

```
In [1]: !pip install scikit-learn xgboost joblib plotly prophet matplotlib seaborn sta
```

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Requirement already satisfied: scikit-learn in c:\users\mohammed hayath rk\anaconda3\lib\site-packages (1.6.1)
Collecting xgboost
    Downloading xgboost-3.1.2-py3-none-win_amd64.whl.metadata (2.1 kB)
Requirement already satisfied: joblib in c:\users\mohammed hayath rk\anaconda3\lib\site-packages (1.4.2)
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Requirement already satisfied: statsmodels in c:\users\mohammed hayath rk\anaconda3\lib\site-packages (0.14.4)
Requirement already satisfied: numpy>=1.19.5 in c:\users\mohammed hayath rk\anaconda3\lib\site-packages (from scikit-learn) (2.1.3)
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Requirement already satisfied: tenacity>=6.2.0 in c:\users\mohammed hayath rk\anaconda3\lib\site-packages (from plotly) (9.0.0)
Requirement already satisfied: packaging in c:\users\mohammed hayath rk\anaconda3\lib\site-packages (from plotly) (24.2)
Requirement already satisfied: cmdstanpy>=1.0.4 in c:\users\mohammed hayath rk\anaconda3\lib\site-packages (from prophet) (1.3.0)
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Requirement already satisfied: kiwisolver>=1.3.1 in c:\users\mohammed hayath rk\anaconda3\lib\site-packages (from matplotlib) (1.4.8)
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```

Installing collected packages: xgboost

Successfully installed xgboost-3.1.2

In [2]: `!pip install requests pandas`

```
Requirement already satisfied: requests in c:\users\mohammed hayath rk\anaconda3\lib\site-packages (2.32.3)
Requirement already satisfied: pandas in c:\users\mohammed hayath rk\anaconda3\lib\site-packages (2.2.3)
Requirement already satisfied: charset-normalizer<4,>=2 in c:\users\mohammed hayath rk\anaconda3\lib\site-packages (from requests) (3.3.2)
Requirement already satisfied: idna<4,>=2.5 in c:\users\mohammed hayath rk\anaconda3\lib\site-packages (from requests) (3.7)
Requirement already satisfied: urllib3<3,>=1.21.1 in c:\users\mohammed hayath rk\anaconda3\lib\site-packages (from requests) (2.3.0)
Requirement already satisfied: certifi>=2017.4.17 in c:\users\mohammed hayath rk\anaconda3\lib\site-packages (from requests) (2025.4.26)
Requirement already satisfied: numpy>=1.26.0 in c:\users\mohammed hayath rk\anaconda3\lib\site-packages (from pandas) (2.1.3)
Requirement already satisfied: python-dateutil>=2.8.2 in c:\users\mohammed hayath rk\anaconda3\lib\site-packages (from pandas) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in c:\users\mohammed hayath rk\anaconda3\lib\site-packages (from pandas) (2025.2)
Requirement already satisfied: tzdata>=2022.7 in c:\users\mohammed hayath rk\anaconda3\lib\site-packages (from pandas) (2025.2)
Requirement already satisfied: six>=1.5 in c:\users\mohammed hayath rk\anaconda3\lib\site-packages (from python-dateutil>=2.8.2->pandas) (1.17.0)
```

```
In [3]: import requests
import pandas as pd
from datetime import datetime, timedelta
import time

API_KEY = "YOUR_OWN_API_KEY"    # <- put your WeatherAPI key here
BASE_URL = "http://api.weatherapi.com/v1"

# Function to fetch historical weather for 1 day
def get_history(city, date):
    url = f"{BASE_URL}/history.json"
    params = {
        "key": API_KEY,
        "q": city,
        "dt": date
    }
    response = requests.get(url, params=params)
    return response.json()

# Convert history JSON → DataFrame (hourly data)
def history_to_df(history_json, city):
    rows = []
    for day in history_json["forecast"]["forecastday"]:
        for hour in day["hour"]:
            hour["city"] = city # Add city column
            rows.append(hour)
    return pd.DataFrame(rows)

# -----
# MULTIPLE CITY INPUT BOX
```

```
# -----
# city_input = input("Enter city names (comma separated): ")
# city_list = [c.strip() for c in city_input.split(",")]

days = int(input("How many past days do you want? (e.g., 30): "))

# -----
# FETCH DATA FOR ALL CITIES
# -----


all_data = []

for city in city_list:
    print(f"\nFetching data for: {city}")
    for i in range(days):
        date = (datetime.today() - timedelta(days=i+1)).strftime("%Y-%m-%d")
        print(f" - {date}")

    try:
        json_data = get_history(city, date)
        df = history_to_df(json_data, city)
        all_data.append(df)
    except Exception as e:
        print("Error:", e)

    time.sleep(1) # avoid hitting API limits

# -----
# MERGE INTO ONE BIG DATASET
# -----


big_df = pd.concat(all_data, ignore_index=True)
print("\nFinal Big Dataset Shape:", big_df.shape)
big_df.head()
```

Fetching data for: Bangalore

- 2025-12-04
- 2025-12-03
- 2025-12-02
- 2025-12-01
- 2025-11-30
- 2025-11-29
- 2025-11-28

Fetching data for: Hyderabad

- 2025-12-04
- 2025-12-03
- 2025-12-02
- 2025-12-01
- 2025-11-30
- 2025-11-29
- 2025-11-28

Fetching data for: Kolkata

- 2025-12-04
- 2025-12-03
- 2025-12-02
- 2025-12-01
- 2025-11-30
- 2025-11-29
- 2025-11-28

Fetching data for: Lucknow

- 2025-12-04
- 2025-12-03
- 2025-12-02
- 2025-12-01
- 2025-11-30
- 2025-11-29
- 2025-11-28

Fetching data for: Patna

- 2025-12-04
- 2025-12-03
- 2025-12-02
- 2025-12-01
- 2025-11-30
- 2025-11-29
- 2025-11-28

Fetching data for: Chennai

- 2025-12-04
- 2025-12-03
- 2025-12-02
- 2025-12-01
- 2025-11-30
- 2025-11-29
- 2025-11-28

Fetching data for: Mumbai

- 2025-12-04
 - 2025-12-03
 - 2025-12-02
 - 2025-12-01
 - 2025-11-30
 - 2025-11-29
 - 2025-11-28

Final Big Dataset Shape: (1176, 35)

