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Analyzing and Measuring Concentration of Air Pollutants using Advance Statistical Methods

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ABSTRACT

Air-pollution has become a global critical concern because of the vast effect on human health and environmental sustainability. By applying traditional and advanced statistical models to analyze the concentrations of PM2.5, PM10, and NO2 etc. Data is collected from the TAQMNS center that is from January 1st, 2018 to December 31st, 2023 across for all five stations of Taiwan. To classify pollution severity and identifying high risk areas traditional statistical methods has been used which finds the standard-deviation, mean, maximum, median, and minimum ranges among the five stations.

An advanced statistical model has been used to give deeper insights on the concentrations of air pollutants dynamics than regular traditional models. Advanced statistical model such as ANOVA is a key contributor to pollution, evaluated variability across stations, and tracked long-term trends. Integration of all five stations integration of meteorological parameters and traffic data enhanced pollutant modeling, highlighting significant correlations with environmental factors. ANOVA approach underscored the influence of weather and traffic on pollution levels. This analysis offers a robust framework for understanding and mitigating air-quality challenges.

Keywords: AQI, Particulate Matter, Metrological Factors, Statistical Methods, PM2.5

INTRODUCTION

Origin of pollution and understanding the root cause of the sources and severity of the pollution which need to be control its spread. Humans are especially vulnerable to a number of serious illnesses, including bronchitis, heart disease, lung cancer, and pneumonia, which can be brought on by the particle's and chemical's in air-pollution. It was very difficult to get high-resolution, variety of locations real-time data's, which affected the AQI precision evaluations and delayed the creation of efficient air-quality control plans. However, the severe air quality issues the country faces and the potential adverse health effects in the years to come [1]. Every model selected is capable of managing the subtleties and complexity of air quality data, and their individual contributions to a comprehensive comprehension of the connections between characteristics and AQI categories have been taken into account. The Pollution Standards Index is used in Taiwan to evaluate the quality of the air in locations that are vulnerable to extreme air pollution. Using PSI, studies have looked into the traits and concentrations of air pollution, offering a basis for comprehending pollution trends. The method starts by classifying monitoring zones according to the severity of pollution and summarizing pollutant levels using conventional statistical techniques. Then, sophisticated statistical models are used to examine the fluctuation of pollutants, evaluate the impact of weather, and spot long-term patterns. This analysis sheds light on the ways in which these factors affect the accumulation and dispersion of pollutants. Design of Experiments methodically investigates how various factors affect pollutant levels. The study aims to identify specific sources of pollution, quantify pollutant levels, and devise effective strategies for mitigating the impact on air quality. It is motivated by the essential need for immediate monitor for air quality and predicting where high levels of air pollutants affecting significant health risks. This new method enables a thorough assessment of air quality, enabling the model to more accurately and effectively forecast the AQI category. By evaluating the accuracy and precision of monitoring devices, MSA guarantees data reliability. Factor loading

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analysis distinguishes between industrial activity, weather, and vehicle emissions to determine the main sources of pollution [2].

