The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume XLVIII-4/W5-2022
7th International Conference on Smart Data and Smart Cities (SDSC), 19–21 October 2022, Sydney, Australia

DATA DRIVEN FRAMEWORK FOR ANALYSIS OF AIR QUALITY LANDSCAPE FOR THE CITY OF LAHORE

A. Rahman*, M. Usama, M. Tahir, M. Uppal

Lahore University of Management Sciences (LUMS), Pakistan
(abdur.rahman, muhammadusama, tahir, momin.uppal)@lums.edu.pk

Commission IV, WG IV/9

KEY WORDS: Air Quality, Air Quality Monitoring System, Low Cost Air Quality Monitoring Stations, Air Quality Data

ABSTRACT:

Several Pakistani cities are among the world's most polluted. In the previous three years, air pollution in Lahore has been considerably over World Health Organization guideline levels, endangering the lives of the city's more than 11 million citizens. In this paper, we investigate the city's capability to combat air pollution by analyzing three essential aspects: *(1) Data, (2) Capacity, and (3) Public awareness*. Several studies have reported the need for expansion of the current air quality monitoring network. In this work, we also provide a context-aware location recommendation algorithm for installing the new air quality stations in Lahore. Data from four publicly available reference-grade continuous air quality monitoring stations and nine low-cost air quality measuring equipment are also analyzed. Our findings show that in order to measure and mitigate the effects of air pollution in Lahore, there is an urgent need for capacity improvement (installation of reference-grade and low-cost air quality sensors) and public availability of reliable air quality data. We further assessed public awareness by conducting a survey. The questionnaire results showed huge gaps in public awareness about the harms of the air quality conditions. Lastly, we provided a few recommendations for designing data-driven policies for dealing with the current apocalyptic air quality situation in Lahore.

1. INTRODUCTION

Air pollution is defined as the contamination of indoor or outdoor air with chemical, physical or biological agents modifying the characteristics of air. Most common sources of outdoor air pollution include exhaust combustion from motor vehicles, industrial emissions, forest fires, livestock farming, fertilizer, and power plants. Major constituents of air pollution are Particulate Matter (PM), Carbon Monoxide (CO), Ozone (O_3), Nitrous (NO_x), and Sulfur oxide (SO_x). PM includes fine particles suspended in the air. These particles are usually 2.5 micrometer ($PM_{2.5}$) and 10 micrometer (PM_{10}) in diameter (Vallero, 2014). These particles are a byproduct of combustion in motor vehicles, burning fossil fuels, industrial processes, and other sources of smoke. Other indirect sources are different chemical reactions of NO_x and SO_x in air. Major health effects of the PM pollutants are decreased lung function, eye, nose, and throat irritation, difficulty breathing, aggravated asthma, nonfatal heart attacks, and even premature deaths in people with a lung or heart disease history.

Particulate matter is a significant contributor to air pollution. Air quality is measured using air quality monitoring systems (AQMS), which are technically validated by organizations such as the United States Environmental Protection Agency (EPA), among others, and are also known as reference-grade AQMS. Reference-grade AQMS are costly and require a significant amount of upkeep. The $PM_{2.5}$ values recorded by these reference-grade stations are regarded authentic and are utilized by appropriate authorities to issue health advisories. In most developed and underdeveloped countries, there is a severe gap in the installed reference-grade AQMS resulting in huge coverage gaps and inconsistent air quality data. Considering sparse resources and the overburdened economies of developing countries, expansion of the current air quality measurement network in a short time is a challenge. On the other hand, low-cost alternatives exist, but the trustworthiness of their reported values is frequently questioned. Many studies have been conducted to enhance the performance of low-cost sensors. According to the literature, a mix of reference-grade AQMS and low-cost sensors can aid in the development of urban city-scale measurement networks while keeping the economic aspects of developing nations in check (Gulia et al., 2015, Usama et al., 2022).

