Predicting PM2.5 and AQI for Chiang Rai: A Submission of Literature, Data, and Technology Research

Part I: Literature Review - Contextualizing PM2.5 Prediction in Northern Thailand

1.1 Introduction: The Public Health Imperative and Research Gap in Chiang Rai

Chiang Rai, a province in Upper Northern Thailand, experiences recurrent and severe episodes of air pollution, characterized by high concentrations of fine particulate matter PM2.5. These episodes, often exacerbated during seasonal agricultural burning periods, pose a significant threat to public health and disrupt daily life, including for the student community at Mae Fah Luang University.[1] The adverse health effects of exposure to PM2.5 are well-documented, ranging from respiratory and cardiovascular diseases to long-term systemic health issues. Consequently, the ability to accurately forecast near-term air quality is not merely an academic exercise but a critical public health necessity.

This project directly addresses this challenge by aiming to develop a machine learning model capable of forecasting next-day PM2.5 levels and their corresponding Air Quality Index (AQI) categories. The initiative is deeply aligned with several United Nations Sustainable Development Goals (SDGs). By providing timely and accessible air quality forecasts, the project supports SDG 3 (Good Health & Well-Being), enabling individuals to take precautionary measures to minimize their exposure to harmful pollutants. Furthermore, it contributes to SDG 11 (Sustainable Cities & Communities) by generating data that can inform local air quality management strategies and public advisories, and to SDG 13 (Climate Action) by raising awareness of the interplay between seasonal emissions, climate patterns, and pollution events.[1]

A comprehensive review of the existing scientific literature is therefore essential.[1] Such a review serves two primary purposes: first, to ground the project's methodology in established scientific precedent and proven analytical techniques for the region; and second, to precisely identify the existing research gaps that this project aims to fill. By systematically analyzing prior work, this review will establish the scientific context, validate the proposed approach, and articulate the novel contributions of this research to the field of air quality forecasting in Southeast Asia.

1.2 Thematic Analysis of Regional Air Quality Research

The body of research on air quality in Northern Thailand provides a robust foundation for predictive modeling. A seminal study by P. S. La-ong-muang et al. (2021) focused on predicting particulate matter PM10 concentrations in Chiang Rai province, offering critical insights into the local dynamics of air pollution.[2] This research is particularly relevant due to its geographical focus and analytical approach.

The methodology employed was Multiple Linear Regression (MLR), a statistical technique used to model the linear relationship between a dependent variable and one or more independent variables. The researchers developed four distinct MLR models tailored to the region's climatic seasons: annual, summer, rainy, and winter. This seasonal segmentation acknowledges the profound influence of cyclical weather patterns on pollutant concentrations.[2] The data for the study was sourced from two local observation stations (station 65 and station 73) operated by the Pollution Control Department (PCD) of Thailand, comprising hourly air pollution and meteorological data spanning from 2011 to 2018.[2]

The key findings of the study underscore the strong seasonality of particulate matter pollution in Chiang Rai. The highest daily PM10 concentrations were consistently observed during the summer season, which corresponds to the region's annual haze episodes driven by biomass burning. Conversely, the lowest concentrations occurred during the rainy season, when precipitation effectively scrubs pollutants from the atmosphere. For instance, at station 65, the maximum 24-hour concentration in summer reached **three hundred seventy-one point one micrograms per cubic meter** while the maximum in the rainy season was only **eighty point six micrograms of substance in every cubic meter of air (or space).**

Crucially, the study demonstrated the predictive power of meteorological variables. It identified significant correlations between PM10 and factors such as temperature, relative humidity, and atmospheric pressure. For example, temperature was found to be positively correlated with PM10 in the summer and rainy seasons, while relative humidity showed a negative relationship. The seasonal MLR models proved effective, with the summer model performing best, achieving a coefficient of determination R square of 0.73 for station 65. This value indicates that the model could explain 73% of the variance in PM10 concentrations during the critical haze season, confirming the viability of using meteorological data for pollution forecasting in this specific locale.[2]

This finding is corroborated by other regional studies noted in the project's foundational proposal, which similarly used meteorological and fire-hotspot data to predict PM2.5 in Upper Northern Thailand and confirmed a strong seasonal dependence.[1] Collectively, this body of work establishes a clear precedent: seasonal, meteorology-driven models are an effective approach for predicting particulate matter concentrations in Chiang Rai.

