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Application of land use regression model to assess outdoor air pollution exposure: A review

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ABSTRACT

In this study, we reviewed the application of land use regression (LUR) models in various regions worldwide to provide insight into approaches utilized for LUR models. We also discuss the variation of air sampling techniques and the transferability capacity of LUR models. A total of 160 articles published between 2009 and 2021 were discovered through keyword searches. The ESCAPE (European Study of Cohorts for Air Pollution Effects) project has become the foremost approach applied in many LUR studies. Alternative air sampling methods such as mobile, campaign and passive sampling have proven to be favourable for estimating air pollutants. The LUR model is generally not transferable from one area to another area. However, several studies found that LUR models are transferable with similar geographic and air pollution ranges and predictor variables. This review only covers studies that created the LUR model for five primary air pollutants. This review also showed that most studies were conducted mainly in areas with high population densities. Therefore, further studies from various regions are highly recommended to explain the wide range of exposures experienced by different populations.

1. Introduction

Air pollution is presently one of the foremost causes of environmental and public health problems worldwide (Anenberg et al., 2019). The Global Burden of Disease Study showed that ambient air pollution from particulate matter with a diameter of less than 2.5 mm ($PM_{2.5}$) is the fifth most significant risk factor for death worldwide, accounting for 4.2 million fatalities. The study also estimated an optional extra 254,000 fatalities were related to exposure to ambient ozone (O_3) (Cohen et al., 2017; Schraufnagel et al., 2019). Air pollution and health studies require accurate exposure assessment to minimize exposure misclassification (Eeftens, Beelen, de Hoogh, Bellander, Hoek, et al., 2012; Jerrett et al., 2005). However, conducting an air pollution exposure assessment on the population remains a difficult challenge because of several factors, such as variability of air pollution dispersion, substantial spatial variation, and complexity of city designs (Jayjock et al. 2007; Weichenthal et al. 2016). The monitoring device or station would be the most accurate exposure assessment method, but it is expensive and time-consuming (Luo et al., 2021; Morley & Gulliver, 2018). Besides, monitoring alone is not feasible enough to capture population exposure to outdoor air pollution due to other surrounding factors that influence the pollution exposure, such as the building and street configuration in the city (Hoek et al., 2008). In order to perform a comprehensive assessment of human exposure to pollutants, researchers are increasingly interested in exploring the function of mathematical models to assess exposure to air pollution (J. G. Su, and Beckerman 2009; X. Li et al. 2015). The exposure model has become an imperative component of assessment because it is ineffective to monitor or measure exposure levels ubiquitously (Nethery et al., 2008; M. Wang et al., 2015).

The land use regression (LUR) model has been a popular tool for determining individual exposure to ambient air pollution in current years (Hoek et al., 2008; Johnson et al., 2010; X. Li et al., 2015; Luo et al., 2021; M. Wang et al., 2012). Due to its ability to explain and forecast spatial variations in air pollution concentrations, LUR has become a widely used application. (Morley & Gulliver, 2018). The LUR model is a statistical and geographical information system (GIS) based

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method that applies land use, geography, traffic characteristics and population density to describe air pollution exposure in the study area (Hoek et al., 2008; Ryan & Lemasters, 2007). LUR modeling incorporates predictor variables acquired through GIS by monitoring air pollution in a few places to formulate stochastic models. Generally, the LUR model is used to estimate air pollution levels in areas without air pollution monitoring or no data on air emission inventories (Hoek et al., 2008; Luminati et al., 2021; Ryan et al., 2008). The LUR model was first introduced in the Small Area Variations in Air Quality and Health (SAVIAH) study by Briggs et al. (1997). The model was called "regression mapping" at first. This method simulates air pollutant concentrations by developing a linear regression model based on a few air pollution monitoring locations and potential predictor variables acquired by GIS technology from different land use types. Then, the model was applied to various unsampled points called "virtual monitoring sites" in the study area. The LUR models have been effectively utilized in the past few years to model annual mean concentrations of nitrogen dioxide (NO_2), nitrogen oxides (NO_x), sulfur dioxide (SO_2), particulate matter (PM_{10}, $PM_{2.5}$) and volatile organic compounds (VOCs) (Eeftens, Tsai, et al., 2012; Z. Liu et al., 2019; Jason G. Su et al., 2010; Van Nunen et al., 2017; M. Wang et al., 2012; Z. Zhang et al., 2018).

Hence, understanding the application of the LUR model is essential for future research and method improvement. Previously, a short review was published by Ryan and Lemasters (2007), who summarised the application of LUR models up to June 2006. Another review by Hoek et al. (2008) discussed the various components of LUR models in 25 studies. However, the review was limited to research articles published up to 2008. Other published reviews were focused on specific interests. For example, the study by Heresh Amini et al. (2017) focused on the LUR model application for VOCs, whilst the study by Luo et al. (2021) focused on the application of well-established LUR models to evaluate the association of air pollution with pregnancy outcomes. Therefore, this review focused on articles published from 2009 to 2021 and LUR models developed for primary outdoor pollutants. Our paper differed from the previously published paper by providing an updated and broad discussion on the LUR model application in various cities worldwide. We also discussed different approaches to applying LUR models and their transferability capacity.