Out[3]:	time_epoch	time	temp_c	temp_f	is_day	condition	wind_mph	wind_kt
0	1764786600	2025-12-04 00:00	20.0	68.0	0	{"text": "Light rain shower", "icon": "//cdn.w..."}	9.6	1
1	1764790200	2025-12-04 01:00	19.9	67.8	0	{"text": "Patchy rain possible", "icon": "//cd..."}	9.6	1
2	1764793800	2025-12-04 02:00	19.4	66.9	0	{"text": "Light rain shower", "icon": "//cdn.w..."}	10.1	1
3	1764797400	2025-12-04 03:00	19.6	67.3	0	{"text": "Patchy rain possible", "icon": "//cd..."}	10.3	1
4	1764801000	2025-12-04 04:00	19.6	67.3	0	{"text": "Patchy rain possible", "icon": "//cd..."}	10.1	1

5 rows × 35 columns

```
In [4]: big_df.shape
```

Out[4]: (1176, 35)

Basic EDA - Exploratory Data Analysis

```
In [5]: import pandas as pd
```

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

sns.set(style="whitegrid")

from warnings import filterwarnings
filterwarnings('ignore')
```

In [6]: # Shape of the Data and information from the columns
print("Shape of dataset:", big_df.shape)
big_df.info()

```
Shape of dataset: (1176, 35)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1176 entries, 0 to 1175
Data columns (total 35 columns):
 #   Column            Non-Null Count  Dtype  
--- 
 0   time_epoch        1176 non-null    int64  
 1   time              1176 non-null    object  
 2   temp_c             1176 non-null    float64 
 3   temp_f             1176 non-null    float64 
 4   is_day             1176 non-null    int64  
 5   condition          1176 non-null    object  
 6   wind_mph           1176 non-null    float64 
 7   wind_kph           1176 non-null    float64 
 8   wind_degree        1176 non-null    int64  
 9   wind_dir            1176 non-null    object  
 10  pressure_mb        1176 non-null    float64 
 11  pressure_in         1176 non-null    float64 
 12  precip_mm           1176 non-null    float64 
 13  precip_in           1176 non-null    float64 
 14  snow_cm             1176 non-null    float64 
 15  humidity            1176 non-null    int64  
 16  cloud               1176 non-null    int64  
 17  feelslike_c         1176 non-null    float64 
 18  feelslike_f         1176 non-null    float64 
 19  windchill_c          1176 non-null    float64 
 20  windchill_f          1176 non-null    float64 
 21  heatindex_c          1176 non-null    float64 
 22  heatindex_f          1176 non-null    float64 
 23  dewpoint_c           1176 non-null    float64 
 24  dewpoint_f           1176 non-null    float64 
 25  will_it_rain         1176 non-null    int64  
 26  chance_of_rain       1176 non-null    int64  
 27  will_it_snow          1176 non-null    int64  
 28  chance_of_snow        1176 non-null    int64  
 29  vis_km                1176 non-null    float64 
 30  vis_miles            1176 non-null    float64 
 31  gust_mph              1176 non-null    float64 
 32  gust_kph              1176 non-null    float64 
 33  uv                     1176 non-null    float64 
 34  city                  1176 non-null    object  
dtypes: float64(22), int64(9), object(4)
memory usage: 321.7+ KB
```

```
In [7]: # Checking the duplicates
big_df.isnull().sum()
```

```
Out[7]: time_epoch      0  
time          0  
temp_c        0  
temp_f        0  
is_day        0  
condition     0  
wind_mph      0  
wind_kph      0  
wind_degree   0  
wind_dir      0  
pressure_mb   0  
pressure_in   0  
precip_mm     0  
precip_in     0  
snow_cm       0  
humidity      0  
cloud         0  
feelslike_c   0  
feelslike_f   0  
windchill_c   0  
windchill_f   0  
heatindex_c   0  
heatindex_f   0  
dewpoint_c    0  
dewpoint_f    0  
will_it_rain  0  
chance_of_rain 0  
will_it_snow  0  
chance_of_snow 0  
vis_km        0  
vis_miles     0  
gust_mph      0  
gust_kph      0  
uv            0  
city          0  
dtype: int64
```

```
In [8]: #Convert columns → correct datatypes
```

```
big_df['time'] = pd.to_datetime(big_df['time'])  
big_df['temp_c'] = pd.to_numeric(big_df['temp_c'])  
big_df['humidity'] = pd.to_numeric(big_df['humidity'])  
big_df['wind_kph'] = pd.to_numeric(big_df['wind_kph'])  
big_df['pressure_mb'] = pd.to_numeric(big_df['pressure_mb'])  
big_df['precip_mm'] = pd.to_numeric(big_df['precip_mm'])
```

