# Assessment of Variation in Concentration of Air Pollutants Within Monitoring Stations in Mumbai

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**Abstract -** *This research paper presents a study on the variation of concentration of air pollutants in various areas of Mumbai, in order to determine the redundancy of maintaining separate Air Quality monitoring stations in those areas. The pollution concentration of 7 pollutants, namely PM2.5, PM10, NO2, NH3, SO2, CO and Ozone, is monitored across 12 stations in Mumbai. A statistical approach was conducted on monthly data for 2020 and 2021 collected from the Central Pollution Control Board (CPCB), India. The presence or absence of significant difference in the means of concentrations of a particular pollutant among monitoring stations is identified using ANOVA Analysis. Tukey's Honest Significant Difference (HSD) Post-Hoc Test is performed to ascertain the stations which show a significant difference in pollutant concentration. Those pairs of stations which show no significant difference in concentration of all 7 pollutants are identified. Recommendations are made based on these observations and the straight-line distance between the pairs of stations. This analysis can form the basis for identifying redundant air quality monitoring stations in Mumbai. This paper also applies a multinomial logistic regression model in order to predict the air quality class based on Tree Cover, Population Density, Petrol Price, Temperature, Humidity, Wind Speed, Air Pressure, Elevation, Coastal Location, Latitude and Longitude.*

***Key Words***: Air Pollutant, AQI, Particulate Matter, ANOVA, Monitoring Station, Logistic Regression.

## 1.INTRODUCTION

Air pollution is a serious problem in many developing countries. Atmospheric concentrations of fine particulate matter, which is one of the worst air contaminants, are several folds higher in a developing country as compared to a developed country [1]. Aerosols are airborne gases, solids, and liquids that contaminate the atmosphere. They are present in a wide range of sizes. There are three ranges in particulate matter, PM10, PM2.5 and PM1, with upper limits of 10 µm, 2.5 µm and 1 µm, respectively. For regulatory reasons, they are most commonly used to define aerosol fractions [2]. The increasing rate of pollutant concentrations is on account of the growing population of humans and vehicles, as well as industries [1]. Indian megacities are among the most polluted in the world. The pollutant concentrations in India are much higher than the level of pollutant concentrations recommended by the World Health Organisation [3].

In 1981, the Government of India introduced the Air (Prevention and Control of Pollution) Act in order to arrest the deterioration in air quality. The Central Pollution Control Board (CPCB) comprises State Pollution Control Boards (SPCB) that are required to perform a number of duties under the Act. Concerns over air quality have grown over the past few years as evidence of harmful effects on health, productivity, and the economy has increased. As a result, between 2015 and 2020, there has been a significant rise in the number of monitoring stations [4]. The National Air Quality Monitoring Program (NAQMP), launched in 1985 and run by the CPCB along with the SPCBs, is the most extensive monitoring network in the country. As of 2022, this program consists of a network of 804 operating manual and real-time monitoring stations across India. The monitoring of pollutants like PM2.5, PM10, SO2 and NO2, is done twice a week for a duration of 24 hours resulting in 104 observations per year. These stations use an estimate called the Air Quality Index (AQI) to track the daily air quality. The greater the AQI value, the more severe the level of pollution. Launched in 2019 by the Ministry of Environment, Forests and Climate Change, the National Clean Air Program (NCAP) aims at the reduction of 20-30% of the concentration of PM10 and PM2.5 by 2024 with 2017 as the base year [5].

Mumbai is transforming into a city primarily focused on commercial activities, rather than being recognised as an industrial city in the past. The transport sector is the main contributor to pollution, followed by power plants, industrial units and waste incineration [6]. In Mumbai, the air quality monitoring stations are operated by the Maharashtra Pollution Control Board (MPCB). Some stations are collocated in pockets, leaving a large area unmonitored.

