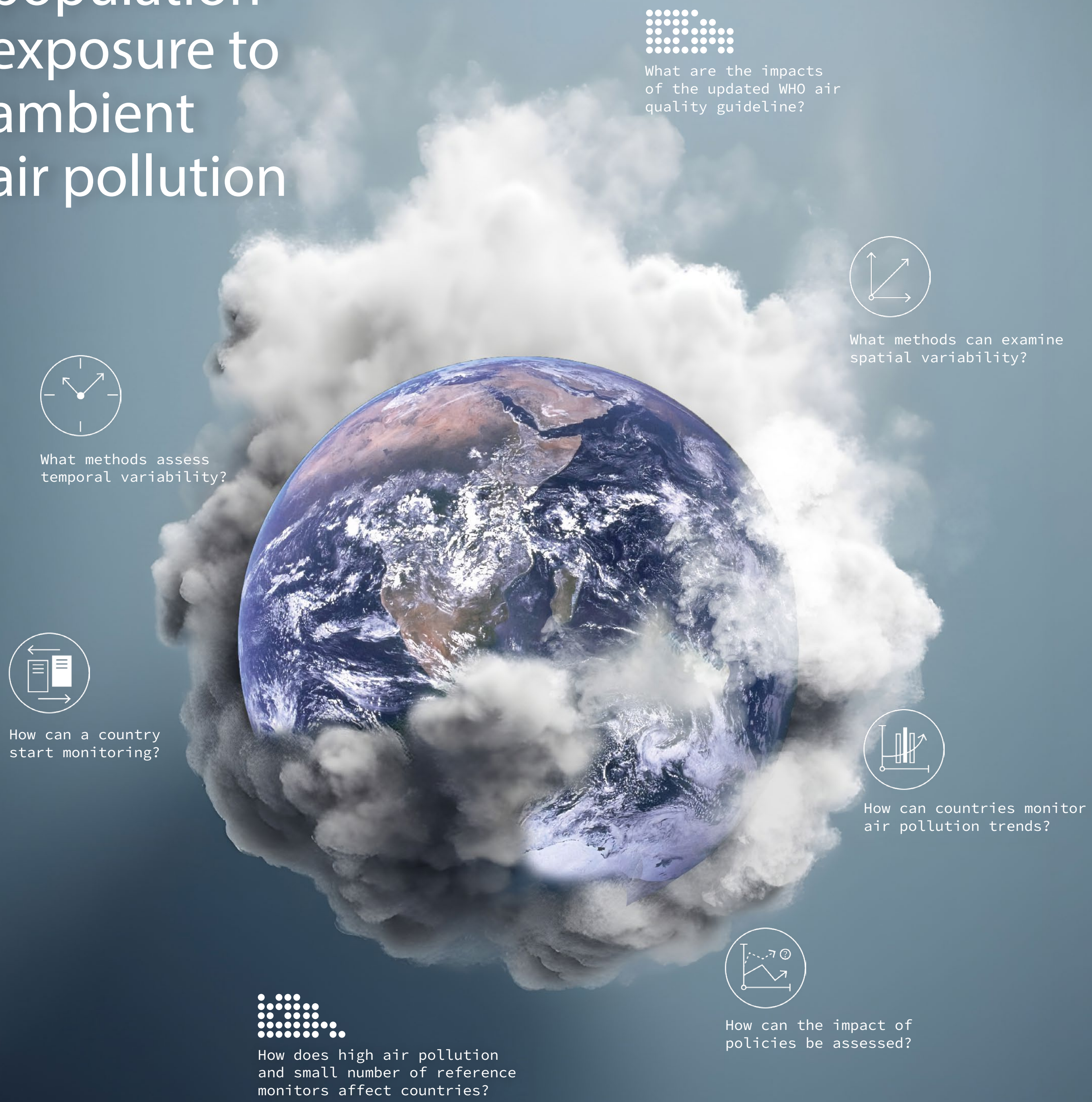
# Overview of methods to assess population exposure to ambient air pollution




World Health Organization

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# Glossary

**Chemical transport model:** A complex atmospheric model that uses emission inventories, meteorological data and complex gas, particle and multi-phase reaction mechanisms to estimate air pollutant concentrations at ground level.

**Dispersion model:** Estimates ground-level air pollution levels by combining emission inventories with topographical and meteorological data to map the dispersion of a plume of pollution.

**Exposure:** Product of the pollutant concentration and the time over which a person is in contact with this pollutant.

**Geostatistical data fusion model:** Refers to a model that combines multiple measurements (e.g. satellite and reference monitors) and modelling (chemical transport model, land-use regression model) methods within a statistical framework to estimate air pollution levels.

**Land-use regression model:** A statistical regression model that estimates air pollution at ground level by mapping the relationship between pollutant measurements and the land-use practices surrounding those measurements.

**Low-cost sensor:** Low cost in this context typically refers to the cost of the basic sensing analytical component (sensor) needed to make a measurement and does not reflect the total operational costs of using sensor systems.

**Machine learning algorithm:** Mathematical model that maps the relationship between training and test dataset to uncover underlying patterns embedded in the data and predict new data.

**Passive diffusion sampler:** Refers to materials that absorb pollutants through passive diffusion. These samplers require chemical analyses to derive the pollutant concentration.

**Personal direct reading instrument:** Portable and/or wearable monitors that measure specific pollutants with fairly good accuracy at a high temporal resolution. These instruments sometimes use similar operating principles to reference-grade instruments. They are usually employed in occupational health and safety assessments.

**Reference-grade monitor:** Instruments that measure specific pollutants with high accuracy at a high temporal resolution. These instruments are based on standardized operating principles for specific pollutants. They are generally used by government agencies to ensure compliance with regulatory requirements.

**Time-integrated data:** A single measurement for the monitoring time period.

**Time-resolved data:** Multiple measurements across the monitoring time period based on the user-specific frequency.

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# Abbreviations

| | |
|---|---|
| **AOD** | aerosol optical depth |
| **AQG** | air quality guidelines |
| **CAMS** | Copernicus Atmosphere Monitoring Service |
| **CCME** | Canadian Council of Ministers of the Environment |
| **CEN** | European Committee for Standardization |
| **CHEOS** | Chinese High-resolution Earth Observation System |
| **CMAQ** | Community Multiscale Air Quality |
| **CO** | carbon monoxide |
| **COPD** | chronic obstructive pulmonary disease |
| **CTM** | chemical transport model |
| **DIMAQ** | Data Integration Model for Air Quality |
| **ECMWF** | European Centre for Medium-Range Weather Forecasts |
| **EEA** | European Environment Agency |
| **EMEP** | European Monitoring and Evaluation Programme |
| **EU** | European Union |
| **GEMS** | Geostationary Environment Monitoring Spectrometer |
| **GEOS-Chem** | Goddard Earth Observing System chemical transport model |
| **GIS** | geographic information system |
| **HEI** | Health Effects Institute |
| **HIC** | high-income countries |
| **IFS** | Integrated Forecasting System |
| **IHD** | ischaemic heart disease |
| **LCS** | low-cost sensor |
| **LMIC** | low- and middle-income countries |
| **LUR** | land-use regression |
| **NASA** | National Aeronautics and Space Administration |
| **NCD** | noncommunicable disease |
| **$NH_3$** | ammonia |
| **NO** | nitric oxide |
| **$NO_x$** | nitrogen oxides |
| **$NO_2$** | nitrogen dioxide |
| **$O_3$** | ozone |
| **OMI** | Ozone Monitoring Instrument |
| **PDRI** | personal direct reading instrument |
| **$PM_{2.5}$** | particulate matter with an aerodynamic diameter of less than 2.5 µm (microns) |
| **$PM_{10}$** | particulate matter with an aerodynamic diameter of less than 10 µm (microns) |
| **PNC** | particle number concentration |
| **ppb** | parts per billion |
| **ppm** | parts per million |
| **RMSE** | root mean square error |
| **SDG** | Sustainable Development Goal |
| **TROPOMI** | TROPOspheric Monitoring Instrument |
| **UFP** | ultrafine particles |
| **UNEP** | United Nations Environment Programme |
| **US EPA** | United States Environmental Protection Agency |
| **VOC** | volatile organic compounds |
| **WHO** | World Health Organization |
| **XGB** | extreme gradient boosting |

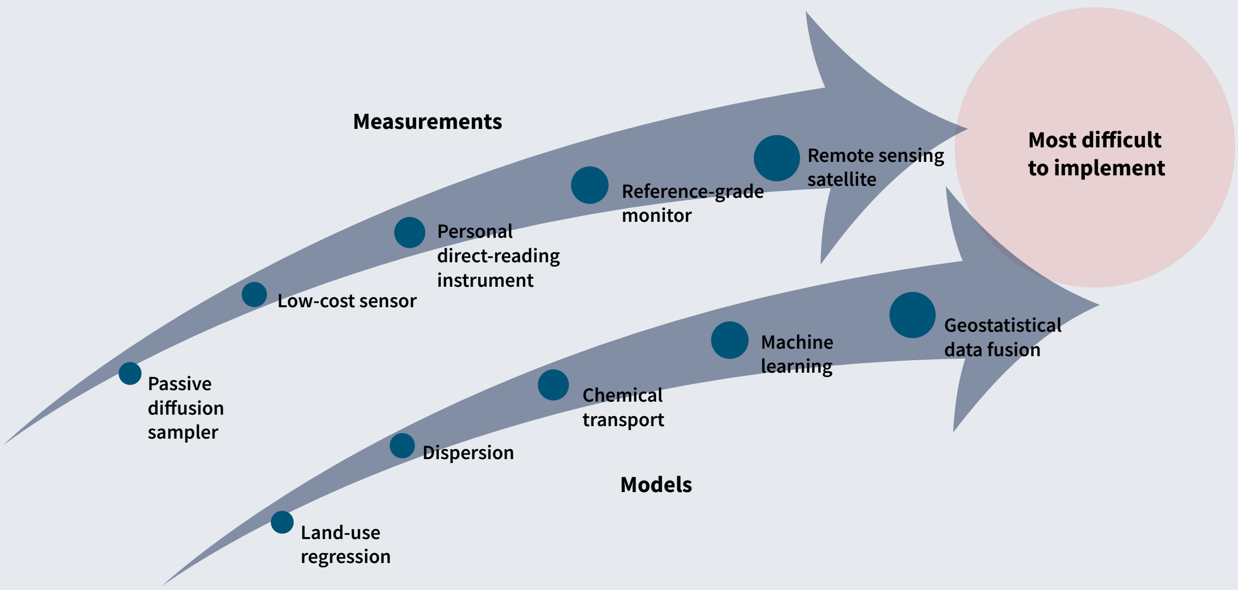
# Executive summary

Exposure to air pollution is the second leading cause of deaths from noncommunicable diseases (NCDs), after tobacco smoking. WHO estimated for 2019 that 6.7 million premature deaths were attributed to ambient and household air pollution from particulate matter (PM) with a diameter less than 2.5 µm (microns) ($PM_{2.5}$). In 2021, WHO issued updated and more stringent air quality guidelines (AQG), reflecting updated evidence that air pollution is associated with adverse health effects at lower concentrations than previously recognized. The recommended annual mean $PM_{2.5}$ level changed from 10 to 5 µg/m$^3$ (WHO, 2021).

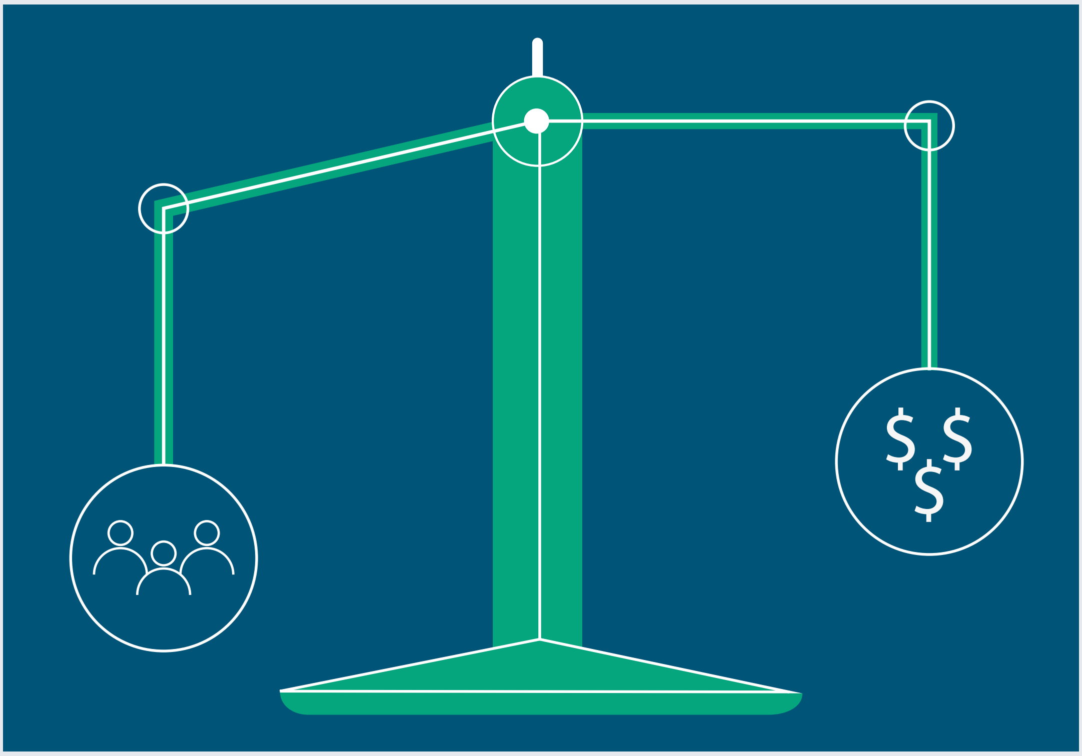
In an effort to support the adoption and implementation of the WHO AQG, this document summarizes several air quality measurement and modelling methods that can be used to estimate ground-level air pollutant concentrations and presents multiple approaches to monitoring ambient air pollution at different spatial and temporal scales. These methods are crucial for estimating population exposures, which can be defined as the product of the pollutant concentration and the time over which a person is in contact with this pollutant.

Air quality measurements and models are presented in order of increasing complexity/technology, starting with the least complex. For each method a brief description is provided followed by its strengths and limitations as well as a few examples of global or regional applications. A comparison with advantages and disadvantages for each monitoring method is then presented, followed by a brief discussion on exposure disparities. Fig. ES1 shows the measurement and modelling methods in order of increasing difficulty of implementation. It is important to note that these methods can be applied to cities, countries and globally, but that no single method is perfect. Usually, multiple methods are used by countries as models require measurements for calibration and validation.

**Fig. ES1 Measurement and modelling methods for monitoring air quality**




*Note:* The most complex methods are the most difficult to implement.




When deciding on how to best develop or improve their air pollution monitoring capability, countries can assess the ease of implementation within constraints: cost (capital and operating); human/technical resources; and computational and energy requirements. For example, a country that has no monitoring may consider setting up a reference-grade monitor and complementing this monitor with passive samplers (low cost, low human resources for deployment, no energy requirement) or low-cost sensors (LCS) (low capital cost but medium operating cost, medium technical resource for calibration and modeller expertise, low energy but medium computing needs for big data) and dispersion modelling (medium capital cost, medium modeller expertise, medium computing needs). Countries with a sparse monitoring network may consider increasing the density of their reference-grade monitors as well as developing locally calibrated chemical transport models (CTMs) (medium capital cost, high modeller expertise, high computing needs).

Policy-makers and government officials can use the available methods summarized in this document to assess their country's baseline air quality levels as well as monitor progress resulting from air pollution reduction policies. The document can further help officials develop plans for air quality monitoring and data management. It is also relevant in assisting national and local authorities responsible for protecting public health from the adverse effects of air pollution. Ideally, every nation should have access to at least one reference-grade monitor – opening the door to many other air quality methods. More importantly, no single method can address the entirety of a country's air quality problem, and nations may want to employ a mixture of measurements and modelling methods to address their local air quality issues while balancing their national priorities and resource availability. Ultimately, multiple methods are needed for a comprehensive air quality management knowledge base and capability. Countries are encouraged to use as many of these approaches as needed, based on their circumstances and capabilities.

# Introduction

# Chapter 1 **Introduction**

Air pollution represents the largest environmental risk to public health worldwide. In 2019, WHO estimated 6.7 million premature deaths from particulate matter, defined as particles smaller than 2.5 µm ($PM_{2.5}$) small enough to penetrate into the alveoli. Over 99% of people worldwide are exposed to harmful levels of $PM_{2.5}$ (WHO, 2022a). However, the distribution of this harmful air pollution varies substantially across the globe, with populations in many low- and middle-income countries (LMIC) suffering from the highest air pollution exposures, and some countries experiencing levels of $PM_{2.5}$ that are five times higher than the WHO AQG.

Exposure, as defined by the WHO, is a product of the pollutant concentration and the time over which a person is in contact with this pollutant (WHO, 2021). While exposure is not the same as concentration, for the purpose of this document, when exposure and concentration are used interchangeably, it refers to the concentration of the pollutant over the time of exposure. In addition, the methods that can be used to assess population exposure for health impact assessments are also used in air quality networks to assess changes in pollutant concentrations.

This document reviews and summarizes the latest measurement and modelling methods and presents multiple methods to monitor ambient air pollution that can be used locally, provincially and nationally for different pollutants and spatial-temporal scales. One of the expected outcomes of this document is a list of monitoring methods that can enable population exposure assessment for epidemiological studies and health impact assessments, which can be incorporated into the existing framework for estimating global exposure to air pollution, specifically $PM_{2.5}$ (Sustainable Development Goal [SDG] Indicator 11.6.2).

Another potential use of this broad overview of methods for ambient air pollution exposure is to present monitoring methods that policy-makers and government officials can use to develop or improve their knowledge base on air pollutant concentrations and on tracking the effectiveness of air pollution reduction policies. By including a diverse range of available methods for monitoring air pollution levels and highlighting their advantages and disadvantages, this document can help LMIC find methods to assess their population exposure to air pollution that are best suited to their country's social, economic and environmental conditions.