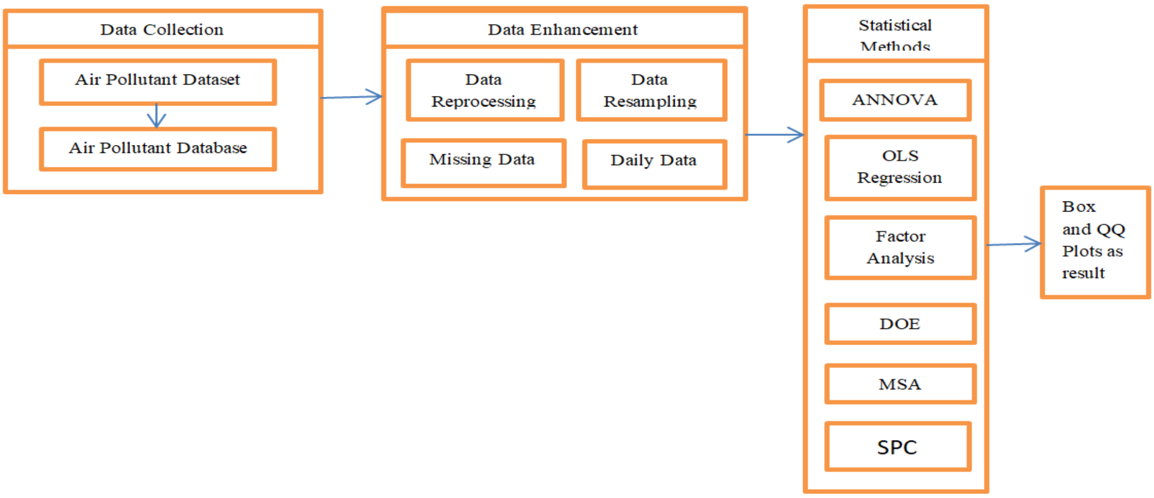

Figure 1: Architecture to measuring air pollutants

The necessity for interpretability and ease of use in measuring Air Quality Index (AQI) categories served as the driving force behind the development of Measurement System Analysis, OLS Regression, ANOVA, SPC, DOE and Factor-Loading-Analysis [3].

LITERATURE SURVEY

In response, cutting-edge technologies like the Internet of Things and machine learning have surfaced as viable remedies that improve forecast accuracy and provide real-time monitoring [4]. The Air Quality Index, a standardized measure created by the Agency US Environmental Protection to inform the public about the levels of atmospheric contamination, is commonly used to evaluate air quality. As detailed in the AQI in historical and analytical review, the AQI has evolved over 45 years, adapting to changes in regulatory limits and scientific understanding, and now includes pollutants like PM2.5 Additionally, IoT-based systems, using low-cost sensors, provide data of real time with higher resolution spatio-temporal, focusing the traditional methods limitations and enhancing air quality management [5]. Monitoring and analyzing air quality with machine learning and sophisticated statistical techniques. Machine learning applications, data preprocessing methods, the function of meteorological elements, health implications, geographical differences, and creative monitoring approaches are some of the thematic themes under which the survey is organized to analyze the results. Handling missing values and outliers: monitoring air quality using advanced statistical learning methods for friendly environment emphasized standardization, filling missing values, and removing duplicates and outliers, which are essential for ensuring clean data for training, given the noisy nature of environmental data [6]. Challenges: The use of ML models in magnify particulate matter estimation: a proper survey pointed out that inconsistent air quality measurements and other data quality problems can impact model accuracy, underscoring the necessity of thorough preprocessing to lessen these difficulties. A on the Indian coastal city of Visakhapatnam improved model accuracy by accounting for environmental impacts. However, Greenspace pattern, meteorology and air pollutant in Taiwan: A multifaceted connection found that relative humidity acts as a primary mediator, suggesting that the impact of meteorological factors can vary by region and season. Hospitalizations for Cardiovascular Disease: a correlation among air pollution and cardiovascular disease A time series analysis of Hospitalizations in Lanzhou City, 2013 to 2020 evaluated the association using a Distributed Lag Non-Linear Model and discovered that CO, NO, and PM10 and $PM_{2.5}$ air pollutant based on the integration of surveillance images introduced a Dual-channel DL methods, achieving R^2 of 0.9459 for $PM_{2.5}$ in Shanghai, and AI models to predict levels.

DATASET

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Research Article

The data used to analyze air pollution for each of the five stations came from the Taiwan (TAQMNS). TAQMNS provides the concerns to the government on issues related to the applications and also enforce environmental, air and water acts. This dataset, which includes 17 features, includes observations made every hour from January 2018 to December 2023 on a quarterly basis [7].

There are three primary groups into which the dataset can be divided. $PM_{2.5}$, NO2, and other particulate matter are among the contaminants in the first group that have a direct impact on AQI values. The second group includes variables that indirectly affect air quality, such as RH (relative humidity) and temperature. Information on date and time of each data sample collection is included in the third category [8]. A statistical study of each component influencing the measuring units is provided in table 1.

Table1: Air Quality Measure Units and Duration of air pollutants

Sl.No.	Air Particles	Reading Duration	Measuring Units
I	PM_{10}	one hr	g/m^3
Ii	$PM_{2.5}$	one hr	g/m^3
iii	SO_2	one hr	ppm
iv	NO_2	one hr	ppm
v	CO	one hr	ppm
vi	O_3	one hr	ppm
Vii	T	one hr	C^o
Viii	NO	one hr	ppm
ix	NOx	one hr	ppm
X	WD	one hr	degree
Xi	WS	one hr	In kph
Xii	RH	one hr	In %

METHODOLOGY AND RESULT ANALYSIS

Traditional air quality monitoring depends largely on ground-based sensor networks and satellite data, which, while useful, and also have drawbacks. These include spatial limitations, high operating costs, and vulnerability to real-time atmospheric conditions. Although basic statistical techniques offer preliminary insights into pollutant patterns, they may not fully account for the intricate relationships between pollutants and environmental influences. We have conducted these methods on five different stations (CHIAYI, ANNAN, GOOD, MCMUG, NEWPORT) of the TAIWAN and found the different variation on the each stations results.