```
In [9]: # Add useful time features
```

```
big_df["year"] = big_df["time"].dt.year  
big_df["month"] = big_df["time"].dt.month  
big_df["day"] = big_df["time"].dt.day  
big_df["hour"] = big_df["time"].dt.hour  
big_df["day_of_week"] = big_df["time"].dt.dayofweek
```

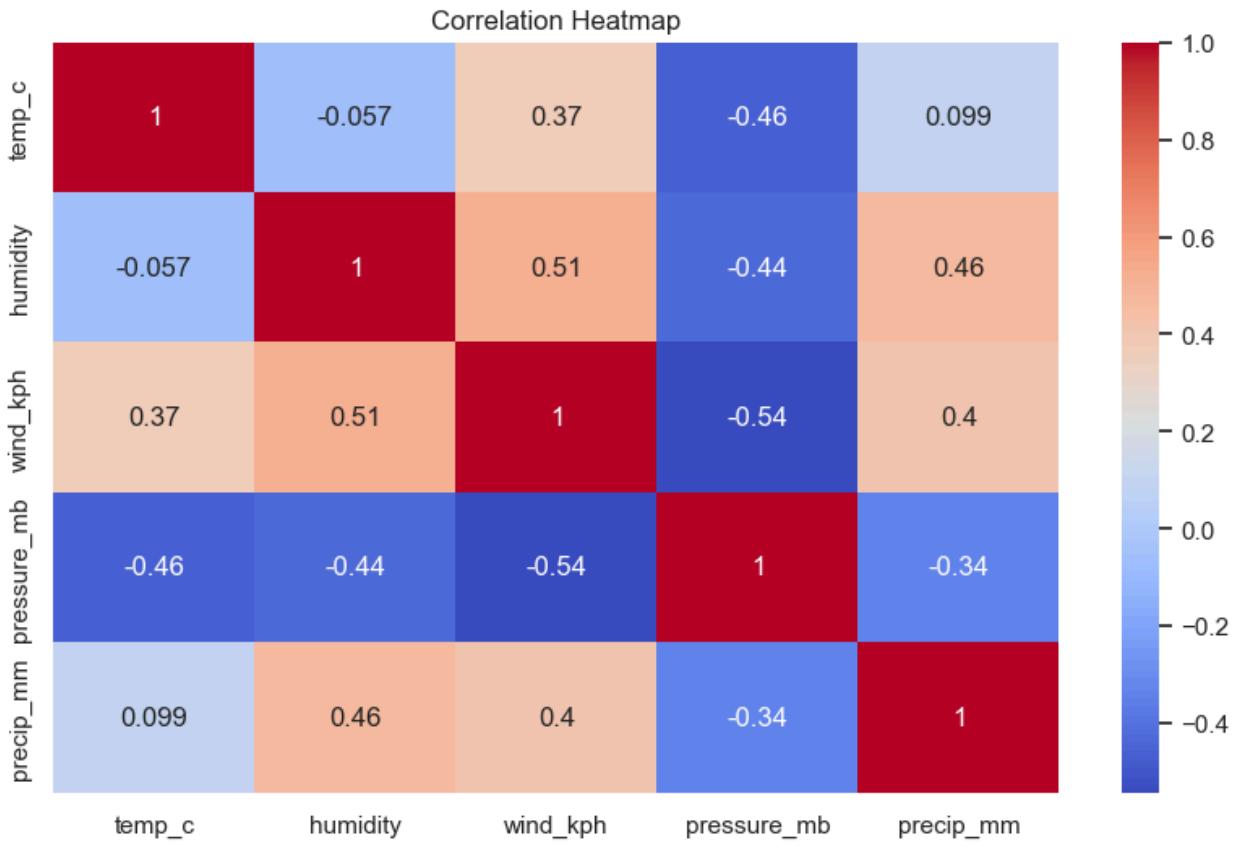
```
In [10]: # City-wise basic statistics  
big_df.groupby("city")[["temp_c","humidity","wind_kph","precip_mm"]].describe()
```

Out[10]:

		temp_c									
		count	mean	std	min	25%	50%	75%	max	count	
	city										
	Bangalore	168.0	19.967857	2.481460	14.7	18.000	19.90	21.600	26.1	168.0	
	Chennai	168.0	25.548810	1.275658	23.1	24.575	25.70	26.400	28.1	168.0	
	Hyderabad	168.0	21.208333	3.341275	15.3	18.675	20.50	24.025	28.2	168.0	
	Kolkata	168.0	23.080952	3.518232	16.4	20.100	22.70	26.425	29.1	168.0	
	Lucknow	168.0	19.728571	3.717706	13.8	16.575	19.10	22.850	26.8	168.0	
	Mumbai	168.0	26.266667	1.753343	23.1	24.900	26.15	27.625	30.0	168.0	
	Patna	168.0	20.152976	3.703954	13.5	17.200	19.40	23.300	26.8	168.0	

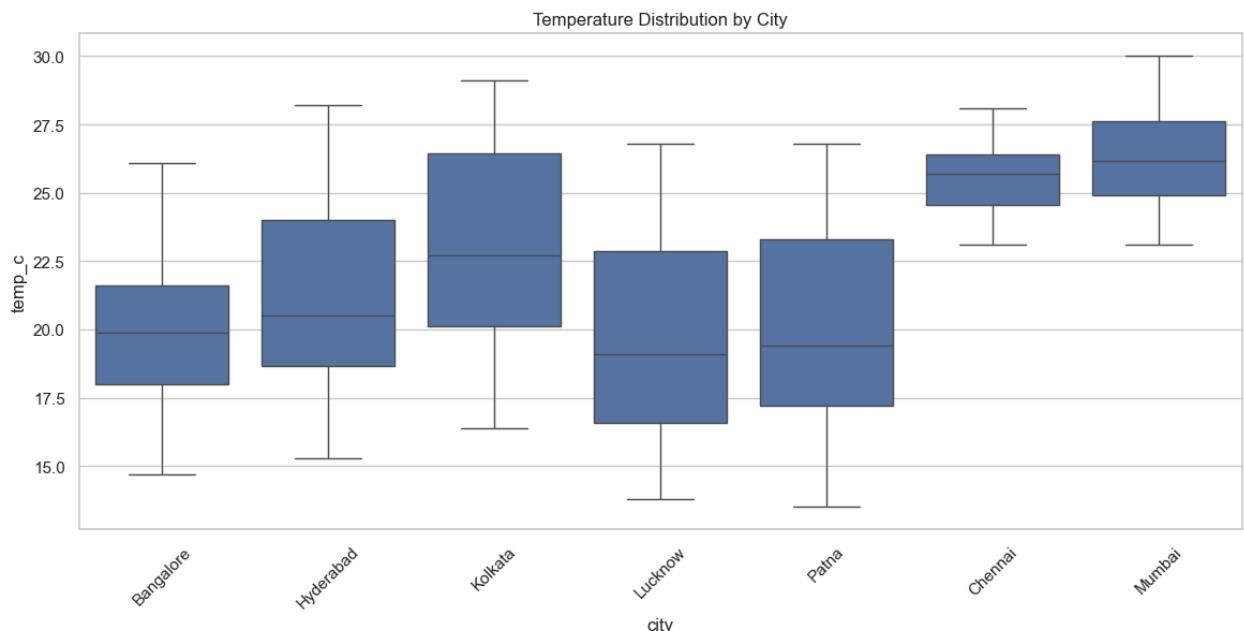
7 rows × 32 columns