## 1.1 Common sources of pollutants and their associated health effects

### Particulate matter

Particulate matter is a mixture of solid particles and liquid droplets and is classified according to its diameter. $PM_{10}$ are particles that have a diameter less than 10 µm, while $PM_{2.5}$ are particles with a diameter less than 2.5 µm. Particles with a diameter less than 0.1 µm are commonly called ultrafine particles (UFP), however, quasi-ultrafine particles refer to particles substantially smaller than 1 µm but larger than 100 nanometres (nm) (WHO, 2021). While $PM_{2.5}$ and $PM_{10}$ are typically measured in terms of mass concentration, UFP are measured in terms of particle number concentration (PNC). Sources of $PM_{10}$ will mainly consist of sea spray and wind-blown dust from agricultural sources, roadways and mining operations. $PM_{2.5}$ and UFP can be derived from primary sources (e.g. combustion of fuels, forest fires, agriculture waste burning) and secondary sources (e.g. chemical reactions between gases). An example of the reaction pathway for the formation of secondary source particles is the reaction of ammonia emitted from, for example, agricultural activities, with nitric acid, which is derived from nitrogen oxides ($NO_x$) mostly emitted from vehicle exhaust or industries, to produce ammonium nitrate particles. UFP can be emitted directly or formed in the air from gaseous precursors from sources such as transportation (e.g. vehicles, planes, ships) and industry (e.g. power plants). While the focus of this report is on measuring ambient air pollution, it is important to note that our total exposure to air pollution occurs both outdoors and indoors. With this in mind, important sources of particulate matter originating from households


(which can be considered as both indoor and outdoor pollution) are also included: cooking, heating and lighting with polluting fuels and technologies such as biomass (e.g. wood, charcoal, crop residue). Additional indoor sources of UFP include electric appliances such as stoves and toasters, tobacco smoking and the burning of candles or incense.

As epidemiological studies have shown that air pollutants can have both adverse short- and long-term effects, most national air quality standards recommend exposure limits for both short-term (e.g. 24-hours) and long-term (e.g. 1 year) averaging times for pollutants (EU, 2021; US EPA, 2023a). Long-term exposure to $PM_{10}$ is moderately associated with increased risk of death from ischaemic heart disease (IHD) and chronic obstructive pulmonary disease (COPD). For $PM_{2.5}$, long-term exposure is strongly associated with lung cancer, IHD, cerebrovascular disease and COPD, and moderately associated with respiratory diseases. Short-term exposure can lead to asthma exacerbations and respiratory infections (Chen and Hoek, 2020). Owing to the smaller size of $PM_{2.5}$, this pollutant can be more harmful to human health as it can reach deeper into the respiratory tract than the larger particles. Short-term effects of exposure to UFP include, emergency department visits, hospital admissions, respiratory symptoms and effects on pulmonary/ systemic inflammation, heart rate variability and blood pressure; long-term effects include mortality (all-cause, IHD, cardiovascular and pulmonary) as well as several morbidity effects (HEI, 2013; Ohlwein et al., 2019). UFP has also been associated with systemic inflammation in children (Clifford et al., 2018). It is important to note that particulate matter can adversely impact health even at low annual average concentrations (Brunekreef et al., 2021; Dominici et al., 2022). Given this, WHO AQG recommend annual mean levels of less than 5 µg/m$^3$ for $PM_{2.5}$ and 15 µg/m$^3$ for $PM_{10}$. For 24-hour means, the guideline values are 15 µg/m$^3$ and 45 µg/m$^3$ for $PM_{2.5}$ and $PM_{10}$, respectively (WHO, 2021).

**Nitrogen dioxide**

Nitrogen dioxide is a gas and the main ambient sources of $NO_2$ are high temperature combustion of fuels used in engines (e.g. motor vehicles and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ships), electrical generation and industrial processes. Household sources of $NO_x$, defined as the sum of nitric oxide (NO) and nitrogen dioxide ($NO_2$), include fuel-burning furnaces, fireplaces and gas stoves and ovens. Exposure to $NO_2$ is associated with asthma hospital admissions and emergency room visits in the short term and mortality from respiratory illnesses in the long term (Huangfu and Atkinson, 2020). The recommended WHO AQG value for $NO_2$ is 10 µg/m$^3$ (annual mean, 5.3 ppb) and 25 µg/m$^3$ (24-hour mean, 13.3 ppb).

### Carbon monoxide

The predominant sources of carbon monoxide (CO) in ambient air are motor vehicles (Krzyzanowski et al., 2005). Similar to $NO_x$, CO can contribute to household air pollution from any process that can result in incomplete combustion of fuels (e.g. furnaces, fireplaces). Short-term exposure to CO has been associated with hospital admissions and mortality from myocardial infarction (Lee, Spath et al., 2020). WHO has recommended a guideline value for CO of 4 mg/m$^3$ (3.5 ppm) for an averaging time of 24 hours.

### Ozone

Ozone ($O_3$) is a gas that can be found in the stratosphere and at ground level. While stratospheric $O_3$ is formed naturally and provides protection from the sun's ultraviolet radiation, ground-level $O_3$ does not. It is a secondary pollutant that is created from chemical reactions involving volatile organic compounds (VOC), $NO_x$ and CO in the presence of sunlight. Unlike primary pollutants which are emitted directly from a source, secondary pollutants are formed through the reaction of other pollutants. Ozone is one of the main components of photochemical smog. It is worth mentioning that $O_3$ can also be generated by household consumer products, such as portable air cleaners that are equipped with $O_3$ generators. Acute exposure to high levels of $O_3$ can lead to reduced lung function and increased airway inflammation. Several studies have shown associations between increased hospital admissions and mortality from respiratory illness and high $O_3$ levels (Huangfu and Atkinson, 2020). WHO recommends a guideline value of 100 µg/m$^3$ (51 ppb) for an 8-hour daily maximum and 60 µg/m$^3$ (30.6 ppb) for an 8-hour mean peak season (WHO, 2021).

# Factors to consider when assessing population exposure to ambient air pollution

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# Chapter 2 **Factors to consider when assessing population exposure to ambient air pollution**

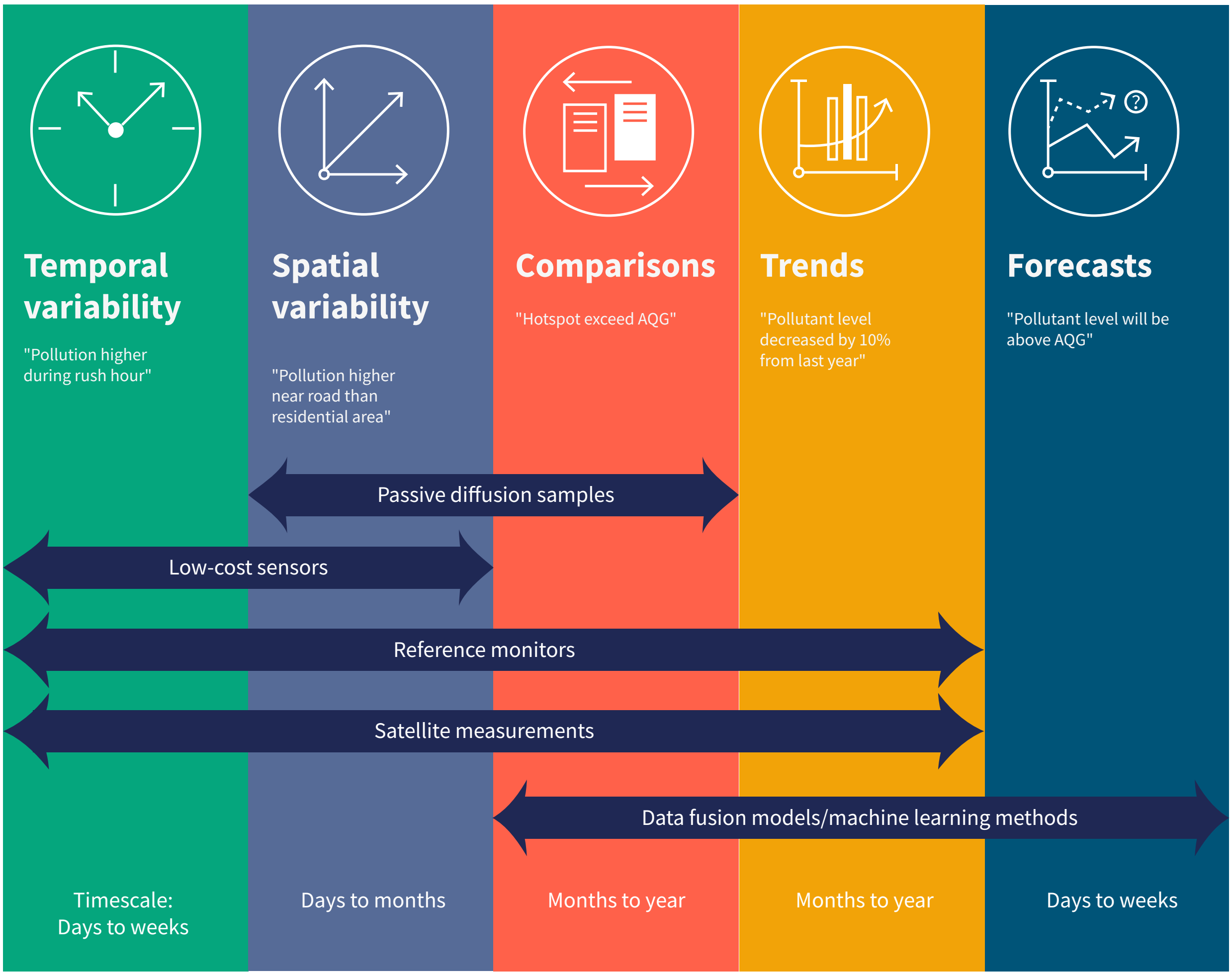
When assessing the global burden of disease from air pollution (SDG Indicator 3.9.1), WHO leverages both model estimates and observed measurements to estimate global air pollution levels. This global estimate of ambient air pollution levels (SDG Indicator 11.6.2) uses a data fusion model, the Data Integration Model for Air Quality (DIMAQ), to derive annual average levels of $PM_{2.5.}$ DIMAQ uses a Bayesian hierarchical modelling framework to combine geophysical satellite-derived estimates of $PM_{2.5}$ with ground-level reference monitors, CTM output and land-use data. A strength of DIMAQ is that it uses a hierarchical modelling approach in which country-specific calibration functions are used and data are "borrowed" from the surrounding regions where local monitoring data are adequate for model calibration (Shaddick, Thomas, Green et al., 2018).

While these global air quality estimates are required for SDG 11.6.2 reporting, and they enable us to monitor the progress of the global burden of disease from air pollution, their applicability for addressing country-specific concerns and/or policies may be limited due to the granular temporal and spatial scale of these annual estimates (Shaddick et al., 2021). Since air pollution tends to be unevenly dispersed across space (e.g. urban vs rural areas), using DIMAQ's annual average concentration, which represents the same population exposure across a 11 km x 11 km grid, can resolve urban and rural differences but it may not identify intra-urban or intra-rural variability within a given country. The more local data (e.g. country-specific measurements and time-activity patterns) that countries can use in population exposure assessments, the greater the likelihood that the estimated population exposure is closer to an individual's exposure as it encompasses total exposures across different microenvironments (e.g. homes, offices, vehicles, cities), which can be very different from the ambient air pollution levels used in global studies (WHO Regional Office for Europe, 1999). The importance of monitoring local air pollution cannot be overstated, but it is also crucial to improve the local data collection duration as a longer duration of historical data can allow more robust exposure estimates and health impact assessments.

Assessing population exposure to air pollution is typically achieved using observed measurements (e.g. reference-grade monitors[1]), model estimates (e.g. CTM) or a combination of these two (e.g. geostatistical data fusion model and land-use regression [LUR] model). The use of reference-grade monitors is traditionally preferred for monitoring networks as they enable the baseline assessment of air quality levels as well as the tracking of long-term progress in air pollution objectives. These reference monitoring networks are valuable because of their precision, and they can also help identify whether the air quality level meets national standards, as well as identify populations with disproportionate exposure to air pollution. Without these monitors, one cannot objectively evaluate if policies have had any impacts. Usually, the question being addressed by the population exposure assessment can influence the suitability of the air quality monitoring method. Furthermore, the choice of the monitoring approach is typically not only driven by the scale considered (i.e. urban, national or regional) but also by the objective of the air quality monitoring network. For example, for a country interested in determining its baseline air pollution levels, reference monitors would be best suited for monitoring temporal and spatial variability. On the other hand, if the country is interested in assessing the impact of policies, then combining reference monitors and data fusion models would be best suited for monitoring trends and forecasting. Fig. 1 illustrates the usability of different population exposure methods for specific applications (e.g. spatial and temporal variability). More often than not, one method can rarely achieve a nation's air quality objectives, and a combination of models and measurements is usually needed.

1 Some government agencies offer guidelines for recommended reference-grade instruments, such as the United States Environmental Protection Agency (US EPA, 2022).

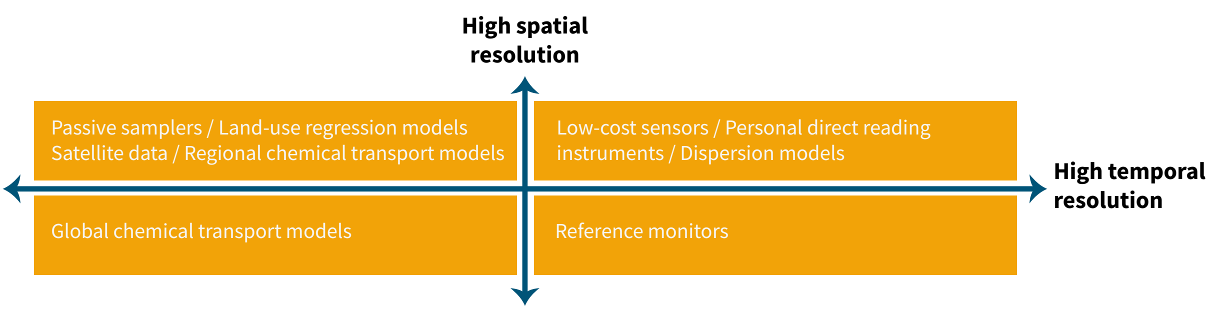
**Fig. 1. Span of current capabilities and applications across different types of air pollution measurement and modelling networks**




*Source:* Adapted from Peltier et al., 2020 *(An update on low-cost sensors for the measurement of atmospheric composition).*

One of the main considerations in monitoring air pollution is the desired temporal and spatial resolution that a country wants to capture. For example, a country that is interested in collecting many air pollution measurements within an hour (e.g. high temporal resolution) may find that reference-grade monitors, personal direct reading instruments (PDRIs) and/or dispersion models are more appropriate for their application (Fig. 2). Alternatively, if the purpose is to collect many measurements across a wide geographical area (i.e. high spatial resolution), the use of multiple passive samplers, satellite data and/or LUR models is more appropriate.

**Fig. 2. A quadrant analysis that clusters air quality measurement and modelling methods across different temporal and spatial resolutions**



Three key factors that countries may want to consider when deciding on how to best develop their capacity and knowledge base for monitoring air pollution include:

- cost – both up-front and long(er) term costs such as full financial modelling of capital costs for acquisition and maintenance of monitors;
- staffing – human resource capacity; and
- computational and energy requirements.

Table 1 illustrates the level of the resources required for each measurement and modelling method. These three selection criteria can be overlaid with country-specific constraints to determine the optimal method for monitoring air pollution and assessing population exposure. For example, a country that has cost constraints may find passive diffusion samplers and LCS more attractive solutions for monitoring air pollution exposure. Additional information on the advantages and disadvantages of each monitoring method is presented in section 3.3.

**Table 1. The cost, human and computational resource requirements associated with each air quality measurement and model**

| | Cost | Human/Technical Resources Required | Computational/Energy Requirements |
|---|---|---|---|
| **MEASUREMENTS** | | | |
| **Passive diffusion samplers**[a] | Low capital | Low for sample deployment | Not applicable |
| **Low-cost sensors** | Low capital and medium operating | Medium maintenance and calibration<br>Medium modeller expertise | Low energy and medium computing needs for big data |
| **Personal direct reading instruments** | Medium capital and operating | Medium maintenance and calibration | Medium energy and computing needs |
| **Reference-grade monitors** | High capital and operating | High maintenance and calibration | High energy and medium computing needs |
| **Remote sensing satellites**[b] | Not applicable | High modeller expertise | Not applicable |
| **MODELS** | | | |
| **Land-use regression models** | Low capital (proprietary geographic information system [GIS] data) | Medium modeller expertise | Low computing needs |
| **Dispersion models** | Medium capital (proprietary software) | Medium modeller expertise | Medium computing needs |
| **Chemical transport models** | Medium capital | High modeller expertise | High computing needs |
| **Machine learning models** | Low capital (open-source algorithms) | Medium to high modeller expertise | Medium computing needs |
| **Geostatistical data fusion models** | Medium capital (proprietary software) | High modeller expertise | High computing needs |

[a] Passive diffusion samplers are analysed by external labs after they have collected air pollution levels derived from natural air flow. While they do not need an energy supply, they cannot measure short-term pollutant levels or non-compliance with standards and these measurements do incur the additional costs of the analysis and shipping to approved laboratories.

[b] Satellites are deployed and maintained by international agencies which makes the cost and energy requirements not applicable for countries. While the measurements (i.e. column densities) collected are usually made publicly available, some modelling is required to convert the satellite measurements into air pollution concentrations. It should be noted that several institutions have developed satellite-based model estimates for public use.

The following sections cover measurement and modelling approaches that can be used to assess a country's ambient air quality level depending on timescale and spatial resolution of interest. Air quality measurements and models are presented in order of increasing complexity/technology starting with the least complex approach. For each method a brief description is provided followed by its strengths and limitations as well as a few examples of global or regional applications.

A comparison of the strengths and weaknesses of individual measurement and modelling approaches, as well as machine learning and geostatistical data fusion methods, which combine air quality measurements and simulation modelling into a statistical model, are presented. The final sections highlight future work that can be done to reduce exposure disparities and improve population exposure assessments.

# Overview of methods for monitoring ambient air pollution and assessing population exposure

# Chapter 3 Overview of methods for monitoring ambient air pollution and assessing population exposure

## 3.1 Air quality measurements

### 3.1.1 Passive diffusion samplers

Passive diffusion samplers are devices (e.g. badges or tubes) that contain chemical reagents to absorb gases of interests without the use of pumps. They are usually set up at multiple locations for a minimum of 1 day to a maximum of 2 weeks to collect time-integrated data (i.e. a single measurement for the monitoring time period). The deployment of the samplers simultaneously or within a couple days apart reduces the influence of synoptic meteorological changes on the data collected. After the samplers have absorbed the ambient pollutants they must be sent to a qualified laboratory to determine the volume concentration of the pollutant absorbed (EEA, 2020). A similar process is applied to tree lignin to quantify air pollution that has been absorbed by plants.

Pollutants that can be quantified by passive diffusion tubes or badges commonly include $NO_x$, VOC and carbon monoxide. It is important to remember that once these samplers become saturated (i.e. they can no longer absorb any more air pollutants) their estimated air pollution concentration can become inaccurate if the time the sampler became saturated is not known (US EPA, 2015).