Air pollution has emerged as a significant issue in the subcontinent. Pakistan has recently seen a yearly "smog" season that lasts from November to February each year. Multiple Pakistani cities have made the list of the world's most polluted cities in recent years. Lahore, the provincial capital of Punjab, is one of the world's three most polluted cities. The current state of Lahore's air quality puts the lives of the city's 11 million residents[1] in grave danger. For the most part of the last three years, the air quality index (AQI) stayed between poor to severe. The AQI is a metric used to quantify the effect of air pollution on human health based on limited exposure. The higher the AQI, the more health risks there are. In winters the smog, fog, and haze results in the closure of the major highways, airports, and transportation incurring economic losses and social unrest. Many road accidents due to smog are also reported resulting in deaths and financial losses.

Conditions deteriorated to the point where the government was compelled to take action to protect the public from additional exposure and pollution. It includes the closure of brick kilns in 2018 and the enforcement of conventional brick kiln conversion to zig-zag technology with lower air pollutants (Mukhtar,

* Corresponding author

[1] `https://www.pbs.gov.pk/content/final-results-census-2017`

2018). In recent years, the government has also issued orders to shut down industries during the pollution season, which has had a disastrous effect on the economy. In 2021, Punjab government also decided to close every Monday for nearly a month to combat smog[2]. These circumstances need a thorough examination of the city's air quality landscape. In this study, we focused on the available $PM_{2.5}$ data sources in Lahore, Pakistan, and investigated the capability of the city to handle the issue of poor air quality.

Air quality and a city's capability to tackle air pollution are quantified using three indicators: *(1) capacity, (2) data, and (3) public awareness*. Here, capacity refers to public and private measurement infrastructure, data refers to the public availability of air quality measurements to develop data-driven policies, and public awareness refers to the general public's interest in the issue and how the public views the ramifications of air quality issues. In this paper, we make the following analysis and contributions

1. We have collected and prepared a dataset of the PM2.5 measurement data from various publicaly available sources (reference-grade AQMS and low-cost sensors) and analyze it to further reflect on the robustness and authenticity of the reported data from the public sources.

2. Based on the prepared dataset and the context information of Lahore city, we have developed an algorithm for recommending deployment positions of new air quality measurement sensors. We have also reflected upon the validity of these results and how more context information can yield better sensor deployment.

3. Perception versus reality plays a vital role in swaying the opinion of the urban public to adopt better practices for ensuring prevention against the hazardous effects of air pollution. We have conducted a survey to gauge perception vs. reality of the air quality in Lahore, and this work also provides the crux of these findings.

The remainder of the paper is structured as follows. In the next section, we will provide specifics on the air pollution data for Lahore city as well as the sources. Section 3 describes the proposed context-based location recommendation approach for air quality sensor placement and the results achieved. Section 4 will discuss the survey conducted during this location recommendation approach to determine how individuals view the issue of air quality in Lahore. Section 5 contains a brief yet informative discussion on the validity of the acquired results. Finally, in Section 6, the work is concluded, along with a discussion on potential future directions.

2. AIR QUALITY DATA OF LAHORE

Needless to say, the poor air quality in the city of Lahore has significantly adverse health effects on its residents. Life Index (AQLI) from the Energy Policy Institute at the University of Chicago (EPIC) released its 2021 annual report on the effects of poor air quality on the health of an average Pakistani citizen (Greenstone and Fan, 2018, Greenstone and Fan, 2020). The AQLI report suggests that an average Pakistani tends to lose 3.9 years of life expectancy if the current levels of air pollution persist (Greenstone and Fan, 2020). It also reports that in a few most polluted areas, the loss in life expectancy can go up to 7 years (Greenstone and Fan, 2020). An average citizen of Lahore is expected to gain 5.3 years' worth of life expectancy if the World Health Organization (WHO) guidelines for $PM_{2.5}$ are met.

Environmental protection departments/agencies often collect air quality data, and health advisories are issued based on pre-defined AQI readings. Pakistan, like any other developing/underdeveloped country, does not have an adequate number of AQMS installed, thus there is a scarcity of available air quality data for most of the country. Only four reference-grade air quality monitors and a few low-cost sensors with publicly available air quality data are available in Lahore. We have confined our investigation to $PM_{2.5}$ because air quality data for majority of Lahore is not accessible for other criteria pollutants. Figure 1 provides the location of the reference-grade and low-cost air quality monitors in Lahore city.

