Global Air Quality Analysis - IDS Semester Project

Reg# 2023-CS-646

In [4]:
```python
# Import Libraries and Create Output Folders
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats
from scipy.stats import zscore
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.preprocessing import StandardScaler, MinMaxScaler, LabelEncoder
from sklearn.linear_model import LinearRegression, LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import (accuracy_score, precision_score, recall_score, f1_s
                             confusion_matrix, classification_report,
                             mean_absolute_error, mean_squared_error, r2_score)
import os
import warnings
warnings.filterwarnings('ignore')

# Create folders for saving graphs
folders = ['graphs/1_preprocessing', 'graphs/2_eda_univariate', 'graphs/3_eda_bi
           'graphs/4_correlation', 'graphs/5_comparative', 'graphs/6_timeseries'
for folder in folders:
    os.makedirs(folder, exist_ok=True)

plt.style.use('seaborn-v0_8-whitegrid')
print("✅ Libraries imported and folders created!")
```

```
✅ Libraries imported and folders created!
```

In [5]:
```python
# Load Dataset
df = pd.read_csv('global_air_quality_dataset.csv')
df_original = df.copy()

print(f"Shape: {df.shape}")
print(f"\nColumns: {list(df.columns)}")
print(f"\nFirst 5 rows:")
df.head()
```

```
Shape: (10000, 12)

Columns: ['City', 'Country', 'Date', 'PM2.5', 'PM10', 'NO2', 'SO2', 'CO', 'O3',
'Temperature', 'Humidity', 'Wind Speed']

First 5 rows:
```

Out[5]:

	City	Country	Date	PM2.5	PM10	NO2	SO2	CO	O3	Temperature	H
0	Bangkok	Thailand	2023-03-19	86.57	25.19	99.88	30.63	4.46	36.29	17.67	
1	Istanbul	Turkey	2023-02-16	50.63	97.39	48.14	8.71	3.40	144.16	3.46	
2	Rio de Janeiro	Brazil	2023-11-13	130.21	57.22	98.51	9.92	0.12	179.31	25.29	
3	Mumbai	India	2023-03-16	119.70	130.52	10.96	33.03	7.74	38.65	23.15	
4	Paris	France	2023-04-04	55.20	36.62	76.85	21.85	2.00	67.09	16.02	

In [6]:

```python
# Dataset Info and Statistics
print("Data Types:")
print(df.dtypes)
print("\nStatistical Summary:")
df.describe()
```

```
Data Types:
City             object
Country          object
Date             object
PM2.5           float64
PM10            float64
NO2             float64
SO2             float64
CO              float64
O3              float64
Temperature     float64
Humidity        float64
Wind Speed      float64
dtype: object

Statistical Summary:
```

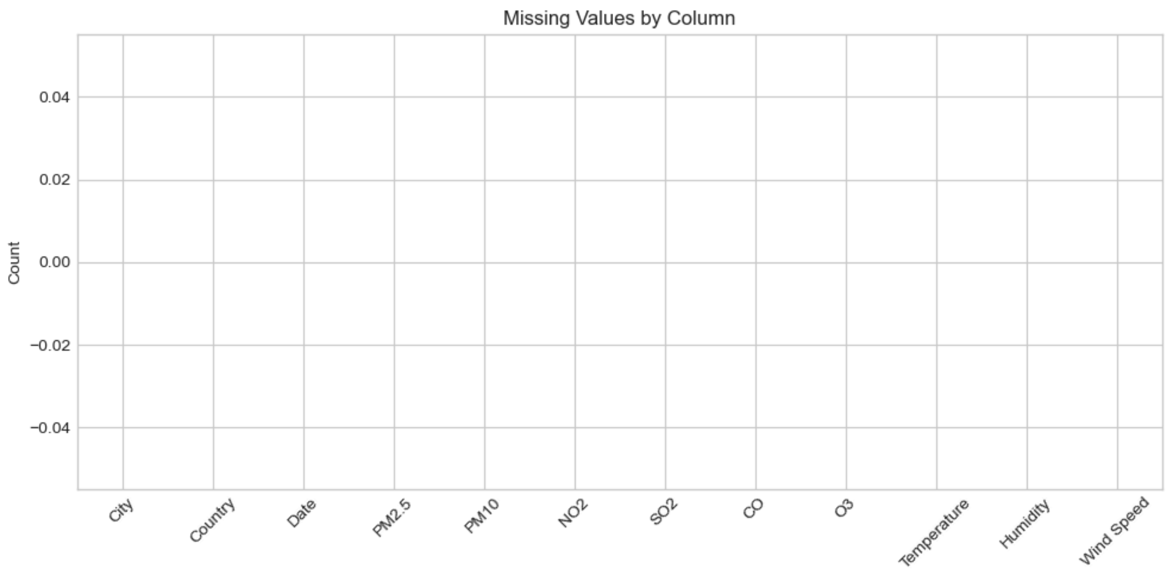
Out[6]:

	PM2.5	PM10	NO2	SO2	CO	
count	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.000
mean	77.448439	104.438161	52.198649	25.344490	5.047984	106.031
std	41.927871	55.062396	27.320490	14.091194	2.852625	55.081
min	5.020000	10.000000	5.010000	1.000000	0.100000	10.040
25%	41.185000	57.137500	28.347500	13.190000	2.560000	58.380
50%	77.725000	103.690000	52.100000	25.350000	5.090000	106.055
75%	113.392500	152.265000	75.705000	37.500000	7.480000	153.982
max	149.980000	200.000000	100.000000	49.990000	10.000000	200.000

1. Data Preprocessing & Cleaning

In [7]:
```
# 1.1 Check and Handle Missing Values
print("Missing Values:")
print(df.isnull().sum())

# Visualize missing values
fig, ax = plt.subplots(figsize=(10, 5))
df.isnull().sum().plot(kind='bar', color=['red' if x > 0 else 'green' for x in c
plt.title('Missing Values by Column')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.tight_layout()
plt.savefig('graphs/1_preprocessing/missing_values.png', dpi=150)
plt.show()

# Impute missing values
numerical_cols = ['PM2.5', 'PM10', 'NO2', 'SO2', 'CO', 'O3', 'Temperature', 'Hum
for col in numerical_cols:
    df[col].fillna(df[col].median(), inplace=True)

print("\n✅ Missing values after imputation:", df.isnull().sum().sum())
```

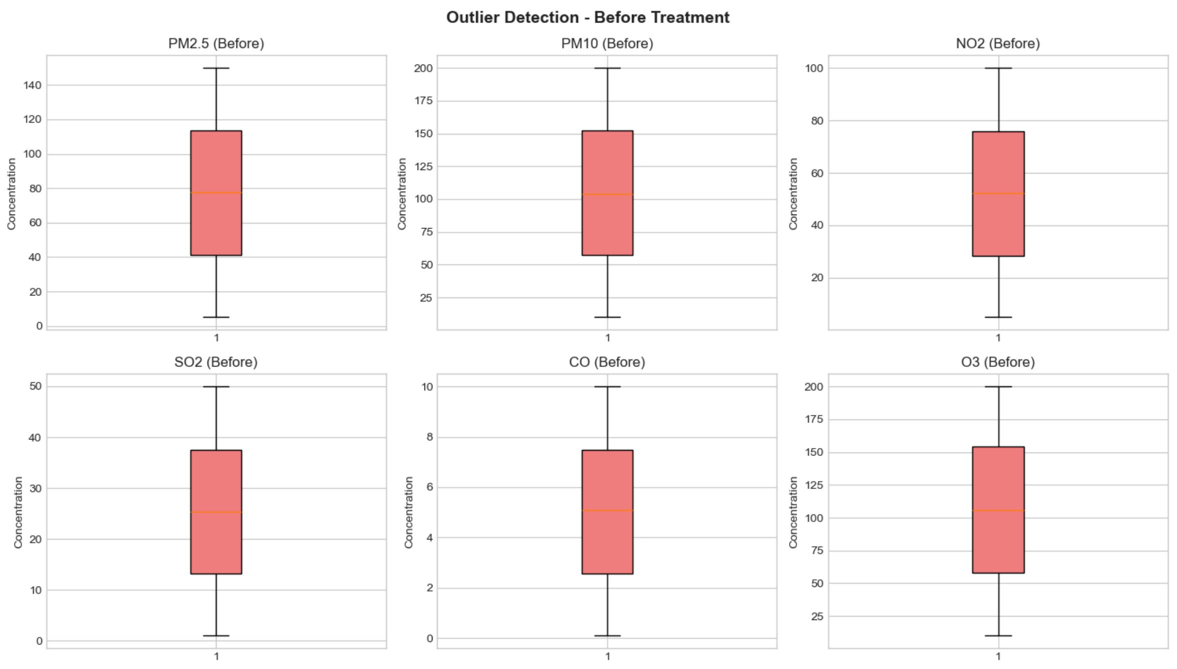
```
Missing Values:
City           0
Country        0
Date           0
PM2.5          0
PM10           0
NO2            0
SO2            0
CO             0
O3             0
Temperature    0
Humidity       0
Wind Speed     0
dtype: int64
```



```
✅ Missing values after imputation: 0
```

In [8]:
```
# 1.2 Outlier Detection - Box Plots Before Treatment
pollutant_cols = ['PM2.5', 'PM10', 'NO2', 'SO2', 'CO', 'O3']
```

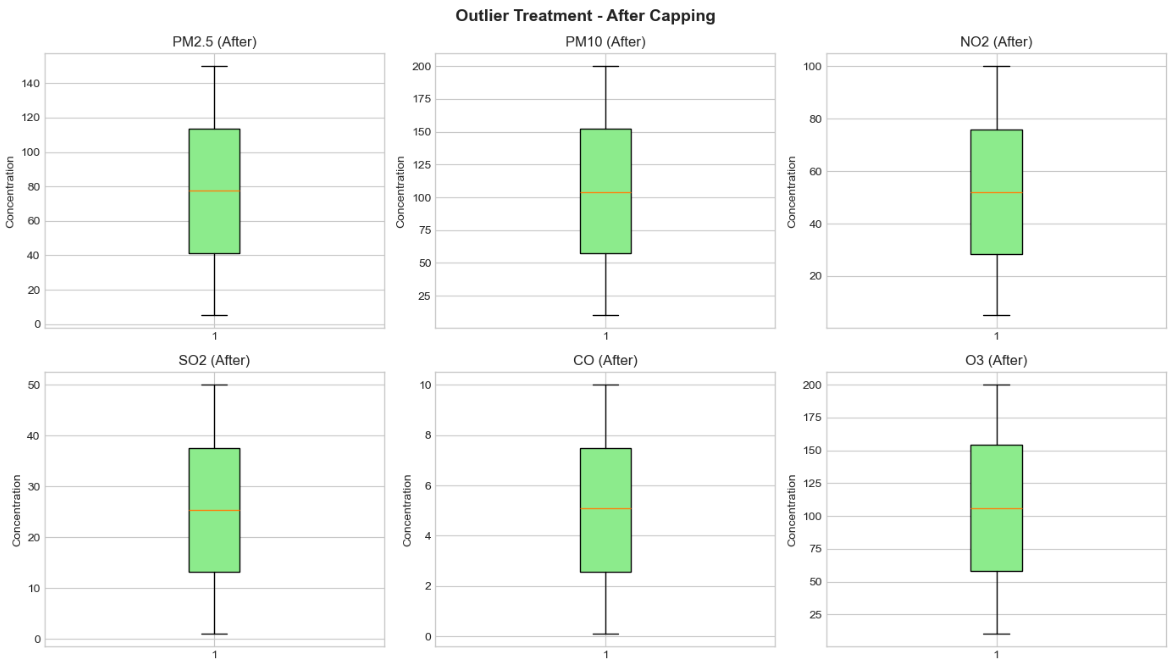
```python
fig, axes = plt.subplots(2, 3, figsize=(14, 8))
axes = axes.flatten()
for i, col in enumerate(pollutant_cols):
    axes[i].boxplot(df[col], patch_artist=True, boxprops=dict(facecolor='lightco
    axes[i].set_title(f'{col} (Before)')
    axes[i].set_ylabel('Concentration')
plt.suptitle('Outlier Detection - Before Treatment', fontsize=14, fontweight='bo
plt.tight_layout()
plt.savefig('graphs/1_preprocessing/outliers_before.png', dpi=150)
plt.show()
```



