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Urban Air Quality Measurements: A Survey

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Abstract—Urban air quality is increasingly becoming a cause for concern for the health of the human population. The poor air quality is already wreaking havoc in major cities of the world, where serious health issues and reduction of average human life by a factor of years are reported. The air quality in developing countries can become worse as they undergo development. The urban air quality varies non-linearly depending upon the various factors such as land use, industrialization, waste disposal, traffic volume, etc. To address this problem, it is necessary to look at the plethora of available literature from multiple perspectives such as types and sources of pollutants, meteorology, urban mobility, urban planning and development, health care, economics, etc. In this paper, we provide a comprehensive survey of the state-of-the-art in urban air quality. We first review the fundamental background on air quality and present the emerging landscape of urban air quality. We then explore the available literature from multiple urban air quality measurement projects and provides the insights uncovered in them. We then take a look at the sources that are significantly contributing to polluting the air quality. Finally, we highlight open issues and research challenges in dealing with urban air pollution.

1 Introduction

Air pollution is defined as the release of pollutants in the air that has detrimental consequences on human health and the planet as a whole. These pollutants can be from man-made sources or natural sources [1]. Natural sources of air pollution include fires, sand storms, volcanic activity, fumaroles, and others. The man-made air pollutants are gases, droplets, particulate matter, and radiation are emitted into the atmosphere due to human activity such as burning wood, coal, gas, oil, alcohol-based fuels, diesel, kerosene, biomass, waste, etc. It also includes power plants and chemical factories that emitted toxic gases, particulate matter, and radiation in the environment. These air pollutants are causing issues such as acid rains, urban smog, ozone depletion/holes, indoor air pollution, and global warming [2]. Air pollution is a complex amalgamation of natural and human activities. The impact of this relationship is evident in metropolitan areas (Beijing, Dehli, etc.), where criteria pollutants, meteorology, infrastructure, and various emission entities collectively deteriorate the air quality. It is iteratively reported in the literature that 70 to 80% of the pollution in the developing world is due to automobile emissions, where vehicles using low-grade oil on poorly planned road infrastructure are major contributors to the poor air quality [3]–[7]. Major cities in the world are suffering from rapid degradation of the air quality that has pernicious outcomes on the health of the citizens, economy, plantation, crops, and livestock [8].

A decline in human life expectancy in metropolitan areas is accredited to their poor air quality. The problem will get even worse with the urban development taking place in underdeveloped countries [9]. In 2013, World Health Organization (WHO) categorized air pollution as a carcinogen for human beings [10]. WHO also estimated two million deaths per year and numerous respiratory illnesses because of poor urban air quality [11]. The global rise in air pollution has resulted in a sharp growth in various allergies and respiratory diseases. The impact of air pollution is not limited to the metropolitan areas, it also affects the environment on a global scale, causing health concerns far away from its origin. In 2015, air pollution alone caused 6.4 million death worldwide, and if the current trend continues, by 2060, the deaths caused by ambient air pollution will be nearly 9 million people per year [12]–[15]. In 2015, out of all cardiovascular deaths, 19% were caused by air pollution, similarly, 23% deaths due to lung cancer were because of air pollution, and air pollution was the reason for 21% of the total deaths caused by strokes [15], [16]. Four million new asthma cases and 2 million premature childbirths per year are attributed to fossil fuel-based air pollutants that cause a dent in the GDP [17]. Furthermore, air pollution appears to be a risk factor (not yet quantified) in neurodevelopmental disorders in kids and neurodegenerative illnesses in adults [15], [18], [19].

Air pollution not only affects human health on a global scale, but it also has an enormous economic cost. The cost for air pollution emitted by burning fossil fuels in 2018 is approximately 2.9 trillion USD that is 3.3% of the global global gross domestic product (GDP) [17]. It is way less than the money needed to reduce the effect of the air pollution caused by burning fossil fuels. The toll of air pollution on the economy is estimated by looking at the six aspects: (1) cost of human life, (2) people's ability to work, (3) effects on the food, (4) reduction in the ability of the ecosystem to work, (5) damages to the historical monuments, and (6) cost of remediation and restoration[1]. The economic burden of air pollution on the GDP of China is 6.6%, for India, it is 5.4%, for Russia, it is 4.1%, for Germany and US, it ranges from 3.0 to 3.5%, for Japan, United Kingdom, and France it ranges from 2.0 to 2.5% [14], [20]. It indicates that a monumental effort is needed to address the air pollution is the need of the hour.

1. https://unece.org/air-pollution-and-economic-development

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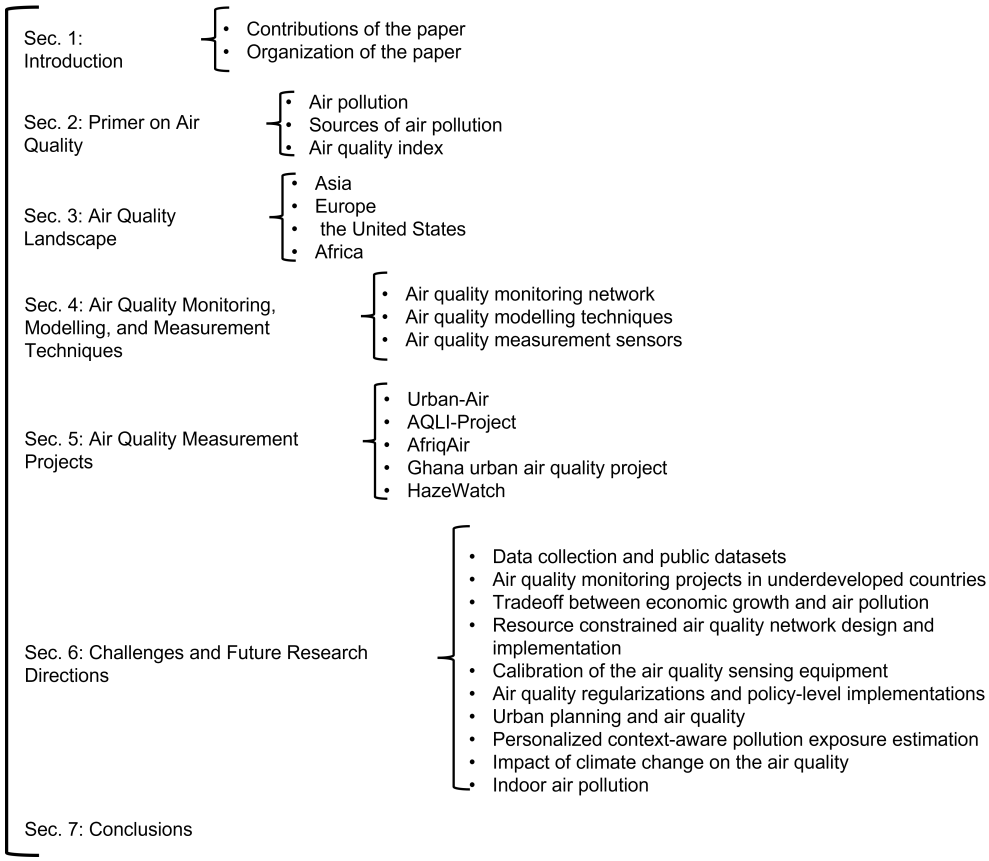

Figure 1: Organization of the Paper

Another victim of air pollution is agriculture, where bad air quality is considered a significant contributor to yield reduction for many decades. Air pollution is rapidly becoming a threat to food production and safety [21]. Effects of air pollution on human health have been covered rigorously in the literature compared to agriculture. The adverse effects of air pollution on the crops vary with the concentration of the pollutants, geographical locations, and meteorology. Burning wood and fossil fuel produce sulfur dioxide that reduces the life and yield of the crops[2]. Rising levels of acid deposition, ammonia, O_3, and CO are also affecting the crops in the developing world[3]. In 2014, India reports a 50% reduction in the wheat and rice crop yield due to ambient air pollution [22], [23]. It also highlights the need for serious reconsideration in environmental policies around the world to ensure food security.

The global temperature has risen by 1.2°C over pre-industrial levels. The climatic catastrophe is upon us. The whole world has started feeling the repercussions like wildfires, heat waves, droughts, etc. Air pollution has played a vital part in this climatic catastrophe. United Nations Sustainable Development Goals (UNSDG) 3.9.1 and 11.6.2 directly aim at reducing the mortality rate due to ambient air pollution and the adverse aspects of particulate air pollution in urban areas by 2030. Achieving these UNSDG goals for reducing the adverse effects of air pollution in underdeveloped and developing countries is perhaps a challenging task.

Identifying the pollution sources, contributions, and root causes spatiotemporal manner are the vital challenges associated with urban air quality measurements. Lastly, based on the spatiotemporal analysis of the urban air quality making policy recommendations for reducing air pollution is the motivation for this study. In this paper, we have tried to answer the following question through a extensive review of the existing literature:

1) What are the major air quality modelling and measurement techniques?
2) What are the major sources of air pollution and how to best classify them?
3) What is the situation of the air quality around the globe and what are the best practices followed for mitigating the poor air quality?
4) How the major air quality measurement and improvement projects are measuring and dealing with the urban air pollution and what challenges are needed to be addressed in order to improve the effectiveness of these projects?
5) What are the open research challenges in measuring the urban air quality?

Contributions of the paper:
In this paper, we build upon the existing literature available on the air quality measurement and provide a comprehensive

2. https://www.britannica.com/technology/agricultural-technology/The-effects-of-pollution
3. https://sustainablefoodtrust.org/articles/the-impact-of-air-pollution-on-crops/

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Paper	Survey/review
[24]	This paper provides a comprehensive comparison of literature available on static, mobile, and community sensors-based air quality monitoring networks in the urban environment. It also identifies shortcomings in the existing air quality monitoring networks.
[25]	This study examines several environmental sensors and discusses the effects of air pollution on human health. It also gives future guidance in the development of individual-centric pollution monitoring tools.
[26]	Reviewed the low-cost sensor-based system for measuring the air quality and the calibrations of the sensors using machine learning techniques. The paper also discusses the research challenges and open challenges in using low-cost sensor-based air quality monitoring systems.
[27]	Reviewed and summarized the low-cost sensing literature for air quality monitoring. The review also discusses the shortcomings in the data obtained from the low-cost sensors and open issues in designing low-cost sensor-based air quality networks.
[28]	Paper provides a brief survey of the techniques of using chemical sensing, crowdsourcing, IoT, and machine learning in air quality assessment. Paper provides the results of a two-year air quality monitoring and data collection.
[29]	The paper examines the literature on the existing IoT-based low-cost air quality monitoring systems and briefly discusses a few challenges.
[30]	This paper reviews the literature on air quality sensor calibration and identifies the origins of biases and errors in a low-cost air quality sensing network. It also studies and compares multiple re-calibration techniques of low-cost air quality sensor networks. Lastly, it also provides the limitations and future avenues in the calibration and re-calibration of the air quality sensors.
[31]	The paper conducts a literature review on the low-cost high spatial and temporal resolution air quality monitoring network. It also suggests future research themes.
[32]	This paper reviews the IoT-based air quality monitoring networks and briefly discusses the challenges in designing air quality measurement networks.
[33]	The paper provides a comparative analysis of machine learning-based urban air quality prediction techniques.
[34]	This paper reviews indoor and outdoor air pollution monitoring using wireless sensor networks.
[35]	The paper reviews multiple papers, reports, white papers, and various websites on the role of urban computing in air quality management. It also covers the techniques of incorporating data-driven mitigation strategies opted by different countries.
[36]	This paper reviews the literature on multiple effects of the air pollution monitoring strategies used in South Africa. It also discusses the challenges involved in designing the air pollution networks in the air pollution monitoring network.
[37]	The research compares stationary, dynamic, and pollution data analysis methodologies in depth. The methodology, hardware components, communication mechanism, assessment, and performance of the air quality system are all compared.
[38]	A comprehensive survey on the unmanned air vehicle-based air quality measurement techniques for criteria pollutants along with challenges and open research directions are covered in this paper.
[39]	This research reviews the literature on air quality sensor technologies and air quality management systems.
[40]	This paper reviews the air quality standards set by various environmental protection organizations in the world. It also gives an overview of several aspects of low-cost sensing equipment and methodologies.
[41]	This paper reviews the literature on IoT-based machine learning-enabled continuous air quality monitoring and prediction literature.
[42]	This paper provides a brief survey of air pollution monitoring systems along with some specific measurement strategies.
[43]	This paper gives a summary of the problems involved in monitoring urban air quality.
[44]	This paper examines the literature on crowdsourcing-based air quality monitoring and identifies possible flaws as well as future research directions.
[45]	Based on the existing literature on the development of an air quality monitoring network, this paper provides the nuts and bolts for designing the next generation of air quality monitoring networks.