```
In [11]: # Correlation Heatmap (Numerical Features)  
plt.figure(figsize=(10,6))  
sns.heatmap(big_df[["temp_c","humidity","wind_kph","pressure_mb","precip_mm"]]  
            annot=True, cmap="coolwarm")  
plt.title("Correlation Heatmap")  
plt.show()
```



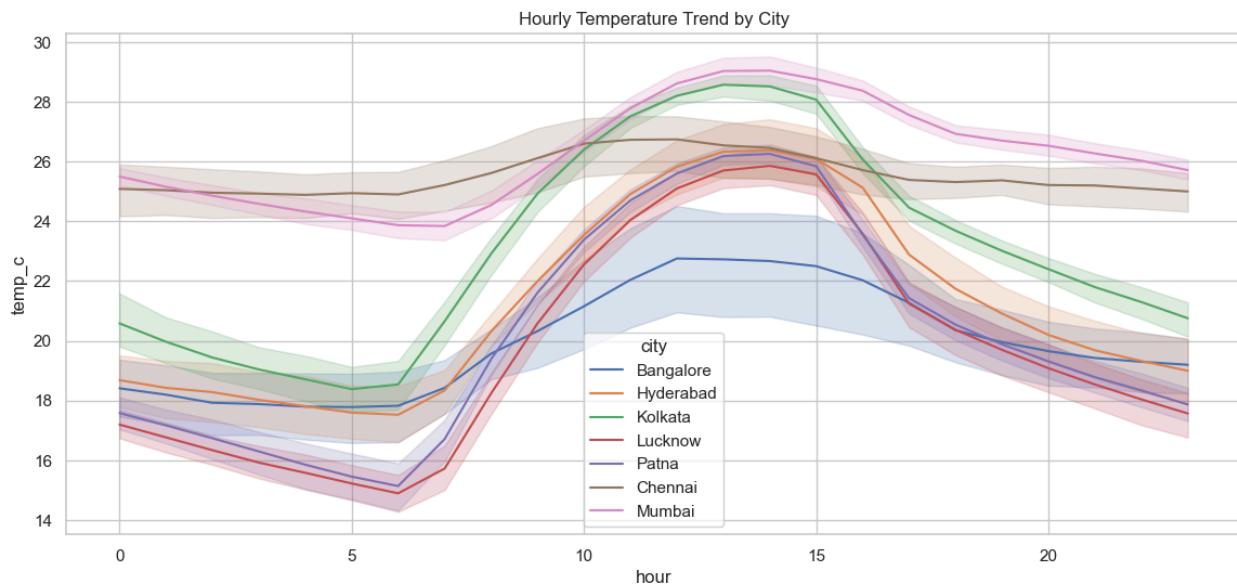
```
In [12]: # City-wise Temperature Distribution
```

```
plt.figure(figsize=(14,6))
sns.boxplot(x="city", y="temp_c", data=big_df)
plt.xticks(rotation=45)
plt.title("Temperature Distribution by City")
plt.show()
```



```
In [13]: # Hourly Temperature Trend for Each City
```

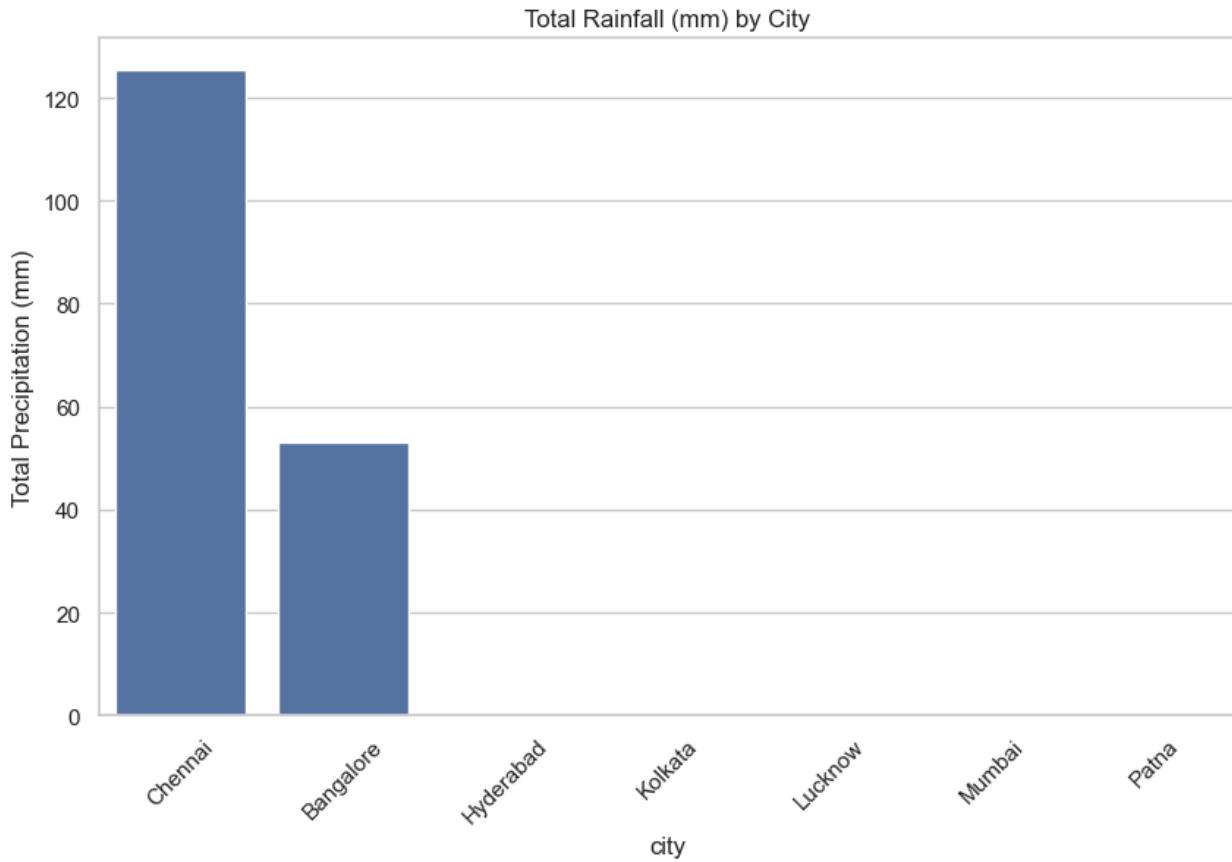
```
plt.figure(figsize=(14,6))
sns.lineplot(data=big_df, x="hour", y="temp_c", hue="city")
plt.title("Hourly Temperature Trend by City")
plt.show()
```



