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A Review of Urban Air Pollution Monitoring and Exposure Assessment Methods

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Abstract: The impact of urban air pollution on the environments and human health has drawn increasing concerns from researchers, policymakers and citizens. To reduce the negative health impact, it is of great importance to measure the air pollution at high spatial resolution in a timely manner. Traditionally, air pollution is measured using dedicated instruments at fixed monitoring stations, which are placed sparsely in urban areas. With the development of low-cost micro-scale sensing technology in the last decade, portable sensing devices installed on mobile campaigns have been increasingly used for air pollution monitoring, especially for traffic-related pollution monitoring. In the past, some reviews have been done about air pollution exposure models using monitoring data obtained from fixed stations, but no review about mobile sensing for air pollution has been undertaken. This article is a comprehensive review of the recent development in air pollution monitoring, including both the pollution data acquisition and the pollution assessment methods. Unlike the existing reviews on air pollution assessment, this paper not only introduces the models that researchers applied on the data collected from stationary stations, but also presents the efforts of applying these models on the mobile sensing data and discusses the future research of fusing the stationary and mobile sensing data.

Keywords: air pollution; interpolation approaches; land-use regression models; dispersion models; mobile sensing; urban data analytic; GPS

1. Introduction

The world energy consumption has increased rapidly due to economic growth, rising populations and industrialization over the last 50 years. This rise in energy consumption is primarily from increased use of fossil fuel. The burning of fossil fuel produces a huge amount of Carbon dioxide (CO_2), which is a greenhouse gas that contributes to global warming, causing the Earth surface temperature rise in response. More harmfully, it emits a number of air pollutants such as Carbon monoxide (CO), Sulfur dioxide (SO_2), Nitrogen oxides (NO_x) and Particulate matters ($PM_{2.5}$ and PM_{10}).

Exposure to these air pollutants has both acute and chronic effects on human health, affecting a number of different systems and organs. These effects range from minor upper respiratory irritation to chronic respiratory and heart disease, lung cancer, acute respiratory infection and asthmatic attacks [1]. In addition, long-term exposures have also been linked with premature mortality and reduced life expectancy. For example, around 90% of human population in European cities are exposed to pollution levels exceeding World Health Organization (WHO) air quality guidelines levels and, as a consequence, it is estimated that the average life expectancy in the European Union is 8.6 months lower [2,3]. The public should be aware of their air quality through pollution monitoring, eventually urging the local and international authorities to take actions on air pollution reduction such as traffic and industrial activity control, land use management, etc.

For legislatory purposes, policymakers have been installing monitoring stations or systems across many cities [4,5]. As a consequence, current systems measure air pollution at a very low spatial resolution, e.g., only 22 stations covering a 50×50 km^2 (113 km^2 per station) in Beijing, 14 stations covering 1572 km^2 (112 km^2 per station) in London, and 61 stations (221 km^2 per station) in Flanders, Belgium. Researchers have also placed pollution sensors to assess the personal exposure to air pollution in places of interest [6–9], such as major roads with heavy traffic and industrial sites. Measurements obtained at these stations or locations can only reflect the air pollution level there or in small areas around there. To estimate these pollutant concentrations at the unmeasured areas using the available measurements, researchers have proposed a variety of methods, e.g., spatial averaging, nearest neighbor, Inverse Distance Weighting (IDW), Kriging, Land-Use Regression (LUR) modeling, dispersion modeling, neural networks, etc. Most studies select one single method to estimate the pollutant concentrations [10–16], while some studies combine several methods together for pollution estimation at different scales [17,18]. Some researchers not only assess the exposure to air pollution, but also study the relationship to specific health effects [17,19,20].

With the development of pollution sensing and Global Positioning System (GPS) technology in the last few decades, mobile sensing systems with integrated pollution sensors and GPS devices have been gradually applied in urban areas. This increases the density of pollutant measurements, which alleviates, but does not eliminate the measurement sparsity since the carriers of the mobile sensing systems mainly explore specific areas or cover city roads. For such purposes, researchers have adopted the methods developed for stationary monitoring data to estimate the air pollution at unexplored areas.

Several general reviews about pollution exposure assessment have been done in the past decades. Jerrett et al. reviewed all available methods for intraurban exposure assessment [21], including interpolation methods, LUR models, dispersion models, hybrid models and so on. Ryan and LeMasters reviewed six studies for a total of 12 LUR models, and summarized the geographic variables commonly used in LUR models [22]. Hoek et al. identified 25 LUR studies in their systematic review [23]. Holmes et al. gave a comprehensive review of dispersion modeling and its application in particle concentration estimation [24]. Wong et al. reviewed the studies of air pollution estimation using spatial interpolation methods [25]. All of these reviews focus on the air pollution studies using stationary monitoring data; however, to the best of our knowledge, there exists no overview on the research using mobile sensing data.

The goal of this paper is to give an overview of the state of the art in air pollution monitoring, including monitoring data acquisition and pollution assessment methods, especially the adoption of these methods in mobile pollution monitoring. The latter seems particularly relevant in the scope of a growing number of citizen science initiatives that aim at implementing mobile sensing approaches for air quality monitoring in their communities [26,27]. Furthermore, we give a detailed overview of derived air quality indicators to facilitate transferability of the best practices among different regions and campaigns.

2. Monitoring Data Acquisition

Traditionally, air pollution concentrations are measured at fixed monitoring stations that are mainly built by environmental or governmental authorities. The main advantages of these stations lie in the measurement availability for a variety of pollutants, and the measurement reliability, which benefits long-term pollution estimation. However, air pollution monitoring using these fixed stations suffers from the low spatial resolution of the data, which may lead to inaccurate assessment over the whole study area.