1.3 Synthesis and Identification of the Research Contribution

The existing literature, particularly the work of La-ong-muang et al., provides a compelling proof-of-concept for the proposed project. It validates the core premise that local weather data can be used to forecast particulate matter levels with a reasonable degree of accuracy.[2] However, the current project extends beyond this foundational work by introducing more advanced methodologies and focusing on a more hazardous pollutant, thereby addressing a critical research gap.

The proposed project's decision to employ non-linear, tree-based machine learning models—specifically Random Forest and Gradient Boosting (XGBoost)—in place of the Multiple Linear Regression used in the prior study is a deliberate and significant methodological advancement.[1] This choice is predicated on a central scientific hypothesis: that the relationships governing the formation, dispersion, and transport of PM2.5 are inherently complex and non-linear. While a linear model like MLR can capture first-order correlations, it is fundamentally limited in its ability to model the intricate interactions and feedback loops present in atmospheric systems.

For example, the effect of wind speed on pollutant concentration is not constant; at low speeds, it may fail to disperse local emissions, leading to high concentrations, while at high speeds, it may transport pollution from distant sources or effectively dilute local pollutants. Similarly, the interaction between temperature, atmospheric stability, and the formation of secondary aerosols is a highly non-linear process. A linear model assumes a constant relationship, whereas a tree-based model can learn these complex, conditional relationships from the data. By partitioning the feature space, models like Random Forest and XGBoost can identify specific thresholds and interactions—such as a particular combination of low humidity, high temperature, and specific wind direction—that lead to extreme pollution events.

Therefore, the primary scientific contribution of this project is to test whether these sophisticated, non-linear models can capture a greater degree of variance in PM2.5 concentrations compared to the established linear approaches. Success in this endeavor would not only yield a more accurate forecasting tool but also provide a deeper, more nuanced understanding of the specific meteorological drivers of air pollution in Chiang Rai.

1.4 Conclusion: Summarizing Key Learnings and Justifying the Project

In conclusion, the review of existing literature confirms that the prediction of particulate matter in Chiang Rai using a seasonal framework and meteorological data is a scientifically sound and viable approach.[1] Prior research has successfully used linear models to establish the strong correlation between weather patterns and pollutant levels, particularly the pronounced peak in concentrations during the summer haze season.[2]

This project will build directly upon this established knowledge base while making several novel and important contributions. First, it will shift the focus from PM10 to PM2.5, the fine particulate matter fraction that poses a greater risk to human health. Second, and most significantly, it will employ advanced machine learning techniques, namely Random Forest and XGBoost, to investigate the non-linear relationships and complex interactions that govern air quality dynamics. This methodological shift from linear to non-linear modeling represents an opportunity to significantly improve predictive accuracy.

Finally, the project's deliverable—a simple, publicly accessible web dashboard—is designed to translate research findings into actionable information for the community.[1] By providing daily AQI forecasts, the project moves beyond academic inquiry to create a practical tool that can empower individuals and local authorities to make informed decisions, mitigate health risks, and ultimately contribute to a healthier and more sustainable urban environment in Chiang Rai.

Part II: Data Research - Sourcing and Strategy for Air Quality and Meteorological Inputs

2.1 Introduction: The Foundational Role of High-Quality Data

The success of any data-driven predictive model is fundamentally contingent upon the quality, granularity, and relevance of its input data. For the task of forecasting PM2.5 concentrations, a robust dataset is not merely a prerequisite but the very foundation upon which model accuracy and reliability are built.[1] The research questions at the core of this project—namely, predicting next-day air quality based on atmospheric conditions—necessitate a thorough exploration and careful selection of appropriate data sources. This requires sourcing two distinct but complementary time-series datasets: historical air quality measurements for Chiang Rai and the corresponding historical meteorological records for the same location and time period.[1] This section details the research, evaluation, and selection of data sources, along with the proposed strategy for data processing and preparation.

2.2 Primary Data Sources: A Detailed Examination

2.2.1 Air Quality Data Acquisition via the OpenAQ Platform

For air quality data, the OpenAQ platform has been identified as the optimal source. OpenAQ is the world's largest open-source, open-access platform for harmonized ground-level ambient air quality data, aggregating information from hundreds of official sources globally.[3] A critical feature of the platform is that it provides raw, physical measurements of specific pollutants, such as PM2.5and PM10, rather than aggregated or pre-calculated values like an Air Quality Index (AQI).[3] This is ideal for this project, as it allows for direct modeling of the physical concentration of PM2.5, which is the primary regression target.