A main advantage of passive samplers is their zero-energy requirement, which allows users to easily deploy them to quantify concentrations near diverse source locations that do not have access to a power source. For example, if a study is interested in measuring air pollution from a roadway, passive samplers can be attached to streetlights or appended to building façades. However, it is recommended that when deployed, passive samplers are co-located with at least one other sampler. This duplication or triplication of samplers allows users to perform quality control checks after the sampling campaign has been completed (CEN, 2019). Other benefits of these samplers are their low cost and light weight. However, the cost (especially for LMIC) associated with outsourcing the quantitative analysis to laboratories that may be located outside the country of interest can significantly increase analysis costs and must be included in users' cost assessments.

Passive diffusion samplers can also be used to assess the spatial distribution of air pollution over a fixed time period (CEN, 2002). As passive samplers can capture a snapshot of spatial variability in air pollution, multiple sampling campaigns are usually conducted to classify the spatial variations in air pollution across different seasons and meteorology. While the spatial scale covered by these samplers is driven by the number of samplers located within a given area, the time-integrated data collected by these samplers can indicate what sources are being recorded. For example, a sampler that collects 2-week average concentrations is likely to represent the average urban background or rural exposure, while a sampler with daily time resolution can potentially detect day-to-day changes in traffic emissions (e.g. weekday vs weekend) as well as the influence of meteorology.

**Box 1. Example of passive diffusion samplers used in regional applications**

These samplers continue to be used by some European countries such as Finland and Germany to supplement their air quality monitoring network as well as to validate national air quality models. An example of this can be seen in Flanders where the Flanders Environment Agency used passive $NO_2$ samplers to develop a reliable spatial mapping of $NO_2$ concentrations, which was then used to improve the predictive capability of the existing air quality model (EEA, 2019b). These samplers were also integral in the development of early land-use regression models (Hoek et al., 2008).

### 3.1.2 Low-cost sensors

The availability of LCS has rapidly increased within the last decade (Morawska et al., 2018). In addition, countries, particularly in regions with no high-quality data, are showing growing interest in measuring and using data from LCS, which can range in size from portable instruments to larger systems more suitable for fixed monitoring sites. Some examples of pollutants measured by LCS monitors that have been used for community/citizen science and live air quality maps include, $NO_2$, CO, $O_3$, VOC, particulate matter and radiation (UNEP, 2023).

The most common limitation associated with LCS is low accuracy, which is exacerbated by interference from other gases and meteorological conditions. For example, the accuracy of particulate matter measurements is heavily influenced by relative humidity levels and temperature. They are also less sensitive to changes in air pollution levels than high-quality monitors (Clements, 2022). These sensors are also prone to drifting baselines due to changes in the sensor's conductivity or resistance over time, with electrochemical sensors showing more long-term drift than metal oxide sensors (Spinelle, Gerboles et al., 2017). For this reason, it is important to periodically calibrate these sensors with reference-grade monitors to ensure that the calculated air pollution concentration is accurate (Castell et al., 2017). For more technical information about the operating principles used in LCS, refer to the Annex.

One of the advantages of LCS is their low capital cost. These sensors can be obtained for a few hundred dollars; however, the operational costs can vary significantly within the range of thousands of dollars (Peltier et al., 2020). They also collect time-resolved data (i.e. multiple measurements within the monitoring time period). For example, metal oxide sensors, which are used to measure gases, tend to have response times ranging from 1 to 5 minutes. Another benefit of LCS is their portability, making it easier to deploy these monitors in locations where it is not feasible to use larger reference-grade monitors or to measure individuals' level of personal exposure to air pollution. In addition, these sensors have low power requirements, which reduces the operating cost and makes the expansion of an air quality monitoring network more cost-effective for LMIC. Further, the low power required to operate these sensors can be fulfilled by solar-powered batteries, which then creates opportunities for monitoring air pollution in rural areas without access to electricity.

A recent report by the World Meteorological Organization (Peltier et al., 2020) assessed several studies that used LCS and concluded that they are not yet suitable for replacing reference-grade monitors but could complement them through more versatile applications. In countries with limited reference monitors, LCS could be added to the monitoring network to improve the spatial coverage of air quality data being collected. The importance of quality assurance and quality control of data from LCS should, however, be emphasized in order to reduce the inaccuracy of their measurements (Karagulian et al., 2019).

**Box 2. Example of low-cost sensors used in regional applications**

In a regional study by Liu et al. (2020), the long-term performance of the community monitoring programme Knowing Our Ambient Local Air-quality (KOALA), in China and Australia, found that particulate matter LCS performed best when relative humidity levels were less than 75% and temperatures were above 0 °C. Furthermore, the sensors were better able to assess $PM_{2.5}$ pollution from background emissions rather than local traffic impacts in urban areas.

LCS are also being used by the European Environment Agency and national environmental protection agencies through the CleanAir@School initiative to improve understanding of children's exposure to air pollutants such as $NO_2$ in the outdoor school environment. For example, in Scotland LCS were used instead of passive samplers so that they could identify when air pollution levels peaked and what activities (e.g. drop-off and pick-up by car vs buses) were associated with those high exposures (EEA, 2019).

### 3.1.3 Personal direct reading instruments

Personal direct reading instruments are portable instruments commonly used by industrial hygienists, and health and safety professionals to assess occupational exposures. These small-scale, "personal" monitors exist for a variety of important pollutants including particulate matter, CO, $NO_x$ and $O_3$. Some instruments collect time-integrated data (i.e. a single measurement for the monitoring period) while others collect time-resolved data (i.e. multiple measurements within the monitoring period based on the user-specific frequency). For more technical information about the operating principles used in different PDRI refer to the Annex. Since these instruments are lightweight and compact, they allow users to collect accurate and high temporal resolution data across the different microenvironments that an individual may be exposed to which is critical to assessing an individual's time-weighted average personal exposure. In addition to being used for regulatory purposes to ensure compliance with occupational health and safety, these instruments are also commonly used by research scientists interested in measuring the spatial and temporal variability of pollution at multiple locations and time periods (Koehler and Peters, 2015). Given their portability, these instruments can be coupled with mobile platforms (e.g. walking, cycling, driving) and global positioning systems to capture a snapshot of air pollution exposures over a wider geographic area. The capital cost associated with these instruments tends to lie between reference-grade monitors (which are typically the most expensive) and LCS; however, there are some PDRIs that are comparable in cost to LCS. These instruments also require periodic calibration and maintenance, which adds to the operating cost. One of the main disadvantages of these instruments is that they cannot collect air quality data over the long term, which is an important consideration as historical data can allow more robust health impact assessments.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**Box 3. Example of personal direct reading instruments used in regional applications**

Numerous studies have been conducted on children's exposure to UFP in several countries (Australia, Bhutan, China, Ghana, Italy) using small instruments that can be carried/worn (Buonanno et al., 2012; Mazaheri et al., 2014; Nyarku et al., 2019 and 2021; Wangchuk et al., 2015). Among other aspects, the studies investigated the impacts of lifestyle and sociocultural factors on the exposure to UFP in different microenvironments, demonstrating the opportunities and urgency for the control of UFP exposure.

The monitoring of UFP faces numerous challenges, one being that there are still discussions about which parameter(s) to measure (Cassee et al., 2019). Particle number/size distributions are most commonly measured with relatively well-established methods; however, there is no agreed standard method, making it difficult to compare results from different exposure/epidemiological studies or use the data for large population-based epidemiological studies. To overcome this, WHO AQG (WHO, 2021) proposed to: "Quantify ambient UFP in terms of particle number concentration (PNC) for a size range with a lower limit of ≤ 10 nm and no restrictions on the upper limit". UFP are currently monitored using PDRI that are small and suitable for personal exposure measurements, as there are no reference-grade instruments or LCS available to measure this pollutant.

### 3.1.4 Reference-grade monitors

Reference-grade monitors are commonly used in air quality monitoring networks and can collect ground-level air pollution measurements in different averaging times (e.g. measurements reported at hourly or daily averages) for regulatory purposes. Traditionally, these monitors are deployed in areas of high population density, or in areas of specific concern, and these monitoring locations do not necessarily capture intra-urban or urban-rural gradients. While these instruments can offer long-term coverage of air pollution at a high temporal resolution, in several countries, reference-grade monitors have not been deployed at the spatial scale needed to measure intra-urban variability, but they could be with adequate financial and human resources. Across the globe in 2019, there were approximately 6700 and 4000 human settlements collecting data on $PM_{10}$/$PM_{2.5}$ and $NO_2$ (WHO, 2022b). However, the spatial distribution and monitoring density of these reference-grade instruments vary significantly across the globe. For example, European countries and the United States of America have two to three and 3.4 monitors, respectively, measuring a million of their inhabitants' air pollution exposure, whereas countries such as India use one monitor for every 6.8 million people (Brauer et al., 2019), roughly one-twentieth the monitoring density of Europe and the United States of America. In several countries in sub-Saharan Africa, reference monitors are non-existent (Amegah and Agyei-Mensah, 2017). Globally, there is inequality in monitoring environmental risk factors and a limited capacity to detect intra-urban spatial variations across LMIC and even high-income countries (HIC).

A crucial aspect that determines the location of a reference monitor within a country is the purpose or objective of the monitor (i.e. what question will be answered by the air pollution data collected by the monitor). Generally, countries locate most reference-grade monitors that are used for regulatory purposes in urban areas where population density is greatest, while fewer instruments are situated in rural areas (EEA, 2022). It is common to locate reference-grade monitors in different areas that represent diverse emissions sources but not too close to any specific source (e.g. very close to a road or major industry). Table 2 illustrates some of the common classifications for monitoring sites and detailed description of each site type (EU, 2008). For example, instruments can be installed in areas close to industrial facilities or major roadways if a country is interested in monitoring the impact of air pollution from industrial or traffic sources, respectively. It is also important to set up a reference monitor in a background location that is far away from any local sources (e.g. traffic or industrial emissions) so as to identify the air pollution levels associated with the regional background or transboundary influences. This approach allows monitoring agencies to calculate the pollution contribution from known or suspected sources by subtracting the regional background difference. Such regional background monitoring sites are fundamental to the European Monitoring and Evaluation Programme (EMEP, 2001). The process of situating a reference-grade monitor is standardized by most government agencies (CCME, 2019; Nagl et al., 2019). As air pollution concentrations can be greatly influenced by the distance of the air sampling inlet from a roadway, height of the sampling inlet and presence of trees or buildings near to the sampling inlet, it is important to carefully consider the location of an instrument before installation. It should also be mentioned that these siting protocols are currently being adapted for LCS (US EPA, 2023b). The type of reference-grade instruments used to record ambient air pollution varies across countries but the scientific principles that these instruments use are generally similar. Some government agencies offer guidelines for recommended reference-grade instruments, such as the European Committee for Standardization (CEN, 2017) and US EPA (US EPA, 2022). For more technical information about the operating principles used in reference monitors refer to the Annex.

**Table 2. Possible monitoring locations relevant to exposure assessment**

| SITE CLASSIFICATION | DESCRIPTION |
|---|---|
| **Urban centre** | An urban location representative of urban centre pollution levels in towns or city centres |
| **Urban background** | An urban location removed from local sources of pollution and representative of city-wide background emissions |
| **Suburban or residential** | A location outside of the urban core situated in a residential area |
| **Near road** | A site within 15 m of a busy road |
| **Industrial** | An area where industrial sources significantly contribute to peak or long-term levels |
| **Rural** | An open area that is far from roads, and industrial areas |
| **Other** | Any location close to special emission sources or vulnerable populations (e.g. hospital, day care centre) |

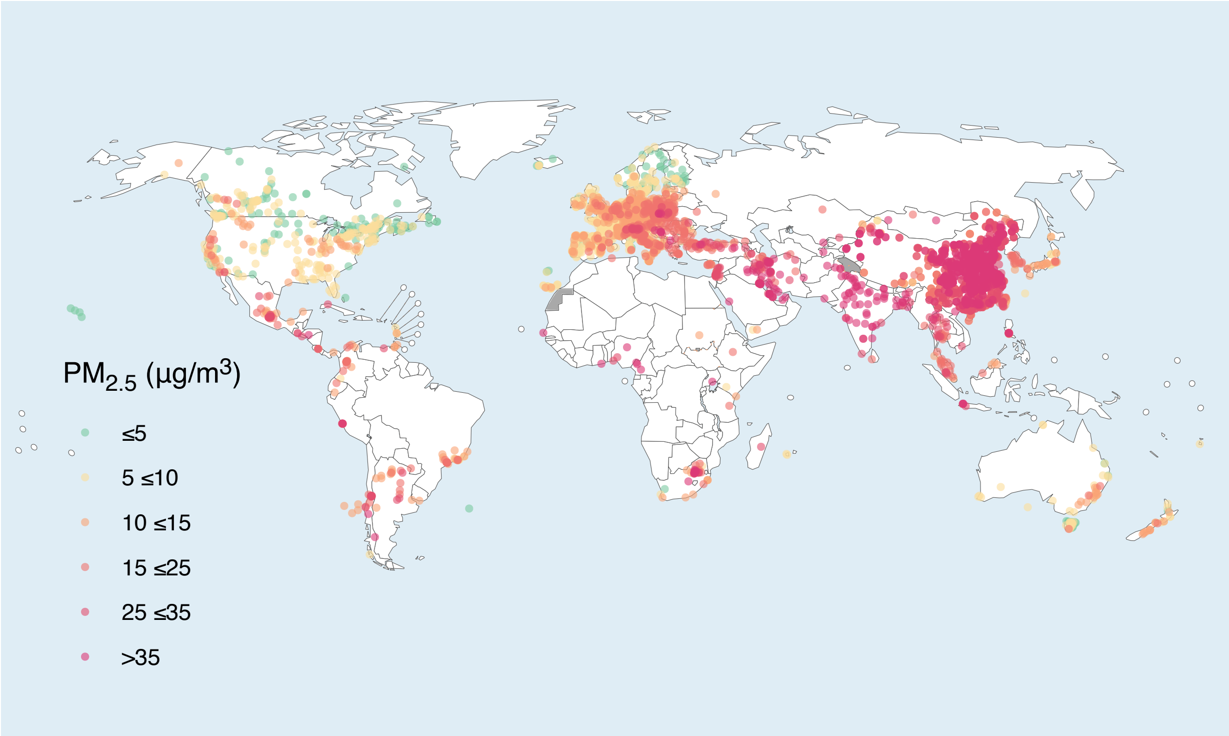
*Source:* Adapted from WHO Regional Office for Europe, 1999 (*Monitoring ambient air quality for health impact assessment).*

While reference-grade monitors are costly, they are considered to be the most reliable and accurate instruments for long-term monitoring of a country's air pollution concentrations, which is essential for assessing health impacts from air pollution exposure. However, it is important to note some of the difficulties that LMIC can face in setting up reference monitors, including continuous power supply, which can be problematic if there are frequent power outages, and periodic calibration and maintenance, which affects the completeness and quality of the data collected in these settings. Also, procurement and delivery of equipment parts or maintenance services can be difficult or delayed by several months which can affect the temporal coverage of a country's data. Despite these constraints, the high temporal resolution, longevity and sensitivity to specific pollutants makes reference-grade monitors the preferred instruments for regulatory agencies to capture short-term emission exceedances as well as long-term pollution trends. Ideally, every nation should have access to at least one reference-grade monitor in an urban centre and another monitor in a rural area.

**Box 4. Example of reference-grade monitors used in a global application**

The WHO ambient air quality database is a compilation of annual mean concentrations of ground-level measurements of $PM_{10}$, $PM_{2.5}$ and $NO_2$ from reference-grade monitors. These measurements are obtained from official national and subnational reports and websites as well as regional networks (WHO, 2022b). The 2022 version of the database includes annual means for $PM_{10}$, $PM_{2.5}$ and $NO_2$ for the years between 2010 and 2019, and it covers around 6700 human settlements in 117 countries worldwide (Fig. 3). Comparison of the ambient air quality database $PM_{2.5}$ and $PM_{10}$ levels by income group showed higher exposure levels in LMIC, by a factor of about three, when compared with HIC. However, a different pattern was observed for $NO_2$ levels, where HIC and LMIC reported more homogeneous concentrations. Globally, only the population within 10% of the assessed settlements were exposed to annual mean levels of $PM_{2.5}$ and $PM_{10}$ that complied with the AQG. This proportion increased to 31% for interim target 4 (2005 WHO AQG: 20 μg/m$^3$ for $PM_{10}$ and 10 μg/m$^3$ for $PM_{2.5}$).

**Fig. 3. Location of settlements with data on $PM_{2.5}$ concentrations, 2010–2019**




*Source:* WHO, 2022b (WHO air quality database).

### 3.1.5 Remote sensing satellite instruments

Satellite data have become increasingly popular for assessing global exposures. Within the last decade there have been rapid improvements in both the temporal and spatial resolution of air pollutant measurements collected by satellite. Several national agencies have deployed satellite instruments for remote sensing measurements including China Aerospace Science and Technology's CHEOS, the European Space Agency's Copernicus, Japan Aerospace Exploration Agency (JAXA) and National Aeronautics and Space Administration's (NASA) Aura (ECMWF, 2022; NASA, 2023). Satellite instruments that monitor $PM_{2.5}$ provide aerosol optical depth (AOD) values, which are atmospheric column density measurements (i.e. all aerosols observed in a column of air reaching from the earth's surface to the upper atmosphere) rather than ground-level concentrations.

In order to estimate $PM_{2.5}$ mass concentrations from column measurements, AOD values need to be combined with other data sources within a statistical model framework to derive the ground-level concentrations[1]. Such conversions require input from multiple data sources such as CTMs, meteorological models, reference-grade monitors and land-use data. Furthermore, operationalizing these different data sources usually requires significant computing resources and expertise in running such models. A few limitations of satellite-derived estimates include their lack of coverage in the presence of clouds and, for some satellites, AOD values are retrieved only when the satellite passes overhead, typically once per day, which may not capture diurnal variability at each location.

1 Some examples of commonly used statistical model frameworks include machine learning, geographically weighted regression.

**Box 5. Example of remote sensing satellite used in global applications**

Recently deployed satellites continue to advance our global exposure assessment through the availability of air pollution column densities at an even finer spatial resolution. For example, while the Ozone Monitoring Instrument (OMI) $NO_2$ resolution was 0.25° (13 km x 24 km), the TROPOMI (TROPOspheric Monitoring Instrument), which was launched in 2018, can provided $NO_2$ column densities at a 0.125° resolution (3 km x 7 km). Similarly, the Geostationary Environment Monitoring Spectrometer (GEMS) satellite-based instrument improves upon OMI spatial resolution with total $O_3$ column densities being recorded at a 0.125° resolution (Xue et al., 2020). Novel approaches to converting the satellite measurements into ground-level air pollution concentrations are being explored with multiple machine learning algorithms within an ensemble-based model. These machine learning and data fusion methods will be covered in more detail in subsequent sections.