Table 1: Various surveys/reviews on various aspects of air quality measurement.

review of the related work. The major contributions of this paper are as follows:

- We provide the fundamentals of air quality measurements along with a non-exhaustive summary of the air pollutants and their potential sources.
- We present a comprehensive survey of the techniques for measuring the urban air quality along with several sensors famously used for measuring the pollutants.
- We also discuss the previous/ongoing air quality measurement projects from various entities and also summarize a few root cause analyses from the literature for determining the contributors in urban air pollution.
- We also highlight the challenges in designing an air quality measurement network and how the urban context information can help bring more useful insights in determining and translating the air-quality.
- Finally, we highlight the open research issues and future directions in measuring and learning from urban air quality.

Organization of the Paper:
The rest of the paper is organized as follows: Section 2 provides a primer on the air quality. It also provides a brief overview of the air quality landscape of the world while also covering the details of the major air pollutants and their sources. Section 4 discusses the various approaches available in the literature for designing an air quality measurement network. This section also provides details of the various sensors available for measuring particular pollutants in the air. Lastly, this section also discusses the diversity in the air quality data, its relationship with the different context variables, and how to ensure proper pre and post-processing. Section **??** provides a comprehensive literature review of the state-of-the-art in urban air quality standards in the world. This section also covers projects from various organizations for measuring and analyzing air quality in different parts of the world. Section 6 discusses the challenges in designing and measuring the urban air quality and also takes a critical look at the available literature for providing an exhaustive list of challenges, trade-offs, tussles, and opportunities in measuring and analyzing the urban air quality. Section **??** discusses the open research issues and future directions. The paper has been concluded in Section 7.

2 Primer on Air Quality

In this section, we discuss the preliminaries of the air quality. Then, we provide an air quality landscape and major pollutants. Lastly, this section provides a discussion on the potential sources of air pollution. Before describing the details of the air pollutants, it is vital to understand the composition of pollutant-free dry air. Dry air is essentially a combination of Nitrogen (78%) and Oxygen (21%). The remaining 1% is a combination of Argon (0.9%) and extremely minute quantities of Carbon Dioxide, Methane, Hydrogen, Helium, and others. Water vapor is also a typical, albeit very variable, component of the atmosphere, ranging from 0.01 to 4% by volume; in humid conditions, the moisture content of air can reach 5%. [4]

4. https://www.adb.org/projects/51199-001/main

Table 2: AQI scale used for indexing the real-time pollution and there impact on human health. Unit followed in this table is $\mu g/m^3$ unless mentioned otherwise.

AQI	Pollution Level	$PM_{2.5}$ 24 Hour	PM_{10} 24 Hour	CO 8 Hour (mg/m^3)	NO_2 24 Hour	SO_2 24 Hour	NH_3 24 Hour	Pb 24 Hour	O_3 8 Hour	Cautionary Statement	Implications on Human Health
0-50	Good	0-30	0-50	0-1.0	0-40	0-40	0-200	0-0.5	0-50	None	No health risk
51-100	Satisfactory	31-60	51-100	1.1-2.0	41-80	41-80	201-400	0.6-1.0	51-100	The extended outdoor activity must be avoided by children, adults, and people with respiratory issues.	The air quality is adequate; nevertheless, some pollutants may pose a considerable health risk to a limited number of people who are very sensitive to air pollution.
101-200	Moderate	61-90	101-250	2.1-10	81-180	81-380	401-800	1.1-2.0	101-168	The extended outdoor activity must be avoided by children, adults, and people with respiratory issues.	Members of sensitive groups may experience health effects. The general population is not likely to be affected.
201-300	Poor	91-120	251-350	10.1-17	18-280	381-800	801-1200	2.1-3.0	169-208	People with respiratory diseases take precautions and avoid extended outdoor activities; everyone else should also limit outdoor activities.	The general population may begin to experience health effects; members of sensitive groups may experience serious health effects.
301-400	Very Poor	121-250	351-430	17.1-34	281-400	801-1600	1201-1800	3.1-3.5	209-748	People with respiratory diseases take precautions and avoid all outdoor activities; everyone else should also limit outdoor activities.	Health warnings of emergency conditions. The entire population is more likely to be affected.
400-500	Severe	250+	430+	34+	400+	1600+	1800+	3.5+	748+	Everyone should avoid all outdoor activities	Health alert: everyone may experience more serious health effects

2.1 Air Pollution

Air pollutants are particles, gases, or droplets emitted in the environment that exceeds the environment's capacity of absorption, dilution, and dissipation. These pollutants are gases, solid particles, liquid droplets, etc. The effect of these pollutants at a scale is termed as air pollution[5]. Air pollution is increasingly becoming a significant contributor in causing public health (heart and lung disease, respiratory diseases, etc.) and environmental issues (global warming, acid rains, reduction in crop yields, depletion of the Ozone layer, etc.) at a global scale.

2.1.1 Criteria Pollutants

US Environmental protection agency (EPA) divided air pollutants into the following six categories that provide sufficient enough information for determining the overall air quality are known as *"criteria pollutants"*.

- **Carbon Monoxide (CO):** Carbon Monoxide is a gas emitted into the atmosphere due to the fossil fuel burning in automotive vehicles. It has no smell or color. It reduces the Oxygen supply to the body parts, thus hindering proper functioning. It also causes headaches, dizziness, heart, and respiratory issues.
- **Nitrogen Oxides:** Nitrogen Oxide is a gas emitted in the atmosphere due to the fossil fuel burning in vehicles and power plants. It has a smell and reddish-brown color. It causes coughs, shortness of breath, and respiratory infections. It is also a major contributor to acid rain that is very harmful to crops, plants, and animals.
- **Sulfur Dioxide (SO_2):** Sulfur Dioxide is a colorless gas emitted into the air due to oil and coal-burning power plants and chemical factories. It has a rotten egg-like smell. It is a contributor to acid rain that is harmful to crops, plants, and animals. It is also very harmful to people with respiratory diseases.
- **Ozone (O_3):** Ozone is not directly emitted in the atmosphere, it is a byproduct of the reaction between Nitrogen Oxide and organic compounds under the sunlight. Nitrogen Dioxide and organic compounds emissions are due to a wide range of processes such as coal/oil-burning power plants, factories, trees, etc. Ozone here must not be confused with the Ozone layer present in the stratosphere. It is the main contributor to smog that can lead to respiratory issues such as Asthama. It also causes ear, nose, and throat (ENT) issues. Ozone is also harmful to crops and plants.
- **Particulate Matter:** Solid/liquid droplets suspended in the air called particulate matter. These particles are inhalable with a width less than 0.1 mm and a size as small as 0.00005 mm. PM_{10} and $PM_{2.5}$ are prime examples of these particles. PM_{10} and $PM_{2.5}$ are inhalable particles with a size less than or equal to 10 micrometers and less than or equal to 2.5 micrometers, respectively. These particulate pollutants cause lungs and heart issues and are harmful to crops and plants.
- **Lead (Pb):** Lead is a toxic metal with many variants. It is emitted into the environment by automotive vehicles burning substandard gasoline. The chemical factories and power plants are also contributors to emitting this toxic metal into the atmosphere. Lead causes kidney issues, strokes, and heart failure [46].

2.2 Sources of air pollution

Sources of air pollution are generally divided into four categories[6]:

2.2.1 Natural sources

Natural events are the initial sources of air pollution in the world. These events are also fundamental parts of the ecosystem and also had an associated planetary cost. Forest fires, volcanic eruptions, dust storms, decomposing organic matter, biological processes in the soil, lightning, and sea spray are a few examples of the natural events degrading the air quality. The natural events result in creating different

5. https://www.britannica.com/science/air-pollution.

6. https://www.nps.gov/subjects/air/sources.htm

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Table 3: LIST OF ACRONYMS

WHO	World Health Organization
GDP	Gross domestic product
UNSDG	United Nations Sustainable Development Group
EPA	Environmental protection agency
CO	Carbon Monoxide
SO_2	Sulfur Dioxide
O_3	Ozone
ENT	Ear, Nose, and Throat
PM	Particulate Matter
Pb	Lead
ENT	Ear, Nose, and Throat
AQI	Air Quality Index
AQLI	Air Quality Life Index
NCAP	National Clean Air Program
NAAQS	National Ambient Air Quality Standard
US	United States
NCAP	National Clean Air Program
NAAQS	National Ambient Air Quality Standard
CASE	Clean Air and Sustainable Environment Project
AQG	Air Quality Guidelines
EEA	European Environmental Agency
MODIS	Moderate Resolution Imaging Spectroradiometer
GAM	Generalized Additive Model
CTM	Chemical Transport Model
POI	Point of Interest (POI)
AMS	American Meteorological Society
ISCST3	Industrial Source Complex Framework
CTDMPLUS	Complex Terrain Dispersion Model
OCD	Offshore and Coastal Dispersion
CMAQ	Community Multiscale Air Quality
CMAQ-DDM	CMAQ Decoupled Direct Method
CMAQ-ISAM	CMAQ Integrated Source Apportionment Method
CAMx	Comprehensive Air quality Model with Extensions
REMSAD	Regional Modeling System for Aerosols and Deposition
UAM-V	Urban Airshed Model Variable Grid
CMB	Chemical Mass Balance
PMF	Positive Matrix Factorization
EPA	Environmental Protection Agency
FRM	Federal Reference Methods
FEM	Federal Equivalence Methods
CRF	Conditional Random Field
ARMA	Auto-Regression-Moving-Average
LR	Linear Regression
NN	Neural Network
RT	Regression Tree
FEP	Frequently Evolving Patterns
GC	Granger-causality
EPIC	Energy Policy Institute at the University of Chicago
GHAir	Ghana Urban Air Quality Project
E-SCRAP	Educating School ChildRen to tackle Air Pollution
AI	Artificial Intelligence
IoT	Internet of Things

types of criteria pollutants, volatile organic compounds, and biological pollutants.

2.2.2 Mobile sources

Mobile sources of air pollution are considered very deadly for human health. Here "traffic" encompasses cars, buses, trucks, trains, planes, etc. Mobile sources are also considered one of the major sources of air pollution. Air pollution is a result of the vehicles used for commuting people and resources [47]. The vehicle exhaust, suspended and re-suspended road dust, brake dust, and tire wear are sources of traffic-related emissions [48]. Mobile emissions sources result in different criteria pollutants and volatile organic compounds with harmful effects on the ecosystem.

2.2.3 Stationary sources

Stationary air pollution sources include power plants, industrial facilities, oil refineries, industries, sewage treatment, and so forth. Stationary sources of air pollution are often known as "point sources." The burning of fossil fuels, metal processing processes, boilers in industries and power plants, oil refining procedures, solvents, glues, and paint thinners are all producers of criterion pollutants such as volatile organic compounds and hazardous pollutants (mercury dioxin, etc.).

2.2.4 Area sources

Air pollution sources such as agricultural areas, fireplaces, construction processes in cities, heating and cooling units in the buildings are categorized as area sources of urban air pollution. The pollutants from area sources result in particulate matter and other criteria pollutants. Household emissions also contribute to the degradation of air quality. Processes like biomass combustion, fossil fuel burning (such as coal, diesel, kerosene oil, etc.), tobacco smoking, and central air conditioning are a few important sources of household emissions. Household emissions create different criteria and biological pollutants. Since this paper only considers ambient air pollution, indoor air pollution sources are out of the scope of this work. We also want to note here that multiple sources from diverse surroundings contribute to urban air pollution, which varies depending on the geographical location of the pollution sources in the city, wind direction and speed, humidity and other meteorological conditions, and so on. Therefore, attributing urban air pollution to a single pollution source is an inaccurate approach to look at this issue. The relationship between criteria pollutants and their sources is provided in table 4. The table is made based on the information provided by the US EPA[7] and NPS[8].

2.3 Air quality index

The air quality index (AQI) is a metric used for quantifying and communicating the air quality in a particular location. AQI suggest the amount of air pollutant in the air over a specific average interval. These air pollution concentration values are measured by a sensor or extrapolated from a simulation/emulation model. The concentration of the pollutant and time window is used to determine the dose of the air pollution, and insights from epidemiological research provide its health impacts. Based on these health impacts, a color code and a health advisory are issued for a specific range of the AQI values. The air quality information varies for different countries based on their air quality standards and thus their air quality indices. AQI value for a given pollutant is determined by the following piecewise linear function (1).

$$I = \frac{I_{High} - I_{Low}}{C_{High} - C_{Low}}(C - C_{Low}) + I_{Low}, \tag{1}$$

where I is the air quality index, C is the concentration of the pollutant, C_{Low} is the concentration breakpoint that is less than or equal to C, C_{High} is the concentration breakpoint that is greater than or equal to C, I_{Low} is the index breakpoint corresponding to C_{Low}, and I_{High} is the index breakpoint corresponding to C_{High}.

Measurement data for AQI is averaged over one hour, there are few pollutants such as Ozone O_3, $PM_{2.5}$, and PM_{10}

7. https://www.britannica.com/science/air-pollution
8. https://www.nps.gov/subjects/air/sources.htm

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Table 4: Relation between criteria pollutants and pollution sources categories along with their environmental risks.