2. Review strategy

2.1. Search strategy

A systematic literature search was conducted in 'PubMed' and 'Science Direct' databases to search published articles on land use regression studies. The search was limited to studies from 2009 to October 2021, and the search keywords were "land use regression", "GIS air pollution", and "regression mapping". Only papers in English were included. Only original research articles that developed LUR models related to outdoor air pollution were considered. Studies were only included if they had developed the LUR model for at least one of the five primary air pollutants, i.e., nitrogen oxide (NO_x, NO_2), carbon oxide (CO, CO_2), sulfur oxide (SO_2), ozone (O_3) and particulate matter (PM). Any potential included articles were checked in the references of identified articles. If the studies used the LUR model created from another publication or/and the model was developed based on simulation practices, they were excluded. The published article of narrative or systematic reviews, proceedings, reports, conference abstracts or if no data or full text was available, were excluded from this review.

2.2. Search result

A total of 280 articles were discovered through keyword searches. After screening for duplicates, 63 articles were excluded. Next, a total of 217 articles were screened for relevance based on title and abstract, and then 41 articles were excluded. The remaining 176 articles were assessed for eligibility based on the type of document, availability of pertinent data, and studies that meet inclusion criteria. Consequently, 16 articles were excluded after being assessed, and 160 articles were included in this review (Fig. 1).

3. Application of the LUR model

The 160 selected articles were categorized based on the region where the LUR models were developed. Forty-five articles were from the European region, and the studies were mainly developed for multi-cities in Europe and Britain. In the Asian region, there were 60 articles on LUR models, of which China dominated with 34 articles. Thirty-seven articles on LUR models were conducted in the North American region, of which 21 were from the United States of America (USA), 15 were from Canada, and one from Mexico. In South America, we only found one article from Brazil. We also found eight articles from Australia, three from New Zealand, four from South Africa, one from Uganda and one study that developed the global LUR model (Table 1).

3.1. Europe

The ESCAPE project was the most notable study in the European region that applied LUR models. The ESCAPE project aimed to investigate the health impacts of chronic exposure to air pollution. They developed the LUR model based on standardized, targeted air monitoring programs in each research location to estimate participant exposure to air pollution at their respective residences. Then, the health data from existing cohort studies were utilized to assess the health effects (Eeftens et al. 2012; Beelen et al. 2013). One of the studies under the ESCAPE project conducted by Eeftens et al. (2012) was to develop the LUR models for particulate matter (PM) pollutants. The study investigated the levels of $PM_{2.5}$, $PM_{2.5}$ absorbance, PM_{10}, and PM_{coarse} at 20 monitoring stations spread across 20 study locations in Europe. The model demonstrated that $PM_{2.5}$ absorbance had the highest R^2 (median 89%, range 56–97%) and PM_{coarse} had the lowest (median 68%, range 32–81%). They found that lower R^2 was associated with low concentration variability or few availabilities of predictor factors, particularly traffic intensity. The study's findings indicated that a careful selection of monitoring locations, scrutiny of significant observations, and asymmetrical variable distributions are crucial requirements for developing reliable LUR models. Another ESCAPE project study was conducted by Beelen et al. (2013), where they developed the LUR models for nitrogen dioxide (NO_2) and nitrogen oxides (NO_x) in 36 study areas in Europe. The results showed that the model explained variances (R^2) ranged from 55% to 92% for NO_2 and 41% to 91% for NO_x. The study demonstrated that developing LUR models for other pollutants was possible using the ESCAPE standardized approach. Most of the studies in Europe adapted the ESCAPE approach in developing their LUR model (de Hoogh et al., 2016; Dons et al., 2013, 2014; Hoek et al., 2015; Kerckhoffs et al., 2017; Naughton et al., 2018; Vienneau et al., 2013; M. Wang et al., 2014).

Even though ESCAPE is the primary method referred to when developing the LUR model, several studies modified or combined with other approaches to develop the model. For example, Dons et al. (2013; 2014) combined the method from Henderson et al. (2007) study with the ESCAPE approach to developing their LUR models where selection variables were based on adjusted R^2 of supervised forward stepwise regression. Meanwhile, Vienneau et al. (2013) followed the supervised stepwise selection from the ESCAPE framework to derive multiple linear regression equations for the models. Several traffic variables were added to the ESCAPE framework for the study in the Netherlands by M. Wang et al. (2014). de Hoogh et al. (2016) combined the satellite-derived (SAT) and chemical transport model (CTM) with the LUR model to improve the performance of LUR models in Europe. The study by (Van den Bossche et al., 2020) followed the standard LUR method by Henderson et al. (2007) and Eeftens et al., (2012), however, for the cross-validation method, they used LASSO linear modeling approach