**Table -1:** Ranges of AQI and their corresponding levels.

| AQI | Health Concern Level | AQI Daily Colour Code | Air Pollution Level |
|---|---|---|---|
| 0-50 | Good | **Green** | 1 |
| 51-150 | Moderate | **Yellow** | 2 |
| 151-200 | Unhealthy | **Orange** | 3 |
| 201-300 | Very Unhealthy | **Red** | 4 |
| >301 | Hazardous | **Purple** | 5 |

Source: https://nepis.epa.gov/

The above table (**Table -1**) indicates the five categories of Air Quality Index, showing the ranges of AQI and their corresponding levels of risk. Greater the AQI, higher is the risk to health. Level 1 indicates satisfactory air quality which poses little to no risk to health. Level 2 pollution may pose a risk only to certain high-risk members of the population. It is considered to be unhealthy for those people exposed to certain diseases such as lung diseases and heart diseases. It is not particularly harmful to those members of the general population without any underlying illnesses. Level 3 is said to be unhealthy. This type of pollution may have some negative health effects on some members of the general public, while sensitive populations may face more severe health problems. Level 4, 'very unhealthy', is the point where a health alert is issued, as the risk of adverse health effects for the population has greatly increased. Lastly, Level 5, is said to be hazardous as the entire population would be affected by the high levels of pollution [7].

This study aims to investigate the need for a large number of monitoring stations in a particular area. The aim of the study is to analyse whether there exists any significant difference in concentration of pollutants between selected monitoring stations in Mumbai, India. There are various factors that can affect air quality, including tree cover, population density, petrol price, temperature, humidity, wind pressure, air pressure, elevation, and coastal location. Understanding the relationships between these factors and air quality is imperative for developing effective plans to improve air quality. This paper also applies a multinomial logistic regression model in order to predict the air quality class on the basis of the aforementioned factors.

## 2. LITERATURE REVIEW

A study of industrial clusters with the majority of the industries in the study region on a moderate to large scale rendered it vulnerable to poor air quality. At 16 research locations, 12 pollutants, including PM10, PM2.5, SO2, NO2, CO, O3, NH3, and heavy metals (Cu, Mn, Ni, Pb, Zn), were monitored throughout the winter. Multivariate analysis was used to evaluate the air quality data further, and the results were displayed using histograms, box plots, cluster analysis, PCA, analysis of variance (ANOVA), and air quality index [8]. It was revealed that while the industrial areas experience deteriorating air quality, they also influence the increasing concentration of toxic metals in the neighbouring regions due to the increase in suspended particles originating in contaminated or eroded soil. Thereby, since 2010, the concentration of Ni & Cu particles in the air has increased every year and is a huge cause for concern [9].

Trends in air pollution and potential sources of emission were identified by the variations in the means of the sites since ANOVA findings were statistically different. This was followed by PCA that identified the sources of air pollution [10]. Following this, the Tukey Kramer test can be implemented to identify the pair of stations which are significantly different with respect to pollutant concentration [11].

Northern India experiences PM10 and PM2.5 exceeding National Ambient Air Quality Standards (NAAQS) by 150% and 100% respectively. For South India, the figures are 50% and 40% respectively. On the other hand, SO2, NO2 and O3 meet the residential NAAQS all over India. The progress of Continuous as well as Manual monitoring Networks in India was compared against US State Department Air-Now Network. While the frequency of observations and quality of data definitely improved, gaps remained in spatial and temporal coverage, thus indicating a requirement for additional monitoring stations [4].

A study employs various machine learning models to predict PM 2.5 levels on the basis of daily atmospheric conditions of a specific city. The paper makes use of a logistic regression model to detect and predict whether a city is polluted or not polluted based on temperature, wind speed, dew point and pressure [12].

## 3. DATA AND METHODOLOGY

The dataset (**Table -2**) contains pollution concentrations of 7 pollutants, PM2.5, PM10, NO2, NH3, SO2, CO, and Ozone, across 12 stations in Mumbai, operated by the Maharashtra Pollution Control Board. These stations are located in industrial as well as residential areas. The study was carried out on data for the years 2020 and 2021. Exploratory data analysis was performed on the raw data to determine patterns and relationships. Furthermore, descriptive statistics were obtained to summarise the data set. The missing values of pollutant concentrations were treated using interpolation. The research identifies redundancy amongst monitoring stations in Mumbai by analysing similar pollutant concentrations.

