city_data.sample(frac=0.8, random_state=42).index
    test_indices = city_data.drop(train_indices).index

    mae, mse, rmse, y_pred, y_test = train_evaluate_model(city_data,
train_indices, test_indices)
    print("Mean Absolute Error (MAE):", mae)
    print("Mean Squared Error (MSE):", mse)
    print("Root Mean Squared Error (RMSE):", rmse)
    print("\n")

    # Visualize the comparison
    plt.figure(figsize=(10, 6))
    sns.histplot(city_data['temperature_2m_mean'], bins=20,
color='blue', alpha=0.5, label='Actual Temperatures')
    sns.histplot(y_pred, bins=20, color='red', alpha=0.5,
label='Predicted Temperatures')
    plt.xlabel('Temperature (°C)')
    plt.ylabel('Frequency')
    plt.title(f'Actual vs Predicted Temperatures - {city_name}')
    plt.legend()
    plt.grid(True)
    plt.show()
```

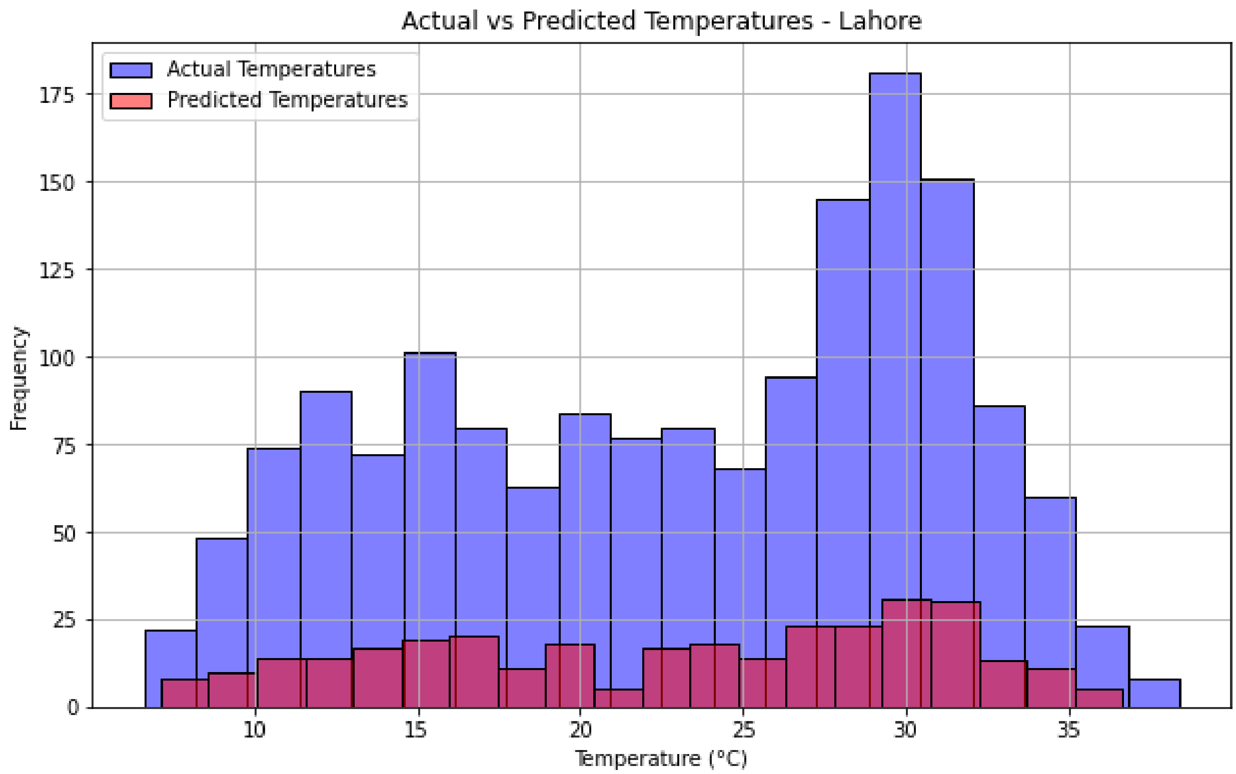
```
City: Islamabad
Mean Absolute Error (MAE): 0.3710591900311516
Mean Squared Error (MSE): 0.20788929595015512
Root Mean Squared Error (RMSE): 0.45594878654313264
```



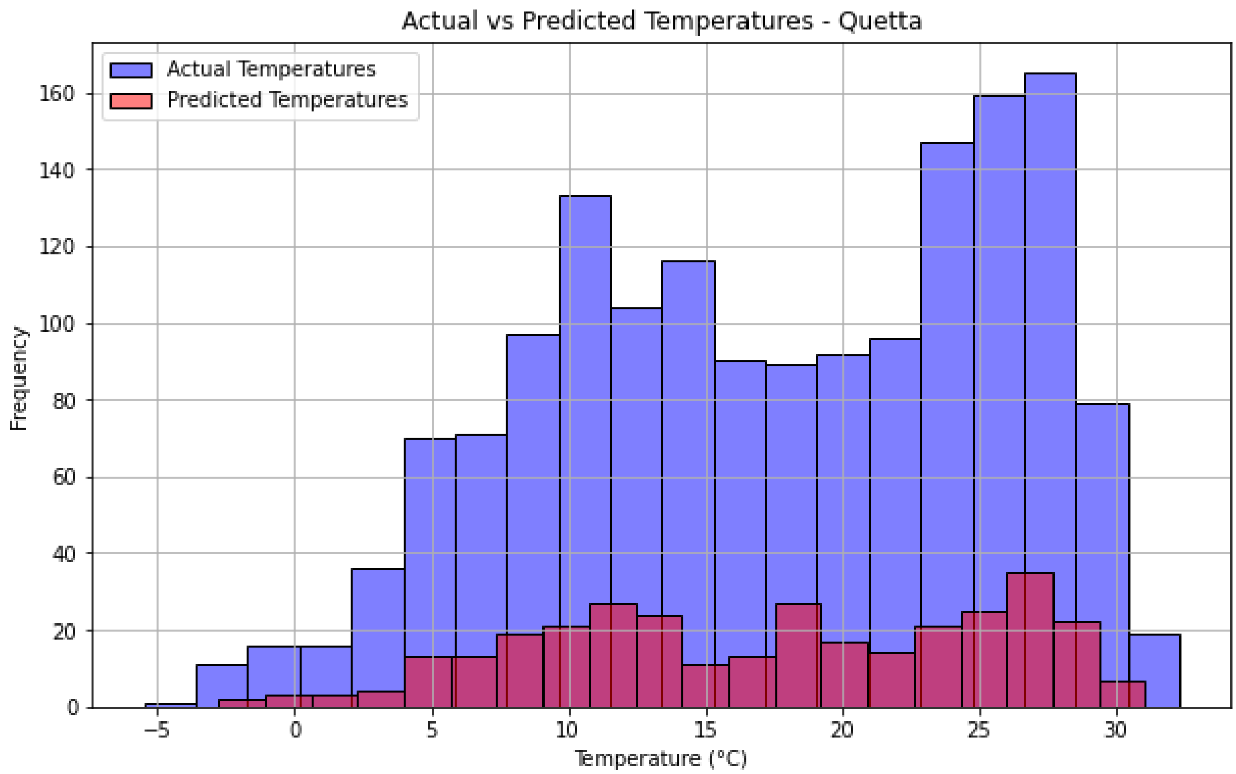