As the development of sensing technology, low-cost portable devices have been increasingly used to monitor the air pollution [28,29]. A number of publications have reported the use of such mobile monitoring equipments. Wallace et al. conducted the mobile surveys on a variety of pollutants in the city of Hamilton, ON, Canada since 2005 [30]. Pollution data with timestamps and GPS coordinates were collected using a monitoring unit consisting of an enclosed van equipped with pollution monitors, a GPS unit, a laptop and an integrated battery pack. Sampling routes were specially designed to cover the areas of "hot spots" such as heavy industries and major highways under various meteorological conditions. During the 2008 Beijing Olympic Games, Wang et al. equipped a van with a large suite of devices for measuring particle size distribution and black carbon concentration [31]. MacNaughton et al. designed a battery-powered mobile monitoring station to study the spatial variation in air pollution [32]. Shi et al. applied a Toyota HiAce vehicle with monitoring sensors to estimate the spatial variation of $PM_{2.5}$ and PM_{10} in the downtown area of Hong Kong [33]. Although different pollutants were measured in the researches aforementioned, utilized mobile platforms share the same key components: a vehicle (e.g., a van and a car), pollution monitors, a GPS unit, and a battery to power the pollution monitors and the GPS unit. In addition, all of the data collection were conducted along the pre-designed routes (mostly on the major roads).

To explore the personal exposure of other road users to air pollutants, researchers have improved the monitoring units to be more compact and flexible. Bigazzi and Figliozzi mounted the pollution measuring instruments to bicycles to monitor the bicyclists' exposure to volatile organic compounds and carbon monoxide [34]. Zwack et al. designed backpacks containing pollution monitoring instruments and a GPS device to be carried along scripted walking routes, so as to cover all roads in the study area. The recorded data was used to build an air pollution map over that area, and to evaluate the contributions of traffic to neighborhood-scale air pollution [35]. Kingham et al. also designed bags with pollutant equipments to collect mobile pollution data for exposure assessment in different modes of transport, including car, bike, and bus [36].

No matter which type of vehicles were utilized to carry the pollution monitors in the research aforementioned, the data collection was conducted only for a short-term period (limited to the power supply), to cover various meteorological conditions or all the roads in the study area. These collected data over a short period of sampling time was sufficient to analyze the impact of the environmental parameters (e.g., wind, weather) and generate pollution statistics. However, longer-period of data collection on a regular basis (such as "daily") is required for more accurate air pollution modeling and prediction. The "daily" mobile monitoring data can be collected by the current road users from their daily commutes, such as buses, taxis and frequent cyclists [37]. Shirai et al. proposed mechanisms for a real-time air quality monitoring system using public transports and had this system tested using garbage trucks in Fujisawa, Japan [38]. Dong et al. developed a mobile sensor network system called Mosaic and mounted them on the cleaning vehicles in Ningbo and buses in Hongzhou, China for city-scale pollution sensing [39,40]. Hasenfratz et al. collected enormous amount of "daily" air pollution data using ten trams of the public transport network of Zurich, Switzerland as carriers for their OpenSense measurement (http://www.opensense.ethz.ch/trac/) [41]. Furthermore, imec developed low-power sensors [42] and employed postal trucks as carriers during "daily" data collection.

Compared to traditional fixed monitoring stations, mobile devices measure pollution close to the people affected by it, or close to the vehicles producing it. They offer high spatial and temporal resolution, albeit concentrated on specific routes and specific time periods (e.g., rush hour). This data is therefore of a very different and complementary nature than fixed sensor data.

3. Pollution Assessment Methods

A variety of techniques has been proposed to estimate the pollutant concentrations and personal exposure to them, ranging from geostatistical techniques, Gaussian models, linear regression, artificial intelligence to compressed sensing. Three of them have been commonly used in literature: spatial interpolation, land-use regression model and dispersion model.

3.1. Spatial Interpolation Approaches

Interpolation methods in general share the same basic mathematical foundation. They all estimate the value at an unmeasured location as a weighted average of the measurements at surrounding monitoring stations. They differ in their choice of sample weights and the surrounding stations. Four interpolation methods are commonly used in air pollution estimation and assessment: spatial averaging, nearest neighbor, inverse distance weighting and kriging approach.

Spatially averaging simply calculates the mean of pollutant measurements from the nearby monitoring stations (located within a predefined grid, a country, or even a city). It assumes equal influence of the measurements at different monitoring stations with various distance to the unmeasured location, which is unrealistic in the air pollution estimation, as it omits any spatial variability (as those caused, for example, by urban street canyon effect) [43–46]. Nearest neighbor assigns the pollutant measurements of the closet monitoring station to the unmeasured location, regardless of the actual distance between them [10–12,47]. The main disadvantage of this technique is that the measurements from other neighboring points are ignored. Because of these limitations, both methods are no longer commonly used in air pollution estimation recently. However, they usually appear in the comparative studies of spatial interpolation methods [19,25,48–51]. In addition, some researchers started applying compressed sensing to estimate the pollution level at unmeasured locations by discovering the spatial correlations among multiple heterogeneous air pollution data [52,53].

3.1.1. Inverse Distance Weighting

Inverse Distance Weighting (IDW) is a deterministic method for spatial interpolation. The value at the unknown location (x, y), $u(x, y)$ is calculated as the weighted average of the measurements at the monitoring stations. This method assumes that the value $u(x, y)$ is more influenced by the close measurements than the distant measurements [54]. In other words, the close locations get greater weights, and the weights diminish as a function of distance. Given the pollutant measurements at N locations surrounding the unknown location (x, y), $u_n(x_n, y_n)$, $n = 1, \ldots N$, the value at the unknown location, $u(x, y)$, is calculated as:

$$u(x,y) = \frac{\sum_{n=1}^{N} \frac{u_n(x_n,y_n)}{d_n}}{\sum_{n=1}^{N} \frac{1}{d_n}}, \tag{1}$$

where $d_n = \sqrt{((x - x_n)^2 + (y - y_n)^2)}^i$ is a commonly squared distance with i chosen as 2.

Hoek et al. applied the inverse distance squared weighted interpolation method to estimate the regional concentration of Black Smoke (BS) and Nitrogen Dioxide (NO_2), using measurements obtained from stations of the National Air Quality Monitoring Network in Netherlands [55]. Their study suggested an association between the cardiopulmonary mortality and living near a major road.