After checking the data for normality and homoscedasticity, one-way ANOVA was performed individually for each of the pollutant to identify whether there was a significant difference in the means between stations [8]. For ANOVA, the null hypothesis states that that all the group means are equal while the alternate hypothesis states that at least one pair of means is significantly different. If the calculated value of F is greater than the tabulated value, then the null hypothesis, which claims that the means of all groups have no significant difference, must be rejected [13]. When the Null Hypothesis is rejected in a One-way ANOVA, it is concluded that not all means are equal. The results of ANOVA, however, do not specify which specific differences between mean pairs are significant [10]. Thus, Tukey's Honest Significant Difference (HSD) Post Hoc Test was performed as a comparison of all pairs of means in order to identify which differences are significant [10]. The null hypothesis of Tukey's HSD test states that the two group means do not differ significantly.

Another dataset (**Table -3**) was created to help in building the predictive logistic regression model for Air Quality levels based on various predictor variables like tree cover, population density, petrol price, temperature, humidity, wind pressure, air pressure, coastal location and elevation. The data was collected from sources available publicly. The study was carried out for 3rd March 2022. Trees play a significant role in absorbing pollutants and improving air quality, while high population density can lead to increased pollution from human activities.

**Table -2:** A snapshot of the data collected for each pollutant.

| Station | Date | PM2.5 | PM10 | N02 | NH3 | S02 | CO | Ozone |
|---|---|---|---|---|---|---|---|---|
| Borivali East, Mumbai - MPCB | 01/01/20 | 115 | 14 | 2 | 3 | 1 | 34 | 13 |
| Borivali East, Mumbai - MPCB | 01/02/20 | 92 | 9 | 2 | 3 | 5 | 22 | 5 |
| Borivali East, Mumbai - MPCB | 01/03/20 | 55 | 77 | 8 | 4 | 5 | 19 | 2 |
| Borivali East, Mumbai - MPCB | 01/04/20 | 26 | 43 | 2 | 1 | 4 | 15 | 3 |
| Borivali East, Mumbai - MPCB | 01/05/20 | 24.4 | 40.2 | 1.8 | 1 | 6 | 13.6 | 3.6 |
| Borivali East, Mumbai - MPCB | 01/06/20 | 22.8 | 37.4 | 1.6 | 1 | 8 | 12.2 | 4.2 |
| Borivali East, Mumbai - MPCB | 01/07/20 | 21.2 | 34.6 | 1.4 | 1 | 10 | 10.8 | 4.8 |
| Borivali East, Mumbai - MPCB | 01/08/20 | 19.6 | 31.8 | 1.2 | 1 | 12 | 9.4 | 5.4 |
| Borivali East, Mumbai - MPCB | 01/09/20 | 18 | 29 | 1 | 1 | 14 | 8 | 6 |
| Borivali East, Mumbai - MPCB | 01/10/20 | 44 | 56 | 1 | 1 | 9 | 15 | 4 |
| Borivali East, Mumbai - MPCB | 01/11/20 | 63 | 46 | 4 | 4 | 12 | 22 | 3 |
| Borivali East, Mumbai - MPCB | 01/12/20 | 82 | 57 | 3 | 7 | 11 | 19 | 18 |
| Borivali East, Mumbai - MPCB | 01/01/21 | 249 | 122 | 4 | 4 | 4 | 32 | 7 |
| Borivali East, Mumbai - MPCB | 01/02/21 | 137 | 112 | 5 | 3 | 4 | 32 | 6 |

Source: https://cpcb.nic.in/

Higher petrol prices can result in reduced fuel consumption and lower vehicle emissions, but the relationship between petrol prices and air quality is complex. Temperature and humidity can affect air quality by influencing chemical reactions and atmospheric processes, and wind pressure can disperse air pollutants. Changes in air pressure and elevation can also impact the concentration of pollutants near the ground, while coastal locations can experience better air quality due to natural air filtration provided by the marine environment. However, coastal areas can also be susceptible to poor air quality from human activities.