In [9]:
```python
# 1.3 Outlier Detection using IQR and Z-Score Methods
print("Outlier Detection Summary:")
print("-" * 60)

for col in numerical_cols:
    # IQR Method
    Q1, Q3 = df[col].quantile(0.25), df[col].quantile(0.75)
    IQR = Q3 - Q1
    iqr_outliers = ((df[col] < Q1 - 1.5*IQR) | (df[col] > Q3 + 1.5*IQR)).sum()

    # Z-Score Method
    z_outliers = (np.abs(zscore(df[col])) > 3).sum()

    print(f"{col}: IQR Outliers={iqr_outliers}, Z-Score Outliers={z_outliers}")
```

```
Outlier Detection Summary:
------------------------------------------------------------
PM2.5: IQR Outliers=0, Z-Score Outliers=0
PM10: IQR Outliers=0, Z-Score Outliers=0
NO2: IQR Outliers=0, Z-Score Outliers=0
SO2: IQR Outliers=0, Z-Score Outliers=0
CO: IQR Outliers=0, Z-Score Outliers=0
O3: IQR Outliers=0, Z-Score Outliers=0
Temperature: IQR Outliers=0, Z-Score Outliers=0
Humidity: IQR Outliers=0, Z-Score Outliers=0
Wind Speed: IQR Outliers=0, Z-Score Outliers=0
```

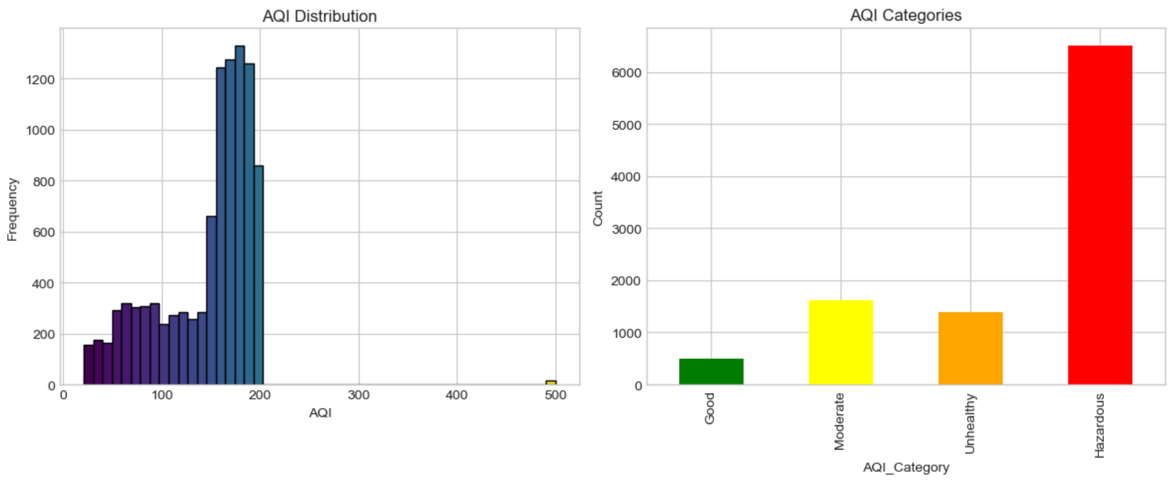
In [10]:
```
# 1.4 Handle Outliers using IQR Capping
for col in numerical_cols:
    Q1, Q3 = df[col].quantile(0.25), df[col].quantile(0.75)
    IQR = Q3 - Q1
    lower, upper = Q1 - 1.5*IQR, Q3 + 1.5*IQR
    df[col] = df[col].clip(lower, upper)

# Box Plots After Treatment
fig, axes = plt.subplots(2, 3, figsize=(14, 8))
axes = axes.flatten()
for i, col in enumerate(pollutant_cols):
    axes[i].boxplot(df[col], patch_artist=True, boxprops=dict(facecolor='lightgr
    axes[i].set_title(f'{col} (After)')
    axes[i].set_ylabel('Concentration')
plt.suptitle('Outlier Treatment - After Capping', fontsize=14, fontweight='bold'
plt.tight_layout()
plt.savefig('graphs/1_preprocessing/outliers_after.png', dpi=150)
plt.show()
print("✅ Outliers handled using IQR capping")
```



```
✅ Outliers handled using IQR capping
```

In [11]:
```
# 1.5 Calculate AQI and Create Categories
pm25_bp = [(0, 12, 0, 50), (12.1, 35.4, 51, 100), (35.5, 55.4, 101, 150),
           (55.5, 150.4, 151, 200), (150.5, 250.4, 201, 300), (250.5, 500, 301,

def calc_aqi(pm25):
    for low, high, aqi_low, aqi_high in pm25_bp:
        if low <= pm25 <= high:
            return ((aqi_high - aqi_low) / (high - low)) * (pm25 - low) + aqi_lc
    return 500

df['AQI'] = df['PM2.5'].apply(calc_aqi)

# Categorize AQI
def aqi_category(aqi):
    if aqi <= 50: return 'Good'
    elif aqi <= 100: return 'Moderate'
    elif aqi <= 150: return 'Unhealthy'
    else: return 'Hazardous'
```

```
df['AQI_Category'] = df['AQI'].apply(aqi_category)
df['AQI_Encoded'] = df['AQI_Category'].map({'Good': 0, 'Moderate': 1, 'Unhealthy

# Visualize AQI Distribution
fig, axes = plt.subplots(1, 2, figsize=(12, 5))
n, bins, patches = axes[0].hist(df['AQI'], bins=50, edgecolor='black')
cmap = plt.cm.viridis
for i, p in enumerate(patches):
    p.set_facecolor(cmap(i / len(patches)))
axes[0].set_title('AQI Distribution')
axes[0].set_xlabel('AQI')
axes[0].set_ylabel('Frequency')


colors = ['green', 'yellow', 'orange', 'red']
df['AQI_Category'].value_counts().reindex(['Good', 'Moderate', 'Unhealthy', 'Haz
    kind='bar', ax=axes[1], color=colors)
axes[1].set_title('AQI Categories')
axes[1].set_ylabel('Count')
plt.tight_layout()
plt.savefig('graphs/1_preprocessing/aqi_distribution.png', dpi=150)
plt.show()

print("AQI Category Distribution:")
print(df['AQI_Category'].value_counts())
```



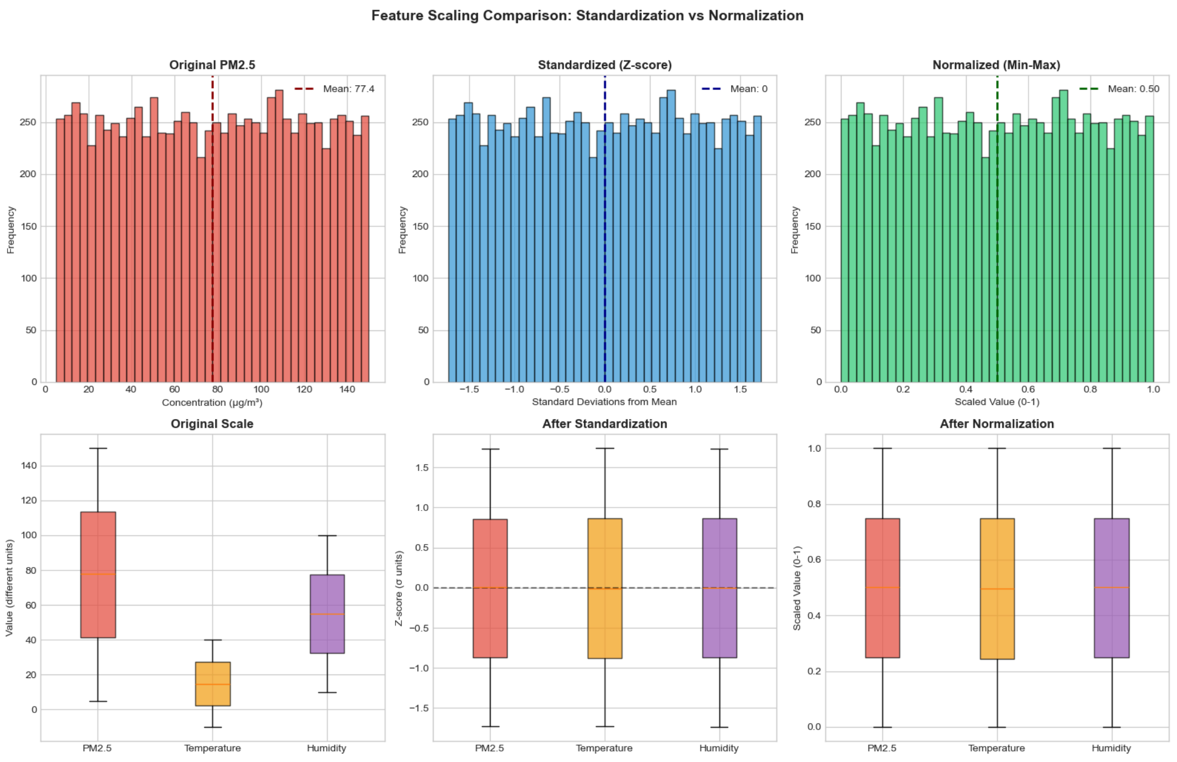
```
AQI Category Distribution:
AQI_Category
Hazardous    6514
Moderate     1609
Unhealthy    1380
Good          497
Name: count, dtype: int64
```

In [12]:

```
# 1.6 Feature Scaling - Standardization and Normalization
features = ['PM2.5', 'PM10', 'NO2', 'SO2', 'CO', 'O3', 'Temperature', 'Humidity'

# Compare scaling methods
scaler_std = StandardScaler()
scaler_mm = MinMaxScaler()

df_std = df.copy()
df_norm = df.copy()
df_std[features] = scaler_std.fit_transform(df[features])
df_norm[features] = scaler_mm.fit_transform(df[features])
```

```
# Enhanced Visualization
fig, axes = plt.subplots(2, 3, figsize=(16, 10))

# Row 1: PM2.5 Scaling Comparison
axes[0,0].hist(df['PM2.5'], bins=40, color='#e74c3c', alpha=0.7, edgecolor='blac
axes[0,0].axvline(df['PM2.5'].mean(), color='darkred', linestyle='--', linewidth
axes[0,0].set_title('Original PM2.5', fontsize=12, fontweight='bold')
axes[0,0].set_xlabel('Concentration (μg/m³)')
axes[0,0].set_ylabel('Frequency')
axes[0,0].legend()

axes[0,1].hist(df_std['PM2.5'], bins=40, color='#3498db', alpha=0.7, edgecolor='
axes[0,1].axvline(0, color='darkblue', linestyle='--', linewidth=2, label='Mean:
axes[0,1].set_title('Standardized (Z-score)', fontsize=12, fontweight='bold')
axes[0,1].set_xlabel('Standard Deviations from Mean')
axes[0,1].set_ylabel('Frequency')
axes[0,1].legend()

axes[0,2].hist(df_norm['PM2.5'], bins=40, color='#2ecc71', alpha=0.7, edgecolor=
axes[0,2].axvline(df_norm['PM2.5'].mean(), color='darkgreen', linestyle='--', li
axes[0,2].set_title('Normalized (Min-Max)', fontsize=12, fontweight='bold')
axes[0,2].set_xlabel('Scaled Value (0-1)')
axes[0,2].set_ylabel('Frequency')
axes[0,2].legend()

# Row 2: Before/After comparison for multiple features
sample_features = ['PM2.5', 'Temperature', 'Humidity']
colors = ['#e74c3c', '#f39c12', '#9b59b6']

# Original scale boxplot
bp1 = axes[1,0].boxplot([df[f] for f in sample_features], patch_artist=True, lab
for patch, color in zip(bp1['boxes'], colors):
    patch.set_facecolor(color)
    patch.set_alpha(0.7)
axes[1,0].set_title('Original Scale', fontsize=12, fontweight='bold')
axes[1,0].set_ylabel('Value (different units)')

# Standardized boxplot
bp2 = axes[1,1].boxplot([df_std[f] for f in sample_features], patch_artist=True,
for patch, color in zip(bp2['boxes'], colors):
    patch.set_facecolor(color)
    patch.set_alpha(0.7)
axes[1,1].axhline(0, color='black', linestyle='--', alpha=0.5)
axes[1,1].set_title('After Standardization', fontsize=12, fontweight='bold')
axes[1,1].set_ylabel('Z-score (σ units)')

# Normalized boxplot
bp3 = axes[1,2].boxplot([df_norm[f] for f in sample_features], patch_artist=True
for patch, color in zip(bp3['boxes'], colors):
    patch.set_facecolor(color)
    patch.set_alpha(0.7)
axes[1,2].set_title('After Normalization', fontsize=12, fontweight='bold')
axes[1,2].set_ylabel('Scaled Value (0-1)')

plt.suptitle('Feature Scaling Comparison: Standardization vs Normalization', fon
plt.tight_layout()
plt.savefig('graphs/1_preprocessing/scaling_comparison.png', dpi=150, bbox_inche
plt.show()
```

```
# Print summary statistics
print("📊 Scaling Methods Summary:")
print("-" * 60)
print(f"{'Method':<20} {'Mean':<15} {'Std':<15} {'Range'}")
print("-" * 60)
print(f"{'Original PM2.5':<20} {df['PM2.5'].mean():<15.2f} {df['PM2.5'].std():<1
print(f"{'Standardized':<20} {df_std['PM2.5'].mean():<15.2f} {df_std['PM2.5'].st
print(f"{'Normalized':<20} {df_norm['PM2.5'].mean():<15.2f} {df_norm['PM2.5'].st
print("-" * 60)
print("✅ StandardScaler: Mean=0, Std=1 (useful for algorithms sensitive to sca
print("✅ MinMaxScaler: Range [0,1] (preserves original distribution shape)")
```