Criteria Pollutant	Pollution Sources	Environmental Risks
Carbon Monoxide (CO)	Mobile, Stationary, and Natural pollution sources	Smog and Asphyxiation in vertebrates
Nitrogen Oxides (NO_x)	Mobile and Stationary pollution sources	Smog, Acid rain, respiratory issues in vertebrates
Sulfur Dioxide (SO_2)	Mobile and Stationary pollution sources	Acid rain and respiratory issues in vertebrates
Ozone (O_3)	Mobile, Stationary, and Area pollution sources	The main contributor of the smog in urban areas
Particular Matter (PM_x)	Mobile, Stationary, Natural, and Area pollution sources	Haze, Acid rain, serious damages to health and buildings.
Lead (Pb)	Mobile and Stationary pollution sources	Reduction in biodiversity and neurological issues

where average over multiple hours is needed to compute a correct AQI value. Table 2 provides a detailed description of different pollution levels of various pollutants for India along with their health advisory and impacts on human health associated with it[9]. Different countries have their air quality policies and thus have different cutoff values[10].

3 Air Quality Landscape

Before proceeding with the discussions of air quality modeling and measurement, it is imperative to examine the current global air quality landscape by gleaning insights from various studies on the impact of air pollution and mitigation initiatives undertaken in various parts of the world. The air quality life index (AQLI) [49] report released in July 2020 suggests that air pollution was the most prominent risk to human health before the pandemic (Covid-19) and after it as well [50]. Many countries are now putting a lot of effort into designing policies for reducing emissions, albeit the progress is slow, and many countries are still struggling to cope with the air quality issue. In this section, we examine the air quality landscapes (particulate air pollution) of various countries, as well as air pollution and the policies used by these countries to address air pollution challenges.

3.1 Asia

3.1.1 China

China is the most populated country in the world. It is home to 18.47% of the total population of the world. 61% of its population lives in cities. In 2013, the concentration of the $PM_{2.5}$ in Beijing city was so high that it seemed that the city will become uninhabitable [51]. At the time, an average person in the Beijing city was exposed to approximately 91 $\mu g/m^3$ of $PM_{2.5}$ air pollution. It is nine times higher than the WHO recommended value for $PM_{2.5}$. In January 2014, the situation got even worse when the $PM_{2.5}$ concentration went 35 to 40 times higher than the WHO recommended value, and the city officials warned people to stay indoors [52]. The Guardian describes it as "Beijing's airpocalypse". Similarly, in Shanghai, the air pollution went beyond the critical level, there the recorded $PM_{2.5}$ concentration was six times more than the WHO recommended value.

Given the situation, in 2014, the Chines government released a national air quality action plan worth 270 Billion USD with the sole purpose of bringing the air pollution down. The plan has three goals:

1) Reduce the PM_{10} by 10% relative to its value in 2012.
2) Reduce the $PM_{2.5}$ by 25% in Beijing-Tianjin-Hebei, by 20% in the Pearl river delta, and by 15% in the Yangtze river delta.
3) Reduce annual $PM_{2.5}$ of Beijing to 60 $\mu g/m^3$.

The national air quality action plan worked for China, by 2017, the $PM_{2.5}$ concentration in Beijing-Tianjin-Hebei went down by 36%. In Pearl and Yangtze delta, the air pollution went down by 27% and 34% respectively. This success was achieved due to a collaborative effort from different government entities in reducing the dependency on coal, controlling car emissions, increasing renewable energy, enforcing emission policies, reducing steel and plastic manufacturing, and replacing coal boilers with natural gas or electric heaters [53]. Though these steps have improved the air quality in China, the war against air pollution is not over, as long-term solutions for bringing air pollution down to the WHO's recommended values are needed.

3.1.2 India

India is the 2nd most populated country in the world with 17.70% of the population of the world. 35% of the total Indian population lives in cities. India is also the 2nd most polluted country in the world. In 2019, the average $PM_{2.5}$ value was 70.3 $\mu g/m^3$ that is seven times higher than the WHO recommended value (10 micrograms/cubic meter). Delhi, Uttar Pradesh, and northern India are the most polluted areas where air pollution is reducing almost a decade of life expectancy of the residents [54], [54]. AQLI India fact sheet [55] also suggests that 40% of the Indian population are exposed to air pollution levels not observed anywhere. In 2019, the concentration of the $PM_{2.5}$ reached an emergency level (440 $\mu g/m^3$).

In 2019, India declared war against pollution and announced a five-year national clean air program (NCAP) with 42 million USD for the first two years [56]. The goal of NCAP is to bring the air pollution down by 20 to 30% in 102 cities (which are over the national ambient air quality standard (NAAQS)) by building institutional capacity in monitoring and mitigating the air pollution [56]. The potential impact of NCAP in the coming years is a 25% improvement in the air quality and an improvement of 2 to 3 years in the total life expectancy of the general public [57].

9. https://app.cpcbccr.com/ccr_docs/FINAL-REPORT_AQI_.pdf
10. https://aqicn.org/scale/

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3.1.3 Indonesia

Indonesia is the 4th most populated country in the world with a 56% urban population. More than 93% of its population is exposed to air pollution that is poorer than the WHO's air quality standards. Indonesia is also facing wildfire issues. In 2015 nearly 100000 wildfires were recorded. The average $PM_{2.5}$ concentration in Indonesia is $40\mu g/m^3$ [58]. Jakarta is the most congested and one the most polluted city in the world, 31.5% of the $PM_{2.5}$ and 70% of PM_{10} particles in Jakarta air pollution are emitted by the automotive vehicles. Ten coal power plants around the city are also adding to the particulate pollution by emitting black carbon [58]. In 1998 the air quality in Sumatra and Kalimantan was below the WHO recommended threshold. In the last 20 years, the air quality in these cities has gone three times poorer than the recommended value. This shift is because of illegal peatland agriculture, deforestation, and wildfires [58].

The Indonesian government has taken initial steps in overcoming the air quality issue by adopting the Euro 4 fuel, enforcing automotive health monitoring policies, and developing a peatland restoration agency. Indonesia's coal-based energy production has doubled in the last ten years, and this is due to the trade-off between the economy and pollution. A lot of collaborative effort is needed to ensure the better air quality in Indonesia.

3.1.4 Pakistan

Pakistan is the fifth most populated country with one of the highest population growth rates (2.0%). On the AQLI pollution ranking, it is ranked 4th in the most polluted countries. Pakistan has seen a 20% increase in the $PM_{2.5}$ concentration in the last two decades [59]. Lahore has the poorest air quality in Pakistan, where PM2.5 concentration is six times higher ($64\mu g/m^3$) than the WHO's recommended value [59]. If this level of pollution concentration is sustained, an average person in Lahore will lose approximately 5.3 years of life expectancy. Almost 99% of the total population is exposed to pollution levels higher than the recommended WHO air pollution values [57].

Citing this looming threat, the Pakistani government started enforcing the air pollution regulations for improving urban air quality. In 2017 following three initiatives are taken to ensure improvement of the air quality:

- Stubble burning is a major contributor to air pollution in Pakistan. The government of Punjab banned stubble burning and promoted alternative methods for getting rid of stubble.
- Emission regulations were enforced on the vehicles, factories, and brick kilns.
- For improving the air quality, Pakistan has also shut down many coal-based power plants for two months. This measure has improved the air quality but resulted in many power outages.

Pakistan can improve air quality sustainably by exploiting renewable power sources and continuously enforcing emission regulations.

3.1.5 Bangladesh

Bangladesh is the 8th most populated country in the world with a 39% urban population. Bangladesh is also the most polluted country in the world [57], [60]. The air pollution there is so intense that an average person loses approximately 6.7 years of life expectancy. Nearly 100% of the Bangladesh population is exposed to air pollution nearly seven times more than the WHO recommended air pollution concentration ($10\mu g/m^3$ for $PM_{2.5}$). Major sources of air pollution in Bangladesh are brick kilns, vehicle emissions, cement factories, unplanned constructions, and steel re-rolling [60]. In metropolitans like Dhaka, the concentration of the particulate pollutants ($PM_{2.5}$ and PM_{10}) stayed manifold higher than the recommended air pollution concentration values. The concentration of other air pollutants like inorganic gases is noted to stay below the recommended values.

Given the dangerous situation of the ambient air quality in major cities, the Bangladesh government has started implementing various countermeasures to control and mitigates air pollution. Bangladesh developed 11 fixed continuous air quality measurement stations in 8 major cities. The stations are capable of measuring the concentration of various types of air pollutants. The recorded data from these monitoring stations helps develop a spatiotemporal map of different air pollutants that translates into the identification of the air pollution trends in the country. Data gathered through these monitoring stations is also used for developing air models and AQI for public information.

On the policy front, many initiatives are taken to enforce the emission policies on brick, cement, and related industries by banning the import of coal with high sulfur content. Bangladesh's government is also incentivizing the industry to move towards renewable and energy-efficient production procedures. Initiatives like Clean Air and Sustainable Environment Project (CASE) and Grater Dhaka Sustainable Transport are also working with the brick, cement, and transport industries to reduce emissions. Strict enforcement and monitoring are necessary to ensure the improvement in the ambient air quality, and the Department of Environment in Bangladesh has started doing that.

3.1.6 Nepal

Nepal is suffering from a grim air pollution problem. Almost all of its population is living in an air pollution concentration higher than the WHO recommended values. According to the AQLI Nepal fact sheet 2019, Nepal is ranked as the third most polluted country in the world with an average $PM_{2.5}$ concentration of $61.2\mu g/m^3$ that is five times higher than the acceptable concentration value. The average person in Nepal is expected to lose at least five years' worth of life expectancy if the current levels of air pollution persist. The brick kiln, fuel burning, vehicle emissions, and road dust are primary contributors to Nepal's air pollution. Nepal is far behind in combating the air quality issues that are affecting the health of its citizens. More details on the air quality about Asian countries such as South Korea [61], Thailand [62], etc. are available on [63].

3.2 Europe

Compared to Asia, Europe already has better air quality. The majority of Europe's concentration of particulate pollutants is below the European Union's air pollution limits ($25\mu g/m^3$) but over three-quarters of Europe's population lives in

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regions that do not satisfy the World Health Organization's (WHO) stricter recommendation of $10\mu g/m^3$ [64]. The entire population of Poland, Belarus, Slovakia, the Czech Republic, Slovenia, Hungary, Lithuania, Armenia, Belgium, Germany, Moldova, Cyprus, and Ukraine, and the Netherlands and San Marino are exposed to pollution levels that do not satisfy WHO guidelines [64]. Warsaw, Po Valley, and Milan are three severely polluted areas in Europe. If particle pollution levels matched WHO guidelines, people would gain one year and two months [63]. Bursa (Turkey's industrial center) suffers from severe particle pollution as well. The population of Bursa will gain one year and one month if the level of pollutants are reduced to meet WHO guidelines. Large-scale biomass burning and unfavorable weather conditions are causing air quality issues in the Northern Fennoscandia region (Norway, Sweden, Finland, and Russia) [65]. In the last two decades, Northern Europe has seen a rise in air pollution due to several large-scale biomass burning episodes in Eastern Europe causing serious consequences for human health and local ecosystems.

According to the European Environmental Agency (EEA) air quality report 2020, 15% of the European population (data gathered from 30 countries) is exposed to the PM_{10} concentration levels more than the EEA limits and 48% more than the WHO air quality guidelines (AQG) value for PM_{10} pollutants. Almost 50% of the deployed air pollution station have reported these statistics. According to EEA standards for $PM_{2.5}$, only 4% of the population is exposed to $PM_{2.5}$ concentrations higher than the EEA standards. As per the WHO AQG guidelines, 74% of the European population was exposed to $PM_{2.5}$ concentrations higher than the recommended values (70% AQ monitoring station reported these statistics.). According to the same air quality report, 34% of the population in Europe is exposed to Ozone concentrations higher than the EEA recommended values. At AQG levels, approximately 99% of the population is exposed to Ozone levels higher than the AQG recommended values. 96% of the air quality monitoring stations have reported Ozone values higher than the AQG recommended values. Only 4% of the population is exposed to NO_2 levels higher than the EEA and WHO AQG values. SO_2 is also on the decline in Europe, only less than 1% of the European population is exposed to concentrations higher than the EEA recommended values and 19% if measured at the WHO AQG values. Due to Covid-19, statistics reported in the EEA air quality 2020 report are based on numbers from 2018.

Europe is leading the way in the developed world in introducing legislation and standards for improving air quality. Over the years, the EU has developed a procedure for member countries to access their air quality and share their data with the EEA. EEA has also provided the member states with ambient air quality values for twelve major air pollutants[11]. Table 7 provides the standard values of air pollution concentration for the EU. EU has prescribed the following principles for member states to measure and report their air quality[12]:

1) Each member state will divide its territory into zones.
2) Measure the air quality in each zone using sensors, modeling, or an empirical method.
3) Report the air quality data to the European Commission accordingly.
4) Zones where the air quality is poorer than the air quality standards (table 7) the member state will provide a plan to address the sources of emission in the zone and ensure compliance with the limit value before the date when the limit value formally enter into force.
5) The member state will disseminate the AQI value to the public.