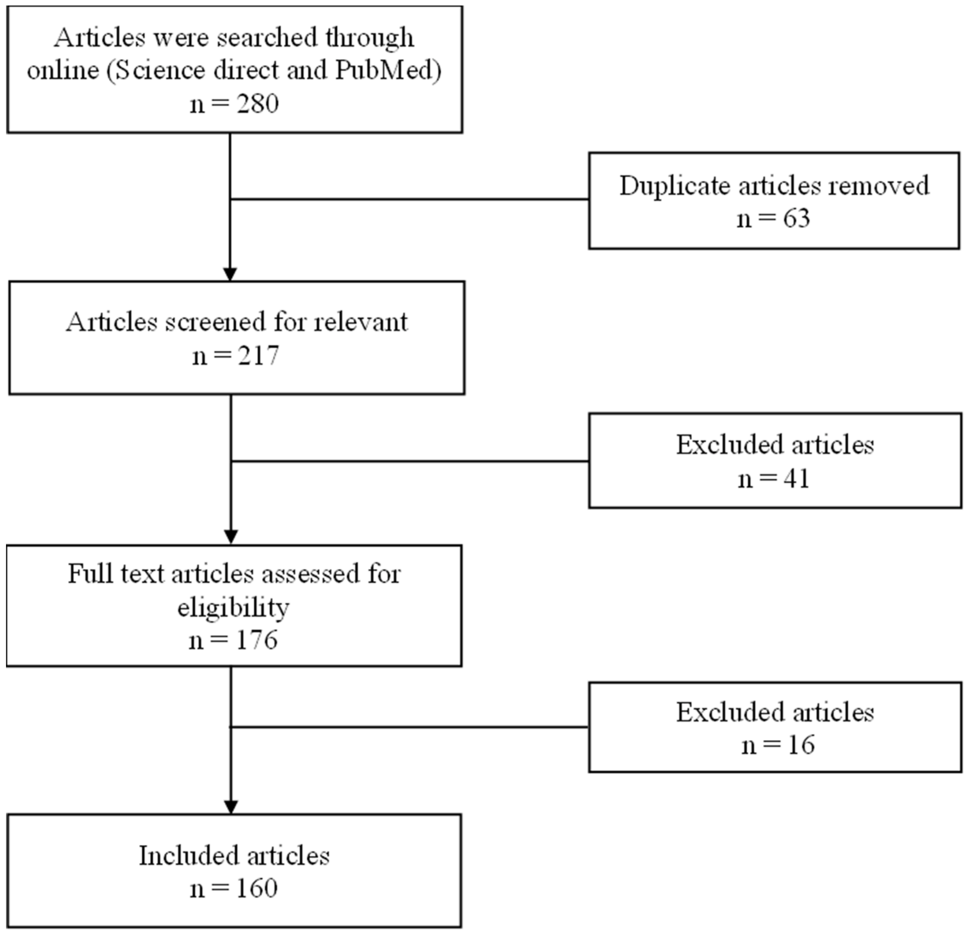

Fig. 1. Flow chart of the literature search strategy.

(Beckerman et al., 2013). In Anna Mölter and Lindley (2021) study, they created the XLUR tool to automate the ESCAPE method. The study proved that the XLUR tool could reduce processing time and human error by automating data extraction, data processing and statistical analysis stages.

3.2. Asia

The LUR model studies are widely presented in China. The majority of the studies were conducted in urban areas with high populations in cities such as Shanghai, Beijing, Tianjin and Nanjing (Meng et al. 2015; J. Wu et al. 2015; C. Liu et al. 2016; L. Huang et al. 2017; M. Liu et al. 2019; Ge et al. 2021). For example, in Shanghai city, Meng et al. (2015) conducted a study to estimate NO_2 from 2008 to 2011 using the LUR model. They compared the performance LUR model with ordinary kriging and inverse distance weighted (IDW) interpolation methods. They found that the LUR model of NO_2 outperformed the kriging and IDW interpolation methods. Meanwhile, in China's capital city, Beijing, J. Wu et al. (2015) developed discrete LUR models to estimate spatio-temporal variations of $PM_{2.5}$. They developed eight LUR models based on annual, seasonal, peak/non-peak, and incremental concentration subsets. They found that the developed LUR models were driven by similar variables except for the models for winter and cumulative concentration, indicating that the spatial variations of $PM_{2.5}$ remain steady most of the time. However, the $PM_{2.5}$ concentrations showed more temporal than spatial variation, signifying the need to establish different models to capture spatiotemporal trends.