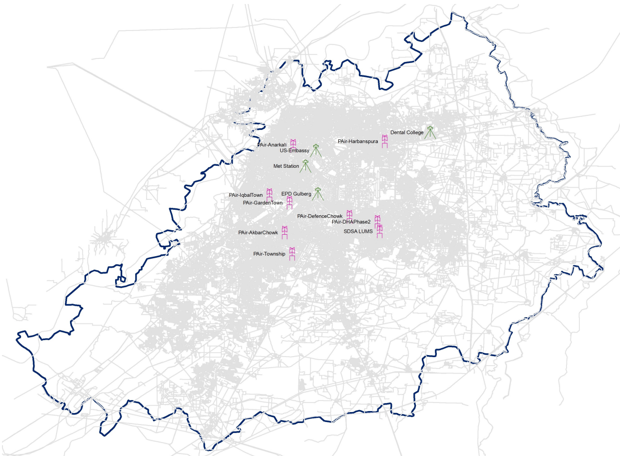

Figure 1. There are four reference-grade and eight low-cost air quality monitoring stations in Lahore. The figure depicts the location of the sensors on the map of Lahore.

Three reference-grade sensors in Lahore are from Environmental Protection Department (EPD), Punjab[3], and one from US consulate[4] air quality station. The data from EPD is available at daily granularity in PDF format. The PDF files were digitized using python-based tools as well as manual scrapping. The data from US Embassy was available at hourly granularity. We have converted both sources to daily granularity for comparison and depicted the data timeline in Figure 2. There are eight low-cost sensors deployed by "PurpleAir"[5] with publicly available $PM_{2.5}$ concentration values in Lahore. We have also converted them in daily granularity, and Figure 3 depicts the timeline of the data availability. Here we also want to note that there are a few other low-cost sensors in Lahore deployed by IQAir[6] but their recorded data is not publicly available.

We have noticed that two of the reference-grade stations stopped reporting $PM_{2.5}$ values in mid-2020 (Dental college station) and mid-2021 (Met station) respectively. Only two reference-grade AQMS are reporting $PM_{2.5}$ concentrations for approximately 670 Square kilometers which is not acceptable

[2] http://sdsa.lums.edu.pk/GrandChallengeFund/BlogArchive/3

[3] https://epd.punjab.gov.pk/aqi

[4] https://www.airnow.gov/international/us-embassies-and-consulates/#Pakistan$Lahore$

[5] https://www2.purpleair.com/

[6] https://www.iqair.com/

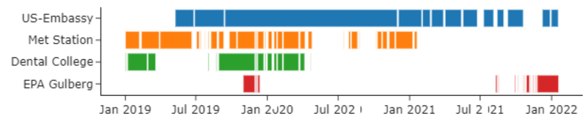

Figure 2. Timeline plot of PM2.5 data for reference grade sensors

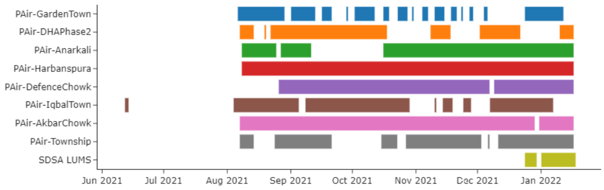

Figure 3. Timeline plot of PM2.5 data for low-cost grade sensors

by any stretch of the imagination. All low-cost sensors came online in mid-August 2021. Their calibration and ability to cater to context while reporting data lacks credibility.