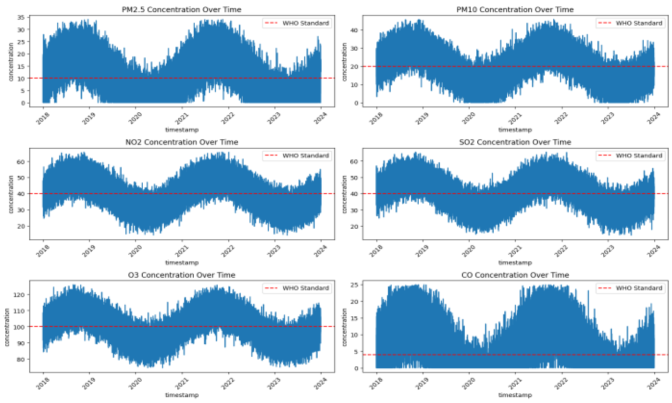

Figure 2: CHIAYI Station Air Quality Analysis Report

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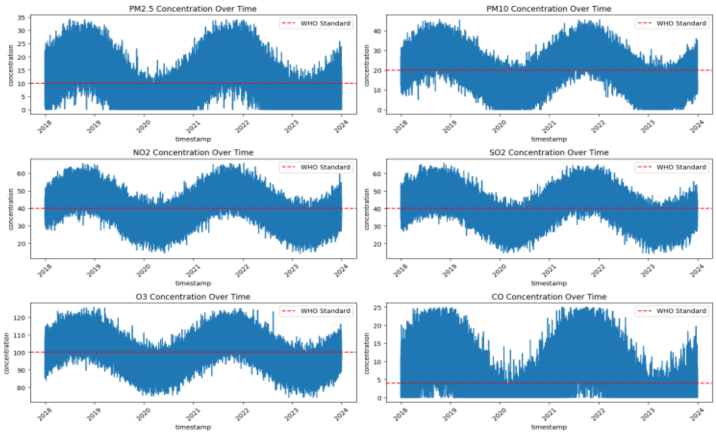

