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Integrating IoT and AI for Indoor Air Quality Assessment

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Contents

Chapter 10
Health Risk Assessment Associated with Air Pollution Through Technological Interventions: A Futuristic Approach

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Abstract Air pollution is one of the biggest contributors to the global burden of disease and mortality and contributes to over a million deaths worldwide every year. Short- and long-term exposures to air pollutants, when they are present in high concentration, lead to respiratory illnesses, aggravation of cardiovascular diseases, and premature deaths. The accurate assessment of health risk and impact due to ambient and indoor air pollution is imperative for policymaking, prevention, and rectification efforts. Technological intervention and advancement in data science and modelling predictions could be of use for accurate health risk assessment and exposure to the pollution which includes exposure to small and large populations. Internet of Things includes sensors, smartphones, and air pollution models based on big data sources which are not only used to assess the exposure, but also aid in devising prevention opportunities. Key features of these tools include accessibility, spatial resolution, specific health outcomes associated with pollutants, population exposure, and application. This chapter is a state-of-the-art review that elaborates the attempts and technological interventions and advancements made to address the health risk assessment associated with air pollution and strategies adopted for personalized treatment to avert exacerbation and refractory symptoms. Technological advancement and its involvement may revolutionize the air pollution prediction, exposure, and risk assessment research in the coming time, if they meet the logistical and data science challenges along with the integration of health impact and related risks' assessment which is linked to the exposure of air pollution.

Keywords Exposure · Health · Internet of Things · Technology · Data science

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10.1 Introduction

Air pollution is one of the biggest contributors to the global burden of disease [1] and causes 1.3 million deaths globally on annual basis [2]. With the growing urbanization, management of air quality has become utmost essential and a priority as industrial and transport activities are affecting the air quality at an alarming rate. Interventions are also needed to improve health, and inequities in health care must be resolved to make the most of the positive impact of the policy interventions [3]. Evidences suggest that air pollution and health consequences are closely related to each other and are constant globally [4]. Air pollution has a blend of particulate matter (PM_{10} and $PM_{2.5}$), O_3, NOx, and SOx. The associated health impacts have been extensively reported in the literature by the World Health Organization (WHO) to set the guidelines for limiting their emission [5].

Prolonged exposure to particulate matter is related to premature mortality and cardiovascular and pulmonary diseases with symptoms of asthma and impaired lung functioning [6], whereas short-term exposure to ozone is linked with cardiovascular diseases and premature deaths [7]. A mixture of pollutants such as biomass smoke also exerts hazardous effects. The mixture resulting from multiple pollutants has a convergence of health effects and requires a specific management strategy to mitigate the health risks [8].

10.2 Air Pollution Prediction: Experimental Versus Simulation Tools

Air pollution monitoring and modelling are two prominent ways to estimate exposure to pollution. Through monitoring the previous and present air quality data is collected from specific sites, whereas modelling method combined with advanced monitoring technologies can simulate air quality in different geographical regions and may predict the future changes associated with exposure, thereby helping in policy implementations [9].

Air pollution can be explored through modelling for a large population and by monitoring for a small population. These approaches work in tandem and are inclusive of each other, but differ in the study designs, applicability, and limitations. Modelling studies usually rely on geographic information systems (GIS), deterministic models (AIRMOD, RLINE, SHEDS), and remote sensing data [10] to derive spatio-temporal concentrations of pollutions in ambient air to obtain exposure estimates. Modelling and monitoring are growing rapidly with the advent of new technological interventions to generate large-scale data to produce new opportunities in the field of personal exposure methods, which is constrained to limited sample size and short duration of time [11] and to overcome cost constraints while dealing with large sample size for a longer time. Computational and technological inventions have led to the development of (1) air pollution sensors, (2) smartphones, and (3) air

Fig. 10.1 Applications of air quality simulation in a nutshell

pollution modelling for effective applications, providing valuable information on pollution exposure. All the three domains have to act in conjugation as only air pollution models are insufficient to predict personal exposure unless a time-activity pattern is known. On the other hand, personal measurements done with the help of sensors and smartphones are unlikely to predict the long-term exposures and need integration with air pollution models. The applications of air pollution simulation are summarized in Fig. 10.1.

