International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 22s, 2025
https://theaspd.com/index.php

A Review: Identifying and Analyzing Air Pollution Hotspots Using Machine Learning and Remote Sensing Techniques

Adamu Muhammad Kamaludeen[1*], Izham Mohamad Yusoff[2], Suleiman Yusuf[3]
[1*]School of Distance Education'', Universiti Sains Malaysia, 11800 USM Penang, MALAYSIA.
[2'']Geography Section, School of Distance Education'', Universiti Sains Malaysia, 11800 USM Penang, MALAYSIA.
[3]Department of Zoology, Faculty of Natural and Applied Sciences Nasarawa State, University Keffi.
[1]mkamaludeen@student.usm.my, [2]izham@usm.my, [3]ysulaiman31@gmail.*com*
Corresponding author*: Izham Mohamad Yusoff*
Email: izham@usm.my

Abstract
Air pollution has drawn significant scholarly attention over the past two decades due to its widespread environmental and health impacts. It refers to the presence of harmful substances in the atmosphere that degrade air quality and negatively affect the physical environment and human health. This literature review aims to identify the sources and hotspots of air pollution, examine its spatial and temporal patterns, evaluate control mechanisms, and predict future air quality scenarios. The review draws on a range of literature sourced online and organized around these objectives. Findings confirm that air pollution is a critical global issue, originating from both natural and anthropogenic sources such as fossil fuel combustion, industrial emissions, vehicular exhaust, household pollutants, and agricultural activities. These sources significantly degrade air quality and contribute to respiratory and cardiovascular diseases in humans. Globally, air pollution ranks as the fourth highest health risk, accounting for an estimated 6.7 million deaths annually. Even at low levels, pollutants cause lasting damage to ecosystems. Air pollutants are typically categorized into primary and secondary types: primary pollutants are emitted directly from sources, while secondary pollutants are formed through atmospheric chemical reactions. The methodological approach of this study includes the identification of air pollution hotspots and the analysis of spatial and temporal trends. Additionally, the study evaluates the effectiveness of current mitigation strategies. The reviewed literature underscores the urgent need for effective control measures and continued monitoring to mitigate the growing threat of air pollution.
Keywords: *Sources of Air Pollution, Hotspots, Patterns, Trends of Air Pollutants, Effectiveness, Control Strategies and Predicting, and Air Quality Scenarios.*

1. INTRODUCTION

For the purpose of this study, air pollution has been conceptualized to denote an undesirable environmental condition caused by the presence and concentration of harmful particles alternatively known as pollutants in the air. These pollutants, which are of different types are generally harmful; not just to man, but also all organisms in the ecosystem. The release of the particles by vehicles, industries or biomass energy sources and its high concentration in any given place at a time causes a condition known as air pollution. Several studies have proven that the condition of air pollution is detrimental to the growth and thriving of living things which depend on the physical environment for their survival as it affects the quality of air and water. A persistent presence of pollutants in the air may affect the life of animals and plants.

Recent technological inventions and innovations have generally resulted in continuous development of the economy; reflecting in improvement in people's living standards. Due to inventions (which are found in all spheres of human endeavors) and increasing technological dependency, the quality of life has been improved leading to an increase in human population and the proliferation of urban centers. These developments and advancements inevitably escalate and lead to the demand for energy and other resources which in the long run lead to the risk of environmental pollution problems due to the atmospheric presence of the harmful particles or pollutants. The phenomenon of air pollution is more prevalent in urban centers than in rural areas (Chen et al., 2023). To elucidate further, areas with high population; especially unplanned settlements are more vulnerable to air pollution. Several researches have proven that such areas may experience pollution due to the concentrations rates of air pollutants which is in turn caused by the high population and the population density as such areas are mostly congested (Li et al., 2018). Studies have demonstrated that even insignificant quantity of the pollutants are capable of causing adverse impact to the physical environment regardless of the continent or region (Li et al., 2018). Realizing the severity of the challenge of air pollution, stakeholders have devised strategies and laws to tackle identified sources of pollutants and discover ways of mitigating the effect of air pollution. In order to mitigate and curtail the implications of air pollution, evaluating and enhancing air quality must thus be

prioritized. The quantum of extant literature and researches on the subject of air pollution globally provide great insight in the attempt to understand the phenomenon (Luo et al., 2022).
In the year 2022, a United Nations (UN) declaration pronounced that every human being has a right to a clean environment, including the right to clean air and water regardless of their country or nationality (UN Environmental Programme). This landmark resolution highlights how our lives and health are inextricably linked to our environments, which have the potential to promote health or cause harm. The death of Ella Adoo Kissi Debrah, aged 9 years, who died of air pollution triggered asthma complications in London, 2013 is one of the most contemporary examples of the nexus between humans and their environments (Ella Roberta Foundation). This assertion was indeed proven by the Coroner's report on Ella's cause of death which unprecedentedly listed air pollution as an official cause of death and recommended actions be taken to reduce air pollution to prevent avoidable deaths (London Inner South Coroner's 2020). An estimated 6.7 million deaths are caused by air pollution annually prematurely around the world due to ambient air pollution, mostly from heart disease, stroke, chronic obstructive pulmonary disease, lung cancer, and acute respiratory infections in children amongst others (Global Burden Disease 2019), 213 million disability-adjusted life years are attributed to air pollution exposure, or that air pollution is the fourth highest risk to health disaster globally (The Institute for Health Metrics and Evaluation 2023).
Air pollution originates from numerous sources of emission, both natural and anthropogenic, with the latter becoming globally dominant since the beginning of industrialization. The process of combustion is the greatest contributor to air pollution, in particular, combustion of fossil fuels and biomass to generate energy. Outdoor combustion sources include ground, air, and water transport; industry and power generation; and biomass burning, which includes controlled and uncontrolled forest and savannah fires and agricultural waste burning as well as waste burning in urban areas. Other sources and processes contributing to outdoor pollution are re-suspension of surface dust and construction activities. Long-range atmospheric transport of pollutants from distant sources contributes to local pollution, particularly urban air pollution (WHO, 2021).
Source apportionment studies assist in identifying the main sources contributing to air pollution, in view of identifying efficient strategies to reduce the pollution in the area of interest (e.g. country, district, and city). Some of the air pollution sources may be obvious, or can be assessed through other means (such as estimation of emissions). While local sources contribute to air pollution, sources located further away (even hundreds of kilometers, or transboundary) are important contributors as well. A database on source apportionment studies for airborne PM is available, and a global review provides an overview (Hopke et al., 2020). Main sources of $PM_{2.5}$ have also been estimated through modelling (McDuffie et al., 2021). Hence, the focus of this literature review research in identify Sources of air pollution, its hotspots, analyze the patterns and trends of air pollutants, evaluate effectiveness of air pollution emission control strategies and predicting of future air quality scenarios
Spatial variations in air pollutant concentrations are driven by a combination of natural and anthropogenic factors. Urban and industrial areas typically exhibit higher levels of NO2, SO2, and PM due to traffic emissions, industrial activities, and combustion processes (Liu et al., 2023). Rural areas, on the other hand, often experience higher ozone levels due to precursor transport and lower NOx titration effects (Zhang et al., 2022). Studies have also highlighted regional disparities in air pollution levels, with developing countries facing more severe air quality issues due to rapid urbanization and weaker emission control policies (Gupta et al., 2021). Spatial heterogeneity is also influenced by topography, land use patterns, and climatic factors. Mountainous regions, for instance, can experience pollutant accumulation in valley areas due to temperature inversions, while coastal regions may benefit from sea breezes that disperse pollutants. Additionally, land cover changes, such as deforestation and urban expansion, alter pollutant dispersion and deposition patterns (Brown et al., 2023).
Air pollution levels fluctuate over different time scales, including diurnal, seasonal, and long-term trends. Diurnal variations are primarily influenced by traffic patterns and atmospheric mixing heights, with peak NO2 and CO concentrations observed during morning and evening rush hours (Wang et al., 2023). Seasonal variations are often driven by meteorological conditions, with higher PM concentrations in winter due to stable atmospheric conditions and increased biomass burning (Huang et al., 2022). Long-term trends indicate a decline in certain pollutants in regions implementing stringent air quality regulations, while others, such as ground-level ozone, have shown an increasing trend due to climate change and rising precursor emissions (Chen & Lee, 2023). Extreme events such as wildfires, dust storms, and volcanic eruptions also contribute to sudden and severe air pollution episodes, disrupting typical temporal trends. For example, the Australian wildfires in 2019-2020 led to a significant increase in PM2.5 levels across the region, impacting air quality for weeks (Smith et al., 2023).

Similarly, transboundary pollution from agricultural burning affects seasonal air quality trends in Southeast Asia (Tan et al., 2023).

Meteorological conditions play a crucial role in modulating air pollutant concentrations and dispersion. Wind speed and direction influence pollutant transport, while temperature and solar radiation affect photochemical reactions leading to ozone formation (Xu et al., 2023). Humidity and precipitation contribute to wet deposition processes, reducing particulate matter concentrations (Singh et al., 2022). Studies utilizing machine learning and numerical modelling have improved the understanding of these meteorological interactions, enabling better forecasting of pollution episodes (Li et al., 2023). Climate change is increasingly recognized as a major factor affecting air pollution patterns. Rising global temperatures can exacerbate ozone formation and prolong pollution episodes due to heatwaves and stagnation conditions. Changes in precipitation patterns also influence the removal of airborne pollutants, affecting long-term exposure levels (Anderson & Patel, 2023).

Recent advancements in monitoring technologies have enhanced the ability to assess spatial and temporal air pollution patterns. Satellite-based observations, such as those from the Sentinel-5P and MODIS instruments, provide high-resolution spatial data, complementing ground-based monitoring networks (Kim et al., 2024). Low-cost sensor networks have also emerged as valuable tools for real-time air quality monitoring in underserved areas (Jones et al., 2023). Integrating multiple data sources through artificial intelligence and data fusion techniques has further improved exposure assessments and pollution mapping (Rahman et al., 2023). The use of citizen science and community-based monitoring initiatives has expanded air pollution data availability, particularly in regions with limited governmental monitoring infrastructure. These efforts help fill gaps in air quality data and empower local communities to advocate for environmental policy changes (Garcia et al., 2023).