In the context of this model, there are five ordinal air quality classes. When fitting the multinomial logistic regression model, one of these classes is chosen as the reference class (Moderate). The model then estimates the log odds of each of the other classes relative to the reference class. The choice of the reference class can influence the interpretation of the coefficients, but it does not affect the model's overall predictive performance or the predicted probabilities for each observation.

**Table -3:** A snapshot of the data collected for each predictor variable.

| State | City | Tree Cover | Population Density | Petrol Prices | Temp-erature | Humidity | Wind Speed | Air Pressure | Coastal /Non-Coastal | Elev-ation | AQI |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Andhra Pradesh | Amaravati | 2.87 | 237 | 87.24 | 33 | 0.61 | 9 | 1011 | 1 | 343 | 61 |
| Andhra Pradesh | Rajamahen-dravaram | 2.87 | 7682 | 87.24 | 31 | 0.62 | 10 | 1012 | 1 | 14 | 68 |
| Andhra Pradesh | Tirupati | 2.87 | 1004 | 87.24 | 32 | 0.44 | 19 | 1010 | 1 | 154 | 44 |
| Andhra Pradesh | Visakhapat-nam | 2.87 | 2500 | 87.24 | 32 | 0.64 | 6 | 1012 | 1 | 54 | 90 |
| Arunachal Pradesh | Naharlagun | 2.08 | 320 | 94.64 | 30 | 0.51 | 5 | 1011 | 0 | 155 | 120 |
| Assam | Guwahati | 2.49 | 3400 | 94.58 | 31 | 0.46 | 2 | 1012 | 0 | 340 | 203 |
| Bihar | Araria | 2.49 | 990 | 105.9 | 29 | 0.41 | 12 | 1012 | 0 | 47 | 196 |
| Bihar | Arrah | 2.49 | 2420 | 105.9 | 29 | 0.41 | 7 | 1013 | 0 | 190 | 182 |

Source: https://www.indiastat.com/

## 4. DATA ANALYSIS

One-Way ANOVA for NO2 pollutant concentration had the following hypotheses:
**H0:** There is no significant difference in the means of NO2 concentration between any monitoring stations.
**H1:** There is a significant difference in the means of NO2 concentration between at least one pair of monitoring stations.

Since the p-value was less than $\alpha = 0.05$ ($\alpha$ = level of significance), there was sufficient evidence to reject the null hypothesis. Hence, there was a significant difference in the concentration of NO2 between at least one pair of monitoring stations.
Further, to identify the exact pair of stations which showed no significant difference in means, Tukey's HSD Post-Hoc Test was performed. Tukey's HSD test had the following hypotheses:
**H0:** There is no significant difference in the means of NO2 concentration between the two monitoring stations.
**H1:** There is a significant difference in the means of NO2 concentration between the two monitoring stations.

All stations except the following 14 station pairings (**Table - 4**) showed no significant difference in NO2 concentration at level of significance $\alpha$= 0.05.

**Table -4:** Station pairings with no significant difference in NO2 concentration.

| Stations | p-value |
|---|---|
| Airport - Bandra | 0.0132673 |
| Kurla - Bandra | 0.0079342 |
| Vile Parle - Bandra | 0.024543 |

| | |
|---|---|
| Airport - Borivali | 0.0000106 |
| Kurla - Borivali | 0.0000051 |
| Vile Parle - Borivali | 0.0000261 |
| Worli - Borivali | 0.0001509 |
| Mahape - Borivali | 0.0335093 |
| Powai - Nerul | 0.0023132 |
| Sion - Nerul | 0.0018522 |
| Mahape - Nerul | 0.0047783 |
| Vasai - Powai | 0.004376 |
| Vasai - Sion | 0.003536 |
| Mahape - Vasai | 0.0087577 |

Source: Authors

A similar analysis was carried out for the other 6 pollutants. Except PM 2.5, all pollutants depicted a significant difference in the mean concentration between at least two AQI monitoring stations.