## 3.2 Air quality model estimates

### 3.2.1 Land-use regression models

In their simplest form, LUR models are statistical formulae that map the relationship between ground-level measurements (e.g. quantified by reference monitors, passive samplers or LCS) and the type of land that surrounds those measurements (e.g. roadways, industrial facilities, agricultural lands, rural forests). These land-use data are typically sourced from GIS data, but the cost and lack of availability of these data in some countries makes the use of publicly available satellite imagery to derive land-use data a more viable option (NASA, 2023). While LUR models have traditionally been developed from measurements collected at fixed sites, there has been a recent surge in models being developed from air pollution measurements collected via mobile platforms (e.g. on foot, bicycles, electric vehicles). This shift in the medium used to monitor air pollution data has also expanded the type of air pollutants that can be studied. For example, historical LUR models have been developed for $PM_{10}$, $PM_{2.5}$ and $NO_2$, while more recent models have examined additional pollutants such as black carbon, UFP, polycyclic aromatic hydrocarbons, VOC and particulate components (Jedynska et al., 2014; Li et al., 2022; Robinson et al., 2019).

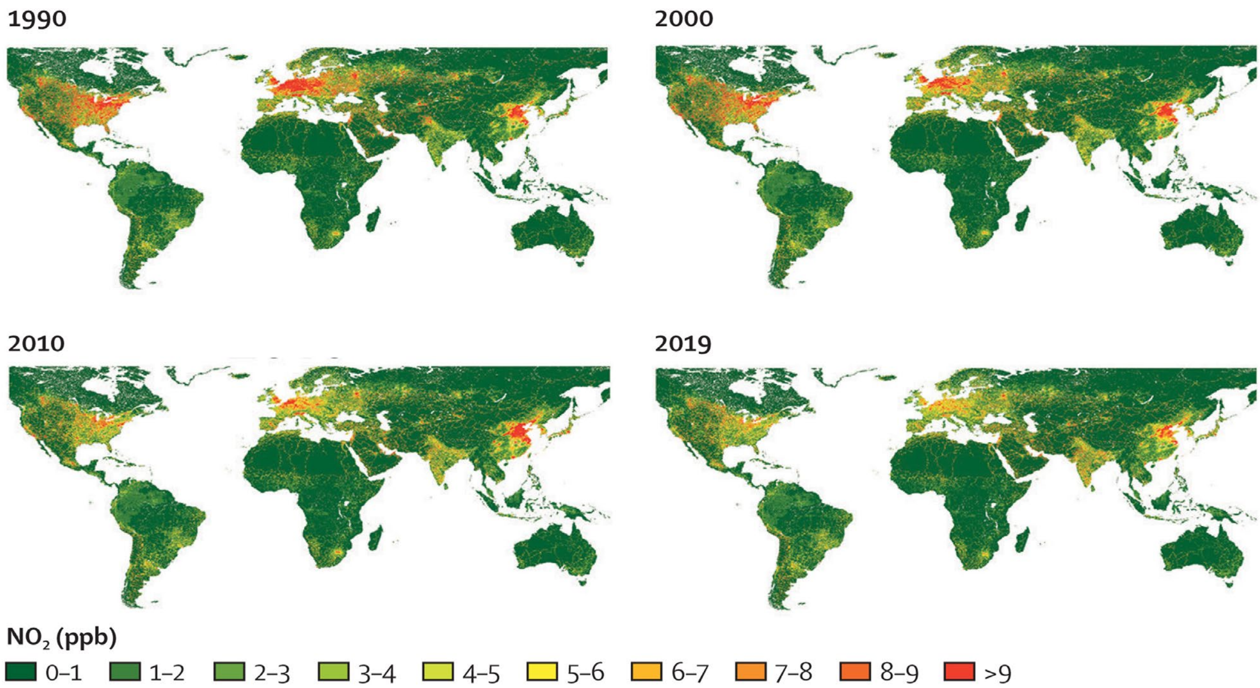
LUR models are commonly used to derive air pollution exposure maps that offer detailed spatial variations in air pollutant concentrations. While these models are inherently temporally static, they allow users to estimate concentrations where there are no measured data. It is for this reason that these models have been commonly used in epidemiological studies that aim to understand the relationship between health impacts and exposure to air pollution. LUR models have been developed over a wide range of spatial scales (from 10 m to 10 km) with models being developed for neighbourhoods (Patton et al., 2015), cities and continents (Coker et al., 2021; de Hoogh et al., 2018; Hystad et al., 2011) and globally (Larkin et al., 2017). When developing regional or global LUR models, common input data are satellite-based air pollution estimates that allow users to account for country-specific differences in their baseline exposure and generally improve the model's performance. However, there are special challenges for continental and global spatial scales, as the model has to accurately represent exposures for a large geographic area yet be quality assured for the specific countries throughout that area. The spatial scale of the final model is a result of the density of the measurements (i.e. the denser the measurement network, the finer spatial variability that the model can map), the spatial heterogeneity of the pollutant (e.g. $NO_2$ may have more near-road variations while $PM_{2.5}$ may have more urban-scale variability) and the spatial resolution of the predictor variables (e.g. land-use variables from GIS data may be available every 10 m while satellite imagery provides 30-m spatial resolution) used in the model's development. For a country that has non-existent or is developing air quality infrastructure, it may be more accessible to start air quality modelling with LUR models.

As with any other regression model, there lies a significant risk of ignoring confounding variables. For example, if a LUR model included predictor variables such as truck volumes and proximity to an industrial facility it is possible that the industry's truck emissions as well as its stack emissions may be contributing to the air pollution. Additionally, as these empirical models ignore processes such as long-range transport and transformation of secondary pollutants, it is more challenging to develop a LUR that can be used to explore future scenarios of emission reductions. For this application, CTMs are more commonly used although they do not yet provide the same high spatial resolution of air pollutant concentrations as LUR models. More details on CTMs will be explored in section 3.2.3.

**Box 6. Example of land-use regression model used in a global application**

A global $NO_2$ LUR model was developed from 2005 to 2019 with a spatial resolution of 50 x 50 $m^2$ and daily, monthly and annual temporal resolutions (Larkin et al., 2022). The spatial-temporal model includes variables such as major roads, built environment, population density, temperature and satellite-based air pollution data. Across all regions, major road density and satellite-based estimates of $NO_2$ were consistently the strongest predictors. Of the 8250 reference-grade monitors used to calibrate the global model, approximately 2.3% of monitors were located in Oceania, South America and Africa. Anenberg et al., 2017 expanded the temporal coverage available for a global LUR model from 1990 to 2019 and showed that 1.85 million paediatric asthma incidences were attributable to $NO_2$ exposure (Fig. 4).

**Fig. 4. Annual average $NO_2$ concentrations from 1990 to 2019**




*Source*: Anenberg, S et al. 2022. *(Long-term trends In urban $NO_2$ concentrations and associated paediatric asthma incidence: estimates from global datasets.)*

**Box 7. Example of dispersion models used in regional applications**

An example of a dispersion model commonly used to identify areas of non-compliance and associated sources is AERMOD. This model predicts the dispersion of pollutant plumes using Gaussian dynamics. Typical inputs for this dispersion model include terrain, processed meteorological data, industrial stack specifications (e.g. height, diameter, exit velocity) and pollutant emission rates for each stack, area source (e.g. ponds, holding facilities) or line source (vehicles). AERMOD also allows users to customize the density and height of receptors (e.g. 2 m above ground level) for which air pollutant estimates are required. In North America, industries seeking environmental approval certificates are required to estimate the cumulative air pollutant concentrations at ground level (US EPA, 2023d). However, in some countries, although air pollution emission permits require the application of dispersion models, the laws are not precise regarding the specific technical rules or guidelines they must comply with. For example, dispersion model estimates for new emission sources that do not account for background concentrations would be lower and more likely to meet the air quality standard than model estimates that include background concentrations (i.e. the cumulative air pollutant concentration).

Another dispersion model which is slightly more sophisticated than AERMOD and is commonly used in scenario analysis for policy-makers is CALPUFF. CALPUFF is a non-steady-state Gaussian puff model that incorporates some chemical reactions (US EPA, 2012). In contrast to AERMOD which is used for near-field applications, CALPUFF is generally employed for long-range applications such as the mapping of transboundary pollution within North America. ADMS-urban and SIRANE models are also commonly used in Europe to simulate air pollutant concentrations at a fine spatial scale (5 to 10 m) and are specifically adapted to evaluate the contribution of road traffic at the city level (Nguyen et al., 2018).

### 3.2.2 Dispersion models

Atmospheric dispersion models describe the turbulent diffusion processes in the atmosphere. These models estimate, at the local scale, ground-level air pollution concentrations by using emission inventories, topographical and meteorological data and land cover characteristics (often with building characteristics) (Turner et al., 1970). While dispersion models can account for, as an example, a simple $O_3$ chemistry scheme, these models do not incorporate complex chemical reactions or transformations but rather estimate the short-scale dispersion of pollutant plumes for passive tracer gases and particles (US EPA, 2023c). It should also be noted that while dispersion models are well suited to study the movement of a plume from a concentrated source, they are less suited to understand the pollution from many dispersed sources. Air dispersion models are also used by public safety responders and emergency management personnel for emergency planning for plumes of pollution (such as accidental chemical releases, wildfire emissions) (Moussiopoulos et al., 1996).

Dispersion models can range from a simple box model to complex fluid dynamics models. The suitability of the model for a given approach varies depending on the complexity of the environment and concentration of pollutants being assessed (Holmes and Morawska, 2006). Generally, dispersion model estimates are considered to be in good agreement with the measured values when the predicted concentrations are within a factor of two of the observed concentration, although some approaches use pollutant-specific thresholds and/or methods. While these models require less computational resources and technical expertise than CTMs, they tend to be less accurate for estimating secondary pollutants that are the result of complex chemical reactions and pollutant transformations (see section 3.2.3 for further information on CTMs). For a country that has limited but foundational air quality infrastructure, dispersion models can be useful to complement their air quality management system.

### 3.2.3 Chemical transport models

A CTM is a complex numerical approximation method, which uses emission inventories of primary pollutants from multiple sectors (e.g. industrial, agricultural, residential, traffic emissions) and meteorological data, embedding complex processes (i.e. wet and dry deposition, dispersion, mixing, aerosol formation, chemical reactions) to estimate air pollutant concentrations in the atmosphere (Byun and Schere, 2006). Although all CTMs require meteorological data, these data can come from mesoscale[2] or global meteorological models[3] which deliver forecasts (every 6 or 12 hours at resolutions varying from 0.1° to 1°) and robust re-analyses.

The main advantages of CTMs include their ability to represent fundamental processes, test policy scenarios and forecast air quality a few days in advance. While they allow users to estimate air pollution over a wide geographic and temporal domain, they require significant expertise and computing infrastructure to use them properly (including, for example, to prepare and run emission and meteorological models and then analyse the results). Like all models, CTM-estimated concentrations are heavily dependent on the quality of the input data (i.e. emissions inventories, ground measurements) but these models can also be biased by the ability of the model's chemical reaction equations to accurately represent real-world atmospheric chemistry.

It is also important to evaluate the model with respect to observed measurements so as to reduce model biases. While traditional CTM air pollution estimates had low spatial resolution, many downscaling approaches now exist and can be applied to produce a gridded scale of 100 m or even 50 m in urban environments (Denby et al., 2020; Kim et al., 2018). For countries that have a well-developed air quality infrastructure in place, CTMs can be useful to address questions that the existing air quality management system and models do not.

Global[4] and regional[5] CTMs can estimate concentrations of multiple atmospheric pollutants such as particulate matter, aerosols, $O_3$, $NO_2$, ammonia ($NH_3$), as well as provide the composition of major components of particles such as organic matter, elemental carbon, sulfate, nitrate and ammonium. While global CTMs can estimate concentrations at a spatial resolution of 1.9° × 2.5°, regional models output data typically at resolutions ranging from 1 to 25 km. However, some regional CTMs can also operate at global and hemispheric scales.[6]

The Copernicus Atmosphere Monitoring Service (CAMS) platform also offers an ensemble of products (e.g. forecast, re-analyses, source attribution services) for air pollution management and decision-making support across the globe (ECMWF, 2022).

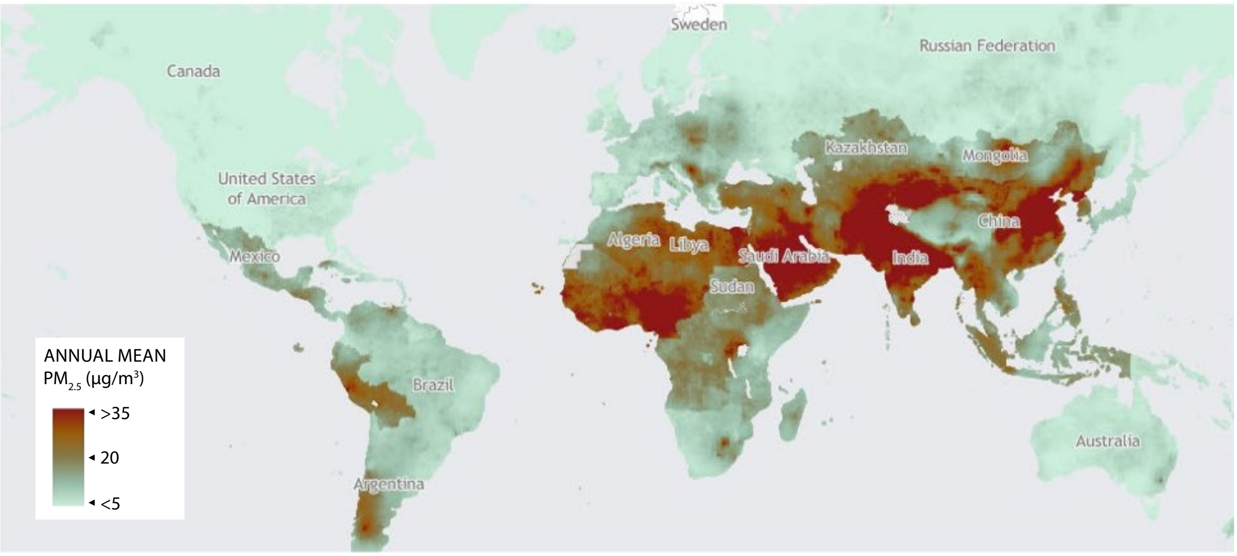
*For additional information on national and regional CTMs refer to the Annex.*

**Box 8. Example of chemical transport model used in global applications**

An example of a CTM that has been used by WHO to estimate global $PM_{2.5}$ levels is GEOS-Chem (Shaddick, Thomas, Amini et al., 2018). GEOS-Chem is a three-dimensional model that uses meteorological data from the NASA GEOS to predict atmospheric chemistry across the globe Fig. 5. GEOS-Chem can predict multiple pollutants including $PM_{2.5}$, $NO_2$ and $O_3$ at approximately 12-km resolution. Since GEOS-Chem simulates pollutant concentrations at different vertical heights within the troposphere, satellite column density data can be calibrated to ground-level concentrations using scaling factors that connect GEOS-Chem column density data with ground-level measurements from reference-grade monitors. The latest version of this model can provide hourly estimates of total $PM_{2.5}$ mass concentration as well as mass concentrations of several $PM_{2.5}$ components (e.g. sulfate, nitrate, ammonium and organic carbon) (Martin et al., 2022).

2 Weather Research and Forecasting (WRF) is a mesoscale meteorological model by the National Center for Atmospheric Research and the National Oceanic and Atmospheric Administration, United States of America.
3 Examples of global meteorological models include the Goddard Earth Observing System (GEOS) model developed by NASA's Global Modelling and Assimilation Office; the Integrated Forecasting System (IFS) model developed by the European Centre for Medium-Range Weather Forecasts (ECMWF); and the Global Forecast System (GFS) model developed by the National Centers for Environmental Prediction, United States of America.
4 Examples of global CTMs include GEOS-Chem, MOZART and LMDz-INCA.
5 Examples of regional CTMs include WRF-Chem, CHIMERE, CMAQ, CAMx, LOTOS-EUROS and EMEP.
6 Examples of regional CTMs that can operate at the global and hemispheric scale are EMEP and CHIMERE respectively.

**Fig. 5 Map of global $PM_{2.5}$ estimates for 2019**




*Source*: Authors based on WHO Data Integration Model for Air Quality

## 3.2.4 Machine learning models

While each measurement and modelling method has its respective strengths and weaknesses, it is not uncommon to combine multiple methods to estimate ambient air pollution concentrations. The driving factor for which methods are chosen is usually the availability of data and technical resources. Ultimately, the optimal method used for estimating air pollution is the method that allows users to achieve their purpose with minimal cost and resources.