Jerrett et al. investigated the influence of personal exposure to ozone (O_3), $PM_{2.5}$ and NO_2 on human health in California, USA [56]. For O_3, they assessed the monthly exposure over 14 years at 73,711 residential locations from 262 monitoring sites, using IDW models. They proved that O_3 is significantly associated with cardiovascular mortality, particularly from Ischemic Heart Disease (IHD). Similarly, Beckerman et al. also used IDW interpolation to model the regional exposures of O_3 and $PM_{2.5}$ in Toronto, ON, Canada, but found no strong association with IHD. This suggests that the association between cardiovascular disease with a specific air pollutant may be region-dependent.

Other researchers have also applied the IDW approach on various pollutants at different spatial levels: at county level (O_3 in [57], O_3 and PM_{10} in [25], O_3 in [49]), at zip code level (O_3, NO_2, PM_{10} and CO in [58], PM, $PM_{2.5}$ and PM_{10} in [50], NO, NO_2 in [59]) and at home address level (NO, NO_2, BS and SO_2 in [18]).

3.1.2. Kriging

Kriging is also a weighted combination of measurements at surrounding monitoring stations. Instead of assuming a function of inverse distance, as IDW method does, kriging assigns weights at each concentration by exploiting the spatial correlation among the observed measurements [12,19,60,61]. A major advantage of kriging interpolation is that it generates both the estimates and their standard errors at the unmeasured sites. These standard errors quantify the degree of uncertainty in the estimates [62].

Two different forms of kriging are commonly used in geostatistics: ordinary and universal. Ordinary kriging assumes a constant unknown mean in the local neighborhood, while universal kriging assumes a general polynomial trend model. Ordinary kriging is the most general and widely used method [63–65]. Universal kriging is usually used when the existence of the trend is certain and the trend is describable [5,66]. Researchers have explored their use in different applications [17,67].

Liu explored the daytime O_3 spatial variation using measurements obtained from 19 monitoring stations in Toronto (ON), Canada [63]. An ordinary kriging model was used to estimate the outdoor ozone concentration levels. Liu evaluated the performance of the model by comparing actual outdoor measurements from 40 homes in this area with the estimated values. Results showed higher estimation accuracy of the kriging technique than the nearest neighbor method. Ferreira et al. measured the air pollution concentrations over the central part of Lisbon using an ordinary kriging model from nine monitoring stations [64]. They also calculated the correlations between traffic patterns and the levels of three pollutants (CO, NO and NO_2). Differently, Janssen et al. developed statistical air pollution interpolation model, which applied an ordinary kriging scheme, but with adding land-use characteristics of the surroundings of the monitoring stations [65]. Using this model, the concentration levels of the pollutants were estimated on 4×4 km^2 grid level in Belgium. A cross-validation procedure demonstrated the superiority of the RIO model over other interpolation techniques.

Künzli et al. generated a surface of $PM_{2.5}$ covered the entire Los Angeles metropolitan area using a combination of a a universal kriging model with a quadratic drift and a multiquadric radial basis function model [66]. The data was obtained from 23 state and local district monitoring stations. They also proved the association between $PM_{2.5}$ concentrations and atherosclerosis, which underlaid many cardiovascular diseases. Jerrett et al. utilized a universal kriging procedure to develop an estimate of pollutant values cross the whole city using data from 23 monitoring stations in Hamilton, ON, Canada [5,68]. They also found significant associations between cardio-respiratory, cancer mortality and the exposure to these pollutants O_3, NO_2, PM_{10}.

Whitworth et al. studied the exposure to ambient air levels of benzene in Harris County, TX, USA from 17 monitoring stations located in Harris and surrounding counties [69]. They assessed both universal and ordinary kriging and proved the ordinary kriging model more appropriate in their application using a Bland–Altman analysis [70].

Moreover, some of the interpolation approaches have been implemented and compared on the same data set. Wong et al. applied all four methods to estimate the concentration levels of O_3 and PM_{10} over the whole USA [25]. All methods produced similar estimations in the areas with low-density monitors; different methods generated vastly different concentration levels in the areas with high-density monitors, such as California. Wu et al. estimated the concentrations of particulate matter (PM, $PM_{2.5}$ and PM_{10}) using monitoring data from 37 PM stations at a zip-code level in southern California, USA [50]. In their research, IDW and kriging methods demonstrated similar performance in areas with a small number of monitoring stations. Bell estimated the O_3 exposure at the county level in Northern Georgia, USA, using hourly measurements obtained from 15 monitoring sites [49].

This research proved a high correlation between the concentrations estimated from kriging and IDW approaches. In addition, the nearest neighbor approach tended to overestimate the concentrations for locations far from the monitoring stations, compared to the area-weighted average. Son et al. compared these four methods on several different air pollutants using measurements obtained from 13 monitors in Ulsan, Korea [51]. Their results showed high correlation between estimates from different methods for PM_{10}, O_3, NO_2 and SO_2, but relevantly low correlation for CO. This research suggests that importance of the interpolation method depends strongly upon the nature of the local monitor network.

3.1.3. Data Driven Spatial Prediction

Modern methods for air pollution data modeling and recovery try to capture dependencies among heterogeneous data such as different types of air pollutants and meteorological data. These statistical approaches are data driven and include models based on copula functions [52] and neural network models [71].

A first machine learning approach to model spatial correlations among different locations is presented in [71] and relies on a multi-view neural network architecture. The proposed model predicts the air quality of a location based on other stations' status consisting of air pollution measurements and meteorological data such as temperature and humidity. A critical step in their method is the partitioning of the spatial space into regions. The spatial neighbors of a station include not only nearby stations but also the stations located in adjacent cities. The spatial model is combined with a temporal model to provide a hybrid approach that aggregates spatial and temporal predictions.