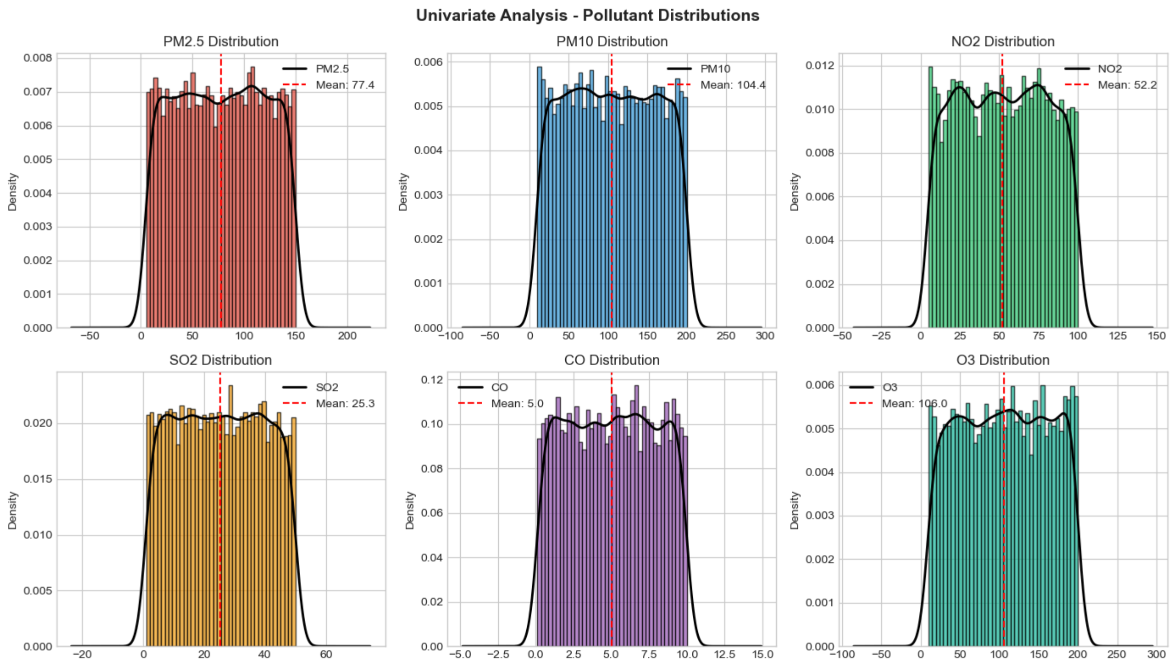
```
📊 Scaling Methods Summary:
------------------------------------------------------------
Method               Mean            Std             Range
------------------------------------------------------------
Original PM2.5       77.45           41.93           [5.0, 150.0]
Standardized         -0.00           1.00            [-1.73, 1.73]
Normalized           0.50            0.29            [0.00, 1.00]
------------------------------------------------------------
✅ StandardScaler: Mean=0, Std=1 (useful for algorithms sensitive to scale)
✅ MinMaxScaler: Range [0,1] (preserves original distribution shape)
```

In [13]:
```
# 1.7 Train-Test Split (80-20)
X = df[features]
y = df['AQI_Encoded']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_

# Scale features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

print(f"Training set: {len(X_train)} samples ({len(X_train)/len(X)*100:.0f}%)")
print(f"Test set: {len(X_test)} samples ({len(X_test)/len(X)*100:.0f}%)")
print(f"\nClass distribution in training set:")
print(pd.Series(y_train).value_counts().sort_index())
```

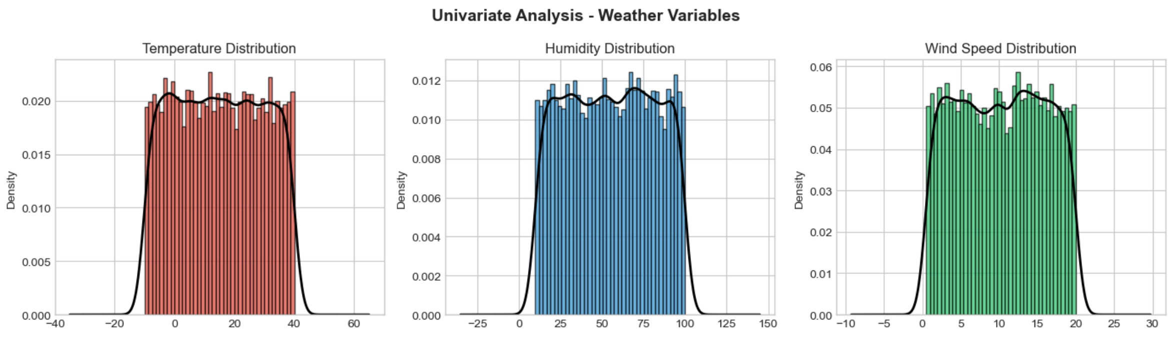
```
Training set: 8000 samples (80%)
Test set: 2000 samples (20%)

Class distribution in training set:
AQI_Encoded
0     398
1    1287
2    1104
3    5211
Name: count, dtype: int64
```

2. Exploratory Data Analysis (EDA)

In [14]:
```
# 2.1 Univariate Analysis - Pollutant Distributions
fig, axes = plt.subplots(2, 3, figsize=(14, 8))
axes = axes.flatten()
colors = ['#e74c3c', '#3498db', '#2ecc71', '#f39c12', '#9b59b6', '#1abc9c']

for i, (col, color) in enumerate(zip(pollutant_cols, colors)):
    axes[i].hist(df[col], bins=40, color=color, alpha=0.7, edgecolor='black', de
    df[col].plot(kind='kde', ax=axes[i], color='black', linewidth=2)
    axes[i].axvline(df[col].mean(), color='red', linestyle='--', label=f'Mean: {
    axes[i].set_title(f'{col} Distribution')
    axes[i].legend()
plt.suptitle('Univariate Analysis - Pollutant Distributions', fontsize=14, fontw
plt.tight_layout()
plt.savefig('graphs/2_eda_univariate/pollutant_distributions.png', dpi=150)
plt.show()
```



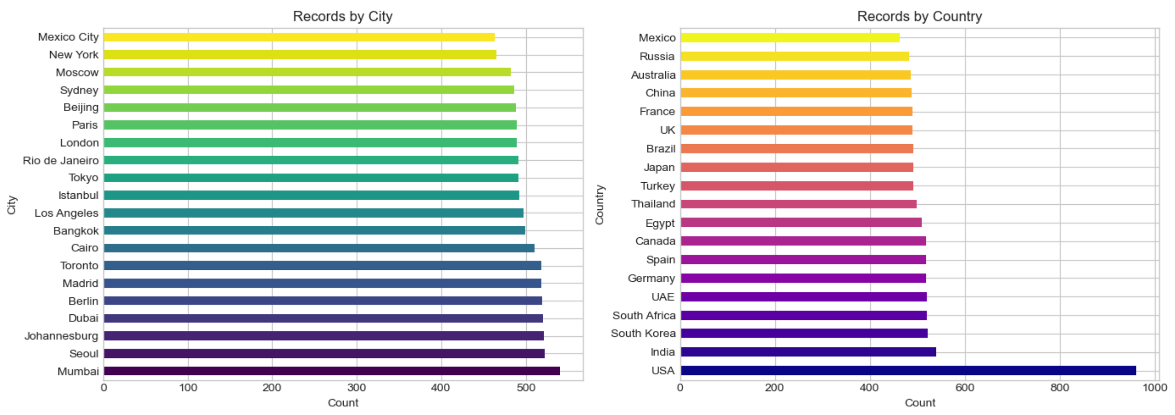
In [15]:
```
# 2.1b Univariate Analysis - Weather Variables
fig, axes = plt.subplots(1, 3, figsize=(14, 4))
weather_cols = ['Temperature', 'Humidity', 'Wind Speed']
weather_colors = ['#e74c3c', '#3498db', '#2ecc71']

for i, (col, color) in enumerate(zip(weather_cols, weather_colors)):
    axes[i].hist(df[col], bins=40, color=color, alpha=0.7, edgecolor='black', de
    df[col].plot(kind='kde', ax=axes[i], color='black', linewidth=2)
    axes[i].set_title(f'{col} Distribution')
plt.suptitle('Univariate Analysis - Weather Variables', fontsize=14, fontweight=
plt.tight_layout()
plt.savefig('graphs/2_eda_univariate/weather_distributions.png', dpi=150)
plt.show()
```



In [16]:
```
# 2.1c Skewness and Kurtosis Analysis
print("Skewness and Kurtosis Analysis:")
print("-" * 50)
for col in numerical_cols:
    skew = df[col].skew()
    kurt = df[col].kurtosis()
    print(f"{col}: Skewness={skew:.3f}, Kurtosis={kurt:.3f}")
```

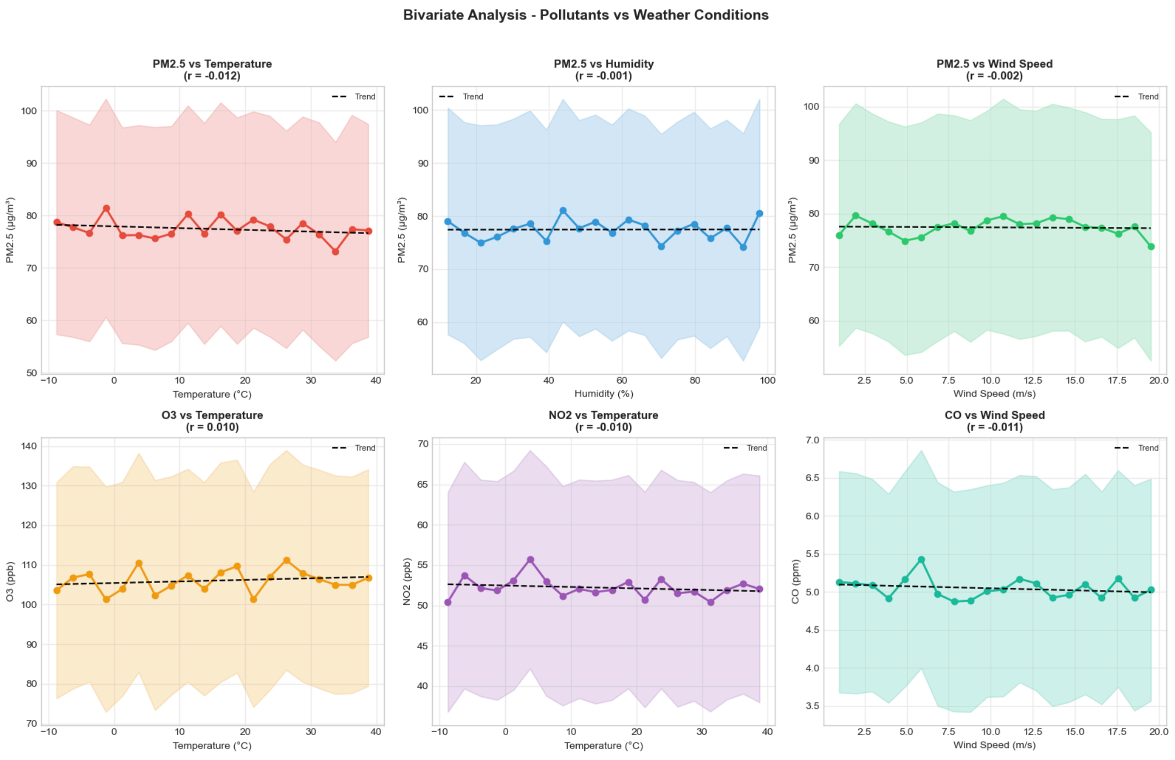
```
Skewness and Kurtosis Analysis:
--------------------------------------------------
PM2.5: Skewness=-0.006, Kurtosis=-1.204
PM10: Skewness=0.011, Kurtosis=-1.201
NO2: Skewness=-0.002, Kurtosis=-1.192
SO2: Skewness=0.007, Kurtosis=-1.192
CO: Skewness=-0.002, Kurtosis=-1.199
O3: Skewness=-0.014, Kurtosis=-1.196
Temperature: Skewness=0.013, Kurtosis=-1.201
Humidity: Skewness=-0.006, Kurtosis=-1.201
Wind Speed: Skewness=-0.008, Kurtosis=-1.209
```