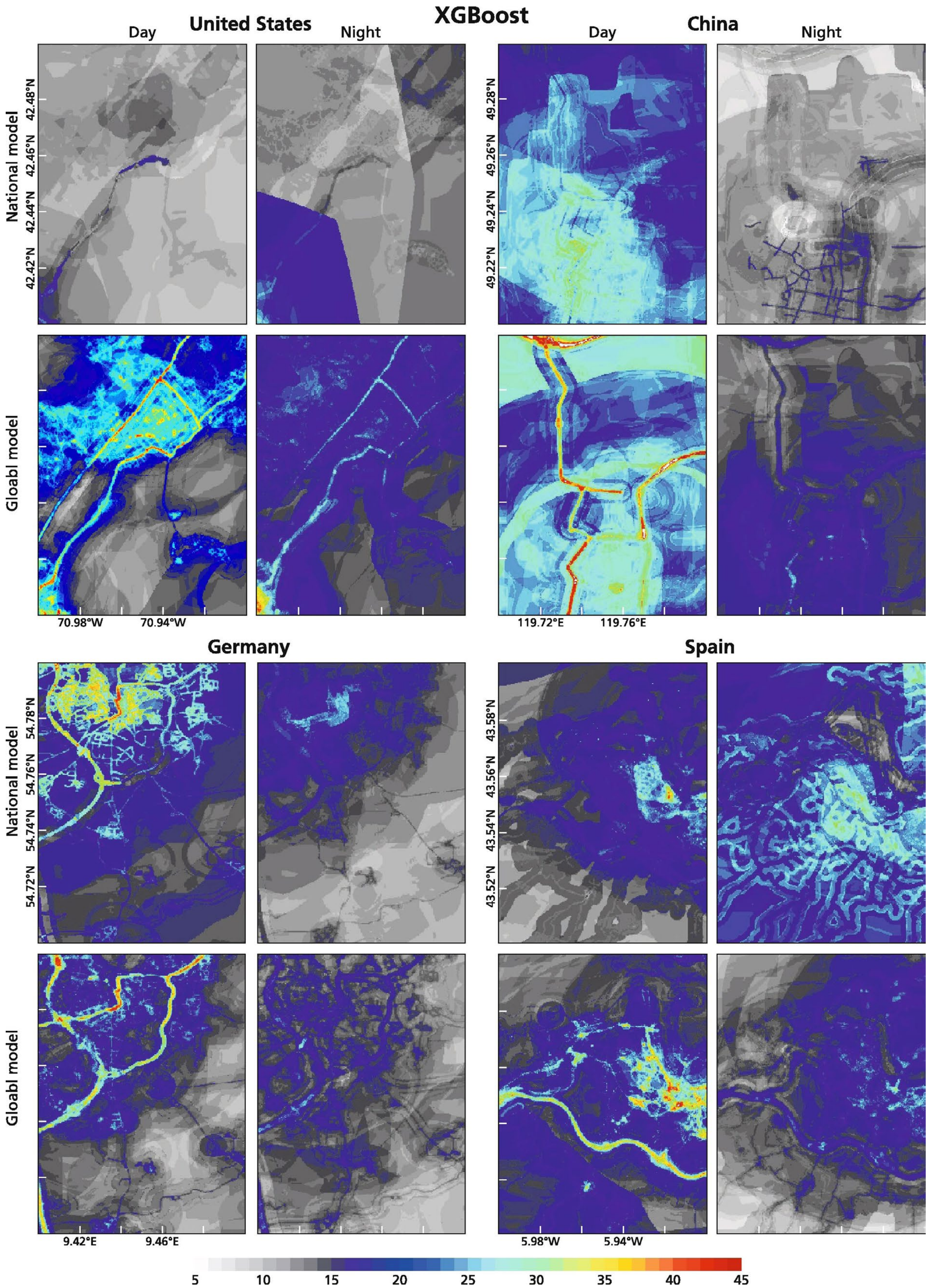
Advances in machine learning algorithms coupled with the availability of open-source data has fostered the development of machine learning based land-use models. Whereas earlier LUR models were based on linear regression approaches, a recent trend in LUR modelling is the inclusion of machine learning approaches such as Bayesian models. Several studies have shown varying levels of improvement in model performance with these machine learning techniques (Ren et al., 2020).[7] The input data for machine learning models depends on the application and can include meteorological data, land-use data, emissions estimates, satellite observations and CTM output.

**Box 9. Example of machine learning models used in global applications**

An example of an ensemble-based model that was developed to estimate global and national $NO_2$ concentrations at a spatial resolution of 25 m used multiple machine learning methods and input data such as TROPOMI satellite values, meteorological data, land-use data and CTM predictions (Lu et al., 2020). Fig. 6 shows the spatial variability predicted by the global and national models for four countries: China, Germany, Spain and United States of America. The observed improvements in the accuracy and spatial resolution of global air pollution estimates for each country highlights how machine learning approaches can be leveraged to use global data sources to identify air pollution exposures at the national level in LMIC.

7 Examples of techniques used include random forests, neural networks, lasso regression, support vector machines and gradient boosting (Li et al., 2020; Lu et al., 2020).

**Fig. 6. Spatial predictions of $NO_2$ (µg/m³) for the four countries using extreme gradient boosting (XGB)**




*Note*: For each country predictions are made using the global and national models separately for daytime and night-time. The United States' tile covers a Massachusetts city called Lynn (42.47° N, 70.94° W). The tile in China covers an inner-Mongolian city called Hulunbuir (49.23° N, 119.76° E). Germany's tile covers a city in the north of Schleswig-Holstein called Flensburg (54.79° N, 9.44° E). Spain's tile covers a city in the region of Asturias called Aviles (43.55° N, 5.92° W).

*Source*: Lu et al., 2020 (*Evaluation of different methods and data sources to optimise modelling of $NO_2$ at a global scale*).

### 3.2.5 Geostatistical data fusion models

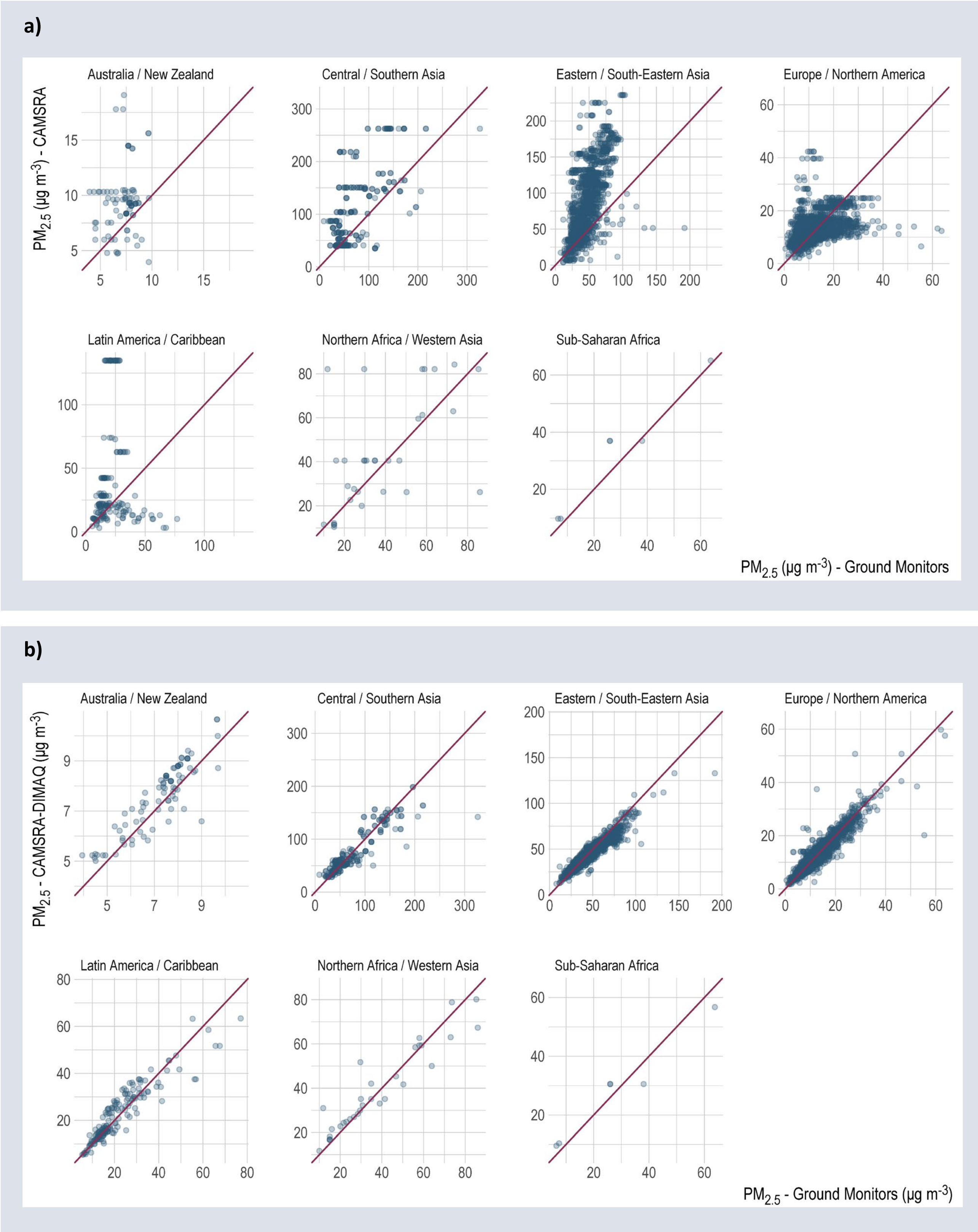
Data fusion models can include a combination of measurements and air quality models, as well merging of multiple air quality models. Data fusion generally aims to take advantage of the strengths of measurements (good accuracy but limited to the location of the measurement) and models (good spatial and temporal coverage, but biased) by combining information from these different sources.

As previously mentioned, WHO coordinated – through a global collaboration – the development of the DIMAQ to provide global estimates for air pollution-related SDG indicators as well as to facilitate global health burden assessments (Brauer et al., 2016). While country-specific ground-level monitors are preferred for health risk assessments, their limited availability in many countries makes it challenging to estimate the global burden of disease. It is for this reason that DIMAQ, a hybrid model that integrates multiple air quality monitoring methods, was developed. Specifically, DIMAQ combines data from ground-level monitors with an output from atmospheric CTM and satellite-derived $PM_{2.5}$ estimates within a machine learning framework, specifically, Bayesian hierarchical modelling.

**Box 10. Example of a geostatistical data fusion model used in global applications**

A global study that explored the integration of satellite data from Copernicus Atmosphere Monitoring Service Re-Analysis of Atmospheric Composition (CAMSRA) into DIMAQ to estimate $PM_{2.5}$ levels (Shaddick et al., 2021) is presented. CAMSRA provides 3-hour averages of $PM_{2.5}$ estimates from 2003 to 2016 at a spatial resolution of 10 km x 10 km in some regions and 70 km x 70 km in other regions. When CAMSRA $PM_{2.5}$ estimates were compared with ground-level measurements for 2016, poor spatial agreement and biases can be seen in some regions more than others (Fig. 7a). In contrast, significant reduction in biases and better spatial agreement were reported when CAMSRA was integrated into the DIMAQ framework (Fig. 7b). Specifically, we see increases in the $R^2$ (i.e. the spatial agreement between observed and estimated $PM_{2.5}$ levels via a linear regression) and decreases in the root mean square error (RMSE) (i.e. the bias between observed and estimated $PM_{2.5}$ levels). For example, for East/South-East Asia using CAMSRA and DIMAQ instead of CAMSRA alone increased the $R^2$ from 0.42 to 0.90 and decreased the RMSE from 55.65 $ug/m^3$ to 6.44 $ug/m^3$. Given the paucity of data in sub-Saharan Africa and to some extent in Asia and the high population densities in these countries, improving the model estimates outputted from DIMAQ can have significant influences on air pollution policies. The coupling of CAMSRA and DIMAQ also opens the possibility of apportioning particulate matter into specific emission sources since CAMSRA data include total $PM_{2.5}$ mass concentrations as well as their components (i.e. dust, organic matter, black carbon, sea salt and sulfates). Furthermore, the higher temporal resolution of CAMSRA data can expand the availability of $PM_{2.5}$ estimates to multiple temporal scales beyond the current annual averages.

**Fig. 7. Comparison between the annual average of $PM_{2.5}$ estimated by a) CAMS multi-annual global re-analysis of atmospheric composition and ground measurements, and b) DIMAQ while using the CAMS multi-annual global re-analysis of atmospheric composition and ground measurements, by region, for 2016**




*Note:* Red lines indicate a one-to-one relationship.

*Source:* Shaddick et al., 2021 *(Global air quality: an inter-disciplinary approach to exposure assessment for burden of disease analyses).*


A geostatistical data fusion model that combined satellite $NO_2$ measurements retrieved from the OMI at a grid cell size of 13 km × 24 km and GEOS-Chem CTM within a LUR modelling framework was developed to derive global estimates of $NO_2$. The $NO_2$ resolution was approximately 10 km x 10 km after integrating the CTM output, and the spatial resolution further improved to 100 m x 100 m after the land-use data were included (Larkin et al., 2017). As satellite data can contain missing values which may be due to the presence of cloud cover or instrument issues, users can acquire $NO_2$ column simulations from CAMS when the percentage of missing data is significant. This dataset is a re-analysis of $NO_2$ satellite estimates through the integration of multiple $NO_2$ satellite instruments within the ECMWF IFS, which includes atmospheric composition modelling.

Another data fusion model combined LCS and satellite measurements within a statistical framework. In a cross-continental study in sub-Sahara Africa and the United States of America, population exposures from the fusion of satellite data and LCS monitors (Malings et al., 2020) were examined. In this study AOD values from MODIS satellites were calibrated with LCS (i.e. PurpleAir and Alphasense) in a simple linear regression to estimate surface $PM_{2.5}$ concentrations in the Democratic Republic of the Congo, Malawi and Rwanda. The sub-Sahara African countries had eight LCS and zero reference-grade monitors. These satellite-based ground-level estimates were compared with estimates in Pittsburgh, United States, that were derived from 62 LCS and five reference-grade monitors. When comparing the ground measurements with the satellite estimates, it was observed that a high density of measurements (from reference-grade monitors or LCS) was more beneficial than the satellite-based estimates for discerning spatial patterns in both locations. However, in Rwanda, where ground monitoring is sparse, satellite data combined with a few LCS monitors provided comparable information about the air pollution spatial distribution as the satellite data estimated for Pittsburgh.

In addition to developing data fusion models through the combination of measurements and air quality models, data fusion models have also been developed from merging multiple air quality models (DeLang et al., 2021). Yim et al. (2015) used the dynamical downscaling approach to evaluate the air quality and health impacts of aviation emissions at global, regional and local level. The study first used the global CTM (GEOS-Chem) to resolve the global scale, then applied CMAQ to further resolve the air quality to a regional level focusing on North America, Europe and Asia. The model was subsequently downscaled using AERMOD to provide air quality at national level to facilitate the evaluation of air quality at more than 1000 airports across the globe. The combined results of the three models were also used to evaluate health impacts at the local level. This kind of dynamical downscaling approach is one example of how data fusion models can address the grid size limitation of an individual model.

## 3.3 Summary of air pollution measurement and modelling methods

There are many ways that we can measure and model air pollution levels for use in epidemiological studies and health impact assessments. A comprehensive list of the advantages and disadvantages associated with each monitoring method is detailed in Tables 3 and 4. The methods are presented in order of complexity with the measurements and models with the lowest technology requirements appearing first.

**Table 3. Advantages and disadvantages associated with each air pollution measurement method**

| Measurement | Advantages | Disadvantages |
|---|---|---|
| Passive diffusion samplers | No power requirement; low cost; portable | Low time resolution; some samplers require a qualified laboratory to analyse the sample; corrupted/damaged samplers are unusable; in highly polluted environments, the samplers can be become saturated and unusable; easily stolen or vandalized if exposed to the public; cannot measure short-term pollutant levels or non-compliance with standards |
| Low-cost sensors | Low cost; portable; low power requirements; medium to high time resolution; a network of low-cost sensors can give an understanding of pollutant spatial distributions and identify hotspots | Low sensitivity; low precision; interference from other pollutants; weather extremes (e.g. high humidity and low temperatures) can lead to greater uncertainty in data; requires knowledge of statistics for big data processing; prone to baseline drift over time from wear and tear or contamination; calibration and validation with a reference monitor at sampling location is recommended; lifespan of the sensor ranges from 1 to 5 years; no standardization for instrument siting; easily stolen or vandalized if exposed to the public |
| Personal direct reading instruments | High time resolution; medium accuracy; portable; enables the collection of personal exposure data; some are battery powered | Medium cost; requires periodic maintenance by competent technician; some instruments may have limited data logging capabilities |
| Reference-grade monitors | High sensitivity; high accuracy; high time resolution lifespan of monitor can be more than 10 years; historical data available for long time period | High capital cost; complex maintenance and calibration that usually requires a qualified technician; not portable; narrow spatial coverage (i.e. monitors air pollution for a specific location); high spatial scale possible with denser network of monitors; continuous energy requirement; repairs usually require shipping to HIC |
| Remote sensing satellites | Openly available to public; wide spatial coverage; historical data available for a long time period | Measurements are not directly outputted as air pollution concentrations, and they generally require modelling/ calibration with chemical transport models; low time resolution (days to weeks); moderate spatial resolution (1 km to 10 km) |

### Table 4. Advantages and disadvantages associated with each air pollution modelling method

| Model | Advantages | Disadvantages |
|---|---|---|
| Land-use regression models | Low computing resources; narrow to wide spatial coverage available; medium to high spatial resolution available depending on the spatial resolution of the input data (100 m to 1 km) | Require access to land-use data from GIS or satellite imagery; require knowledge of statistical principles; exposures are temporally static (i.e. represent the time-period that the air pollution was sampled); require access to ground measurements for model calibration |
| Dispersion models | Low to medium temporal resolution (hourly to annual); medium to high spatial resolution (100 m to 1 km) | Cover a narrow spatial domain; low to medium computing resources; require moderate training/experience; atmospheric chemistry is not included in air pollution estimates; require detailed emissions inventory; not suitable for widely dispersed sources |
| Chemical transport models | Cover a wide spatial domain; medium temporal resolution (hours to days); model complex atmospheric physical and chemical processes including interactions among air pollutants; provide multiple pollutant concentrations per simulation output; facilitate forecasting of air pollution; facilitate source apportionment; enable evaluation of air pollution interventions/what-if scenarios | High computing resources; model operation requires extensive training/experience; low spatial resolution (1 km to 100 km); require detailed emissions model input; require meteorological model input |
| Machine learning models | Narrow to wide spatial coverage available; medium to high spatial resolution available depending on the spatial resolution of the input data; many machine learning algorithms are open-sourced | Low to medium computing resources; require moderate training/experience; require access to several input datasets, require ground measurements for model calibration |
| Geostatistical data fusion models | Cover a wide spatial domain; model complex atmospheric aerosol interactions; facilitate forecasting of air pollution; enable evaluation of air pollution interventions/what-if scenarios | High computing resources required; model operation requires extensive training/experience; require detailed emissions model input; require meteorological model input; require access to ground measurements for model calibration |

