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Review

Road traffic air and noise pollution exposure assessment – A review of tools and techniques

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HIGHLIGHTS

- Review of literature based on air pollution and noise originating from urban road traffic
- Discussion of various assessment techniques pertaining to both exposures
- Quantification of reported air-noise correlations in the selected studies
- Discussion of several parameters and exposure assessment techniques affecting air-noise correlations
- Study highlighted potential of a combined tool for simultaneous assessment of both pollution exposures

GRAPHICAL ABSTRACT

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ABSTRACT

Road traffic induces air and noise pollution in urban environments having negative impacts on human health. Thus, estimating exposure to road traffic air and noise pollution (hereafter, air and noise pollution) is important in order to improve the understanding of human health outcomes in epidemiological studies. The aims of this review are (i) to summarize current practices of modelling and exposure assessment techniques for road traffic air and noise pollution (ii) to highlight the potential of existing tools and techniques for their combined exposure assessment for air and noise together with associated challenges, research gaps and priorities.

The study reviews literature about air and noise pollution from urban road traffic, including other relevant characteristics such as the employed dispersion models, Geographic Information System (GIS)-based tool, spatial scale of exposure assessment, study location, sample size, type of traffic data and building geometry information. Deterministic modelling is the most frequently used assessment technique for both air and noise pollution of short-term and long-term exposure. We observed a larger variety among air pollution models as compared to the applied noise models. Correlations between air and noise pollution vary significantly (0.05–0.74) and are affected by several parameters such as traffic attributes, building attributes and meteorology etc. Buildings act as screens for the dispersion of pollution, but the reduction effect is much larger for noise than for air pollution. While, meteorology has a greater influence on air pollution levels as compared to noise, although also important for noise pollution.

There is a significant potential for developing a standard tool to assess combined exposure of traffic related air and noise pollution to facilitate health related studies. GIS, due to its geographic nature, is well established and has a significant capability to simultaneously address both exposures.

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Contents

1. Introduction . . . 662
2. Methodology . . . 662
3. Results . . . 663
4. Exposure assessment techniques . . . 663
 4.1. Deterministic modelling . . . 663
  4.1.1. Models used for air pollution . . . 666
  4.1.2. Models used for noise . . . 666
 4.2. Stochastic modelling . . . 668
 4.3. Measurements . . . 668
 4.4. Summary of techniques . . . 669
5. Pollution indicators . . . 669
6. Spatial scale and sample size . . . 670
7. Traffic attributes . . . 670
8. Buildings' attributes . . . 671
9. Meteorology . . . 671
10. The role of GIS in air-noise exposures . . . 671
11. Conclusions . . . 673
Acknowledgements . . . 673
Appendix A. Supplementary data . . . 673
References . . . 673

1. Introduction

Ambient air pollution and environmental noise have a direct influence on human health. Air pollution alone poses the single largest environmental risk factor in Europe today, responsible for more than 430,000 premature deaths (EEA, 2015), while at least 10,000 premature deaths occur yearly due to environmental noise (EEA, 2016). Due to their adverse health effects, air and noise pollution have been marked as the top two stressors in terms of environmental burden of disease (Hänninen et al., 2014). Among various shared sources of air and noise pollution in an urban setting, road traffic is considered to be the main contributor to both pollutions (EMEP/EEA, 2013). According to the recent assessments published by the European Environment Agency, road traffic is by far the largest source of noise pollution (EEA, 2017) and estimated to contribute more than 64% to air pollution (NOx, NO_2, PM) in Europe (EEA, 2012).

Presently approx. 54% of the world's population resides in urban settlements (UN, 2014), which are usually effected by numerous emission sources of air and noise pollution. In particular, commuting in urban micro-environments (street canyons) create complex conditions of human exposure to air and noise pollution. Consequently, exposure assessments focused either on traffic air pollution or noise may lead towards ambiguous epidemiological findings (Schwela et al., 2005). Before 1999, only few studies have taken into account simultaneously air and noise pollution either to study their spatial relationship (Davies et al., 2009; Allen et al., 2009) or their combined effects on human health (Klaeboe et al., 2000); most of them reported confounding associations.

Recently, there has been growing number of studies that reflects the increasing concern on both pollutions' combined exposure and its links with the socio-economic status of the urban populations (The European Commission, 2016a). Halonen et al. (2016) also highlighted that there is a considerable potential for confounding of traffic pollution effects by socio-economic factors. Moreover, Tenailleau et al. (2016) has pointed out the evaluation of combined exposures as one of the biggest challenges of the next decade. Thus, further research in a context of combined exposure to air and noise pollution is needed to improve the understanding of their mutual and/or confounded associations in an urban environment. However, the tools that would allow and accelerate such studies might not be available yet nor widely known to the research community.

Presently, there are several tools and techniques to study road traffic air and noise pollution exposures. Among such tools, GIS has become a mature technology for pollutions mapping and exposure assessment. In this regard, open source and commercial geospatial tools (hereafter referred as GIS tools) and techniques have been extensively used by researchers across the world, e.g. Reed et al. (2012); Deng et al. (2016); Kumar et al. (2016a, 2016b). Figs. S1 and S2 (Supplementary material, Appendix A) show an example of GIS-based air and noise pollution maps. Due to the geographic nature of air and noise pollution in an urban environment, GIS could be a significant tool for their combined assessment. Recently, a combined and freely available tool was developed within the BioShare-EU project (see: https://www.bioshare.eu/) that uses two models i.e., AERMOD (The United States EPA, 2017) and Common Noise Assessment Methods in EU member states (CNOSSOS-EU) (Kephalopoulos et al., 2012). The tool was applied for traffic air and noise pollution mapping in selected European cities. A number of commercial noise modelling software (e.g. SoundPLAN, IMMI, CadnaA) offer ad-on integrated air pollution models. Likewise, there exists a large number of models and software which are being used for either air or noise pollution mapping worldwide.

The aim of this review study is to summarize current practices of road traffic related air and noise pollution modelling and exposure assessment. Therefore, we explored and reviewed studies addressing exposures of air and noise pollution simultaneously and in terms of their correlation and implication to human health. In parallel, potential tools for such studies, together with the associated challenges, research gaps and priorities have also been investigated.

2. Methodology

A systematic literature search was performed to identify relevant studies based on road traffic air and noise pollution modelling and/or exposure assessment. The search was performed for the articles published in English between January 1999 and May 2017 and available via Science Direct and PubMed platforms. Due to large amount of published literature in air or noise pollution related studies, a specific search methodology was adopted. Keyword sets based on “road traffic”, “air pollution”, “noise”, “modelling”, “exposure”, and “assessment” etc. were used to improve search criteria, although, the main focus of literature search was on studies related to road traffic air and noise pollution. It was observed that a lot of air-noise pollution studies made use of GIS-based tools and techniques in their analyses. Thus, the search was substantially expanded to identify as many relevant studies as possible (see Table S1 for the combination of keywords). Moreover, for this reason the discussion of GIS in terms of air-noise pollution modelling/exposure assessment has been subsequently included in this work. The literature search was limited to journal articles, conference papers and review articles including technical and policy reports. Papers with focus only on either air or noise pollution were excluded, as well as, commentaries, editorials, news articles, bulletins and studies not performed on humans. The initial number of 858 articles (including duplicates) was manually screened, mainly using the above criteria, and reduced to 57 potentially relevant articles (see Fig. 1). All these studies are listed in Table 1 and characterized on the basis of air and noise pollution models, pollution metrics/indicators, spatial scale of exposure assessment, GIS tool employed, study location, nature of input datasets etc.

3. Results

In the following paragraphs, we present results of our literature review with associated discussions. In our identified studies (Table 1), some researchers investigated associations between air and noise pollution (e.g. Tenailleau et al., 2016; Dekoninck et al., 2015; Örgen and Molnar, 2014), while others evaluated the relationship between various health outcomes and air and noise pollution exposures (e.g. Tonne et al., 2016; Sørensen et al., 2015; De Roos et al., 2014). Furthermore, majority of the identified studies ($n = 28$) utilized GIS-based tools to assess exposures to air and noise pollution (e.g. Halonen et al., 2015; Bodin et al., 2016).