Another working direction in spatial prediction includes models that employ the Compressed Sensing (CS) paradigm [72,73]. Let us denote with $x \in \mathbb{R}^N$ a vector containing air pollution measurements at various geographical locations. Assume that only a subset of the entries of x is known. This partial observation mechanism is equivalent to a linear mapping of the form

$$y = \Phi x, \tag{2}$$

where Φ is a matrix defined as follows: let m be the number of known entries of the N-dimensional vector x. Let Ω be the m-length ordered set of indexes of the known entries of x. We construct a $m \times N$ matrix Φ such as the i-th row of Φ contains only one entry equal to 1 at the column position defined by the i-th element of Ω; all the rest of the entries are equal to zero.

The subsampling process formulated in Label (2) is known as compressed sensing [72,73]. Unique identification of a signal from a few measurements is feasible, if x has a sparse representation θ under a basis $\Psi \in \mathbb{R}^{N \times N}$, that is,

$$x = \Psi\theta, \tag{3}$$

with $\|\theta\|_0 = s$, where $\|\cdot\|_0$ is the ℓ_0 quasi-norm counting the non-vanishing coefficients of the treated signal; s is the sparsity level of θ. Then, the unknown θ can be computed with well-known numerical algorithms [74,75]. After recovering θ, the actual complete data x can be reconstructed from Equation (3).

When, besides the incomplete measurements y, additional information related to x is available, then CS with side information [76] can lead to improved estimation accuracy. Recent methods, proposed in [52,53], exploit spatial correlations among multiple heterogeneous air pollution data sets to provide significant recovery performance improvements. In [53], side information is employed in the reconstruction precess via an ℓ_1 - ℓ_1 minimization algorithm. In [52], the proposed model is based on a copula-based design to capture the correlation among the different types of data. Copula functions are used to model the marginal distributions and the dependence structure among data separately; to select the most appropriate marginal distribution, fitting tests are performed with training data. Then, a copula-based belief propagation method is developed to reconstruct unknown measurements.

Table 1. Spatial interpolation studies.

Method	Reference	Pollutants	Study Area	MS Number	Sampling Period	Health Effects Assessment
IDW	Beckerman et al. [14]	$PM_{2.5}$, O_3	Toronto, ON, Canada	14 ($PM_{2.5}$), 16 (O_3)	2002, 2004	respiratory disease
	Beelen et al. [18]	BS, NO, NO_2, SO_2	Netherlands	40	1976–1996	mortality
	Hoek et al. [55]	BS, NO_2	Netherlands	–	1987–1990	chronic respiratory disease
	Jerrett et al. [56]	O_3	Los Angeles, CA; New York, NY, United States	262	1988–2002	ischemic heart disease
	Hubbell et al. [57]	O_3	United States	–	2000-2002	premature mortality, respiratory disease
	Salam et al. [58]	CO, NO_2, PM_{10}, O_3	CA, United States	–	1975–1987	reduced birth weight
Kriging	Jerrett et al. [5]	PM	Hamilton, ON, Canada	23	1985–1994	cardio-respiratory, cancer
	Brunekreef et al. [17]	BS, NO_2, $PM_{2.5}$	Netherlands	–	1976–1996	respiratory, cardiovascular, lung cancer
	Kim et al. [19]	$PM_{2.5}$	Los Angeles, CA, United States	22	2002	cardiovascular disease
	Sahsuvaroglu et al. [20]	NO_2	Hamilton, ON, Canada	100	1994–1995	childhood asthma
	Wong et al. [25]	PM_{10}, O_3	United States	732 (PM_{10}), 739 (O_3)	1990	–
	Bell [49]	O_3	Northern Georgia, United States	15	15–18 August 1995	–
	Wu et al. [50]	PM, $PM_{2.5}$, PM_{10}	Southern California, United States	37	2003	
	Son et al. [51]	NO_2, PM_{10}, O_3, SO_2, CO	Ulsan, Korea	13	2003–2007	–
	Liu and Rossini [63]	O_3	Toronto, ON, Canada	19	June–August 1992	–
	Ferreira et al. [64]	CO, NO, NO_2	Lisbon, Portugal	9	January–March 1997	–
	Janssen et al. [65]	NO_2, PM_{10}, O_3	Belgium	50	2006	–
	Künzli et al. [66]	$PM_{2.5}$	Los Angeles, CA, United States	23	2000	atherosclerosis
	Finkelstein et al. [67]	PM, SO_2	Redlands, AB, Canada	29 (PM), 19 (SO_2)	1993–1995 (PM), 1992 –1994 (SO_2)	circulatory disease
	Whitworth et al. [69]	benzene	Harris County, TX, United States	17	1998–2000	–

BS = Black Smoke, CO = Carbon Monoxide, MS = Monitoring Station, CO_2 = Carbon Dioxide, NO = Nitrogen Oxide, NO_2 = Nitrogen Dioxide, O_3 = Ozone, PM = Particulate Matter, SO_2 = Sulfur Dioxide.

The main disadvantage of IDW and kriging interpolation approaches is that they do not take other environmental factors into account such as land use, terrain, traffic density, wind speed, etc. These techniques also suffer from the low data availability in the areas with low-density stations configuration, particularly when certain pollutants are known to vary significantly over small scales, e.g., NO_2. The overview of spatial interpolation studies is given in Table 1.

3.2. Land-Use Regression Models

Land-Use Regression (LUR) models are based on the principle that the pollutant concentrations at any location depend on the environmental characteristics of the surrounding area. The models are developed through construction of multiple regression equations describing the relationship between the pollutant measurements at the monitoring stations and the predictor variables usually obtained through Geographic Information Systems (GIS), such as traffic intensity, road length, distance to the major road, road type, population density, land cover, wind speed, etc. The model function is presented below:

$$\hat{y} = \beta_0 + \beta_1 x_1 + \ldots + \beta_n x_n, \tag{4}$$

where $x_1, \ldots x_n$ represent the predictor variables, $\hat{y}$ is the predicted value of the pollution level, and β_0, $\ldots \beta_n$ represent the coefficients of the predictor variables that indicate the influence of the predictor variables on the pollution level.