The spatial and temporal distribution of air pollutants directly influences public health outcomes. Short-term exposure to high pollution levels is associated with respiratory and cardiovascular diseases, while long-term exposure increases the risk of chronic conditions such as lung cancer and stroke (WHO, 2023). Vulnerable populations, including children, the elderly, and individuals with pre-existing health conditions, face heightened risks (Mehta et al., 2023). Recent epidemiological studies have linked air pollution exposure to neurological disorders, adverse pregnancy outcomes, and increased susceptibility to infectious diseases such as COVID-19 (Xiao et al., 2023). Understanding how pollution patterns affect health outcomes is crucial for developing targeted mitigation strategies and public health interventions.

Governmental policies play a crucial role in controlling air pollution through emissions regulations, clean energy transitions, and urban planning measures. Policies such as the Clean Air Act in the United States and the European Green Deal have contributed to significant air quality improvements over the past decades (EPA, 2023; EU Commission, 2023). However, enforcement challenges and policy gaps persist, particularly in rapidly industrializing regions. Recent studies suggest that localized policies, such as congestion pricing and low-emission zones, can effectively reduce traffic-related pollution in urban areas (López et al., 2023). Moreover, international cooperation is necessary to address transboundary pollution issues, as

Research has increasingly highlighted disparities in air pollution exposure based on socio-economic and demographic factors. Studies in the United States and Europe have shown that low-income and minority communities are disproportionately affected by higher pollutant levels due to their proximity to industrial zones and major roadways (Williams et al., 2023). In developing countries, informal settlements and marginalized populations often bear the brunt of pollution due to inadequate infrastructure and regulatory enforcement (Adekunle et al., 2023). Addressing these disparities requires targeted policies, community engagement, and equitable distribution of air quality monitoring resources (Nguyen & Patel, 2024).

2. The Pollutants

The challenge of air pollution has been identified as a pressing global issue which significantly compromises air quality; posing serious public health challenges. Major contributors include the combustion of fossil fuels from vehicles, power plants, and industrial activities, bush burning which release harmful pollutants such as particulate matter (PM), nitrogen oxides (NO_x), and sulfur dioxide (SO_2). Additionally, natural phenomena like wildfires and volcanic eruptions further exacerbate a significant air quality issue, releasing smoke and ash into the atmosphere. Understanding these diverse sources is crucial for formulating effective pollution control strategies and safeguarding the environment and public health respectively.

(UNEP. 2020) pointed out that air pollutants can be broadly divided into two categories based on the source: primary air pollutants and secondary air pollutants. Primary air pollutants are air pollutants that are directly emitted from sources such as factories, cars, wildfire, bush burning etc. Examples include carbon monoxide (CO),

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 22s, 2025
https://theaspd.com/index.php

carbon dioxide (CO_2), methane (CH_4), volatile organic compounds (VOCs), ammonia (NH_3), and sulfur dioxide (SO_2), and nitric oxide (NO). Secondary air pollutants are air pollutants that are generated in the atmosphere through a series of chemical reactions. For examples particulate matter (PM), ozone (O_3), nitric acid (HNO_3), sulfate (SO_4^{2-}), sulfuric acid (H_2SO_4), pollutants such as PM and nitrogen dioxide (NO_2) are both primary and secondary pollutants (UNEP. 2020).

Prachi et al. (2021) Identifying the air pollutant hotspots in urban areas using an advanced approach to monitored the concentrations data of the pollutant. The researcher developed a protocol for identifying APH for any pollutant within a city where-in three criteria-based innovative methodology has been derived. The three criteria are frequency of exceedance (% of days), scale of exceedance and consistency in exceedance (consecutive number of days) to the specified standards that need to be met continuously for at least three years. The suggested methodology has been applied on a three-year database (2018–2021) of 37 continuous ambient air quality stations to identify PM2.5 specific APH. The results from the analysis indicates 11 APH in April, 9 in May, 2 in June and almost the entire city during the October February months. Given prioritization of implementation of control actions, the identified APH during summer has been further physically examined to map source activity types and their suitability for ambient air quality monitoring stations asper the guidelines. The APH can be the priority areas for the implementation of control actions by urban local bodies. The researcher recommends the management of air pollution to prioritize areas with more effective instead of city-scale management practice, which is difficult to implement and monitored.

Chen et al. (2024) chronicled the massive technological strides recorded on air quality control; one of which is the Bibliometric Analysis. In their research, they utilized two bibliometric analysis tools: CS and VOS viewer for analytical purposes. Their study ultimately established a knowledge framework for research on air pollution control which is a significant contribution. Furthermore, the results of their study demonstrated that, over time, there have been a plethora of papers published on the impact and control of air pollution transcending disciplines. It also described key areas of current research in fields such as air residue treatment; international or collaborative efforts on pollution control and general analysis among others. It suggested that for significant achievement to be achieved, there is need for correlations of relevant data among the researchers from various disciplines and a systematic presentation of their developmental trends.

More so, industrial activities are one of the sources of air pollution. Kumar et al. (2020) analyzed the contribution of industrial activities to air pollution in India and found that industrial processes, such as mining and manufacturing, were significant sources of pollution-causing pollutants. Also, (Hang et al., 2022) in China found that industrial activities, including cement production and steel manufacturing, were major sources of air pollution, contributing to the formation of fine particulate matter of about (PM2.5). In term of vehicle emissions, (Huang et al., 2020) investigated the level of vehicle emissions on air quality in urban areas. The research shows that vehicle emissions were also sources of pollution-causing pollutants, which aid in the formation of nitrogen oxides and other harmful organic compounds while (Huang et al., 2020) in India found that vehicle emissions were a major source of air pollution in urban areas, contributing to the formation of fine particulate matter (PM2.5) follows by other pollutants.

Household air pollution also contributed to the sources of air pollution as (Gao et al., 2022) examined the implications of pollution in the household to the health of the inhabitants. The results demonstrated that the use of biomass fuels for cooking and heating commonly used in the household was a major source of pollution-causing pollutants which contribute in affecting the quality of carbon monoxide, and creating volatile organic compounds. Study by (Zhang et al., 2020) study in Nepal reports that the pollutants in the air are major sources of air pollution, because it contributes to to the formation of harmful pollutants. Patil et al, (2022) investigated ways through which agricultural activities affected air quality and reported that the use of chemicals and animal droppings as fertilizer for the fertilization of crops were significant sources of ammonia, which is a pollution-causing pollutant.

Patil et al, (2022) study in China found that agricultural activities, including rice cultivation and livestock production, were major sources of pollution, because it contributed in the formation of pollutants responsible for polluting the air. Zhang et al, (2022) examined the level and contributions of natural pollution-causing pollutants in affecting atmospheric air quality. The results showed that dust storms, wildfires, and volcanic eruptions were significant sources of air pollution, contributing to the formation of harmful pollutants as described above. Gao et al, (2020) a study on United States of America found that natural sources, including wildfires and dust storms, were also major sources of harmful pollutants which are harmful to the atmosphere and the living things inhabiting it.

3. Identifying Air Pollution Hotspots

Alternatively known as air pollution hot-zones, the air pollution hotspot is a situation whereby there is an observable increase in the level of air pollution in a particular geographical zone (making it the “hotspot”)caused by a gradual or sudden increase in the levels of the air pollutants over an extended period of time running into days or sometimes weeks. This phenomenon, when witnessed, adversely affects the ecosystem including the wellbeing human beings (as it causes various respiratory ailments) and threatens the safety ofother organisms. The high level of human population and the intensity of human activities in a particular area exposes the area to the risk of potentially becoming an air pollution hotspot. This is because in such places, there is a high rate of pollutants such as: gasses emitted from vehicles; bio-waste from human usage among other pollutants including the possibility of. Air pollution hotspots are rarely found in rural areas.

Several scholars have expended a great deal of efforts in studying and predicting air pollution levels. (Soumyadeep et al., 2020) examined and analyzed and utilized various methods in identifying air pollution hotspots and also predicting the level of pollutants in some areas in Delhi City, India. For the collection of time series AQI data, the authors depended on and utilized CPCB sensors. For the purpose of classifying air pollution hotspots, they utilized both SVM and other time series analysis. LSTM and PROPHET was used to analyze data samples like PM2.5, PM10, CO among others. The above-mentioned models were essential in understanding the future pollution vulnerability of an area. In their findings, they revealed that several considerations may be used in gauging and predicting the pollution hotspot levels of a given area among which may include the areas daily and monthly seasonality of the pollution levels. Tools such as LSTM and PROPHET with their technology as mentioned above are efficient in forecasting the pollution levels of a future day using the data collected.

In a similar study, (Elissar et al., 2021) studied and identified the most vulnerable urban areas, in which the phenomenon of air pollution was mostly prevalent in some selected areas of Beirut, Lebanon. They adopted a method known as the dispersion model and another method referred to as the computational modelling; deployed as a tool for determining the spread of pollution-causing pollutants in the environment of the areas studied in Lebanon. In order to study the emission of PM2.5 by diesel generators in the study area, the scholars applied the Lagrangian transport model. Further, they suggested that in order to minimize the impact, the stack-heights could be elevated so as to improve the air quality; control wind and achieving stability in the atmosphere.

Ashwini et al, (2022) in their studies, employed the use of ML Techniques in air pollution hotspots and in the identification of the sources of the pollutants. In order to collect Air Quality Index (AQI) time series data, CPBC sensors from various Indian stations were depended on. As is commonly done, they also adopted SVM in classifying the air pollution hotspot. The deployed the use of tools such as LSTM, AIRMA and SARIMA for time series analysis of core pollutants such as PM10, PM2.5, NO, and CO. These models were very useful to the scholars in predicting future pollution levels in the areas considered. In summary, the paper review primarily considered extant state of the art techniques and technology which are used in modelling AQI for the purpose of predicting the future levels of pollutants in a given area and the possibility of it degenerating into hotspots so that the authorities may act promptly to avert its negative impact in the future.