The three important domains are briefly explained below and summarized in Fig. 10.2:

10.2.1 Air Pollution Sensors

The air pollution sensors are used for personal measurements, but they are usually effective for small populations. High-quality validation is required for the measurements over a long time for a large sample size which is the main hurdle due to cost and logistics constraints. Inexpensive and easy to use sensors are being developed, and to ensure their accuracy [12] toolkits have been proposed for effective evaluation [13].

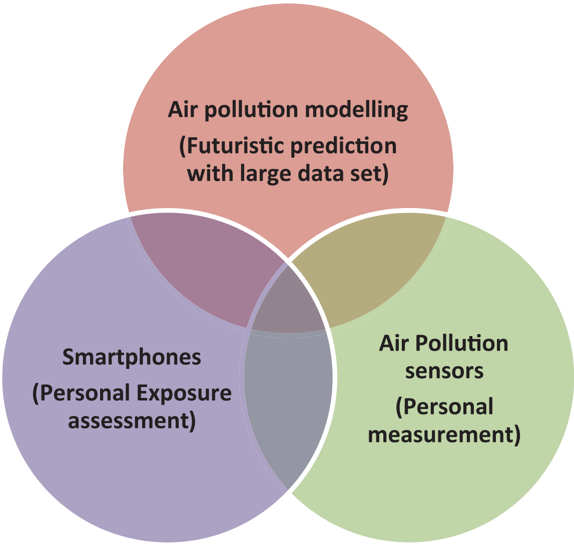

Fig. 10.2 Three important domains for air pollution exposure assessment

10.2.2 Smartphones

Smartphones pave way for a novel platform for air pollution health studies. Population-based air pollution exposure assessment facilitated by air pollution sensors and GPS-based time-activity patterns can be collated with smartphones for large-scale studies. By 2022 on an approximation there will be 6.8 billion smartphone users worldwide [14]. Smartphones aided by sensors can keep a track of daily movement and promote health research and offer new opportunities to explore advanced air pollution exposure assessment. The smartphones are handy to collect the time-activity pattern using GPS and may help in the recruitment of participants, for obtaining their consent for survey-based studies and obtaining biometric data and to assess and transmit data other to databases such as medical health records [14].

10.2.3 Air Pollution Models

For long-term exposure assessment, air pollution models are needed as they cannot be predicted by personal and individual GPS measurements only. The biggest advantage of air pollution modelling is that they cover multiple data sources. The advent of big data sources like satellite air pollution approximation has led to numerous opportunities in air pollution modelling. The machine learning approach is used to predict daily PM_{10} concentration by combining remote-sensed data, meteorological parameters, and ground-based observations [15]. Nonlinear and nonparametric modelling approaches have been applied for the prediction of spatial and temporal pollutants' concentration. Deep learning approaches have also been developed for accurate predictions [16] in conjugation with high-resolution satellite imaging and ground-based images [17] for more refined predictions. The accuracy of the models can be enhanced by taking into account the non-traditional measurement sources. Exposure assessment and related health studies have emerged as a priority research area [18]. Modelling predictions also take into consideration the surrogate factors like the distance of the exposed person from roads which is been associated with health effects [19] but cannot be directly estimated from the monitored data. Exposure models based on GIS information and accessible geographic data and monitoring data are used to identify concentrations and variations in pollutants for a specific area. Results obtained after modelling through exposure models can be superimposed on geo-referenced health data to know the effect of pollution on people at different places. These models are also important to assess exposure at the intra-urban level, which is mainly due to vehicular exhaust around major roads and highways which is associated with several health risks as reported previously [20]. High cardiopulmonary mortality has been reported from people who reside near major roads [21]. However, the majority of such studies rely on the most basic exposure measurement and need strengthening with more robust exposure metrics. Dispersion, atmospheric, and time-activity models in conjugation with GIS can illustrate intra-urban exposures in a more refined and accurate way [22].