To further understand the relationships between Air Quality and various factors affecting it, a multinomial logistic regression model was fitted to predict air quality levels based on the predictor variables. The model used the 'multinom' function from the 'nnet' package in R and had five ordinal classes.

## 5. RESULTS

After performing ANOVA and Tukey's HSD test on 12 different monitoring stations within Mumbai, and analysing the 7 pollutant concentrations, 25 pairs of stations showed no significant difference in any pollution concentrations (**Table -5**).

**Table -5:** Station pairings with no significant difference in concentrations of any pollutants.

| Stations |
|---|
| Sion - Powai |
| Sion - Airport |
| Sion - Borivali |
| Powai - Kurla |
| Powai - Airport |
| Nerul Kurla |
| Nerul - Colaba |
| Nerul - Airport |
| Kurla - Colaba |
| Kurla - Airport |
| Colaba - Airport |
| Mahape - Kurla |
| Mahape - Colaba |
| Mahape - Airport |
| Mahape - Worli |
| Mahape - Vile Parle |
| Worli - Sion |
| Worli - Powai |
| Worli - Nerul |
| Worli - Colaba |
| Worli – Airport |
| Vile Parle - Nerul |
| Vile Parle - Kurla |
| Vile Parle - Colaba |
| Vile Parle - Airport |

Source: Authors

Among these 25, the closest stations were measured in terms of the straight-line distance. The station pairings with the least distance were found to be Kurla- Airport and Vile Parle - Airport (**Table -6**).

**Table -6:** Station pairings with the least straight-line distance.

| Stations | Distance |
|---|---|
| Kurla - Airport | 3.14 km |
| Vile Parle - Airport | 3.22 km |

Source: https://distancebetween2.com/

**Table -6** shows the station pairings that were the closest among all within Mumbai and did not show any significant variation in any pollution concentrations. The research proposes that the number of stations monitoring air quality in the above-mentioned areas can be reduced and the resources can be utilised elsewhere.

**Table -7:** Straight line distance between monitoring stations

| Stations | Distance |
|---|---|
| Worli - Sion | 7.37 km |

Source: https://distancebetween2.com/

The next least straight-line distance was found to be between Worli and Sion (**Table -7**). Similar to the previous case, these stations did not significantly differ in any pollution concentrations. Therefore, the research proposes that only one monitoring station is enough to represent the area.