3. AIR QUALITY MONITORING NETWORK OF LAHORE

In a recent verdict[7], the Lahore High Court ordered the Punjab government to take concrete steps to curb the air pollution in Lahore. The court also stated that corporations should also fulfill their corporate social responsibility and reduce emissions, and government must enforce the already existing suggestions from the Lahore smog commission report and Punjab clean air act to mitigate the smog situation. The Lahore smog commission report[8] recommended that the Punjab government must increase the active reference-grade air quality monitoring stations from three to twelve. Based on the smog commission report, EPD Punjab needs to install nine more reference-grade AQMS. Here the challenging bit is to determine the optimal location for the installation of AQMS. Several factors need to be considered before deciding on the optimal installation location. A few of these factors are namely; availability of land, possible conflicts with future urban construction and expansion plans, accessibility to maintenance staff and other services, security of the site, and some heuristic constraints developed by previous experiences, etc. Despite the fact that these conditions are strong administrative markers for the installation, research on air quality sensor placement suggests that a context-aware data-driven method can give optimal installation locations.

Sun et al. proposed a citizen-centric air quality sensor placement technique, where they have used Cambridge city traffic patterns, point of interest values, and demographic statistics as context information. They modelled the location recommendation as a linear integer programming model in which both the objective function (location) and the constraints (context) are considered to be linear, which we believe will result in a high rate of false positive locations as the number of sensors (to be placed) increases (Sun et al., 2019). Kelp et al. presented a $PM_{2.5}$ sensor placement approach where they used multiresolution dynamic mode decomposition (mrDMD) on 16 years of historical $PM_{2.5}$ data to suggest new sensor location (Kelp et al., 2022). Zhou et al. compared five sensor placement techniques (random, minimization of the matrix condition number for sensor placement, empirical interpolation method for sensor placement, local extrema-based techniques, and QR-factorization method for sensor placement) from the control theory and fluid dynamics literature on a couple of satellite-derived huge $PM_{2.5}$ datasets from China (Zhou et al., 2022). Though the compared techniques are well embedded in the literature, we do not have this sort of high-resolution spatiotemporal dataset available for Lahore city. Mohar et al. used QR factorization, singular value decomposition (SVD), and machine learning-based techniques to design an optimal sensor placement technique for signal reconstruction in control systems (Manohar et al., 2018). Though this technique has shown promise in sensor and actuator placement given the small number of sensors (in our case 09) and limited untrustworthy sparse historical data the technique is highly likely to produce false positives. There are a few other optimal sensor placement techniques from communication systems and traditional sensors network literature (Younis and Akkaya, 2008) but these techniques are not optimal for a gappy, untrustworthy, sparse, and small dataset to determine the best locations for sensor placement in Lahore city.

Microsoft's Urban Air Project[9] is at the cutting edge of sensor placement research for air quality measurements. They have developed a method that uses attributes from the previously installed sensors and historical air quality data from existing stations to suggest suitable locations for future air quality stations (Hsieh et al., 2015). Hsieh et al. used an affinity graph-based technique to determine the optimal location for AQMS placement for Bejing city in China. The proposed procedure also incorporates the historical $PM_{2.5}$ concentrations, meteorology data, road network, POI data, etc., to ensure that appropriate context is also incorporated in the optimal location selection (Hsieh et al., 2015), (Zheng et al., 2013). The technique proposed in this paper is an extension of the affinity graph-based approach where we have included various context features collected from Lahore city and used whatever historical air quality data is available.

3.1 Affinity Graph Based Location Recommendation System

Hsieh et al. used affinity graphs with a greedy entropy minimization model to develop a location recommendation system for AQMS installation location recommendation (Hsieh et al., 2015). Initially, the city is divided into graph nodes and edges. Where every edge has an associated weight, and every node has an associated set of features (road networks, residential areas, commercial areas, industrial areas, public spaces, meteorological features, and other factors that may contribute to variation in air pollution). Since most location recommendation techniques are designed and tested for developed countries with historical data on air pollution and related context features are publicly available, the location recommendation for the new AQMS becomes a simple task. Since we are trying to predict the location of the AQMS for an underdeveloped/developing

[7] https://data.lhc.gov.pk/reported_judgments/green_bench_orders

[8] \footnote{\url{https://epd.punjab.gov.pk/system/files/Smog\%20commission\%20report.pdf}}