On the other hand, L. Huang et al. (2017) explored the applicability of conducting LUR models for four key air pollutants of $PM_{2.5}$, SO_2, NO_2 and O_3 in Nanjing city, China. The air pollutants data were collected from national monitoring networks, representing different area characteristics in Nanjing, China. The LUR models of these four air pollutants performed well in explaining the city's variance of air pollutants. The adjusted variance of the LUR models was highest for NO_2 (87%) and lowest for O_3 (65%). The study showed that the concentrations of $PM_{2.5}$, SO_2, and NO_2 at the annual average level were mainly associated with the local pollution emission, while O_3 was more heavily influenced by regional emission. Many studies have been conducted to develop the LUR model locally or regionally throughout the nation to estimate air pollution in China (L. Chen et al., 2018; H. Xu et al., 2019; Z. Zhang et al., 2018). They developed the LUR models to estimate air pollutant concentrations at residential addresses throughout China. The developed models demonstrated high accuracy and predictive ability with high spatial resolution and could be applied in studies focusing on the chronic health effects of air pollution.

In India, Saraswat et al. (2013) developed LUR models to assess air pollutants variability of $PM_{2.5}$, black carbon (BC) and ultrafine particle concentrations (UFPN) in the capital city, New Delhi. They developed the models separately for morning and afternoon in order to assess the temporal variability. They found that the temporal variability was higher than the spatial variability for $PM_{2.5}$ and BC. Furthermore, the magnitude and spatial variability of pollutants concentration were higher during the morning than in the afternoon. They identified that the population density and road variables were significant predictors for the models. In contrast, the study by Sanchez et al. (2018) and Nori-Sarma et al. (2020) focused on less urbanized areas with fewer resources for air quality monitoring. In Sanchez et al. (2018) study, they used satellite images and manually collected data from a

Table 1
List of included articles by region.

Region (n)	Country (n)	References
Europe (45)	Belgium (5)	(Dons et al., 2013, 2014; Van den Bossche et al., 2018, 2020; Van den Hove et al., 2020)
	Multi-cities Europe (9)	(Eeftens et al. 2012; Vienneau et al. 2013; Beelen et al. 2013; M. Wang et al. 2014; Alam and McNabola 2015; de Hoogh et al. 2016; Van Nunen et al. 2017; Gulliver et al. 2018; Vizcaino and Lavalle 2018)
	Germany (3)	(Fritsch & Behm, 2021; Ghassoun & Löwner, 2017; Hellack et al., 2017)
	Ireland (2)	(Basu et al., 2019; Naughton et al., 2018)
	Italy (5)	(Boniardi et al., 2019; Cattani et al., 2017; Cordioli et al., 2017; Gaeta et al., 2016; Marcon et al., 2015)
	Netherlands (7)	(Hoek et al., 2015; Kerckhoffs et al., 2015, 2017; Lu et al., 2020; M. Wang et al., 2012; A. Yang, Hoek, et al., 2015; A. Yang, Wang, et al., 2015)
	Spain (1)	(Rivera et al., 2012)
	Sweden (2)	(Habermann et al., 2015; Korek et al., 2017)
	Switzerland (2)	(Aguilera et al., 2015; Eeftens et al., 2016)
	Britain (8)	(Gulliver et al., 2011, 2013, 2016; A. Mölter et al., 2010; Anna Mölter & Lindley, 2021; Tang et al., 2013; H. Wu et al., 2017; Z. Yang et al., 2020)
Asia (60)	China (34)	(Cai et al., 2020; L. Chen et al., 2010, 2012, 2017, 2018, 2021; Dong et al., 2021; Ge et al., 2021; Guo et al., 2019; Han et al., 2020; Harper et al., 2021; L. Huang et al., 2017; Jin, Berman, Warren, et al., 2019; Jin, Berman, Zhang, et al., 2019; R. Li et al., 2018; X. Li et al., 2015; C. Liu et al., 2016; M. Liu et al., 2019; T. Liu et al., 2019; W. Liu et al., 2015; Z. Liu et al., 2019; Meng et al., 2015, 2016; Mo et al., 2021; T. Shi, Dirienzo, et al., 2020; T. Shi, Hu, et al., 2020; Song et al., 2019; J. Wang & Xu, 2021; J. Wu et al., 2015; H. Xu et al., 2019; X. Xu et al., 2021; L. Zhang et al., 2021; P. Zhang et al., 2021; Z. Zhang et al., 2018)
	Hong Kong (4)	(M. Lee et al., 2017; Y. Shi et al., 2016, 2017, 2018)
	India (3)	(Nori-Sarma et al., 2020; Sanchez et al., 2018; Saraswat et al., 2013)
	Iran (4)	(Hassan Amini et al., 2014; Karimi & Shokrinezhad, 2021; Miri et al., 2019; Taghavi-Shahri et al., 2020)
	Japan (3)	(Araki et al., 2020; Kashima et al., 2009, 2018)
	Taiwan (9)	(Chang et al., 2021; T. H. Chen et al., 2020; Ho et al., 2015; C.-S. S. Huang et al., 2019; H. J. Lee & Koutrakis, 2014; P.-Y. Y. Wong et al., 2021; P. Y. Wong et al., 2021; C.-D. Da Wu et al., 2017, 2018)
	South Korea (1)	(Kim & Guldmann, 2015)
	Pakistan (1)	(Y. Shi et al., 2020)
	Thailand (1)	(Chalermpong et al., 2021)
North America (37)	USA (21)	(Bechle et al., 2015; Di et al., 2016; Hankey & Marshall, 2015; Jones et al., 2020; H. J. Lee & Koutrakis, 2014; Mao et al., 2012; Masiol et al., 2018, 2019; Mercer et al., 2011; Messier et al., 2018; Michanowicz, Shmool, Cambal, et al., 2016; Michanowicz, Shmool, Tunno, et al., 2016; Mukerjee et al., 2009, 2012; Novotny et al., 2011; Patton et al., 2017; Ren et al., 2020; Tripathy et al., 2019; M. Wang et al., 2016; L. Weissert et al., 2020; Wilton et al., 2010)
	Canada (15)	(Allen et al., 2011; Bertazzon et al., 2015; Hatzopoulou et al., 2017; Larson et al., 2009; Maddix & Adams, 2020; Minet et al., 2017; Sabaliauskas et al., 2015; Shairsingh et al., 2019, 2021; T. Shi, Dirienzo, et al., 2020; J. G. Su et al., 2009; R. Wang et al., 2013; Weichenthal, Ryswyk, et al., 2016; Weichenthal, Van Ryswyk, et al., 2016; J. J. Y. Zhang et al., 2022)
	Mexico (1)	(Son et al., 2018)
South America (2)	Brazil (1)	(Luminati et al., 2021)
Oceania (11)	Australia (8)	(Cowie et al., 2019; Dirgawati et al., 2015, 2016; Knibbs et al., 2014, 2018; Rahman et al., 2017, 2020; Rose et al., 2011)
	New Zealand (3)	(Ma et al., 2019; L. F. Weissert et al., 2019; L. F. F. Weissert et al., 2018)
Africa (5)	South Africa (4)	(Muttoo et al., 2018; Saucy et al., 2018; Tularam et al., 2020, 2021)
	Uganda (1)	(Coker et al., 2021)
Others (1)	Global (1)	(Larkin et al., 2017)

