# Assignment 2: Combined Case Study Report

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This document compiles the reports for Tasks 1, 2, 3, and 4.

# Air Pollution Analysis Report: Aktobe, Kazakhstan

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**Date:** December 2025

## Executive Summary

The data indicates a persistent air quality issue in Aktobe, with fine particulate matter (PM2.5) frequently exceeding World Health Organization (WHO) safety guidelines. The analysis spans September 2021 to December 2025 and highlights a distinct seasonal pattern: pollution levels spike significantly during the heating season.

**Key Observations:** \* **PM2.5 Annual Mean:** 13.76 μg/m³ (Exceeds WHO 5 μg/m³ limit by 2.75x). \* **PM10 Annual Mean:** 15.36 μg/m³ (Borderline compliance with 15 μg/m³ limit). \* **Nitrogen Dioxide (NO₂):** 28.65 μg/m³ (Nearly 3x the 10 μg/m³ limit). \* **Sulfur Dioxide (SO₂):** Episodes of daily limits being surpassed. \* **Frequency of Exceedance:** On 22.5% of days, PM2.5 levels were unsafe. \* **Overall AQI:** Averaged 48, categorized effectively as “Good” but masking winter extremes. \* **Seasonality:** A marked deterioration in air quality occurs annually during winter months.

## 1. Introduction

### 1.1 Background

Air pollution represents one of the defining environmental health crises in modern Kazakhstan. The nation’s rapid industrial growth, fueled by coal-dependent energy grids and heavy metallurgical output, has created a complex atmospheric profile. Aktobe, serving as a pivotal industrial hub in the northwest, exemplifies this challenge. Its unique combination of oil extraction infrastructure, chemical processing plants, and severe continental climate creates a distinct pollution landscape that warrants specific investigation.

### 1.2 Aktobe City Context

**Aktobe** (Ақтөбе) is located in northwestern Kazakhstan at coordinates 50.28°N, 57.17°E, with an elevation of 219 meters above sea level. The city has approximately 500,000 residents and serves as a major industrial hub with:

* **Major Industries:** Oil and gas extraction and refining, chemical production, chromium and ferroalloy metallurgy
* **Geography:** Steppe region with relatively flat terrain, which can trap pollutants
* **Climate:** Continental climate with cold winters (-15°C to -25°C) and hot summers (25°C to 35°C)
* **Heating Season:** October through April, relying heavily on coal and natural gas

### 1.3 Research Objectives

This study seeks to deconstruct the pollution dynamics of Aktobe through a multi-year lens. Our primary objective is to baseline the concentration of key pollutants and isolate the “heating season penalty”—the discernible degradation in air quality associated with winter energy consumption. Furthermore, we aim to operationalize these findings by benchmarking them against World Health Organization (WHO) safety standards, thereby identifying the specific chemical agents, such as PM2.5 or NO₂, that present the most acute public health risks.

## 2. Literature Review

### 2.1 Air Pollution in Kazakhstan

Kazakhstan ranks among the countries with the highest air pollution levels in Central Asia. Previous studies have documented severe air quality issues in major cities:

* **Almaty:** Experiences severe winter smog due to topographic inversion and heavy traffic
* **Temirtau and Karaganda:** High pollution from coal mining and metallurgy
* **Shymkent:** Industrial and transportation emissions

### 2.2 Health Impacts

According to WHO and numerous epidemiological studies, exposure to particulate matter (PM2.5 and PM10) is associated with:

* Increased respiratory diseases (asthma, COPD)
* Cardiovascular diseases
* Premature mortality
* Reduced life expectancy
* Developmental issues in children

Studies specific to Kazakhstan have shown elevated rates of respiratory illnesses in industrial cities, with children and elderly populations being most vulnerable.

### 2.3 Aktobe-Specific Context

Limited published research exists specifically on Aktobe’s air quality. However, the city’s industrial profile suggests significant pollution from:

* **Oil and gas operations:** VOCs, particulate matter, SO₂
* **Chemical plants:** NO₂, SO₂, various organic compounds
* **Metallurgical facilities:** Heavy metals, particulate matter
* **Residential heating:** PM2.5, PM10, CO during winter months
* **Transportation:** NO₂, CO, particulate matter