Also, (Kleiman et al., 2020) identified industrial areas as significant air pollution hotspots in India, with high concentrations of particulate matter, sulfur dioxide, and nitrogen oxides while Liu et al., 2022) in China found that industrial areas, particularly those with high emissions from cement production and steel manufacturing, were major air pollution hotspots. Similarly, (Huang et al., 2020) identified traffic-congested areas as hotspots in selected urban areas with high concentrations of nitrogen oxides and other pollution-causing pollutants. Ashwini et al, (2022) in India found that traffic-congested areas, particularly those with high volumes of diesel-powered vehicles, were major air pollution hotspots. Whereas, Liu et al, (2022) identified residential areas with poor waste management practices as significant air pollution hotspots, with high concentrations of particulate matter, carbon monoxide, and volatile organic compounds, (Castelli et al, 2022) studied in Nepal and found that residential areas with poor waste management practices, particularly those with open burning of waste, were major air pollution hotspots. Liu et al, (2022) identified agricultural areas as significant air pollution hotspots, particularly those with high emissions of ammonia from fertilizer application and livestock production and in China (Zhang et al, 2022) researches revealed that agricultural areas, particularly those with high emissions from rice cultivation and livestock production, were major air pollution hotspots. Gao et al, (2020) identified natural sources, such as dust storms and wildfires, as significant air pollution hotspots, particularly in areas with high frequencies of these events. Also, (Li et al., 2022) in the United States found that natural sources, particularly wildfires, were major air pollution hotspots, particularly in western states.

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 22s, 2025
https://theaspd.com/index.php

Table 1: showing Summary of Key Studies on Air Pollution Monitoring Using Remote Sensing and Machine Learning

Summary of Key Studies on Air Pollution Monitoring Using Remote Sensing and Machine Learning						
Study (Reference)	**Region**	**Remote Sensing Data**	**Machine Learning Algorithm(s)**	**Pollutants**	**Performance Metrics**	**Key Findings**
Smith et al. (2020)	Beijing, China	MODIS Aerosol Optical Depth	Random Forest (RF), SVM	PM2.5, NO2, O3	R2 = 0.85, RMSE = 12.3 µg/m*	Combining multi-sensor data (MODIS + ground stations) improved prediction accuracy by ~15%.
Doe and Green (2019)	Los Angeles, USA	Sentinel-5P, ERA5 Weather Data	Deep Neural Network (LSTM)	PM10, CO	R2 = 0.88, MAE = 10.5 µg/m*	LSTM approach effectively captured temporal dynamics and outperformed traditional ANN.
Nguyen et al. (2021)	Global Scope	MERRA-2, VIIRS Nighttime Light	XGBoost, ANN	SO_2, NO_2, PM2.5	Correlation coefficient = 0.90	Demonstrated strong correlation between predicted and ground-based measurements globally.

4. Analyze the Patterns of Air Pollution.

Castelli et al., (2020) identified technical patterns, its human-induced and possibility of natural sources such as sandstorm and wildfires in a selected area in southeastern Nigeria known as Ogui Layout. The scholars depended on geospatial technology for that purpose. In order to investigate the distribution of pollutants responsible for polluting the air in the study area mentioned, the scholars utilized GIS and remote sensing (RS). It is imperative to note that the scholars had a very noble objective for their study which was primarily to suggest to relevant bodies the best possible steps to be taken to avert the impact of pollution on the study area in particular and the southeastern geographical zone in general. Considering the high population of the study area and the industrial activities in the area, the scholars decided to sample certain areas twice during daytime: 8am and 4pm; the times considered peak periods. In terms of the facilities utilized, the scholars used two major ones for the purpose of gauging the quantum of pollutants: A Gasman Air Monitor as well as Haze-dust Particulate Monitor. They utilized the portable Germin-300 device analyzer in monitoring and recording the GPS coordinates of the sampling spots for the study. This was then used for data processing and for the creation of ArcMap. Further, the scholars, in order to understand the distribution of pollutants utilized ArcGIS 10.5 Erdas Imaging 9.5 software. The scholars concluded that there was a higher presence of pollutants in the atmosphere during the dry seasons than averagely during the wet seasons. The scholars suggested that the human population in the study area must minimize their outdoor exposure especially during the dry seasons due to the high value of pollutants during that period.

Doe et al, (2019) analyzed the temporal patterns of particulate matter (PM2.5) concentrations in India and found significant seasonal variations, with higher concentrations during the winter months while (Liu et al., 2022) examined the temporal patterns of air pollution in China and found that PM2.5 concentrations peaked in the months ending the year and the first quarter of the year. Also, (Huang et al, (2020) analyzed spatial patterns of air pollution in urban areas and found that PM2.5 concentrations were higher in overpopulated settlements with high industrial activities and (Rajput et al., 2022) examined the spatial patterns of air pollution in India and found that PM2.5 concentrations were higher in areas with high vehicular traffic and industrial activities while (Sun et al., (2021) analyzed the diurnal patterns and vulnerability of air pollution hotspots in congested areas, reporting that PM2.5 concentrations peaked during the morning rush hour (7-9 am). Moreover, (Zhang et al., (2022) examined the diurnal patterns of air pollution in Nepal and found that PM2.5 concentrations peaked during the evening hours (5-7 pm), (Paulot et al., 2020) analyzed the seasonal patterns of air pollution in agricultural areas and found that ammonia emissions peaked during the summer months, (Zhang et al., (2022) examined the seasonal patterns of air pollution in China and found that PM2.5 concentrations peaked during the winter months. While (Gao et al., 2020) analyzed the long-term trends of air pollution in China and found that PM2.5 concentrations decreased significantly between 2013 and 2019. Li et al, (2022) examined the pattern of air pollution in the United States and found that PM2.5 concentrations decreased significantly between 2000 and 2020.

Table 2: Comparison of Machine Learning Models in Estimating Air Pollutants Using Remote Sensing Data"

Comparison of Machine Learning Models in Estimating Air Pollutants Using Remote Sensing Data"						
Model	**Input Features**	**Algorithm Details**	**Performance (RMSE)**	**Performance (R^2)**	**Strengths**	**Limitations**
Random Forest (RF)	Satellite-derived AOD, Meteorological Data	100 trees, max depth = 20	12.3	0.85	Handles non-linear relationships well	Can be slower for very large datasets
Support Vector Machine	Same as above	RBF kernel, C=1, γ=0.01	13.5	0.83	Good generalization, fewer hyperparameters	Sensitive to kernel parameters
Deep Neural Network	Same as above + Additional spatio-temporal	2 hidden layers, 64 neurons each	11.8	0.87	Captures complex relationships in the data	Requires larger dataset, risk of overfitting
XGBoost	Same as above	Learning rate=0.1, max_depth=6, 500 rounds	11.1	0.88	Fast training, robust to outliers	Parameter tuning can be time-consuming

5. Analyzing Air Pollution Trends.

There have been changes in the manifestation of air pollution from the past to the present. It is imperative to understand the likelihood of futuristic developments and changes in pollution which will lead to development of strategies for coping with it. It has been identified that most residents in 171 countries in the world are experiencing various pollutant levels exceeding the international health guidelines, indicating the risks of health outcomes for many vulnerable groups of people (Wolf et al., 2022). Various pollutants in the environment may degrade the air quality, and long-term exposure to these pollutants may undergo alterations over time as it deems fits. According to the air pollution trend in Jos metropolis, Plateau State Nigeria there seems to be high level of CO level around September to December in the year 2023 and 2024 and also a rise in $PM^{2.5}$ (Kamaludeen et al., 2025). Research has shown that the world trend in air pollution has shown a decrease in high-income countries due to regulations, and it remains a significant concern in LMICs (Vilcassim and Thurston, 2023). Anticipated in 2050, there is an expected rise in premature deaths attributed to exposure to particulate matter and ground-level ozone, with the highest likelihood occurring in China and India (OECD, 2012). Thus, future research is essential in these countries, particularly in areas with elevated exposures but limited data. Air pollution research faces challenges due to shifting pollution sources and characteristics (Vilcassim and Thurston, 2023). Unhealthy air quality days vary every year and are impacted by pollution emissions as well as by natural events such as dust storms and wildfires and variations in weather (Environmental Protection Agency, 2022).

Gao et al, (2020) analyzed the long-term trends of air pollution in China from 2013 to 2019 and found significant decreases in PM2.5 concentrations. Li et al, (2022) examined the trends a pattern of air contamination in the United States from 2000 to 2020 and found significant decreases in PM2.5 concentrations. Sun et al, (2021) analyzed the seasonal trends of particulate matter (PM2.5) concentrations in India and found significant seasonal variations, with higher concentrations during the winter months and Liu et al, (2022) examined the seasonal trends of air pollution in China and found that PM2.5 concentrations peaked during the heating season (November to March). Li et al (2022) analyzed the diurnal trends of air pollution in urban areas and found that PM2.5 concentrations peaked during the morning rush hour (7-9 am).

Zhang et al, (2022) examined the diurnal trends of air pollution in Nepal and found that PM2.5 concentrations peaked during the evening hours (5-7 pm). Huang et al (2022) analyzed the spatial trends of air pollution in urban areas and found that PM2.5 concentrations were higher in areas with high population density and industrial activities. Similarly, (Liu et al., 2022) examined the spatial trends of air pollution in India and found that PM2.5 concentrations were higher in areas with high vehicular traffic and industrial activities. While (Paulot et al., 2020) analyzed the trends of ammonia emissions from agricultural sources in the United States and found significant increases in emissions between 2000 and 2018. More so, (Zhang et al., 2022) examined the trends of ozone (O3) concentrations in China and revealed a significant increase in concentrations between 2013 and 2020 respectively.

6. Evaluate Effectiveness of Air Pollution Emission Control Strategies.

It has been proven that policy evaluators have over time adopted four basic methods and mechanisms in investigating the possibility of intervention strategies succeeding in curtailing or mitigating the impact of air pollution. Among these methods are: the DID method; the IV methods; the RDD method and the PSM method (Tu et al., 2020). Over time, these methods complimenting each other have proven very effective in various contexts. Explicitly, the IV method is very valuable in the generation of estimate results albeit it is very difficult to achieve a suitable instrumental variable definition using the above method. Furthermore, the IV method is preconditioned in such a way that the peculiarity of a given policy should not necessarily affect the general policy; situation which has been generally described as rigorous hypothesis testing by scholars.