Fig. 2 shows a world map with marks for the study location of the 57 studies included in the present review (Table 1). We found that most of the air and noise pollution studies have been conducted in cities of Europe e.g. London in United Kingdom (Tonne et al., 2016; Halonen et al., 2016; Fecht et al., 2016), Copenhagen and Aarhus in Denmark (Sørensen et al., 2012, 2013, 2014, 2015), Madrid in Spain (Linares et al., 2006; Arroyo et al., 2016), Antwerp in Belgium (Can et al., 2011); Oslo in Norway (Klaeboe et al., 2000), Stockholm in Sweden (Selander et al., 2009) and Leipzig in Germany (Weber et al., 2014). We also observed that only a small number of studies has been conducted in other parts of the world (Fig. 2), for example South America, Africa and Oceania. More research should be conducted in these regions to fill this potential research gap.

During the review process we extracted reported correlations between air and noise pollution from the selected studies (Fig. 3). In the next paragraphs, we present a brief overview of these correlations as well as the parameters affecting them.

Fig. 3 shows the enormous variation among the reported correlation coefficients (r), from almost no correlation (0.05) to good correlation (0.74). Also, there seems to be no pattern in correlation ranges. This high variation could be attributed to a number of parameters belonging to one or more categories: a) exposure techniques, b) heterogeneity of the pollution indicators having varying spatial patterns, c) spatial scale of exposure assessment and sample size, d) the traffic attributes, e) the buildings' attributes, f) the meteorology, g) the urban landscape, and h) background contributions. Table 2 summarizes the potential parameters commonly affecting air and noise pollution in an urban setting. Following sections elaborate on these parameters, except for urban landscape and regional contributions owe to lack of adequate data to extract useful and concrete conclusions, although briefly mentioned in some studies.

Investigating the specific health effects and how these correlate with the pollution exposure was beyond the scope of this study.

4. Exposure assessment techniques

This section provides a brief overview of studies covering the various air and noise pollution exposure assessment techniques, their combinations, and the employed air and noise pollution models. Thus selected studies have been grouped (see Table 1) according to the three general types of techniques (Nieuwenhuijsen, 2015): (1) deterministic modelling, (2) stochastic/statistical modelling including land use regression (LUR) models and (3) measurements/sampling including both passive/active and mobile/static (hereafter, referred as measurements). However, some studies employ different techniques or an indirect use of techniques for air and noise pollution exposure assessment. For example, stochastic modelling, and deterministic modelling, use field measurements for validation or data assimilation. Therefore, Table 1 lists all the related studies grouped as per the employed primary techniques.

4.1. Deterministic modelling

Deterministic modelling takes into account the relationship between variables mathematically on the basis of knowledge of the physical, chemical and/or biological mechanisms governing these relationships (Brunekreef, 1999). In addition, it involves representations of critical static and dynamic parameters such as urban built, land cover, meteorology etc. to reflect the actual atmospheric environment (Zannetti, 2013).

This type of models is so widespread and accessible that the majority of the identified studies (Table 1) employed a deterministic modelling approach for air and/or noise pollution exposure assessment.

For example, Roswall et al. (2017) studied the long-term residential exposure to traffic noise and NO_2 in Copenhagen, Denmark by combining a street canyon pollution model and a commercial noise mapping tool based on a Nordic noise prediction method. While, Dzhambov

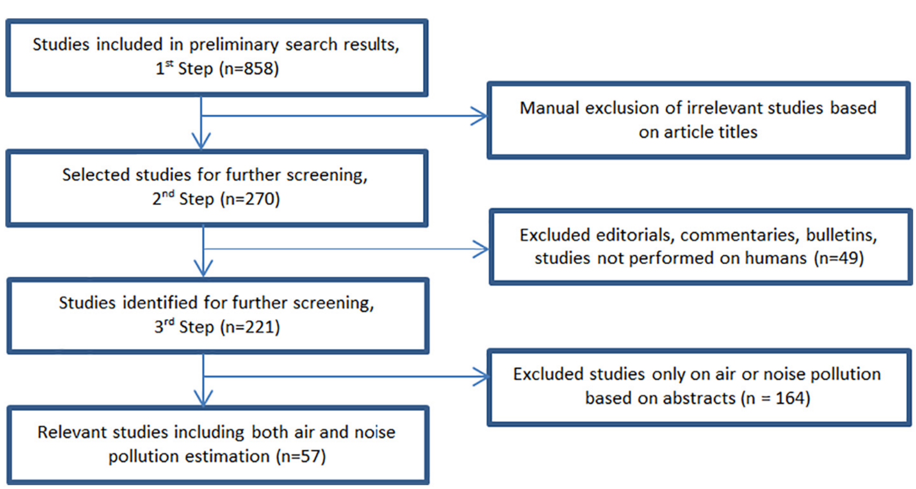

Fig. 1. Process of the manual screening and refining of the retrieved articles and studies.

Table 1
Characterization of selected studies relating to air and noise pollution exposure, sorted by publication year and grouped into general type of exposure assessment (Deterministic modelling, Stochastic modelling, Measurement).