3.3 United States

The United States (US) is the 3rd most populated country in the world, with 4.25% of the world population living there. Over 83% of the total population lives in the cities. The US is a success story when it comes to air pollution mitigation. In 1970, the US introduced the "clean air act" and after that, the air pollution gone down by 61% [66]. This decay in pollution has added 1.4 years to the life expectancy of US citizens. Los Angeles, once known as the smog capital of the world now reduced air pollution by 59%. Only 7% of the total US population is exposed to air quality poorer than the WHO recommended air quality guidelines [66].

3.4 Africa

West and Central Africa have 27 countries with a 605 million total population. The average air pollution concentration ($PM_{2.5}$) is around $20\mu g/m^3$ that is twice the WHO recommended values for the $PM_{2.5}$. With current levels of air pollution, an average person tends to lose approximately 2.1 years of life expectancy. Benin, Congo (Republic of the Congo and the Democratic Republic of the Congo), Ghana, Nigeria, and Togo are among the top air polluted countries in the region. These countries are also ranked among the countries having the worst air quality in the world. According to the AQLI air pollution ranking, Nigeria is ranked 6th in the most polluted country. In few Nigerian cities (Onitsha, Lagos, etc.), an average person is expected to lose four to six years of life expectancy. Brazzaville in the Republic of Congo has the worst concentration of $PM_{2.5}$ ($41.5\mu g/m^3$) and resulting in 2.3 years of reduction in the total life expectancy of an average person. The Volta region in Ghana is also suffering from a poor air quality situation, where the air pollution concentration is four times the WHO AQG values. The air quality meeting the WHO AQG values will add three years to the life expectancy of an average person in Ghana. Burning fossil fuels is the primary reason for air pollution in Central and West Africa. Coal consumption is expected to increase exponentially in the coming years.

The African countries have to strike a balance between economic growth and air pollution. Air quality data gathering and environment preservation policies are still not designed. Only Cameron has introduced the National Air Quality standard for particulate pollution. The African countries need a coordinated effort to control the emissions and implementation of air quality standards and environmental preservation policies.

11. https://ec.europa.eu/environment/air/quality/index.htm
12. https://eur-lex.europa.eu/summary/chapter/environment.html?root_default=SUM_1_CODED%3D20%2CSUM_2_CODED%3D2005&locale=en

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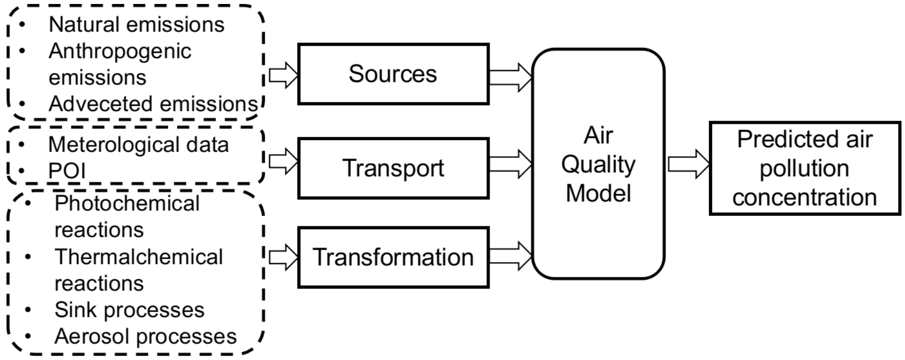

Figure 2: Nuts and bolts of a comprehensive air quality model. The figure is opted and improved from [67].

4 Air quality monitoring, modelling, and measurement techniques

In this section, we discuss air quality monitoring, modeling, and measurement techniques. We divide this section into four major components along with a necessary discussion and lesson learned subsection. The four major components are air quality monitoring networks, air quality modeling techniques, air quality measurement techniques, and air quality data.

4.1 Air quality monitoring network

An air quality monitoring network is used to acquire consistent, objective, and standardized information regarding a region's air quality. This information may include concentrations of target pollutants. It also allows for necessary steps to be taken in any environmental protection and public health safety effort. These steps include determination and control of emission sources and keeping the public informed about the state of the air quality [68]. Madruga et al. [69] discuss the air quality monitoring network with the perspective of public exposure to pollutants. In literature, air quality network design usually proceeds in two steps: generation of the fine spatial distribution of pollutants, and based on that, optimization of the location of the new sensor to add to the system. Usero et al. [68] describe the establishment of an air quality monitoring network in Seville, Spain, to monitor nitrogen dioxide and ozone levels following the European Union's ambient air quality assessment legislation. Mofarrah et al. [70] have used the multiple-criteria method with spatial correlation to determine the optimal number of air quality monitoring stations in an air quality monitoring network in Riyadh, Saudi Arabia.

By far, efforts in establishing air quality monitoring networks are broadly categorized in the following groups:

4.1.1 Fixed station air quality monitoring

Fixed air quality monitoring stations are the most reliable, standardized, accurate, and highly expensive method. Fixed air quality stations require highly trained staff and resources to manage the measurement and maintenance operation. Sometimes these costs even exceed the purchase cost of the station. Thus, most of the fixed air quality monitoring stations around the globe are installed and operated by government agencies. In US, 4000 air quality stations are installed by state environmental agencies[13]. The EEA receives data from 3000, 2500, and 1000 stations for measuring NO_2, PM_{10}, and $PM_{2.5}$ respectively[14].

Various efforts have been made to create an ideal air quality monitoring network that can offer comprehensive air quality measurements. Elkamel et al. [78] use a multiple-cell approach to create a monthly spatial distribution for pollutants and use it in a heuristic optimization algorithm to identify the optimal configuration of a monitoring network. Hsieh et al. [74] use a semi-supervised inference model to predict air quality of unknown areas and an entropy-minimization model to predict the best locations for establishing new stations. Zhu et al. [73] use Bayesian Maximum Entropy with a multi-objective optimization model to optimize the design of an air quality monitoring network. Kang et al. [71] derive an air quality inference model using a higher-order graph convolution network. They employed a greedy method to minimize information entropy, which offers a prioritized list of places for additional air quality measurement stations to be installed. The air quality measurement node placement method [71] enhances overall network performance as well as air quality prediction for a specific urban area of the city.

As cities continue to expand and city dynamics are always changing, an optimal method to analyze and redistribute the installed network is required. Hao et al. [79] employs an atmospheric dispersion model and genetic algorithm to maximize coverage with minimum overlap. Yu et al. [80] use satellite observations to assess the representativeness of installed air quality stations using a stratified sampling method. Efforts have also been put into developing, and assessment of low-cost air quality monitoring alternatives [81]–[83].

4.1.2 Mobile air quality monitoring

Given the price and the nature of the fixed air quality monitoring stations, there has been a lot of attention to the development of mobile air quality monitoring stations. Mobile air quality monitoring stations offer a cost-effective solution with several promising features such as high-resolution spatial pollutant mapping and cross-validation of air quality measurements. Some of the most prominent

13. https://www.epa.gov/outdoor-air-quality-data/air-data-basic-information
14. https://www.concawe.eu/wp-content/uploads/2018/04/EAQ_Trends_digital.pdf

Papers	Input data	Spatial distribution generation method	Location recommendation technique
[71]	1 year of data from 17 stations, met data, POIs, road networks	Graph convolutional neural-network	Greedy entropy minimization
[72]	Fixed station data integrated with data generated through COPERT III	Generative Adversarial Networks	KL divergence and K-Means clustering
[73]	1 year of fixed station and met data	Bayesian maximum entropy	Multi-objective optimization
[74]	14 months of data from 22 fixed stations, met data, POIs, road networks	Affinity-graph based inference model	Greedy entropy minimization
[75]	Met data with simulated data from EPA CMAQ and CAMx models	Simulated through CMAQ and CAMx models	Objective function and cost minimization
[70]	Generated based on traffic composition	Industrial Source Complex (ISC) model	Multi-objective optimization
[76]	Integration of satellite data with ground station data	Mathematical model	Multi-objective optimization
[77]	2 years of sampling campaign	Spatial inverse distance weighted interpolation	Multi-objective optimization
[78]	6 years of met and pollution data	-	Multi-objective optimization

Table 5: Review of research on air quality network design

research efforts in developing and utilizing mobile air quality stations are summarized in Table 6.

4.1.3 Satellite based air quality monitoring

The use of satellite-based sensors for the determination of air quality has been gaining momentum for a long time now. Li et al. [102] use MODIS (Moderate Resolution Imaging Spectroradiometer) data along with meteorological factors to analyze their relationship with ground-based PM_{10} stations. They use a non-linear regression model to predict PM10 forecast. Fowlie et al. [103] analyze the relationship of ground-based PM10 stations with satellite-based estimates and their effect on the Environmental Protection Agency's policies. Kim et al. [104] discuss the launch of the GEMS satellite for monitoring air quality. They discuss the techniques of sensing different air quality parameters through satellites. Stebel et al. [105] explore the use of existing satellite data to derive particulate matter estimates and their correlation with ground-based stations. They have also extended the sensing algorithm to report more on the air quality parameters.

4.1.4 Integrating satellite data with ground stations

Sullivan et al. [106] evaluate the need for satellites to cover the gaps in the existing installed fixed station air quality monitoring network and the impacts it can produce. Alvarado et al. [107] have done a comprehensive analysis on the integration of satellite data into a prediction of ground air quality for low-income countries. They have used two models to predict ground-level $PM_{2.5}$, namely, Generalized Additive Model (GAM) and Chemical Transport Model (CTM). After analyzing the results, they provide further recommendations on the ability of satellite estimates to bolster air quality monitoring networks. Li et al. [108] discuss the integration of a low-cost air quality sensor network with fixed ground stations and satellite data to enhance pollution mapping. Their studies have shown that integrating the three datasets can vastly improve spatial distribution and resolution. Their system can also perform quite well under different weather conditions where the satellite remote sensing data alone tends to be biased.

4.2 Air quality modelling techniques

The environment is a complex reactive system where multiple physical and chemical processes are happening continuously. The air quality measurement at a specific location and time provides a conditional spatiotemporal snapshot of the environment. The interpretation of spatiotemporal air quality information requires a conceptual understanding of atmospheric dynamics that is not possible without a sophisticated air quality model. Measurement alone is also not enough for policymakers to devise an effective plan to address the looming challenge of air quality. The air quality models provide necessary mathematical information for understanding the complex interactions between different variables affecting air quality. Therefore a combination of air quality measurement and air quality models can yield real progress in understanding and solving the air quality issues in urban centers.

A comprehensive air quality model is supposed to take into consideration the meteorology, chemical transformations, emission patterns, known source information, point of interest (POI), and removal processes and provide spatiotemporal emission fluxes and pollutant concentrations. It also highlights the relation between the rate of change in pollution concentrations and the potential sources [67]. Figure 2 illustrates the bare minimum inputs and output of an air quality model. The three most commonly used air quality modeling approaches are dispersion, photochemical, and receptor modeling. We briefly describe all three modeling techniques along with their different variants. Air quality is not a local phenomenon. Understanding the contribution of different variables in the air quality landscape is a challenging task. Modeling these contributions is not possible through classical air quality modeling techniques. For completeness, we have included the famous classical air quality modeling techniques. Though these techniques are not suitable to model the complex relationships between different contributing variables in the air quality at a scale, many advanced modeling techniques are designed based on the insights from these classical techniques.