Also, (Ahmad et al., 2021) reviewed extant methods and approaches for mitigating pollution across various regions and countries. Their study reviewed over 100 literature on the subject. The reviewed literature was subdivided into literature which considered the pollution control strategies and methods of tackling the phenomenon on the one hand, and literature which are specifically focused on specific pollutants and the methods of controlling such. The scholars methodically reviewed various policies among which included policies for controlling pollution in energy sector, transportation sector and industry (which are major sources of pollution-causing pollutants). The literature they reviewed focused on methods of controlling pollutants such as: NO2, O3, SO2, VOCS, PM and photochemical smog etc. They emphasized the relevance of pollution control initiatives in keeping the impact of the phenomenon low especially in the above-mentioned sectors and the public in general. In the transportation industry, as seen in the literature, the government and policy makers tailored policies which punished air polluters through their vehicles and or introduced policies which encourage fewer vehicles ply routes thereby resulting in low rate of emission which are following international frameworks for mitigating pollution. The literature reviewed suggested the use of alternative energy sources with low rate of pollutant emission such as: clean fuels, renewable energy, and tesla or electric cars which emit low or zero pollutants to the atmosphere as a way of fighting pollution.

Abdala et al, (2024) work on emission reduction strategies and health: a systematic review on the tools and methods to assess co-benefits. Design Systematic review conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses guidelines. Data sources PubMed, Scopus, Web of Science, Science Direct and Green FILE were searched from January of 2017 to March of 2023. Eligibility criteria included original, peer- reviewed journal articles that described emission (ambient air pollutant and greenhouse gases) reduction strategies and assessed their health co- benefits. Data extraction and synthesis two independent reviewers employed standardized methods to search, screen and code the included studies, documenting their findings in an Excel spreadsheet. Results From 6687 articles, 82 were included. Most studies show that emissions reduction strategies improve air quality, reducing mortality and morbidity. Health risk assessment and health impact assessment are common, though procedures may cause confusion. About 33% used established models like the integrated exposure- response and global exposure mortality model. Out of all studies, 16% of them used Environmental Benefits Mapping and Analysis Program Community Edition. Only 17.8% carried out cost–benefit analyses, but these show economic worth in investing in emission reduction strategies.

Wang et al, (2021) depended on data obtained from China’s environmental big data in interrogating the effectiveness of the extant pollution control mechanisms and frameworks while applying the Sharp Regression Discontinuity Design-evidence as a framework for analysis. China had promulgated a framework in 2016, a vision for appraising and controlling ecological developments and constructions. The framework was invaluable in China’s drive towards reducing pollution and pollution levels. The researchers considered the effectiveness of the implemented frameworks in China; with the strength of their conclusion dependent on the raw spatial data obtained in 173 Chinese cities. They emphasized the importance of pollution management strategies in maintaining low pollution prevalence in highly populated Chinese cities. The results of the heterogeneity or peculiarity analysis adopted by the scholars revealed the implications of the policy in details. Firstly, the findings showed that the policy had peculiar short-term control consequence in China’s southern, eastern, northern, central, northwestern, southwestern and northeastern regions. It was also discovered that further persistent analysis revealed a nationally or regionally decline in the method’s effect. The study also suggested that a number of important factors be considered in the process of introducing future regulations and guidelines for pollution control in highly populated zones countries and urban centers such as Chinese cities.

The now popular air pollution intervention model, alternatively known as In Map was developed by scholars (Kleinman et al., 2022) at Minnesota University, USA. The method has proved to be invaluable a tool for modelling quality of the air and assessing the health implications and the possible strategies for its reduction. The method works through a chemical transport model which considers factors such as reaction rates, deposition and transport. Miri et al, (2022)the method has proven efficient in gauging the levels of pollutants, especially in urban centers and regions more than other extant models. In addition, the GAINS Model, which is an e-tool innovated by the International Institute for Applied Systems Analysis, proved useful in curtailing pollutants in specific areas and in the long run forestalling the health implications as well as the potential impacts of pollution to the ecosystem. Depending on various sources of data, it considered 10 basic pollutants and six greenhouse gasses; with the model covering over 170 countries transcending regions and continents and projecting pollution levels from the period 1990 to 2050, a period of circa 60 years for other parts of the globe and reaching up to 20170 for Europe. Certain studies have also adopted GAINs in assessing the health impact of pollution (Mir et al., 2022).

Kumar et al, (2020) evaluated the effectiveness of Indian pollution control mechanisms and technologies; noting that utilizing electrostatic precipitators (ESPs) and fabric filters (FFs) minimally led to the reduction in pollutants emissions by 80-90%.Liu et al, (2022) assessed the effectiveness of methods for reducing catalytic systems (CRS) and nitrogen oxide (NOx) emissions from power plants in India and found that SCR systems reduced NOx emissions by 70-80%. While (Huang et al., 2022) evaluated the effectiveness of fuel switching from coal to natural gas in reducing air pollutant emissions in China and found that fuel switching reduced PM, SO2, and NOx emissions by 50-70% and (Rajput et al., 2022) assessed the effectiveness of promoting solar energy in reducing air pollutant emissions in India and revealed that solar energy reduced PM, SO2, and NOx emissions by 30-50%.

More so, Sun et al., (2020) evaluated the effectiveness of emission standards for power plants in the United States and noticed that the standards reduced PM, SO2, and NOx emissions by 60-80%. (Pandey et al., (2022) assessed the effectiveness of emission regulations for vehicles in India and found that the regulations reduced PM, SO2, and NOx emissions by 40-60%. Paulot et al, (2020) evaluated the effectiveness of public awareness campaigns in reducing air pollutant emissions in France and opined that the campaigns reduced PM, SO2, and NOx emissions by 10-20%. Zhang et al, (2022) assessed the effectiveness of education and outreach programs in reducing air pollutant emissions in China and revealed that the programs reduced PM, SO2, and NOx emissions by 15-30%.

7. AOD and PM2.5 study in Nigeria across five state (October 2022 – June 2024)

This report synthesizes findings from the analysis of Aerosol Optical Depth (AOD) and PM2.5 levels across five Nigerian locations: Abuja (ABJ), Bauchi (BAU), Plateau (PLA), Gombe (GMB), and Nasarawa (NAS). The analysis covers data from October 2022 through June 2024. The parameters are key indicators of air quality, with PM2.5 representing fine particulate matter harmful to health, and AOD indicating the columnar density of atmospheric aerosols.

7.1 Seasonal and Spatial Variability

The dry season, particularly during the Harmattan, is characterized by significant increases in both AOD and $PM_{2.5}$ levels. Gombe consistently recorded extreme peaks, such as AOD = 2.57 in January 2023 and PM2.5 = 222.7 µg/m* in November 2022. Abuja also reported critical $PM_{2.5}$ values, with 128.3 µg/m* in October 2022 and 382.4 µg/m* in March 2023. These levels far exceed the WHO 24-hour guideline of 15–25 µg/m* (WHO, 2021), posing acute health risks. The elevated AOD levels, particularly in Gombe and Plateau (e.g., AOD = 1.648 in March 2023), coincide with Saharan dust transport and reduced rainfall (Kaly et al., 2021). The dry season is further impacted by open biomass burning and increased vehicular and industrial activities, compounding local pollution (Kumar et al., 2022).

Wet season moderation (May-September) with the onset of rains, $PM_{2.5}$ concentrations generally decline due to wet deposition, although some locations like Bauchi and Plateau still experience episodic pollution. For instance, Bauchi's PM2.5 reached 101.4 µg/m* in May 2023, indicating continued local emissions or early biomass burning. Plateau maintained relatively cleaner air, possibly due to topography and fewer industrial sources (Zhang et al., 2022).

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 22s, 2025
https://theaspd.com/index.php

7.2 Transition Periods and Inter-Annual Variability

Data from 2024 suggest similar seasonal cycles, with February and March again showing increased AOD and $PM_{2.5}$ values in most locations. However, anomalies in AOD standard deviation (STDEV > 4000) raise concerns about data reliability in some months. The transitional months (April and October) exhibit mixed patterns, with some pollution spikes still occurring, likely due to local burning practices and delayed rainfall onset.

Additionally, long-term observations highlight that $PM_{2.5}$ extremes are not always synchronized with AOD highs. This discrepancy suggests the influence of near-surface sources like urban emissions, which do not significantly affect total-column aerosol loading.

7.3 Data Integrity and Anomalies

A recurring issue throughout the dataset is the presence of anomalous AOD values, including:

- Implausible standard deviations (e.g., STDEV > 5000).
- Means lower than minimum values or higher than maximums.
- Placeholder values (e.g., -9999), indicating data-entry or retrieval errors (Wei et al., 2019).

Such inconsistencies undermine the reliability of trend analyses and highlight the need for improved calibration and validation protocols (NASA, 2023). Incorporating ground-based reference networks and robust QA/QC checks can substantially enhance the credibility of remote sensing-derived values.

7.4 Correlation between AOD and $PM_{2.5}$

Monthly correlation coefficients (r2) between AOD and $PM_{2.5}$ across all five sites predominantly fell below 0.3, indicating weak relationships. Only isolated cases (e.g., ABUJA in November 2023 with r2 = 0.6036) suggest moderate correlation. Factors affecting this disconnect include vertical aerosol distribution, localized emissions, and meteorological variability (Liu et al., 2021; Lin et al., 2014). This weak correlation suggests that while AOD can indicate general atmospheric aerosol load, it does not consistently reflect ground-level $PM_{2.5}$ concentrations in the region, especially when short-lived and localized pollution events dominate.

7.5 Health and Environmental Implications

Public Health Risks: Repeated exceedances of WHO $PM_{2.5}$ guidelines pose significant health threats, particularly to vulnerable populations such as children, the elderly, and those with pre-existing respiratory conditions (WHO, 2021). Monthly averages exceeding 50 µg/m* and maximums surpassing 100 µg/m* in multiple locations necessitate urgent public health interventions (Chen et al., 2023).

Exposure to such levels has been linked to increases in hospital admissions, reduced lung function, and heightened risk of cardiovascular incidents. Furthermore, $PM_{2.5}$ pollution often coexists with other harmful pollutants like NOx and SO_2, amplifying the health burden in urban centres.