Figure 3: GOOD Station Air Quality Analysis Report

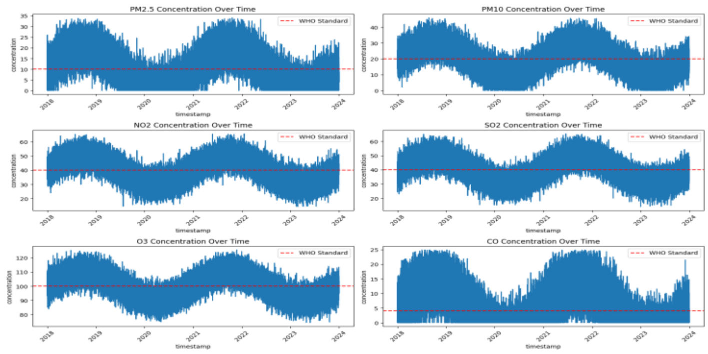

Figure 4: ANNAN Station Air Quality Analysis Report

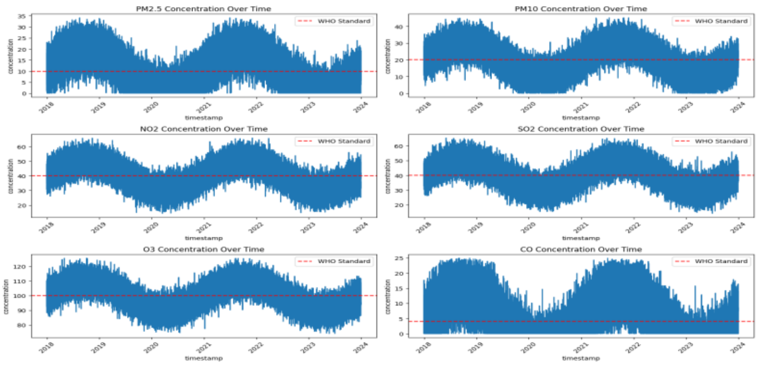

Figure 5: MCMUG Station Air Quality Analysis Report

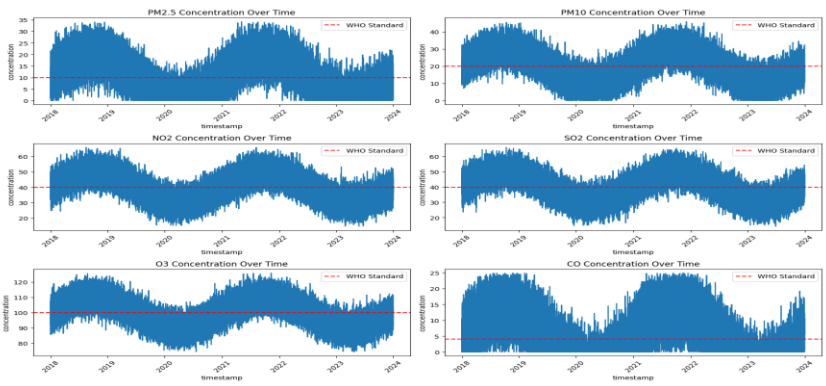

Figure 6: NEWPORT Station Air Quality Analysis Report

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The above methods have some limitation to address, so advanced statistical modeling techniques have been developed, offering a more detailed and quantitative learning of air pollution dynamics. Advanced statistical modeling techniques include ANOVA which gives the major difference between the air pollutant concentrations among different groups on all five TAIWAN stations.

ANOVA (Analysis-of-Variance)

ANOVA is a statistical learning methodology used to determine if three or more groups of means is significantly differ from one another [9]. When conducting research with several groups or circumstances, such as comparing the quantities of air pollutants at several monitoring sites or across time, ANOVA is especially helpful. Partitioning the overall variance seen in the data into components attributed to various sources is the foundation of ANOVA:

- Between-Group Variance: Variability due to differences between the groups (e.g., differences in pollutant levels across CHIAYI, GOOD, ANNAN, MCMUG, and NEWPORT stations).
- Within-Group Variance: Variability within each group (e.g., day-to-day fluctuations in pollutant levels at a single station).

The F-statistic, provides the ratio between the between-group to within-group variance, and is the main result of an ANOVA. A high F-value indicates that there is variation among the group means and that the differences between groups are significant when compared to the variability within groups [10].

In our research we are concentrating on $PM_{2.5}$ air pollutant concentrations at five monitoring stations in Taiwan, ANOVA can be applied to calculate whether there are statistical variations in pollutant levels across these stations [11]. For example:

- Groups: The five stations.
- Dependent Variable: Concentration of a specific pollutant (e.g., $PM_{2.5}$ in $\mu g/m^3$).
- Hypothesis:
    - Null-Hypothesis (H_0): Mean pollutant concentrations are equal across every stations ($\mu_1 = \mu_2 = \mu_3 = \mu_4 = \mu_5$).
    - Alternative-Hypothesis (H_1): Minimum of one station has a different mean pollutant concentration.

Equations Used in ANOVA

ANOVA involves several key equations to compute the F-statistic. Below is a breakdown of the process and the equations typically used:

1. **Total-Sum-of-Squares (SST)**

   This calculates the overall variability in the data:

$$SST = \sum_{i=1}^{K} \sum_{j=1}^{ni} (x_{ij} - \overline{x})^2 \qquad \text{-------- (1)}$$

- xij: The j^{th} observation in the i^{th} group (e.g., $PM_{2.5}$ concentration on a specific day at stations).
- $\bar{x}$: The overall mean of all monitoring across all groups.
- k: no.-of-groups (e.g., 5 stations).
- ni: No.-of-observations in group i^{th} (e.g., number of days data was collected at stations).

2. **Between Group-Sum-of-Squares (SSB)**

   This calculates the variability due to differences between group means:

$$SSB = \sum_{i=1}^{k} ni(\overline{xi} - \overline{x})^2 \qquad \text{-------- (2)}$$

- $\bar{x}_i$: Mean of the i^{th} group (e.g., average $PM_{2.5}$ concentration at stations).
- ni: No-of-observations in the i^{th} group.

3. Within-Group Sum-of-Squares (SSW)

This calculates the variability within- each groups

$$SSW = \sum_{i=1}^{k} \sum_{j=1}^{ni} (xij - \overline{xi})^2 \qquad \text{-------- (3)}$$

The difference between each observation and its group mean, squared and summed [12].