Air pollution (Exposure indicator)	Air pollution (Dispersion model and exposure technique)	Traffic noise (Exposure indicator)	Traffic noise (Model and exposure technique)	Spatial scale	GIS tool[a]	Nature of traffic data	Study location	Sample size	Building geometry?[b]	Source
Deterministic		**Deterministic**								
NO_2	AirGIS/OSPM	L_{Aeq}	SoundPLAN	Urban	–	Avg[c]	Copenhagen/Aarhus (Denmark)	57,053	Yes	Roswall et al. (2017)
NO_2	AERMOD	L_{den}	SoundPLAN	Regional	ArcGIS	Avg	Skåne Region (Sweden)	13,512	Yes	Bodin et al. (2016)
$PM_{2.5}$, BaP	SELMA[GIS]	L_{den}	LimA v.5	Urban	ArcGIS	Avg	Plovdiv (Bulgaria)	513	Yes	Dzhambov and Dimitrova (2016)
NOx (NO_2/NO), $PM_{2.5}$, PM_{10}, O_3	KCL-Urban, ADMS	L_{Aeq24h}, L_{den}, L_{Aeq16h}, L_{night}	TRANEX	Regional	PostgreSQL, PostGIS	Hourly[d]	Greater London area (UK)	9 million	Yes	Fecht et al. (2016)
$PM_{2.5}$, PM_{10}, NOx, NO_2, O_3	KCL-Urban	L_{Aeq16h}	TRANEX	Regional	PostgreSQL, PostGIS	Hourly	Greater London area (UK)	5482	Yes	Halonen et al. (2016)
NO_2	ADMS-Urban	L_{Aeq24h}	MITHRA-SIG	Urban	ArcGIS	Avg	Besancon (France)	10,825	Yes	Tenailleau et al. (2016)
NO_2, NOx, $PM_{2.5}$, PM_{10}, O_3,	KCL-Urban, Road Source Model	L_{Aeq16h}	TRANEX	Regional	PostgreSQL, PostGIS	Hourly	Greater London area (UK)	18,138	Yes	Tonne et al. (2016)
$PM_{2.5}$, NOx	KCL-Urban	L_{Aeq16h}, L_{night}	TRANEX	Regional	PostgreSQL, PostGIS	Hourly	Greater London area (UK)	8.61 million	Yes	Halonen et al. (2015)
NO_2, $PM_{2.5}$	AirGIS/OSPM	L_{den}	SoundPLAN	Urban	ArcGIS	Avg	Copenhagen (Denmark)	39,863	Yes	Sørensen et al. (2015)
$PM_{2.5}$, PM_{10}	EURAD-CTM	L_{night}, L_{den}	END method	Urban	ArcView	Avg	Ruhr (Germany)	4861	Yes	Kälsch et al. (2014)
NOx	GDM	L_{Aeq}	Nordic method	Urban	QGIS	Avg	Gothenburg (Sweden)	–	Yes	Örgen and Molnar (2014)
NOx, NO_2	AirGIS/OSPM	L_{day}, L_{eve}, L_{night}, L_{den}	SoundPLAN	Urban	ArcGIS	Avg	Copenhagen, Aarhus (Denmark)	57,053	Yes	Sørensen et al. (2014)
PM_{10}	UFIPOLNET	L_{day}, L_{eve}, L_{night}, L_{den}	IMMI	Urban	ArcGIS	Avg	Leipzig (Germany)	–	Yes	Weber et al. (2014)
EC, PM_{10}, NO_2	Other	L_{den}	SKM2, Urbis	Urban	Other[e]	Avg	Eindhoven (Netherlands)	18,213	Yes	De Kluizenaar et al. (2013)
NO_2	KCL-Urban, EMPARA Luvotool	L_{Aeq24h}, L_{night}	Other	Regional	ArcGIS	Avg	UK, Germany, Italy, Greece, Sweden, Netherlands	4861	Yes	Floud et al. (2013)
NOx, PM_{10}	AirGIS/OSPM	L_{Aeq}, L_{day}, L_{eve}, L_{night}, L_{den}	SoundPLAN	Urban	ArcGIS	Avg	Aarhus, Copenhagen (Denmark)	57,053	Yes	Sørensen et al. (2013)
NO_2	ADMS-Roads, OSPM	L_{Aeq16h}	Other	Urban	ArcGIS	Avg	London (UK)	719	Yes	Clark et al. (2012)
PM_{10}, NO_2	PolluMap	L_{day}, L_{night},	STL86+, SONBASE	Urban	–	Avg	Switzerland	5603	Yes	Dratva et al. (2012)
NOx, PM_{10}	AirGIS/OSPM	L_{Aeq}, L_{day}, L_{eve}, L_{night}, L_{den}	SoundPLAN	Urban	ArcGIS	Avg	Aarhus, Copenhagen (Denmark)	57,053	Yes	Sørensen et al. (2012)
$PM_{2.5}$, PM_{10}, O_3	EURAD-CTM	L_{day}, L_{eve}, L_{night}, L_{den}	Other	Urban	ArcView	Avg	Ruhr (Germany)	4814	Yes	Fuks et al. (2011)
NO_2	AIRVIRO	L_{Aeq24h}	Nordic method	Urban	MapInfo	Avg	Stockholm (Sweden)	5452	Yes	Selander et al. (2009)
CO	OSPM	L_{A10}, L_{Aeq}	CoRTN	Urban	ArcView, Avenue scripting	Hourly	Macau (China)	–	Yes	Tang and Wang (2007)
NO_2, NOx, $PM_{2.5}$, PM_{10}	EPISODE	$L_{Aeq,24h}$	Nordic method	Urban	Other	Avg	Oslo (Norway)	3265	Yes	Klaeboe et al. (2000)
Stochastic		**Stochastic**								
NO_2	Spatial regression	L_{Aeq}	Spatial regression	Urban	GDAL	Avg	Montreal (Canada)	–	Yes	Apparicio et al. (2016)
Stochastic		**Deterministic**								
$PM_{2.5}$, PM_{10}, NOx, NO_2	LUR, EURAD-CTM	L_{night}, L_{den}	Other	Urban	Other	Avg	Ruhr (Germany)	4814	Yes	Tzivian et al. (2016)
$PM_{2.5}$, PM_{10}, NO_2	LUR	L_{den}	EMPARA	Urban	Other	Avg	Netherlands	3963	Yes	Bilenko et al. (2015)
PM_{10}, NO_2		L_{day}, L_{eve}, L_{night}, L_{den}, L_{Aeq16h}	CNOSSOS-EU	Regional	PostgreSQL, PostGIS	Hourly	Oxford (UK), Turin (Italy), Norway, Netherlands	742,950	Yes	Cai et al. (2015)
$PM_{2.5}$		L_{DN}	CadnaA	Urban	Other	Avg	Augsburg (Germany)	4261	Yes	Babisch et al. (2014)
NO_2, NOx, $PM_{2.5}$, PM_{10}		L_{den}	Other	Urban	ArcGIS	Avg	Barcelona (Spain)	6438	Yes	Dadvand et al. (2014)
BC, $PM_{2.5}$, NO_2, NO, SO_2, CO, O_3		L_{day}, L_{eve}, L_{night}, L_{den}	CadnaA	Regional	–	Avg	Vancouver, Victoria (Canada)	678,361	Yes	De Roos et al. (2014)

Table 1 (*continued*)

Air pollution (Exposure indicator)	Air pollution (Dispersion model and exposure technique)	Traffic noise (Exposure indicator)	Traffic noise (Model and exposure technique)	Spatial scale	GIS tool[a]	Nature of traffic data	Study location	Sample size	Building geometry?[b]	Source
NO_2		L_{night}		Urban	–	Avg	Girona (Spain)	3836	Yes	Foraster et al. (2014)
$PM_{2.5}$, PM_{10}, NO_2, NO, CO		L_{den}		Urban	ArcGIS	Avg	Vancouver (Canada)	68,326	Yes	Gehring et al. (2014)
BC, $PM_{2.5}$, NO_2, NO		L_{den}		Urban	–	Avg	Vancouver (Canada)	445,868	Yes	Gan et al. (2012)
NO_2, PM_{10}		$L_{Aeq,7\text{-}23h}$	Other	Urban	–	Avg	Amsterdam (the Netherlands)	553	Yes	van Kempen et al. (2012)
NO_2, $PM_{2.5}$		L_{day}, L_{eve}, L_{night}	EMPARA	Regional	ArcInfo	Avg	The Netherlands	120,852	Yes	Beelen et al. (2009)
Stochastic		**Measurement**								
NOx, PM_{10}, SO_2, O_3, TSP	Other	L_{eqd}, L_{eqn}	Static[f], measured data[g]	Urban	–	Avg	Madrid (Spain)	2500	Yes	Linares et al. (2006)
Measurement		**Measurement**								
NO_2, O_3, PAH	Passive[h], static, field campaign	$L_{Aeq,1s}$	Mobile[i], field campaign	Urban	Other	Avg	Gothenburg (Sweden)	–	–	Klingberg et al. (2017)
$PM_{2.5}$, PM_{10}, O_3, NO_2	Passive, static, measured data	L_{eqd}, L_{eqn}	Static, measured data	Urban	–	Avg	Madrid (Spain)	3287	No	Arroyo et al. (2016)
EC, BC, NO_2	Passive, static, field campaign	$L_{Aeq,10min}$	Static, field campaign	Urban	–	Avg	Barcelona (Spain)	2897	No	Forns et al. (2016)
$PM_{2.5}$	Active[j], mobile, field campaign	L_{Aeq}, L_{A10}, L_{A90}	Mobile, field campaign	Street	–	Avg	New York (USA)	–	No	King et al. (2016)
CO, O_3, SOx, NOx	Passive, static, field campaign	L_{A10}, L_{A50}, L_{A90}, L_{Aeq}	Static, field campaign	Street	–	Avg	Delhi (India)	–	–	Bhandari et al. (2015)
PM, SO_2, NOx, NO_2	Passive, static, field campaign	$L_{eq125Hz}$, L_{eq2kHz}, L_{AeqL50}, L_{lineq}, $L_{lineqL50}$	Static, field campaign	Street	Other	Avg	Maastricht (Netherlands)	–	No	Severijnen (2015)
NO_2, SO_2, CO	Passive, static, field campaign	L_{Aeq}	Mobile, field campaign	Street	–	–	Bucharest (Romania)	–	No	Danciulescu et al. (2015)
BC, UFP	Active, mobile, field campaign	$L_{A01,1h}$, $L_{A05,1h}$, $L_{A50,1h}$, $L_{A95,1h}$, $L_{Aea,1h}$	Mobile, field campaign	Urban	Other	Avg	Ghent (Belgium)	–	No	Dekoninck et al. (2015)
NO_2, NO, $PM_{2.5}$, BC, EC	Passive, static, field campaign	$L_{Aeq,1s}$	Static, campaign	Urban	Other	Avg	New York (USA)	–	No	Kheirbek et al. (2014)
$PM_{2.5}$, UFP	Passive, static, field campaign	L_{Aeq}	Static, field campaign	Street	Other	Avg	California (USA)	–	No	Shu et al. (2014)
CO, BC, $PM_{2.5}$	Active, mobile, field campaign	L_{Aeq}	Mobile, field campaign	Street	–	–	Beijing (China)	40	No	Huang et al. (2013)
SO_2, NO, NO_2, NOx, CO, O_3, TSP, PM_{10}, $PM_{2.5}$, CH_4	Passive, static, field campaign	L_{Aeq}	Static, field campaign	Urban	–	Avg	Seoul (Korea)	–	No	Kim et al. (2012)
VOC, CO, Benzene	Active, mobile, field campaign	L_{Aeq}	Mobile, field campaign	Urban	Other	Avg	Thessaloniki (Greece)	–	Yes	Vlaschokostas et al. (2012)
UFP, NOx	Passive, static, field campaign	L_{Aeq}	Static, field campaign	Street	–	Avg	Antwerp (Belgium)	–	No	Can et al. (2011)
EC, $PM_{2.5}$, NO, NO_2, HC	Passive, static, field campaign and measured data	L_{Aeq1h}, L_{Aeq}	Static, field campaign	Street	–	Avg	New York (USA)	–	No	Ross et al. (2011)
PNC, $PM_{2.5}$	Active, mobile, field campaign	$L_{Aeq,1min}$	Mobile, field campaign	Regional	–	Avg	Netherlands (eleven Dutch cities)	–	Yes	Boogaard et al. (2009)
NO_2, NOx	Passive, static, field campaign	$L_{eq,5min}$	Static, field campaign	Urban	ArcGIS	Avg	Vancouver (Canada)	–	No	Davies et al. (2009)
NO, NO_2, UFP	Passive, static, field campaign	$L_{Aeq,5min}$	Static, field campaign	Urban	ArcGIS	Avg	Chicago, Riverside (USA)	–	No	Allen et al. (2009)
Measurement		**Deterministic**								
PM_{10}, NO_2	Passive, static, measured data	L_{den}	TRANEX	Urban	PostgreSQL,PostGIS	Hourly	New Zealand	26,610	Yes	Briggs et al. (2015)
PM_{10}, NO_2,	Passive, static, field campaign	L_{den}	EASY MAP model	Urban	ArcGIS	Avg	Île-de-France Region (France)	7290	Yes	Méline et al. (2013)
NO_2	Passive, static, field campaign	L_{day}, L_{night}, L_{Aeq24h}	CadnaA	Urban	Other	Avg	Girona (Spain)	–	Yes	Foraster et al. (2011)