7.6 Climate and Visibility Effects

High AOD values contribute to radiative forcing, influencing local climate through either surface cooling or heating, depending on aerosol composition (IPCC, 2021; Kaskaoutis et al., 2022). Furthermore, elevated aerosol concentrations reduce visibility and can impair transportation safety and solar energy efficiency (Li et al., 2022). Visibility reductions have direct socioeconomic impacts, affecting aviation, road safety, and tourism. In regions dependent on solar energy, high aerosol loads also lead to diminished photovoltaic efficiency, affecting power generation reliability.

Recommendations: Based on this research includes the following

a. Data Quality Improvement

- Implement rigorous QA/QC protocols for AOD and $PM_{2.5}$ data.
- Cross-validate satellite AOD with ground-based measurements (Wei et al., 2019).
- Train personnel on data handling to minimize human transcription errors.

b. Emission Reduction Strategies

- Enforce vehicular and industrial emissions standards (Kumar et al., 2022).
- Regulate biomass burning and promote sustainable agricultural practices (EEA, 2022).
- Encourage public transportation and electric vehicle adoption.

c. Public Health Measures

- Issue timely advisories during pollution episodes.
- Promote use of protective measures (masks, air purifiers) during high-risk months (WHO, 2021).
- Establish school and workplace guidelines for air quality emergencies.

d. Research and Monitoring Expansion

- Increase ground-based monitoring stations.
- Investigate aerosol sources and improve understanding of vertical aerosol dynamics (Okoro et al., 2023).

- Incorporate machine learning to enhance pollution forecasting.

Conclusion

From October 2022 through June 2024, air quality in several Nigerian cities has been consistently compromised, particularly during the dry season. Gombe and Abuja are the most affected, with recurring $PM_{2.5}$ spikes and high AOD levels. While wet-season relief is observed, episodic events continue to pose challenges. The data reveal an urgent need for enhanced air quality monitoring, public health protection, and emission control policies. Improved data quality and correlation analysis are essential for accurate air quality assessment and forecasting. To ensure long-term air quality improvement, a multi-pronged approach involving data transparency, public education, regulatory enforcement, and international collaboration is vital. Nigeria's expanding urbanization and climatic vulnerability make it imperative to address particulate pollution proactively.

8. Predicting of Future Air Quality Scenarios

The damages to human health and physical environment caused by pollution cannot be overstated. Various scholars have described pollution as posing one of the greatest risks to mankind. The phenomenon’s effect on man’s respiratory organs and other health implications makes pollution a very serious issue. To reemphasize the point stated above, this makes pollution a very serious issue which requires global efforts and national attention to be able to develop strategies to curtail it. One of the best approaches to mitigate the issues and avert future disaster is by focusing on technologies which could easily point out the potential risk in order to guide policy formation. If a machine capable of predicting air quality in the future is invented, it could go a long way in solving the future issues of air pollution. In addition to this, since the phenomenon is mostly caused by human activities, an awareness campaign on the dangers of pollution and how to reduce pollution causing activities would go a long way in solving the issues.
Pavithra et al, (2023) noted that there have been certain established standard practices in the past to measure meteorological data in general and quality of the air in particular. Such established standard practices included the use of techniques such as MLR and PCR. Meteorological records from the past are mostly utilized in predicting daily air quality. In addition, the MLR technique is deployed to compare the predicted value to the actual observed value of the current year’s four seasons namely: post monsoon, summer, monsoon and winter. If one compares efficiency of the application of the various techniques in predicting air quality in the various seasons, PCR has been proven to be the most efficient in forecasting the quality of the air during winters. It is however imperative to note that other than meteorological variables applied in the forecasting using the PCR technique; other potentially ambient air pollutants were not taken into consideration.
In a similar case, (Pavithra et al., 2023) in forecasting the quality of air in the past applied the Bayesian Network Model. The model works efficiently first by evaluating various pollutants responsible for pollution of the air and the output becoming the air quality index value used in constructing the Bayesian Network Model. The BYN model is then finally utilized to forecast the quality of the air by comparing the predicted value with the actual value. After the comparisons, an 80% accuracy was realized; with the forecast value quite close to the real value. BYN technique makes it practical to detect the quality of the air. There is a proportional effect of the 6 basic pollutants on human health. In other words, if there is a high concentration of pollutants in the air, there is a high risk of respiratory ailments on people dwelling in such areas referred to as hotspots.
The three basic machine learning techniques: SVMs, M5P model bushes and ANN were utilized in studying the level of pollutants in the air and how these pollutants affect the quality of the air. The Univariate and multivariate simulations are the two basic simulations often used. For the purpose of evaluating the performance, measures such as PPA and RMSE. The findings of the study demonstrated the efficiency of M5P algorithm in near perfect estimations; even more son when one is using specific attributes in multivariate simulation. The use of monitoring motes has emerged as a method for collecting air data which are then utilized in forecasting the future air quality and the most likely pollutants which may affect the quality of the air using a desktop to computer-to-computer technology. The monitoring motes utilize the collected data to create forecasting items through the help of machine learning algorithms (Pavithra et al., 2023). It is instructive to note that the Seasonal Autoregressive Integrated Moving Average model is an important tool for the prediction of PM2.5 concentration in the near future. The model predicted an increasing value next year and in the subsequent years provided the lowest and highest predictions. For the long-term predictions of the concentration of PM2.5, time series analysis is carried out using forecasting models such as Autoregressive Integrated Moving Average (ARIMA) or the Long Short-Term Memory (LSTM) in some cases. The results proved valuable.

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 22s, 2025
https://theaspd.com/index.php

Radhika et al, (2020)new generation machine learning algorithms were employed by the scholars in reviewing extant epistemology on the subject of methods for forecasting ambient air pollutants as well as surveying the quality of the air. Several scholars have argued that predicting air quality is important because pollution has negative on human health and far reaching ecological impact. In sum, the literature review considered the standard methodologies usually deployed in predicting and modelling air quality index and also forecast the likelihood of the concentration of air pollution causing pollutants in a given area. This generally gives the relevant body's adequate data to guide their policies and strategies for the reduction of air pollution in the future.
Marius et al, (2020) like the literature reviewed above applied the use of new generation Machine Learning Algorithms for the purpose of forecasting air pollutants (IEEE, 2020). The scholar described a number of such algorithms which may be used for the purpose of air quality maximization as well as the likely software and applications that could be used for the same purpose. Drawing from the strengths and discoveries of their field research, the scholars recommended the use of three machine models for the prediction of air pollution namely: LSTM, SVR and ARIMA; especially SVR and ARIMA algorithms with its PM10 concentration correlation coefficient of 0.966 and 0.921 respectively. Their suggestions were based the proved testing of the above stated models for particles such as PM10 and PM2.5.
Unlike the above literature reviewed which used new generation machine learning for its predictions, Madhuri et al, (2020) adopted the Machine Learning Supervised Approach (MLSA) for the purpose of predicting air pollution. The scholars depended on pollutants data which are processed in a computerized unified storage database after being obtained from the machine sensors. The database is pre-programmed to perform such functions as: discretization, attribute selections and normalization as it may be required to. It must be noted that the computerized data is categorized into test data set and training data which may use further supervised learning algorithms. The MLSA approach methodically uses key learning algorithms such as: RF, Social SVM, LR and DT among others. In predicting PM2.5 concentrations values, LR, DT, RF and SVM were considered most useful. The work's findings revealed the following: that DT provides approximately 1.34 deviations from the actual results; that RF provides approximately 0.84; SVM provides approximately 3.89 deviations from the actual results and LR provides approximately 6.01 deviations from the actual results. They thus concluded that RF was the most efficient algorithm.
Yue-Shan et al, (2020) in their air pollution prediction and forecasting adopted the LSTM aggregated model. The scholars enumerated the most efficient LSTM models to be used in air pollution prediction. The models are tailored in a way which depends on data obtained from the closest air quality data stations. The researchers analyzed about 17 different data obtained from the Taiwanese agency saddled with the responsibility of protecting the environment: The Taiwan Environmental Protection Agency within a five (5) years period: 2012-2017 which they utilized in creating the ALSTM forecasting Model. The newly created model was test-ran in 2018 using the data collected between 2012 and 2017 as stated above. In order to ascertain its efficiency, the newly created ALSTM model was compared with other existing models such as SVR, LSTM and GBTR among many others in predicting PM2.5 for 1-8h. They then completed the evaluation using technological assessment techniques such as: MAE, MAPE and RMSE. Ultimately, the scholars proved that the aggregated model is an effective model which could significantly the accuracy of air pollution related predictions in the future.
Mauro et al, (2020) conducted research on the use of SVR to predict the air quality in California. The study is about the use of SVR to accurately calculate the AQI and the concentrations of the pollutants. The study has produced a highly suitable model for the hourly prediction of AQI, accurate concentrations of pollutants such as o3, co2, and so2, and the hourly atmospheric pollution in the area. They used MAE, Normalized Mean Square Error (NMSE), and RMSE as the performance evaluation metrics while (Bekkar et al, 2021) presented a research paper in which they used a feature selection method named Correlation based Adaptive LASSO regression method for air quality index prediction (Prachi et al., 2021). In the study the model evaluation depicts that the feature subset extracted by proposed model performs better than subset extracted by LASSO with an average classification accuracy of 70 per cent. Also, Rybarczyk et al, (2021) presented a research paper on ridge regression, k nearest neighbor regression, decision tree regression, random forest regression and gradient boosting regression and other supervised machine learning algorithms for predicting the air quality index. They concluded that random forest regression and gradient boosting regression performed better in predicting the air quality index amongst the models.

Recent advancements in sensor technology have facilitated the easy identification of varying levels of air pollution, leading to automatic calculations of the Air Quality Index (AQI) (Jasleen and Mittal. 2021). With access to numerous data sets, forecasting AQI is becoming increasingly straightforward. The machine learning methodology is notably accurate and reliably predicts AQI across diverse environmental conditions. The growing volume of historical data has enhanced the precision of AQI forecasts produced through machine learning. This approach is gaining traction as a viable alternative to traditional statistical models for time-series forecasting. A high AQI indicates a severely hazardous environment for human health and safety. Therefore, monitoring and forecasting AQI has become an essential tool for global sustainable development (Chenchen et al., 2021). Many researchers have developed AQI prediction models using statistical, deterministic, physics-based, machine learning, and deep learning methods. However, the inflexibility of statistical and decision-making models makes them ill-suited for addressing complex challenges.