```
In [14]: # Rainfall Analysis (Which city rains more?)
```

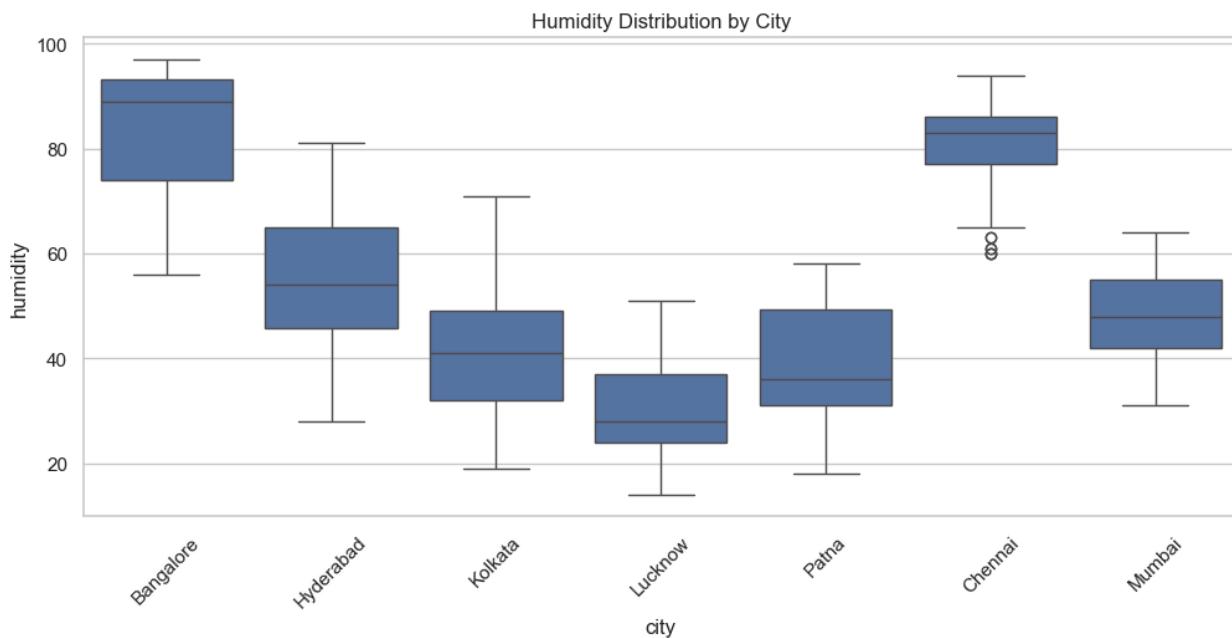
```
rain_df = big_df.groupby("city")["precip_mm"].sum().sort_values(ascending=False)

plt.figure(figsize=(10,6))
sns.barplot(x=rain_df.index, y=rain_df.values)
plt.title("Total Rainfall (mm) by City")
plt.xticks(rotation=45)
plt.ylabel("Total Precipitation (mm)")
plt.show()
```



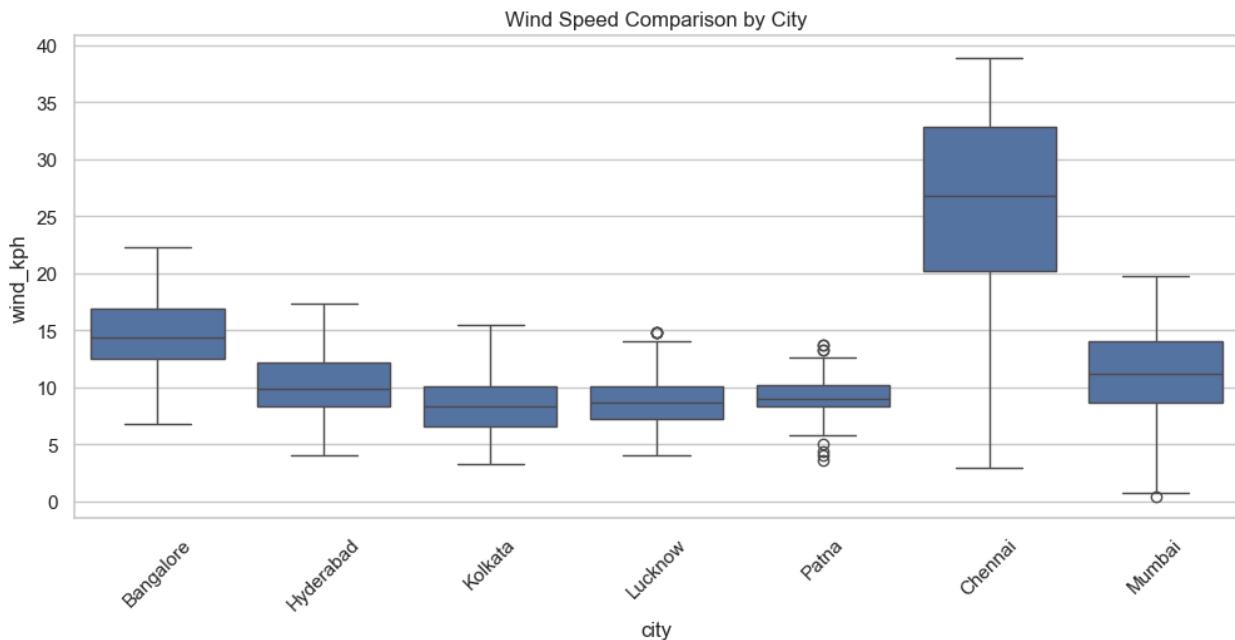
```
In [15]: # Humidity Comparison (City-wise)
```

```
plt.figure(figsize=(12,5))
sns.boxplot(data=big_df, x="city", y="humidity")
plt.xticks(rotation=45)
plt.title("Humidity Distribution by City")
plt.show()
```



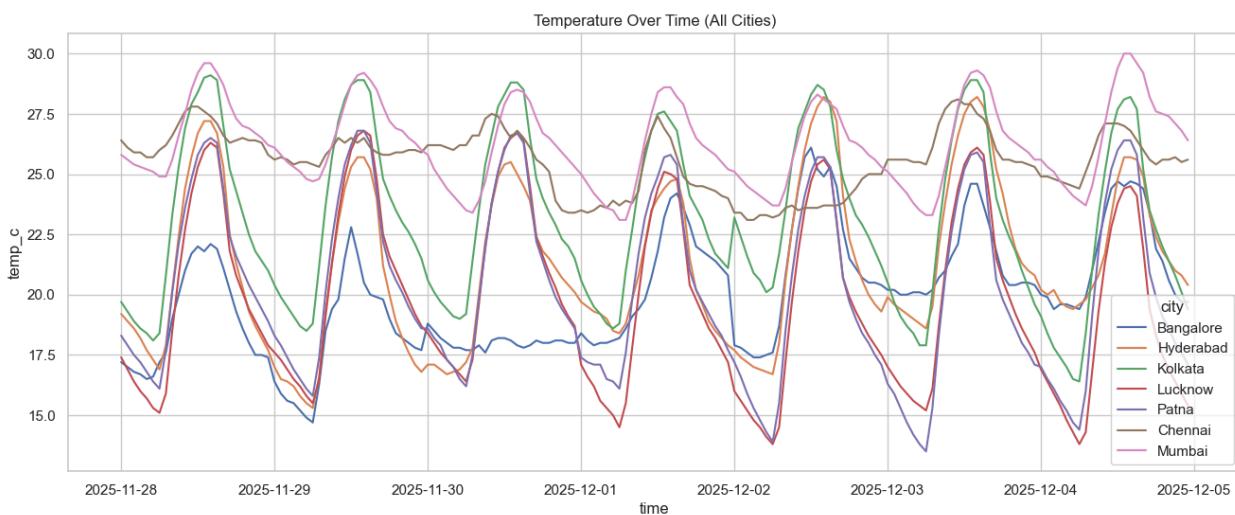
```
In [16]: # Wind Speed Comparison
```