In [17]:
```
# 2.1d Categorical Variables Distribution
fig, axes = plt.subplots(1, 2, figsize=(14, 5))

df['City'].value_counts().plot(kind='barh', ax=axes[0], color=plt.cm.viridis(np.
axes[0].set_title('Records by City')
axes[0].set_xlabel('Count')

df['Country'].value_counts().plot(kind='barh', ax=axes[1], color=plt.cm.plasma(n
axes[1].set_title('Records by Country')
axes[1].set_xlabel('Count')

plt.tight_layout()
plt.savefig('graphs/2_eda_univariate/categorical_distribution.png', dpi=150)
plt.show()
```



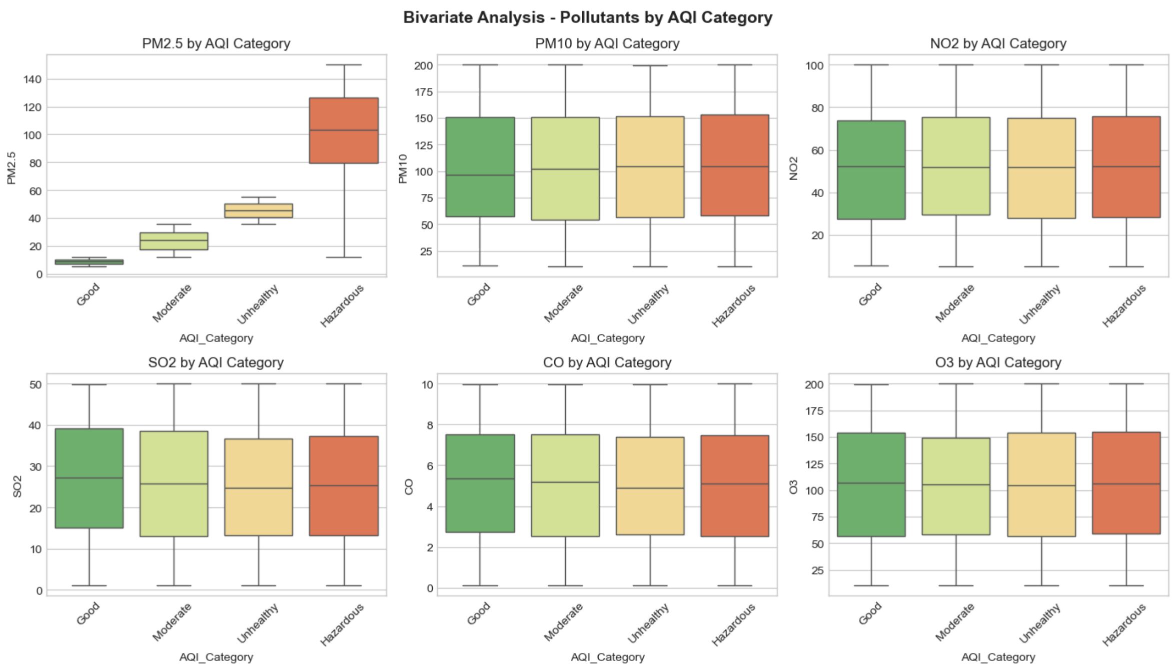
In [18]:
```
# 2.2 Bivariate Analysis - Pollutants vs Weather (Line Charts with Trend)
fig, axes = plt.subplots(2, 3, figsize=(16, 10))

# Helper function to create binned line chart with trend
def plot_bivariate_line(ax, x_col, y_col, color, xlabel, ylabel, title):
    # Create bins for x variable
    df_temp = df[[x_col, y_col]].dropna()
    df_temp['bin'] = pd.cut(df_temp[x_col], bins=20)
    grouped = df_temp.groupby('bin')[y_col].agg(['mean', 'std']).reset_index()
    grouped['bin_mid'] = grouped['bin'].apply(lambda x: x.mid)
    grouped = grouped.dropna()

    # Plot line with confidence band
    ax.plot(grouped['bin_mid'], grouped['mean'], marker='o', linewidth=2, color=
    ax.fill_between(grouped['bin_mid'],
                    grouped['mean'] - grouped['std']/2,
                    grouped['mean'] + grouped['std']/2,
                    alpha=0.2, color=color)

    # Add trend line
    z = np.polyfit(grouped['bin_mid'], grouped['mean'], 1)
    p = np.poly1d(z)
    ax.plot(grouped['bin_mid'], p(grouped['bin_mid']), '--', color='black', line

    # Calculate correlation
    corr = df[x_col].corr(df[y_col])
    ax.set_xlabel(xlabel, fontsize=10)
    ax.set_ylabel(ylabel, fontsize=10)
    ax.set_title(f'{title}\n(r = {corr:.3f})', fontsize=11, fontweight='bold')
    ax.legend(loc='best', fontsize=8)
    ax.grid(True, alpha=0.3)

# Row 1: PM2.5 relationships
plot_bivariate_line(axes[0,0], 'Temperature', 'PM2.5', '#e74c3c',
                    'Temperature (°C)', 'PM2.5 (μg/m³)', 'PM2.5 vs Temperature')
plot_bivariate_line(axes[0,1], 'Humidity', 'PM2.5', '#3498db',
                    'Humidity (%)', 'PM2.5 (μg/m³)', 'PM2.5 vs Humidity')
plot_bivariate_line(axes[0,2], 'Wind Speed', 'PM2.5', '#2ecc71',
                    'Wind Speed (m/s)', 'PM2.5 (μg/m³)', 'PM2.5 vs Wind Speed')

# Row 2: Other pollutants
plot_bivariate_line(axes[1,0], 'Temperature', 'O3', '#f39c12',
                    'Temperature (°C)', 'O3 (ppb)', 'O3 vs Temperature')
plot_bivariate_line(axes[1,1], 'Temperature', 'NO2', '#9b59b6',
                    'Temperature (°C)', 'NO2 (ppb)', 'NO2 vs Temperature')
plot_bivariate_line(axes[1,2], 'Wind Speed', 'CO', '#1abc9c',
                    'Wind Speed (m/s)', 'CO (ppm)', 'CO vs Wind Speed')
```

```python
plt.suptitle('Bivariate Analysis - Pollutants vs Weather Conditions', fontsize=1
plt.tight_layout()
plt.savefig('graphs/3_eda_bivariate/pollutants_vs_weather.png', dpi=150, bbox_in
plt.show()

print("📊 Key Observations:")
print("-" * 50)
print(f"  Temperature ↔ PM2.5:  r = {df['Temperature'].corr(df['PM2.5']):.3f}")
print(f"  Humidity ↔ PM2.5:     r = {df['Humidity'].corr(df['PM2.5']):.3f}")
print(f"  Wind Speed ↔ PM2.5:   r = {df['Wind Speed'].corr(df['PM2.5']):.3f}")
print(f"  Temperature ↔ O3:     r = {df['Temperature'].corr(df['O3']):.3f}")
print(f"  Temperature ↔ NO2:    r = {df['Temperature'].corr(df['NO2']):.3f}")
print(f"  Wind Speed ↔ CO:      r = {df['Wind Speed'].corr(df['CO']):.3f}")
```

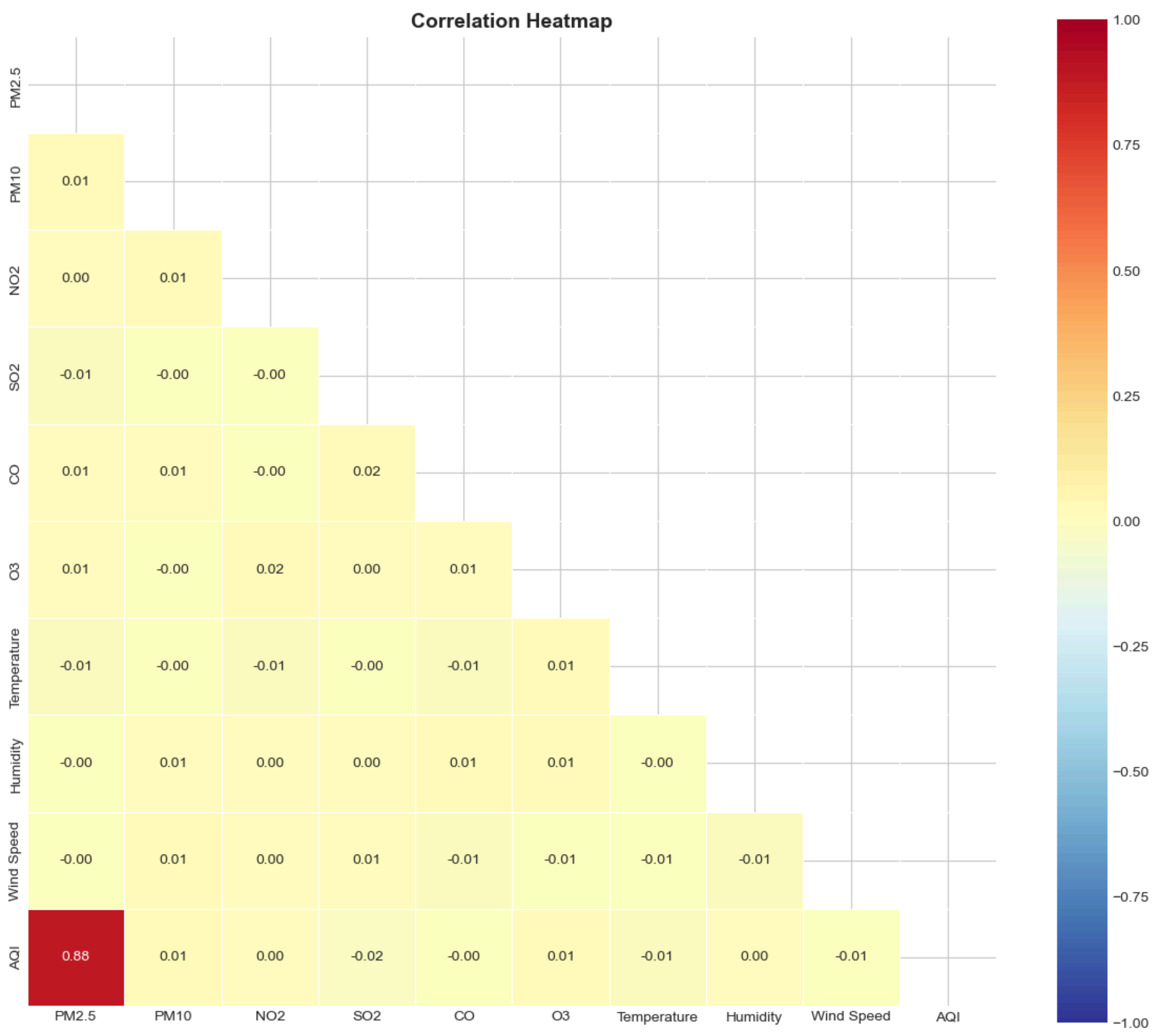


```
📊 Key Observations:
--------------------------------------------------
  Temperature ↔ PM2.5:  r = -0.012
  Humidity ↔ PM2.5:     r = -0.001
  Wind Speed ↔ PM2.5:   r = -0.002
  Temperature ↔ O3:     r = 0.010
  Temperature ↔ NO2:    r = -0.010
  Wind Speed ↔ CO:      r = -0.011
```

In [19]:
```python
# 2.2b Bivariate - Pollutants by AQI Category
fig, axes = plt.subplots(2, 3, figsize=(14, 8))
axes = axes.flatten()
order = ['Good', 'Moderate', 'Unhealthy', 'Hazardous']

for i, col in enumerate(pollutant_cols):
    sns.boxplot(data=df, x='AQI_Category', y=col, ax=axes[i], order=order, palet
    axes[i].set_title(f'{col} by AQI Category')
    axes[i].tick_params(axis='x', rotation=45)
plt.suptitle('Bivariate Analysis - Pollutants by AQI Category', fontsize=14, fon
plt.tight_layout()
plt.savefig('graphs/3_eda_bivariate/pollutants_by_aqi.png', dpi=150)
plt.show()
```