- **Box models:** The box model is the simplest model for estimating the concentrations of air pollutants. The box model compares a domain's airshed to a rectangular box within which the pollutant's mass is entirely contained [109]. It is used for lab-scale air quality experiments. It is also suitable for modeling indoor air quality. More information on the box model is available on [67], [109].
- **Gaussian models:** Gaussian models are the most popular air quality models used in the literature to

No.	Paper	Mobile Platform	Sensing Platform	Sensing Parameters	Study Area	Time of the study
1	[84]	Mixed	Customized hardware	CO, NO_2, O_3	California, US	06 Weeks
2	[85], [86]	Cycle, bike, bus, train, walk	Customized hardware	CO, NO_2, O_3	California, US	04 Weeks
3	[87], [88]	Driving, cycling, jogging	NODE sensors	CO	Sydney, Australia	01 Week
4	[89]	Driving, cycling, jogging	NODE sensors	CO	Sydney, Australia	01 Week
5	[83], [90], [91]	Walking, driving, cycling	Teco envboard	PM_x	Germany	24 Hours
6	[92]	Walking	Customized hardware	CO_2, O_3	Switzerland	06 Month
7	[93]	Walking, cycling, bike, car, bus, train,	Customized hardware	CO, NO_2, O_3	California, US	01 Month
8	[94]	Cycle, Bike, Car	HazeWatch node	CO, NO_2, O_3	New South Wales, Australia	01 Week
9	[95]	Cycle	Magee microAeth AE5, low-cost sensors	PM_x, TSP, Black Carbon, CO	Antwerp, Belgium	10 Days
10	[96]	Car	Custom hardware, NODE sensors	CO, PM_x	New York, New Jersey, US	-
11	[97]	Bus	Customized hardware	$PM_{2.5}$	Hangzhou, China	-
12	[98]	Google Street View vehicle	Laboratory grade analyzers	Black Carbon, NO_x	Oakland, US	1 Year
13	[99]	Mixed	Customized hardware	CO, CO_2, CH_4	India	-
14	[100]	Trash Trucks	Customized hardware	PM_x	Cambridge, US	04 Months
15	[101]	Car	Customized hardware	CO, CO_2, NO	Chennai, India	-

Table 6: Review of research on mobile air quality sensing

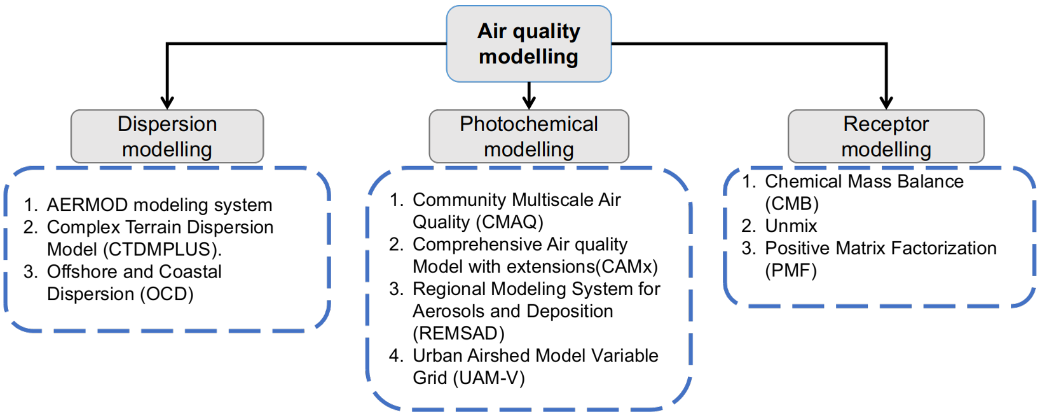

Figure 3: A non-exhaustive taxonomy of air quality modelling techniques from US EPA.

model the repercussions of air pollution in various use cases. These models are frequently used in regulatory applications. The Gaussian model assumes that the plume spread is a result of molecular diffusion. Pollutant concentrations in the plume spread horizontally and vertically [110]. The solution to the diffusion equation with varying initial value and boundary conditions results in a Gaussian distribution of the pollutant concentrations [67]. For further details on the Gaussian air quality models we refer the reader to [67], [110]–[112].

- **Eulerian models:** The Eulerian air quality modeling approach is considered one of the most significant modeling techniques. It is often known as the "grid model" technique. In this technique, the area under consideration is divided into equal size small grid cells, and conservation of the mass equation is solved for a specific type of pollutant's concentrations [113]. A set of mathematical equations in a given coordinate system explain the transport, diffusion, transformation, and deposition of pollutant emissions in each cell [114]. This modeling approach is used for studying and simulating long-range transport, air quality over the entire airshed. Further details on the Eulerian air quality modeling we refer the reader to [67], [113], [114].
- **Lagrangian models:** The Lagrangian models calculate the wind trajectories and the transportation of the plume along these trajectories. For source-oriented models, these trajectories are calculated forward in time, and for receptor-based models, these trajectories are calculated back in time [114]. Lagrangian model-

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ing is frequently used to span a longer time duration, up to years. These models are also used to model the concentrations of the particulate matter in the air. For more information on the Lagrangian models, we refer the reader to [67], [113]–[115].

4.2.1 Dispersion modelling

Air dispersion models formulate and simulate the dispersion of the pollutants emitted by different sources. The simulation provides an estimation of the downward air pollutant concentration. Dispersion models are used to predict the concentration for specific scenarios such as the change of the pollution source. These models are more suited for pollutants that react in the environment and spread over large distances. The models are also widely used by regulatory bodies during the preparation and evaluation of air permit applications. Public safety and emergency response personals utilize these models to determine toxicity in the air due to possible gas release events. Environmental protection agencies around the globe measure the effect of emissions from different sources and pollution control strategies by using the dispersion models.

1) **AERMOD modeling system:** The American Meteorological Society (AMS)/US EPA Regulatory Model Improvement Committee (AERMIC), a joint working group of scientists from the AMS and the EPA, created the AERMOD dispersion modeling system. It is a steady-state Gaussian plume model that includes air dispersion based on planetary boundary layer turbulence structure and scaling ideas, as well as handling of complex terrain, simple and intricate topography. It generates pollutant concentrations in the ambient air on a daily, monthly, and yearly basis. It is an updated version of the Industrial Source Complex (ISCST3) framework proposed by the USEPA for analysing the influence of industrial sources on air quality in the coming years [116], [117]. AERMOD consists of a dispersion model for short-range dispersion of air pollutants from various sources, a meteorological data pre-processor (AERMET), and a terrain pre-processor (AERMAP) [118], [119]. The AERMOD dispersion model takes pre-processed meteorological parameters and pre-processed relation between complex terrain features and air pollution plumes to produce an air quality model [117], [120]. Further details on various versions of its source codes, implementation details, and variable details are available at [121].
2) **CTDMPLUS:** Perry et al. [122] proposed the technical formulation of the Complex Terrain Dispersion Model (CTDMPLUS). Later, Paumier et al. [123] provided a performance characterization study of CTDMPLUS. The objective for this project by US EPA was to design a dispersion model that can model and predict the air pollution concentration in the mountainous terrain. CTDMPLUS is a point source Gaussian air quality model for complex terrain that uses a flow algorithm to provide the deformation in the plume trajectory caused by the mountainous terrain. It is capable of simulating the flow and distortions in the plume near predefined three-dimensional (3D) terrain features while remaining simple by applying flow-distortion adjustments to flat-terrain, Gaussian, and bi-Gaussian pollution distributions [121], [122]. The CTDMPLUS requires a significant amount of information on the topography and weather to produce an efficient dispersion model, which often represents a bottleneck in many circumstances. More information on various versions of the CTDMPLUS source code, implementation details, and variable details are available at [121], [122].
3) **OCD:** Hanna et al. [124] introduced the Offshore and Coastal Dispersion (OCD) model, which can simulate the impacts of offshore emission sources on coastal air quality. It is based on a steady-state Gaussian model that can cater to the varying dispersion characteristics between over and underwater, sea-land interface, and aerodynamic effects. Hourly meteorological data from water and land sites is necessary for the OCD model to predict air quality. Turbulence intensities are also frequently used along with the hourly meteorological data but they are not mandatory. More information on various versions of the CTDMPLUS source code, implementation details, and variable details are available at [121], [125].

Though US EEA recommends AERMOD, CTDMPLUS, and OCD for air quality modeling, they also provide an alternative list of models that can be used by the regulatory applications on a case-by-case justification.

4.2.2 Photochemical modelling

Photochemical air quality models are often used to evaluate the effectiveness of the control strategies for regulatory analysis and attainment demonstrations. Photochemical models can model the air quality at different spatial scales (local, regional, national, global, etc.). Photochemical air quality models are also known as photochemical grid models. These models are used to evaluate the changes in the concentrations of the criteria pollutants due to the changes in the associated variables (meteorological conditions, emission sources, etc.). Similarly, these models are also used for accessing the sensitivity of the pollutant predictions in different use cases. Photochemical grid models are also used to evaluate the performance of pollution control policies. They simulate the concentration of the air pollutants at a large scale by using a complex set of mathematical equations to characterize different atmospheric processes (physical and chemical). Two types of commonly used photochemical air quality models are the Lagrangian trajectory model and the Eulerian grid model. The Lagrangian trajectory model uses the moving frame of reference for modeling the air quality whereas, the Eulerian grid model applies fixed 3D geometric models to the ground to model the air quality of a particular geographical area.

1) **Community Multiscale Air Quality (CMAQ):** CMAQ modeling system is a state-of-the-art photochemical air quality modeling system. It uses 3D Eulerian modeling system to simulate the effect of the criteria pollutants in urban-to-regional-

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to-hemispheric scale. CMAQ[15] is developed and distributed by US EPA as an open-source suite of air quality modeling programs that can simulate multiple air pollution use cases and predicts the concentrations based on the historical data of the criteria pollutants. CMAQ is used to simulate and estimate the performance of EPA missions for understanding and forecasting air pollution, human exposure to air pollution, watershed acidification [126], deposition of nitrogen and sulfur [127], and many other air pollution-related use cases. Three common types of CMAQ are:

- *WRF-CMAQ:* Wong et al. [128] proposed a combination of weather research and forecasting with the inputs of the CMAQ (e.g., aerosol concentration) to introduce the effect of the chemistry into the weather. This coupled design (meteorology from CMAQ and the chemistry from weather research and forecasting component) is known as WRF-CMAQ. Information from CMAQ, such as aerosol concentration, is transmitted into WRF so that the chemistry can influence the weather. More details on the WRF-CMAQ are available in [128].
- *CMAQ-DDM:* CMAQ decoupled direct method (CMAQ-DDM) offers concentrations and deposition sensitivity statistics for user-specified parameters [129]. The motivation for CMAQ-DDM comes from the desire to measure the concentrations of the pollutants by changing one or a few parameters out of many predefined air quality model parameters [130]. Air quality models usually take emissions as input and predict their concentrations CMAQ-DDM provides the ability to the policymakers to look at the pollution landscape by tweaking the parameters of interest or emission sources (e.g., wildfires, vehicles, etc.). More details on the CMAQ-DDM are available in [129], [131].
- *CMAQ-ISAM:* CMAQ Integrated Source Apportionment Method (CMAQ-ISAM) is a variant of CMAQ that measures the attribution of the source in the overall value of the pollutant concentrations predicted/outputted by the air quality models. For example, identifying the proportion of the smog created by the stubble burning in a neighboring city. This can be achieved by running the CMAQ twice (first with all emission use cases and second by removing the source of interest) but this will be complex and computationally expensive. CMAQ-ISAM this issue by calculating source attribution of many sources directly by the model in one simulation. Simon et al. [132] used CMAQ-ISAM for characterizing CO and Nitrogen oxides sources in the Baltimore area. Kwok et al. [133] used CMAQ-ISAM to understand the $PM_{2.5}$ sources and their effects on the air quality. More details on the CMAQ-ISAM are available in [130], [133].

2) **Comprehensive Air quality Model with extensions (CAMx):** CAMx[16] is another famous air quality model in photochemical modeling. CAMx modeling system models the air quality with all criteria pollutants for a large scale (city, state, country, continent level). It takes emissions, meteorology data, land use, surface topography, initial and boundary conditions, and chemistry-related values as input and performs source attribution, sensitivity, and process analyses. Estes et al. [134] used CAMx to model the exceptional air quality events in near real-time in Taxes to estimate the ozone impact in three use cases (biomass burning in Mexico, stratospheric ozone intrusion, anthropogenic emissions in Mexico). Few critical resources where CAMx based modeling is used for air quality policymaking are available in [135], [136].
3) **Regional Modeling System for Aerosols and Deposition (REMSAD):** REMSAD[17] is another air quality modeling system that models the particulate, haze, and other criteria pollutants. It is a regional scale modeling system that can simulate the physical and the reactive processes in the environment to show the effects of the spatiotemporal changes in the air pollutant concentration on the overall ambient air quality.
4) **Urban Airshed Model Variable Grid (UAM-V):** In the early 1970s, the most commonly used air modeling system was UAM-V Photochemical Modeling System[18]. UAM-V was widely used for air quality studies focused on Ozone. It is a 3D photochemical grid model that can model the effects of the chemical and physical processes in the environment on the concentrations of air pollutants. UAM-V also provided a spatiotemporal distribution of the emissions of various air pollutants. UAM-V is outdated and no longer used for air quality modeling.

4.2.3 *Receptor modelling*

The third category of the air quality models is called receptor models. These models are mathematical techniques for recognizing and quantifying the origins of air pollution at a particular receptor location [137]. Receptor models are different from dispersion and photochemical air quality models. They do not require meteorological, chemical, and emission data to estimate the participation of the pollution sources in the air pollution concentrations at the receptor. The receptor model uses the chemical and inert properties of gases (SO_2, CO, etc.) and the particulate matter particles to determine to contributions of the emission sources in the pollution concentrations at the receptor [138], [139].

1) **Chemical Mass Balance (CMB):** The CMB [140] is a model for estimating the contribution of the emission sources to air pollution at the receptor locations. CMB uses spatial ambient data and information

15. https://github.com/USEPA/CMAQ
16. https://www.camx.com/
17. http://remsad.icfconsulting.com/
18. http://uamv.icfconsulting.com/

about the pollution sources to determine the source contributions. CMB quantifies the contributions at the receptor based on the distinct source types rather than individual emission sources. A drawback of CMB is its inability to distinguish between emission sources with the same chemical and physical properties. More details on the CMB are available in [140].