# Moving beyond population-weighted air pollution exposures to exposure disparities

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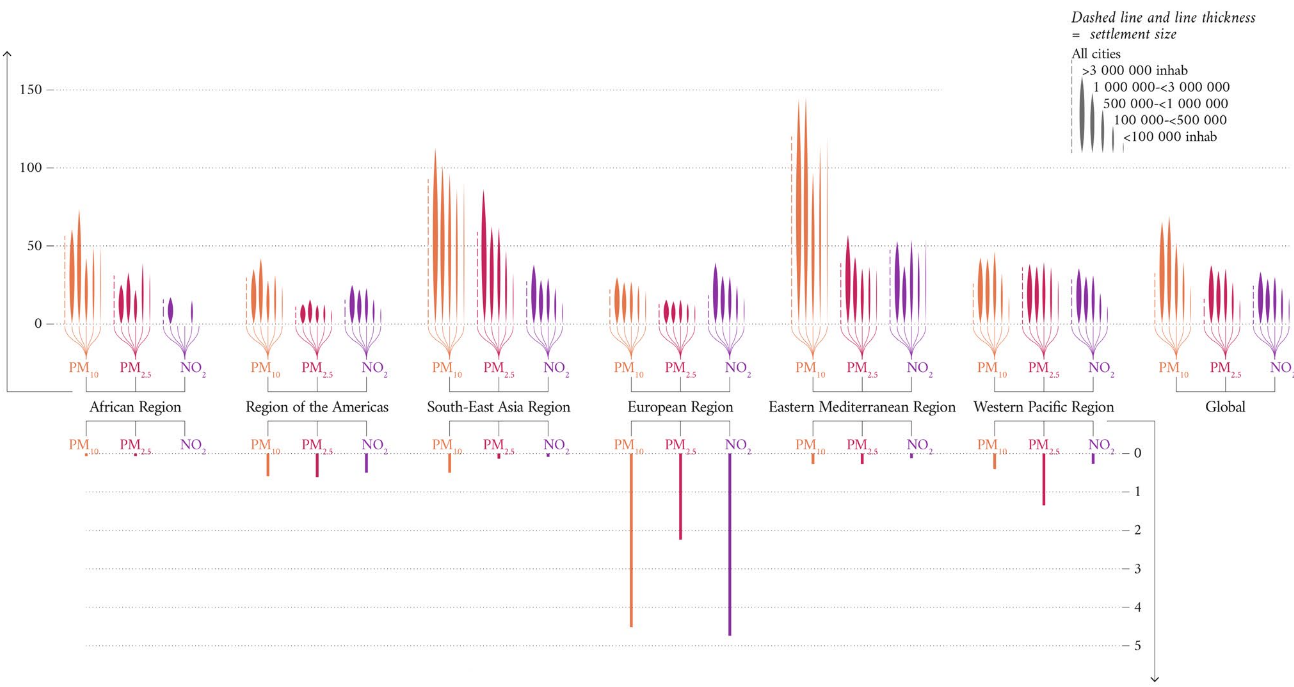
# Chapter 4 **Moving beyond population-weighted air pollution exposures to exposure disparities**

According to the WHO 2022 air quality database, of the 6700 human settlements located across the globe with $PM_{10}$ and/or $PM_{2.5}$ ground-level data; fewer than 60 settlements are located in Africa (WHO, 2022b). Countries with a smaller number of reference-grade monitors available for quantifying air pollution exposure tended to report higher $PM_{2.5}$ levels, which further exacerbates this exposure disparity (Fig. 8). In addition, countries in sub-Sahara Africa and South-East Asia that recorded elevated ambient levels also have higher population sizes which leads to a greater burden of disease from air pollution (Shaddick et al., 2020). Furthermore, as LMIC have a lower capacity to monitor air pollution and less accessibility to protective measures against NCDs, it is important to consider how sociodemographic and socioeconomic factors can contribute to environmental inequities.

In 2019, WHO released a comprehensive report which documented that disadvantaged groups within Europe which had limited access to health promoting amenities/ services (e.g. portable water, sanitation services) were also exposed to harmful environmental risk factors (e.g. air and noise pollution, lack of green spaces) (WHO Regional Office for Europe, 2019). Additional studies are revealing similar findings – that individuals of different socioeconomic status, ethnicities, gender or age are also exposed to disparate levels of air pollution (Fairburn et al., 2019; Hajat et al., 2015), extreme weather events (EEA, 2019b) and many more climate change impacts.

**Fig. 8. $PM_{10}$, $PM_{2.5}$ and $NO_2$ annual means and data accessibility, by region and settlement size, the latest year in the period 2010—2019**




*Source:* WHO, 2022b WHO (air quality database).

## 4.1 Data and methods commonly used for assessing exposure disparities

When evaluating air pollution exposure inequalities, it is important to have air pollution concentrations as well as sociodemographic and socioeconomic data at similar spatial scales. Examples of socioeconomic and sociodemographic data include ethnicity, gender, relationship status, income, education attainment, employment status and household occupant density, to name a few. Most of these data can be accessed from national census statistics. However, the most beneficial geographic domain (e.g. census division or postal code) varies according to the objective of the study. For example, when examining intra-urban inequalities it would be beneficial to use the highest spatial resolution available, such as postal code level data.

One of the greatest barriers to assessing socioenvironmental inequalities is the limited availability of socioeconomic and sociodemographic data in LMIC. Given these data constraints, it is worth considering using satellite imagery to develop proxy indicators. Some studies have shown that the socioeconomic status of a neighbourhood can be predicted when a machine learning model combines satellite imagery and census-level socioeconomic status indicators (Abitbol and Karsai, 2020). Another study in the United Kingdom illustrated the potential of complementing survey data with satellite data to estimate social, environmental and health indicators (Suel et al., 2019). While applying such models to other countries may be less accurate than the country it was designed for, the integration of local survey or administrative data can offer LMIC a starting point for assessing their exposure disparities.

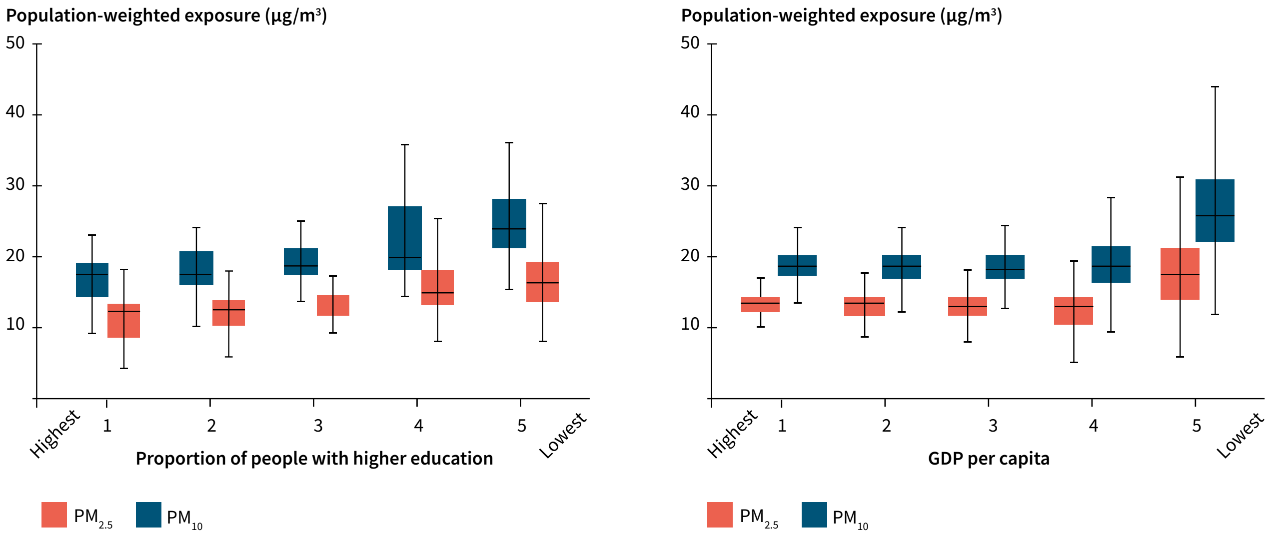
A 2018 report from the European Environment Agency explored unequal exposures to air pollution at different spatial scales (EEA, 2019b). Table 5 displays the potential socioeconomic indicators that were available at different spatial scales in the European assessment. For regional evaluation of environmental inequities, the authors used gross domestic product per capita and $PM_{2.5}$ exposures, and they observed that the most disadvantaged regions had 30% higher particulate matter exposures (Fig. 9). In addition, the regions with the lowest proportion of persons with higher education were also exposed to higher levels of particulate matter. A similar observation was reported across the three most densely populated Canadian cities; neighbourhoods with more undesirable environmental factors (i.e. high $NO_2$ levels, low walkability and low greenness) also had high material deprivation, while areas with low deprivation exhibited more desirable environmental factors (Doiron et al., 2020). A meta-analysis of environmental inequality literature from Africa, Asia, New Zealand and North America showed that low socioeconomic status communities were commonly exposed to higher air pollution (Hajat et al., 2015). Given the presence of environmental inequities, it is possible that health inequities could exist due to environmental factors, socioeconomic factors, or both.

**Table 5. Indicators of social vulnerability used in the pan-European assessment of exposure to air pollution, noise and extreme temperatures**

| | SPATIAL UNIT | | |
|---|---|---|---|
| | **CITIES** | **NATIONAL** | **REGIONAL** |
| **AGE** | Percentage of young children (under 5 years old) in population | Percentage of young children (under 5 years old) in population | |
| | Percentage of elderly people (75 years old or older) in population | Percentage of elderly people (75 years old or older) in population | |
| **SOCIOECONOMIC STATUS** | | Household income (per capita after social transfers, purchasing power standard) | Per capita gross domestic product, purchasing power standard |
| | Unemployment rate (percentage of economically active population) | Long-term unemployment rate (12 months or more; percentage of economically active population) | |
| | Percentage of people (aged 25 to 64) without higher education | Percentage of people (aged 25 to 64) without higher education | |

*Source:* EEA, 2019b *(Unequal exposure and unequal impacts: social vulnerability to air pollution, noise and extreme temperatures in Europe).*

**Fig. 9. Differences in exposure to $PM_{2.5}$ and $PM_{10}$ (µg/m³) among regions in Europe, classified according to the proportion of people with higher education in the population (left) and GDP per capita (right), 2013–2014**




*Source*: EEA, 2019b (*Unequal exposure and unequal impacts: social vulnerability to air pollution, noise and extreme temperatures in Europe*).

Given the strong correlation between air pollution levels and socioeconomic and sociodemographic factors, health studies may need to employ dimension reduction strategies to reduce the negative impact of highly correlated input data on the model output. See the Annex for more technical information about dimension reduction methods. An example of this can be seen in a United States study where researchers used a hierarchical clustering approach to combine multiple air pollution exposures ($NO_2$ and $PM_{2.5}$) and several socioeconomic factors to isolate the health impact of these multiple risk factors (Coker et al., 2016). It was observed that pregnant women with the highest risks for low-term birth weight tended to live in neighbourhoods with more disadvantaged characteristics (i.e. below median income, non-white) and they were also exposed to the highest air pollution. Lack of standardization in the measurement of sociodemographic and socioeconomic status and the subsequent evaluation of the potential confounding role across studies could lead to disparities in the health effect estimates observed in epidemiological studies (Klompmaker et al., 2021).

Another dimension to these environmental inequities is that disadvantaged populations also tend to be more vulnerable to adverse health outcomes and have less access to protective measures against these environmental risks. In Rome it was observed that even though individuals with high income levels were exposed to higher levels of $PM_{10}$, the mortality attributed to air pollution was greater for the individuals with lower economic positions as these individuals had a greater susceptibility to chronic health conditions such as diabetes mellitus, hypertension, heart failure and COPD (Forastiere et al., 2007). The intersection of these multiple risk factors highlights the presence of health inequities and the need for urban planning that focuses on both air pollution, and sociodemographic and socioeconomic factors when developing public health policies.

# Conclusion

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# Chapter 5 **Conclusion**

## 5.1 The way forward

Epidemiological studies and health impact assessments that have assessed the effect of long-term health impact of air pollution have commonly used reference-grade monitors, LUR models, satellite instruments, dispersion models and/or geostatistical data fusion models to estimate population exposures (Hoek, 2017; Jerrett et al., 2005). For the development of the WHO global burden of disease attributed to air pollution, $PM_{2.5}$ estimates are derived from a geostatistical data fusion model that combines reference-grade monitors, satellite information and CTMs. In this report, we present several methods that can be used to improve assessments of the health impacts of a population's exposure to air pollution. These air quality monitoring methods fall into two main categories:

- measurements from technologies such as passive diffusion samplers, reference monitors and satellites; and
- model estimates from LUR, chemical transport, machine learning and geostatistical data fusion models.

Of all the methods highlighted, reference-grade monitors are a critical part of a comprehensive air quality management programme. In addition to their accuracy, they enable the monitoring of long-term air pollution exposures which are pivotal for health studies, and they are also critical for the objective evaluation of compliance with standards as well as the effectiveness of air pollution reduction policies. Countries that do not have reference-grade monitors are showing increasing interest in LCS. However, the evidence suggests that LCS have the capability to show qualitative changes in spatial variability and short-term temporal variability, but there is limited evidence that these sensors can independently provide reliable annual concentrations in the long term (Peltier et al., 2020). For this reason, reference-grade monitors are the preferred method for assessing baseline levels and tracking of long-term progress in air quality, and nations should strive to have at least one reference monitor in an urban centre and one in a rural area.

While it is important to start somewhere, nations should balance their national priorities with available resources and employ a mixture of approaches to best address their air quality problems. Pivotal to the success of any air quality management programme is the awareness of the advantages and disadvantages of each approach: cost, technical complexity, outputs and the recognition that some methods require the prior presence of other measurement methods to be useful. For example, modelling approaches require local measurements to develop accurate model estimates. Air quality decision-makers can use the methods that have been summarized in this document to identify the air quality monitoring method that is best suited to address their issues, while keeping in mind that no single method can achieve all their objectives. Since reference monitors are well suited to track long-term changes in air quality, despite their high purchase and operating costs, they should be viewed as the first step in an air quality monitoring programme. That being said, a combination of models and measurements is usually needed to track the long-term progress in air pollution for the entire country's geographic domain. Several scientists are currently developing hybrid models that can improve air pollution exposures for future health impact assessments; some of these advances are highlighted in the second part of the conclusion.

## 5.2 Areas for future improvements

Despite the increasing availability of methods to assess population exposure, associations between air pollution and health effects across epidemiological studies have not been consistent. The disparity in the direction or magnitude of health effect estimates in health studies may be due to differences in population exposure methods, exposure measurement errors, and sensitivity to adjustment for confounders (Gariazzo et al., 2021; Jerrett et al., 2017; Klompmaker et al., 2021).

Methodological improvements to assess exposures to air pollution will be aimed at decreasing exposure measurement errors while increasing the temporal and spatial resolutions of the air quality concentrations. The rapid advances in satellite measurements with higher spatial and temporal resolution coupled with the integration of downscaling methods in CTMs have increased the spatial resolution of air pollution estimates to enable subnational exposure assessments (van Donkelaar et al., 2019). Enhancing the spatial resolution of air pollution estimates allows the integration of time-activity profiles into the exposure estimates; this has revealed stronger associations between ambient air pollution and health outcomes in some studies (Ragettli et al., 2015, Setton et al., 2011). Furthermore, increasing the temporal resolution of air pollution estimates can enable the assessment of specific morbidities associated with short-term exposures such as higher risks of pre-term birth with elevated air pollution exposures during the first trimester (He et al., 2022).

As satellite imagery becomes more accessible, the development of LUR models which use these images rather than GIS data to represent land-use practices will become more common. Another change in the landscape of LUR models involves the combining of satellite imagery and satellite estimates of air pollution to derive population exposures. This shift can reduce the barrier to access that is associated with GIS data and allow LMIC to develop national LUR models. However, it is important to acknowledge that fundamental to these model improvements is access to high-quality, reliable air quality measurements, from, for example, reference-grade monitors, to calibrate and validate the models.

The coupling of open access computing resources for satellite data analysis and machine learning algorithms creates potential opportunities for LMIC to develop baseline air pollution concentrations and population exposure estimates for local health impact assessments. Future population exposure assessments will likely involve combinations of geostatistical data fusion models and machine learning approaches as well as a greater density of local air quality measurements, preferably reference-grade monitors. In advancing the evidence of the health impacts attributed to air pollution, it is important to have accurate and long-term air quality data that cover the entire country, with more monitors being situated in densely populated areas, especially areas with vulnerable groups and exposure disparities.

# References

Abitbol J and Karsai M. Interpretable socioeconomic status inference from aerial imagery through urban patterns. Nat Mach Intell. 2020;2:684-692 (https://doi.org/10.1038/s42256-020-00243-5, accessed 18 April 2023).

Amegah A and Agyei-Mensah S. Urban air pollution in sub-Saharan Africa: time for action. Environ Pollut. 2017;220:738-743 (https://doi.org/10.1016/j.envpol.2016.09.042, accessed 24 April 2023).

Anenberg S, Mohegh A, Goldberg D, Kerr G, Brauer M, Burkart K et al. Long-term trends in urban NO2 concentrations and associated paediatric asthma incidence: estimates from global datasets. The Lancet Planetary Health. 2022;6,1:49-58 (https://doi.org/10.1016/S2542-5196(21)00255-2, accessed 28 June 2023)

Brauer M, Freedman G, Frostad J, van Donkelaar A, Martin RV, Dentener F, et al. Ambient air pollution exposure estimation for the Global Burden of Disease 2013. Environ Sci Technol. 2016;5;50(1):79-88. doi: 10.1021/acs.est.5b03709.

Brauer M, Guttikunda S, Nishad K, Dey S, Tripathi S, Weagle C, et al. Examination of monitoring approaches for ambient air pollution: a case study for India. Atmospheric Environ. 2019;216 (https://doi.org/10.1016/j.atmosenv.2019.116940, accessed 18 April 2023).

Brunekreef B, StrakJie M, Chen J, Andersen Z, Atkinson R, Bauwelinck M, et al. Mortality and morbidity effects of long-term exposure to low-level $PM_{2.5,}$ BC, $NO_2$, and $O_3$: an analysis of European cohorts in the ELAPSE Project. HEI Report; 2021.

Buonanno G, Marini S, Morawska L, Fuoco F. Individual dose and exposure of Italian children to ultrafine particles. Sci Total Environ. 2012;438:271-277 (https://doi.org/10.1016/j.scitotenv.2012.08.074, accessed 18 April 2023).

Byun D and Schere K. Review of the governing equations, computational algorithms, and other components of the models-3 Community Multiscale Air Quality, CMAQ Modeling System. Appl Mech Rev. 2006;59:51-77 (https://doi.org/10.1115/1.2128636, accessed 24 April 2023).

Cassee F, Morawska L, Peters A. Ambient ultrafine particles: evidence for policy makers. White paper. Prepared for the European Federation of Clean Air and Environmental Protection Associations; 2019 (https://efca.net/files/WHITE%20PAPER-UFP%20evidence%20for%20policy%20makers%20(25%20OCT).pdf, accessed 18 April 2023).

Castell N, Dauge F, Schneider P, Vogt M, Lerner U, Fishbain B, et al. Can commercial low cost sensor platforms contribute to air quality monitoring and exposure estimates? Environ Int. 2017;99:293-302 (https://doi.org/10.1016/j.envint.2016.12.007, accessed 24 April 2023).