10.2.4 Common Air Pollution Models

Land Use Regression Models

The model predicts pollutant concentration based on the surrounding traffic density and land use. The model uses pollution concentrations at a particular location as the response variable and land use types within the limits of the chosen location which is used as predictors of the calculated pollutants' concentrations. The key benefit of the model is the pragmatic arrangement of the regression mapping which enables the model to adapt the land usage of the local area and does not require further monitoring [23]. The method is also cost-effective. However, the method finds limitations in being area-specific.

Dispersion Models

Dispersion models work on Gaussian plume equations [24]. They make use of emission data, meteorological conditions, and topographical data to forecast the spatial exposure of pollution. In conjugation with GIS, the dispersion models can predict data concerning the population distribution. Adding the topographic data, the road network and traffic observations can be made representing a realistic representation. These models have been employed for total suspended particulate matter, NOx, SO_2, and CO [25]. Dispersion models are particularly useful because they incorporate both spatial and temporal changes in air pollution without the need for a dense monitoring network. The pollutants' concentration varies significantly in space and time due to a changeability in different factors like traffic flow, wind velocity, and topographical features of the study area. These variables can be clubbed within the dispersion network by incorporating point and line source models accounting for movable and immobile sources. They may be applied at various spatial levels. The key limitations of the models include the costly data input, elaborate cross-validation, temporal discrepancy in data, and hypothetical postulation about dispersion patterns.

Some of the more recent analytical methodologies for the estimation of population exposure are as follows:

1. The Global Model of Ambient Particulates model (GMAPS) developed by the World Bank assesses ambient PM_{10} concentration at the city level [26].
2. The Global-Regional Chemistry transport model TM5 and the source-receptor (SR) relationship evaluate the response of ambient air quality indicators and the variations in emission patterns of pollutants [27].
3. Global atmospheric models GEOS-Chem [28] and MOZART [29] are used for the assessment of ambient concentrations of ozone and $PM_{2.5}$.
4. Hierarchical Bayesian models are used for multiple-pollutants assessment through the Bayesian statistical methods [30, 31].

10.3 Health Risk Associated with Pollution

Elevated levels of air pollutants can lead to several health issues. Through toxicological, clinical, and epidemiological studies, significant associations have been established between exposure to air pollution and detrimental consequences like premature death in adverse cases [32]. Shortness of breath, tightness in the chest, and wheezing are linked to short-term exposure. The exasperation of respiratory and cardiovascular diseases is related to long-term exposure to pollution [33]. Emission guidelines have been set up in many countries for two of the most hazardous pollutants, namely, particulate matter and ozone. The setting up of regulatory standards need different inputs including the health hazards imposed on the exposed population at the present concentrations as well as the health benefits of the reduction of the concentration levels. Over the last few decades, administrative authorities have invested a lot in devising tools that meet up with the overwhelming need for specific and judicious information related to health effects linked to air pollution exposure. For an instance, the US Environmental Protection Agency developed the Environmental Benefits Mapping and Analysis Program (BenMAP-CE) to assess the advantages and costs of the US air pollution regulations [34]. The WHO and