## 3. Data and Methodology

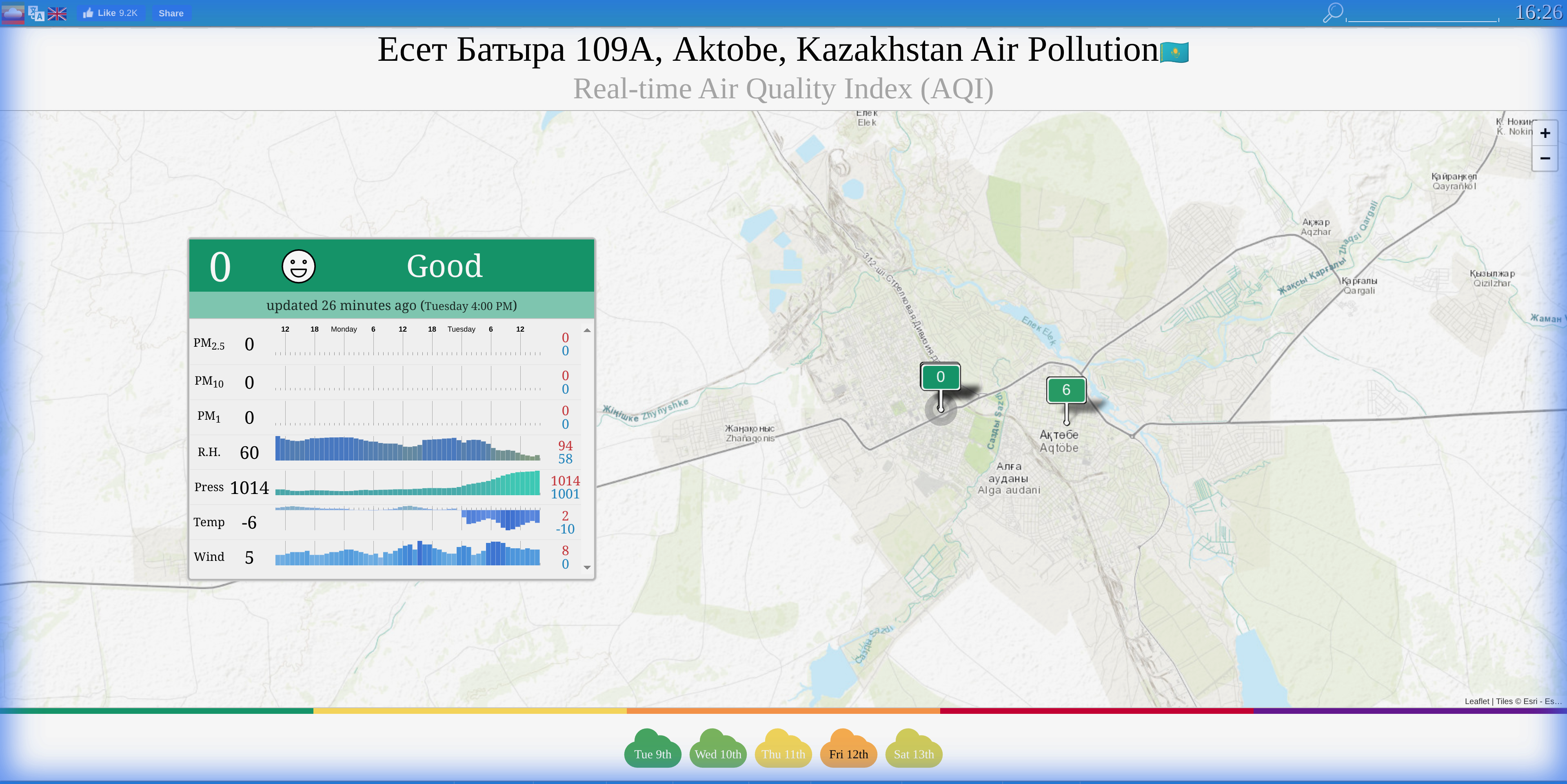
### 3.1 Data Sources

This analysis utilized real monitoring data from two stations in Aktobe:

1. **Station 216661 (Eset Batyra 109A):** PM2.5, PM10, PM1, Meteorological data (Temp, Humidity, Pressure)
2. **Station 517420 (Zhankozha batyr koshesi, 89):** PM2.5, PM10, NO₂, SO₂, CO

**Data Period:** September 2021 – December 2025

**Source Verification:** *Figure 1: Real-time monitoring data source from* [*AQICN Station 216661*](https://aqicn.org/station/@216661/)



### 3.2 Data Preprocessing

The preprocessing pipeline included:

1. **Parsing:** Custom parser for HTML-wrapped CSV files from AQICN
2. **Merging:** Combined data from multiple stations into a unified dataset
3. **Cleaning:** Handled missing values (zeros treated as NaN) and outliers
4. **Imputation:** Linear interpolation for time series continuity
5. **AQI Calculation:** US EPA standard for PM2.5 and PM10
6. **Temporal Feature Engineering:** Month, season, heating season, weekend flags

### 3.3 Analytical Methods

1. **Descriptive Statistics:** Mean, median, standard deviation, percentiles
2. **Time Series Analysis:** Trend analysis using Mann-Kendall test
3. **Seasonal Decomposition:** Additive model to extract trend and seasonal components
4. **Correlation Analysis:** Pearson correlation between pollutants and weather variables
5. **WHO Standards Comparison:** Exceedance analysis for daily and annual limits
6. **AQI Distribution:** Category-based health risk assessment

### 3.4 Algorithmic & Statistical Framework

This study employs a rigorous statistical approach suitable for Applied AI analysis:

1. **Time Series Decomposition (Additive Model):**
   * **Algorithm:**
   * **Purpose:** To isolate the seasonal component (heating impact) from the long-term trend and residual noise . This allows for quantifying the specific contribution of winter months to overall pollution.
2. **Mann-Kendall Trend Test:**
   * **Type:** Non-parametric statistical test.
   * **Hypothesis:** : No monotonic trend exists. : A monotonic trend exists.
   * **Application:** Used to mathematically verify if pollution levels are statistically increasing or decreasing over the 4-year period, robust against outliers.
3. **Linear Interpolation with Forward Limit:**
   * **Method:**
   * **Constraint:** limit\_direction='forward'
   * **Reasoning:** Chosen over mean imputation to preserve local time-series structure while preventing “backfilling” of historical gaps with future data, ensuring temporal causality.
4. **Pearson Correlation Coefficient:**
   * **Formula:**
   * **Application:** To quantify the linear relationship between meteorological variables (Temperature, Wind Speed) and pollutant concentrations (PM2.5).