2) **Unmix:** Unmix[19] model uses a formula-based on a form of factor analysis to determine the chemical species in the air and their sources. It does not take the chemical profile of the pollution sources as input instead, it generates the chemical profile to estimate the number of pollution sources, their syntheses, and their participation in the air pollution at the receptor location.
3) **Positive Matrix Factorization (PMF):** PMF [141] is another air quality model which takes different features from sediments, wet deposition, surface water, ambient air, indoor air, etc., to identify the species of air pollutants. PMF also determines the contributions of the pollution sources at the receptor. The US EPA no longer updates PMF, and it no longer supports newer operating systems.

4.3 Air quality measuring sensors

The air quality sensors are the most crucial component of any air quality monitoring network. These sensors are used to determine the concentration of pollutants in the air. Typically, these sensors are built with a Lego connection for the data acquisition card, and data telemetry is accomplished using WiFi or cellular communication. In practice, data processing is done on the cloud rather than on the sensor, however there have been a few situations where data is preprocessed on the air quality sensors. Specifications of air quality sensors are broadly given by the following parameters:

1) **Accuracy:** This is a measure of how close the readings of sensors would be as compared to the actual pollutant value.
2) **Precision:** This is a measure of how well the sensor reproduces the same reading. A sensor with low precision can give different readings at different times with the same pollutant level.
3) **Range and detection limitations:** This is the measure of range of pollutant concentration that the sensor is able to detect correctly. Sensor performance may vary with different concentration of pollutant.
4) **Co-pollutant interference**: Cross interference from other pollutants also affect sensor readings. It is intended to minimize the co-pollutant interference when measuring a certain pollutant.
5) **Environmental interference:** Sensor performance may vary under different environmental conditions such as low and high temperature, humidity, sunlight etc.
6) **Noise:** Noise is the source of inaccuracy in sensor readings. The effect of noise should be minimized to produce more precise and accurate sensor readings.
7) **Signal drift:** This is the drift in readings which occurs due to inherent sensor measurement methods and degradation of sensor's components. Many air quality sensors suffer from signal drift. When selecting a sensor, it should be ensured that the drift can either be handled or it does not affect the readings to a significant level.
8) **Response time:** Different sensors can produce readings with different minimum time intervals. It should be ensured that the selected sensor is able to produce readings with acceptable time intervals.
9) **Multi-site measurement performance:** This is an indicator that generalizes the co-pollutant interference and the environmental interference of sensor.

4.3.1 Measurement Techniques

A summary of the types of sensors and measurement techniques has been show in figure 4

- **Particulate Matter:** Measurement of particulate matter concentration is broadly categorized in three methods: gravimetric, microbalance and optical measurements (Whalley et al. [142]). Gravimetric method is widely used by regulatory and certification authorities. It is based on weight difference of a filter medium before and after the gas is passed through the filter. Microbalance method uses the change in resonant frequency to measure the particulate matter concentration. By far the most popular choice for measurement commercial real-time particulate matter sensors is the optical method. Scattering or absorption of a light beam is measured to determine the concentration of particulate matter.
- **Gases:** The two major sensor types used for sensing gaseous pollutants are electrochemical sensor [143] and metal oxide sensors. Metal oxide sensors typically require more power to heat up to very high temperatures to enable significant sensitivity to target detection gas. That also increases the start up time of sensor. Electrochemical sensors require less power to operate and thus allow for fast startup time and cost savings generated over life time of sensor[20].

4.3.2 Sensing Solutions

- **OEM Sensors:** OEM sensors comprise of just the sensing element. Further interfacing and signal conditioning is required to convert the sensor output to meaningful numbers. These sensors are popular choice for original equipment manufacturers.
- **Sensing Systems:** Sensing systems are built upon the OEM sensors and the output is provided in digital format. Sensing systems are available for both indoor and outdoor air quality monitoring. Apart from digital output, many sensors are also available with extra features such as WiFi or cellular connectivity and mobile application to view the sensor outputs as well as the resulting air quality index. For many commercial and indoor air quality measurement

19. https://www.epa.gov/air-research/unmix-60-model-environmental-data-analyses

20. https://www.emerson.com/documents/automation/white-paper-electrochemical-vs-semiconductor-gas-detection-en-5351906.pdf

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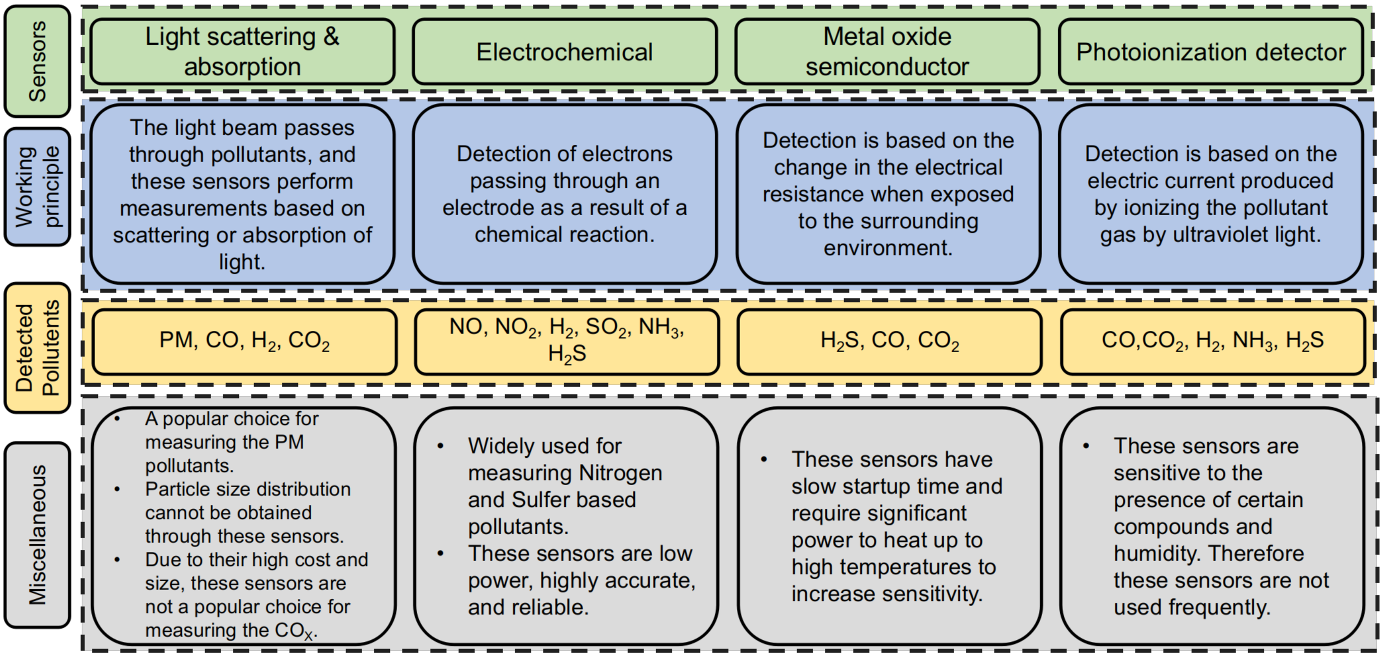

Figure 4: The figure shows a taxonomy of air quality sensors along with their working principle and detected pollutants.

systems, high accuracy is not required and thus are free from regulatory requirements. These systems are widely available in market and their price is usually below $5000. The data available through such sensors is not accurate and it can sometimes produce unknown errors. Weather conditions can also affect such sensing systems.
To mitigate all of the above problems and to provide a standard measurement system, the government defines a certain set of regulations to conform to for the measurement of air quality and pollutants. Detailed specifications of measurement and reporting of the concentration of pollutants is often provided by the country's environmental protection agency. In US, Environmental Protection Agency (EPA) provides Federal Reference Methods (FRM) and Federal Equivalence Methods (FEM) for measurement of pollutants. FRMs specify the most scientifically sound technique to report the concentration of pollutant and it becomes the basis of criteria for evaluation of other measurement methods. FEM provides techniques that are cost-effective and easier to implement and yet can provide comparable level of accuracy with the FEMs. Such systems are very expensive and their price can range up to $40000. They also highly trained technical staff for its operation and maintenance. Annual operating expenses may also exceed the system cost. On the other hand, the data provided through these systems is highly consistent and accurate in a variety of weather and environmental conditions [144].

Table 7: Air Quality Standards for the European Union

Pollutants	Concentration	Averaging Period	Permitted exceedences each year
$PM_{2.5}$	$25\mu g/m^3$	1 Year	N/A
SO_2	$350\mu g/m^3$	1 Hour	24
	$125\mu g/m^3$	24 Hour	3
NO_2	$200\mu g/m^3$	1 Hour	18
	$40\mu g/m^3$	24 Hour	N/A
PM_{10}	$50\mu g/m^3$	24 Hour	35
	$40\mu g/m^3$	1 Year	N/A
Lead (Pb)	$0.5\mu g/m^3$	1 Year	N/A
CO	$10mg/m^3$	8 Hours mean	N/A
Benzene	$5\mu g/m^3$	1 Year	N/A
O_3	$120\mu g/m^3$	8 Hour mean	25 days average over 3 years
Arsenic (As)	$6ng/m^3$	1 year	N/A
Cadmium (Cd)	$5ng/m^3$	1 Year	N/A
Nickel (Ni)	$20ng/m^3$	1 Year	N/A
Polycyclic Aromatic Hydrocarbons	$1ng/m^3$	1 Year	N/A

5 Air Quality Measurement Projects

5.1 Urban-Air

Urban Air is a Microsoft-funded initiative that began in 2012. It is a sub-project of Microsoft's Urban Computing [145], which intends to use big data (e.g., traffic flow, human mobility, and geographical data) to solve key urban issues such as pollution, transportation congestion, and energy consumption. The primary goal of Urban Air was to measure, analyze, forecast, and assist in the improvement of urban air quality in cities such as Beijing, China. In addition, Urban Air sought to discover relationships between various air quality trends to determine the sources of pollution in different urban locations.

The Urban Air project consists of four steps:

1) Inferring fine-grained air quality,
2) Forecasting air quality at each station,
3) Optimal deployment of air quality monitoring stations,
4) Root cause analysis of urban air pollution.

Following is a brief description of each step.

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Table 8: Air Quality Standards for the United States

Pollutant	Primary /Secondary	Averaging Time	Level	Form
Carbon Monoxide	Primary	8 hours	9 ppm	Not to be exceeded more than once per year
		1 hour	35 ppm	
Lead	Primary and Secondary	Rolling 3 month average	0.15 $\mu g/m^3$	Not to be exceeded
Nitrogen Dioxide	Primary	1 hour	100 ppb	98th percentile of 1 hour daily maximum concentrations averaged over 3 years
	Primary and Secondary	1 year	53 ppb	Annual mean
Ozone	Primary and Secondary	8 hours	0.07 ppm	Annual 4th highest daily maximum 8-hour concentration averaged over 3 years
PM2.5	Primary	1 year	12 $\mu g/m^3$	Annual mean, averaged over 3 years
	Secondary	1 year	15 $\mu g/m^3$	Annual mean averaged over 3 years
	Primary and Secondary	24 hours	35 $\mu g/m^3$	98th percentile averaged over 3 years
PM10	Primary and Secondary	24 hours	150 $\mu g/m^3$	Not to be exceed more than once per year on an average of 3 years
Sulphur Dioxide	Primary	1 hour	75 ppb	99th percentile of 1 hour daily maximum concentrations averaged over 3 years
	Secondary	3 hours	0.5 ppm	Not to be exceeded more than once per year

5.1.1 Inferring fine-grained air quality

As a first step, the Urban Air Project sought to infer air quality in areas where air quality stations were not available [146]. It is a difficult undertaking since accessible Air Quality data is sparse and limited. To tackle this challenge, Zheng et al. [146] gathered context data from a range of additional sources (meteorology, road networks, traffic flow, PoI, and human mobility) that have an indirect impact on air quality. After acquiring the context data, it is fused with sparse AQI data from known locations. Then spatial and temporal classifiers are used for inferring the AQI values at unknown places. The **Spatial classifier** is an Artificial Neural Network (ANN) that takes a subset of data and tries predicting AQI for unknown nodes by using Pearson Correlation of known features between nodes. The **Temporal classifier** takes the time-dependent factors and tries predicting AQI for unknown nodes using a linear-chain Conditional Random Field (CRF). The training is performed by iteratively adding unknown nodes to the set of known nodes that are classified confidently by the model(s). For inferring AQI value at some unknown location/grid, features are applied to each classifier independently. Only those AQI values are reported where both classifiers have higher confidence. Results of the experiment are compared with different interpolation techniques like Linear, Gaussian, Classical Dispersion Model, Decision tree, CRF, and ANN. The initial step of Urban Air only inferred PM_{10} and NO_2 values for Beijing and Shanghai. In subsequent work, Zheng et al. [147] combined the spatiotemporal model with a real-time feature extraction database to make user-friendly web and mobile applications.