```
plt.figure(figsize=(12,5))
sns.boxplot(data=big_df, x="city", y="wind_kph")
plt.xticks(rotation=45)
plt.title("Wind Speed Comparison by City")
plt.show()
```



```
In [17]: # Temperature Over Time for Each City
```

```
plt.figure(figsize=(16,6))
sns.lineplot(x="time", y="temp_c", hue="city", data=big_df)
plt.title("Temperature Over Time (All Cities)")
plt.show()
```



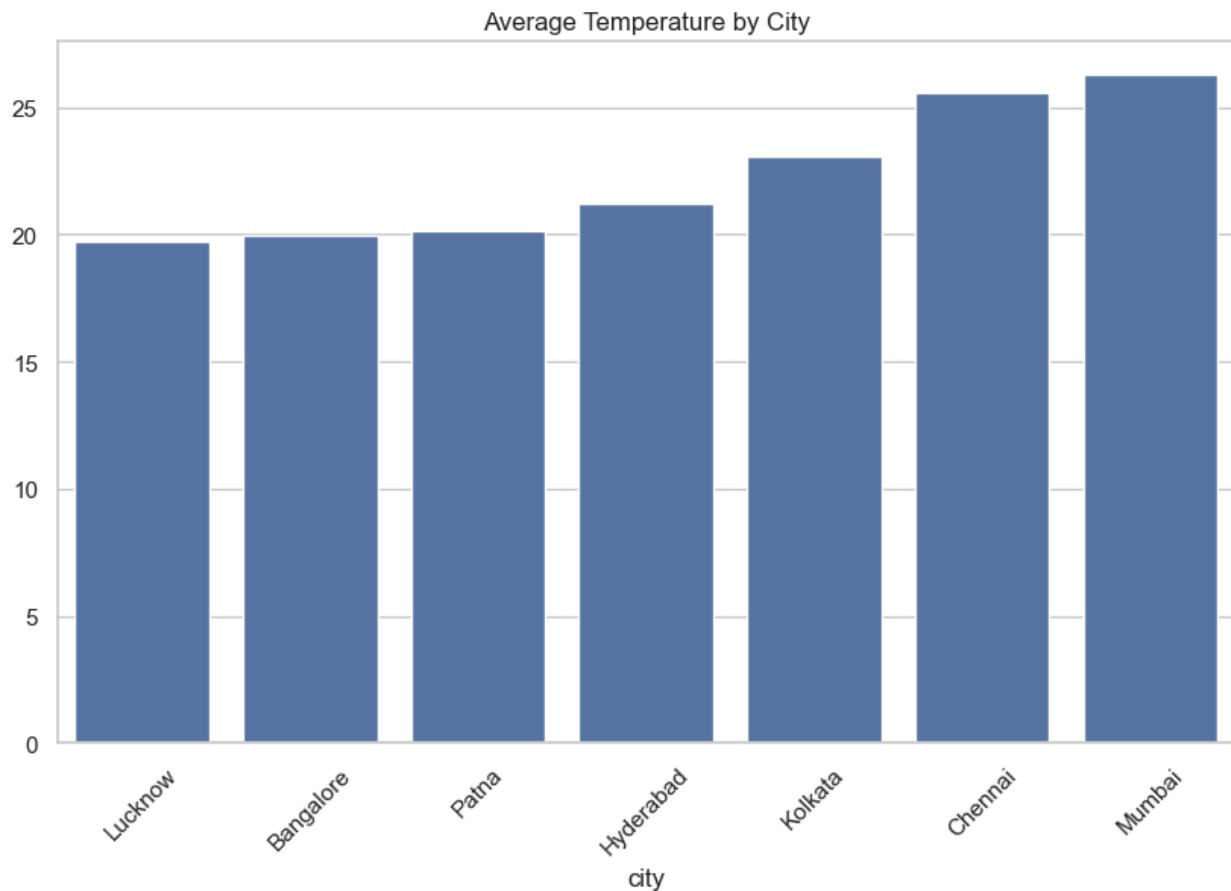
```
In [18]: # City-wise Average Temperature Ranking
```

```

avg_temp = big_df.groupby("city")["temp_c"].mean().sort_values()

plt.figure(figsize=(10,6))
sns.barplot(x=avg_temp.index, y=avg_temp.values)
plt.xticks(rotation=45)
plt.title("Average Temperature by City")
plt.show()

```



1. Feature Engineering

1.1.create features for ML

```

In [19]: df = big_df.copy() # keep original intact
# Ensure types
df['time'] = pd.to_datetime(df['time'])
for col in ['temp_c','humidity','wind_kph','precip_mm','pressure_mb']:
    if col in df.columns:
        df[col] = pd.to_numeric(df[col], errors='coerce')

# Basic time features
df['year'] = df['time'].dt.year
df['month'] = df['time'].dt.month
df['day'] = df['time'].dt.day

```

```

df['hour'] = df['time'].dt.hour
df['dayofweek'] = df['time'].dt.dayofweek
df['is_weekend'] = df['dayofweek'].isin([5,6]).astype(int)

# Rolling and lag features (per city)
df = df.sort_values(['city','time']).reset_index(drop=True)
window_hours = [1,3,6,24] # adjust as needed

for w in window_hours:
    df[f'temp_roll_mean_{w}'] = df.groupby('city')['temp_c'].transform(lambda x: x.rolling(w).mean())
    df[f'temp_lag_{w}'] = df.groupby('city')['temp_c'].shift(w)