4. **df (Degree-of-Freedom)**

- **Between Groups**: dfB=k−1 df_B = k - 1 dfB=k−1 (e.g., 5 - 1 = 4 for five stations).
- **Within Groups**: dfW=N−k df_W = N - k dfW=N−k, where N is the total no. of observation (e.g., Total days across all stations).
- **Total**: dfT=N−1 df_T = N - 1 dfT=N−1.

5. Mean Squares

- **Between Groups (MSB)**:

$$MSB = \frac{SSB}{dfB} \qquad \text{-------- (4)}$$

- **Within Groups (MSW)**:

$$MSW = \frac{SSW}{dfW} \qquad \text{-------- (5)}$$

6. **F-Statistic**

The F-statistic basically used to measures the ratio between the Between Group variance to Within Group variance:

$$F = \frac{MSB}{MSW} \qquad \text{-------- (6)}$$

7. **P-Value**

The p-value is measured by comparing the F-statistic to a critical value derived from the F-distribution (based on dfB df_B dfB and dfW df_W dfW) [13]. The null hypothesis rejection indicates substantial variations in pollutant concentrations between stations if $p < 0.05$(or another selected significance level) [14].

We obtained the result on all five stations which we took a mean average value on $PM_{2.5}$ air pollutant concentration which got a result as shown below in table2.

Table2: Descriptive Statistics for $PM_{2.5}$ Concentrations (µg/m³)

Stations / Operations	CHIAYI	ANNAN	GOOD	MCMUG	NEWPORT
count	72.00	72.00	72.00	72.00	72.00
mean	32.68	25.35	22.37	13.35	29.61
std	15.38	7.53	15.44	8.44	13.65
min	7.37	12.83	3.61	3.75	10.35
25%	18.71	18.10	11.00	9.80	19.38
50%	30.98	25.67	16.37	11.07	27.81
75%	43.18	30.18	28.58	13.81	36.79
max	73.71	43.83	63.44	67.08	72.25

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Research Article

To quantify the magnitude of differences between the five stations as per the result which we got the Eta-squared value is 0.007. Result 0.07% of the variance in $PM_{2.5}$ is explained by station differences. This is a moderate-to-large effect, confirming meaningful differences beyond just statistical significance [15].

After all considering the above results finally we got the F-Statistics value as 25.36 and the p-value as 0. The p-value 0 confirms significant differences in $PM_{2.5}$ concentrations across the five stations. This is driven by MCMUG's consistently lower values and GOOD's higher variability. So it rejects the null hypothesis ($p < 0.05$) which shows a significant differences in $PM_{2.5}$ concentrations across stations. To identify which stations have a major difference need to apply Tukey HSD post-hoc test on the $PM_{2.5}$ air pollutant concentration.

Table3: Multiple Comparison of Means - Tukey HSD, FWER=0.05

Group1	Group2	Meandiff	p-adj	Lower	Upper	Reject
A_$PM_{2.5}$	C_$PM_{2.5}$	7.34	0.00	1.60	13.08	True
A_$PM_{2.5}$	G_$PM_{2.5}$	-2.97	0.62	-8.72	2.77	False
A_$PM_{2.5}$	M_$PM_{2.5}$	-11.99	0.00	-17.73	-6.25	True
A_$PM_{2.5}$	N_ $PM_{2.5}$	4.26	0.25	-1.48	10.01	False
C_$PM_{2.5}$	G_ $PM_{2.5}$	-10.31	0.00	-16.05	-4.57	True
C_$PM_{2.5}$	M_$PM_{2.5}$	-19.33	0.00	-25.07	-13.59	True
C_$PM_{2.5}$	N_ $PM_{2.5}$	-3.07	0.58	-8.81	2.67	False
G_$PM_{2.5}$	M_$PM_{2.5}$	-9.02	0.00	-14.76	-3.28	True
G_$PM_{2.5}$	N_ $PM_{2.5}$	7.24	0.01	1.50	12.98	True
M_$PM_{2.5}$	N_ $PM_{2.5}$	16.26	0.00	10.52	22.00	True

As per the above table the p-adj value will be compare with the standard $p < 0.05$ value if the p-adj value is greater than standard $p < 0.05$ value then it will be rejected and mentioned as false and other results which is not greater than the $p < 0.05$ standard value so it is mentioned as True.