Linear regression aims to find estimated values of the coefficients $\beta_0, \ldots \beta_n$ that will provide the "best" fit in the data points—for instance, a line that minimizes the sum of squared residuals (differences between the observed and predicted values of the pollution level) for ordinary least squares regression and a line that minimizes the penalized residual sum for ridge regression. The resulting models are then used to predict pollutant concentrations for the target locations, utilizing the given predictor variables at the target locations [77].

Briggs et al. introduced an LUR approach for air pollution mapping in the SAVIAH (Small Area Variations In Air quality and Health) study [78]. Results showed good predictions of the mean annual concentration of NO_2 in Amsterdam (Netherlands), Huddersfield (England) and Prague (Czech Republic). Since then, LUR models have generally been applied to model annual mean concentrations of air pollutants in different settings, especially in European and North American cities.

Gilbert et al. developed a LUR model to estimate the NO_2 concentrations in Montreal, QC, Canada [79]. Their study suggested positive associations between NO_2 and the following land-use variables: traffic count on nearest highway, nearby major road length and local population density. Wang et al. applied LUR models to estimate the NO and NO_2 concentrations in Metro Vancouver, BC, Canada [80]. They built LUR models with the same predictor variables using measurements made at similar locations in 2003 and 2010, respectively. This study proved the temporal stability of LUR models over a period of seven years. Beelen et al. developed LUR models for the ESCAPE project to estimate the NO_2 and NO_x concentrations in 36 areas in Europe [81]. Their results showed the importance of the accuracy of local traffic intensity as predictor variables in the model development.

Kashima et al. introduced LUR models to NO_2 estimation in Shizuoka, Japan [82]. Except NO_x [13,14,18] , LUR models have also been applied successfully for predicting other traffic-related pollutants such as fine PM and benzene [15–17,83–86]. Besides the commonly used predictor variables such as traffic intensity, road length, population, Chen et al. added meteorological variables into their LUR models, including wind index, temperature, humidity and wind speed [87].

Table 2. Land-use regression studies.

Reference	Pollutants	Study Area	MS Number	Sampling Period	Predictor Variables
Henderson et al. [13]	NO, NO_2	Vancouver, BC, Canada	116	2006	land cover, population density
Beckerman et al. [14]	NO_2	Toronto, ON, Canada	143	2002, 2004	road length, traffic intensity, land cover, physical geography, population
Clougherty et al. [16]	NO_2, $PM_{2.5}$	Boston, MA, United States	44	2003–2005	traffic count, road length, distance to the nearest major road
Brunekreef et al. [17]	BS , NO_2, $PM_{2.5}$	Netherlands	–	1976–1996	traffic intensity, land cover
Beelen et al. [18]	BS, NO, NO_2, SO_2	Netherlands	40	1976–1996	region, population, land cover, traffic intensity
Jerrett et al. [56]	NO_2, $PM_{2.5}$	Los Angeles, CA; New York, NY, United States	262	1988–2002	land cover
Marshall et al. [59]	CO, NO, NO_2, O_3	Vancouver, BC, Canada	13, 14, 14, 15	2000	traffic intensity, land cover, altitude, elevation, population
Sahsuvaroglu et al. [77]	NO_2	Hamilton, ON; Toronto, ON; Montreal, QC, Canada	>100	October 2002, May 2004	land cover, road type, population density, distance to lake, wind intensity, traffic density
Briggs et al. [78]	NO_2	Amsterdam, Netherlands; Huddersfield, United Kingdom; Prague, Czech Republic	80 per area	8 weeks in 1993, 1994	traffic intensity, land cover, altitude, road network
Gilbert et al. [79]	NO_2	Montreal, QC, Canada	67	14 days in 2003	distance from the nearest highway, traffic count, land cover, major road length, population
Wang et al. [80]	NO, NO_2	Vancouver, BC, Canada	73	2003, 2010	elevation, distance to the nearest highway, road length, land cover, population density, traffic density
Beelen et al. [81]	NO_2, NO_x	36 areas in Europe	40–80 per area	October 2008–April 2011	land cover, road length, distance to the nearest road, population density, altitude
Kashima et al. [82]	NO_2	Shizuoka, Japan	67	April 2000–March 2006	road type, traffic intensity, land use, physical component
Slama et al. [84]	NO_2, $PM_{2.5}$	Munich, Germany	40	March 1999–July 2000	road traffic, road type, road length, land cover
Ross et al. [85]	NO_2	San Diego, CA, United States	39	2003	traffic density, road length, distance to the Pacific coast
Gulliver et al. [86]	PM_{10}	London, United Kingdom	52	1997–2005	traffic intensity, land cover, altitude
Chen et al. [87]	NO_2, PM_{10}	Tianjin, China	30	2006	land cover, road length, wind index, temperature, humidity, wind speed
Lee et al. [90]	NO_2, NO_x	Taipei	40	October 2009–September 2010	land use, road length, distance to the major road, number of inhabitants, number of households
Kerckhoffs et al. [91]	O_3	Netherlands	90	2012	traffic density, major road length, land use
Meng et al. [92]	NO_2	Shanghai, China	38	2008–2011	major road length, number of industrial sources, land use, population
Marcon et al. [93]	NO_2	Veneto, Italy	47	2010	road length, altitude, land use, distance to motorways
Liu et al. [94]	NO_2, PM_{10}	Changsha, China	74, 36	2010, April 2013–April 2014	road length, land use and nine meteorological variables
Wolf et al. [95]	NO_X, PM_{10}, $PM_{2.5}$, O_3, UFP	Augsburg, Germany	20	2014–2015	land use, traffic density, population, altitude, building density
Mercer et al. [96]	NO_x	Los Angeles, CA, United States	150	2006–2007	population, land use, distance to industrial source, distance to primary highways and roads
Li et al. [97]	NO_2, NO_x	Los Angeles and Orange county, CA, United States	240	2008	land surface temperature, traffic flow, truck flow, atmospheric stability, land use, distances to major freeways and local streets, road length
Kanaroglou et al. [98]	SO_2	Hamilton, ON, Canada	29	2005–2010	land use, road length, elevation, distance to major industrial area

BS = Black Smoke, CO = Carbon Monoxide, CO_2 = Carbon Dioxide, MS = Monitoring Station, NO = Nitrogen Oxide, NO_2 = Nitrogen Dioxide, O_3 = Ozone, SO_2 = Sulfur Dioxide, PM = Particulate Matter, UFP = UltraFine Particle.