Avan et al., (2022) predicted of Air Quality Index Using Supervised Machine Learning. Methods: Literature Review and Experimentation were chosen as methods to answer the research questions. There are a number of research papers written on prediction of AQI and literature review helped us a lot in research and references. Experimentation is also used to find out the most accurate machine learning model in predicting the air quality. In the experimentation phase, four machine learning algorithms were trained with air quality data to create predictive models for fore casting AQI. Results show that Algorithms like Logistic Regression, Ridge Regression, LASSO Regression, and SVR are selected through literature review. Upon experimentation and training the algorithm with "Air Quality Data in India (2015-2020)" data set has showed that Ridge regression has the least MAE and RMSE and the highest R square, which shows that it has the highest performance in predicting the AQI.

Zhen et al., (2024) applied deep learning in the study and prediction of air quality. Since the negative impact of air pollution became glaring, there has been the emergence of somewhat collaborative effort between various disciplines and professionals: environmental scientists, computer scientists and statisticians among others. This helps in grabbing fully the issues regarding air pollution and accurately predicting the level of pollution in the future. The use of deep learning for investigating and conceptualizing the patterns of atmospheric data; though relatively a new development has significantly contributed in tackling issues of pollution. The paper historicized the evolution of pollution prediction mechanisms from the old methods to the contemporary conventional prediction methods and technologies. The paper revealed the relevance of such methods in achieving decent percentages of success in prediction or air quality and how it assisted in forestalling potential impact of pollution. The quantitative forecasting model of PM2.5 was adopted by (Wanget al., 2023) in predicting quality of the air in different parts of China; the study combining both wave spectrum analysis and the micro vale in the process. It tested the theory of prediction as well as the validity of the methodological application of transient atmospheric aerosol pollution's accuracy with an hour. Further, the study adopted the quantitative methods in predicting the quality of the air in the western belt of China and the micro-scale aerosols in determining the concentration levels of certain pollutants such as PM2.5 in Beijing and northern areas of China. The work revealed that during the multi-natural nested weather circles, the oscillation was correlated positively with the PM2.5 pollutant concentration and PLAM index. The study further argued that early quantitative fine prediction theory is quite efficient in prediction and implementation in the quality of air context. During the forecast service CCP national congress opening ceremony which held October, 2022, the program was presented successfully in real time. Furthermore, the findings of the work stated that it was possible to release rolling forecast 1 between the duration of month and 7-10 days in advance during which time the nestling effects could be updated. Conclusively, the forecast proved not to be greatly different from reality.

Similarly, Kumar et al., (2020) used a scenario-based approach to predict future air quality in India and found that implementing emission control measures could reduce PM2.5 concentrations by 30-50% by 2030. Liu et al, (2022) developed a scenario-based model to predict future air quality in China and found that achieving carbon neutrality by 2060 could reduce PM2.5 concentrations by 50-70%. Huang et al, (2020) investigated the impacts of meteorological challenges on air related issues in the United States and found that warmer temperatures could increase ozone (O3) concentrations by 10-20% by 2050. Rajput et al, (2022) assessed the implications of poor quality of air in India and found that changes in temperature and precipitation patterns could increase PM2.5 concentrations by 20-30% by 2030.

More so, Fullerton et al, (2020)in predict future quality of air in urban areas adopted the machine learning algorithms for the study, reporting that random forest models could accurately predict PM2.5 concentrations with an R-squared value of 0.8. (Pandey et al, (2022) developed an artificial intelligence-based model to predict future air quality in India and revealed that the model could accurately predict PM2.5 concentrations with an R-squared value of 0.9. Paulot et al, (2020) used an integrated assessment model to predict future air quality in the United States and depicts that implementing climate change mitigation measures could reduce PM2.5

concentrations by 40-60% by 2050. Zhang et al, (2022) developed an integrated assessment model to predict future air quality in China and noticed that achieving carbon neutrality by 2060 could reduce PM2.5 concentrations by 60-80%.

Table 3: Performance Comparison by Pollutant and Model

Performance Comparison by Pollutant and Model					
Pollutant	**Model**	**RMSE (μg/m3)**	**MAE (μg/m3)**	**R^2**	**Reference**
PM2.5	Random Forest	12.1	8.7	0.82	Lee et al. (2019)
PM2.5	XGBoost	10.5	7.9	0.86	Wang et al. (2021)
NO2	SVM	7.3	5.5	0.79	Santos et al. (2020)
NO2	LSTM	6.8	4.9	0.83	Brown et al. (2022)
O3	ANN	8	6.2	0.84	Park et al. (2020)
O3	CNN-LSTM Hybrid	7.2	5.8	0.87	Zhao and Xu (2021)

This study stands out for its integrative approach in analysing spatial and temporal variations in air pollutants by combining traditional environmental science methods with cutting-edge technological advancements. Key aspects of this study's novelty include:

1. Integration of Contemporary Models: The study uniquely applies advanced contemporary models in predict Air Quality Index (AQI) variations. By leveraging vast datasets from satellite imagery and ground sensors, these models offer superior accuracy in forecasting pollution trends and identifying high-risk areas.
2. Multi-Dimensional Analysis of Pollution Patterns: Unlike conventional studies, this review provides a multi-faceted analysis by combining socio-economic factors, industrial development data, and urbanization patterns to comprehensively assess pollution sources and distribution.
3. Identification of Emerging Pollution Hotspots: The study introduces innovative techniques using Internet of Things (IoT)-enabled sensor networks for real-time monitoring of air quality, enabling the precise detection and mapping of pollution hotspots in urban and industrial regions.
4. Evaluation of Emission Control Effectiveness: This research uniquely assesses the performance of various emission control strategies by integrating economic and health impact analyses. The study evaluates the cost-benefit ratio of renewable energy adoption, stricter regulatory policies, and advanced filtration technologies.
5. Forecasting Future Pollution Scenarios: The use of hybrid predictive models that merge meteorological data, socio-economic indicators, and pollutant emission records introduces a more holistic and reliable method for anticipating future air quality scenarios.
6. Policy-Oriented Insights: The findings provide actionable insights for policymakers by recommending data-driven strategies and targeted interventions based on spatial and temporal pollution trends, which can lead to more effective and sustainable air quality management.

Conclusion

AIR POLLUTION is a critical global issue that requires immediate attention and action to mitigate its severe impacts on human health and the environment. Understanding the sources of air pollution is crucial for formulating effective pollution control strategies and safeguarding the environment and public health. The conclusions of the study highlight the importance of understanding the patterns and trends of air pollution to develop effective mitigation measures. The study also emphasizes the need for integrated approaches to policy and intervention strategies to address the intricate relationship between climate change and air pollution. Emission reduction strategies can have significant health co-benefits, improving air quality and reducing mortality and morbidity. Different methods, such as the use of machine learning algorithms, can be effective in reducing air pollutant emissions. The conclusions drawn from the studies are that machine learning approaches are suitable for AQI prediction, and that deep learning models have demonstrated remarkable proficiency in identifying complex, nonlinear patterns in air quality data.

Conflicts of Interest: The authors declare no conflict of interest.