[9] https://www.microsoft.com/en-us/research/project/urban-air/

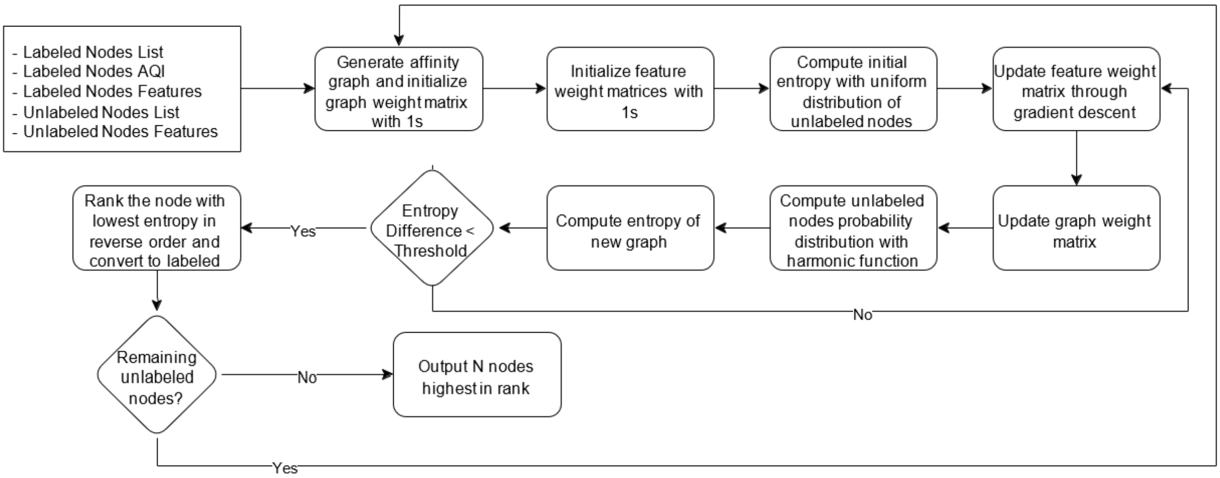

Figure 4. Flow chart of the station location recommendation algorithm.

city where the available historical data is sparse and untrustworthy and context features are also not available, the simple learning task becomes a real hassle.

For Lahore, we have collected historical air quality data from all known publicly available sources. The data was cleaned and preprocessed by following the data science principles (cleaning, normalization, outlier detection, etc). We have combined the reference-grade AQMS data with low-cost sensors data to further improve the volume of the dataset. Gathering the context data for Lahore city is challenging as to the best of our knowledge, it is not publicly available. We have employed Geographic Information Systems (GIS) tools for collecting context information such as commercial hubs, industrial areas, traffic hotspots, etc. The meteorology data was available. The road network was extracted using satellite imagery and machine learning techniques. Figure 5 depicts the identified commercial hubs, industrial areas, drainage streams, and traffic hotspots.