Jerrett et al. exploited LUR models to assess the $PM_{2.5}$ and NO_2 exposures in Los Angeles, CA and New York, NY, United States at a zip-code level [56,88]. This study showed a strong association between NO_2 and lung cancer. Jerrett and his colleagues later estimated the O_3 exposure in Quebec, QC, Canada using a variety of models, including a Land-Use mixed-effects Regression (LUR) model, a mixture of a Bayesian Maximum Entropy (BME) model and the land-use mixed model as well as a kriging method model [89]. The experimental results proved the superiority of the mixture model (BME-LUR). Beckerman et al. also applied different techniques on different pollutants [14]. Regional exposures to $PM_{2.5}$ and O_3 were modeled using inverse distance weighted interpolation, while local NO_2 exposures were modeled using LUR. Their results suggested that NO_2 was significantly associated with ischemic heart disease.

Although researchers chose different predictor variables according to local environments in their LUR models, most of them used linear regression to model the relationship between the pollutant level and the predictor variables [13,15,16,77–95]. One of the assumptions for linear regression is that the observations should be independent of each other. The regression residuals are therefore supposed to be independent. However, the observations in air pollution monitoring tend to be similar at nearby locations. This violates the independence assumption for the linear models. Few researchers have proposed methods to deal with the spatial correlation of the observations. Mercer et al. proposed a two-step approach to predict the NO_x concentrations in Los Angeles, CA, United States [96]. This approach combined the prediction of local means by standard linear regression with universal kriging of the regression residuals to handle the spatial structure in the model residuals. Their experimental results showed that their spatial LUR model performed as well or better than non-spatial LUR models, in terms of Cross-Validated (CV) R^2. Li et al. proposed a two-stage model combining a Generalized Additive Model (GAM) with cokriging of spatial residuals [97]. This spatial model predicted NO_x and NO_2 concentration surfaces well with high CV R^2 values. Kanaroglou et al. first applied a linear regression model on their entire data set [98]. They then used a spatial autoregressive model to remove the spatial autocorrelation in the linear regression residuals if any exists [99].

Hoek et al. reviewed different components of LUR models in 25 studies [23], including how to choose the number and distribution of the monitoring stations, the monitoring periods, significant predictor variables (road length, traffic intensity, distance and emission), and the performance of the LUR models for different pollutants ($PM_{2.5}$, NO, NO_x and VOC). They concluded that the LUR method typically performs better than, or equivalent to, the geo-statistical methods such as interpolation and dispersion models. Ryan and LeMasters summarized four important predictor variables used in 12 LUR models from six studies: road type, traffic count, elevation and land cover. They concluded an LUR model as an important tool of incorporating traffic and geographic information in air pollution exposure assessment [22]. The general overview of LUR studies is given in Table 2.

3.3. Dispersion Models

Dispersion models simulate the physical and chemical processes of the dispersion and transformation of atmospheric pollutants, so as to predict the pollutant concentrations associated with emission sources, as well as their spatial and temporal variations [100,101]. Dispersion models have been widely used in vehicular pollution prediction with making use of the environmental characteristics, such as traffic intensity, vehicle speed, terrain elevation, obstruction height, meteorological conditions, etc. The dispersion models vary depending on the mathematics used to develop the model.

Gaussian-based dispersion models are the most commonly used models for pollutant dispersion analysis. In these models, the dispersion in downwind direction is a function of the mean wind speed blowing across the Gaussian plume under steady state conditions [102]. Chock proposed a simple line-source model, which is referred to as GM, to describe the downwind dispersion of pollutants near the roadway [103]. California Department of Transportation developed four generations of California Line Source Dispersion Model, of which CALINE3 and CALINE4 are commonly used. These models were used to predict the concentrations of CO, NO_2 and suspended PM near highways and arterial streets, given traffic emissions, site geometry and meteorology [104,105]. Mcconnell et al. applied CALINE4 to model traffic-related pollution exposure from roadways near home and near schools [106]. American Meteorological Society (AMS) and U.S. Environmental Protection Agency (EPA) Regulatory Model (AERMOD) Improvement Committee proposed a near field steady state Gaussian plume model AERMOD to model particle dispersion [107]. Researchers later expanded its use to gas phase dispersion [108]. Some other Gaussian-based dispersion models have been proposed to model the local air pollution dispersions, such as the United Kingdom Atmospheric Dispersion Modeling System (UK-ADMS) [109], Contaminants in the Air from a Road, by the Finnish Meteorological Institute (CAR-FMI) [110], etc. Some of them specifically focus on dispersion modeling under low-speed wind conditions [111–113]. Levitin et al. evaluated the performance of CALINE4 and CAR-FMI models in modeling NO_2 and NO_x dispersion near a major road [114]. Vardoulakis et al. reviewed four of Gaussian-based dispersion models in street canyons [100].

Researchers also developed other non-Gaussian dispersion models for air pollution assessment. The Flemish institute for technological research (VITO in Dutch) proposed an integrated air quality model to calculate the pollutant concentrations within a street canyon using a steady state box model [115]. The Norwegian Institute for Air Research developed a Lagrangian-Eulerian Models model EPISODE to estimate the exposures to NO_2 and NO_x in Oslo, Norway [116]. Oftedal et al. applied EPISODE to assess the outdoor air pollution personal exposure for children [117]. Oettl et al. used the Gaussian-based model CAR-FMI and the Lagrangian dispersion model (GRAL, Graz Lagrangian Model) together to estimate the pollutant concentrations near a major road on low wind speed conditions [118].