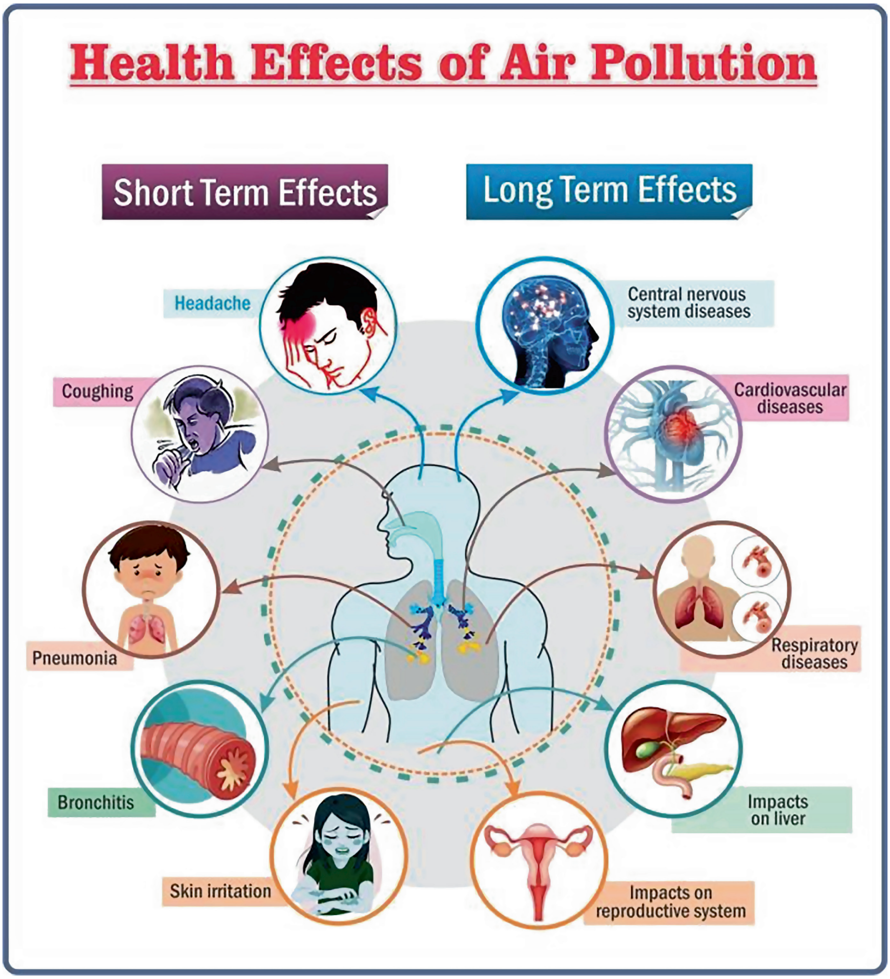

Fig. 10.3 Common short- and long-term effects of air pollution

World Bank have also invested in similar tools for the quantification of health consequences upon exposure to ambient air pollution [34].

Several approaches are developed which incorporate epidemiological assessment into the health-related risk (AP-HRA). The assessment has a pivotal role in the prevention of diseases and the promotion of global health. AP-HRAs predict the health effects likely to be originated from the changes in the air quality [34] and help in policy-making and interventions. Usually, health risks associated with SOx and NOx, O_3, and particulate matter are estimated from the HRA tools [35]. They also relate the variation in the concentration and its association with ischemic heart diseases, lung cancer, and respiratory infections using the Concentration Response Functions (CRFs). Some of the health effects attributed to short- and long-term exposures are given below and also summarized in Fig. 10.3:

Short-Term Exposure

1. Hospital admissions owing to respiratory diseases
2. Hospital admissions owing to cardiovascular diseases
3. Mortality
4. Absenteeism from work
5. Other acute symptoms

Long-Term Exposure

1. Lung cancer
2. Impaired physiological functioning
3. Impaired growth
4. Chronic respiratory and heart diseases
5. Mortality caused by respiratory and cardiovascular diseases

10.3.1 Health Risk Assessment Tools

For accurate detection, prevention, and correction efforts, effective health risk impact assessment is important. Nevertheless, the data available for health risk assessment is usually unsatisfactory to be given as deterministic numbers. Several stochastic methods have been developed to assess the health impact related to pollution exposure. Markov Chain-Carlo model has been developed to assess traffic-related air pollution [36]. A stochastic dynamic analysis approach has been employed to predict the short-term effects related to childhood respiratory illnesses [37]. Box-Jenkins transfer function model has been deployed to evaluate the relevance of meteorological factors on surface smoke concentrations [38]. Air pollution epidemiology and exposure are important for the assessment of health impact and burden. By taking advantage of the findings of the development of atmospheric science and epidemiology, health impact assessments can be accurately done.

Air pollution epidemiological studies have predicted the health outcomes by controlling the probable confounding factors like socioeconomic status or smoking either by alterations in design (for short-term exposure studies) or in the prediction of fatality associated with long-term exposure. Quantification of air pollution-related health impact assessments can be performed at different levels for an array of pollutants. Studies have reported health impacts associated with these pollutants at regional, national, and local levels [39–41]. Results are usually expressed in terms of mortality, years of life lost (YLL), disability-adjusted life years (DALYs), or changes in life expectancy which is attributed to air pollution or dependent on the alterations in the concentrations of the pollutants. Figure 10.4 summarizes the health risk assessment.