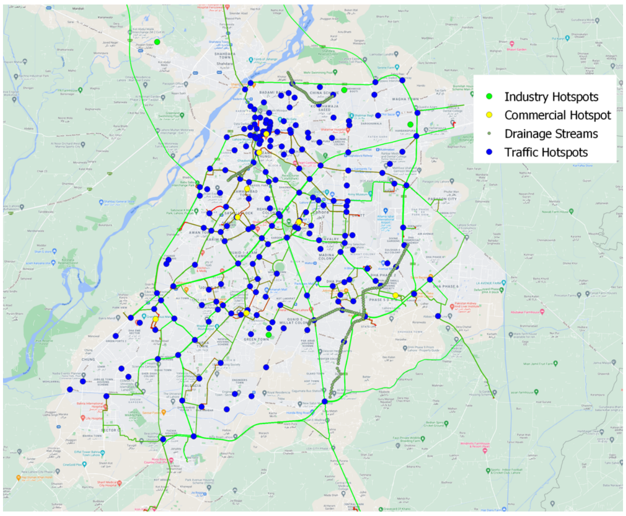

Figure 5. Identified pollution hotspots in Lahore

Since the proposed method is inspired from (Hsieh et al., 2015), we recommend the interested reader to see (Hsieh et al., 2015) for in-depth details on how affinity g raphs c an b e leveraged for designing location recommendation algorithms. Our model works in two stages. The first step is to compute the probability distribution of unlabeled nodes using feature weight matrices, graph weight matrices, and labeled nodes. The entropy for each node is computed in the second phase, and the node with the lowest entropy is marked as the labeled node and given the lowest rank for a recommendation for the installation of a new air quality station. The model is given a new set of labeled and unlabeled nodes iteratively. A more detailed description of the AQMS location inference method in the following steps:

1. The input to the proposed location inference technique is labeled node list, labeled node air quality values (historical), context features associated with each node, unlabelled node list (candidate node locations), and features associated with the unlabelled candidate nodes.

2. Based on the input, an affinity graph is created, and graph weight initialization is performed (in our case, we have initialized it with all 1's).

3. After the initialization, we have computed the initial entropy with the uniform underlying distribution of unlabeled nodes, and the feature weight matrix is updated using gradient descent. The probability distribution of the updated unlabelled nodes is estimated using a harmonic function, and the entropy of the updated graph is computed.

4. The difference between the entropy of pre and post-graph updates is computed and subjected to a difference threshold. If the entropy difference is less than the predefined threshold value, we ranked the node with the lowest entropy in the reverse order and assigned the node to a labeled node (predicted AQI assignment). Whereas, if the entropy difference is greater than the predefined threshold, the algorithm will go back and update the graph, and feature weights and entropy is recomputed.

5. If there is no unlabeled node left in the graph, the proposed algorithm will output the "N" highest-ranked nodes, which in our case are the first nine nodes. Since we have converted Lahore into a graph grid, the label of the top "N" nodes will also provide their location information on the map.

6. We observed an inherent problem of clustering multiple recommended nodes in this algorithm. We noticed that

the conversion of unlabeled nodes from near the labeled nodes converged to the point where none of the nodes were labeled because the node with the lowest entropy was tagged as a labeled node. It is an issue when the number of recommended locations is more than one. Thus multiple nodes were recommended in a cluster. To tackle this problem, we introduced another loop to recommend only one location in every iteration and use the previous recommended location as a labeled node in the next iteration.

The flow chart for the algorithm used for inferring the optimal AQMS placement is depicted in Figure 4.

We tested the proposed algorithm with the available air quality data for Lahore city and the collected context features. The proposed AQMS location recommended algorithm provided 09 recommended for new AQMS deployment. The output of the proposed model for the recommendation of 09 stations for Lahore city is provided in Figure 6. Reference-grade AQMS are usually deployed by the environmental protection department/agencies, which EPD Punjab will do in the future, though for now, we are planning to deploy 09 low-cost on the recommended locations to collect $PM_{2.5}$ concentrations. In future work, we intend to analyze the efficiency of the proposed location algorithm using the reported data from all air quality measurement sources.

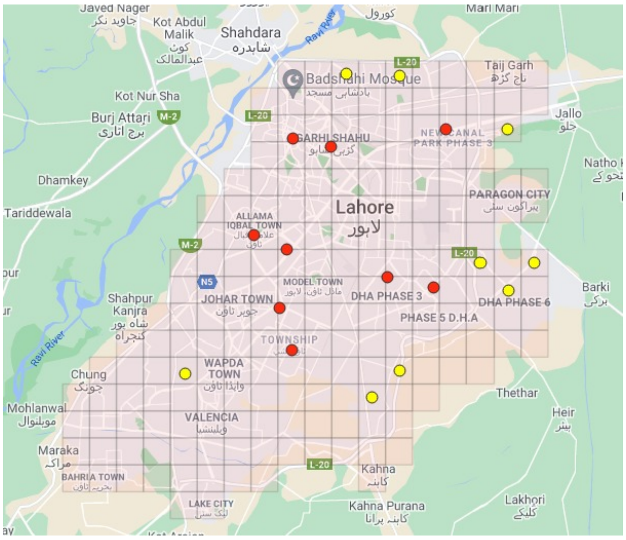

Figure 6. Recommended locations for installation of air quality stations (yellow) with the locations of currently installed stations (red)