Data from the OpenAQ platform is programmatically accessible through a well-documented REST API, which delivers data primarily in JSON format.[4] For this project, data acquisition will be streamlined through the use of the py-openaq Python library.[4] This official software development kit (SDK) provides a convenient interface for interacting with the API and includes functionality to directly convert the JSON response into a pandas DataFrame.[4] This capability significantly simplifies the data ingestion and initial processing steps, allowing for efficient filtering by location (Chiang Rai), parameter PM2.5 and date range. The selection of OpenAQ is justified by its commitment to open data, comprehensive global coverage, and robust, developer-friendly tools, which align perfectly with the requirements of an academic research project.[7]

2.2.2 Meteorological Data: A Comparative Analysis of APIs

For meteorological data, two primary candidates were evaluated: Open-Meteo and OpenWeather.[1] A systematic comparison reveals that Open-Meteo is the superior choice for this project's specific needs due to its accessibility, data availability, and licensing terms.

Open-Meteo is an open-source weather API that aggregates data from a variety of high-resolution national and global weather models.[9] Its most significant advantage is its accessibility for non-commercial use. It does not require an API key for up to 10,000 daily API calls, which is more than sufficient for this project's data collection phase.[10] Furthermore, it provides free access to extensive historical weather data, with some datasets going back as far as 1940, delivered in hourly resolution.[10] The data is provided under a Creative Commons Attribution 4.0 International (CC BY 4.0) license, requiring only appropriate credit.[12]

In contrast, OpenWeather, while a popular and powerful service, presents several barriers. Access to its API universally requires a unique API key.[13] Although its "One Call API 3.0" includes a free tier of 1,000 calls per day, access to its comprehensive historical data archive (beyond a few days) is generally restricted to paid subscription plans.[15] This combination of a mandatory API key and potential cost for essential historical data makes it a less suitable option for a student-led research project with limited resources.

The following table provides a clear, side-by-side comparison, solidifying the rationale for selecting Open-Meteo.

Table 1: Comparative Analysis of Meteorological Data APIs

Feature	Open-Meteo	OpenWeather
Access Requirement	No API key required for non-commercial use	API key required for all calls
Cost (Non-Commercial)	Free (up to 10,000 calls/day)	Free tier available, but historical data is largely a paid feature
Historical Data	Extensive historical data	Limited historical data in

Availability	(back to 1940) available for free	free tier; comprehensive access requires subscription
Data Formats	JSON	JSON, XML, HTML
Licensing	Creative Commons Attribution 4.0 (CC BY 4.0)	Proprietary; use governed by service terms
Key Advantage for Project	Unrestricted, free access to essential historical data, simplifying project setup	Broad adoption and extensive documentation

2.3 Data Description and Preprocessing Strategy

The final dataset for this project will be constructed by integrating data from the selected sources. The specific variables to be collected are:

- **From OpenAQ:** PM2.5 concentration.
- **From Open-Meteo:** Temperature, Relative Humidity (%), Wind Speed (km/h), Wind Direction (degrees), Precipitation (mm), and Atmospheric Pressure (hPa).[1]

The raw data, which will be collected at an hourly resolution, will be aggregated to daily averages. This temporal aggregation aligns with the project's primary objective of forecasting the *next-day* average PM2.5 level and AQI category.[1]

A structured preprocessing pipeline will be implemented to ensure the data is clean, consistent, and ready for modeling [1]:

1. **Merging:** The air quality and weather datasets will be merged into a single time-series DataFrame, using the date as the common key.
2. **Handling Missing Values:** A strategy for imputing missing data points will be implemented. Given the time-series nature of the data, methods such as linear interpolation or forward/backward fill are appropriate candidates to maintain temporal continuity.
3. **Feature Normalization:** All numerical features will be scaled to a common range (e.g., using Min-Max scaling or Standardization). This step is crucial for many machine learning algorithms, including the baseline linear model, to prevent features with larger magnitudes from disproportionately influencing the model.

4. **Temporal Splitting:** The final dataset will be split into a training set and a testing set. This split will be done chronologically (e.g., using the first 80% of the timeline for training and the final 20% for testing) to accurately simulate a real-world forecasting scenario where the model predicts future values based on past data.