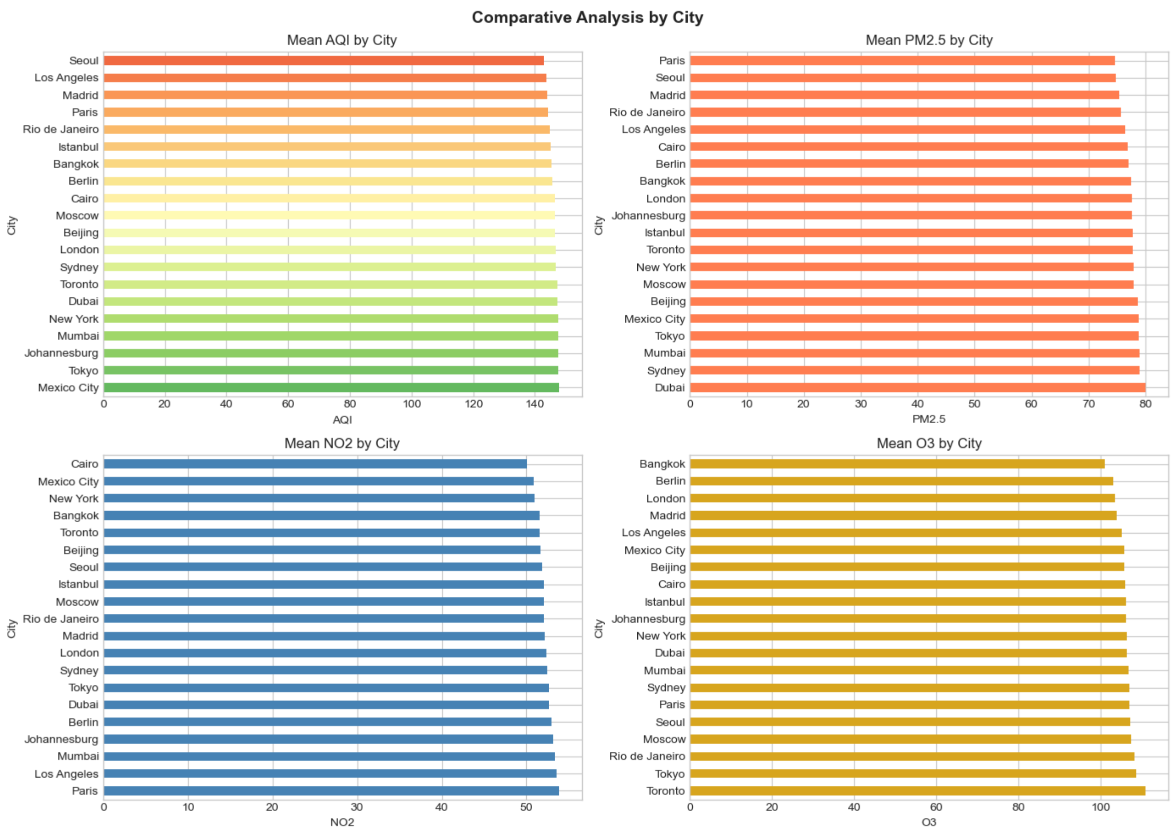


In [20]:
```
# 2.3 Correlation Analysis
corr_cols = numerical_cols + ['AQI']
corr_matrix = df[corr_cols].corr()

plt.figure(figsize=(12, 10))
mask = np.triu(np.ones_like(corr_matrix, dtype=bool))
sns.heatmap(corr_matrix, mask=mask, annot=True, fmt='.2f', cmap='RdYlBu_r',
            center=0, square=True, linewidths=0.5, vmin=-1, vmax=1)
plt.title('Correlation Heatmap', fontsize=14, fontweight='bold')
plt.tight_layout()
plt.savefig('graphs/4_correlation/correlation_heatmap.png', dpi=150)
plt.show()

# Strong correlations
print("Strong Correlations (|r| > 0.5):")
for i in range(len(corr_matrix.columns)):
    for j in range(i+1, len(corr_matrix.columns)):
        if abs(corr_matrix.iloc[i, j]) > 0.5:
            print(f"  {corr_matrix.columns[i]} ↔ {corr_matrix.columns[j]}: {corr
```



```
Strong Correlations (|r| > 0.5):
  PM2.5 ↔ AQI: 0.883
```

In [21]:
```python
# 2.4 Comparative Analysis - By City
fig, axes = plt.subplots(2, 2, figsize=(14, 10))

city_aqi = df.groupby('City')['AQI'].mean().sort_values(ascending=False)
city_aqi.plot(kind='barh', ax=axes[0,0], color=plt.cm.RdYlGn_r(np.linspace(0.2,
axes[0,0].set_title('Mean AQI by City'); axes[0,0].set_xlabel('AQI')

city_pm25 = df.groupby('City')['PM2.5'].mean().sort_values(ascending=False)
city_pm25.plot(kind='barh', ax=axes[0,1], color='coral')
axes[0,1].set_title('Mean PM2.5 by City'); axes[0,1].set_xlabel('PM2.5')

city_no2 = df.groupby('City')['NO2'].mean().sort_values(ascending=False)
city_no2.plot(kind='barh', ax=axes[1,0], color='steelblue')
axes[1,0].set_title('Mean NO2 by City'); axes[1,0].set_xlabel('NO2')

city_o3 = df.groupby('City')['O3'].mean().sort_values(ascending=False)
city_o3.plot(kind='barh', ax=axes[1,1], color='goldenrod')
axes[1,1].set_title('Mean O3 by City'); axes[1,1].set_xlabel('O3')

plt.suptitle('Comparative Analysis by City', fontsize=14, fontweight='bold')
plt.tight_layout()
plt.savefig('graphs/5_comparative/city_comparison.png', dpi=150)
plt.show()
```

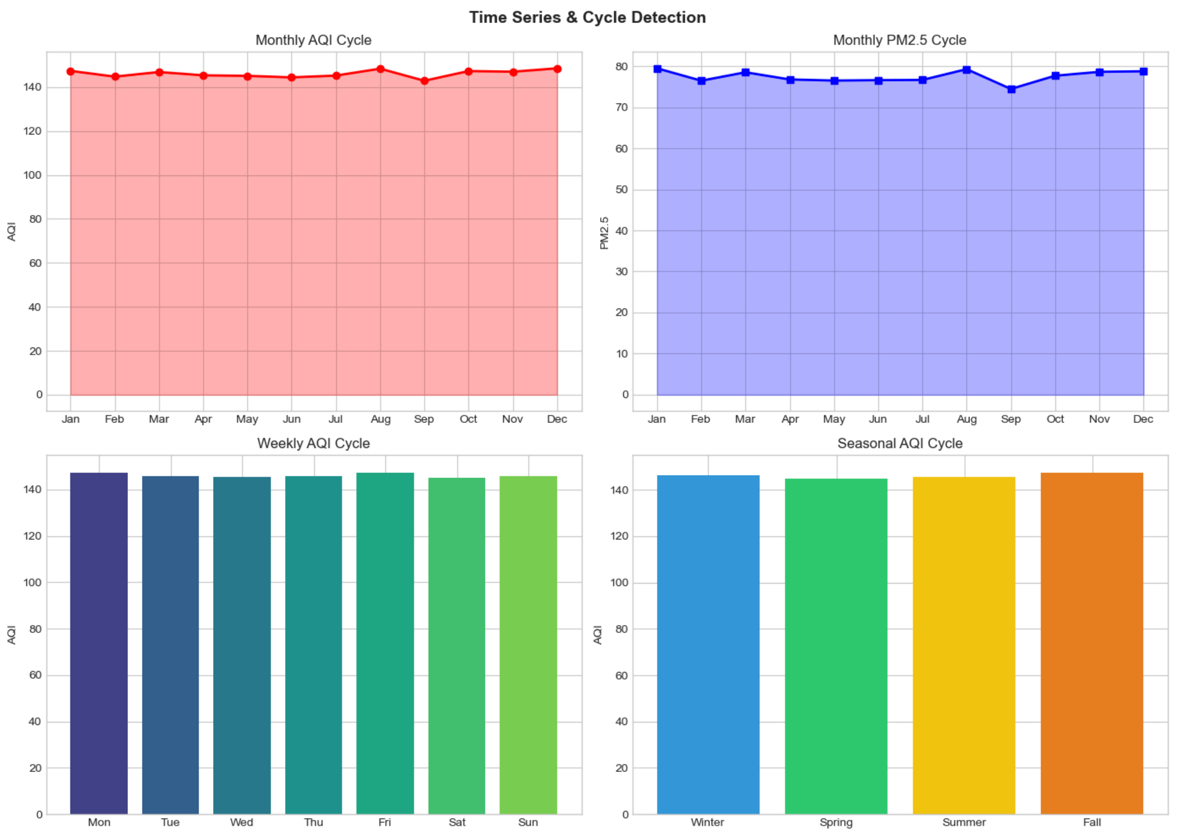


In [22]:
```python
# 2.4b Comparative Analysis - By Country

print("Mean Pollutants by Country:")
print(df.groupby('Country')[pollutant_cols + ['AQI']].mean().round(2))
```

```
Mean Pollutants by Country:
              PM2.5    PM10    NO2    SO2    CO      O3     AQI
Country
Australia     78.93  103.37  52.47  25.68  5.02  106.82  146.86
Brazil        75.67  105.44  52.10  24.58  4.91  108.07  144.86
Canada        77.83  103.87  51.55  24.80  4.95  110.85  147.27
China         78.63  103.19  51.62  24.90  5.09  105.74  146.48
Egypt         76.89  102.99  50.06  24.99  5.13  105.93  146.33
France        74.69  104.64  53.82  24.57  4.94  106.91  144.13
Germany       76.97  104.37  52.96  24.51  4.97  102.93  145.65
India         78.90  105.84  53.34  25.03  5.08  106.64  147.51
Japan         78.87  105.04  52.67  27.98  5.10  108.48  147.64
Mexico        78.86  104.53  50.86  26.02  5.14  105.69  147.73
Russia        77.88  105.94  52.03  26.11  5.12  107.29  146.34
South Africa  77.67  105.14  53.15  24.67  5.09  106.18  147.62
South Korea   74.80  105.00  51.88  25.01  4.89  107.02  142.83
Spain         75.43  105.87  52.14  25.15  4.89  103.78  143.89
Thailand      77.46  103.93  51.51  25.58  5.26  101.00  145.43
Turkey        77.71  103.14  52.02  25.77  5.12  106.18  145.16
UAE           80.01  103.89  52.68  24.96  5.08  106.40  147.40
UK            77.61  103.84  52.33  25.50  4.95  103.31  146.77
USA           77.11  104.29  52.30  25.67  5.12  105.69  145.50
```

In [23]:
```python
# 2.5 Time Series & Cycle Detection
df['Date'] = pd.to_datetime(df['Date'])
df['Year'] = df['Date'].dt.year
df['Month'] = df['Date'].dt.month
df['DayOfWeek'] = df['Date'].dt.dayofweek
df['Quarter'] = df['Date'].dt.quarter
```

```
month_names = ['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun', 'Jul', 'Aug', 'Sep', 'O
day_names = ['Mon', 'Tue', 'Wed', 'Thu', 'Fri', 'Sat', 'Sun']

# Monthly Cycle
fig, axes = plt.subplots(2, 2, figsize=(14, 10))

monthly_aqi = df.groupby('Month')['AQI'].mean()
axes[0,0].plot(monthly_aqi.index, monthly_aqi.values, marker='o', linewidth=2, c
axes[0,0].fill_between(monthly_aqi.index, monthly_aqi.values, alpha=0.3, color='
axes[0,0].set_xticks(range(1, 13)); axes[0,0].set_xticklabels(month_names)
axes[0,0].set_title('Monthly AQI Cycle'); axes[0,0].set_ylabel('AQI')

monthly_pm25 = df.groupby('Month')['PM2.5'].mean()
axes[0,1].plot(monthly_pm25.index, monthly_pm25.values, marker='s', linewidth=2,
axes[0,1].fill_between(monthly_pm25.index, monthly_pm25.values, alpha=0.3, color
axes[0,1].set_xticks(range(1, 13)); axes[0,1].set_xticklabels(month_names)
axes[0,1].set_title('Monthly PM2.5 Cycle'); axes[0,1].set_ylabel('PM2.5')

# Weekly Cycle
weekly_aqi = df.groupby('DayOfWeek')['AQI'].mean()
axes[1,0].bar(weekly_aqi.index, weekly_aqi.values, color=plt.cm.viridis(np.linsp
axes[1,0].set_xticks(range(7)); axes[1,0].set_xticklabels(day_names)
axes[1,0].set_title('Weekly AQI Cycle'); axes[1,0].set_ylabel('AQI')

# Seasonal Cycle
season_map = {1: 'Winter', 2: 'Spring', 3: 'Summer', 4: 'Fall'}
df['Season'] = df['Quarter'].map(season_map)
seasonal_aqi = df.groupby('Season')['AQI'].mean().reindex(['Winter', 'Spring', '
axes[1,1].bar(seasonal_aqi.index, seasonal_aqi.values, color=['#3498db', '#2ecc7
axes[1,1].set_title('Seasonal AQI Cycle'); axes[1,1].set_ylabel('AQI')

plt.suptitle('Time Series & Cycle Detection', fontsize=14, fontweight='bold')
plt.tight_layout()
plt.savefig('graphs/6_timeseries/cycles.png', dpi=150)
plt.show()
```