4. PUBLIC AWARENESS

The third component of accessing the ability of a city to deal with the air quality issue is its public awareness. Following the tradition in the literature (Liu et al., 2017, Pantavou et al., 2017, Lou et al., 2022, Maione et al., 2021), we have designed a survey with only ten simple questions addressing the perception of the air quality among citizens and how this perception is built, and whether they are taking any measures to avoid detrimental consequences of the air pollution in Lahore city. The questionnaire varied from general public perception of air pollution and public information sources to the self-reported levels of health impact due to air pollution.

We have conducted this survey from 21st December 2021 to 10th January 2022. We have received 177 responses from different universities in Lahore. As expected, nearly 60% of the participants were between 18-22 years old. 67% of the responses came from males, and 37% from female participants. We collected responses from 11 different public and private universities in Lahore. Nearly 73% of the responses suggested that the air quality in Lahore ranges from very poor to severe (44% said severe and 29% said very poor). Nearly 81% of the responses suggested that smog/fog/haze is their sensory perception for air quality. This response statistics also show that many people think that air pollution only exists in winter, and as soon as the smog is gone, the air quality is back to normal, which is not the case. This response also suggests the lack of information about air pollution among young people. Our result also shows that news, mobile applications, and social circles are dominant ways to get air quality-related information. Nearly 15% of people responded that they do not take any precautions to deal with air pollution. 31% of the total responses suggested that they have a respiratory condition, and out of those 31% people, 40% said that their condition aggravated due to poor air quality in Lahore. Lastly, 38% of people suggested that transport is the major contributor to poor air quality in Lahore. The rest of the people responded in favor of industries, agriculture, etc. The responses distribution about the potential sources of the survey are depicted in Figure 7. More details on our survey and results are available on our blog-post[10].

This survey suggests the need to raise public awareness about the dangers of air pollution, and we suggest that including components on air pollution, its causes, and ways to deal with it must be included in the school, college, and university curriculum. We also recommend public meetings, town halls, and seminars to increase awareness among people. We also suggest the give incentives to the residential and commercial areas where the air quality improves.

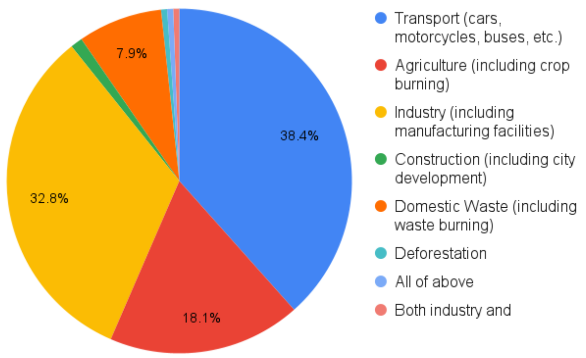

Figure 7. Public awareness survey response on the perception about the potential air pollution sources in Lahore.

5. DISCUSSION AND RECOMMENDATIONS

In this article, we assessed Lahore's ability to cope with the growing air pollution problem in three areas: data, capability, and public awareness. Our findings show that Lahore's present air quality monitoring network has significant gaps, and the city is unable to deal with the ever-increasing menace of air pollution. Lahore does not have enough AQMS installed, and the available AQMS data is gappy, unreliable, and does not reflect the severity of the air pollution. We suggest that EPD Punjab needs to increase the reference-grade AQMS and also support

[10] `http://sdsa.lums.edu.pk/GrandChallengeFund/BlogArchive/4`

the deployment of low-cost sensors. EPD also has to ensure an ample amount of calibration and chemical analysis facilities to further the quality of sensing and source apportionment. The development of a public dashboard is prevalent where all public and private data on the air quality is gathered and analyzed and made available to the public. There is a dire need for academic and industrial partners to further enhance the agenda on gathering reliable air quality data and using machine learning and other predictions technique to prepare the EPD for upcoming air quality challenges.