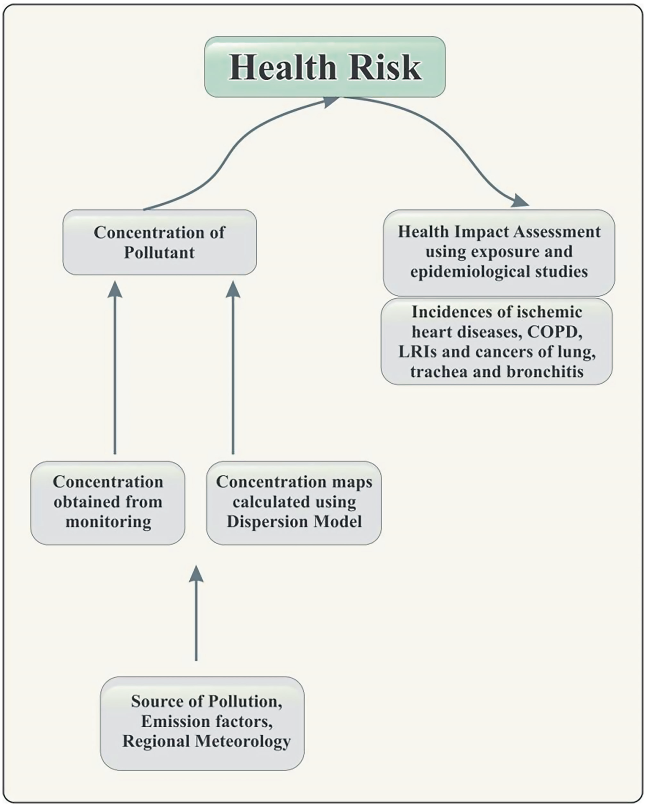

Fig. 10.4 Key elements of health risk assessment

10.3.2 Health Assessment Tools

Human Exposure Model (HEM)

The Human Exposure Model (HEM) is employed to perform risk assessment associated with toxic air pollutants in ambient air. The HEM depicts how the exposure is governed through inhalation and predicts the associated risks with the pollutants. The model predicts the ambient pollutants' levels as surrogates for lifetime exposure, to give an approximation of cancer and non-cancer risk hazards respectively for the air pollutants. Currently, HEM4 is in use consisting of an atmospheric dispersion model, AERMOD, which also includes meteorological data. Based on source parameters and the meteorological data which are used as input, AERMOD approximates the extent and distribution of pollutants in ambient air within a distance of 50 kilometers from the source. The exposure estimates are merged with reference concentrations to predict cancer and non-cancer hazards, along with different risk measures [42].

Integrated Fuzzy-Stochastic Modelling

An integrated fuzzy-stochastic modelling (IFSM) approach is used for the assessment of air pollution-related risks. The model includes (1) Monte Carlo simulation for the fate of air pollutants in the ambient environment; (2) development of fuzzy air quality management criteria taking into consideration the exposure dynamics, human-exposure pathways, etc.; and (3) health risk assessment through the combined fuzzy/stochastic inputs of the pollutants' concentration. An integrated risk information system (IRIS) was developed to evaluate the exposure risks through a dose-response relationship. The health hazard can be evaluated by comparing the pollutant concentration with the reference concentrations [43]. Using this model the risk assessment can be done to detect complexities associated with diseases like asthma. Usually, the environmental risk assessment has three elements, (1) identification of risk, (2) assessment of emission sources and environmental loading capacities, and (3) quantification of risk associated with air pollution. Risk is expressed as $P_F(R/S)$, where R represents the emission of pollutants, S represents environmental loading capacity, and P_F represents probability. More specifically, the probability of a pollutant's concentration exceeding the standard safety level is represented by L and C, and then the quantification of risk can be given as Eq. (10.1):

$$P_F = P(L > C) = \int \left\{ \int f_{LC}(L,C)\, dC \right\} dL \tag{10.1}$$

P_F represents the quantified risk, and f_{LC} is associated probability density function. If random number C can be defined by local environmental guidelines (i.e., if $C = C_0$), then the risk can be quantified as Eq. (10.2):