```
City: Karachi
Mean Absolute Error (MAE): 0.25041744548286615
Mean Squared Error (MSE): 0.13597915264797497
Root Mean Squared Error (RMSE): 0.36875351204832607
```




```
City: Lahore
Mean Absolute Error (MAE): 0.4124485981308417
Mean Squared Error (MSE): 0.29891538940810075
Root Mean Squared Error (RMSE): 0.5467315515022896
```




```
City: Quetta
Mean Absolute Error (MAE): 0.38361682242990697
Mean Squared Error (MSE): 0.2526373489096581
Root Mean Squared Error (RMSE): 0.5026304297489937
```



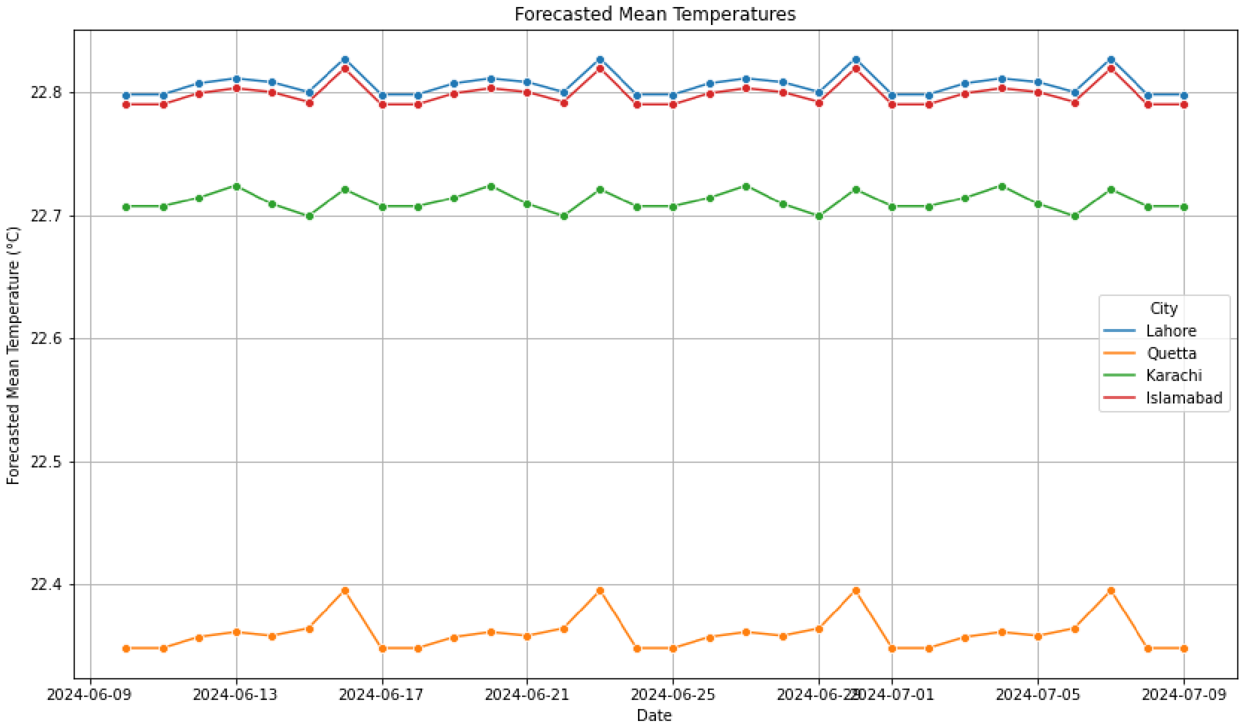
forecasting

```
import requests
import pandas as pd
from datetime import datetime, timedelta
from sklearn.ensemble import RandomForestRegressor
import matplotlib.pyplot as plt
import seaborn as sns

# Load the preprocessed weather data
weather_data = pd.read_csv('weather_data_all_cities.csv')

# Feature Engineering
# Extracting temporal features
weather_data['date'] = pd.to_datetime(weather_data['time'])  # Convert
'time' column to datetime
weather_data['day_of_week'] = weather_data['date'].dt.dayofweek  #
Extract day of the week (Monday=0, Sunday=6)
weather_data['month'] = weather_data['date'].dt.month  # Extract month

# Lagged variables (previous day's temperature)
weather_data['prev_day_temp_mean'] = weather_data.groupby('city')
['temperature_2m_mean'].shift(1)

# Drop unnecessary columns after feature engineering
```

```
weather_data.drop(columns=['time', 'date'], inplace=True)  # Drop
'time' and 'date' columns as we have extracted temporal features

# Remove rows with missing values
weather_data.dropna(inplace=True)

# Define a function to train the model
def train_model(city_data, train_indices):
    X = city_data.drop(columns=['temperature_2m_mean', 'city'])  #
Features excluding target variable and city
    y = city_data['temperature_2m_mean']  # Target variable (mean
temperature)

    # Split the data into training and testing sets using specific
indices
    X_train, X_test = X.loc[train_indices], X.drop(train_indices)
    y_train, y_test = y.loc[train_indices], y.drop(train_indices)