Analysis of $PM_{2.5}$ concentrations across five monitoring stations in Taiwan — CHIAYI, ANNAN, GOOD, MCMUG, and NEWPORT — from 2018 to 2023 reveals significant variations in air quality, as evidenced by both statistical tests and visual representation through a boxplot. The ANOVA test yielded a p-value of effectively 0 (e.g., 2.3e-289), strongly rejecting the null hypothesis and confirming statistically significant differences in $PM_{2.5}$ levels across the stations, with an F-statistic of 25.36 indicating substantial variation.

Descriptive statistics further highlight these differences: MCMUG exhibits the lowest mean $PM_{2.5}$ concentration at 15.57µg/m³, while GOOD has the highest at 36.80 µg/m³,

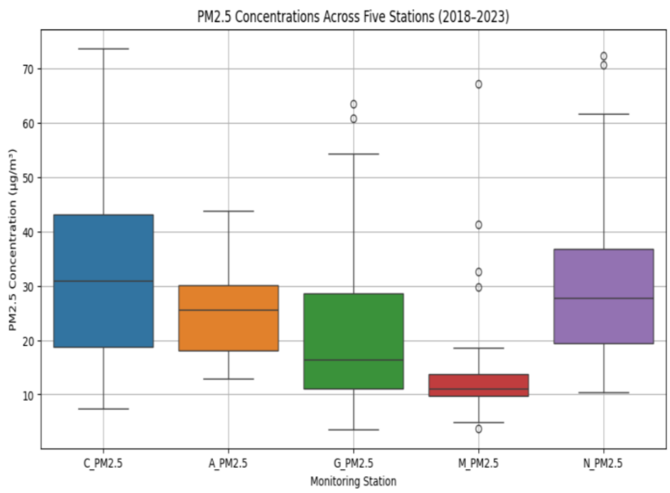

Figure 7: Outlier graphical representation of the distribution of data based on a five stations