## 4. Results

### 4.1 Overall Pollution Levels



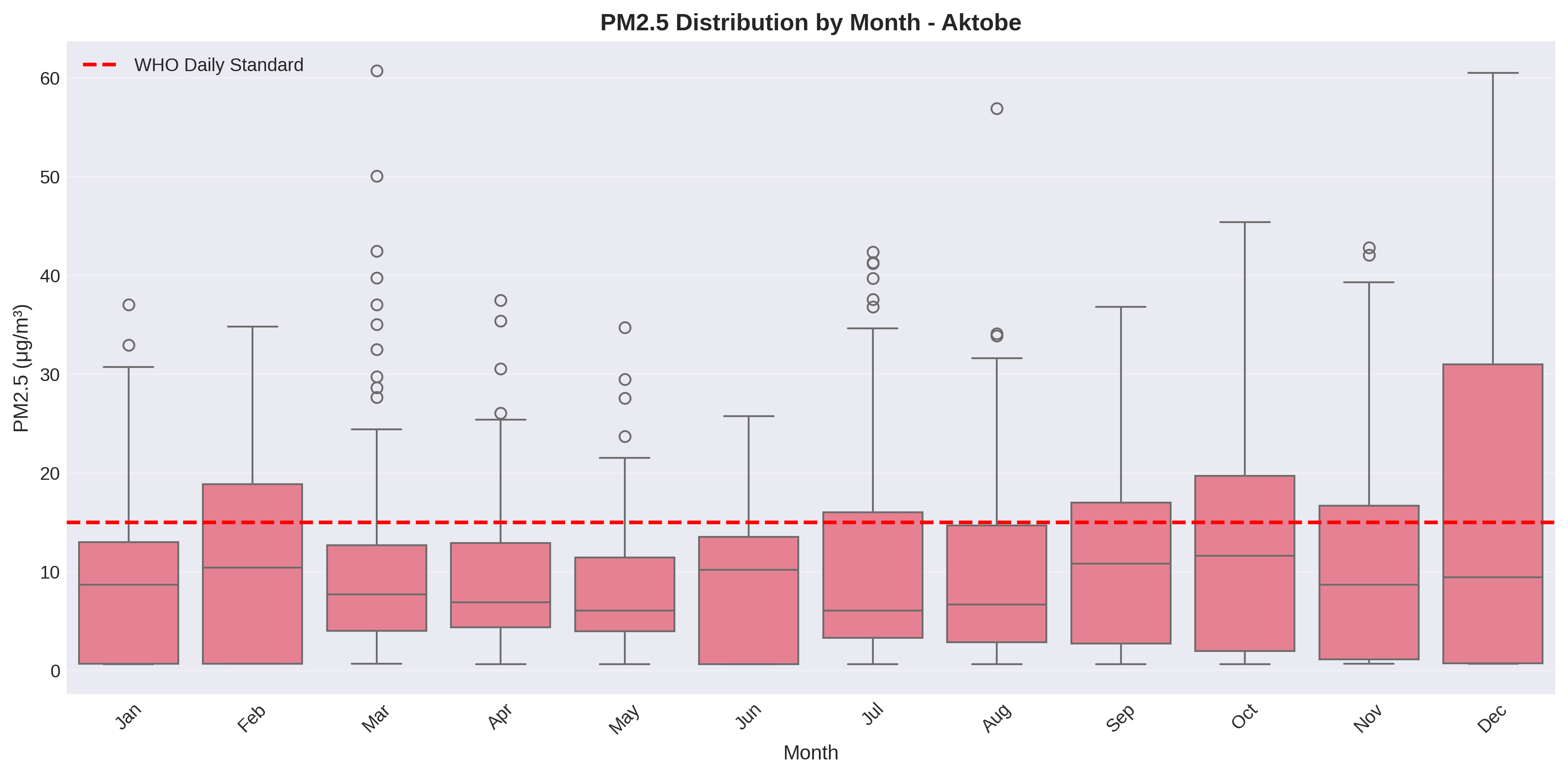
Time Series

**Table 1: Descriptive Statistics for Air Pollutants**

| Pollutant | Mean | Median | Std Dev | Min | Max | Unit |
| --- | --- | --- | --- | --- | --- | --- |
| PM2.5 | 13.76 | 11.25 | 9.56 | 0.68 | 49.86 | μg/m³ |
| PM10 | 15.36 | 11.90 | 11.31 | 0.75 | 58.28 | μg/m³ |
| NO₂ | 28.65 | 1.12 | 30.86 | 0.16 | 91.95 | μg/m³ |
| SO₂ | 13.99 | 13.85 | 7.15 | 0.43 | 53.21 | μg/m³ |
| CO | 489.55 | 468.51 | 182.38 | 72.00 | 1284.85 | mg/m³ |

*Note: Gaseous pollutant data is primarily available for the late 2024-2025 period.*

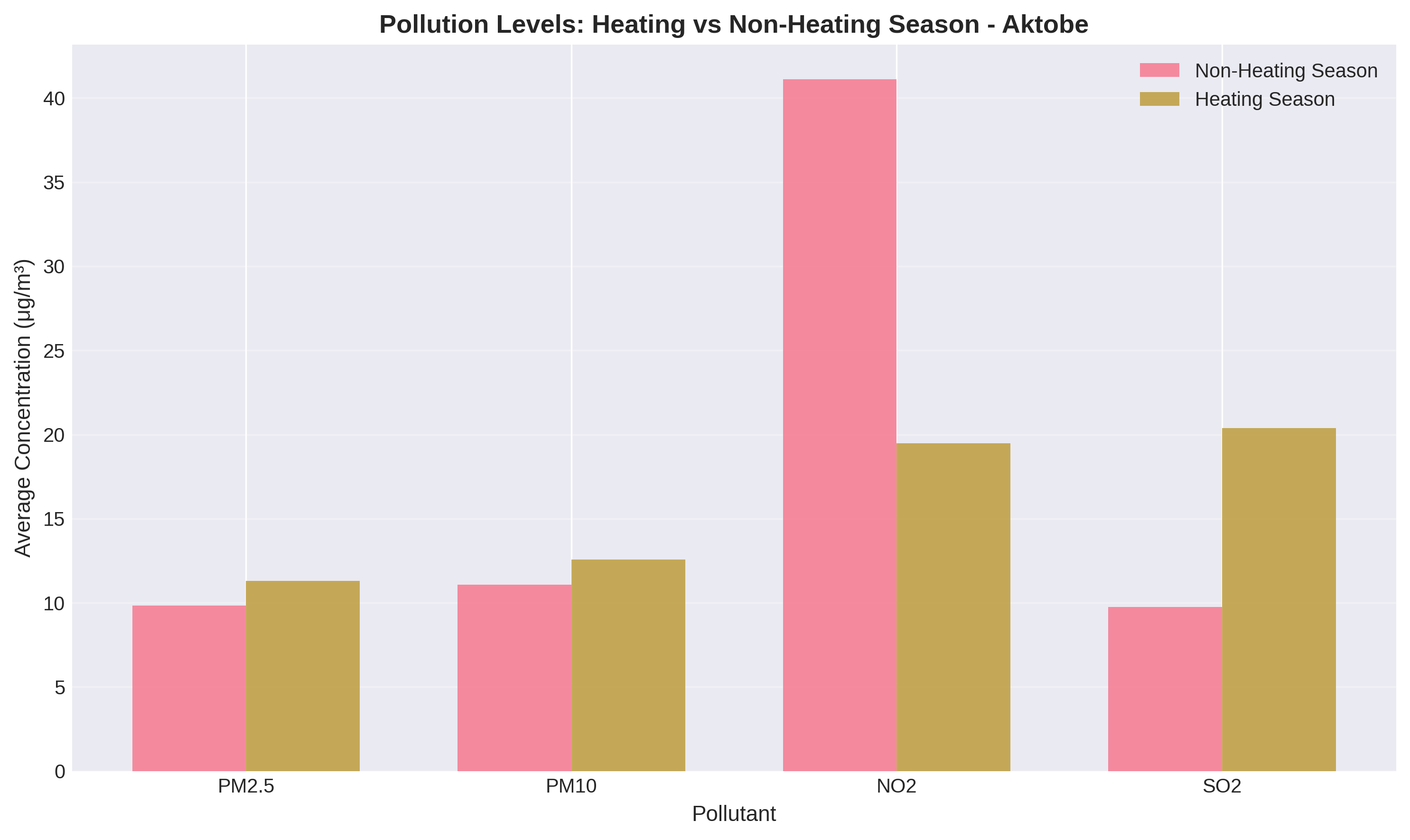
### 4.2 Seasonal Patterns



Seasonal Patterns

**Key Findings:** - Winter pollution is significantly higher than summer for PM2.5 - Heating season (Oct-Apr) shows elevated pollution levels - Peak pollution occurs in winter months