5.1.2 Forecasting air quality at each station

Following the successful inference of AQI values at arbitrary sites, the next phase in the Urban Air project was to forecast AQI values at specific station locations [148]. Forecasting AQI values is critical because it allows policymakers to better understand air pollution trends and develop preventative and mitigation policies. The method of estimating the next AQI value at a certain time granularity based on prior AQI values is known as AQI forecasting. Various connected aspects, such as meteorology, wind speeds, temperature, and so on, might have an impact on the forecasting process. Therefore, a real-time database is utilized to give meteorological data (humidity, temperature, and wind speed) as well as weather forecasts and AQI values for each station site.

The forecasting component of the Urban Air project gathers data from 2,296 stations in 302 Chinese cities, with each instance having concentrations of six air pollutants: NO_2, SO_2, O_3, CO, $PM_{2.5}$, and PM_{10}. Zheng et al. [148] employed the four predictors listed below to forecast the AQI value at a station.

- A temporal predictor is used to anticipate the AQI value using a linear regression model on the data.
- A spatial predictor is used to provide the surrounding context to a neural network, which forecasts an AQI value based on the context data.
- A prediction aggregator trains a regression tree to give various weights to the first two predictions under different scenarios.
- Finally, an inflection predictor is employed to simulate any rapid changes in AQI values and is only utilized in exceptional cases (rain, etc.).

For the first 1-6 hours, the AQI value after each hour is predicted, while for the next 7-12h, 13-24h, and 25-48h, a min-max range of AQI is forecasted. Zheng et al. [148] performed forecasting for 36 Air Quality Stations in Beijing and compared their results with techniques like Auto-Regression-Moving-Average (AMRA), linear regression (LR-ALL), neural network (ANN-ALL), and regression tree (RT-ALL).

5.1.3 Deployment of air quality monitoring stations

The placement of air quality sensors in suitable places is critical for obtaining relevant air quality data. Hsieh et al. [74] solve the sensor placement problem with a restricted budget in the Urban Air project. Hsieh et al. [74] used a two-stage technique to handle this problem. The first phase is to infer the air quality at an unknown place, and the second is to pick candidate locations depending on the confidence of the inference. The city of Beijing has split into 1km x 1km patches for inference, with each patch referred to as a node. By linking these nodes with known and unknown AQI values, a network is formed. Some of the linkages are made with the help of historical, geographical, and environmental factors. Local meteorology, road network data, and PoIs are used to provide weight to edges. Once the graph is complete, an unknown AQI value is calculated using a weighted sum of AQI values from known modes. Instead of only obtaining a single value for AQI, a distribution is learnt at each unknown node. The weights of the graph are modified over numerous rounds to get a better distribution (minimize entropy loss).

For recommending the locations of the station, first find the node with the best distribution (or lower entropy loss) and rank it the last in the list. After assigning a rank to this node, label it as a known node and again run the inferring algorithm to find new inference. After this, find the node with the best distribution and assign it second last. This step is repeated until all nodes are ranked.

5.1.4 Identification of root cause of air pollution

The placement of air quality stations is motivated by the need to identify the root causes of air pollution. Urban Air also seeks to identify the underlying causes of urban air

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pollution. Understanding the root cause of air pollution is extremely beneficial to policymakers in government and environmental protection agencies. Because data collection involves noise, collecting insights for establishing the root cause of air pollution becomes a difficult job. Zhang et al. [149] and Nguyen et al. [150] integrated historical data with Bayesian learning approaches [151], [152] to uncover air pollution causal pathways. Data used in [149], [150] includes measurements of six air pollutants: $PM_{2.5}$, PM_{10}, NO_2, CO, O_3, SO_2, and five meteorological measurements: temperature, pressure, humidity, wind speed, and wind direction, which are updated hourly, for three areas: North China, Yangtze River Delta, and Pearl River Delta. Understanding the root cause of air pollution is based on pattern mining and Bayesian learning. The initial stage in pattern mining is to locate Frequently Evolving Patterns (FEP). It is accomplished by first identifying patterns that happen often at the station and then applying a projection to them, as done by PrefixScan [153]. Then FEPs of neighboring stations are compared, and possible causative agents for each sensor/station are retrieved. The pattern mining module decreases the number of variables, which aids in decreasing computation cost for the next stage in learning the BN structure ($2^{O(n^2)}$ in the worst-case scenario).

The Bayesian learning module of the root cause identification pipeline combines the concentration measurements of each pollutant at the target node with the spatial data from candidate causers at the multiple time stamps. Following data integration, initial routes for the "N" most significant sensor for the target location/station are created. Each of these paths is then assigned a Granger-causality (GC) score [154], [155]. Once the score is assigned to the pathways, the context data is integrated with pathways. Zhang et al. [149] determine the number of sub-classes using a "hidden confounding variable," and then repeatedly optimize the initial paths by reducing EM loss.

The Urban Air project was a great success as it helped in reducing air pollution in China. Based on the insights from this project, the environmental protection agencies and the Chines government have taken policy-level steps, and the air pollution in China is under control.

5.2 AQLI project

The Air Quality Life Index (AQLI) is another famous air quality measurement project by the Energy Policy Institute at the University of Chicago (EPIC). AQLI project introduced a new metric for measuring the impact of air quality called air quality life expectancy. Instead of the conventional AQI metric, this new metric translates the impact of air pollution on the life expectancy of a human being.

The AQLI work is based on the $PM_{2.5}$ data collected via satellite monitoring combined with the global population data obtained from the 2018 Global LandScan Global Population Database [156]. The AQLI index is an extension of the previous work done by Greenstone et al. in understanding and quantifying the impact of particulate air pollution on the expectancy of human life [157]. Once both datasets are collected, a grid-cell-based procedure is used for combining global population data with the satellite-driven $PM_{2.5}$ data. Loss in life expectancy is calculated for each grid, where each grid corresponds to a 6km x 6km area on the ground. The loss in life expectancy due to $PM_{2.5}$ is computed based on the previous work by Ebenstein et al. [157] which shows that with every $10\mu g/m^3$ of sustained exposure to PM2.5, life expectancy decreases by 0.98 years. Assuming that life expectancy varies linearly with PM2.5 exposure, the loss in life expectancy is multiplied by 0.98 for each incremental exposure to $10\mu g/m3$ of PM2.5 beyond the WHO threshold level ($10\mu g/m^3$ of PM2.5).

The AQLI project has resulted in AQLI Index[21] which provides a country-level loss in life expectancy based on the $PM_{2.5}$ concentrations. This project provides a thorough analysis of the air pollution situation in many countries and also covers the policy level steps taken by different countries (e.g., China, India) for mitigating the impact of air pollution on the life expectancy of their citizens. Though this project only covers the impact of $PM_{2.5}$, the insights, and policy level suggestions provided in the AQLI reports can help improve the air quality of any part of the world. This project is also an excellent example of how to set up an air quality indexing study for other criteria pollutants.

5.3 AfriqAir

Air pollution is a major problem in Africa, with research indicating that air pollution causes around 800,000 premature deaths every year [158]. Unfortunately, there aren't many reference-grade air quality monitoring stations in Africa, therefore it is difficult to interpolate the actual situation of the air pollution. The AfriqAir project tries to tackle this issue by developing a continent-scale air quality monitoring network. AfriqAir is an African air quality monitoring initiative [159]. The initiative employs a network of both high-quality and low-cost air quality sensors. By mid-2020, there are approximately 50 nodes spread throughout 11 African nations (Ghana, Rwanda, Uganda, Kenya, South Africa, Democratic republic of Congo, Cote dI'voire, Niger, Congo, etc.). AfriqAir has the following three goals for improving the air quality situation in Africa:

1) Creating the physical infrastructure required to measure and monitor air quality across the continent. It entails a mix of high-quality and low-cost air quality assessment equipment, as well as the necessary power sources and data telemetry systems.
2) Local capacity building to use, manage and analyze the developed physical infrastructure.
3) Finally, ensure that the physical infrastructure's data and insights are accessible and actionable.

The data gathered through these 50 measurement platforms across Africa is open-sourced in daily, hourly, and 15-minute granularity and can be readily used for air quality research[22].

5.4 Ghana Urban Air Quality Project (GHAir)

Urban Air and AQLI projects are being carried out on a global scale, using cutting-edge technology and techniques for planning, modeling, monitoring, and extracting insights. Many underdeveloped countries with limited resources do

21. https://aqli.epic.uchicago.edu/the-index/
22. http://www.afriqair.org/

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not have this opportunity. With the Ghana Urban Air Quality Initiative (GHAir), we hope to show the reader how a relatively impoverished nation may set up an air quality monitoring project.

Ghana is West Africa's second-most populated country, behind Nigeria. Ghana is dealing with severe pollution problems, and it is reported, that air pollution killed over 28,000 people in 2018 [160]. In 2019, Ghana started the GHAir project to solve the problem through cutting-edge research. The environmental protection agency of Ghana has limited resources and proper technical human resources. To solve these issues, GHAir uses low-cost air quality sensors to bridge the data gap. Various studies have highlighted that low-cost sensors might be a great chance to overcome the air pollution data gap in underdeveloped countries [143], [161]–[164].

GHAir has the following four objectives that are also in line with the UNSDGs [165]:

1) Creating a dense low-cost air quality sensor network in metropolitan areas to collect real-time spatiotemporal air quality data that may be used to impact air pollution management policy.
2) Launching public awareness campaigns about the effects of urban air pollution and how residents may safeguard their health in areas with poor air quality.
3) Improving the air quality by introducing behavioral changes in the communities.
4) Performing epidemiological research to highlight the health issues of air pollution exposure in vulnerable populations for the public health department.

The GHAir presently employs a mix of low-cost PurpleAir sensors, Clarity nodes, RAMPs, and Modulair-PM sensors. These sensors have been installed in six of Ghana's major cities (Accra, Tema, Cape Coast, Takoradi, and Kumasi). GHAir has also just placed ten sets of TEOM 1400ab PM monitoring sensors provided by the UK Environmental Agency (Automatic Urban and Rural Network) [165]. The GHAir presently employs a mix of low-cost PurpleAir sensors, Clarity nodes, RAMPs, and Modulair-PM sensors. These sensors have been installed in six of Ghana's major cities (Accra, Tema, Cape Coast, Takoradi, and Kumasi). GHAir has also just placed ten sets of TEOM 1400ab PM monitoring sensors provided by the UK Environmental Agency (Automatic Urban and Rural Network) [165]. GHAir project is also going to launch a program called E-SCRAP (Educating School ChildRen to tackle Air Pollution) project with the help of the Royal Society. The project's goal is to create awareness among schoolchildren about air quality and how they may help to improve it. The motto of the project is "School children as agents for improved air quality".

They are now experiencing several difficulties in getting data from sensors. These concerns include the availability of WiFi at deployment sites for data telemetry and sensor power supply. To address these issues, GHAir is experimenting with solar energy to power the sensors [165]. Furthermore, they are attempting to leverage GPRS for data telemetry. Despite these challenges, the GHAir project has enormous potential for bridging Ghana's data gap on air quality.

5.5 Hazewatch

PM2.5 concentrations above WHO standards have been found in New South Wales, Australia, particularly in Sydney. The Department of Environment, Climate Change, and Water (DECCW) has already placed 15 stations in various sites across Sydney, and data is published hourly. AQI levels and corresponding health advisories are provided based on this pollution data. Unfortunately, these stations are separated by tens of kilometers, resulting in inadequate spatial resolution. Because of the low spatial resolution, complicated interpolation procedures are needed to report AQI values. As a result, the DECCW AQI monitoring network does not represent actual levels of air pollution and exposure. To overcome these shortcomings, Sivaraman et al. [87] designed a low-cost urban air quality monitoring system known as *HazeWatch*. HazeWatch utilizes many low-cost mobile sensor units installed in cars to measure air pollution concentrations, as well as users' mobile phones to tag and upload data in real-time. The outcome of the projects is its cost-effectiveness, better spatial resolution, and personalized exposure tools. The project measured NO_2, CO, and O_3. Though HazeWatch filled the gap in spatial resolution, it has faced multiple challenges in calibration, sensor design, mass deployment, health outcome interpretation, etc. The project has resulted in multiple research publications on designing pollution monitoring sensors [166]–[168], data transmission [169], [170], database connectivity [171], android interface design [172], pollution modeling [87], data visualization [173], and exposure modeling [174].