CCME, 2019. Ambient air monitoring and quality assurance/quality control guidelines. Canadian Council of Ministers of the Environment; 2019 (https://ccme.ca/en/res/ambientairmonitoringandqa-qcguidelines_ensecure.pdf, accessed 18 April 2023).

CEN, 2002. CEN/TC 264/WG 11 – Ambient air quality – diffusive samplers for the determination of gases and vapours - requirements and test methods. European Committee for Standardization; 2002.

CEN, 2017. CEN/TC 264/WG 15 – Ambient air – reference gravimetric measurement method and equivalence procedure for the determination of the pm 2.5 micron mass fraction of suspended particulate matter. European Committee for Standardization; 2017.

CEN, 2019. CEN/TC 264/WG 42 – Ambient air – Air quality sensors. European Committee for Standardization; 2019.

Chen J and Hoek G. Long-term exposure to PM and all-cause and cause-specific mortality: a systematic review and meta-analysis. Environ Int. 2020;143:105974. doi: 10.1016/j.envint.2020.105974.

Clements A, Duvall R, Greene D, Dye T. The enhanced air sensor guidebook. Washington, DC: United States Environmental Protection Agency; 2022.

Clifford S, Mazaheri M, Salimi F, Ezz W, Yeganeh B, Choy S, et al. Effects of exposure to ambient ultrafine particles on respiratory health and systemic inflammation in children. Environ Int. 2018;114:167-180 (https://doi.org/10.1016/j.envint.2018.02.019, accessed 18 April 2023).

Coker E, Amegah A, Mwebaze E, Joel S, Bainomugisha E.  A land use regression model using machine learning and locally developed low-cost particulate matter sensors in Uganda. Environ Res. 2021;199:111352 (https://www.sciencedirect.com/science/article/abs/pii/S0013935121006460, accessed 18 April 2023).

Coker E, Liverani S, Ghosh J, Jerrett M, Beckerman B, Li A, et al. Multi-pollutant exposure profiles associated with term low birth weight in Los Angeles County. Environ Int. 2016;91:1-13 (https://doi.org/10.1016/j.envint.2016.02.011, accessed 18 April 2023).

de Hoogh K, Chen J, Gulliver J, Hoffmann B, Hertel O, Ketzel M, et al. Spatial $PM_{2.5}$, $NO_2$, $O_3$ and BC models for Western Europe – evaluation of spatiotemporal stability. Environ Int. 2018;120:81-92 (https://doi.org/10.1016/j.envint.2018.07.036, accessed 18 April 2023).

DeLang M, Becker J, Chang K, Serre M, Cooper O, Schultz M, et al. Mapping yearly fine resolution global surface ozone through the Bayesian Maximum Entropy data fusion of observations and model output for 1990–2017. Environ Sci Technol. 2021;55:4389-4398. doi: 10.1021/acs.est.0c07742.

Denby B, Gauss M, Wind P, Mu Q, Grøtting Wærsted E, Fagerli H, et al. Description of the uEMEP_v5 downscaling approach for the EMEP MSC-W chemistry transport model. Geosci Model Dev. 2020;13:6303-6323 (https://doi.org/10.5194/gmd-13-6303-2020, accessed 18 April 2023).

Doiron D, Setton E, Shairsingh K, Brauer M, Hystad P, Ross N, et al. Healthy built environment: spatial patterns and relationships of multiple exposures and deprivation in Toronto, Montreal and Vancouver. Environ Int. 2020;143:106003 (https://doi.org/10.1016/j.envint.2020.106003, accessed 18 April 2023).

Dominici F, Peng R, Barr C, Bell M. Protecting human health from air pollution: shifting from a single-pollutant to a multipollutant approach. Epidemiol. 2010;21(2):187-194. doi: 10.1097/EDE.0b013e3181cc86e8

Dominici F, Zanobetti A, Schwartz J, Sabath D, Wu X. Assessing adverse health effects of long-term exposure to low levels of ambient air pollution: implementation of causal inference methods. Research report 211. Health Effects Institute; 2022.

ECMWF, 2022. Global forecast plots. Copernicus Atmosphere Monitoring Service. Brussels: European Commission; 2022 (https://atmosphere.copernicus.eu/global-forecast-plots, accessed 18 April 2023).

EEA, 2019a. Citizen science initiative CleanAir@School.  European Environment Agency; 2019 (https://www.eea.europa.eu/themes/air/cleanair-at-school, accessed 18 April 2023).

EEA, 2019b. Unequal exposure and unequal impacts: social vulnerability to air pollution, noise and extreme temperatures in Europe. European Environment Agency; 2019 (https://www.eea.europa.eu/publications/unequal-exposure-and-unequal-impacts/, accessed 18 April 2023).

EEA, 2020. Assessing air quality through citizen science. European Environment Agency; 2020 (https://www.eea.europa.eu/publications/assessing-air-quality-through-citizen-science, accessed 18 April 2023).

EEA, 2022. Air quality e-reporting. European Environment Agency; 2022 (https://www.eea.europa.eu/data-and-maps/data/aqereporting-9, accessed 18 April 2023).

EMEP, 2001. European Monitoring and Evaluation Programme (EMEP) under the Convention on Long Range Transboundary Air Pollution (CLRTAP). EMEP; 2001 (https://www.emep.int/, accessed 18 April 2023).

EU, 2008. European Union Directive 2008/50/EC of the European Parliament and of the Council on ambient air quality and cleaner air for Europe. European Union; 2008 (https://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2008:152:0001:0044:en:PDF, accessed 18 April 2023).

EU, 2021. European Environment Agency air quality standards. European Union; 2021  (https://www.eea.europa.eu/themes/air/air-quality-concentrations/air-quality-standards#:~:text=Air%20quality%20standards.%20The%20European%20Union%20%28EU%29%20has,be%20exceeded%20in%20a%20given%20period%20of%20time, accessed 18 April 2023).

Fairburn J, Schüle S, Dreger S, Karla Hilz L, Bolte G. Social inequalities in exposure to ambient air pollution: a systematic review in the WHO European Region. Int J Environ Res Public Health. 2019;16(17):3127 (https://doi.org/10.3390/ijerph16173127, accessed 18 April 2023).

Forastiere F, Stafoggia M, Tasco C, Picciotto S, Agabiti N, Cesaroni, G, et al. Socioeconomic status, particulate air pollution, and daily mortality: differential exposure or differential susceptibility. Am J Ind Med. 2007;50:208-216. doi: 10.1002/ajim.20368.

Gariazzo C, Carlino G, Silibello C, Tinarelli G, Renzi M, Finardi S, et al. Impact of different exposure models and spatial resolution on the long-term effects of air pollution. Environ Res. 2021;192:110351. doi: 10.1016/j.envres.2020.110351.

Gu Y and Yim S. The air quality and health impacts of domestic trans-boundary pollution in various regions of China. Environ Int. 2016;97:117-124 (https://doi.org/10.1016/j.envint.2016.08.004, accessed 24 April 2023).

Gu Y, Wong T, Law S, Dong G, Ho K, Yang Y, et al. Impacts of sectoral emissions in China and the implications: air quality, public health, crop production, and economic costs. Environ Res Lett. 2018;13:084008. doi: 10.1088/1748-9326/aad138.

Hajat A, Hsia C, O'Neill M. Socioeconomic disparities and air pollution exposure: a global review. Curr Envir Health Rpt. 2015;2:440-450 (https://doi.org/10.1007/s40572-015-0069-5, accessed 18 April 2023).

He Y, Jiang Y, Yang Y, Xu J, Zhang Y, Wang Q, et al. Composition of fine particulate matter and risk of preterm birth: a nationwide birth cohort study in 336 Chinese cities. J Hazardous Materials. 2022;425:127645 (https://doi.org/10.1016/j.jhazmat.2021.127645, accessed 18 April 2023).

HEI, 2013. Understanding the health effects of ambient ultrafine particles. HEI Review Panel on Ultrafine Particles. Boston: Health Effects Institute; 2013.

Hoek G. Methods for assessing long-term exposures to outdoor air pollutants. Curr Environ Health Reports. 2017;4(4):450-462. doi: 10.1007/s40572-017-0169-5.

Hoek G, Beelen R, de Hoogh K, Vienneau D, Gulliver J, Fischer P, et al. A review of land-use regression models to assess spatial variation of outdoor air pollution. Atmos Environ. 2008;42:7561-7578 (https://doi.org/10.1016/j.atmosenv.2008.05.057, accessed 18 April 2023).

Holmes NS and Morawska L. A review of dispersion modelling and its application to the dispersion of particles: an overview of different dispersion models available. Atmos Environ. 2006;40(30):5902-28 (https://doi.org/10.1016/j.atmosenv.2006.06.003, accessed 24 April 2023).

Huangfu P and Atkinson R. Long-term exposure to $NO_2$ and $O_3$ and all-cause and respiratory mortality: a systematic review and meta-analysis. Environ Int. 2020;144:105998. doi: 10.1016/j.envint.2020.105998.

Hystad P, Setton E, Cervantes A, Poplawski K, Deschenes S, Brauer M, et al. Creating national air pollution models for population exposure assessment in Canada. Environ. Health Perspect. 2011;119:1123-1129 (https://doi.org/10.1289/ehp.1002976, accessed 24 April 2023).

Jedynska A, Hoek G, Wang M, Eeftens M, Cyrys J, Keuken M, et al. Development of land use regression models for elemental, organic carbon, PAH, and hopanes/steranes in 10 ESCAPE/TRANSPHORM European study areas. Environ Sci Technol. 2014;48:14435-14444.

Jerrett M, Arain A, Kanaroglou P, Beckerman B, Potoglou D, Sahsuvaroglu T, et al. A review and evaluation of intraurban air pollution exposure models. J Expo Sci Environ Epidemiol. 2005;15(2):185 (https://doi.org/10.1038/sj.jea.7500388, accessed 19 April 2023).

Jerrett M, Turner M, Beckerman B, Pope C, van Donkelaar A, Martin R, et al. Comparing the health effects of ambient particulate matter estimated using ground-based versus remote sensing exposure estimates. Environ Health Perspect. 2017;125(4):552-559 (http://dx.doi.org/10.1289/EHP575, accessed 19 April 2023).

Karagulian, F, Maurizio B, Alexander K, Michel G, Friedrich L, Annette B. Review of sensors for air quality monitoring. EUR 29826 EN. JRC technical report. Luxembourg: Publications Office of the European Union; 2019. doi: 10.2760/568261.

Keller J, Drton M, Larson T, Kaufman J, Sandler D, Szpiro A. Covariate-adaptive clustering of exposures for air pollution epidemiology cohorts. Ann Appl Stat. 2017;11(1):93-113. doi: 10.1214/16-AOAS992.

Kim Y, Wu Y, Seigneur C, Roustan Y. Multi-scale modeling of urban air pollution: development and application of a street-in-grid model (v1.0) by coupling MUNICH (v1.0) and Polair3D (v1.8.1). Geosci Model Dev. 2018;11(2):611-629 (https://doi.org/10.5194/gmd-11-611-2018, accessed 19 April 2023).

Klompmaker J, Janssen N, Andersen Z, Atkinson R, Bauwelinck M, Chen J, et al. Comparison of associations between mortality and air pollution exposure estimated with a hybrid, a land-use egression and a dispersion model. Environ Int. 2021;146:106306. doi: 10.1016/j.envint.2020.106306.

Koehler K and Peters T. New methods for personal exposure monitoring for airborne particles. Curr Envir Health Rpt. 2015;2:399-411 (https://doi.org/10.1007/s40572-015-0070-z, accessed 19 April 2023).

Krzyzanowski M, Kuna-Dibbert B, Schneider J. Health effects of transport-related air pollution. Copenhagen: WHO Regional Office for Europe; 2005.

Larkin A, Anenberg S, Goldberg D, Mohegh A, Brauer M, and Hystad P. A global spatial-temporal land use regression model for nitrogen dioxide air pollution. ESS Open Archive. 2022 (https://doi.org/10.1002/essoar.10511382.1, accessed 19 April 2023).

Larkin A, Geddes J, Martin R, Xiao Q, Liu Y, Marshall J, et al. Global land use regression model for nitrogen dioxide air pollution. Environ Sci Technol. 2017;51(12):6957-6964. doi: 10.1021/acs.est.7b01148.

Lee S, Hong YC, Park H, Kim Y, Ha M, Ha E. Combined effects of multiple prenatal exposure to pollutants on birth weight: the Mothers and Children's Environmental Health (MOCEH) study. Environ Res. 2020;181:108832. doi: 10.1016/j.envres.2019.108832.

Lee K, Spath N, Miller M, Mills N, Shah A. Short-term exposure to carbon monoxide and myocardial infarction: a systematic review and meta-analysis. Environ Int. 2020;143:105901. doi: 10.1016/j.envint.2020.105901.

Li Z, Ho K, Dong G, Lee H, Yim S. A novel approach for assessing the spatiotemporal trend of health risk from ambient particulate matter components: case of Hong Kong. Environ Res. 2022;204(A):111866 (https://doi.org/10.1016/j.envres.2021.111866, accessed 24 April 2023).

Li Z, Yim S, Ho K. High temporal resolution prediction of street-level $PM_{2.5}$ and $NO_x$ concentrations using machine learning approach. J Clean Prod. 2020;268:121975 (https://doi.org/10.1016/j.jclepro.2020.121975, accessed 24 April 2023).

Liu X, Jayaratne R, Phong Thai J, Kuhn T, Zing I, Christensen B, et al. Low-cost sensors as an alternative for long-term air quality monitoring. Environ Res. 2020;185:109438 (https://doi.org/10.1016/j.envres.2020.109438, accessed 24 April 2023).

Lu M, Schmitz O, de Hoogh K, Kai W, Karssenberg D. Evaluation of different methods and data sources to optimise modelling of $NO_2$ at a global scale. Environ Int. 2020;142:105856 (https://doi.org/10.1016/j.envint.2020.105856, accessed 19 April 2023).

Malings C, Westervelt D, Hauryliuk A, Presto A, Grieshop A, Bittner A, et al. Application of low-cost fine particulate mass monitors to convert satellite aerosol optical depth to surface concentrations in North America and Africa. Atmos Meas Tech. 2020;13:3873-3892 (https://doi.org/10.5194/amt-13-3873-2020, accessed 19 April 2023).

Martin R, Eastham S, Bindle L, Lundgren E, Clune T, Keller C, et al. Improved advection, resolution, performance, and community access in the new generation (version 13) of the high performance GEOS-Chem Global Atmospheric Chemistry Model (GCHP). Geosci Model Dev. 2022;15(23):8731-8748 (https://doi.org/10.5194/gmd-2022-42, accessed 19 April 2023).

Mazaheri M, Clifford S, Jayaratne E, Mokhtar M, Fuoco F, Buonanno G, et al. School children's personal exposure to ultrafine particles in the urban environment. Environ Sci Technol. 2014;48(1):113-120 (https://doi.org/10.1021/es403721w, accessed 19 April 2023).

Morawska L, Thai P, Liu X, Asumadu-Sakyi A, Ayoko G, Bartonova A, et al. Applications of low-cost sensing technologies for air quality monitoring and exposure assessment: How far have they gone? Environ Int. 2018;116:286-299 (https://doi.org/10.1016/j.envint.2018.04.018, accessed 23 April 2023).

Moussiopoulos N, Berge E, Bøhler T, de Leeuw F, Grønskei K, Mylona S, et al. Ambient air quality, pollutant dispersion and transport models. European Environment Agency; 1996 (https://www.eea.europa.eu/publications/92-9167-028-6, accessed 19 April 2023).

Nagl C, Spangl W, Buxbaum I. Sampling points for air quality. Study for the Committee on the Environment, Public Health and Food Safety. Policy Department for Economic, Scientific and Quality of Life Policies. Luxembourg: European Parliament; 2019.

NASA, 2023. Global Modeling and Assimilation Office. National Aeronautics and Space Administration; 2023 (https://gmao.gsfc.nasa.gov/, accessed 19 April 2023).

Nguyen C, Soulhac L, Salizzoni P. Source apportionment and data assimilation in urban air quality modelling for $NO_2$: the Lyon case study. Atmosphere. 2018;9(1):8 (https://doi.org/10.3390/atmos9010008, accessed 19 April 2023).

Nyarku M, Buonanno G, Ofosu F, Jayaratne E, Mazaheri M, Morawska L. School children's personal exposure to ultrafine particles in and near Accra, Ghana. Environ Int. 2019;133(Part B):105223 (https://doi.org/10.1016/j.envint.2019.105223, accessed 19 April 2023).

Nyarku M, Buonanno G, Ofosu F, Jayaratne E, Mazaheri M, Morawska L. Ultrafine particles in key microenvironments in rural and urban areas of Ghana. Atmospheric Pollut Res. 2021;12:101212 (https://doi.org/10.1016/j.apr.2021.101212, accessed 19 April 2023).

Ohlwein S, Kappeler R, Kutlar Joss M, Künzli N, Hoffmann B. Health effects of ultrafine particles: a systematic literature review update of epidemiological evidence. Int J Public Health. 2019;64(4):547-559. doi: 10.1007/s00038-019-01202-7.

Patton A, Zamore W, Naumova E, Levy J, Brugge D, Duran, J. Transferability and generalizability of regression models of ultrafine particles in urban neighborhoods in the Boston Area. Environ Sci Technol. 2015;6051-6060 (https://doi.org/10.1021/es5061676, accessed 24 April 2023).

Peltier R, Castell N, Clements A, Dye T, Hüglin C, Kroll J, et al. An update on low-cost sensors for the measurement of atmospheric composition. Geneva: World Meteorological Organization; 2020 (https://library.wmo.int/doc_num.php?explnum_id=10620, accessed 19 April 2023).

Ragettli M, Phuleria H, Tsai M, Schindler C, De Nazelle A, Ducret-Stich R, et al. The relevance of commuter and work/school exposure in an epidemiological study on traffic related air pollution. J Expos Sci Environ Epidemiol. 2015;25(5):474-81. doi: 10.1038/jes.2014.83.

Ren X, Mi Z, Georgopoulos P. Comparison of machine learning and land use regression for fine scale spatiotemporal estimation of ambient air pollution: modeling ozone concentrations across the contiguous United States. Environ Int. 2020;142:105827 (https://doi.org/10.1016/j.envint.2020.105827, accessed 24 April 2023).

Robinson E, Shah R, Messier K, Gu P, Li H, Apte J, et al. Land-use regression modeling of source-resolved fine particulate matter components from mobile sampling. Environ Sc Technol. 2019;53:8925-8937 (https://doi.org/10.1021/acs.est.9b01897, accessed 24 April 2023).