A critical and previously unstated step in the methodology involves the conversion of the predicted PM2.5 concentration into an AQI category. The project aims to deliver both a regression output and a classification output (AQI category like "Good," "Moderate," etc.).[1] However, the data source provides only the raw pollutant concentration.[3] Therefore, after the regression model predicts a numerical PM2.5 value for the next day, this value must be passed through a function that implements an official AQI calculation standard (such as the one defined by the U.S. Environmental Protection Agency or the Thai PCD). This function will map the concentration value to its corresponding AQI number and qualitative category. This clarifies that the classification aspect of the project is not a separate modeling task but rather a deterministic post-processing step applied to the primary model's output.

2.4 Conclusion: Rationale for Selected Data and Anticipated Insights

In conclusion, the data research phase has identified OpenAQ and Open-Meteo as the optimal sources for acquiring the necessary air quality and meteorological data, respectively. These platforms provide reliable, high-resolution, and programmatically accessible data under open-access terms that are highly conducive to academic research.[1] The proposed strategy for data aggregation, preprocessing, and feature engineering is designed to create a robust and clean dataset suitable for training advanced machine learning models. It is anticipated that this carefully curated dataset will enable the discovery of complex temporal patterns and meteorological dependencies in Chiang Rai's air quality, ultimately leading to the development of an accurate and valuable predictive tool for the local community.

Part III: Technology Review - Selecting the Optimal Machine Learning and Deployment Stack

3.1 Introduction: Aligning Technological Choices with Project Goals

The selection of an appropriate technology stack is a critical determinant of a project's success. For this initiative, the technological choices must serve two distinct but interconnected goals: first, to implement a predictive model capable of achieving the highest possible accuracy in forecasting PM2.5 concentrations; and second, to develop a lightweight and intuitive web application for disseminating these forecasts to the public.[1] This review provides a comprehensive evaluation of the proposed machine learning models and web development frameworks, culminating in the justification for a cohesive technology stack that is technically sound, efficient to implement, and perfectly aligned with the project's end-to-end objectives.

3.2 Evaluation of Predictive Modeling Techniques

3.2.1 Baseline Modeling: The Role of Linear Regression

The first model to be implemented will be Linear Regression. While not expected to be the highest-performing model, its inclusion is methodologically crucial. Linear Regression is simple to implement and highly interpretable, allowing for a clear understanding of the linear relationships between the input meteorological features and the target PM2.5 concentration.[1] Most importantly, it will serve as a vital performance baseline. The effectiveness of more complex models can only be properly assessed by comparing their performance against this simple benchmark. Furthermore, implementing a linear model provides a direct point of comparison to the Multiple Linear Regression methodology used in the key regional study by La-ong-muang et al., grounding this project's results within the context of existing literature.[2]

3.2.2 Advanced Ensemble Methods: A Comparative Analysis

To capture the anticipated non-linear dynamics of air pollution, the project will employ advanced ensemble learning methods. The two primary candidates are Random Forest and XGBoost.[1]

Random Forest (RF) is an ensemble technique based on the principle of bagging (Bootstrap Aggregating). It constructs a multitude of decision trees during training, each on a different random subset of the data and features. The final prediction is the average of the predictions from all individual trees.[17] This averaging process makes Random Forest highly robust against overfitting, especially in the presence of noisy data. It is also relatively easy to interpret through metrics like feature importance, which can quantify the contribution of each weather variable to the prediction.[17]

XGBoost (Extreme Gradient Boosting) is a more sophisticated ensemble technique based on the principle of boosting. Unlike Random Forest, which builds trees in parallel, XGBoost builds them sequentially. Each new tree is trained to correct the errors made by the previous ones, iteratively improving the model's overall performance.[17] XGBoost is renowned for its superior predictive accuracy and high computational efficiency. It incorporates built-in regularization techniques (L1 and L2 penalties) to rigorously control for overfitting, a feature not present in standard Random Forest implementations.[17] It has also demonstrated superior performance on datasets with class imbalances, which could be relevant if certain AQI categories are rare.[18]

A significant limitation of all tree-based models, including RF and XGBoost, is their inability to extrapolate, meaning they cannot predict values outside the range of the target variable seen during training.[19] In a time-series context with a potential underlying trend (e.g., gradually worsening or improving air quality over years), this is a critical flaw. A model trained on historical data would be incapable of forecasting a record-breaking pollution day.