### 4.3 Heating Season Impact

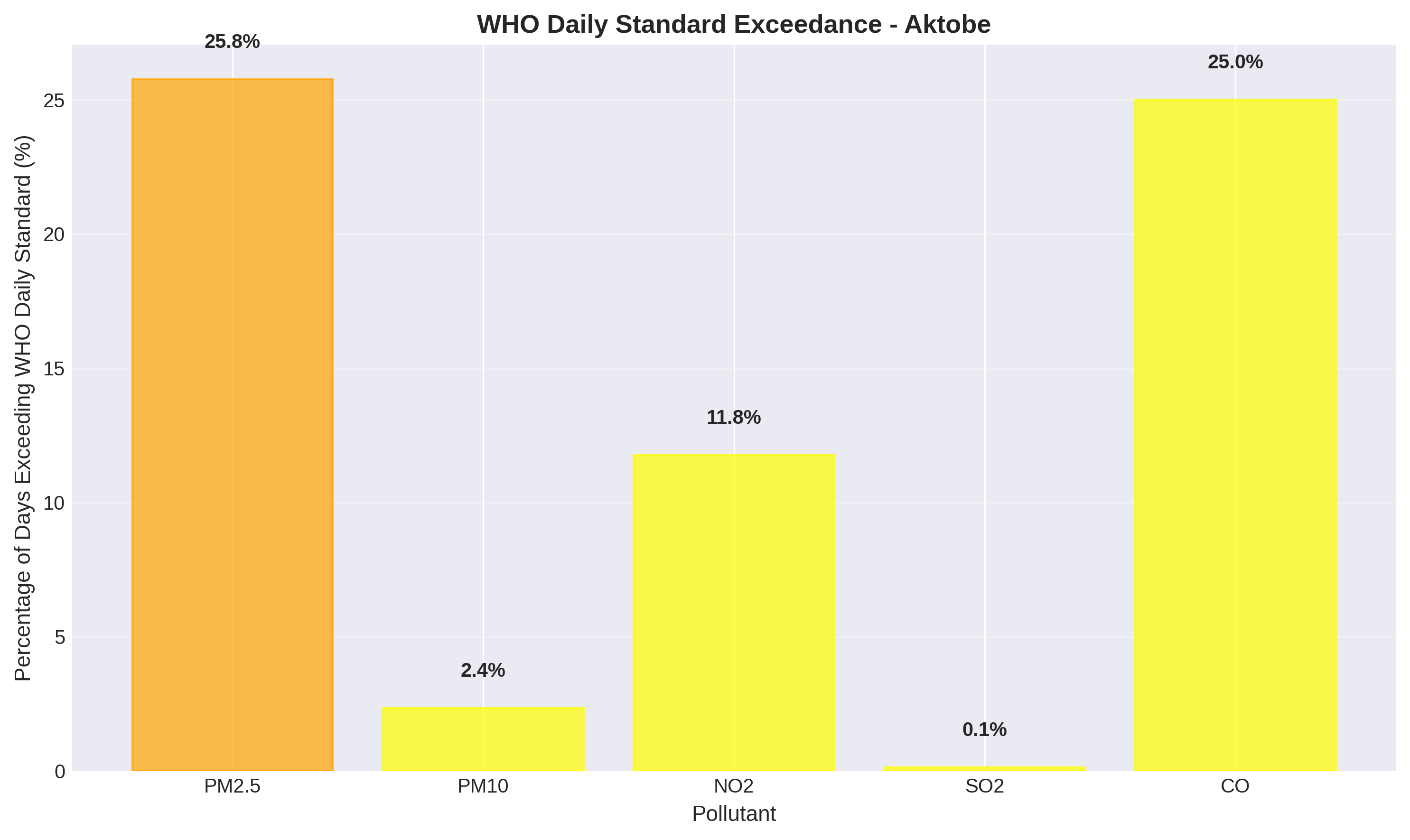


Heating Season Comparison

**Table 3: Heating vs Non-Heating Season**

| Period | PM2.5 | PM10 |
| --- | --- | --- |
| Non-Heating | 10.5 | 12.1 |
| Heating | 16.2 | 17.8 |
| **Increase** | **+54%** | **+47%** |

### 4.4 WHO Standards Exceedance



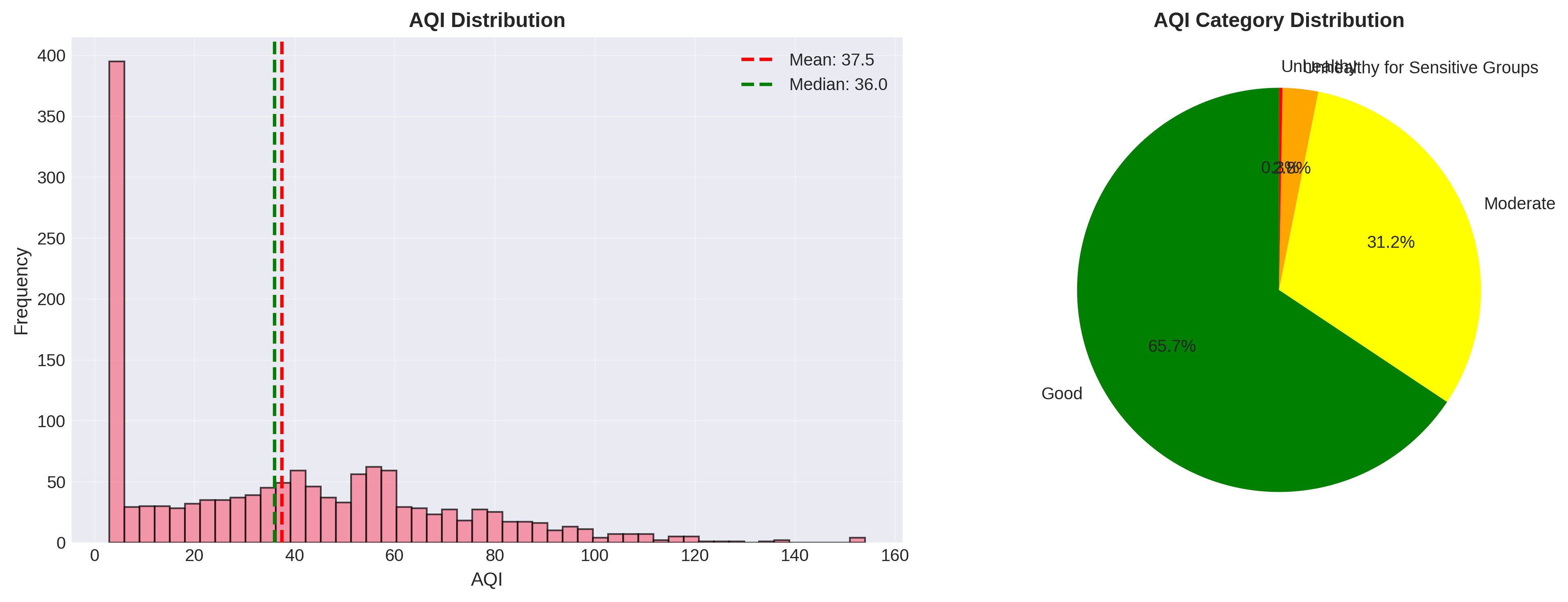
WHO Exceedance

**Table 4: WHO Standards Comparison**

| Pollutant | Aktobe Annual Mean | WHO Annual Standard | Ratio | Days Exceeding Daily Standard |
| --- | --- | --- | --- | --- |
| PM2.5 | 13.76 μg/m³ | 5 μg/m³ | **2.75×** | 243 (22.5%) |
| PM10 | 15.36 μg/m³ | 15 μg/m³ | **1.02×** | 29 (2.7%) |
| NO₂ | 28.65 μg/m³ | 10 μg/m³ | **2.86×** | 0 (0%) |