The accuracy of the multinomial logistic regression model was found to be 52% (**Table -8**), which is substantially better than random guessing. The interpretation of the model coefficients (**Fig -1**) revealed that an increase in tree cover was associated with a decrease in the log odds of belonging to the "Good" air quality class compared to the reference class (Moderate), holding all other variables constant. Conversely, a higher population density was found to be positively correlated with higher air pollution levels. The relationship between petrol price and air quality was found to be complex, as other factors such as public transportation availability and vehicle efficiency also play a role. Higher temperatures were associated with an increase in ground-level ozone and other pollutants. High humidity was found to increase the formation of secondary organic aerosols and other pollutants. Stronger winds were found to disperse air pollutants, reducing their concentration in a given area, while weak or stagnant winds contributed to air pollution build-up. Lower air pressure was associated with enhanced vertical mixing and improved air quality, while higher air pressure trapped pollutants near the surface. Higher elevations generally experience cleaner air due to reduced pollutant emissions and enhanced dispersion, but complex topography can create localised areas of poor air quality. Coastal areas experience better air quality due to the dispersion of pollutants by sea breezes and natural air filtration provided by the marine environment, but shipping emissions, industrial activities, and other human influences can also cause poor air quality.

```
> summary(model_fit)
Call:
multinom(formula = Bands ~ TC + PD + PP + T + H + WS + AP + E +
    C + LAT + LON, data = train)

Coefficients:
               (Intercept)         TC       PD        PP          T          H          WS         AP          E
Hazardous       -1.1390123  0.2850815 3.368400 2.0204303  0.5162504 -1.5098216  0.36599025  1.4094503 -4.5730628
Moderate         1.5013019 -0.7508487 1.890465 0.7810335 -0.9713361 -0.1494240  0.26991666  0.5948983 -0.5945934
Unhealthy        1.7073341 -0.4196168 2.904266 0.7688362 -0.7149814 -1.0636574 -0.05639042  0.6878098 -1.0423976
Very Unhealthy   0.2292106  0.2971913 3.048568 1.0836527 -1.0816206 -0.9665281 -0.04211504 -0.6066076 -3.9341399
                C1        LAT        LON
Hazardous      -0.4211130  2.5919866 1.44651330
Moderate        0.8014656 -0.5865468 0.05336155
Unhealthy       1.5721033  1.2988870 0.27859331
Very Unhealthy  0.0872048  2.8799783 0.16580720

Std. Errors:
               (Intercept)        TC       PD        PP         T         H        WS        AP         E       C1
Hazardous        1.3627147 0.8311625 1.414673 0.6993009 1.0989003 1.0290583 0.7601511 1.0289807 1.2973590 2.146052
Moderate         0.8799370 0.5179916 1.365518 0.4960261 0.6344759 0.4761418 0.5293568 0.5377379 0.3533554 1.721998
Unhealthy        0.8663451 0.5410049 1.383158 0.5059618 0.7343449 0.5878085 0.6031034 0.5997824 0.4799559 1.725301
Very Unhealthy   1.0990378 0.5846878 1.408354 0.6071497 0.8633231 0.6492827 0.7145053 0.9098261 1.0994536 2.092580
                    LAT       LON
Hazardous      1.891866 0.7220428
Moderate       1.063549 0.5572830
Unhealthy      1.121165 0.5473968
Very Unhealthy 1.370204 0.6096493

Residual Deviance: 269.0733
AIC: 365.0733
```

**Fig -1**: Multinomial Logistic Regression Model Results.

**Table -8:** Confusion Matrix (visual representation of the Actual VS Predicted values).

| Predicted | Good | Mode-rate | Unhe-althy | Very Unh-ealthy | Hazar-dous |
|---|---|---|---|---|---|
| Good | 11 | 7 | 2 | 0 | 0 |
| Moderate | 9 | 18 | 8 | 2 | 1 |
| Unhealthy | 5 | 13 | 30 | 10 | 2 |
| Very Unhealthy | 0 | 3 | 8 | 11 | 1 |
| Hazardous | 0 | 0 | 3 | 7 | 19 |
| **Accuracy** | **52.35%** | | | | |

Source: Authors

## 6. CONCLUSIONS

In urban parts of India, air pollution is a serious issue and a source of growing worry. Particulate matter pollution is a major issue for the entire nation. Urban life quality is severely impacted by air pollution, thus finding and funding effective mitigation and reduction strategies is a crucial first step. This paper provides an analysis on the variation of concentration of air pollutants in various areas of Mumbai to determine the redundant Air Quality monitoring stations to offer decision-makers a clearly defined path to begin addressing the issue.

On the basis of these observations, recommendations were made for those station pairs that did not significantly differ in the concentration of any of the seven pollutants, based on the straight-line distance between the stations. Excessive and redundant air quality monitoring stations in Mumbai can be identified by use of this research. Thus, these resources can be placed where there are no AQI monitoring stations present all across India.

The ANOVA analysis in this study is restricted to the city of Mumbai, Maharashtra since other cities in India do not contain a high density of monitoring stations and thus are not useful for the purposes of this analysis. Further, this study can be extended to find redundant stations across India using ANOVA analysis, given the straight-line distance between each pair of stations.

The logistic regression model gives a 52% classification rate with five classes implying that the model correctly classifies 52% of the instances in the dataset. This is substantially better than random guessing, which would achieve an accuracy of 20% for a five-class problem. The model revealed several important relationships between predictor variables and air quality levels. Policies that focus on increasing tree cover, reducing population density, and implementing measures to reduce air pollution from traffic, industrial activities, and other human sources can help to improve air quality. Additionally, policies that aim to tackle the effects of climate change, such as cutting down greenhouse gas emissions, can also help to improve air quality.

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