    # Initialize the Random Forest Regression model
    rf_model = RandomForestRegressor(random_state=42)

    # Train the model on the training data
    rf_model.fit(X_train, y_train)

    return rf_model

# Train the model on the entire dataset (for demonstration purposes)
train_indices, _ = train_test_split(weather_data.index, test_size=0.2,
random_state=42)
rf_model = train_model(weather_data, train_indices)

# Function to fetch the latest weather data for a city
def fetch_current_weather_data(lat, lon):
    url = "https://api.open-meteo.com/v1/forecast"
    params = {
        "latitude": lat,
        "longitude": lon,
        "current_weather": "true",
        "timezone": "auto"
    }
    response = requests.get(url, params=params)
    if response.status_code == 200:
        data = response.json()
        if 'current_weather' in data:
            return data['current_weather']
        else:
            print("No current weather data found.")
            return None
    else:
        print("Failed to fetch current weather data. Status code:",
```

```
response.status_code)
        return None

# Cities with their respective latitudes and longitudes
cities = {
    "Lahore": {"latitude": 31.5204, "longitude": 74.3587},
    "Quetta": {"latitude": 30.1798, "longitude": 66.9750},
    "Karachi": {"latitude": 24.8607, "longitude": 67.0011},
    "Islamabad": {"latitude": 33.6844, "longitude": 73.0479}
}

# Forecasting for the next 7 days using the latest data from the API
forecast_horizon = int(input("Enter the number of forecasting days:
"))
forecast_results = []

# Get the current date
current_date = datetime.now().date()

for city, coords in cities.items():
    lat = coords["latitude"]
    lon = coords["longitude"]

    # Fetch the latest weather data
    current_weather = fetch_current_weather_data(lat, lon)

    if current_weather:
        # Prepare the feature vector using the latest weather data
        recent_data = {
            'temperature_2m_max': current_weather['temperature'],
            'temperature_2m_min': current_weather['temperature'],
            'precipitation_sum': 0,  # Assuming no precipitation in
current data
            'wind_speed_10m_max': current_weather['windspeed'],
            'wind_gusts_10m_max': current_weather['windspeed'],
            'shortwave_radiation_sum': 0,  # Assuming no radiation
data in current data
            'et0_fao_evapotranspiration': 0,  # Assuming no
evapotranspiration data in current data
            'prev_day_temp_mean': current_weather['temperature'],
            'day_of_week': current_date.weekday(),
            'month': current_date.month
        }

        for i in range(forecast_horizon):
            # Prepare the feature vector for prediction
            feature_vector = pd.DataFrame([recent_data])

            # Predict the mean temperature
            forecast_temp = rf_model.predict(feature_vector)[0]
```

```
            # Append the result
            forecast_results.append({
                'city': city,
                'forecast_date': current_date + timedelta(days=i),
                'forecasted_mean_temp': forecast_temp
            })

            # Update the recent_data for the next prediction
            recent_data['prev_day_temp_mean'] = forecast_temp
            recent_data['day_of_week'] = (recent_data['day_of_week'] +
1) % 7
            if recent_data['day_of_week'] == 0:
                recent_data['month'] = (recent_data['month'] % 12) + 1
    else:
        print(f"Failed to fetch current weather data for {city}.
Skipping forecast.")

# Convert forecast results to a DataFrame
forecast_df = pd.DataFrame(forecast_results)

# Visualize the forecast results
plt.figure(figsize=(14, 8))
sns.lineplot(data=forecast_df, x='forecast_date',
y='forecasted_mean_temp', hue='city', marker='o')

plt.title('Forecasted Mean Temperatures')
plt.xlabel('Date')
plt.ylabel('Forecasted Mean Temperature (°C)')
plt.legend(title='City')
plt.grid(True)
plt.show()

# Compare the forecasted temperatures
for city in forecast_df['city'].unique():
    city_forecast = forecast_df[forecast_df['city'] == city]
    print(f"\nForecasted Mean Temperatures for {city}:")
    print(city_forecast[['forecast_date', 'forecasted_mean_temp']])