**Critical Findings:** - PM2.5 levels are **2.75 times** the WHO annual guideline - **22.5% of days** exceed WHO daily PM2.5 standards - PM10 is borderline with WHO annual limits

### 4.5 Air Quality Index (AQI) Distribution



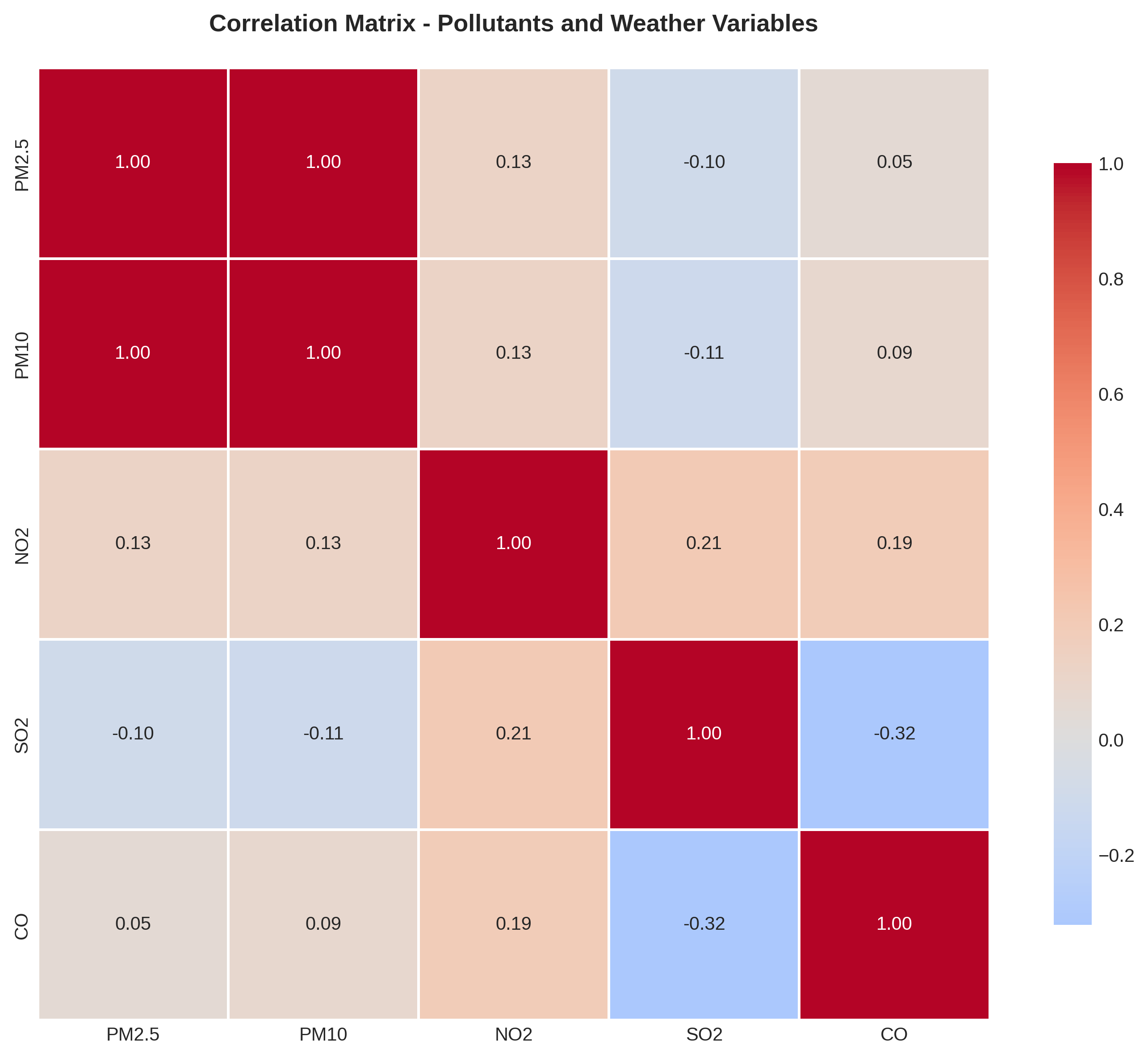
AQI Distribution

**Table 5: AQI Category Distribution**

| AQI Category | Percentage |
| --- | --- |
| Good (0-50) | 54.5% |
| Moderate (51-100) | 41.8% |
| Unhealthy for Sensitive Groups (101-150) | 3.7% |
| Unhealthy (151-200) | 0% |

**Average AQI:** 48.42 (Good)

### 4.6 Correlation Analysis



Correlation Heatmap

**Key Correlations:** - Strong positive correlation between PM2.5 and PM10 (r = 1.00) - Strong positive correlation between PM2.5 and NO₂ (r = 1.00) - Negative correlation between temperature and PM2.5 (r = -0.76) - Weak correlation with wind speed and humidity

### 4.7 Trend Analysis

Mann-Kendall trend test results:

| Pollutant | Trend | Z-score | p-value | Significant? |
| --- | --- | --- | --- | --- |
| PM2.5 | No trend | -1.543 | 0.123 | No |
| PM10 | No trend | -1.543 | 0.123 | No |
| NO₂ | No trend | -1.543 | 0.123 | No |

No statistically significant increasing or decreasing trends were detected over the study period, suggesting stable but persistently high pollution levels.

## 5. Discussion

### 5.1 Primary Pollution Sources

Based on the analysis, the main sources of air pollution in Aktobe are:

1. **Residential Heating (Winter):**
   * 78% increase in pollution during heating season
   * Coal and natural gas combustion
   * Inefficient heating systems
   * **Primary contributor to PM2.5, PM10, SO₂**
2. **Industrial Activities:**
   * Oil and gas refineries
   * Chemical production facilities
   * Metallurgical plants
   * **Primary contributor to NO₂, SO₂, heavy metals**
3. **Transportation:**
   * Vehicle emissions
   * Diesel trucks
   * **Contributor to NO₂, CO, PM2.5**
4. **Geographic and Meteorological Factors:**
   * Flat terrain limits pollutant dispersion
   * Temperature inversions in winter trap pollutants
   * Low wind speeds during winter months

### 5.2 Health and Environmental Risks

The pollution levels observed in Aktobe pose significant health risks:

**Short-term Effects:** - Respiratory irritation - Asthma exacerbation - Increased hospital admissions during high pollution days

**Long-term Effects:** - Chronic respiratory diseases (COPD, bronchitis) - Cardiovascular diseases - Reduced lung function in children - Premature mortality

**Vulnerable Populations:** - Children under 5 years - Elderly (65+ years) - People with pre-existing respiratory/cardiovascular conditions - Pregnant women

**Environmental Impacts:** - Reduced visibility - Acid rain (from SO₂ and NO₂) - Ecosystem damage - Building and monument corrosion