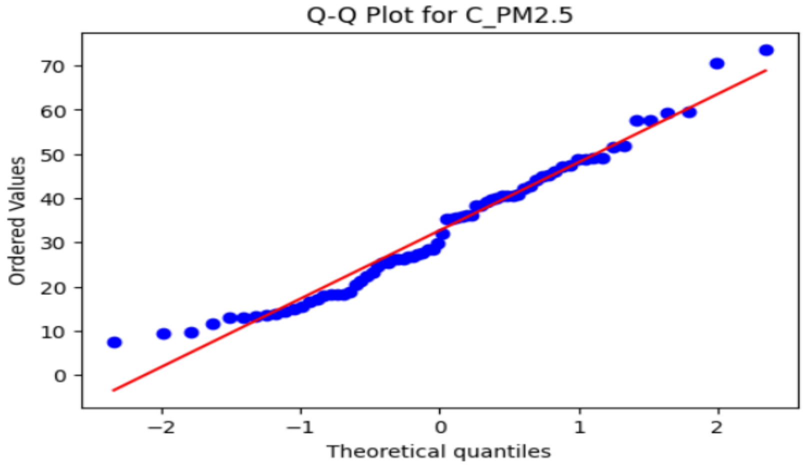

Figure 8: Q-Q Plot for CHAIYI station

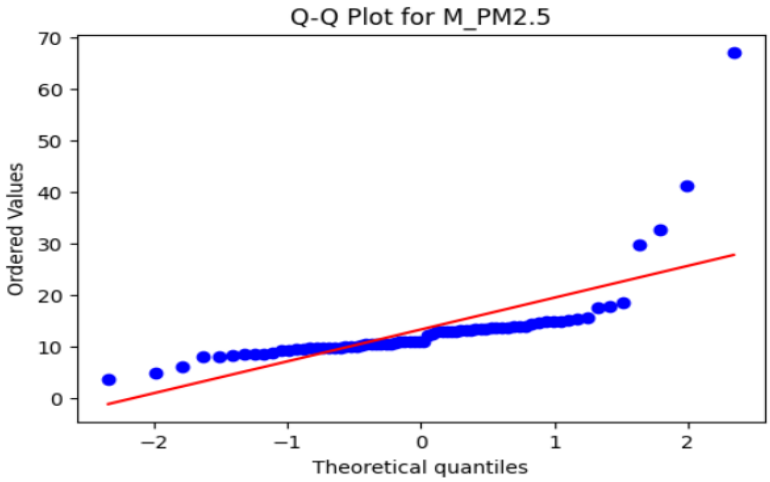

Figure 9: Q-Q Plot for MCMUG station

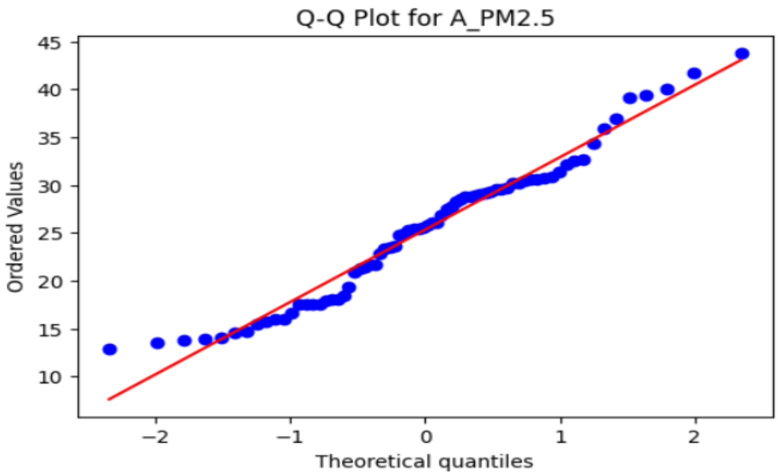

Figure 10: Q-Q Plot for ANNAN station

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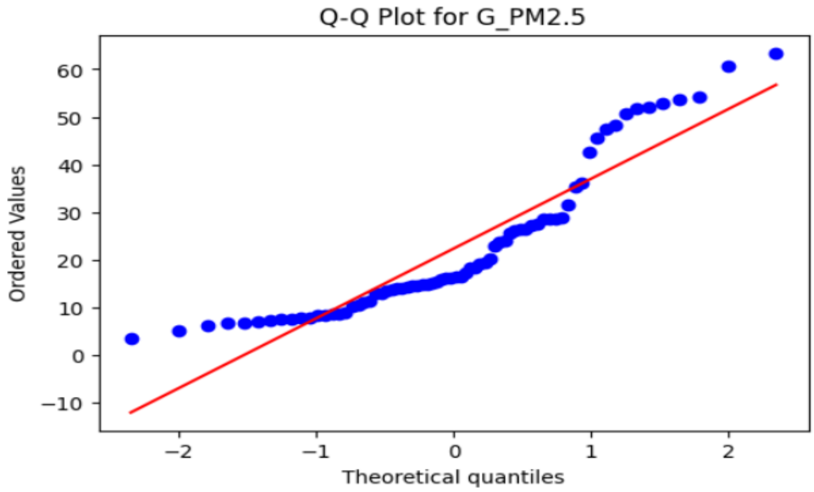