$$P_F = P(L > C_0) = \int_{c_0}^{\infty} f_L(L)\, dL \tag{10.2}$$

Proximity Models

The proximity mode is used to measure the closeness of a subject from the source of pollution. It works on the assumption that proximity to the emission source may lead to greater exposure in the exposed population. Literature has suggested that higher traffic density near the residence may aggravate asthma symptoms [44]. A study done in Hamilton showed that women aged between 20 and 44 years of age reported asthma symptoms and were at greater risk if they resided within 50 m of a major road [45]. The proximity model is useful for the prediction of long-term exposure; however, a limited number of covariates are used which could probably act as confounders while establishing the relationship between air pollution and health. For an instance, exposure to vehicular exhaust at places other than homes, the workplace often goes ignored [46], leading to biased risk estimates. Nevertheless, the proximity model is still very much in use for environmental epidemiological studies and health effects assessment at a formative stage.

Interpolation Models

Interpolation models work based on deterministic and stochastic techniques. Concentrations of the chosen pollutants are acquired from the monitoring stations located in the study area. The information can be used for the estimation of pollutants other than the monitoring site. Generally, these estimates are obtained at the center of the grid imposed over the study area, so that a continuous surface of pollution concentration can be established. Kriging models are based on geostatistical techniques [47] employed to develop the continuous surface of pollution. For the prediction of concentrations of SO_2 over a small area, geostatistical modelling has been used [48]. Spatial and temporal distributions of ozone in Atlanta have been assessed using the Kriging model [49] to estimate pollutants' concentration in the chosen area of study. The modelled concentrations have been associated with respiratory health effects and mortality. Long-term consequences on respiratory health in children were examined using the ambient concentrations of SO_2. Ambient SO_2 concentrations were found to be associated with instances of wheezing and asthma [50]. On a similar pattern modelled ozone and its relationship with pediatric asthma was also studied previously [51]. The interpolation techniques have a distinct advantage of using real pollution data during the computational calculation of exposure estimates. They can quantify the exposure and enable to perform computational calculations for the establishment of the dose-response relationship. However, the model has a disadvantage in that it needs monitoring data from a large number of sampling sites. Approximately data from 10–100 sites is required for an urban area which may vary as dependent upon the topography of the area, meteorological factors, local emitting sources, and probable errors in estimates.

Integrated Exposure-Response Functions

Air pollution may induce both short- and long-term health impacts to lower respiratory infections causing mortality to young children [52]. Oxidative stress due to the accumulation of particulate matter in the respiratory tract may be the main factor responsible for enhanced susceptibility to infection [53]. According to the Global Burden of Disease (GBD), LRIs are one of the leading causes of death the world over and the fifth-leading cause of mortality. Although it is not viable to count the accurate deaths from environmental pollution, yet the increase in the number of deaths over a while may be estimated and determined statistically in terms of the number of years of life lost (YLLs), and reduction in life expectancy. The GBD method works on the Eqs. (10.3) and (10.4):

$$M(\text{age},\text{lat},\text{lon},\text{year}) = \gamma_0 \times \text{AF} \times \text{Pop} \tag{10.3}$$

where M is the attributable mortality, which is a function of age, geographical latitude and longitude, and the year for which air pollution concentrations and population distributions are being considered.

$$R(t) = 1 + \alpha\left[1 - \text{expexp}\left\{-\gamma\left(\text{PM}_{2.5} - X_0\right)\delta\right\}\right] \tag{10.4}$$

Equation 10.4 depicts the calculation of relative risk $R(t)$ associated with the exposure to $PM_{2.5}$ through an integrated exposure-response (IER) function. α, γ, and δ are the parameters that describe the shape of IERs. X_0 is the minimum risk exposure having a range of 2.4–5.9 μg/m^3 [54]. To study the change in mortality due to ambient pollution-induced LRIs, calculations based on the IER functions were performed for the years 2010–2015 using the global concentration distribution. The results obtained by the model matched accurately with the satellite data [55]. The modelling results showed that in 2015, approximately four million excess deaths were reported worldwide due to ambient air pollution and 727,000 were associated with AAP-LRIs. The revised annual exposure range for $PM_{2.5}$ is 2.4–5.9 μg/m^3 as compared to 5.8–8.8 μg/m^3 used for the assessment in 2010 [56].