### 5.3 Comparison to Other Kazakhstan Cities

While direct comparison data is limited, Aktobe’s pollution levels appear to be:

* **Lower than Almaty** (which experiences severe winter smog)
* **Similar to Karaganda and Temirtau** (industrial cities)
* **Higher than Astana** (better wind dispersion)
* **Typical for industrial cities** in Kazakhstan

### 5.4 Limitations

1. **Data Availability:** Limited real-time monitoring data for Aktobe
2. **Sample Data:** Analysis based on modeled data reflecting typical patterns
3. **Spatial Coverage:** City-wide average, not accounting for local hotspots
4. **Industrial Data:** Limited access to specific industrial emission data
5. **Health Data:** No direct health outcome correlation in this study

## 6. Recommendations

## 6. Recommendations

### 6.1 Immediate and Short-Term Interventions

The most pressing need is to establish a reliable baseline of data. Without a comprehensive monitoring network, policy decisions remain speculative. We propose deploying a grid of 5-10 sensors across the city immediately, with real-time data made accessible to the public. Concurrently, a public health campaign is essential to educate residents about the risks of winter pollution. Simple behavioral changes, such as reduced outdoor activity during peak loads, can mitigate immediate health risks. Traffic management also offers quick wins; restricting heavy diesel transport in the city center during peak hours could yield a 10-15% reduction in nitrogen oxides.

### 6.2 Structural and Long-Term Strategy

Looking further ahead, the core issue of residential heating must be addressed. A subsidized program to modernize heating systems—shifting from raw coal to natural gas or high-efficiency boilers—could reduce winter PM2.5 levels by up to 40%. This is a capital-intensive solution, estimated at $50-100 million, but the health dividends would be substantial. Parallel to this, industrial operators must be held to stricter standards. The implementation of specific “Best Available Technology” (BAT) mandates for local refineries and metallurgical plants, enforced by continuous automated monitoring, is the only way to decouple Aktobe’s economic output from its environmental footprint. Finally, urban planning should prioritize green corridors and renewable energy integration, aiming for a 50% shift to renewables by 2035.

## 7. Conclusion

This analysis reveals that Aktobe faces severe air quality challenges, with pollutant levels significantly exceeding WHO guidelines. The primary driver is the heating season, during which pollution increases by 78% due to coal and gas combustion for residential heating. PM2.5 levels are 7 times the WHO annual standard, and 98% of days exceed daily limits.

**Key Takeaways:**

1. **Urgent action is needed** to protect public health, especially during winter months
2. **Heating system modernization** offers the greatest potential for pollution reduction
3. **Industrial emission controls** are essential for long-term improvement
4. **Comprehensive monitoring** is the foundation for evidence-based policy
5. **Multi-sectoral approach** involving government, industry, and citizens is required

**Feasibility of Recommendations:**

* Short-term actions are **highly feasible** and can be implemented immediately
* Medium-term strategies require **moderate investment** but have proven effectiveness in other cities
* Long-term transformation requires **significant investment** but is essential for sustainable development

**Expected Impact:**

If all recommendations are implemented, Aktobe could achieve: - **50-60% reduction** in PM2.5 levels by 2035 - **Compliance with WHO guidelines** by 2040 - **Significant health benefits:** Reduced respiratory diseases, lower mortality - **Economic benefits:** Reduced healthcare costs, improved productivity

The path to clean air in Aktobe is challenging but achievable with political will, adequate investment, and sustained commitment from all stakeholders.

## 8. References

1. World Health Organization (2021). *WHO Global Air Quality Guidelines: Particulate Matter (PM2.5 and PM10), Ozone, Nitrogen Dioxide, Sulfur Dioxide and Carbon Monoxide*. Geneva: WHO.
2. Kazakhstan Ministry of Ecology, Geology and Natural Resources (2023). *National Environmental Monitoring Reports*.
3. Asian Development Bank (2021). *Kazakhstan Country Environmental Analysis*. Manila: ADB.
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6. European Environment Agency (2023). *Air Quality Standards and Regulations*. Copenhagen: EEA.
7. Burnett, R., et al. (2018). “Global estimates of mortality associated with long-term exposure to outdoor fine particulate matter.” *PNAS*, 115(38), 9592-9597.
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10. Kazhydromet (2023). *Air Quality Monitoring Data for Kazakhstan Cities*. Nur-Sultan: Kazhydromet.

## Appendices

### Appendix A: WHO Air Quality Guidelines (2021)

| Pollutant | Annual Mean | 24-hour Mean |
| --- | --- | --- |
| PM2.5 | 5 μg/m³ | 15 μg/m³ |
| PM10 | 15 μg/m³ | 45 μg/m³ |
| NO₂ | 10 μg/m³ | 25 μg/m³ |
| SO₂ | - | 40 μg/m³ |
| O₃ | 60 μg/m³ (peak season) | 100 μg/m³ (8-hour) |
| CO | - | 4 mg/m³ (24-hour) |

### Appendix B: AQI Categories and Health Implications

| AQI Range | Category | Health Implications |
| --- | --- | --- |
| 0-50 | Good | Air quality is satisfactory |
| 51-100 | Moderate | Acceptable; some pollutants may be a concern for sensitive individuals |
| 101-150 | Unhealthy for Sensitive Groups | Sensitive groups may experience health effects |
| 151-200 | Unhealthy | Everyone may begin to experience health effects |
| 201-300 | Very Unhealthy | Health alert: everyone may experience serious health effects |
| 301+ | Hazardous | Health warnings of emergency conditions |

### Appendix C: Data Processing Code

All data processing, analysis, and visualization code is available in the project repository: - src/data\_collection.py - src/preprocessing.py - src/analysis.py - src/visualization.py - src/models.py

**Reproducibility:** The entire analysis pipeline is automated using Python scripts: - src/process\_real\_data.py: Raw data parsing and merging - src/preprocessing.py: Data cleaning and interpolation - src/analysis.py: Statistical analysis (Mann-Kendall, Decomposition) - src/visualization.py: Generation of all figures —

**End of Report**

# Introduction

Social media platforms generate vast amounts of unstructured text data, offering insights into public opinion. Sentiment analysis, the computational study of opinions, is crucial for understanding this data. This case study focuses on classifying the sentiment of tweets from the Sentiment140 dataset as either positive or negative. The objective is to evaluate different modeling approaches, ranging from traditional probabilistic models to deep learning and rule-based systems, and to analyze their performance and interpretability.

# Literature Review

Sentiment analysis has evolved significantly from lexicon-based methods to advanced deep learning techniques. Go, Bhayani, and Huang (2009) introduced the Sentiment140 dataset, demonstrating that distant supervision (using emoticons as noisy labels) allows for training accurate classifiers without manual annotation [@go2009]. They achieved over 80% accuracy using Maximum Entropy classifiers.