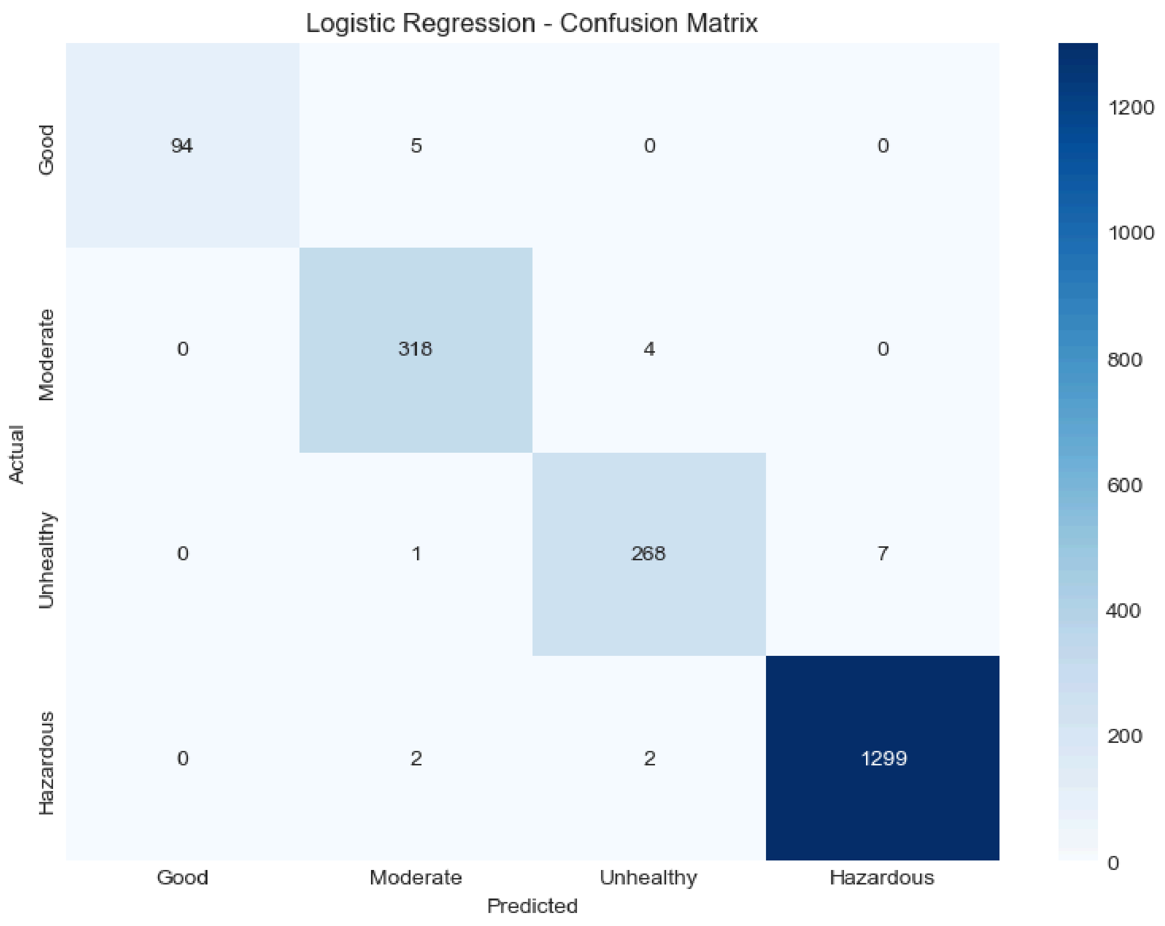
3. Model Building & Prediction

In [24]:
```
# Model Evaluation Function
label_map = {0: 'Good', 1: 'Moderate', 2: 'Unhealthy', 3: 'Hazardous'}
results = []

def train_evaluate_model(name, model):
    model.fit(X_train_scaled, y_train)
    y_pred = model.predict(X_test_scaled)

    acc = accuracy_score(y_test, y_pred)
    prec = precision_score(y_test, y_pred, average='weighted', zero_division=0)
    rec = recall_score(y_test, y_pred, average='weighted', zero_division=0)
    f1 = f1_score(y_test, y_pred, average='weighted', zero_division=0)
    cv = cross_val_score(model, X_train_scaled, y_train, cv=5).mean()

    results.append({'Model': name, 'Accuracy': acc, 'Precision': prec, 'Recall':

    print(f"\n{'='*50}")
    print(f"MODEL: {name}")
    print(f"{'='*50}")
    print(f"Accuracy: {acc:.4f} | Precision: {prec:.4f} | Recall: {rec:.4f} | F1
    print(f"\nConfusion Matrix:\n{confusion_matrix(y_test, y_pred)}")

    return model, y_pred
```

In [36]:
```
# Model 1: Logistic Regression
lr_model, lr_pred = train_evaluate_model('Logistic Regression', LogisticRegressi

fig, ax = plt.subplots(figsize=(8, 6))
sns.heatmap(confusion_matrix(y_test, lr_pred), annot=True, fmt='d', cmap='Blues'
            xticklabels=label_map.values(), yticklabels=label_map.values())
```

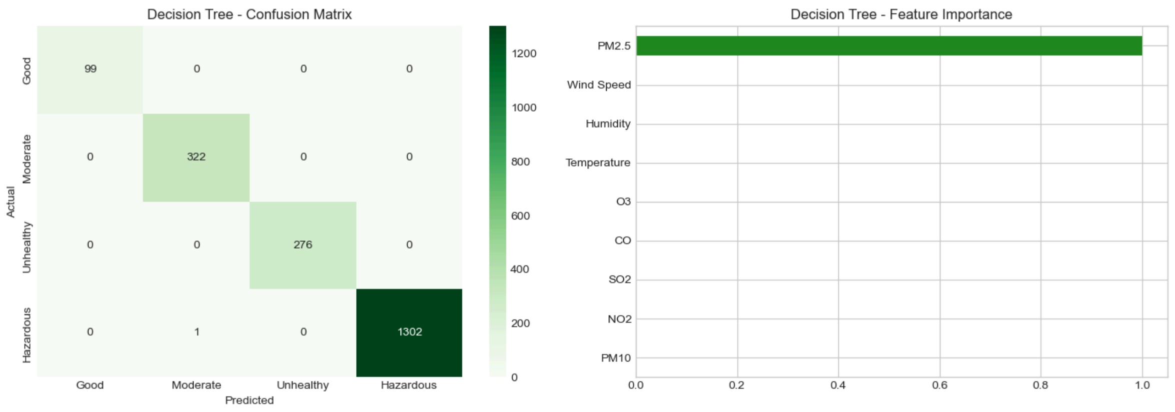
```
plt.title('Logistic Regression - Confusion Matrix'); plt.xlabel('Predicted'); pl
plt.tight_layout()
plt.savefig('graphs/7_models/logistic_regression_cm.png', dpi=150)
plt.show()
```

```
==================================================
MODEL: Logistic Regression
==================================================
Accuracy: 0.9895 | Precision: 0.9895 | Recall: 0.9895 | F1: 0.9895

Confusion Matrix:
[[  94    5    0    0]
 [   0  318    4    0]
 [   0    1  268    7]
 [   0    2    2 1299]]
```



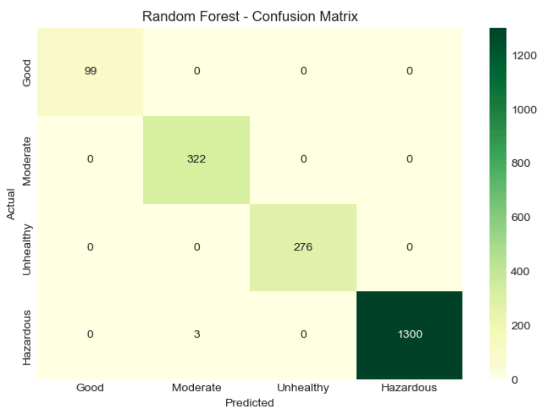
In [37]:
```
# Model 2: Decision Tree
dt_model, dt_pred = train_evaluate_model('Decision Tree', DecisionTreeClassifier

fig, axes = plt.subplots(1, 2, figsize=(14, 5))
sns.heatmap(confusion_matrix(y_test, dt_pred), annot=True, fmt='d', cmap='Greens
            xticklabels=label_map.values(), yticklabels=label_map.values())
axes[0].set_title('Decision Tree - Confusion Matrix'); axes[0].set_xlabel('Predi

dt_importance = pd.Series(dt_model.feature_importances_, index=features).sort_va
dt_importance.plot(kind='barh', ax=axes[1], color='forestgreen')
axes[1].set_title('Decision Tree - Feature Importance')
plt.tight_layout()
plt.savefig('graphs/7_models/decision_tree.png', dpi=150)
plt.show()
```

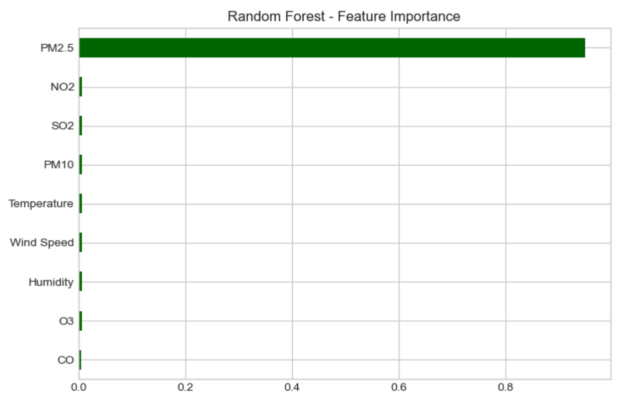
```
==================================================
MODEL: Decision Tree
==================================================
Accuracy: 0.9995 | Precision: 0.9995 | Recall: 0.9995 | F1: 0.9995

Confusion Matrix:
[[  99    0    0    0]
 [   0  322    0    0]
 [   0    0  276    0]
 [   0    1    0 1302]]
```



In [46]:
```python
# Model 3: Random Forest
rf_model, rf_pred = train_evaluate_model('Random Forest', RandomForestClassifier

fig, axes = plt.subplots(1, 2, figsize=(14, 5))
sns.heatmap(confusion_matrix(y_test, rf_pred), annot=True, fmt='d', cmap='YlGn',
            xticklabels=label_map.values(), yticklabels=label_map.values())
axes[0].set_title('Random Forest - Confusion Matrix'); axes[0].set_xlabel('Predi

rf_importance = pd.Series(rf_model.feature_importances_, index=features).sort_va
rf_importance.plot(kind='barh', ax=axes[1], color='darkgreen')
axes[1].set_title('Random Forest - Feature Importance')
plt.tight_layout()
plt.savefig('graphs/7_models/random_forest.png', dpi=150)
plt.show()
```