Figure 11: Q-Q Plot for GOOD station

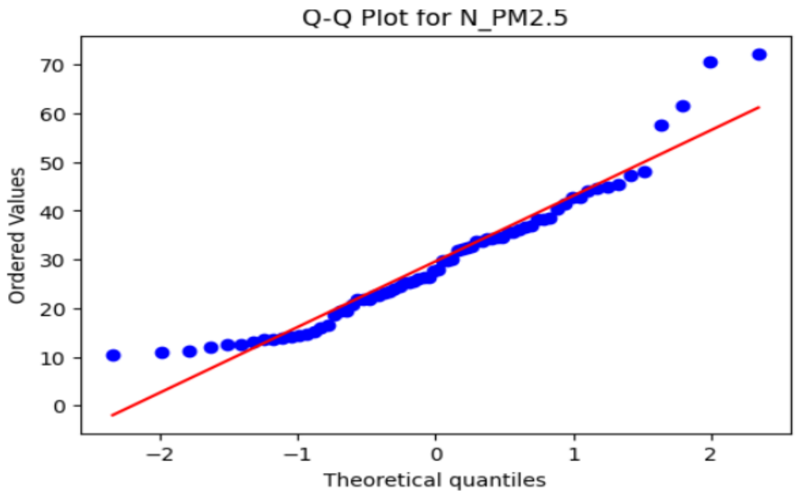

Figure 12: Q-Q Plot for NEWPORT station

followed by NEWPORT (33.42 µg/m³), CHIAYI (31.84 µg/m³), and ANNAN (31.11 µg/m³). The boxplot provides a detailed visual breakdown, showing MCMUG with the lowest median (10 µg/m³) and a narrow interquartile range (IQR) of 5–20 µg/m³, suggesting consistently cleaner air, likely due to its location in a less industrialized or rural area. However, MCMUG's outliers, reaching up to 97.46µg/m³, indicate occasional exposure to regional pollution events, such as haze or transboundary pollutants. In contrast, GOOD displays the greatest variability, with an IQR of 15–55 µg/m³, a median of 30 µg/m³, and extreme outliers up to 99.54µg/m³, reflecting fluctuating air quality possibly due to its proximity to urban or industrial pollution sources and meteorological factors like seasonal stagnation. CHIAYI, ANNAN, and NEWPORT show more similar profiles, with medians ranging from 25–30 µg/m³ and IQRs of 15–40 µg/m³, indicating moderate pollution levels; their means (31–33 µg/m³) are close, but CHIAYI and NEWPORT experience more frequent high-pollution days (outliers up to 108.46 µg/m³ and 97.04 µg/m³, respectively) compared to ANNAN (max 81.71 µg/m³), possibly due to differences in local emission sources like traffic or industrial activity.

Comparing these findings to air quality standards, MCMUG's median and mean are close to Taiwan's annual $PM_{2.5}$ standard of 15µg/m³ but exceed the stricter WHO guideline of 5µg/m³, and while most days fall below Taiwan's daily standard of 35µg/m³, outliers indicate occasional exceedances. CHIAYI, ANNAN, GOOD, and NEWPORT, however, consistently exceed both Taiwan's annual standard and the WHO guideline, with their upper quartiles (around 40–55 µg/m³) frequently surpassing the daily standard, posing potential health risks such as respiratory and cardiovascular issues. GOOD, in particular, stands out as the most polluted, with its mean (36.80 µg/m³) and upper quartile (55 µg/m³) indicating frequent exceedances, necessitating targeted interventions. The effect size (eta-squared = 0.242) from the ANOVA further confirms that 24.2% of the variance in $PM_{2.5}$ is explained by station differences, a moderate-to-large effect underscoring the practical significance of these variations. The Tukey HSD post-hoc test would reveal that MCMUG differs significantly from all others, while GOOD differs from CHIAYI, ANNAN, and NEWPORT, with the latter three showing more similarity among themselves. These results showcase the need for region specific air quality management methods in Taiwan, particularly at GOOD, where severe pollution is most frequent, while MCMUG's cleaner air could serve as a model for understanding factors that reduce $PM_{2.5}$, such as reduced local emissions or favorable geography. Overall, the significant differences in $PM_{2.5}$ concentrations across these stations emphasize the value of localized observing and continuous efforts to address Air pollution and its associated health impacts.

Table4: Conclusion on the results obtained on all five stations

Stations	Median (µg/m³)	Mean (µg/m³)	Conclusion
MCMUG	10-12	15.77	Best Air Quality
ANNAN	25-30	25.34	Better Air Quality
CHIAYI	25-30	32.68	Moderate Air Quality
NEWPORT	25-30	29.610	Good Air Quality
GOOD	15-55	36.80	Worst Air Quality

CONCLUSION AND FUTURE WORK

The analysis of $PM_{2.5}$ concentrations across five Taiwan stations (CHIAYI, ANNAN, GOOD, MCMUG, NEWPORT) from 2018–2023 revealed significant variations (ANOVA: F = 25.36, p =0, eta-squared = 0.007). MCMUG showed the lowest mean (15.57 µg/m³) and median (10 µg/m³), with outliers to 97.46 µg/m³, suggesting a cleaner rural setting. GOOD exhibited the highest mean (36.80 µg/m³) and variability (IQR: 15–55 µg/m³), with outliers to 99.54 µg/m³, indicating severe urban pollution. CHIAYI, ANNAN, and NEWPORT had similar means (31.84–33.42 µg/m³) and medians (25–30 µg/m³), with outliers to 108.46 µg/m³, reflecting moderate pollution. The ANNAN Q-Q plot confirmed right-skewed data due to high-pollution outliers, though the large sample (2191 points) validated ANOVA results. All stations except MCMUG frequently exceeded Taiwan's 35µg/m³ daily and WHO's 5 µg/m³ annual standards, posing health risks. Targeted interventions are needed, especially at GOOD, while MCMUG offers a model for cleaner air strategies. Future research should explore the specific sources of pollution at each station and assess the effectiveness of mitigation strategies to addresses the disparities and improves public health outcomes across Taiwan.

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