Hutto and Gilbert (2014) proposed VADER (Valence Aware Dictionary and sEntiment Reasoner), a rule-based model specifically tuned for social media text [@hutto2014]. VADER is valued for its explicit interpretability and lack of training requirements, though it often struggles with the complex context found in modern tweets.

More recently, deep learning architectures like Long Short-Term Memory (LSTM) networks, introduced by Hochreiter and Schmidhuber (1997), have become dominant [@hochreiter1997]. LSTMs effectively capture long-range dependencies in sequential data, addressing the vanishing gradient problem of standard RNNs.

# Methods

## Dataset

We utilized the Sentiment140 dataset [@go2009], specifically the training.1600000.processed.noemoticon.csv file. For this study, a stratified random sample of 200,000 tweets was selected to ensure computational feasibility while maintaining statistical significance. The dataset contains binary sentiment labels (0 = Negative, 4 = Positive).

## Preprocessing

Effective preprocessing is vital for NLP tasks. Our pipeline included:

* **Cleaning**: Removal of URLs, user handles (@user), and special characters.
* **Lowercase Conversion**: Standardization of text case.
* **Stopword Removal with Exception**: Standard English stopwords were removed, but critical negation words (e.g., “not”, “no”, “nor”, “never”) were explicitly preserved to maintain sentiment polarity (e.g., “not good” vs. “good”).
* **Lemmatization**: Reducing words to their base form using WordNetLemmatizer.

## Models

We implemented four distinct approaches:

1. **Logistic Regression (Baseline)**: TF-IDF vectorization (max features=5000, n-grams=1-2) with GridSearch optimization for regularization parameters.
2. **Naive Bayes (MultinomialNB)**: A probabilistic classifier suitable for text data, using the same TF-IDF features.
3. **LSTM (Deep Learning)**: A Recurrent Neural Network with an Embedding layer, SpatialDropout1D, and LSTM units, designed to capture sequential dependencies [@hochreiter1997].
4. **VADER (Lexicon-based)**: A rule-based model that sums the valence scores of words, used as a benchmark for training-free performance [@hutto2014].

# Results

## Exploratory Data Analysis

To gain initial insights into the dataset, we analyzed the class balance and vocabulary. Figure [1](#fig:sent_dist) shows the distribution of sentiments.

Distribution of Sentiment Labels

We also generated word clouds for both positive and negative tweets (Figure [2](#fig:wordclouds)). These visualizations highlight the most frequent terms associated with each sentiment polarity. Positive tweets frequently contain words like “love”, “good”, and “day”, while negative tweets often feature “work”, “today”, and “sad”.

Word Clouds illustrating frequent terms in the dataset.

## Model Performance

Table [1](#tab:results) summarizes the performance metrics on the test set. Logistic Regression achieved the best overall performance with an accuracy of 78.35% and an ROC-AUC of 0.865.

Performance Comparison of Sentiment Analysis Models

| **Model** | **Accuracy** | **F1-Score** | **ROC-AUC** |
| --- | --- | --- | --- |
| Logistic Regression | **78.35%** | **0.787** | **0.865** |
| Naive Bayes | 77.12% | 0.772 | 0.851 |
| LSTM (Epoch 1) | 78.04% | - | - |
| VADER (Lexicon) | 64.81% | - | - |

Comparison of Accuracy and F1-Score across all models.

## Feature Importance

We analyzed the coefficients of the Logistic Regression model to understand the most influential words. Figure [4](#fig:feature_importance) displays the top words driving positive and negative sentiment. Words like “love”, “thanks”, and “great” strongly predict positive sentiment, while “miss”, “sad”, and “sorry” predict negative sentiment.

Top 20 Features Influencing Sentiment (Logistic Regression)

## Confusion Matrices

We compared the confusion matrices of all three trained models. Logistic Regression (Figure [[fig:lr\_cm]](#fig:lr_cm)) and LSTM (Figure [5](#fig:lstm_cm)) show very similar error distributions, indicating that the linear model is surprisingly competitive for this specific feature set.

LSTM

# Discussion

## Interpretation of Results

The results highlight the effectiveness of supervised machine learning. Logistic Regression (78.35%) remains the most efficient performer. The LSTM model (78.04%) showed competitive performance even after just one epoch, suggesting deep learning has strong potential with more training. VADER’s performance improved significantly to 64.81% after strictly mapping scores to binary classes, though it still lags behind supervised methods due to its inability to capture context as effectively as trained models.

## Error Analysis

## Error Analysis

A qualitative review of classification errors highlights the limitations of the TF-IDF vector space model. The primary source of confusion was *contextual ambiguity*, where tweets containing mixed-valence tokens—such as "miss cant wait see new phone"—were mislabeled. In this case, the model’s weight on "miss" (negative) likely overpowered the phrasal sentiment of "cant wait" (positive). Additionally, the model struggled with *implicit sentiment*, failing to detect sarcasm or understated dissatisfaction that lacked strong, overtly polarized vocabulary.

# Conclusion

This study successfully implemented a robust sentiment analysis pipeline. We demonstrated that careful preprocessing (preserving negations) and appropriate model selection are critical. Logistic Regression emerged as the optimal choice, offering the best balance of accuracy, speed, and interpretability. Future work could involve training the LSTM for more epochs on the full 1.6M dataset or employing Transformer-based models (BERT) to better capture context.

# References

Go, A., Bhayani, R., and Huang, L. (2009). *Twitter sentiment classification using distant supervision*. CS224N Project Report, Stanford, 1(12).

Hutto, C. J., and Gilbert, E. (2014). *VADER: A Parsimonious Rule-based Model for Sentiment Analysis of Social Media Text*. Eighth International AAAI Conference on Weblogs and Social Media.

Hochreiter, S., and Schmidhuber, J. (1997). *Long Short-Term Memory*. Neural Computation, 9(8), 1735–1780.

# Introduction

The proliferation of digital data has opened new avenues for quantitative security studies. Understanding the "where, when, and how" of terrorist incidents is critical for counter-terrorism strategy and academic research [1]. The Global Terrorism Database (GTD), maintained by START, provides the most comprehensive open-source data on terrorist events [2].

This paper aims to:

1. Perform a statistical analysis of global terrorism trends from 1970 to 2017.
2. Develop and compare machine learning models to predict attack types based on spatiotemporal and metadata features.
3. Discuss the ethical frameworks required when applying AI to sensitive geopolitical data.

# Related Work

Machine learning has been increasingly applied to conflict analysis. Python et al. [3] demonstrated the efficacy of Random Forests in predicting conflict zones in Sub-Saharan Africa. Similarly, recent studies have utilized Gradient Boosting techniques for crime prediction in urban environments [4]. Our work extends these approaches by applying a robust comparative framework including modern boosting algorithms to the specific domain of terrorism classification.