and Dimitrova (2016) evaluated the regional exposure to air and noise pollution in Plovdiv, Bulgaria using a US EPA standard air-quality model and a commercial noise mapping tool based on EU directives. Furthermore, studies making use of deterministic modelling to study both stressors' exposure reported moderate positive to slightly higher positive air-noise correlations (Fig. 3) (e.g. Örgen and Molnar, 2014; Sørensen et al., 2015). Although deterministic models have been criticized in the literature, e.g. that the majority fails to predict "extreme" concentrations (Khare and Sharma, 2002), they are considered powerful and flexible tools, especially when combined with GIS.

4.1.1. Models used for air pollution

The most frequently listed deterministic models for air pollution exposure assessment in this study are AirGIS/OSPM and KCL-Urban. The AirGIS is a GIS based air pollution and human exposure modelling system (Jensen et al., 2001) that incorporates as key element the street pollution model OSPM (Berkowicz, 2000; Kakosimos et al., 2010) to estimate air pollution at address level. However, the system operates at three different spatial scales (i) regional, with a 5.6 km^2 resolution (ii) urban, in a 1 km^2 grid (iii) street, with address resolution. Both AirGIS and OSPM have been validated (Ketzel et al., 2011). Many of the investigated studies (Table 1), utilizing AirGIS/OSPM, were led by the Danish Cancer Society research group (e.g. Sørensen et al., 2012, 2013, 2014, 2015). All focused on the health effects and conducted in Aarhus and Copenhagen (Denmark). A similar modelling system has also been applied in Macau (China) to study the influence of urban forms on traffic induced pollution (Tang and Wang, 2007).

The KCL-Urban model (part of King's London Air Quality Toolkit) uses a kernel modelling technique based upon the ADMS (CERC, 2017) to address the initial dispersion from each emissions source (see User's Guide, KCL-Urban for details). Kernels are created using hourly based meteorological data. Then, the contribution from each emission source is computed by applying each kernel summed onto a fixed 20 m^2 grid. In KCL-Urban, vehicle emissions factors are based on London Atmospheric Emissions Inventory (LAEI) (Greater London Authority, 2013). Several groups used KCL-Urban to evaluate health impacts in the Greater London Area (UK) e.g. Halonen et al. (2016), Tonne et al. (2016) and Halonen et al. (2015). This model was also used by, Fecht et al. (2016) to study the spatial and temporal associations of traffic induced pollution. The KCL-Urban has also been applied in a regional cohort study across Europe (UK, Germany, Italy, Greece, Sweden, and the Netherlands) (Floud et al., 2013).

Among the less frequently used models (Table 1) are EURAD-CTM (e.g. Kälsch et al., 2014; Fuks et al., 2011) and AERMOD (e.g. Bodin et al., 2016). EURAD-CTM – one of the sub-modules of EURAD model - uses meteorological input and emissions inventories to estimate the dynamic behavior of air pollutants in the region of interest (RIU, 2017). AERMOD (The United States EPA, 2017) is an integrated dispersion modelling system, freely available to the scientific community. Although, only rarely employed in our identified studies (Table 1), AERMOD is a popular model in general air pollution related studies (e.g. Seangkiatiyuth et al., 2011; Kesarkar et al., 2007).

There is large number of studies and reviews that list and compare the available atmospheric dispersion models (e.g. Jerrett et al., 2005a). Further details about each identified model are provided in Table S2.

4.1.2. Models used for noise

The most frequently used models for noise exposure assessment, in conjunction with air pollution, are SoundPLAN (SoundPLAN GmbH, 2017), CadnaA (DataKustik GmbH, 2017) and TRANEX (Gulliver et al., 2015). Hadzi-Nikolova et al. (2012) indicated SoundPLAN as leading environmental noise prediction software. It is a commercial software package offering high-end simulation modules for both air and noise pollution calculations. To calculate road traffic noise, several European modelling methods are implemented in SoundPLAN including e.g., French (NMPB2008) (Sétra, 2009), German i.e. RLS90 (Ministry of Economy, Labor and Housing, 2013), and several Nordic methods: RTN 96 (Jonasson and Nielsen, 1996), Nord2000 Road (The Danish EPA, 2006). Bodin et al. (2016) used SoundPLAN in a regional scale health related study in Skåne (Sweden). Similarly, Sørensen et al. (2012, 2013, 2014, 2015) also used SoundPLAN to evaluate the effects of traffic noise exposure on human health in Denmark. SoundPLAN includes an air pollution module, based on a simple Gaussian model and the Austal2000 (The German Federal Environment Agency, 2017); however, we could not find an application of the SoundPLAN Air Pollution module in the scientific literature.