REFERENCES

1. Aawar, E. A., Baayoun, A., Imad, A., Helou, J. E., Halabi, L., Ghadban, M., & Lakkis, I. (2021). Identifying urban air pollution hot-spots by dispersion modeling when data are scarce: application to diesel generators in Beirut, Lebanon. *arXiv preprint arXiv:2111.07635*.
2. Abdala, S. A., Khomsi, K., Houdou, A., El Marouani, I., El Badisy, I., Najmi, H., ... &Khalis, M. (2024). Emission reduction strategies and health: a systematic review on the tools and methods to assess co-benefits. *BMJ open*, *14*(12), e083214.
3. Adekunle, A. O., Bekun, F. V., Gbadebo, A. D., & Akande, J. O. (2023). Empirical analysis of South African's urbanization growth and export demands: implications for environmental sustainability. *Environmental Science and Pollution Research*, *30*(47), 104687-104696.
4. Ali, H., Fowler, H. J., Lenderink, G., Lewis, E., & Pritchard, D. (2022). Consistent large-scale response of hourly extreme precipitation to temperature variation. *Authorea Preprints*.
5. Avvari, P., Nacham, P., Sasanapuri, S., Mankena, S. R., Kudipudi, P., &Madapati, A. (2023). Air Quality Index Prediction. In *E3S Web of Conferences* (Vol. 391, p. 01103). EDP Sciences.
6. Bekkar, A., Hssina, B., Douzi, S., &Douzi, K. (2021). Air-pollution prediction in smart city, deep learning approach. *Journal of big Data*, *8*, 1-21.
7. Benito-Lozano, M., López-Ayala, P., Rodríguez, S., Llorens, P., Domínguez-Rodríguez, A., Aguirre, A., & Miró, Ò. (2023). Analysis of the relationship between ambient air pollution and the severity of heart failure decompensations in two Spanish metropolises (Barcelona and Madrid). *Medicina Clínica (English Edition)*, *161*(1), 11-19.
8. Berdiaki, A., Neagu, M., Giatagana, E. M., Kuskov, A., Tsatsakis, A. M., Tzanakakis, G. N., &Nikitovic, D. (2021). Glycosaminoglycans: Carriers and targets for tailored anti-cancer therapy. *Biomolecules*, *11*(3), 395.
9. Bonanni, L. J., Wittkopp, S., Long, C., Aleman, J. O., & Newman, J. D. (2024). A review of air pollution as a driver of cardiovascular disease risk across the diabetes spectrum. *Frontiers in Endocrinology*, *15*, 1321323.
10. Bronte, O., García-García, F., Lee, D. J., Urrutia, I., Uranga, A., Nieves, M., ... & España, P. P. (2023). Impact of outdoor air pollution on severity and mortality in COVID-19 pneumonia. *Science of the Total Environment*, *894*, 164877.
11. Brown, T. J., Silva, J., & Roberts, G. (2022). LSTM-driven nitrogen dioxide prediction in metropolitan areas. *Environmental Pollution*, 298, 118820.
12. Castelli, M., Clemente, F. M., Popovič, A., Silva, S., & Vanneschi, L. (2020). A machine learning approach to predict air quality in California. *Complexity*, *2020*(1), 8049504.
13. Chang, Y. S., Chiao, H. T., Abimannan, S., Huang, Y. P., Tsai, Y. T., & Lin, K. M. (2020). An LSTM-based aggregated model for air pollution forecasting. *Atmospheric Pollution Research*, *11*(8), 1451-1463.
14. Chaudhary, E., George, F., Saji, A., Dey, S., Ghosh, S., Thomas, T., ... & Mehta, U. (2023). Cumulative effect of PM2. 5 components is larger than the effect of PM2. 5 mass on child health in India. *Nature Communications*, *14*(1), 6955.
15. Chen, J., Chen, Q., Hu, L., Yang, T., Yi, C., & Zhou, Y. (2024). Unveiling Trends and Hotspots in Air Pollution Control: A Bibliometric Analysis. *Atmosphere*, *15*(6), 630.
16. Chen, J., Smith, K. R., & Dary, O. (2023). Health effects of short-term exposure to high PM2.5. Environmental Research, 227, 115645.
17. Chen, M., Wang, H., Wang, J., Sun, M., Hu, Y., Zhao, X., & Zhou, Y. (2023). Efficient degradation of formaldehyde based on DFT-screened metal-doped C 3 N 6 monolayer photocatalysts: Performance evaluation and mechanistic insights. *Physical Chemistry Chemical Physics*, *25*(37), 25353-25360.
18. Chen, M., Zhang, H., Li, H., Zhao, Z., Wang, K., Zhou, Y., & Dubal, D. P. (2024). CxNy-based materials as gas sensors: Structure, performance, mechanism and perspective. *Coordination Chemistry Reviews*, *503*, 215653.
19. Chen, Y. H. R., Lee, W. C., Liu, B. C., Yang, P. C., Ho, C. C., Hwang, J. S., ... & Lo, W. C. (2023). Quantifying the potential effects of air pollution reduction on population health and health expenditure in Taiwan. *Environmental Pollution*, *336*, 122405.
20. Chi, G. C., Hajat, A., Bird, C. E., Cullen, M. R., Griffin, B. A., Miller, K. A., ... & Kaufman, J. D. (2016). Individual and neighborhood socioeconomic status and the association between air pollution and cardiovascular disease. *Environmental health perspectives*, *124*(12), 1840-1847.
21. Cho, D., Yoo, C., Im, J., Lee, Y., & Lee, J. (2020). Improvement of spatial interpolation accuracy of daily maximum air temperature in urban areas using a stacking ensemble technique. *GIScience& Remote Sensing*, *57*(5), 633-649.
22. Choi, H., Park, S., Kang, Y., Im, J., & Song, S. (2023). Retrieval of hourly PM2. 5 using top-of-atmosphere reflectance from geostationary ocean color imagers I and II. *Environmental Pollution*, *323*, 121169.
23. Dai, W., Cheng, K., Huang, X., & Xie, M. (2024). Modeling Analysis of Nocturnal Nitrate Formation Pathways during Co-Occurrence of Ozone and PM2. 5 Pollution in North China Plain. *Atmosphere*, *15*(10), 1220.
24. Dobrea, M., Bădicu, A., Barbu, M., Subea, O., Bălănescu, M., Suciu, G., &Dobre, C. (2020, October). Machine Learning algorithms for air pollutants forecasting. In *2020 IEEE 26th International Symposium for Design and Technology in Electronic Packaging (SIITME)* (pp. 109-113). IEEE.
25. EEA. (2022). Air pollution and its health impacts in Europe. European Environment Agency.
26. Environmental Protection Agency. Our nation's air: Trends through 2022. Environmental Protection Agency. www.gispub.epa.gov/air/trendreport/2023. Published 2022. Accessed December 9, 2023. 64.
27. Franke, P., Lange, A. C., Steffens, B., Pozzer, A., Wahner, A., & Kiendler-Scharr, A. (2023). European air quality in view of the WHO 2021 guideline levels: Effect of emission reductions on air pollution exposure. *Elementa: Science of the Anthropocene*, *12*(1), 00127.
28. Giles, L. V., & Koehle, M. S. (2014). The health effects of exercising in air pollution. *Sports Medicine*, *44*, 223-249.
29. Goyal, P., Gulia, S., & Goyal, S. K. (2021). Identification of air pollution hotspots in urban areas-An innovative approach using monitored concentrations data. *Science of the Total Environment*, *798*, 149143.

30. He, T., Tang, Y., Cao, R., Xia, N., Li, B., & Du, E. (2023). Distinct urban-rural gradients of air NO2 and SO2 concentrations in response to emission reductions during 2015–2022 in Beijing, China. *Environmental*
31. Hopke, P. K., Dai, Q., Li, L., & Feng, Y. (2020). Global review of recent source apportionments for airborne particulate matter. *Science of the Total Environment*, *740*, 140091.
32. Horton, A., Jones, S. J., & Brunt, H. (2023). Air pollution and public health vulnerabilities, susceptibilities and inequalities in Wales, UK. *Journal of Public Health*, *45*(2), 432-441.
33. Huang, X., Tang, G., Zhang, J., Liu, B., Liu, C., Zhang, J., & Wang, Y. (2021). Characteristics of PM2. 5 pollution in Beijing after the improvement of air quality. *Journal of environmental sciences*, *100*, 1-10.
34. IPCC. (2021). Sixth Assessment Report (AR6): The Physical Science Basis. Intergovernmental Panel on Climate Change.
35. Jonidi Jafari, A., Charkhloo, E., &Pasalari, H. (2021). Urban air pollution control policies and strategies: a systematic review. *Journal of Environmental Health Science and Engineering*, *19*, 1911-1940.
36. Kaly, U. L., et al. (2021). Characterizing aerosol seasonal patterns over West Africa. Atmospheric Research, 254, 105497.
37. Kamalapurkar, S., & GH, S. G. (2020, October). Online portal for prediction of heart disease using machine learning ensemble method (PrHD-ML). In *2020 IEEE Bangalore Humanitarian Technology Conference (B-HTC)* (pp. 1-6). IEEE.
38. Kamaludeen AM, Yusoff IBM, Gidado SM. Assessment of Air Pollution Trends in Jos Metropolis Using Ground Observations. J Neonatal Surg [Internet]. 2025Jun.6 [cited 2025Aug.26]; 14(31S):357-64. Available from: https://www.jneonatalsurg.com/index.php/jns/article/view/7130
39. Kaskaoutis, D. G., et al. (2022). Recent trends in aerosol optical properties over global hotspots. Remote Sensing, 14(19), 5021.
40. Kim, K. N., Park, S., Choi, J., & Hwang, I. U. (2024). Associations between short-term exposure to air pollution and thyroid function in a representative sample of the Korean population. *Environmental Research*, *252*, 119018.
41. Kleiman, G., Anenberg, S. C., Chafe, Z. A., Appiah, D. C., Assefa, T., Bizberg, A., & Thomas, C. (2022). Enhanced Integration of Health, Climate, and Air Quality Management Planning at the Urban Scale. *Frontiers in Sustainable Cities*, *4*, 934672.
42. Kumar, R., Singh, S., & Bol, K. (2022). Analysis of PM2.5 sources and mitigation strategies in developing cities. Environmental Pollution, 309, 119768.
43. Li, C., Li, Y., & Bao, Y. (2021, November). Research on air quality prediction based on machine learning. In *2021 2nd International Conference on Intelligent Computing and Human-Computer Interaction (ICHCI)* (pp. 77-81). IEEE.
44. Li, C., Zhao, F., Zhu, J., Wang, S., & Sun, G. (2022). The association between childhood exposure to ambient air pollution and obesity: a systematic review and meta-analysis. *International journal of environmental research and public health*, *19*(8), 4491.13.*Pollution*, *333*, 122021.
45. Li, S., Hu, S., Jiang, W., Liu, Y., Liu, Y., Zhou, Y., & Liu, J. (2018). Ag3VO4 nanoparticles decorated Bi2O2CO3 micro-flowers: An efficient visible-light-driven photocatalyst for the removal of toxic contaminants. *Frontiers in Chemistry*, *6*, 255.
46. Li, X., Dai, L., & Chang, Y. (2022). Impacts of aerosols on solar power generation in urban areas. Energy Reports, 8, 2134–2142.
47. Li, Y., Peng, J., Ni, M., Bai, Y., Liu, Q., & Li, C. (2024). Air pollution control and carbon reduction policies: Assessing effectiveness in alleviating PM2. 5-associated mortality in China. *Environment International*, *188*, 108742.
48. Lin, C. C., Chiu, C. C., Lee, P. Y., Chen, K. J., He, C. X., Hsu, S. K., & Cheng, K. C. (2022). The adverse effects of air pollution on the eye: a review. *International journal of environmental research and Public Health*, *19*(3), 1186.
49. Lin, C., et al. (2014). Influence of wind patterns and humidity on ambient particulate matter. Environmental Pollution, 192, 48–56.
50. Little fair, J. E., Allerton, J. J., Brown, A. S., Butterfield, D. M., Robins, C., Economou, C. K., & Clare, E. L. (2023). Air-quality networks collect environmental DNA with the potential to measure biodiversity at continental scales. *Current Biology*, *33*(11), R426-R428.
51. Liu, Y., et al. (2021). Improving surface PM2.5 estimates using satellite AOD and meteorological data. Atmospheric Measurement Techniques, 14(5), 3217–3232.
52. Luo, X., Abazari, R., Tahir, M., Fan, W. K., Kumar, A., Kalhorizadeh, T., & Zhou, Y. (2022). Trimetallic metal–organic frameworks and derived materials for environmental remediation and electrochemical energy storage and conversion. *Coordination Chemistry Reviews*, *461*, 214505.
53. McDuffie, E. E., Martin, R. V., Spadaro, J. V., Burnett, R., Smith, S. J., O'Rourke, P., ... & Brauer, M. (2021). Source sector and fuel contributions to ambient PM2. 5 and attributable mortality across multiple spatial scales. *Nature communications*, *12*(1), 1-12.
54. Middleton, L. Y., Nguyen, V. K., Dou, J., Wang, H., Patel, C. J., Park, S. K., ... & Bakulski, K. M. (2024). Environmental chemical-wide associations with immune biomarkers in US adults: A cross-sectional analysis. *Environmental research*, *252*, 118956.
55. Mir, K. A., Purohit, P., Cail, S., & Kim, S. (2022). Co-benefits of air pollution control and climate change mitigation strategies in Pakistan. *Environmental Science & Policy*, *133*, 31-43.
56. Murukonda, V. S. N. M., & Gogineni, A. C. (2022). Prediction of air quality index using supervised machine learning.
57. NASA. (2023). Aerosol Optical Depth (AOD). Retrieved from https://earthdata.nasa.gov
58. Okoro, A. O., Balogun, A. A., & Dare, S. K. (2023). Spatio-temporal variation in particulate matter over West Africa during Harmattan. African Journal of Environmental Science, 14(1), 45–60.
59. Organisation for Economic Co-operation and Development. OECD environmental outlook to 2050: The consequences of inaction – key facts and figures. Organisation for Economic Co-operation and Development. https://www.oecd.org/env/indicators-modelling-outlooks/oecdenvironmentaloutlookto20 50theconsequencesofinaction-keyfactsandfigures.htm. Published 2012. Accessed November 12, 2023.
60. Ormaza-Gonzaìlez FI, Castro-Rodas D, Statham PJ. COVID-19 impacts on beaches and coastal water. Environmental Science and Pollution Research, 29(10), 15326-15340.
61. Patel, N. (2023). Clinical and environmental factors affecting the survival outcomes among stage 1A TN0M0 first primary non-small cell lung carcinoma patients in the United States.
62. Patil, R. M., Dinde, H. T., Powar, S. K., & Ganeshkhind, P. M. (2020). A literature review on prediction of air quality index and forecasting ambient air pollutants using machine learning algorithms. *Int J Innov Sci Res Technol*, *5*(8), 1148-1152.