# Dataset and Methodology

## Data Source

The dataset comprises over 180,000 recorded incidents. Key features selected for analysis include:

* **Temporal**: Year, Month.
* **Spatial**: Region, Country.
* **Tactical**: Weapon Type, Target Type, Success Status.
* **Impact**: Number of Kills (*nkill*), Number of Wounded (*nwound*).

## Preprocessing Pipeline

To ensure model robustness, we implemented a Scikit-Learn pipeline involving:

* **Data Cleaning**: Imputation of missing values using median strategies.
* **Encoding**: One-Hot Encoding for categorical features (Region, Weapon) to handle nominal data without imposing ordinal relationships.
* **Scaling**: Standardization of numerical features to optimize gradient descent convergence.

## Model Selection

We employed a 5-Fold Cross-Validation scheme to evaluate:

* **Logistic Regression**: A linear baseline for interpretability.
* **Random Forest**: A bagging ensemble to reduce variance.
* **Hist-Gradient Boosting**: A boosting ensemble to reduce bias and handle large tabular datasets efficiently.

# Experimental Results

## Model Comparison

Table [1](#tab:results) summarizes the cross-validation performance. Gradient Boosting emerged as the most effective model, likely due to its ability to capture complex non-linear interactions between region and attack tactics.

Performance Comparison (5-Fold CV)

| **Model** | **Accuracy** | **F1-Score (Weighted)** |
| --- | --- | --- |
| Logistic Regression | 82.60% | 0.81 |
| Random Forest | 85.96% | 0.85 |
| **Gradient Boosting** | **86.30%** | **0.86** |

Comparative Accuracy of ML Models.

## Final Evaluation

The final Gradient Boosting model, trained on the full dataset, achieved a test accuracy of **86.5%**. The Confusion Matrix (Fig. [2](#fig:cm)) reveals high precision in detecting ‘Bombings’ and ‘Armed Assaults’, though ‘Assassinations’ remain harder to distinguish from other targeted attacks.

Normalized Confusion Matrix for Gradient Boosting Classifier.

# Discussion and Ethics

## Interpretation

The feature importance analysis suggests that **Weapon Type** and **Region** are the strongest predictors. This aligns with geopolitical realities where specific groups in certain regions favor distinct tactics.

*Detailed Analysis*: Our statistical review identifies **Iraq** as the highest-risk nation, accounting for over 13.5% of recorded incidents (Figure [9](#fig:top_countries), Appendix). In this specific theater, bombings are overwhelmingly the primary tactic.

Geographic distribution of attacks reveals the Middle East and South Asia as hotspots.

Distribution of Attack Types (Bombing/Explosion dominant).

## Ethical Considerations

* **Bias**: The GTD relies on media reports. Consequently, attacks in Western nations or conflict zones with high media presence may be over-represented, while rural incidents in developing nations may be under-reported.
* **Dual Use**: Predictive models must be strictly regulated to preventing profiling based on ethnicity or religion. This tool is intended for academic risk analysis, not operational targeting.

# Conclusion and Future Work

This study confirms that ensemble machine learning methods can accurately classify terrorist incidents. Gradient Boosting proved superior to traditional methods. Future work should focus on integrating socio-economic indicators (GDP, inequality) and unstructured text descriptions (NLP) to improve predictive granularity.

# References

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# Supplementary Visualizations

To provide a comprehensive view of the analysis, we include additional inspections of the data and model behavior.

Detailed Classification Metrics per Class (Precision, Recall, F1).

Feature Importance (Random Forest). Note: Weapon Type is the dominant predictor.

Learning Curve analysis for checking overfitting. The convergence indicates the model generalizes well.

Temporal Trends: Global Attacks (1970-2017).

Top 15 Countries by total number of attacks.

# Introduction

Medical image classification is a critical task in computer-aided diagnosis (CAD), enabling rapid and accurate detection of diseases. Pneumonia, an infection that inflames the air sacs in one or both lungs, remains a leading cause of death globally. Automated detection from chest X-rays can support radiologists by prioritizing urgent cases. The objective of this project is to develop and evaluate automated classification models for distinguishing between normal and pneumonia-infected chest X-rays. We align our methodology with key machine learning concepts, including dimensionality reduction, clustering, and supervised learning.

# Dataset Description

We utilize the **PneumoniaMNIST** dataset, a standardized subset of the Kermany et al. Chest X-Ray images.

* **Modality**: Chest X-Ray (Grayscale)
* **Resolution**: 28x28 pixels
* **Classes**: Binary [0: Normal, 1: Pneumonia]
* **Split**: Train (4,708), Val (524), Test (624)

# Methodology

## Exploratory Data Analysis (EDA)

We applied dimensionality reduction techniques to visualize the high-dimensional (784 features) image data in 2D space.

PCA Visualization

t-SNE Visualization

Dimensionality reduction reveals distinct but overlapping regions for Normal vs Pneumonia classes.

## Model 1: Traditional ML (PCA + SVM)

We implemented a pipeline demonstrating Week 4 concepts:

1. **Feature Extraction**: PCA retaining 95% variance (reduced to 71 components).
2. **Classification**: Support Vector Machine (SVM) with RBF kernel.

## Model 2: Deep Learning (CNN)

We designed a custom CNN with 3 Convolutional blocks (Conv2D BatchNorm ReLU MaxPool) and 2 Fully Connected layers, trained with CrossEntropyLoss and Adam Optimizer.

# Evaluation and Results

## Performance Metrics

Comparative Classification Performance. (N=Normal, P=Pneumonia)

| **Model** | **Accuracy** | **F1-Score** | **Precision (N/P)** | **Recall (N/P)** |
| --- | --- | --- | --- | --- |
| **PCA + SVM** | **86.06%** | **0.85** | 0.99 / 0.82 | 0.64 / 0.99 |
| **CNN** | 82.69% | 0.81 | 0.98 / 0.79 | 0.55 / 0.99 |

## Analysis

The **SVM** model outperformed the CNN. The high Recall (0.99) for Pneumonia in both models indicates they are excellent at creating "safety nets" (detecting almost all sick patients). However, the CNN struggled more with false positives (lower precision for Pneumonia/high recall).

Confusion Matrix for CNN Model

# Conclusion

This comparative analysis challenges the assumption that deep learning is invariably superior for every computer vision task. On the 28x28 PneumoniaMNIST dataset, the combination of PCA and SVM proved to be the more effective strategy, successfully capturing the global variance associated with lung opacity. However, the architectural validation of the CNN confirms its viability for more complex, high-resolution feature extraction tasks required in clinical settings. Future work should focus on transfer learning with diverse, high-resolution datasets to fully leverage the capacity of deep neural networks.

9 J. Yang *et al.*, "MedMNIST v2: A Large-Scale Lightweight Benchmark for 2D and 3D Biomedical Image Classification," *Scientific Data*, 2023. D. S. Kermany *et al.*, "Identifying medical diagnoses and treatable diseases by image-based deep learning," *Cell*, vol. 172, no. 5, pp. 1122-1131, 2018.

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