Computer Aided Noise Abatement (CadnaA) is another leading software, for the prediction of road traffic noise. Again, multiple standards e.g., German (RLS-90), French (NMPB-Routes-08) (Dutilleux et al., 2010), Austrian (RVS 04.02.11) (FSV, 2006), Swiss (SonRoad) (Heutschi, 2004), Nordic RTN-96 etc. are available in CadnaA. The model system has been used in urban (Gan et al., 2012; Gehring et al., 2014; Foraster et al., 2014) and regional scale (De Roos et al., 2014) health impact assessment studies at many cities worldwide. Chung et al. (2008) and Karantonis et al. (2010) compared CadnaA with SoundPLAN in terms of traffic noise predictions of arterial roads. Both authors reported that CadnaA is as accurate and effective as SoundPLAN.

Interestingly, open source models for noise mapping/prediction are getting increasingly popular due to their easy availability and good performance. This is evident from a few recently published studies e.g. Gulliver et al. (2015). TRANEX (Gulliver et al., 2015) is one of the frequently used open source models (Table 1). It is a parametrized noise model based on the modified CoRTN method (UK's Calculation of Road Traffic Noise) (UK's Department of Transport, 1988). de Lisle (2016) compared CoRTN against field measurements and reported that CoRTN over-estimated noise levels at most urban freeways. However, TRANEX has shown high correlations between modelled and measured noise in two English cities i.e., Leicester ($r = 0.95$) and

Notes to Table 1:
See Appendix A (Table S2 and S3) for models and methods definitions and other Supplementary information.
Deterministic modelling: use of dispersion model and measurements/model validation;
Stochastic modelling: statistical modelling including LUR models and measurements/model validation.
Measurement: direct measurements/use of offline (passive sampling) and online (active sampling) measurements datasets.
Spatial scale: the extent or size of the area studied or described (with large approximation).
Street: exposure assessment performed along a major street or highway.
Urban: exposure assessment performed on a city-scale.
Regional: exposure assessment performed for a larger region of interest (multi-city level exposure assessments etc.).
[a] The use of GIS based tool/technique and/or software (both commercial and open source) for air and/or noise pollution exposures modelling/assessment.
[b] Inclusion of building geometry parameters for air and/or noise pollution modelling.
[c] Monthly or yearly average traffic composition values.
[d] Hourly traffic composition values.
[e] The use of GIS programming (e.g. spatial regression and/or LUR), GIS-based maps for pollution exposure and/or for monitoring sites etc.
[f] Static: stationary or fixed-point pollutants' measurements.
[g] Measured data: measurements dataset obtained from local monitoring stations (or previous studies).
[h] Passive sampling (air pollution) i.e. when pollutants only reach the container/passive sampler through their own movement and diffusion.
[i] Mobile: pollutants' measurements using moving (walking, driving, cycling etc.) probe including personal measurements.
[j] Active monitoring (air pollution) i.e. well-defined volume flux of pollutants pumped through the measurement device.

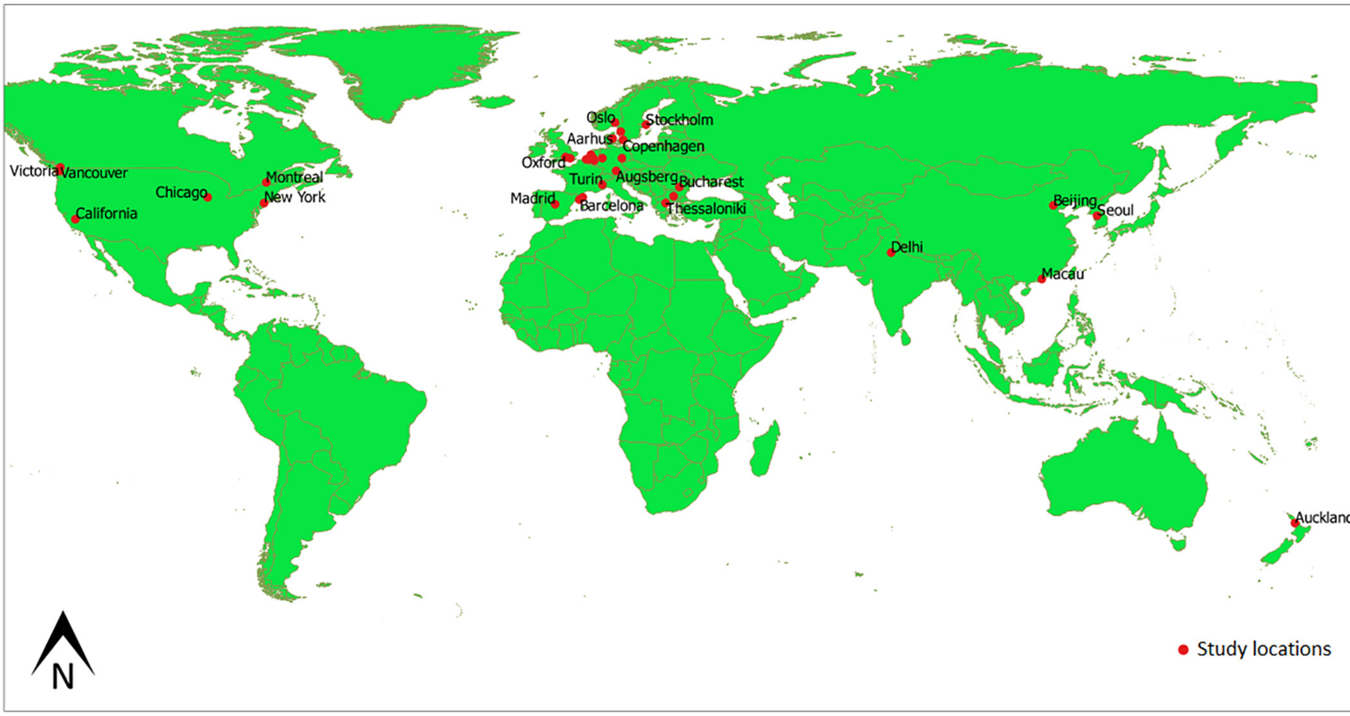

Fig. 2. Study locations of the selected articles of this review.

Norwich (r = 0.85) (Gulliver et al., 2015). Thus, it has a significant potential for use in noise mapping and/or health related studies. Halonen et al. (2016) and Tonne et al. (2016) used TRANEX in their work to assess urban population's traffic noise exposure in Greater London area (UK) and investigated health outcomes.

Another open source and more recent model is CNOSSOS-EU (Kephalopoulos et al., 2012) that includes several modules for road, railway, aircraft and industrial noise. CNOSSOS-EU (road module) computes long-term noise L_{den} in a similar way as compared to the Nordic noise prediction method Nord2000 Road (The Danish EPA, 2006) and differently than TRANEX (Gulliver et al., 2015). CNOSSOS-EU was developed through a Joint Research Center – European Commission project (No. 070307/2008/511090 and 070307/2009/549280) and has been applied at several locations around EU (e.g. The BioShare EU, 2015; Cai et al., 2015). In contrast to the atmospheric dispersion models, European Commission publications (The European Commission, 2016b) recommend a specific method, the CNOSSOS-EU for the strategic noise mapping (as per the European Noise Directive 2002/49/EC, 2002) and health impact assessment studies.