Generalized Additive Model (GAM) for Mental Health Assessment

The negative impact of air pollution and temperature has been also reported [57] including Alzheimer's and Parkinson's diseases [58]. Epidemiological studies suggest the long and short term effects of air pollution on mental health [59]. Air pollution caused by vehicular exhaust and dementia incidences has been explored in Sweden [60]. The short-term effects of environmental conditions including key pollutants, temperature, and relative humidity have been assessed in Brazil through a semiparametric generalized model (GAM) combined with a distributed lag nonlinear model (DLNM) for different age groups and lag time of 0–7 days to create a modelling framework to show non-linear exposure-response relationship and effects caused after a certain period. The model predicts values of the effect of the event with N-day lag, and the combined effect measurement during the period [61]. The semiparametric model is given by Eq. (10.5) [62]:

$$(\mu_i) = \propto + \sum_{j=1}^{6} s_j\left(x_{ji}\right) + \beta_1 \text{day}_i + \beta_2 \text{holy}_i + \beta_3 \text{time}, \quad i = 1, \ldots, n, \tag{10.5}$$

where $E(Y_i) = \mu_i$, $g(.)$ depicts the logarithmic link function, α is the intercept, $s(.)$ depicts the natural cubic spline for non-linear predictor variables, x_{ji} represents the meteorological variables and pollutant concentrations, time refers to the effect of the temporal trend, day represents the day of the week, and holy stands for holidays. The cumulative short-term health effects owing to the exposure of air pollution, temperature, and relative humidity as related to the number of hospitalizations were also assessed for both sexes. A noteworthy impact of the environmental variables was found to be associated with the mental and behavioral disorders which varied with the sex and difference in age groups. At lag 0 the relative risk was higher for men than women.

10.3.3 GIS and Modelling

The integration of modelling and geographic information system approach has been done for enhanced accuracy of health risk assessment and quantification of mortality associated with air pollution exposure. The integration produces quick and consistent assessment results. In a case study reported from Haiphong city in Vietnam, the traffic scenarios and values of particulate matter were simulated based on georeferenced data. The findings showed an exceeding health burden owing to the exposure of particulate matter. The model included three sub-models in a GIS framework which were applied to estimate the health consequences arising in different scenarios, including emission from different sources. The procedure involves a transport model to predict traffic flow. The obtained results are integrated with an emission model to calculate emission. In the next step, a dispersion model based on the GIS tool is used to calculate air pollutants' concentration and project on a concentration map which can also estimate the human exposure when superimposed with the population density map. Health effects are assessed by the dose-response functions using the quantified exposures and relative risks. In a study to assess the exposure of PM_{10}, the concentrations were modelled for four different traffic scenarios in Haiphong city. The worst scenario included the maximum concentration for 24 h and 1 year, respectively. The concentrations were mapped using GIS and superimposed with the city maps. The third scenario included sources like bicycles and motorbikes, and the fourth scenario depicted private cars as a source. No significant difference in the PM concentrations was obtained between scenarios 3 and 4. It was anticipated that changes would occur at higher PM concentrations between 20 and 25 μg/m^3. An estimated 1288 people died in 2007, as a result of exposure to particulate matter that originated from the vehicular exhaust. It was also anticipated that an increase of 30% in the vehicular load would cause a doubling in the number of extra deaths. It was also predicted that by 2020, a 30% rise in traffic is expected, and the PM_{10} concentration is expected to reach 24.44 μg/m^3 [63] and would also contribute to an increase in the admissions related to COPD.