The main advantage of dispersion models is that they do not require a dense network of monitoring stations. The disadvantages of dispersion models relate to the input data and assumptions about dispersion patterns: (1) the variety of input data is obtained at a relatively expensive cost; (2) these assumptions may be unrealistic or limited to local environments.

Some researchers applied multiple methods to assess air pollution exposure and compared their performance. Gulliver et al. employed four different methods for long-term exposure assessment: nearest neighbor, kriging, dispersion model and LUR model [86]. They compared the performance of these four methods in the term of their ability to predict mean annual PM_{10} concentrations in London, UK. Their results suggested the superiority of LUR models over other methods in long-term exposure assessment in complex urban environments. Marshall et al. also implemented all of these three general approaches to estimate within-urban spatio-temporal variability in ambient concentrations [59]. They concluded that different methods reflected different spatial scales: urban scale for interpolation approaches and dispersion models, and neighborhood scale for LUR models.

Researchers have also combined different methods together to assess the air pollution at different levels. Brunekreef et al. assessed the long-term exposure to traffic-related air pollutants using a combination of exposure indicators, interpolation of measurements and LUR [17]. They first interpolated the pollutant measurements at regional scale using both ordinary kriging and inverse distance weighted interpolation. Results showed high correlation between estimates obtained with these two interpolation methods. At urban scale, regression models were developed to assess background concentrations of the pollutants. Beelen et al. estimated the long-term outdoor exposure as a function of a regional, an urban and a local component [18]. Different components were estimated using different techniques. They applied IDW interpolation to estimate the regional component, and LUR model on the urban component. The local component was assessed by using a GIS and a digital road network with linked traffic intensities. The cooperation of three different-level components takes into account small-scale variations in air pollution assessment.

3.4. Approaches for Mobile Monitoring

To process mobile data on air pollution, researchers have often applied methods designed for fixed sensor networks, even though they are not always well suited for this purpose. For instance, Shi et al. developed LUR models from their street-level estimation [33]. Minet et al. presented LUR models for NO_2 exposure assessment, based on sub-segments, categorized in terms of the number of visits per road segment [119]. They also studied the influence of number of road segments and the number of visits per road segment on the performance of LUR models. In Hatzopoulou's work, the number of locations and the frequency of each location being visited were used as variables in the LUR models, except the commonly used predictor variables such as land use and road length [120]. Hasenfratz et al. used nonlinear LUR models to develop temporal air pollution map with a high spatial resolution of $100 \times 100\ m^2$ for Zurich, Switzerland [41,121]. Other LUR model applications in mobile monitoring can be found in [122–125]. Zwack et al. used a combination of regression models derived from mobile monitoring data and a dispersion model called Quick Urban Industrial Complex (QUIC) for the air pollution evaluation [35].

Adams and Kanaroglou extended the LUR modeling approach with neural networks to combine both mobile and stationary monitoring data for air pollution prediction [126]. Mobile monitoring data was modeled with a number of predictor variables, including air pollution concentrations from fixed monitoring stations, meteorological conditions and land-use characteristics. Their model was capable of predicting air pollution concentrations for any location in real time. However, they relied on a standardized data collection under various meteorological conditions. To ensure data quality, the mobile monitoring unit, i.e., an industrial van equipped with pollution monitors, GPS device and a laptop, halted in areas of hot spots, and retraced a planned route as slowly as possible to reduce the influence of outliers.

The general overview of mobile air pollution monitoring studies is given in Table 3. Some of the studies focused on finding the pollution resources or analyzing some specific environmental factors instead of the estimating the pollutant concentrations. Their methods are therefore not listed in the table.

Regarding the fusion between methods designed for fixed sensor networks and mobile data, the main challenge arises from inherently different nature of spatio-temporal observations. Whereas mobile data is a time series of measurements along the carrier's trajectory (a sequence of geographical locations), the fixed sensors measure air pollution at a fixed rate, producing time series of measurements at fixed locations. Thus, existing research efforts focused on transition of methods designed for fixed sensor networks towards mobile data often neglect the temporal variation between different locations such as the velocity of the sensor, which affects the pollution readings but also can provide information on the current traffic density and fluidity. Furthermore, mobile sensors mainly do not cover all areas at all times either and cannot provide uninterrupted data for specific locations (e.g., little data in low traffic conditions or at night); therefore, high spatial resolution is achieved with the cost of temporal resolution for mobile monitoring data. Additional challenge, regarding the transition between fixed sensor networks and mobile data for air pollution estimation, arises from long-term estimation potential and transferability of findings between these two inherently different data collection approaches. A comparative study in this area would be beneficial for future developments in this field.

3.5. Air Quality Indicators

The air pollution estimation approaches are in their essence applicable for different pollutants, but expressing the overall air quality levels in different areas in a comparable manner is a challenge many organisations and citizen science initiatives face daily. The primary reason for this is that different initiatives, local authorities and researchers focus on local issues and consequently measure only a limited set of pollutants in the scope of their campaigns. Thus, comparing the effect of different measures to improve air quality in the area becomes challenging and hinders the transferability of the best practices.

Table 3. Studies on mobile air pollution monitoring.