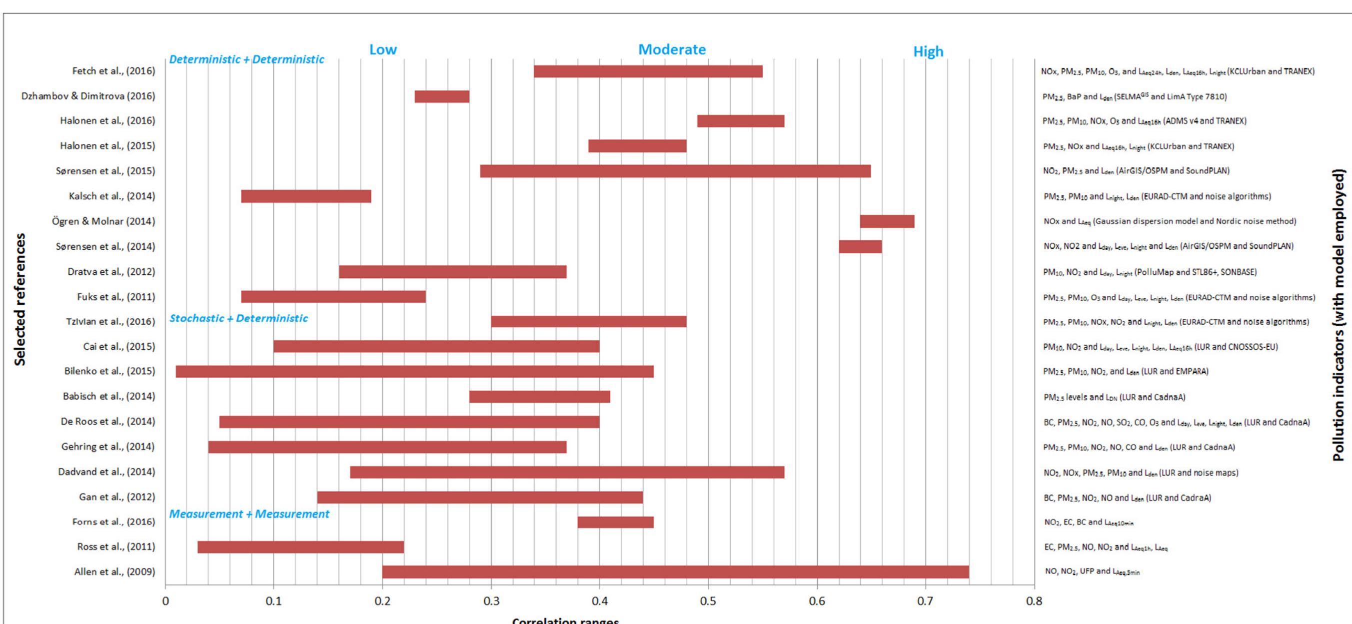

Fig. 3. Correlation ranges between air and noise pollution reported in the selected studies of this review, sorted by publication year and grouped into general type of exposure assessment i.e. Deterministic modelling, Stochastic modelling, Measurement (Nieuwenhuijsen, 2015). Pollution indicators and employed models/methods associated with each correlation range are also shown.

Table 2
A list of potential parameters and methods choice, commonly affecting air and noise pollution levels and their correlations. Nr = chapter in this paper for detailed discussion.

Category	Nr	Parameter	References
Exposure assessment techniques	4	Deterministic Stochastic Measurement	[a]
Pollution indicators	5	Oxides of nitrogen (NOx, NO_2 etc.) PM (PM_{10}, $PM_{2.5}$ etc.) Ozone and others (BC, SO_2 etc.) Noise indicator (L_{den}, L_{Aeq24h} etc.)	[a]
Spatial unit of analysis	6	Spatial scale	Gan et al. (2012), Fecht et al. (2016)
Traffic attributes	7	Vehicle distribution (LDV and HDV share)	Davies et al. (2009), Shu et al. (2014)
		Traffic speed	Gan et al. (2012), Shu et al. (2014)
		Traffic volume	Tang and Wang (2007), Davies et al. (2009), Boogaard et al. (2009), Foraster et al. (2011), Gan et al. (2012), Shu et al. (2014)
Buildings' attributes	8	Building heights	Tang and Wang (2007), Shu et al. (2014), Weber et al. (2014), Fecht et al. (2016)
		Building density	Foraster et al. (2011), Shu et al. (2014); Weber et al. (2014)
Meteorology	9	Wind speed	Can et al. (2011), Ross et al. (2011), Gan et al. (2012), Kim et al. (2012), King et al. (2016)
		Wind direction	Allen et al. (2009), Gan et al. (2012), Ross et al. (2011), King et al. (2016)
		Temperature	Kim et al. (2012), King et al. (2016)
Urban landscape	–	Land use	Tenailleau et al. (2016)
		Land cover	Tang and Wang (2007), Tenailleau et al. (2016)
		Distance from road to sidewalks	Foraster et al. (2011)
		Distance to freeways	Shu et al. (2014)
Background contribution	–	Regional or local sources of background contribution	Allen et al. (2009), King et al. (2016)

[a] Not explicitly discussed in one single paper.

A good number of studies applied directly a standardized method (e.g. RTN-96) for the estimation of the noise models instead of a readily available software/model. For example, many studies implemented the Nordic method (Örgen and Molnar, 2014; Selander et al., 2009; Klaeboe et al., 2000) and a few used noise algorithms defined in Directive 2002/49/EC (e.g. Kälsch et al., 2014). There is no single study that compares all these models and methods but interesting reader can find some discussions on their differences and performance in Chung et al. (2008) or Garg and Maji (2014).

4.2. Stochastic modelling

Stochastic modelling is based on the statistically derived relationships between the effects (pollution levels or health effects) and causes (sources). Unlike deterministic approaches, stochastic models do not rely on fundamental knowledge of the underlying physical or chemical phenomena and their methodology is independent of the stressor (i.e. air and noise) (Nieuwenhuijsen, 2015). Land use regression (LUR) models are the most characteristic examples of stochastic modelling in air and noise pollution studies. LUR models investigate and develop the correlations/predictors, through statistical regression, between land use characteristics (e.g. roadways), their activity/intensity level (e.g. traffic volumes and composition) and measured pollutant levels. Then, these relationships are "extrapolated" to estimate pollutant levels at different times and locations, within the study area. GIS plays a significant role in LUR models, both for the development of the predictors and estimation of the results. More details can be found in Ryan and LeMasters (2007) or Hoek et al. (2008).

One of the main strengths of LUR models is the empirical structure of regression mapping which allows accounting for small scale variability in intra-urban pollutant concentrations without any additional monitoring or data acquisition as reported by Jerrett et al. (2005a). However, the lack of cause-effect relationship (Gokhale and Khare, 2004), large input requirements (Kanaroglou et al., 2005; Kumar, 2009) and measurements' cost (Brauer et al., 2003) are some of the major disadvantages of LUR. Furthermore, the extrapolation of LUR method beyond the original study area and period is problematic (Isakov et al., 2011), as well as the retrospective exposure assessment studies (Hoek et al., 2008).

Although LUR can be applied similarly for noise pollution, there is only one study that used a stochastic modelling approach for both air and noise (Apparicio et al., 2016). The authors reported a very weak negative correlation between the two measures of exposure (not shown in Fig. 3). In contrast, there are a good number of noise only related studies that used LUR models. Aguilera et al. (2015) demonstrated the successful use of a LUR across three European cities. Similarly, Ramírez and Domínguez (2013) applied and compared stochastic and deterministic models for urban traffic noise. Nevertheless, most frequently, LUR models have been applied for air pollution and combined with a deterministic noise model (Table 1) (e.g. Gan et al., 2012; Babisch et al., 2014; Bilenko et al., 2015) or noise measurements (Linares et al., 2006).

4.3. Measurements

Air pollution measurement techniques are usually classified as active or passive sampling (IARC Working Group, 2016), based on the air-volume driving force i.e. forced (Gouin et al., 2005) or natural (Assael et al., 2010), while the use of markers e.g. biomarkers (Delfino et al., 2011) is also common. There is no such classification for noise measurement techniques, typically conducted using a calibrated microphone as per the ISO standard (IEC 61672-1, 2013). Although, measuring campaigns involve significantly higher costs than modelling, they are more straightforward and thus frequent in the literature, especially in conjunction with LUR models.

A large number of studies (28%, Table 1) (e.g. Can et al., 2011; Danciulescu et al., 2015; Klingberg et al., 2017) conducted new field campaigns for the measurement of both air-pollutants and noise levels. In this case, yielded air-noise correlations seem to be higher (e.g. Allen et al., 2009) (Fig. 3). It should be noted that stochastic models are based on measured and/or modelled pollutants' data but measured data are also been used separately as evident from Table 1. Kim et al. (2012) used measurements at eight locations across Seoul, Korea to study the relationship between air and noise pollution levels. Generally, measured data are frequently employed in model development (e.g., calibration) and model evaluation (Detels et al., 2015).