built-environment survey such as roads, industries, and non-residential places to develop LUR models for $PM_{2.5}$ and BC for non-urbanized areas in Hyderabad, India. In the study by Nori-Sarma et al. (2020), they utilized the active and passive sampling of NO_2 to develop the LUR model in Mysore, India. The results showed that the LUR models from both studies demonstrated R^2 of more than 0.50. Thus, this study provides supporting evidence for the applicability of the LUR approach in the non-urban area. Moreover, the study showed that in settings with limited data availability, the practice of manually collected data could improve the performance of LUR models.

In Taiwan, the study conducted by J.-H. Lee et al. (2014) utilized the ESCAPE modelling approach to assess outdoor NO_x and NO_2 exposure for children in the Taipei Metropolis, Taiwan. Then, they compared the exposure of NO_x and NO_2 for children by the developed LUR models and the kriging methods. They found that the LUR models gave a broader variation in estimating NO_x and NO_2 exposures than the ordinary kriging method. The study indicated that the ESCAPE approach could be applied to develop NO_x and NO_2 LUR models in Asia cities with topography and urban settings different from European cities. Most LUR studies in Asia focus on urban areas with high population density and industrial activities. For example, in Iran, the studies were conducted in Tehran, Iran's capital city and industrial cities in Sabzevar and Arak (Hassan Amini et al., 2014; Karimi & Shokrinezhad, 2021; Taghavi-Shahri et al., 2020). Similar to the studies by Kim & Guldmann (2015) and Chalermpong et al. (2021) where the studies were conducted in the capital cities of Seoul in South Korea and Bangkok in Thailand.

3.3. North America

The LUR studies are broadly explored in the United States of America (USA) and Canada. The studies conducted in the USA usually integrate other model data or information to develop the LUR models. For example, Michanowicz et al. (2016) and Wilton et al. (2010) incorporated a line source dispersion model, Caline3, as an independent covariate into the LUR models. The Caline3 model is a prediction model that assumes the vehicle unit emission factor for all roadway segments. Both studies found that overall, R^2 values were improved with the inclusion of Caline3 data. Several other studies combine the satellite remote sensing data, such as the aerosol optical depth (AOD) data from the Moderate Resolution Imaging Spectroradiometer (MODIS), to predict the distribution of $PM_{2.5}$ in Florida, USA (H. J. Lee & Koutrakis, 2014). Other examples of the model used for integration are atmospheric dispersion modelling, AERMOD, for $PM_{2.5}$ estimation in Pittsburgh (Michanowicz, Shmool, Tunno, et al., 2016) and chemical transport modelling (CTM) for ozone and $PM_{2.5}$ evaluation in Los Angeles M. Wang et al. (2016). Generally, LUR models were developed to estimate within areas variability of air pollution. While in the study by Novotny et al. (2011) and Bechle et al. (2015) developed the LUR model throughout the contiguous United States. Given sufficient ambient monitoring and road network data, the studies provide a promising approach that could readily be applied to other countries or regions.