Enter the number of forecasting days: 30
```




```
Forecasted Mean Temperatures for Lahore:
   forecast_date  forecasted_mean_temp
0     2024-06-10                22.798
1     2024-06-11                22.798
2     2024-06-12                22.807
3     2024-06-13                22.811
4     2024-06-14                22.808
5     2024-06-15                22.800
6     2024-06-16                22.827
7     2024-06-17                22.798
8     2024-06-18                22.798
9     2024-06-19                22.807
10    2024-06-20                22.811
11    2024-06-21                22.808
12    2024-06-22                22.800
13    2024-06-23                22.827
14    2024-06-24                22.798
15    2024-06-25                22.798
16    2024-06-26                22.807
17    2024-06-27                22.811
18    2024-06-28                22.808
19    2024-06-29                22.800
20    2024-06-30                22.827
21    2024-07-01                22.798
22    2024-07-02                22.798
23    2024-07-03                22.807
```

```
24    2024-07-04                22.811
25    2024-07-05                22.808
26    2024-07-06                22.800
27    2024-07-07                22.827
28    2024-07-08                22.798
29    2024-07-09                22.798

Forecasted Mean Temperatures for Quetta:
   forecast_date  forecasted_mean_temp
30    2024-06-10                22.348
31    2024-06-11                22.348
32    2024-06-12                22.357
33    2024-06-13                22.361
34    2024-06-14                22.358
35    2024-06-15                22.364
36    2024-06-16                22.395
37    2024-06-17                22.348
38    2024-06-18                22.348
39    2024-06-19                22.357
40    2024-06-20                22.361
41    2024-06-21                22.358
42    2024-06-22                22.364
43    2024-06-23                22.395
44    2024-06-24                22.348
45    2024-06-25                22.348
46    2024-06-26                22.357
47    2024-06-27                22.361
48    2024-06-28                22.358
49    2024-06-29                22.364
50    2024-06-30                22.395
51    2024-07-01                22.348
52    2024-07-02                22.348
53    2024-07-03                22.357
54    2024-07-04                22.361
55    2024-07-05                22.358
56    2024-07-06                22.364
57    2024-07-07                22.395
58    2024-07-08                22.348
59    2024-07-09                22.348

Forecasted Mean Temperatures for Karachi:
   forecast_date  forecasted_mean_temp
60    2024-06-10                22.707
61    2024-06-11                22.707
62    2024-06-12                22.714
63    2024-06-13                22.724
64    2024-06-14                22.709
65    2024-06-15                22.699
66    2024-06-16                22.721
```

```
67    2024-06-17                22.707
68    2024-06-18                22.707
69    2024-06-19                22.714
70    2024-06-20                22.724
71    2024-06-21                22.709
72    2024-06-22                22.699
73    2024-06-23                22.721
74    2024-06-24                22.707
75    2024-06-25                22.707
76    2024-06-26                22.714
77    2024-06-27                22.724
78    2024-06-28                22.709
79    2024-06-29                22.699
80    2024-06-30                22.721
81    2024-07-01                22.707
82    2024-07-02                22.707
83    2024-07-03                22.714
84    2024-07-04                22.724
85    2024-07-05                22.709
86    2024-07-06                22.699
87    2024-07-07                22.721
88    2024-07-08                22.707
89    2024-07-09                22.707

Forecasted Mean Temperatures for Islamabad:
    forecast_date  forecasted_mean_temp
90     2024-06-10                22.790
91     2024-06-11                22.790
92     2024-06-12                22.799
93     2024-06-13                22.803
94     2024-06-14                22.800
95     2024-06-15                22.792
96     2024-06-16                22.819
97     2024-06-17                22.790
98     2024-06-18                22.790
99     2024-06-19                22.799
100    2024-06-20                22.803
101    2024-06-21                22.800
102    2024-06-22                22.792
103    2024-06-23                22.819
104    2024-06-24                22.790
105    2024-06-25                22.790
106    2024-06-26                22.799
107    2024-06-27                22.803
108    2024-06-28                22.800
109    2024-06-29                22.792
110    2024-06-30                22.819
111    2024-07-01                22.790
112    2024-07-02                22.790
```

113	2024-07-03	22.799
114	2024-07-04	22.803
115	2024-07-05	22.800
116	2024-07-06	22.792
117	2024-07-07	22.819
118	2024-07-08	22.790
119	2024-07-09	22.790