5.6 CITI-SENSE

Developing a country-wide air quality network based on reference-grade, near-reference, and low-cost air quality monitoring sensing solutions for each pollutant is a complicated endeavor. It requires a lot of money, infrastructure, and technical expertise; thus environmental governance through citizen empowerment is gaining traction. The purpose of these programs is to encourage individuals in deploying low-cost, sometimes near-reference-grade monitoring equipment and share air quality data. The integration of data from residents and reference-grade sensing equipment can assist in obtaining a more granular picture of air quality, resulting in more effective air quality improvement measures. The European Commission has financed "CITI-SENSE"[23] (2012-2016), a project that uses cutting-edge Earth observation technology to build and test environmental monitoring systems. The project's goal was to create citizen observatories that would allow residents to gather and monitor environmental data in order to formulate community policies. The CITI-SENSE project produced a number of air quality sensor devices, as well as mobile and other communication technologies. The key contributions of the CITI-SENSE project were:

- Studying and mitigating hurdles in the citizens' involvement in environmental decision making.
- Designing the tools and technologies to enable the citizens in collecting urban environmental data.
- Providing low-cost measuring solutions and data fusion methods for scientific analysis.

23. https://cordis.europa.eu/project/id/308524

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- Integrating newer sensing technologies (IoT and other ICT technologies), cloud platforms, data analysis, and learning techniques to enhance community participation in the form of personal environmental monitoring devices.

The CITI SENSE initiative distributed 324 air quality monitoring units around Europe, and 400 volunteers helped test the personal air quality monitoring devices. A total of 24 citizen observatories were also developed in nine major cities of Europe (Barcelona, Belgrade, Edinburgh, Haifa, Ljubljana, Oslo, Ostrava, Vienna, and Vitoria-Gasteiz). An air perception application was also a critical part of the project, and 1200 people used it to report and get air quality information. In 2015-2016, nearly 9.4 million environmental observations were collected using the CITI-SENSE sensor network and other additional observation tools. Further involvement of the citizens was ensured by feedback surveys, questionnaires, focus group discussions, and interviews. The CITI-SENSE initiative resulted in environmental monitoring systems across Europe as well as citizen engagement in environmental governance. The insights from the CITI-SENSE project has resulted in many research publications dealing with low-cost air quality sensing and performance assessments [81], [175]–[178], pollution hotspot detection [179]–[181], data assimilation [175], [182], missing data imputation methods [183], epidemiology studies [184], air quality sensor calibrations [175], [185]–[189], localized real-time pollution effects [177], [180], [181], [190], zero emission studies [191], wireless and distribution network design suggestions for air quality networks [192], pollution exposure assessment [81], [180], end-user feedback [180], [193], [194], toolkits for monitoring urban air quality [195], and new citizen observatory design [196].

5.7 OpenSense II

Generating a comprehensive spatiotemporal map of air pollution requires a lot of data from multiple sources. Only reference-grade air quality data is not enough as they are very expensive and there can be a few reference-grade air quality monitors in a city. OpenSense II aims to integrate data from heterogeneous devices and crowdsourcing with reference grade measurements to generate a spatiotemporal map of urban air pollution and estimate the health impacts due to air pollution exposure. OpenSense II project generates granular air pollution maps of Zurich and Lausanne and also studies the impact of air pollution exposure on human health. OpenSense II uses data (air pollution data, communication platforms, sensors, personalized health recommendations, etc.) from another project known as "Nano-Tera project OpenSense". The data from the Nano-Tera project is combined with crowdsourcing and human-centric computation techniques for high-resolution air pollution maps. The air quality data is also gathered by deploying sensing systems on buses and electric cars. OpenSense II also pushed the state-of-the-art in generating high-resolution spatiotemporal air quality maps [**?**], [197], [198], mobile sensor networks for air quality monitoring [199], [200], and estimating the impact of PM_x on human health and personalized health recommendations [201].

5.8 Root cause analysis of the urban air pollution

The efforts put into designing, modeling, measuring, and developing cutting-edge air quality measurement facilities are only to understand the root cause of urban air pollution and how it affects human health and the global temperature. Many studies have been conducted using air quality data acquired from air quality networks to identify the causes/contributors of air pollution. Karagulian et al. [202] performed a systematic analysis on the air quality data of 51 countries from the WHO website and highlighted the major sources of air pollution. According to their study of available data, traffic emissions contribute 25% of air pollution (PM2.5), industrial activities contribute 15%, domestic fuel burning contributes 20%, natural dust and salt contribute 18%, and unidentified causes linked to humans contribute 22% [202]. Jiang et al. [203] investigated the spatiotemporal features of air pollution in six Chinese cities and applied the Granger causality test [204] to evaluate the impact of a city's air quality on surrounding cities and vice versa. According to their study, air pollution is very high in the winters and early springs and stays low in summer and autumn. They also discovered a unidirectional association between the air quality of Baoding and Beijing, where the air pollution from Baoding has a significant impact on Beijing's air quality (since Baoding is more polluted than Beijing) [203].

Wang et al. [205] found that particulate matter from transportation, industry, agricultural activities, fuel burning, construction, and demolition accounts for 85 to 90% of overall air pollution in China. Wang et al. [205] also discovered that the 2013 extended Haze event in central-eastern China was caused by a shift in meteorological conditions. [205] employed synthetic atmospheric circulation to determine the sources of air pollution. Traffic emissions and high levels of energy consumption are identified as contributors to the Haze and poor air quality in central-eastern China [205]. Recently there has been a surge in data-driven root cause analysis techniques [206]–[209]. These techniques are motivated by the success of big data and artificial intelligence (AI) in many other domains. For detecting and comprehending the root cause of urban air pollution, we advocate a combination of traditional modeling/causal methodologies with cutting-edge AI techniques.

6 Urban Air Quality: Challenges

Despite a plethora of work in measuring and understanding air quality, there are various challenging aspects in tracking and measuring air quality. In this section, we take a look at the challenges needed to be addressed for rapid improvement in ambient and indoor air pollution.

6.1 Data collection and public datasets

Collecting the air quality data is a challenging task as it involves different concentrations of air pollutants. Given the environmental cost and health risks of poor urban air quality, it is imperative to develop a central real-time air quality data measurement and processing system. Two paradigms for gathering urban data (i.e., air quality data, POI, meteorological data, etc.) are sensor-centric data collection and crowd-centric data collection. The sensor-centric paradigm has two categories. These categories are based on whether the data collecting sensors are mobile (deployed on a moving object) or static (deployed on a fixed location). The crowd-centric data collection is also divided into two categories; active(data generated via participatory surveys and check-ins) or passive (data generated by users passively while using the urban infrastructure).

Gathering air quality and related data via these two paradigms is difficult because of the following challenges:

- In static sensor-centric air quality data collection, sensors are deployed at a fixed location, and they communicate at a predefined frequency to the central database (i.e., cloud server). This static sensor deployment makes the air quality measurement a resource constraint system (limited budget, land use, workforce for maintaining the system, etc.). As a result, data gathered from very few sensors fixed at different locations in an urban environment is sparse and not sufficient representative of the air quality situation of the city.
- In static sensor-centric air quality data collection where the number of sensors is limited, the optimal placement of the air quality sensors for gathering representative enough data becomes a challenge.
- Though mobile sensor-centric data collection help resolve the issues faced in air quality data gathering due to the fixed nature of the static sensor-centric approach, it has its challenges. The air quality data gathered from the sensors mounted on moving objects such as buses, bikes, taxis, UAVs, etc., is skewed by the movement of these moving objects. For example, buses are usually used as a means of the commute from a busy fixed route, the gathered data will provide a good representation of the air quality along the bus's route but it will not provide a true depiction of urban air quality.
- Another challenge in mobile sensor-centric air quality data is the redundancy in the collected data. Since the sensors-mounted vehicle will be following a route (especially buses), the data collected will be redundant, and the data from less traversed routes will be sparse. It will result in an imbalanced data distribution. Any deduction made from the distribution will be biased towards the most frequent route.
- Human as a sensor is another way of getting the data for inferring the air quality. Data generated by the citizens passively while accessing the urban infrastructure (call data record, public Wifi, passenger bus card swipes, taxi pick and drop locations, etc.) is useful in determining the context of urban pollution. Here the key challenges are the privacy of the users, the security of the service providers, and meeting the legal requirements of data protection.
- Participatory crowdsensing is a procedure opted for gathering the context data used for inferring the urban air quality where the measurement campaigns and surveys are used to collect the data. imbalance data coverage, unavailability of ground truth to measure the quality of the collected air quality data, and noisy and fake data reporting are a few challenges associated with the participatory crowdsensing for air quality-related data.

To overcome these challenges in air quality data collection along with its proper context requires a great deal of planning and understanding of the urban environment. Selecting the right kind of sensors, an acceptable level of measurement granularity, designing a proper measurement campaign, choosing the appropriate cloud/database, and ensuring the quality of the collected air pollution data and the motivation to make it public can help develop a comprehensive air quality dataset for determining the correct air quality values. Nevertheless, a hybrid approach combining sensor-centric, expert-in-the-loop data collection techniques can yield better air quality data collection.

6.2 Air quality monitoring networks in underdeveloped countries

The air quality situation in underdeveloped nations is dire, yet they are unable to address it due to a lack of air quality monitoring networks. Deploying these networks across the country necessitates large sums of money and planning that in many underdeveloped countries is not available. Without an adequate and extensive air quality monitoring network in place, economically developing nations are unable to gather air quality data and, as a result, lack policies for monitoring and combating air pollution trends. Low-cost air quality monitoring stations are used instead of actual weather stations and deployed in a few countries. Developing a country-wide low-cost air quality sensors-based network remains a very challenging task.

6.3 Trade-off between economic growth and air pollution

The trade-off between economic growth and air pollution implies that economic expansion is connected to industrialization and transportation, which necessitates the combustion of gasoline and other energy sources, resulting in air pollution. Finding the right balance between economic growth and air pollution is a daunting task for many countries. Other variables such as population, urban density, and urban planning exacerbate the difficulty of this task.

6.4 Regularization and air quality measurements

Even though there are several environmental regulatory bodies and a plethora of regulatory rules but we continue to see that air quality in urban areas is becoming a predicament. The implementation of these standards is an issue that many governments are unable to address for a variety of reasons, including a lack of education, financial resources, political and religious divisions, lack of global and regional cooperation, and so on [210].

6.5 Urban planning and air quality

Urban planning plays a vital role in improving the air quality of the city. Unfortunately, many metropolitans around the world are suffering from the worst air quality due to exponential growth in population, traffic congestions, high built densities, and lack of urban planning. Canyon street (the

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street design in which both sides of the roadway are bordered by buildings) has a poor dispersion rate, thus vehicle exhaust remains in greater quantities than usual, producing severe health issues and air pollution. Avoiding canyon street design in urban planning might help to reduce urban air pollution. Reducing urban air pollution from traffic is strongly linked to initiatives for encouraging active commuting (travel by low energy-consuming vehicles) and lowering carbon emissions. Urban planning and its relationship with different urban environmental concerns is an area in which much ingenuity is required.

6.6 Personalized context-aware air quality measurement applications

Designing context-aware air quality monitoring systems are gaining traction. Air quality is heavily reliant on several context factors (PoIs, meteorology, etc.), and interpreting air quality measurements without taking the context into account might create bias in the measurements. People with respiratory or ocular diseases are especially sensitive to air pollution and should be warned about it. The AQI measurements are insufficient for these patients. It is very challenging to develop context-aware custom-made air quality monitoring applications. A few emerging applications use the Internet of Things (IoT) and tailored context to deliver customized warnings on the severity of air pollution in a specific city location [29], [211]–[217].

6.7 Impact of climate change on the air quality

Climate change has started causing many problems in different parts of the world. Climate change can influence the local air quality and vice versa. An increase in the ground-level O_3 is observed as the atmosphere gets warmer due to climate change, and this ground-level O_3 is expected to cause dense smogs in urban areas. The jury is out on the effectiveness of climate change on particulate matter-based air pollution [24].

6.8 Indoor air pollution

Air quality within the buildings (houses, schools, shopping malls, airports, etc.) concerning the health of the people health is termed as indoor air quality (IAQ). It is described in the literature that the IAQ in homes is 2 to 5 times more polluted than the ambient air pollution [218]. CO, microbiological contamination owing to moisture, insufficient ventilation, fuel burning, incorrect building design, and commonly used construction materials are a few of the causes of increased indoor air pollution levels. Long-term (respiratory disorders, cancer, heart disease) and short-term (ENT irritations, headaches, tiredness, nausea) health problems can be caused by poor IAQ. People have been staying indoors for the last two years as a result of the Covid-19 restriction, and indoor air pollution in homes [219], [220], and hospitals has skyrocketed [221]. With this exceptional circumstance, IAQ improvement is both vital and challenging [222].

24. https://www.epa.gov/air-research/air-quality-and-climate-change-research

7 Conclusions

The urban air quality is turning out to be daunting health and economic challenge for the metropolitan centers around the globe. The lack of measuring infrastructure is making this situation even harder. This paper provides a non-exhaustive yet comprehensive survey of the urban air quality measuring methodologies, standards, and initiatives operating throughout the globe. We have also emphasized the challenges restricting the urban air quality measurement. We also invite the readers to ponder upon these challenges and offer suggestions for better air quality in our cities.

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