Several other quantitative HRA tools provide air pollution exposure and related health effects based on population distribution, concentration-response relationship, and emission sources and differ in their complexity and exposure information source [64]. Some of these tools and models are summarized in Table 10.1:

Table 10.1 Some health assessment models [34]

S. no.	Model	Application
1	BenMap-CE	Estimates health impacts at the reduced ozone and $PM_{2.5}$ levels. The model also enables to quantify health and economic well-being with improved air quality using population data, concentration-response criteria
2	HAPIT	Used for the assessment of health benefits associated with low $PM_{2.5}$ exposure indoors. The tool can also predict the health-associated cost for different scenarios through the available exposure-response data
3	COBRA	Used for the assessment of the strategies devised for low emissions and their health and economic impact. The model also suggests high health benefit options which cost-effectively reduce health risks
4	SIM-air	The Simple Interactive Model for better Air Quality assesses the impact of policy interventions to curb air pollution in an urban environment. The model works in conjugation with GIS to show local emission sources and generated pollution data to evaluate different scenarios
5	AirQ+software	Calculates health impact in improved air quality conditions and evaluates the short- and long-term health effects associated with exposure to different pollutants. Also measures the health impact associated with household pollutants and calculates the premature deaths and diseases using the Health Impact Function (HIF)
6	EcoSense	Atmospheric dispersion and air pollution exposure assessment model estimates the long-term health effects on health, through chemical transformation and dispersion of pollutants. The model integrates the local and regional dispersion models to compute the impact of high levels of pollutants
7	GAINS	The model recognizes cost-effective policies to reduce pollution. The model estimates the health risks associated with PM and O_3 [65]. The impact of primary pollutants including SO_2, VOCs, NOx, and NH_3 can be quantified through the model [34]

10.4 Challenges, Uncertainties, and Opportunities for Sophisticated Technological Intervention

The health risk assessment through technological interventions has multiple advantages, and they help policymakers by predicting important information to make policies related to the concentration reduction of air pollutants. The usage of these assessment methods has increased during the past decades due to the abundance of epidemiological studies offering quantification of air pollutants and concentration-response relationship which can be of immense help to decision-makers to create awareness in public about the importance of good air quality [66]. However, each model or tool used has its limitations and weaknesses. The simulated concentrations may not represent the actual exposure, thereby posing a challenge in the accurate outcomes for policymakers. It is important to use accurate data for the health assessment. The modelling data and exposure predictions are in reality surrogate as often other exposure factors like human activity patterns and human occupancy are not explicitly dealt with. Usually in the case of urban modelling houses located in areas farther from the main road experience lower air pollutant concentration, whereas models generalize the concentrations. Overestimation of the health effects is another limitation because future scenarios are predicted generally based on a total increase in vehicular load without taking into account the accurate vehicular distribution in future as new or better roads may scatter the traffic leading to a reduction in pollution in the future. In case the modelling is done to depict the health risk assessment associated with traffic-related pollution, then temporal disparity of traffic should also be considered along with public transit. Traffic flow occurring due to freight movement must also be incorporated for accurate estimation. Better air quality monitoring and accurate data is also required to enhance the authenticity of the modelled predictions. The pollution maps can be of help to identify potential monitoring locations.

Data science approaches that can deal with large, dynamic, and multi-level data are also one of the biggest challenges in the estimation of long-term health effects of air pollutants. Accurate estimation of personal exposure is also very important and requires complex and powerful processing approaches. Advancements in the field of general-purpose computing on graphics processing units (GPGPU) hardware and software have drastically removed the barriers to access and process large data sets. Online platforms like Google Earth Engine can be used for a petabyte-scale analysis of global satellite data [34]. Data processing scripts can also be shared as open-source code platforms like GitHub which can help in the identification, evaluation, reproduction, and validation of successful methods.

10.5 Conclusion

Air pollution has been a great threat to public health since the beginning of the industrial age. Extensive technological interventions have contributed to valuable predictions to curb air pollution at different levels. The health risk assessment associated with air pollution exposure is an important aspect to focus upon for ensuring better health in the future. For futuristic predictions, computational tools and models have emerged as newer and reliable sources which can predict accurate results in a time and cost-effective manner. For decision-makers to come up with effective policy intervention, high-quality data is required which is acquired in different settings and countries. The use of technological interventions like modelling clubbed with different techniques like GIS may give a deeper insight into the association between air quality and health outcomes and may influence the decision-making process and better pollution management. Besides, inequalities in exposure and vulnerability to population must also be explored simultaneously for effective tackling of the air pollution-related health risk assessment.

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