We observed that most of the researchers employed static (fixed-point) measurements for air-noise assessment (e.g. Allen et al., 2009; Ross et al., 2011; Shu et al., 2014; Forns et al., 2016). While, some authors used mobile (including personal) measurements to study both exposures. E.g. Boogaard et al. (2009) used mobile (cycling and driving) measurements to assess exposure to both types of pollution in 11

Dutch cities. Some of the studies utilized measured pollution datasets made available by the local monitoring stations network. Linares et al. (2006) and Arroyo et al. (2016) used air-noise measured data obtained from Madrid's Municipality Pollution Monitoring Grid to analyze children's daily hospital admissions and effects on preterm birth in Madrid (Spain). Similarly, Ross et al. (2011) and Kheirbek et al. (2014) made use of measured datasets provided by New York State Department of Environmental Conservation (NYSDEC, 2017) and New York Community Air Survey in their studies.

Measurements provide a way to assess direct personal exposure to pollution levels and consequently health impacts in epidemiological studies (Watson et al., 1988). Huang et al. (2013) used personal measurements of air-noise in a designated traffic center and an appointed park in Beijing (China) to study heart rate variability of 40 subjects. However, it is important to note that personal monitoring is inevitably labor intensive as well as expensive and not suitable for large epidemiological studies (Nieuwenhuijsen, 2015). Thus, limited measurements can be synergistically used with modelling to improve the understanding of health impacts originating from both stressors in urban commuting environments. Recently, Dekoninck et al. (2015) reported that measurements with low cost sensors provide the means to increase the spatial resolution of data and enable long-term monitoring campaigns.

4.4. Summary of techniques

Overall, most of the studies (Table 1) used the same technique for both stressors i.e. deterministic modelling ($n = 22$ references). Nonetheless, all possible combinations of air and noise pollution assessment techniques have been used either directly or indirectly. The most commonly used deterministic modelling is often combined with stochastic modelling (e.g. Dadvand et al., 2014, see Table 1); a combination usually referred as "hybrid modelling" (Jakeman et al., 1988; Gokhale and Khare, 2004; Gokhale and Khare, 2005). Fig. 4 depicts the distribution and combinations of the exposure assessment techniques in the identified studies of this review.

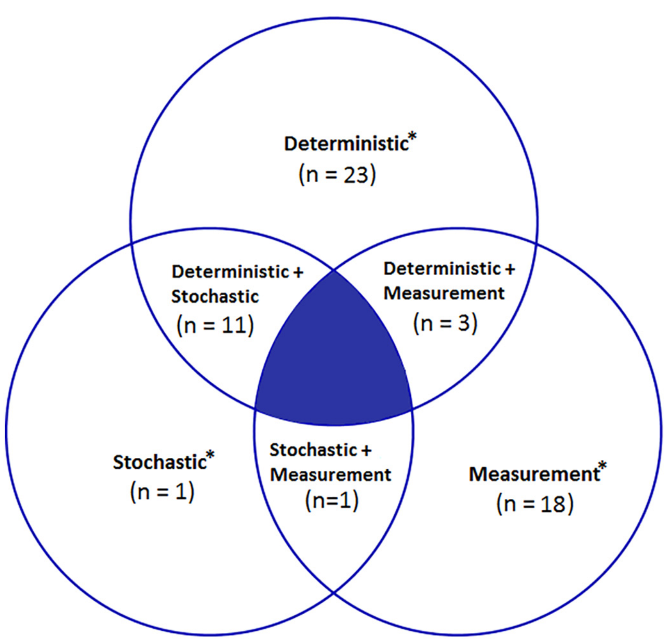

Fig. 4. The distribution of exposure assessment techniques and their combinations in assessed studies ($n = 57$) of this review (Table 1). *For both air and noise pollution exposures.

5. Pollution indicators

Exposure to traffic induced pollution is assessed on the basis of "pollution indicators". Pollution indicators characterize the levels of exposure to a contaminant, at a given spatial and temporal scale, which has the potential to cause environmental damage, health issues etc. The choice of indicators may depend on various characteristics such as study location or, geographical unit of analysis etc. Moreover, different exposure indicators typically have different patterns over space and time (Foraster et al., 2011) calling for their careful selection. This is probably why we observed (see Table 1) a large heterogeneity in employed air and noise pollution indicators and associated air-noise correlations (Fig. 3).

All noise pollution indicators are based on the time integral of squared frequency-weighted sound pressure over a stated time interval (IEC 61672-1, 2013). The most commonly used frequency weighting is the *A-weighting* (NoiseMeters Inc., 2017), usually denoted by L_A. It covers full audio range (20 Hz to 20 kHz) perceivable by the human ear (IEC 61672-1, 2013; Gracey and Associates, 2017). Many different time intervals have been proposed in literature and international standards. For example, L_{day} indicates day-time equivalent noise level over the 12-hour period between 07:00 and 19:00. Others are more sensitive towards specific time intervals by introducing sound level penalties e.g. L_{den} introduces 10 dB penalty between 23:00 and 07:00 and 5 dB penalty between 19:00 and 23:00. The most common noise indicators are shown in Fig. 5 and explained in Table S3. L_{den} (35%), L_{night} (28%) and L_{Aeq} (24.5%) are the most frequently used noise indicators (Table 1, e.g. Kälsch et al., 2014; Tzivian et al., 2016) (Fig. 5). While, some of them appear equivalent e.g. L_{day}, L_{eve} and $L_{Aeq,24h}$ but correspond to different time intervals based on the study region and are moderately used (e.g. Selander et al., 2009; Clark et al., 2012). Also, short-term noise indicators such as $L_{Aeq,5min}$ (e.g. Davies et al., 2009), $L_{Aeq,1min}$ (e.g. Boogaard et al., 2009) etc. have been proposed but rarely used. The European Commission (2016c) requires L_{den} and L_{night} to be used as the appropriate EU traffic noise indicators for strategic noise mapping.

There is an even greater variety of air pollution indicators proposing compared to noise indicators. Air pollution indicators have more different time scales and more different contaminants. The most commonly used air contaminants are shown in Fig. 6 and defined in Table S3. NO_2 (66%), $PM_{2.5}$ (44%), PM_{10} (39%) and NOx (30%) have been frequently used (e.g. Roswall et al., 2017; Örgen and Molnar, 2014) (Fig. 6). While, O_3, CO, NO, BC and SO_2 (e.g. De Roos et al., 2014) have been moderately used, and EC, UFP, TSP, BaP, VOC, SOx, CH_4 and C_6H_6 (e.g. Kim et al., 2012) have been rarely used to assess air pollution

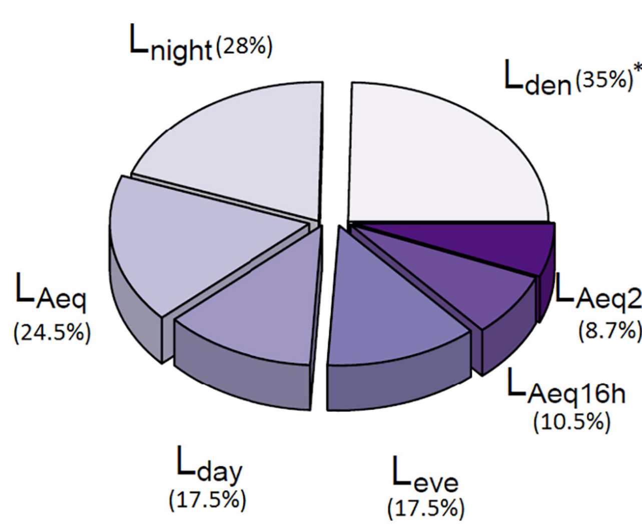

Fig. 5. Distribution of the selected studies on the basis of road traffic noise exposure indicators. *Shows the usage of exposure indicator in % studies of this review.