Reference	Pollutants	Sampling Period	Study Area	Sensor Carrier	Methods
Wallace et al. [30]	NO_2, $PM_{2.5}$	2005–2013	Hamilton, ON, Canada	an enclosed van	LUR models
Wang et al. [31]	BC, PM	August 2008	Beijing, China	a van	–
MacNaughton et al. [32]	BC, CO, CO_2, NO_2, O_3	–	Boston, MA, United States	a bicycle	–
Shi et al. [33]	$PM_{2.5}$, PM_{10}	2014–2015	Hongkong, China	a Toyota HiAce vehicle	LUR models
Bigazzi and Figliozzi [34]	CO, VOC	9 days, 2013	Portland, OR, United States	bicycles	regression models
Zwack et al. [35]	$PM_{2.5}$, UFP	June 2007	Williamsburg, NY, United States	six pedestrians	LUR models, dispersion models
Kingham et al. [36]	CO, PM, UFP	–	Christchurch, New Zealand	bus, car, bicycle	–
Shirai et al. [38]	CO, NO_2, O_3, $PM_{2.5}$, ultraviolet, dust, pollen, two types of air contaminants	January 2015–2016	Fujisawa, Japan	garbage trucks	–
Dong et al. [39], Gao et al. [40]	$PM_{2.5}$	24 February–3 April 2015 (Hangzhou), 13 December 2014–2016 (Ningbo)	Hangzhou, Ningbo, China	buses (Hangzhou), cleaning vehicles (Ningbo)	–
Minet et al. [119]	NO_2	2015	Montreal, QC, Canada	pedestrians	LUR models
Hatzopoulou et al. [120]	NO_2, UFP	2009	Montreal, QC, Canada	a car	LUR models
Hasenfratz et al. [41,121]	UFP	2012–2015	Zurich, Switzerland	ten public trams	nonlinear LUR models
Klompmaker et al. [122]	BC, UFP	2013	Amsterdam, Rotterdam, Netherlands	a car	LUR models
Peters et al. [123]	BC, UFP	February–March 2012	Antwerp, Belgium	a bicycle	linear
Van den Bossche et al. [124]					regression models
Hankey and Marshall [125]	BC, $PM_{2.5}$	rush hour	Minneapolis, MN, United States	a bicycle	LUR models
Adams and Kanaroglou [126]	NO_2, $PM_{2.5}$	2005-2013	Hamilton, ON, Canada	an enclosed van	NN models

BC = Black Carbon, BS = Black Smoke, CO = Carbon Monoxide, CO_2 = Carbon Dioxide, LUR = Land Use Regression, NO = Nitrogen Oxide, NO_2 = Nitrogen Dioxide, NN = Neural Network, O_3 = Ozone, PM = Particulate Matter, SO_2 = Sulfur Dioxide, UFP = UltraFine Particle, VOC = Volatile Organic Compound.

To overcome this challenge, several strategies have been proposed in the literature [8]. The first group of strategies departs from direct measurements and relies on expressing the overall air quality in terms of fuel consumption in the target area. The logic behind this is that the burning of fossil fuel is one of the major contributors to air pollutions. Thus, the total fuel consumption is considered as a proxy for the impact on air quality [127]. Mainly, the indicators derived from this approach are fuel consumption per vehicle-kilometre or per person-kilometre [8]. However, the main drawback of this strategy is that the indicator expresses fuel efficiency, rather than emissions of air pollutants [128]. In this context, the fuel consumption per capita or per GPD (Gross Domestic Product) seem more appropriate alternatives [127] yielding comparable results among different regions. Having said this, it should be noted that measures based on fuel consumption do not consider one important aspect of cleanliness of the vehicle fleet. For example, one can install filters on vehicles to reduce emissions and this would have no effect on this indicator, as the fuel consumption would be invariable. This aspect could be incorporated by considering the average age of the fleet or by evaluating the average level of maintenance of vehicles, but these are very indirect measures that are hard to quantify, and, usually, the required insights are not easy to obtain for, for example, citizen science initiatives.

The second group of strategies relies strongly on direct measurements [129], from either fixed or mobile monitoring stations, described in previous chapters. In this context, to achieve comparable indicators, it is necessary to either consider several pollutants separately; select one pollutant as determining for this indicator or aggregate different pollutants into one measure. The latter is, for example, possible by converting pollutants into "emission costs" by monetizing the impact of different pollutants [130] or by expressing the air pollution through the insight into traffic related emissions of greenhouse gases. Here, the greenhouse gases can be converted into CO_2 equivalents, according to their Global Warming Potential (GWP) [131]. The GWP describes the cumulative effect of a gas over a time horizon, which is usually 100 years, compared to that of the CO_2. Having said this, it should be noted that there is no unanimous approach suggested among different global and regional organisations nor scientists. For example, the Worldbank [132], OECD [133] and Environmental Protection Agency [134] consider the emission of CO_2, while the United Nations Economic and Social affairs [135] advise taking the variety of greenhouse gases into account. Furthermore, total amounts of air polluting emissions have the problem of being scale-dependent, thus comparability between different citizens observatory campaigns characterized by different sized target areas might be hindered, as values are not comparable between areas of different sizes. For this reason, the total amount of emissions needs to be scaled. Literature suggests several scaling options as air pollution per GPD [127] or air pollution per capita [127].

Finally, the third group of strategies considers the resulting concentration of pollutants in the environment, obtained by direct measurements and/or estimation approaches, in regard to some referent value. For example, one can express air quality in terms of percentage of the population that is exposed to air pollution levels exceeding the, for example, EU limit values set for the protection of human health [136]. Alternatively, a number of times per year that limit values for selected air pollutants that are also exceeded [137] can be considered.

4. Conclusions

The paper aimed to give a detailed literature review of urban air pollution monitoring and exposure assessment methods coupled with evidence of potential applications on mobile sensing campaigns. Regarding the assessment of the exposure to traffic-related pollutants using mobile monitoring data, it can be said that the researchers on combining mobile and fixed pollution data is still in its infancy. To process mobile monitoring data, researchers have often applied methods designed for fixed sensor networks, even though they are not always well suited for this purpose. Among all the methods mentioned above, the land regression modeling is the most popular one used in pollution estimation from mobile data. However, several challenges remained for future research on applicability of mobile campaigns for air pollution monitoring and exposure assessment:

(i) strategies for handling the temporal variation between different locations such as the velocity of the sensor, which affects the pollution readings and was not present in traditional fixed monitoring station networks; (ii) strategies to overcome reduced and inconsistent temporal resolution of mobile sensing campaigns (for example, little data in low traffic conditions or at night); (iii) strategies to support longitudinal air pollution monitoring in the context of transitions between existing fixed monitoring station networks and emerging mobile sensing, campaigns as well as fusion of measurements between both networks collected during the same time horizon.

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