In this work, we also did our bit by designing an AQMS placement algorithm that incorporates the local context to provide optimal location. This effort is also a candidate solution to efficiently using the limited financial resources available. Here we also want to note that deploying 09 AQMS in Lahore will not solve the data availability issue, general public, housing societies, and institutions also have to play an active role in the densification of the air quality monitoring network. We recommend that all government and private housing societies, universities, industries, hospitals, etc., install AQMS (near reference or low-cost) and make the date available to the public and government.

Public awareness is the third component of accessing the ability of Lahore city to cope with the air quality issues. Our survey indicates the lack of awareness about the air quality issues. Our survey also reveals disparities between public perception and real air quality. There is an urgent need to raise public knowledge about air quality through awareness campaigns and community activities. The general public is unaware of the various resources for reporting air quality. More emphasis should be placed on preventative measures such as wearing masks, installing air purifiers, and reducing outside activity during pollution. Studies on source apportionment may aid in quantifying the sources of air pollution in Pakistan. We recommend including air quality and associated information in school, college, and university curricula, collaborating with religious experts to emphasize the issue of air quality in Friday sermons and other religious gatherings, supporting public awareness events such as seminars and town halls, and offering incentives to the residential and commercial areas where the air quality improves.

5.1 Challenges

There are a few significant obstacles and trade-offs that developing/underdeveloped nations must confront, which necessitate a concerted global effort to address the air pollution problem. Following are a few challenges (keeping in view the underdeveloped/developing countries):

1. **Data collection and public datasets**: Collecting air quality data is a difficult process since varying concentrations of air contaminants are involved. Given the environmental and health dangers associated with poor urban air quality, it is critical to creating a centralized real-time air quality data monitoring and processing system. Sensor-centric data collection and crowd-centric data collection are two approaches for obtaining urban data (e.g., air quality data, POI, meteorological data, etc.). There are two types of sensor-centric paradigms. These classifications are based on whether the sensors gathering data are mobile (deployed on a moving item) or static (deployed on a fixed location). There are two types of crowd-sourced data collection: active (data created through participation surveys and check-ins) and passive (data generated by users passively while using the urban infrastructure). It is important to understand what type of approach can help gather the most reliable and larage amount of air quality data (Usama et al., 2022).

2. **Trade-off between economic growth and air pollution**: Most developing countries are trying to manage their economies, and the balance between economic expansion and air pollution is almost always skewed toward economic growth. Finding a middle ground between economic growth and air pollution is a challenging task. Health and environmental budgets are diminishing, making it difficult for developing countries to detect, report, and improve the air quality (Xu and Li, 2018, Usama et al., 2022).

3. **Regularization and air quality measurements**: Underdeveloped/developing countries must implement data-driven policies, with regularisation based on data and local context. Once these policies are developed, the administration must guarantee that they are executed (Yamineva and Romppanen, 2017, Usama et al., 2022).

4. **Public awareness**: Unfortunately, in underdeveloped/developing nations, public understanding of the hazards of air pollution and efforts to ameliorate its consequences is relatively low. With the development of social media applications and the Internet penetration, the government may easily overcome this challenge. The administration should use social media platforms, television shows, print and digital platforms, town halls, seminars, hackathons, conferences, and so on to disseminate as much information as possible about the effects of air pollution on human health and the local economy, major air pollution sources, and what options the public has to help reduce emissions.

6. CONCLUSIONS

In this article, we assessed Lahore's potential to deal with the looming challenges of air pollution across three dimensions: data, capacity, and public awareness. The goal of gaining access to Lahore's ability to deal with air quality on the aforementioned verticals is to establish the groundwork for building a framework for developing an air quality network for underdeveloped countries. We also proposed an optimal placement suggestion approach for installing air quality monitoring stations. Finally, we have identified a few challenges that developing nations must solve in order to avert the air apocalypse.

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This contribution has been peer-reviewed.
https://doi.org/10.5194/isprs-archives-XLVIII-4-W5-2022-167-2022