To mitigate this fundamental weakness, a more advanced modeling strategy will be adopted: **hybrid trend-residual modeling**. This approach decomposes the time-series forecasting problem into two parts. First, a simple model (e.g., linear regression against a time index) will be used to capture the long-term trend in the PM2.5 data. Second, the powerful XGBoost model will be trained not on the raw PM2.5 values, but on the *residuals*—the short-term fluctuations that remain after the trend has been removed. The final forecast for any given day will be the sum of the values predicted by the trend model and the residual predicted by the XGBoost model. This hybrid approach leverages the strengths of both model types: the linear model's ability to extrapolate trends and XGBoost's power to model the complex, non-linear relationships between meteorological variables and short-term pollution variations.[19]

The following table summarizes the comparison of the candidate models.

Table 2: Comparative Evaluation of Machine Learning Models

Feature	**Linear Regression**	**Random Forest**	**XGBoost**
Model Type	Statistical / Linear	Ensemble (Bagging)	Ensemble (Boosting)

Core Principle	Fits a linear equation to the data	Averages predictions from multiple independent trees	Sequentially adds trees to correct prior errors
Performance	Low (Baseline)	High	Very High / State-of-the-art
Speed	Very Fast	Slower training, fast prediction	Optimized for speed; fast training and prediction
Overfitting Control	N/A (low complexity)	Robust due to averaging	Built-in L1/L2 regularization
Interpretability	High	Moderate (feature importance)	Low (complex interactions)
Handles Non-Linearity	No	Yes	Yes (highly effective)

3.3 Selection of a Web Application Framework

The project deliverable includes a small web dashboard to display the daily AQI forecast.[1] The choice of framework for this task must prioritize speed of development and ease of use for a data science-focused team. The two options considered are Streamlit and Next.js.

Streamlit is an open-source Python framework explicitly designed for data scientists and machine learning engineers to turn data scripts into shareable web applications with minimal effort.[21] It allows developers to build interactive user interfaces using simple Python commands, eliminating the need for any front-end development experience (HTML, CSS, JavaScript).[23] Its core principle of re-running the Python script in response to user interactions makes it exceptionally fast for prototyping and deploying data-centric applications.[23] For a project whose primary focus is on the data model, Streamlit is an ideal tool for creating the "small web dashboard" specified in the project goal.[1]

Next.js is a powerful and popular JavaScript framework built on top of React.[21] It is designed for building large-scale, production-ready, and highly optimized web applications. It offers advanced features like server-side rendering, static site generation, and route pre-fetching.[22] While an excellent tool for professional web development, it is vastly over-scoped for this project's needs. Adopting Next.js would require the project team to learn and work in a completely different language and ecosystem (JavaScript/React), significantly increasing development time and diverting focus from the core machine learning task.

The choice between these two frameworks is therefore not just a technical one, but a strategic one. The project team's expertise lies in Python, data analysis, and machine learning. Streamlit is designed for this exact persona, allowing them to leverage their existing skills to build the required deliverable efficiently. Opting for Next.js would introduce unnecessary complexity and risk. Therefore, Streamlit is the unequivocally correct choice.

The table below highlights the key differences from the perspective of a data scientist.

Table 3: Comparison of Web Dashboard Frameworks

Feature	**Streamlit**	**Next.js**
Primary Language	Python	JavaScript / TypeScript (React)
Target User	Data Scientist, ML Engineer	Front-End Web Developer
Development Speed	Very Fast (minutes to hours)	Slower (days to weeks)
Ease of Use (for Data Scientist)	Extremely High	Low (requires web dev skills)
Customization	Limited but sufficient for data apps	Extremely High
Best Fit for Project	Ideal	Overkill and inefficient

3.4 Conclusion: A Cohesive Technology Stack for an End-to-End Solution

In conclusion, this technology review has resulted in the selection of a cohesive and strategically optimized stack designed to ensure the successful and efficient completion of the project.[1] Each component has been chosen to align with the project's goals and the team's core competencies. The final proposed technology stack is as follows:

- **Data Ingestion:** The py-openaq Python library and direct API calls to the Open-Meteo API.
- **Data Processing and Analysis:** The pandas library for data manipulation and preparation.
- **Predictive Modeling:** The scikit-learn library for the Linear Regression baseline and the XGBoost library for the primary predictive model, implemented using the proposed hybrid trend-residual methodology to ensure robustness for time-series forecasting.
- **Web Application Deployment:** The Streamlit framework for the rapid development of the public-facing dashboard.

This integrated stack provides a complete, end-to-end solution, from raw data acquisition to the final communication of results. It prioritizes predictive accuracy through the use of a state-of-the-art model while ensuring the project's deliverable can be created efficiently, minimizing technical overhead and maximizing focus on the core data science challenges.

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