# Precipitation lag and binary rain target for classification
df['precip_mm'] = df['precip_mm'].fillna(0)
df['precip_lag_1'] = df.groupby('city')['precip_mm'].shift(1).fillna(0)
# Binary target: will it rain next hour? (1 if next hour precip > 0)
df['rain_next_hour'] = (df.groupby('city')['precip_mm'].shift(-1) > 0).astype(int)

# Temperature target for regression: next hour temp
df['temp_next_hour'] = df.groupby('city')['temp_c'].shift(-1)

# Drop rows with NA in target columns
df = df.dropna(subset=['temp_next_hour']).reset_index(drop=True)

print("Feature engineering done. Shape:", df.shape)
df.head()

```

Feature engineering done. Shape: (1169, 53)

	time_epoch	time	temp_c	temp_f	is_day	condition	wind_mph	wi
0	1764268200	2025-11-28 00:00:00	17.2	63.0	0	{"text": "Partly cloudy", "icon": "//cdn.weath...	8.3	
1	1764271800	2025-11-28 01:00:00	17.0	62.6	0	{"text": "Partly cloudy", "icon": "//cdn.weath...	8.1	
2	1764275400	2025-11-28 02:00:00	16.8	62.2	0	{"text": "Partly cloudy", "icon": "//cdn.weath...	7.6	
3	1764279000	2025-11-28 03:00:00	16.7	62.1	0	{"text": "Partly cloudy", "icon": "//cdn.weath...	8.7	
4	1764282600	2025-11-28 04:00:00	16.5	61.7	0	{"text": "Partly cloudy", "icon": "//cdn.weath...	9.2	

5 rows × 53 columns

2. Train/Test Splitting (time-aware)

```
In [20]: from sklearn.model_selection import TimeSeriesSplit

# Choose features for both tasks
features = [
    'hour', 'dayofweek', 'is_weekend', 'temp_c', 'humidity', 'wind_kph',
    'temp_roll_mean_1', 'temp_roll_mean_3', 'temp_roll_mean_6', 'temp_roll_mean_2',
    'temp_lag_1', 'temp_lag_3', 'temp_lag_6', 'temp_lag_24',
    'precip_lag_1'
]
# ensure features exist
features = [f for f in features if f in df.columns]
print("Using features:", features)

# Sort by time
df = df.sort_values('time').reset_index(drop=True)

# Simple holdout split: last 20% time as test
split_index = int(len(df) * 0.8)
train_df = df.iloc[:split_index].copy()
test_df = df.iloc[split_index: ].copy()

print("Train shape:", train_df.shape, "Test shape:", test_df.shape)
```

Using features: ['hour', 'dayofweek', 'is_weekend', 'temp_c', 'humidity', 'wind_kph', 'temp_roll_mean_1', 'temp_roll_mean_3', 'temp_roll_mean_6', 'temp_roll_mean_24', 'temp_lag_1', 'temp_lag_3', 'temp_lag_6', 'temp_lag_24', 'precip_lag_1']
Train shape: (935, 53) Test shape: (234, 53)

3. Rain Prediction (Classification) — RandomForest + XGBoost

```
In [21]: !pip install joblib

Requirement already satisfied: joblib in c:\users\mohammed hayath rk\anaconda3\lib\site-packages (1.4.2)

In [22]: from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, roc_auc_score
import joblib
import os

# Prepare X/y
X_train = train_df[features].fillna(-999)
y_train = train_df['rain_next_hour']

X_test = test_df[features].fillna(-999)
y_test = test_df['rain_next_hour']
```

```
In [23]: # Train RandomForest
rfc = RandomForestClassifier(n_estimators=200, random_state=42, n_jobs=-1, class_weight='balanced')
rfc.fit(X_train, y_train)
```

```
Out[23]: RandomForestClassifier
RandomForestClassifier(class_weight='balanced', n_estimators=200, n_jobs=-1,
random_state=42)
```

```
In [24]: # Predict & evaluate
y_pred = rfc.predict(X_test)
y_proba = rfc.predict_proba(X_test)[:,1]
```

```
In [26]: print("Classification Report (RandomForest):")
print(classification_report(y_test, y_pred))
print("ROC AUC:", roc_auc_score(y_test, y_proba))

# Create directory if it doesn't exist
os.makedirs("models", exist_ok=True)

# Save the model
joblib.dump(rfc, "models/rain_rf_model.joblib")

print("Model saved successfully!")
```

```
Classification Report (RandomForest):
precision    recall   f1-score   support
          0       0.97      0.97      0.97      191
          1       0.86      0.86      0.86       43

accuracy                           0.95      234
macro avg       0.91      0.91      0.91      234
weighted avg     0.95      0.95      0.95      234
```

ROC AUC: 0.978692317058322

Model saved successfully!

```
In [27]: city_models = {}
for city in df['city'].unique():
    sub = df[df['city']==city].sort_values('time').reset_index(drop=True)
    if len(sub) < 500: # skip tiny datasets
        continue
    si = int(len(sub)*0.8)
    Xtr, Xte = sub.iloc[:si][features].fillna(-999), sub.iloc[si:][features].fillna(-999)
    ytr, yte = sub.iloc[:si]['rain_next_hour'], sub.iloc[si:]['rain_next_hour']
    m = RandomForestClassifier(n_estimators=150, random_state=42, n_jobs=-1)
    m.fit(Xtr, ytr)
    city_models[city] = m
    print(city, "trained; test size:", len(yte))
```

4. Temperature Forecasting (Regression) — RandomForest / XGBoost

```
In [28]: from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_absolute_error, mean_squared_error
import numpy as np

# Regression target
X_train_r = train_df[features].fillna(-999)
y_train_r = train_df['temp_next_hour']
X_test_r = test_df[features].fillna(-999)
y_test_r = test_df['temp_next_hour']
```

```
In [29]: rf_reg = RandomForestRegressor(n_estimators=200, random_state=42, n_jobs=-1)
rf_reg.fit(X_train_r, y_train_r)
pred_r = rf_reg.predict(X_test_r)

print("MAE:", mean_absolute_error(y_test_r, pred_r))
print("RMSE:", np.sqrt(mean_squared_error(y_test_r, pred_r)))

joblib.dump(rf_reg, "models/temp_rf_model.joblib")
```

MAE: 0.317108974358974
RMSE: 0.4544784262836517

Out[29]: ['models/temp_rf_model.joblib']

5. Time-Series Model (Prophet) — per city daily or hourly

```
In [31]: from prophet import Prophet
from sklearn.metrics import mean_absolute_error

city = 'Bangalore'
city_df = df[df['city'] == city].sort_values('time').reset_index(drop=True)