In Canada, J. G. Su et al. (2009) propose a systematic way of optimizing the variable selection process through the “A Distance Decay Regression Selection Strategy” (ADDRESS) method. The method selects the highest correlation variables through a series of distance decay curves in a multi-step selection process. Their findings suggested that the ADDRESS method generated better results than a manual stepwise selection process. The study by R. Wang et al. (2013) attempted to assess the temporal stability of the LUR models for over seven years in Metro Vancouver, Canada. They compared a set of NO and NO_2 LUR models based on 116 measurements developed in 2003 with the same set of the model in 2010. The models proved to deliver reliable estimates for seven years and are expected to remain the same or improve prediction settings. A recent study in Nova Scotia, Canada (J. J. Y. Zhang et al., 2022) utilized the machine learning method to develop the LUR models. The random forest method was used to develop the model (RF-LUR) and compare it with the standard method LUR by ordinary least squares (OLS-LUR). They found that the OLS-LUR model demonstrated over-prediction of final exposure. At the same time, RF-LUR provides more accurate and interpretable predictors for the final exposure. Several studies in Canada also assessed different types of air monitoring, which we will discuss in detail in the next subtopic.

3.4. Other regions

The study on the LUR models was also widely conducted in other regions, and most of the studies utilized the ESCAPE approach for their model. For example, the study conducted by Muttoo et al. (2018) in South Africa developed a LUR model to estimate NOx exposure among pregnant women in the South Durban region. The developed LUR model used three predictor variables: length of minor roads (1000m radius), length of major roads (300m radius), and area of open space (1000m radius). As a result, the model demonstrated 73% variance in ambient NO_x measurements. Therefore, the results indicated that high levels of NO_x in South Durban were attributed mainly to traffic. In addition, several recent studies have included machine learning (ML) integration in LUR to improve prediction (Coker et al., 2021; P. Y. Wong et al., 2021; J. J. Y. Zhang et al., 2022; P. Zhang et al., 2021). For example, the study by Coker et al., (2021) in Uganda explored the application of machine learning (ML) to improve the LUR predictions compared to ordinary least squares (OLS) regression. They found substantial improvement in R^2 for non-parametric ML in LUR prediction with R^2 range between 0.50 to 0.83. The study’s most significant predictors were the monthly precipitation, the percentage of people who cook with solid fuels, distance to the lake, and greenspace.

In Sydney, Australia, a study by Cowie et al. (2019) developed the regular LUR model and compared their results to those from the national satellite-based LUR model (Sat-LUR) from Knibbs et al. (2014) study and the region Bayesian Maximum Entropy (BME) model from Hanigan et al. (2017) study. The findings revealed that the average projections from the regular LUR model were 4% higher than Sat-LUR and 8% lower than BME estimates. Despite the models’ various data inputs and spatial dimensions, the interclass-correlation coefficient for LUR against Sat-LUR and LUR over BME was 0.73, suggesting good agreement between the models. The study reasserts the position for standard LUR model methods, particularly when applying more complex models may be difficult due to a lack of data or computational resources.

The LUR models were usually established for a particular area, region or country. However, the study by Larkin et al. (2017) attempted to develop a global LUR model. They created the global NO_2 LUR model for 2011 using annual measurements from 5,220 air monitors in 58 countries with accessible global predictor datasets. The model showed 54% ($R^2 = 0.54$) of NO_2 variation, ranging from $R^2 = 0.42$ (Africa) to 0.67 (South America). Their final model included ten predictor variables, and the distinguished contributions were major roads within 100m and satellite-derived NO_2. The model demonstrated the robustness of the first global NO_2 LUR model, which depicts the important fine-scale spatial variability of NO_2 air pollution.

4. Air sampling method for LUR model

The LUR models applied several methods for air samplings, such as fixed station, campaign, mobile, and passive monitoring. Fixed station monitoring is a routine air sampling usually conducted by the responsible agency. Meanwhile, the campaign and mobile monitoring are carried out within a certain period. Passive sampling is an alternative method to collect air samples without using the pump device. One early study that constructed the LUR model by the fixed station was conducted by Kashima et al. (2009). They attempted to determine whether they could build LUR models utilizing a regulatory monitoring system in Shizuoka, Japan. They created the LUR models to estimate the levels of suspended particulate matter (SPM) and NO_2. The models were built with four different types of geographic variables, including road type, traffic intensity, land use, and physical component. The results showed that the NO_2 model had R^2 of 0.54, whereas the SPM model had a lower R^2 value of 0.11. Based on the study, LUR models using air quality data from regulatory monitoring were able to estimate NO_2 relatively well. The findings of this study motivate the widespread use of LUR models in Asian countries.