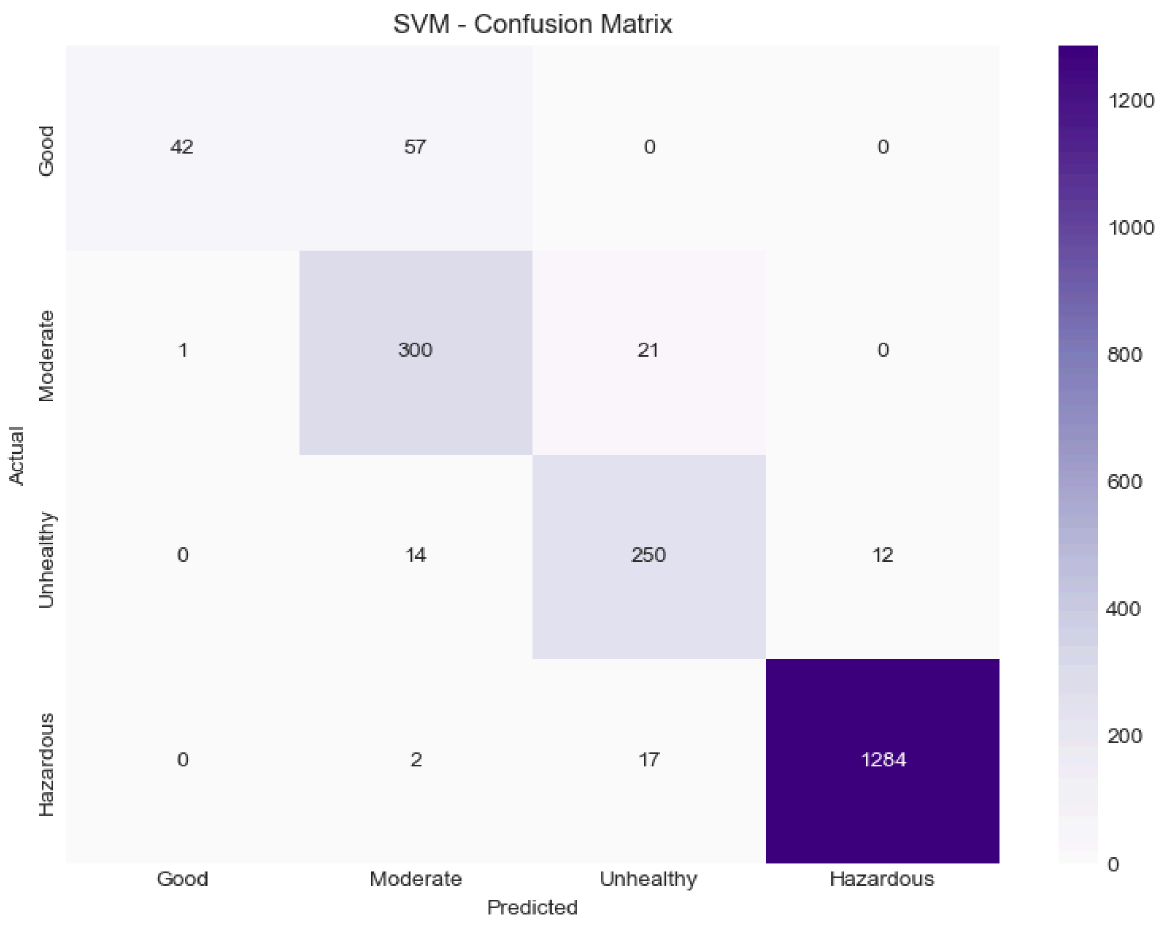
```
==================================================
MODEL: Random Forest
==================================================
Accuracy: 0.9985 | Precision: 0.9985 | Recall: 0.9985 | F1: 0.9985

Confusion Matrix:
[[  99    0    0    0]
 [   0  322    0    0]
 [   0    0  276    0]
 [   0    3    0 1300]]
```





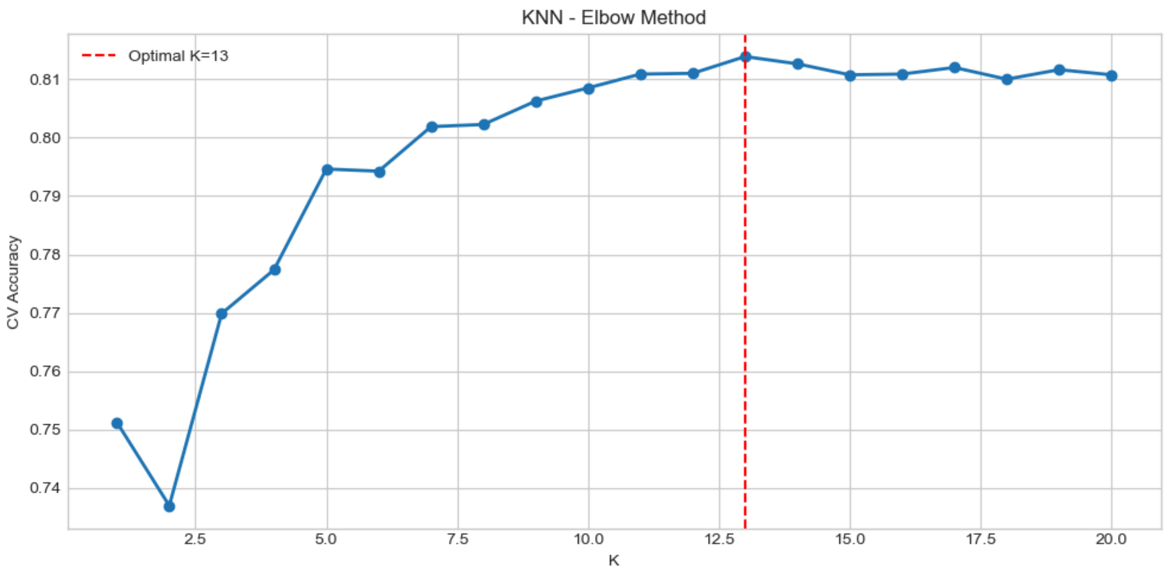
In [39]:
```python
# Model 4: Support Vector Machine (SVM)
svm_model, svm_pred = train_evaluate_model('SVM (RBF)', SVC(kernel='rbf', random

fig, ax = plt.subplots(figsize=(8, 6))
sns.heatmap(confusion_matrix(y_test, svm_pred), annot=True, fmt='d', cmap='Purpl
            xticklabels=label_map.values(), yticklabels=label_map.values())
plt.title('SVM - Confusion Matrix'); plt.xlabel('Predicted'); plt.ylabel('Actual
plt.tight_layout()
plt.savefig('graphs/7_models/svm_cm.png', dpi=150)
plt.show()
```

```
==================================================
MODEL: SVM (RBF)
==================================================
Accuracy: 0.9380 | Precision: 0.9431 | Recall: 0.9380 | F1: 0.9343

Confusion Matrix:
[[  42   57    0    0]
 [   1  300   21    0]
 [   0   14  250   12]
 [   0    2   17 1284]]
```

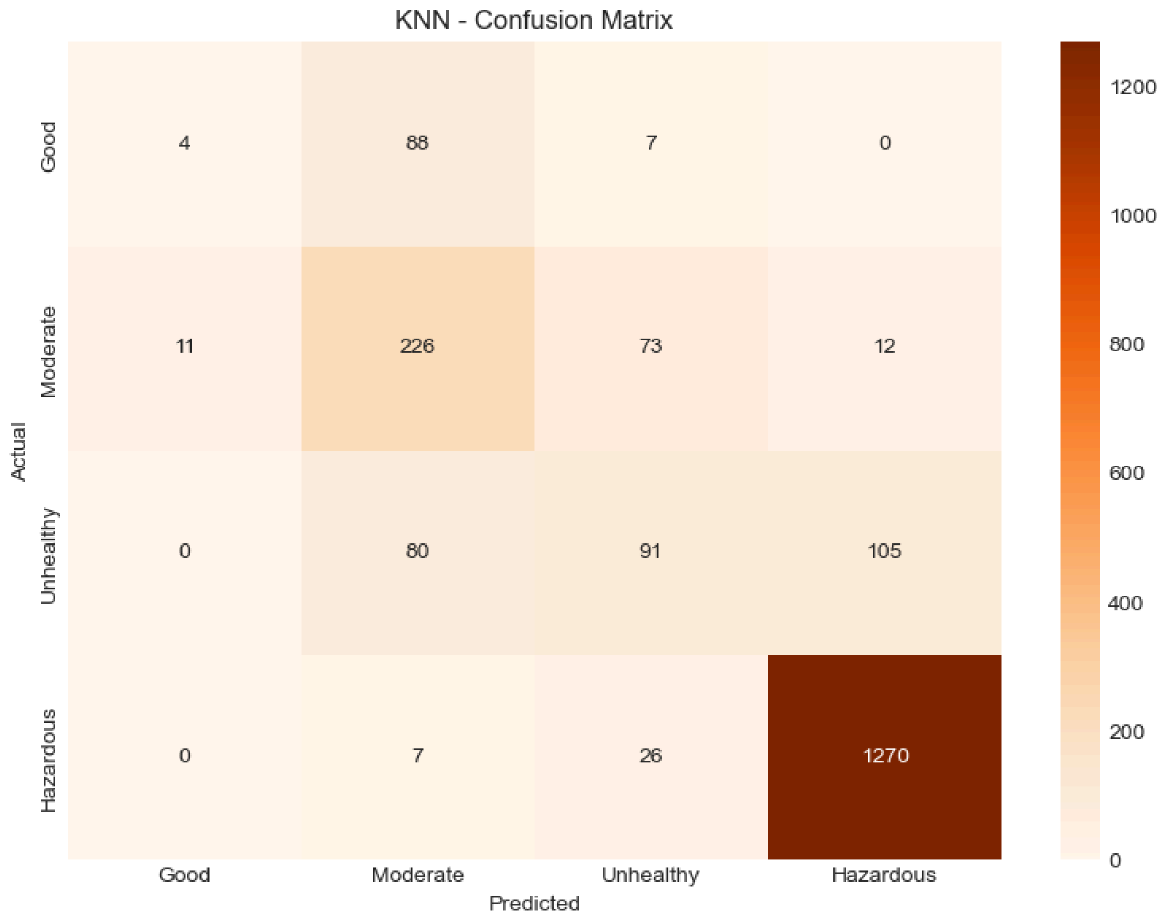


In [40]:

```
# Model 5: K-Nearest Neighbors (KNN) with Elbow Method
k_scores = []
for k in range(1, 21):
    knn = KNeighborsClassifier(n_neighbors=k)
    cv_score = cross_val_score(knn, X_train_scaled, y_train, cv=5).mean()
    k_scores.append(cv_score)

optimal_k = np.argmax(k_scores) + 1

fig, ax = plt.subplots(figsize=(10, 5))
ax.plot(range(1, 21), k_scores, marker='o', linewidth=2)
ax.axvline(optimal_k, color='red', linestyle='--', label=f'Optimal K={optimal_k}
ax.set_xlabel('K'); ax.set_ylabel('CV Accuracy'); ax.set_title('KNN - Elbow Meth
ax.legend()
plt.tight_layout()
plt.savefig('graphs/7_models/knn_elbow.png', dpi=150)
plt.show()

knn_model, knn_pred = train_evaluate_model(f'KNN (K={optimal_k})', KNeighborsCla

fig, ax = plt.subplots(figsize=(8, 6))
sns.heatmap(confusion_matrix(y_test, knn_pred), annot=True, fmt='d', cmap='Orang
            xticklabels=label_map.values(), yticklabels=label_map.values())
plt.title('KNN - Confusion Matrix'); plt.xlabel('Predicted'); plt.ylabel('Actual
plt.tight_layout()
plt.savefig('graphs/7_models/knn_cm.png', dpi=150)
plt.show()
```