Sampedro J, Smith S, Arto I, González-Eguino M, Markandya A, et al. Health co-benefits and mitigation costs as per the Paris Agreement under different technological pathways for energy supply. Environ Int. 2020;136:105513 (https://doi.org/10.1016/j.envint.2020.105513, accessed 24 April 2023).

Setton E, Marshall J, Brauer M, Lundquist K, Hystad P, Keller P, et al. The impact of daily mobility on exposure to traffic-related air pollution and health effect estimates. J Expos Sci Environ Epidemiol. 2011;21(1):42-8. doi: 10.1038/jes.2010.14.

Shaddick G, Salter J, Peuch V, Ruggeri G, Thomas M, Mudu P, et al. Global air quality: an inter-disciplinary approach to exposure assessment for burden of disease analyses. Atmosphere. 2021;12:48 (https://doi.org/10.3390/atmos12010048, accessed 19 April 2023).

Shaddick G, Thomas M, Amini H, Broday D, Cohen A, Frostad J, et al. Data Integration for the assessment of population exposure to ambient air pollution for Global Burden of Disease assessment. Environ Sci Technol. 2018;52(16):9069-9078. doi: 10.1021/acs.est.8b02864.

Shaddick G, Thomas M, Green A, Brauer M, van Donkelaar A, Burnett R, et al. Data integration model for air quality: a hierarchical approach to the global estimation of exposures to ambient air pollution. J R Stat Soc Ser C Appl Stat. 2018;67:231 (https://doi.org/10.48550/arXiv.1609.00141, accessed 19 April 2023).

Shaddick G, Thomas M, Mudu P, Ruggeri G, Gumy S. Half the world's population are exposed to increasing air pollution. npj Clim Atmos Sci. 2020;3:23 (https://doi.org/10.1038/s41612-020-0124-2, accessed 19 April 2023).

Spinelle L, Gerboles M, Villani M, Aleixandre M, Bonavitacola F. Field calibration of a cluster of low-cost commercially available sensors for air quality monitoring. Part B: NO, CO and CO2. Sens Actuators B Chem. 2017;238:706-715 (https://doi.org/10.1016/j.snb.2016.07.036, accessed 19 April 2023).

Spinelle L, Kotsev A, Signorini M, Gerboles M. Evaluation of low-cost sensors for air pollution monitoring. Effects of interfering compounds and meteorological conditions. JRC technical report. Luxembourg: Publications Office of the European Union; 2017 (https://op.europa.eu/en/publication-detail/-/publication/23e1a2c7-3c41-11e7-a08e-01aa75ed71a1, accessed 19 April 2023).

Suel E, Polak J, Bennett J, Ezzati M. Measuring social, environmental and health inequalities using deep learning and street imagery. Sci Rep. 2019;9:6229 (https://doi.org/10.1038/s41598-019-42036-w, accessed 19 April 2023).

Thunis P, Degraeuwe B, Pisoni E, Trombetti M, Peduzzi E, Belis C, et al. $PM_{2.5}$ source allocation in European cities: a SHERPA modelling study. Atmos Environ. 2018;187:93-106 (https://doi.org/10.1016/j.atmosenv.2018.05.062, accessed 19 April 2023).

Thunis P, Pisoni E, Bessagnet B, Wilson J, Vignati E, et al. Urban $PM_{2.5}$ atlas: air quality in European cities: 2021 report. Luxembourg: Publications Office of the European Union; 2021 (https://op.europa.eu/en/publication-detail/-/publication/defbc83c-2c93-11ec-bd8e-01aa75ed71a1, accessed 19 April 2023).

Turner B. Workbook of atmospheric dispersion estimates: an introduction to dispersion modeling, second Edition. U.S. Department of Health, Education, and Welfare, Public Health Service, Environmental Health Service, 1970.

UNEP, 2023. Real-time air pollution exposure. World Environment Situation Room. Nairobi: United Nations Environment Programme; 2023 (https://wesr.unep.org/airvisual, accessed 19 April 2023).

US EPA, 2012. Evaluation of chemical dispersion models using atmospheric plume measurements from field experiments. Washington, DC: United States Environmental Protection Agency; 2012 (https://www.epa.gov/sites/default/files/2020-10/documents/plume_eval_final_sep_2012v5_0.pdf, accessed 19 April 2023).

US EPA, 2015. Passive samplers for investigations of air quality: method description, implementation, and comparison to alternative sampling methods. Washington, DC: United States Environmental Protection Agency; 2015 (https://nepis.epa.gov/Adobe/PDF/P100MK4Z.pdf, accessed 19 April 2023).

US EPA, 2022. List of designated reference and equivalent methods. Washington, DC: United States Environmental Protection Agency; 2022 (https://www.epa.gov/system/files/documents/2022-12/List_of_FRM_and_FEM.pdf, accessed 19 April 2023).

US EPA, 2023a. National ambient air quality standards. Washington, DC: United States Environmental Protection Agency; 2023 (https://www.epa.gov/criteria-air-pollutants/naaqs-table, accessed 19 April 2023).

US EPA, 2023b. A guide to siting and installing air sensors. Washington, DC: United States Environmental Protection Agency; 2023 (https://www.epa.gov/air-sensor-toolbox/guide-siting-and-installing-air-sensors, accessed 19 April 2023).

US EPA, 2023c. Air quality dispersion modeling – preferred and recommended models. Washington, DC: United States Environmental Protection Agency; 2023 (https://www.epa.gov/scram/air-quality-dispersion-modeling-preferred-and-recommended-models, accessed 19 April 2023).

US EPA, 2023d. AERMOD modeling system development – documents. Washington, DC: United States Environmental Protection Agency; 2023 (https://www.epa.gov/scram/aermod-modeling-system-development-documents, accessed 19 April 2023).

US EPA, 2023e. Air sensors toolbox. Washington, DC: United States Environmental Protection Agency; 2023 (https://www.epa.gov/air-sensor-toolbox, accessed 19 April 2023).

van Donkelaar A, Martin R, Li C, Burnett R. Regional estimates of chemical composition of fine particulate matter using a combined geoscience-statistical method with information from satellites, models, and monitors. Environ Sci Technol. 2019;53(5):2595-2611.

Wangchuk T, Mazaheri M, Clifford S, Dudzinska M, He C, Buonanno G, et al. Children's personal exposure to air pollution in rural villages in Bhutan. Environ Res. 2015;140:691-698 (https://doi.org/10.1016/j.envres.2015.06.006, accessed 19 April 2023).

WHO, 2021. WHO global air quality guidelines. Particulate matter ($PM_{2.5}$ and $PM_{10}$), ozone, nitrogen dioxide, sulfur dioxide and carbon monoxide. Geneva: World Health Organization; 2021 (https://apps.who.int/iris/handle/10665/345329, accessed 18 April 2023).

WHO, 2022a. SDG Indicator 11.6.2 concentrations of fine particulate matter ($PM_{2.5}$). Global Health Observatory. Geneva: World Health Organization; 2022 (https://www.who.int/data/gho/data/indicators/indicator-details/GHO/concentrations-of-fine-particulate-matter-(pm2-5), accessed 18 April 2023).

WHO, 2022b. WHO ambient air quality database, 2022 update: status update. Geneva: World Health Organization; 2023 (https://apps.who.int/iris/handle/10665/368432, accessed 19 June 2023).

WHO Regional Office for Europe, 1999. Monitoring ambient air quality for health impact assessment. WHO Regional Office for Europe; 1999 (https://apps.who.int/iris/handle/10665/107332, accessed 18 April 2023).

WHO Regional Office for Europe, 2019. Environmental health inequalities in Europe: second assessment report. WHO Regional Office for Europe; 2019 (https://apps.who.int/iris/handle/10665/325176, accessed 18 April 2023).

Xue T, Zheng Y, Geng G, Xiao Q, Meng X, Wang M, et al. Estimating spatiotemporal variation in ambient ozone exposure during 2013–2017 using a data-fusion model. Environ Sci Technol. 2020;54(23):14877-14888.

Yim S, Lee G, Lee I, Allroggen F, Ashok A, Caiazzo F, et al. Global, regional and local health impacts of civil aviation emissions. Environ Res Lett. 2015;10:034001 (https://doi.org/10.1088/1748-9326/10/3/034001, accessed 19 April 2023).

# **Annex:** Technical specifications and/or operating principles for air quality measurements and models

## Passive diffusion samplers

There are a few different types of passive samplers. Button or badge samplers are better for occupational exposure assessment where concentrations may be higher, so that enough material is collected on the small substrate to be detected via an analytical instrument. There are also larger passive samplers for collecting ambient pollution; it is helpful to co-locate these with concentration monitors to determine composition.

## Low-cost sensors

While gaseous pollutants can be monitored with LCS based on electrochemical, metal oxide semiconductor, photoionization detector or non-dispersive infrared technologies, particulate matter monitoring is achieved with optical particle counters or light-scattering based optical sensors (e.g. nephelometers). Given the suite of pollutants that are generally included when assessing the burden of disease from air pollution (i.e. particulate matter, $NO_{2,}$ $O_{3,}$ CO), this document focuses on electrochemical, metal oxide and optical-based sensors.

For optical-based LCS, the operating principle is similar to that reported for PDRIs that measure particulate matter. Briefly, particulate matter sensors can either measure the intensity of the light scattered by the particles or count the number and size of particles within the volume of air. In an electrochemical sensor, gaseous pollutants react with the sensor's electrolyte, and the concentration of the air pollutant is determined by the magnitude of the chemical reaction which is proportional to the electrical signal outputted (e.g. electric current). For metal oxides, when a gas passes over their surface the resistance or conductivity of the metal surface changes, and the magnitude of this conductivity change is proportional to the concentration of gas adsorbed onto its surface.

Since the raw data outputted from LCS are proxies for particle or gaseous concentrations (e.g. light absorption, electrical voltage/current or conductivity), these raw data require conversion factors or models to represent the data as air pollution mass or volume concentrations. An integral part of the accuracy of LCS monitors is the calibration of these sensors. The correction/conversion factors applied (for instance, for gaseous sensors) are often calibrations against "zero gas" or gas of varying concentrations. These calibrations and conversions are thus overlapping in many contexts. While some LCS have factory calibration settings which provide users with a simple conversion factor to derive air pollution concentrations, other monitors have a more complex data management system that provides an internal post-processing system to convert the raw data into concentration data. Since the operating conditions under which these conversion models were developed may be quite different from the environment that the LCS is deployed in, it is recommended that users develop conversion factors in an environment with similar conditions (e.g. temperature and relative humidity) to the environment that the monitor will be deployed (Spinelle, Kotsev et al., 2017). This can be accomplished by co-locating the LCS with a reference instrument for a few weeks. Another advantage of developing in-house conversion factors is that it allows users to detect when the sensor's baseline is drifting or if there is an error in the conversion model. It is also beneficial to have multiple sensors deployed in tandem so as to be able to better detect any abnormalities in the sensor network. Furthermore, comparing data from multiple monitors over a few weeks is critical when assessing the reliability of these LCS monitors. Additional information on developing conversion factors and assessing the performance of LCS can sourced from the data quality objective of the European Air Quality Directive (EU, 2008) or the US EPA air sensor toolbox (US EPA, 2023e). It is also important to highlight that companies offer this calibration service, but these services are subject to annual contracts for data management, which makes the cost of continuous and permanent calibration moderately expensive and thus reduces the accessibility of this technology to communities in LMIC.

## Personal direct reading instruments

Examples of PDRIs that measure $PM_{10}$ and $PM_{2.5}$ are photometers which record optically based measurements of particulate matter (i.e. light scattered by the particles) and then convert it to mass concentrations. It is worth mentioning that gravimetric methods for quantifying personal exposure to particulate matter can be achieved through the deployment of encased polytetrafluoroethylene filters attached to an air pump, with or without a small, size-selective inlet (such as an impactor or cyclone), for 24 hours. Nitrogen dioxide levels (i.e. mixing ratios) can be measured using direct absorbance of the gas at a specific wavelength (i.e. 405 nm) while $O_3$ levels can be recorded using the operating principle of ultraviolet absorbance. It is important to note that PDRIs being used for research purposes should be able to log data. While most of these instruments can record air pollution data every few seconds, the use of a lower time resolution (e.g. 1 minute) is recommended so as to reduce the noise associated with these measurements. It should also be mentioned that these personal monitors should be corrected with a calibration factor that is derived from the slope of the reference instrument vs the personal monitor values during co-location of these instruments.

A few other commonly used standardized personal monitors that allow continuous monitoring of air pollutants at a high time resolution that are available include: micro-aethalometers for measuring black carbon; particle counters for recording UFP counts; and portable probes for monitoring $CO_2$, CO, VOC, relative humidity and temperature.

## Reference-grade monitors

For high time resolution data, particulate matter is measured using tapered element oscillating microbalances or beta attenuation monitors which determine the mass density of particulate matter. $PM_{10}$ and $PM_{2.5}$ can also be recorded by photometers or nephelometers which use light-scattering principles to derive mass concentrations. It should be noted that photometers and nephelometers must convert the light-scattering intensity to mass concentration and this conversion step is influenced by particle size and chemical composition whereas beta attenuation monitors do not require this conversion step. Particulate matter collected at a lower time resolution can be measured by gravimetric analysis, i.e. weighing the mass of deposited particles on the filter over a 24-hour period. Other operating principles that are used to give high time resolution air pollution measurements include laser absorption spectroscopy or chemiluminescence reaction principles, which determine the volume concentration of $NO_2$. Photometric principles are used for $O_3$ monitors which employ ultraviolet absorption while CO monitors use infrared radiation absorption to determine volume concentration.

## Land-use regression models

LUR models are derived from spatial and temporal predictor variables. Some examples of common spatial predictor variables are proximity to roadways, industries, city centre, green and blue spaces; proportion of area within a given circular buffer that contains open, commercial, industrial and residential areas. For temporal predictor variables, temperature, wind speed, wind direction and air pollution concentrations from a reference-grade monitoring station are useful for accounting for pollutant variability due to seasonal and day-to-day meteorological changes. It is worth mentioning that LUR models derived from mobile sampled air pollution tend to have a lower coefficient of determination, $R^2$, (i.e. the squared correlation between estimated and measured concentrations) than models developed from fixed site measurements; however, the model estimates are still representative of the observed spatial variability.

## Chemical transport models

An example of a global CTM is the Trace Model version 5 (TM5) which provides estimates of atmospheric gases (e.g. $O_3$, $NO_x$, sulphur oxides), VOC, ammonia and $PM_{2.5}$ components (e.g. sulfates, nitrates), black carbon, organic carbon, sea salt and mineral dust. TM5 uses meteorological data from the ECMWF to output hourly air pollutant estimates at a spatial resolution of 1° × 1°. The TM5-FAst Scenario Screening Tool (TM5-FASST) is a reduced-form global source-receptor model that is based on TM5. This simplified version of the TM5 model uses inputs derived from annual pollutant emission data aggregated at national level which reduces the computing time but can still provide $PM_{2.5}$ and $O_3$ concentrations in a receptor grid with 1° × 1° resolution.

The strength of this model lies in its ability to enable countries to examine different what-if policy scenarios or emission pathways and evaluate the impact on ecosystems and human health (Sampedro et al., 2020). TM5-FASST can also be used to complement source apportionment studies.

Along the same lines, the SHERPA Screening Tool developed by the Joint Research Centre is a CTM reduced-form source-receptor model that provides $NO_2$, $PM_{2.5}$ and $O_3$ concentrations in a receptor grid with 10 × 10 km resolution over Europe (Thunis et al., 2018). This model enables countries, regions and cities to examine different what-if policy scenarios or emission pathways and evaluate the impact on ecosystems and human health. Similar to FASST, SHERPA is useful to complement source apportionment studies. One application example is the quantification of the most important sources of emissions in 150 cities in Europe (Thunis et al., 2021).

A well-established regional CTM in Europe is the EMEP model which was developed more than three decades ago to support negotiations in relation to long-range transboundary air pollution within the United Nations Air Convention. More recently, the European Commission set up CAMS, which includes global and regional scale modelling. For the regional (European) Service, CAMS relies on an ensemble of 11 CTMs developed and operated by European teams at a resolution of 10 km for both forecast and past re-analyses. These models include CHIMERE (France), DEHM (Denmark), EMEP (Norway), EURAD-IM (Germany), GEM-AQ (Poland), LOTOS-EUROS (Netherlands [Kingdom of the]), MATCH (Sweden), MINNI (Italy), MOCAGE (France), MONARCH (Spain) and SILAM (Finland). Such an extended list is illustrative of the diversity of modelling approaches available, even for operational purposes.

Alternative approaches use downscaling methodology built on classical Gaussian plume modelling and integrated into CTMs such as the EMEP model providing model physical parameterizations and emission data in such a way as to provide a consistent model description from regional to local scales. Unlike other urban-scale models, the resulting model called uEMEP (Denby et al., 2020) is intended not just to achieve local-scale modelling for an individual city or area but to provide local-scale modelling over entire countries or continents, providing high-resolution modelling over large areas and allowing air quality assessment and exposure calculations at high resolution everywhere. Similar approaches are proposed with the MUNICH model (Kim et al., 2018) coupled with the Polair3D model and CHIMERE to account for emission variability to assess the exposure at local scale (Kim et al., 2018).

At the regional scale, CMAQ was applied with a spatial resolution of 27 km to evaluate the impacts of sectoral emissions in China on air quality (including $PM_{2.5}$ and $O_3$), human health, crop production and economic costs (Gu et al., 2018). In another study, CMAQ was also used to assess the air quality and health impacts of domestic transboundary air pollution in China at a spatial resolution of 27 km (Gu and Yim, 2016).

## Dimension reduction methods

One approach to account for the synergistic effect of multiple pollutants is to use a statistical regression model that contain multiple pollutants as predictor variables and an interaction term for each pair of pollutants. While this method may work well for uncorrelated pollutants, if two or more highly correlated pollutants are included in the model, the model can become unstable. Another option could be to conduct some degree of dimension reduction on the multiple pollutants prior to using the data as predictor variables for the regression model. Dimension reduction methods such as lasso regression, principal component analysis (Lee, Hong et al., 2020), k-means clustering (Keller et al., 2017), factor analysis or hierarchical clustering allow highly correlated predictor variables to be grouped into one “cluster” or “factor”. One of the benefits of dimension reduction methods that are also used for source apportionment is that these techniques can provide useful information about the sources and processes that contribute to air pollution. Such information can be valuable for regulatory agencies that are exploring different air pollution reduction policies or interventions (Dominici et al., 2010).

**Air Quality and Health Unit**

**World Health Organization**
**20 Avenue Appia**
**1211 Geneva 27**
**Switzerland**

**https://www.who.int/teams/environment-climate-change-and-health/air-quality-and-health**

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