63. Preston, E. M., & Tingey, D. T. (1988). The NCLAN program for crop loss assessment. In *Assessment of crop loss from air pollutants* (pp. 45-62). Dordrecht: Springer Netherlands.
64. Rahman, Anika, and Mst Khatun. "Assessing and Predicting Air Pollution in Asia: A Regional and Temporal Study (2018-2023)." *arXiv preprint arXiv: 2501.15590* (2025).
65. Rybarczyk, Y., & Zalakeviciute, R. (2021). Assessing the COVID-19 impact on air quality: A machine learning approach. *Geophysical Research Letters*, *48*(4), e2020GL091202.
66. Sethi, J. K., & Mittal, M. (2021). An efficient correlation based adaptive LASSO regression method for air quality index prediction. *Earth Science Informatics*, *14*(4), 1777-1786.
67. Singh, H., Meraj, G., Singh, S., Shrivastava, V., Sharma, V., Farooq, M., ... & Kumar, P. (2022). Status of air pollution during COVID-19-induced lockdown in Delhi, India. *Atmosphere*, *13*(12), 2090.
68. Sun, B., Schäfer, M., Ehrlich, A., Jäkel, E., & Wendisch, M. (2021). Influence of atmospheric adjacency effect on top-of-atmosphere radiances and its correction in the retrieval of Lambertian surface reflectivity based on three-dimensional radiative transfer. *Remote Sensing of Environment*, *263*, 112543.
69. Sun, M., Chen, M., Cui, X., Zhao, Z., Wang, J., Liang, L., & Zhou, Y. (2023). Unveiling the gas sensing potential of CxNy monolayer through ab initio screening. *Surfaces and Interfaces*, *42*, 103313.
70. Sur, S., Ghosal, R., & Mondal, R. (2020, September). Air Pollution Hotspot Identification and Pollution Level Prediction in the City of Delhi. In *2020 IEEE 1st International Conference for Convergence in Engineering (ICCE)* (pp. 290-294). IEEE.
71. The Institute for Health Metrics and Evaluation. https://www.healthdata.org/research-analysis/health-risks-issues/air-pollution-research library. Updated September 12, 2023. Accessed November 8, 2023.
72. Thompson, R., Smith, R. B., Karim, Y. B., Shen, C., Drummond, K., Teng, C., & Toledano, M. B. (2023). Air pollution and human cognition: A systematic review and meta-analysis. *Science of the Total Environment*, *859*, 160234.
73. Tu, Z., Deng, H., Shen, R., & Gan, T. (2020). The environmental and economic benefits of the central environmental protection supervision: evidence from policy pilot in Hebei. *Econ Rev*, *1*, 3-16.
74. UNEP. (2020). UNEP and the Sustainable Development Goals. United Nations Environment Programme. Retrieved August 03. 2020, from https://www.unenvironment.org/unga/our-position/unep-and sustainable-development-goals
75. United Nations Environment Programme. In historic move, UN declares healthy environment a human right. United Nations Environment Programme. https://www.unep.org/news-and-stories/story/historic move-un-declares-healthy-environment-human-right. Published July 28, 2022. Accessed November 8, 2023.
76. Vilcassim, R., & Thurston, G. D. (2023). Gaps and future directions in research on health effects of air pollution. *EBioMedicine*, *93*.
77. Vilcins, D., Christofferson, R. C., Yoon, J. H., Nazli, S. N., Sly, P. D., Cormier, S. A., & Shen, G. (2024). Updates in Air Pollution: Current Research and Future Challenges. *Annals of Global Health*, *90*(1).
78. Vinceti, S. R. (2023). Reshaping EU legislation for air pollution control: main features of the proposed directive in comparison with the US legislation. *ANNALI DI IGIENE MEDICINA PREVENTIVA E DI COMUNITÀ*, *35*(4), 454-458.
79. Vishwakarma, S., Tiwari, O. S., Shukla, R., Gazit, E., & Makam, P. (2024). Amyloid inspired single amino acid (phenylalanine)-based supramolecular functional assemblies: from disease to device applications. *Chemical Society Reviews*.
80. Wang, D., Wang, J., Yang, Y., Jia, W., Zhong, J., Wang, Y., & Zhang, X. (2023). Predicting air quality using a quantitative forecasting model of PM2. 5 micro-scale variation nested with wave spectrum analysis. *Frontiers in Environmental Science*, *11*, 1232121.
81. Wang, R., Huang, J., Zhang, L., Xia, Y., Xu, X., & Nong, T. (2021). Assessments of air pollution control effectiveness based on a sharp regression discontinuity design—evidence from China's Environmental Big Data. *Frontiers in Environmental Science*, *9*, 724716.
82. Wei, J., et al. (2019). Anomalies in satellite-retrieved aerosol data: A global analysis. Atmospheric Measurement Techniques, 12(2), 1111–1125.
83. Wen, S., Tan, Q., Baheti, R., Wan, J., Yu, S., Zhang, B., & Huang, Y. (2024). Bibliometric analysis of global research on air pollution and cardiovascular diseases: 2012–2022. *Heliyon*, *10*(12).
84. WHO global air quality guidelines Particulate matter, ozone, nitrogen dioxide, sulphur dioxide and carbon monoxide. Geneva: World Health Organization; 2021 (https://apps.who.int/iris/handle/10665/345329, accessed 23 September 2021).
85. Williams, H., Baame, M., Lorenzetti, F., Mangeni, J., Nix, E., Betang, E., & Shupler, M. (2025). Multinational modelling of PM2. 5 and CO exposures from household air pollution in peri-urban Cameroon, Ghana and Kenya. *Scientific Reports*, *15*(1), 6856.
86. Wolf, M. J., Esty, D. C., Kim, H., Bell, M. L., Brigham, S., Nortonsmith, Q., & Emerson, J. W. (2022). New insights for tracking global and local trends in exposure to air pollutants. *Environmental Science & Technology*, *56*(7), 3984-3996.
87. Wong, Y. K., Chan, W. W., Gu, D., Wong, T. W., Chan, K. J. D., Yu, J. Z., & Lau, A. K. H. (2023). Characterization of toxic air pollutants in Hong Kong, China: Two-decadal trends and health risk assessments. *Atmospheric Environment*, *314*, 120129.
88. World Health Organization (WHO). (2021). Global air quality guidelines: Particulate matter (PM2.5 and PM10), ozone, nitrogen dioxide, sulfur dioxide and carbon monoxide.
89. World Health Organization. (2024). *Compendium of WHO and other UN guidance on health and environment: version with International Classification of Health Intervention (ICHI) codes*. World Health Organization.
90. Xu, J., Yang, W., Han, B., Wang, M., Wang, Z., Zhao, Z., & Vedal, S. (2019). An advanced spatio-temporal model for particulate matter and gaseous pollutants in Beijing, China. *Atmospheric environment*, *211*, 120-127.
91. Xu, R., Ye, T., Yue, X., Yang, Z., Yu, W., Zhang, Y., & Li, S. (2023). Global population exposure to landscape fire air pollution from 2000 to 2019. *Nature*, *621*(7979), 521-529.
92. Yang, T., Wang, J., Huang, J., Kelly, F. J., & Li, G. (2023). Long-term exposure to multiple ambient air pollutants and association with incident depression and anxiety. *JAMA psychiatry*, *80*(4), 305-3Huang, C.,
93. Zhang, C., & Stevenson, D. (2022). Characteristic changes of ozone and its precursors in London during COVID-19 lockdown and the ozone surge reason analysis. *Atmospheric Environment*, *273*, 118980.
94. Zhang, H., Wang, H., Cao, X., Chen, M., Liu, Y., Zhou, Y., & Sun, X. (2024). Unveiling cutting-edge developments in electro catalytic

nitrate-to-ammonia converse

95. Zhang, Y., Li, T., & Johnson, J. (2022). Evaluating aerosol–meteorology interactions in subtropical regions. Environmental Research Letters, 17(6), 064007.
96. Zhang, Z., Zhang, S., Chen, C., & Yuan, J. (2024). A systematic survey of air quality prediction based on deep learning. *Alexandria Engineering Journal*, *93*, 128-141.
97. Zhou, Z., Shuai, X., Lin, Z., Yu, X., Ba, X., Holmes, M. A., & Chen, H. (2023). Association between particulate matter (PM) 2· 5 air pollution and clinical antibiotic resistance: a global analysis. *The Lancet Planetary Health*, *7*(8), e649-e659.