Meanwhile, mobile monitoring was used in the Larson et al. (2009) study in Canada to describe the regional variability in black carbon levels for LUR modeling. They measured the particle light absorption factor during summer times at high afternoon traffic at 39 locations using the particle soot absorption photometer in a moving vehicle. The particle light absorption values at each site were modeled using the LUR method. As a result, the model demonstrated better performance for mobile monitoring improved the model performance with R^2 range between 0.68 to 0.72, while fixed-location samplers with R^2 range between 0.51 to 0.55. The study indicated that a similar approach could be applied to other urban areas to assist in developing LUR models for particulate matter.

The study by Sabaliauskas et al. (2015) attempted to integrate fixed and mobile monitoring to evaluate geographical gradients between and within communities. In residential areas around Toronto, Canada, they assessed particle number (PN) concentrations between June and August 2008. The fixed monitoring locations included four residential sites between 6 and 15 kilometers from the city center. At the same time, the mobile monitoring involved 112 road segments from 10 routes that collected samples periodically over three different days. The LUR model was developed using mobile data, and the fixed sites were used for validation. This hybrid sampling technique helped create a solid LUR model by balancing the competing demands of maximizing sampling time and spatial coverage. The study showed that temporal correction factors applied to the mobile PN concentration data could be reduced by taking measurements simultaneously and choosing days with similar climatic circumstances.

In a different study, Kashima et al. (2018) assessed the reliability of LUR models for NO_2 using data from routine and campaign monitoring in Suita city, Osaka, Japan. They create LUR models for the city based on data collected from campaign monitoring (campaign-LUR) and routine monitoring in all sites (routine-LUR-All). Additionally, they developed the models using data from background stations used for routine monitoring (routine-LUR-BS) and data from sites along roadways (routine-LUR-RS). Each model’s predictability was calculated. Finally, they contrasted the mean annual NO_2 concentrations obtained at assessment locations with the projected NO_2 values from each model. With adjusted R^2 values of 0.68 and 0.76, respectively, and root means square errors of 3.4 and 2.1 ppb, the routine-LUR-All and routine-LUR-BS models accurately predicted NO_2 concentrations. Furthermore, the LUR models developed based on regular networks, particularly those built on all monitoring stations, clearly depict the city’s road conditions. The study concluded that in areas where high-density networks of routine monitoring stations are available, the routine monitoring stations should be utilized to create LUR models instead of campaign monitoring sites.

Passive sampling is commonly utilized for the collection of NO_2 and NO_x concentrations. For example, the ESCAPE project used Ogawa passive sampler to collect NO_2 and NO_x at 40 to 80 sites in 36 study areas in Europe (Beelen et al., 2013). The same study by Maddix and Adams (2020) used passive sampling to collect NO_2 at three different scales of sampling (31 km^2, 94 km^2, and 292 km^2). They allocate 33 samples to each sampling site. They discovered that every model performed well, showing that linear LUR modeling is resilient to changes in the geographical scales of sampling. The summarization of air sampling types is presented in Table 2.

5. Transferability of the LUR model

The LUR model is often constructed for local applications only. But when the air measurements are absent, the air pollution concentrations could be estimated by transferring LUR models from other areas. Similar predictors are frequently found in models across cities, indicating that models could be transferrable between cities with comparable characteristics. In addition, building new models may require less time and cost if a LUR model could be applied to areas outside its initial region.

Table 2
Air sampling types, approaches, advantages, and disadvantages.

Air sampling types	Approach	Advantage	Disadvantage
Fixed station	Routine monitoring where air sampling pump devices continually collect the air samples Sampling devices are placed in a permanent designated area Generally conducted by the government or responsible agency	Continuous air quality data Reliable data as the sampling being operated by the skilled person	High cost to set up the air monitoring station High cost for labour and maintenance
Campaign	Continuous monitoring within a certain period using air sampling devices Sampling devices are placed in selected locations based on activities in the study area	Specific sampling location based on study objective	The limited time of data Less cost for maintenance
Mobile	Mobile measurement using a portable sampling device Samples collection carried out on specific routes by motor vehicles or bicycle	Good spatial coverage High spatial resolution measurement up to sub-street level Required a smaller number of the sampling device	Data collected only in a limited time Temporal Sparsity in the sampling location
Passive	Gas monitoring using a diffuse sampler by allowing the air to pass over a medium such as a sorbent without a pump device Sampling locations were selected based on activities in the study area	Easier to handle or required less technique to conduct	Limited for gas measurement Less sensitive to environmental influences such as wind speed or humidity

Several studies have explored the transferability of models for local and national models (Allen et al., 2011; Marcon et al., 2015; M. Wang et al., 2014).