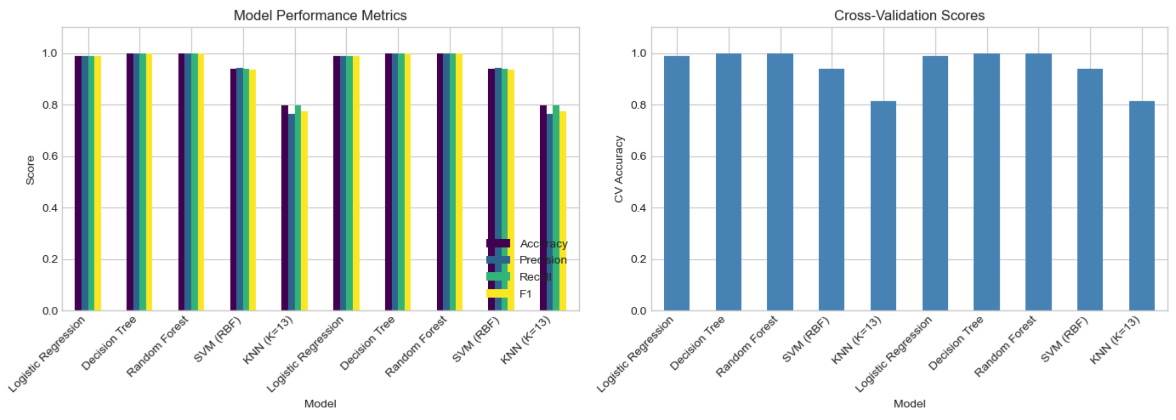
```
==================================================
MODEL: KNN (K=13)
==================================================
Accuracy: 0.7955 | Precision: 0.7642 | Recall: 0.7955 | F1: 0.7724

Confusion Matrix:
[[   4   88    7    0]
 [  11  226   73   12]
 [   0   80   91  105]
 [   0    7   26 1270]]
```



```
In [41]: # Model Comparison
         results_df = pd.DataFrame(results)
         results_df = results_df.set_index('Model')
         print("=" * 80)
```

```python
print("MODEL COMPARISON SUMMARY")
print("=" * 80)
print(results_df.round(4).to_string())
print("\nBest Model:", results_df['F1'].idxmax(), f"(F1: {results_df['F1'].max()

fig, axes = plt.subplots(1, 2, figsize=(14, 5))

results_df[['Accuracy', 'Precision', 'Recall', 'F1']].plot(kind='bar', ax=axes[0
axes[0].set_title('Model Performance Metrics'); axes[0].set_ylabel('Score')
axes[0].set_xticklabels(axes[0].get_xticklabels(), rotation=45, ha='right')
axes[0].legend(loc='lower right'); axes[0].set_ylim(0, 1.1)

results_df['CV Score'].plot(kind='bar', ax=axes[1], color='steelblue', capsize=5
axes[1].set_title('Cross-Validation Scores'); axes[1].set_ylabel('CV Accuracy')
axes[1].set_xticklabels(axes[1].get_xticklabels(), rotation=45, ha='right')
axes[1].set_ylim(0, 1.1)

plt.tight_layout()
plt.savefig('graphs/7_models/model_comparison.png', dpi=150)
plt.show()
```

```
================================================================================
MODEL COMPARISON SUMMARY
================================================================================
                     Accuracy  Precision  Recall      F1  CV Score
Model
Logistic Regression    0.9895     0.9895  0.9895  0.9895    0.9898
Decision Tree          0.9995     0.9995  0.9995  0.9995    0.9999
Random Forest          0.9985     0.9985  0.9985  0.9985    0.9991
SVM (RBF)              0.9380     0.9431  0.9380  0.9343    0.9391
KNN (K=13)             0.7955     0.7642  0.7955  0.7724    0.8139
Logistic Regression    0.9895     0.9895  0.9895  0.9895    0.9898
Decision Tree          0.9995     0.9995  0.9995  0.9995    0.9999
Random Forest          0.9985     0.9985  0.9985  0.9985    0.9991
SVM (RBF)              0.9380     0.9431  0.9380  0.9343    0.9391
KNN (K=13)             0.7955     0.7642  0.7955  0.7724    0.8139

Best Model: Decision Tree (F1: 0.9995)
```



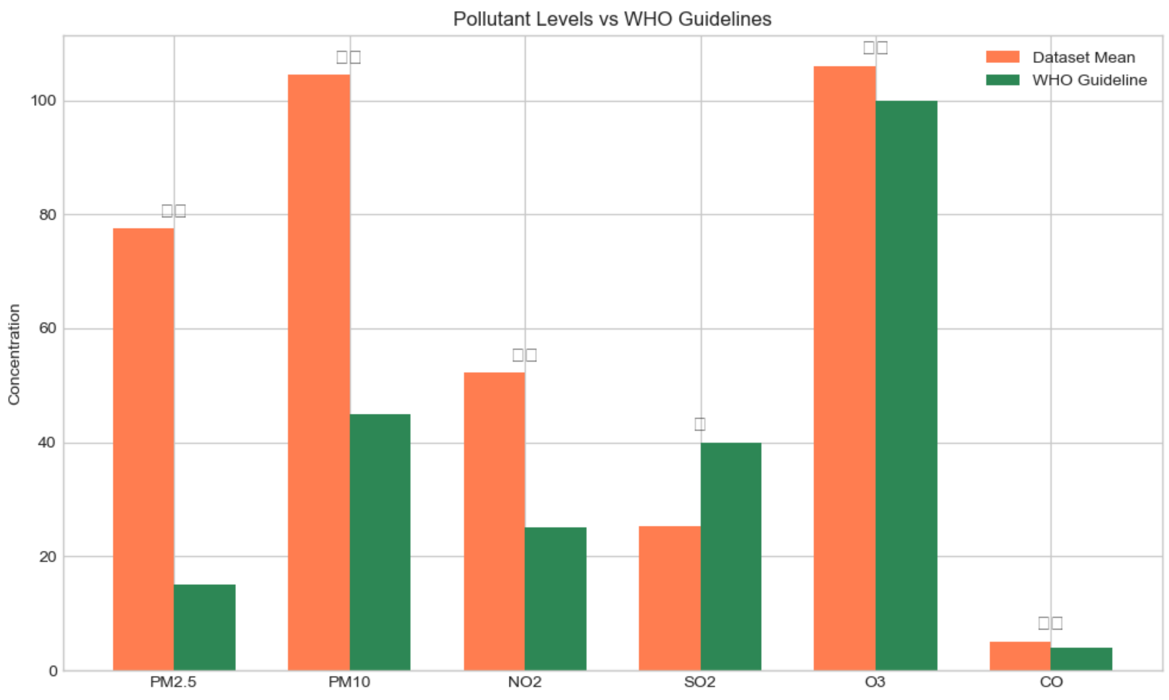
In [ ]:

```python
# Feature Importance (from Random Forest)
feature_importance = pd.DataFrame({
    'Feature': features,
    'Importance': rf_model.feature_importances_
}).sort_values('Importance', ascending=True)

fig, ax = plt.subplots(figsize=(10, 6))
ax.barh(feature_importance['Feature'], feature_importance['Importance'], color='
ax.set_xlabel('Importance'); ax.set_title('Random Forest - Feature Importance')
```

```
for i, v in enumerate(feature_importance['Importance']):
    ax.text(v + 0.01, i, f'{v:.3f}', va='center')
plt.tight_layout()
plt.savefig('graphs/7_models/feature_importance.png', dpi=150)
plt.show()

print("\nTop 5 Most Important Features:")
print(feature_importance.tail().to_string(index=False))
```

In [33]:

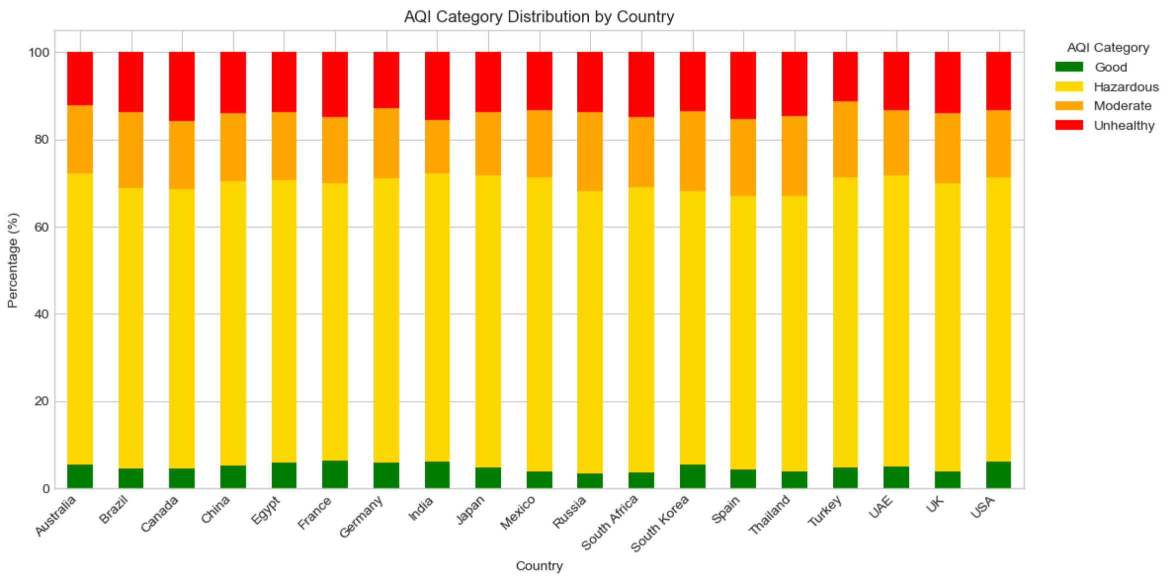
```
# Health Impact Analysis - WHO Guidelines Comparison
who_guidelines = {'PM2.5': 15, 'PM10': 45, 'NO2': 25, 'SO2': 40, 'O3': 100, 'CO'
actual_means = df[list(who_guidelines.keys())].mean()

fig, ax = plt.subplots(figsize=(10, 6))
x = np.arange(len(who_guidelines))
width = 0.35
ax.bar(x - width/2, actual_means.values, width, label='Dataset Mean', color='cor
ax.bar(x + width/2, list(who_guidelines.values()), width, label='WHO Guideline',
ax.set_xticks(x); ax.set_xticklabels(who_guidelines.keys())
ax.set_ylabel('Concentration'); ax.set_title('Pollutant Levels vs WHO Guidelines
ax.legend()
for i, (v1, v2) in enumerate(zip(actual_means.values, who_guidelines.values())):
    status = '⚠️' if v1 > v2 else '✓'
    ax.annotate(status, (i, max(v1, v2) + 2), ha='center', fontsize=12)
plt.tight_layout()
plt.savefig('graphs/5_comparative/who_comparison.png', dpi=150)
plt.show()

print("\nHealth Risk Assessment:")
for pollutant, who_val in who_guidelines.items():
    actual = actual_means[pollutant]
    pct = ((actual - who_val) / who_val) * 100
    status = "EXCEEDS" if actual > who_val else "WITHIN"
    print(f"  {pollutant}: {actual:.2f} ({status} WHO limit by {abs(pct):.1f}%)"
```



```
Health Risk Assessment:
  PM2.5: 77.45 (EXCEEDS WHO limit by 416.3%)
  PM10: 104.44 (EXCEEDS WHO limit by 132.1%)
  NO2: 52.20 (EXCEEDS WHO limit by 108.8%)
  SO2: 25.34 (WITHIN WHO limit by 36.6%)
  O3: 106.03 (EXCEEDS WHO limit by 6.0%)
  CO: 5.05 (EXCEEDS WHO limit by 26.2%)
```

In [34]:

```
# AQI Category Distribution by Region
fig, ax = plt.subplots(figsize=(12, 6))
aqi_by_country = df.groupby(['Country', 'AQI_Category']).size().unstack(fill_val
aqi_by_country = aqi_by_country.div(aqi_by_country.sum(axis=1), axis=0) * 100
aqi_by_country.plot(kind='bar', stacked=True, ax=ax,
                    color=['green', 'gold', 'orange', 'red', 'purple', 'maroon']
ax.set_ylabel('Percentage (%)'); ax.set_title('AQI Category Distribution by Coun
ax.legend(title='AQI Category', bbox_to_anchor=(1.02, 1))
ax.set_xticklabels(ax.get_xticklabels(), rotation=45, ha='right')
plt.tight_layout()
plt.savefig('graphs/5_comparative/aqi_by_country.png', dpi=150)
plt.show()
```



In [ ]:

```
# Summary Statistics and Key Findings
print("=" * 80)
print("PROJECT SUMMARY: GLOBAL AIR QUALITY ANALYSIS")
print("=" * 80)
print(f"\nDataset: {len(df)} records from {df['Country'].nunique()} countries, {
print(f"\nAQI Distribution:")
for cat in df['AQI_Category'].value_counts().index:
    pct = (df['AQI_Category'] == cat).sum() / len(df) * 100
    print(f"  {cat}: {pct:.1f}%")

print(f"\nBest Performing Model: {results_df['F1-Score'].idxmax()}")
print(f"  - F1-Score: {results_df['F1-Score'].max():.4f}")
print(f"  - Accuracy: {results_df.loc[results_df['F1-Score'].idxmax(), 'Accuracy

print(f"\nTop 3 Important Features:")
for _, row in feature_importance.tail(3).iterrows():
    print(f"  - {row['Feature']}: {row['Importance']:.4f}")

print("\nKey Recommendations:")
print("  1. Focus monitoring on PM2.5 and PM10 as primary health risk indicators
print("  2. Implement targeted interventions in regions with 'Unhealthy' or wors
print("  3. Use ML models for real-time AQI prediction and early warning systems
print("  4. Weather conditions (temp, humidity) significantly influence pollutan
print("=" * 80)
```

```
In [ ]: # Save Final Results to CSV
results_df.to_csv('model_results.csv')
feature_importance.to_csv('feature_importance.csv', index=False)
print("Results saved to CSV files!")
print(f"\nAll graphs saved to organized folders:")
for folder in sorted(os.listdir('graphs')):
    files = os.listdir(f'graphs/{folder}')
    print(f"  📁 graphs/{folder}/ ({len(files)} files)")
    for f in files:
        print(f"      └── {f}")
```