# Include humidity in prophet dataframe
prophet_df = city_df[['time', 'temp_c', 'humidity']].rename(
    columns={'time': 'ds', 'temp_c': 'y'}
)

# Initialize model
m = Prophet(
    daily_seasonality=True,
    yearly_seasonality=True,
    weekly_seasonality=True
)
```

```

# Add regressor
m.add_regressor('humidity')

# Split 80%
split = int(len(prophet_df) * 0.8)

# Fit model WITH regressor
m.fit(prophet_df.iloc[:split])

# Build future dataframe
future = m.make_future_dataframe(periods=len(prophet_df) - split, freq='H')

# Add humidity values to future (Prophet requires it)
future['humidity'] = prophet_df['humidity']

# Predict
forecast = m.predict(future)

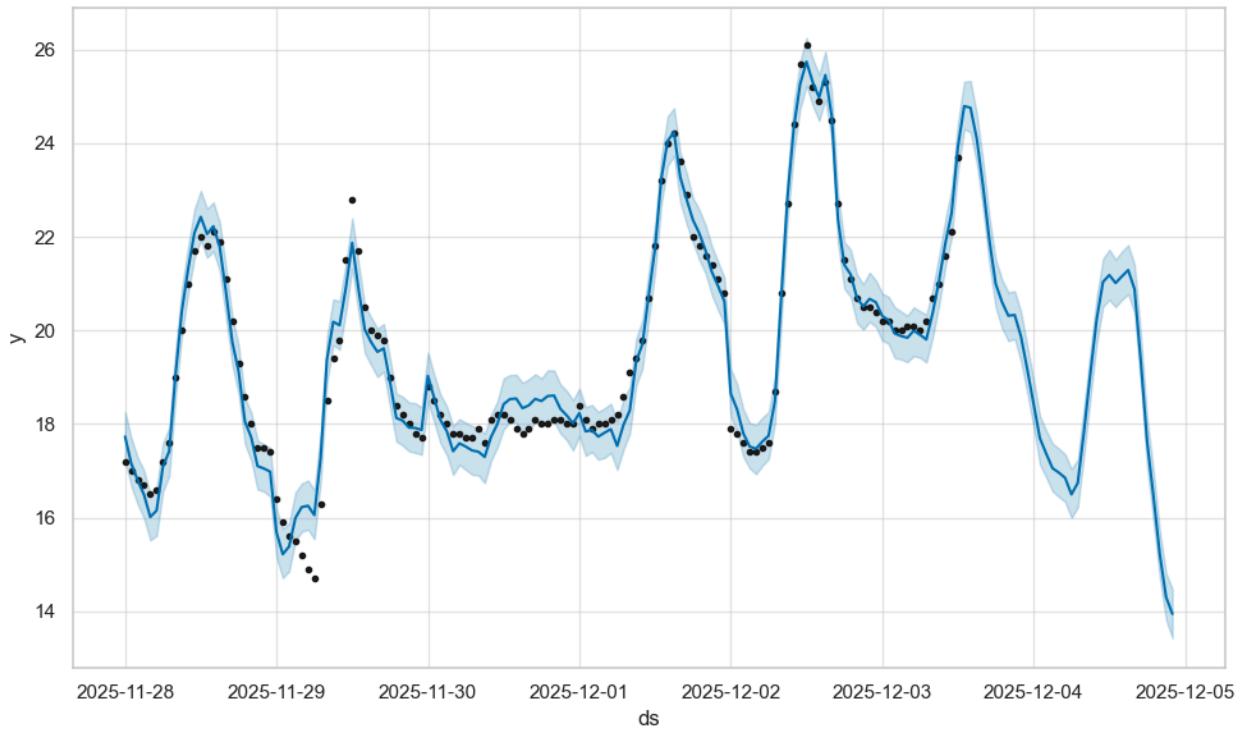
# Evaluate
pred = forecast.iloc[split:]['yhat'].values
true = prophet_df.iloc[split:]['y'].values

print(city, "Prophet MAE:", mean_absolute_error(true, pred))

# Plot forecast
fig = m.plot(forecast)

```

00:27:23 - cmdstanpy - INFO - Chain [1] start processing
00:27:24 - cmdstanpy - INFO - Chain [1] done processing
Bangalore Prophet MAE: 2.4587280347100595



6. Model Diagnostics & Feature Importance

```
In [32]: # Feature importances for the RF regression model  
  
fi = pd.DataFrame({'feature': features, 'importance': rf_reg.feature_importances_})  
fi.head(20)
```

```
Out[32]:
```

	feature	importance
6	temp_roll_mean_1	0.491230
3	temp_c	0.458038
0	hour	0.014422
8	temp_roll_mean_6	0.008104
11	temp_lag_3	0.005730
9	temp_roll_mean_24	0.004544
7	temp_roll_mean_3	0.004531
10	temp_lag_1	0.003522
12	temp_lag_6	0.002797
4	humidity	0.002651
5	wind_kph	0.002345
13	temp_lag_24	0.001243
1	dayofweek	0.000648
2	is_weekend	0.000102
14	precip_lag_1	0.000094

6. Simple Plotly Dashboard (interactive)

```
In [34]: import plotly.express as px  
import plotly.graph_objects as go  
  
# 1) Interactive time series for chosen city  
city_choice = input("Enter city to visualize (e.g., Delhi): ").strip()  
vis_df = df[df['city']==city_choice].sort_values('time')  
  
fig = px.line(vis_df, x='time', y='temp_c', title=f'{city_choice} - Temperature')  
fig.show()  
  
# 2) Interactive scatter: temperature vs humidity colored by city
```

```
fig2 = px.scatter(df.sample(min(2000,len(df))), x='temp_c', y='humidity', colc
fig2.update_layout(title="Temp vs Humidity (sample)")
fig2.show()

# 3) Map-style: if you have lat/lon columns
if 'lat' in df.columns and 'lon' in df.columns:
    latest = df.sort_values('time').groupby('city').tail(1)
    fig3 = px.scatter_mapbox(latest, lat='lat', lon='lon', hover_name='city',
    fig3.update_layout(mapbox_style="open-street-map")
    fig3.show()
```

8. Save Models and Pipelines

```
In [35]: import joblib  
joblib.dump(rf_reg, "models/temp_rf_model.joblib")  
joblib.dump(rfc, "models/rain_rf_model.joblib")  
# Example: save label encoders / scalers if used
```

```
Out[35]: ['models/rain_rf_model.joblib']
```