The study by Allen et al. (2011) assessed the capacity to transfer NO and NO_2 LUR models across Edmonton, Alberta and Winnipeg, Manitoba. The LUR models' ability to estimate benzene and toluene concentrations was also evaluated. According to the findings, NO_2 local LUR models had better R^2 values than NO (R^2 = 0.55-0.56) for variability. On the other hand, the NO_2 (R^2 = 0.37 0.52) and NO (R^2 = 0.24-0.41) transferred models did not perform as effectively as the local models. The transferred models, however, had a more remarkable ability to account for variability than either straightforward binary or continuous road proximity measurements. Even though the local LUR model provides better prediction, the transferred model can offer a cost-effective alternative for exposure assessment studies.

In the study by M. Wang et al. (2014), LUR models for Europe and specific regions were created, and their applicability to regions not included in the model was then investigated. This study is one of the ESCAPE studies in which they combined standard measurement data from 17 (for PM) and 23 (for NO_2) ESCAPE study areas across 14 European countries for PM and NO_2 to assess LUR models for NO_2 and particulate matter ($PM_{2.5}$, $PM_{2.5absorbance}$). In the regions not included in the model development, they discovered that transferred models accurately predicted a small to a substantial portion of the variability (median R^2: NO_2, 59%; $PM_{2.5}$, 42%; $PM_{2.5absorbance}$, 67%). They developed LUR models for NO_2 and PM that accurately predicted observations at different sites and regions using a large data collection from 23 European study areas. This study supported the concept that other European regions with equivalent geographies, predictors and regional background concentration availability could benefit from using their combined models. Since the locations were clearly described, any background location in a new area can be evaluated using the same standards. This strategy can only be effective if the new area's pollution characteristics or elements are measured. This discovery assists in determining exposure in health research projects performed in regions where no measurements were recorded.

The transferability of the LUR model from a regional to an urban setting was investigated by Marcon et al. (2015). The Veneto area of northern Italy's LUR model for NO_2 concentrations was initially created. Then, they applied the developed model to 40 separate sites in a city in the Veneto region. Using this approach, they also estimated the regulatory network's average NO_2 concentrations in 2008, 2009, and 2011. The LUR model successfully explained five of the 33 provided predictor variables (R^2=0.75). The majority of the geographical variability in NO_2 concentrations was described (R^2=0.68) by the number of buildings in 5,000m buffers, the area of industry in 1,000m buffers, and altitude, all of which primarily indicates large-scale air pollution distribution patterns. The findings showed that the model performed poorly overall (R^2=0.18) when applied to urban settings, but it performed better when it was restricted to predicting inner-city background levels (R^2=0.52). When implying NO_2 concentrations at the regulatory stations in 2008, 2009, and 2011, model performance was improved by calibrating LUR coefficients (R^2 between 0.67 and 0.80). They discovered that when applied to a city located within that region, the model created for a region using regulatory data was not able to predict small-scale variation in NO_2 concentrations at traffic sites. This result demonstrated that the LUR models were unable to be applied to regions with different features and air pollution concentration ranges.

6. Conclusion

In this review, we presented an overview of the application of the LUR model for assessing air pollution worldwide. Generally, LUR models have been widely applied in Europe, Asia, and North American regions but less in other parts of the world. The ESCAPE project has become a prominent approach used in many studies. The applicability of the

ESCAPE approach is not only limited to Europe but has also been utilized in Asia, North America, Africa, and Oceania. This review showed that China is the leading country worldwide that applies the LUR model for air pollution assessment. In more recent studies, there is an increasing trend in researchers using the combination of LUR models with other models and machine learning to improve the accuracy of the forecasting model. Although a routine air monitoring station is the best way to collect air quality data, several studies have explored different types of air sampling to collect the air quality data, such as campaign sampling, mobile monitoring, and passive sampling. The alternative method has been proven beneficial in estimating air pollutants concentrations. We also discussed the transferability of the LUR model to other areas. From the studies, we could conclude that the LUR models are only transferable when the areas have similar geographic, predictor variables and standard ranges of air pollution concentrations. However, our review only included published studies up to October 2021 and was limited to the LUR model of five primary air pollutants. In this review, we provided a descriptive explanation and emphasized those that provide key insight into methods and implementation that will be useful for future research. This review also demonstrated that most studies were mainly carried out in urban areas with high population densities. Further studies from different regions are highly recommended to describe the wide range of exposures experienced by diverse populations.

CRediT authorship contribution statement

Wan Nurul Farah Wan Azmi: Conceptualization, Writing – original draft. **Thulasyammal Ramiah Pillai:** Methodology, Supervision, Funding acquisition. **Mohd Talib Latif:** Supervision, Validation. **Shajan Koshy:** Supervision. **Rafiza Shaharudin:** Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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