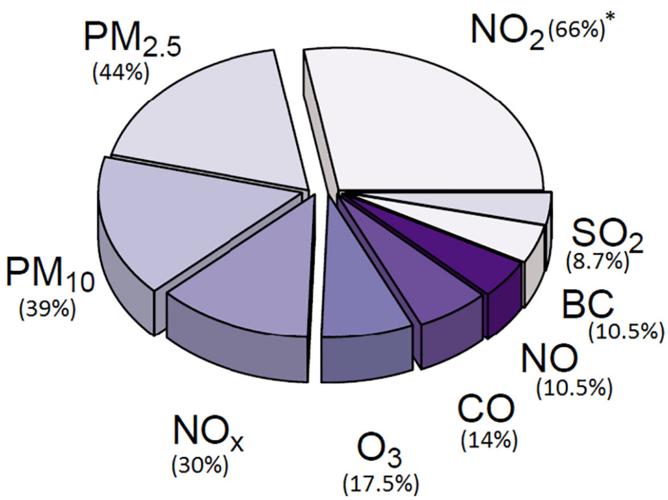

Fig. 6. Distribution of the selected studies on the basis of road traffic air pollution exposure indicators. *Shows the usage of exposure indicator in % studies of this review.

exposure (not shown in Fig. 6). In the literature, NO_2/NOx and $PM_{2.5}$, PM_{10} have been indicated as primary indicators of traffic air pollution (Querol et al., 2001; Pandey et al., 2008; Pérez et al., 2010). Concerning the time scale, many different averaging schemes have been used i.e., yearly, monthly, daily. Air Quality Indices have been broadly applied in air pollution studies (Adams and Kanaroglou, 2016; Schweizer et al., 2017) but no use was noted here in combined studies of air and noise pollution.

However, King et al. (2016) demonstrated an air-noise pollution reduction index (ANP_r), proposed in King et al. (2009), to quantify the level of reduction in environmental pollutants at a pedestrian level. ANP_r is a simple index calculated by finding the average percentage reduction of both pollutants and calculating the mean of the two. The authors suggested that the index may be used for urban planning and informative purposes.

6. Spatial scale and sample size

Spatial scale represents – with large approximation – the extent or resolution of the area (Wikipedia, 2017). For example, local or street scale (1 m^2–1 km^2), city or urban scale (1 km^2–5000 km^2) and regional scale (5000 km^2–10,000 km^2). Fig. 7 shows the distribution of the reviewed studies on the basis of spatial scale i.e. extent of the study area.

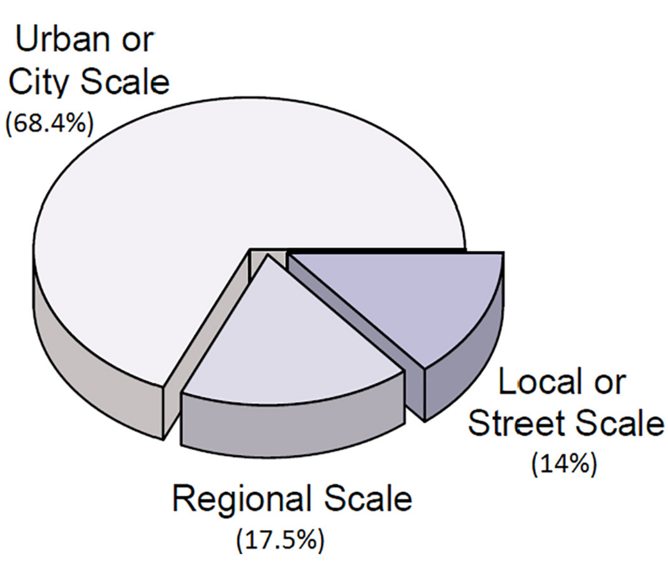

Fig. 7. Distribution of the selected studies ($n = 57$) on the basis of spatial scale of exposure assessment.

Most studies were identified on urban scale (68%) (Table 1) focusing on health impact assessment (e.g. Klaeboe et al., 2000; Fuks et al., 2011; Dratva et al., 2012; Foraster et al., 2014; Sørensen et al., 2015) and the spatial and statistical relationships between air and noise pollution (e.g. Tang and Wang, 2007; Foraster et al., 2011; Vlachokostas et al., 2012). A smaller number of studies (18%) performed regional scale analysis, with similar objectives i.e. stressors' spatial relationship (e.g. Fecht et al., 2016) and health affects (e.g. Floud et al., 2013). Local scale studies are lesser (14%) and all except one investigated the spatial and statistical relationship of air and noise pollution (e.g. Can et al., 2011; Shu et al., 2014). The majority of local studies are based on measurements. The study of Huang et al. (2013) is based on measurements, as well, but researched the heart rate variability owe to exposure to both stressors.

Multi-scale studies provide a useful insight on the spatial and temporal associations between modelled air and noise pollution levels at different spatial scales. Fecht et al. (2016) studied these associations for London Boroughs, neighborhoods and 1 km^2 grid cells. Authors reported an increased correlation of air-noise by decreasing the size of spatial unit from London Boroughs to 1 km^2 grid cells and neighborhoods. Thus, studies related to both exposures assessment should be performed at different spatial scales (e.g. city scale etc.) due to the role of relevant geographical units in air-noise interaction (Fecht et al., 2016).

Often, field campaigns incorporate "test persons" either subjecting them to medical and health related assessments or for personal sampling (see Section 4.3). Sample size represents the number of these participants and/or the number of residents in the study area. A varying sample size was observed (Table 1). The minimum sample size was $N = 40$ subjects in Beijing in a health related study (Huang et al., 2013) while maximum was $N = 9$ million residents in London in air-noise spatial and temporal relationship study (Fecht et al., 2016).

7. Traffic attributes

Traffic volume or traffic density based on annual average daily traffic number (AADT), vehicle distribution (share of light and heavy-duty vehicles i.e. LDV and HDV) and traffic speed is one of the governing factors to determine the degree of correlation between air-noise pollution levels. Majority of the studies included in this review (Table 1) used (daily or annual) average traffic datasets (84%) while only few used hourly traffic data (12%) (Fig. S3). In some cases, it was difficult to characterize the study due to lack of information.

Air pollution emissions dependency on traffic speed is similar to a parabola shape (van Beek et al., 2007) while, ideally, noise is linear (Iannone et al., 2013). However, this dependence (air and noise) is also related to the vehicle's age (Caserini et al., 2013) as well as vehicle's type (Ntziachristos et al., 2009), tire-road interaction (Czuka et al., 2016) and types of road surface (Ho et al., 2013). In terms of air pollution, emissions can vary depending on the varying (increasing, decreasing, constant) traffic speed (EEA, 2011). While, in terms of noise, reducing speeds by 6 mph (9.7 km/h) would cut noise levels by up to 40% in urban areas (The UK Noise Association, 2009).

Davies et al. (2009) indicated vehicle type (LDV or HDV), road characteristics (number of lanes) and presence of intersection as key contributors to the variability of road traffic noise level and concentration of NO_2/NOx in an urban setting. Foraster et al. (2011) studied the $L_{Aeq,24h}$-NO_2 correlation in terms of stratified traffic density (cut-off ADT: 1000 vehicles/day). The authors reported that the correlation between $L_{Aeq,24h}$ and NO_2 was stronger in the low ADT group but their interaction was not statistically significant. While, Ross et al. (2011) explored temporal relationships among traffic (categorized by vehicle type), noise (in three frequency strata i.e. low, medium and high) and air pollution at a high-traffic location in New York City (USA). The authors reported a varying range of correlation (Fig. 3). Moreover, Boogaard et al. (2009) reported only moderately positive correlation between both pollution levels which might be caused by the fact that the complex road-traffic interactions depending on road surface have higher impact on noise emission than air pollution emission.

8. Buildings' attributes

Building layout or building geometry affects air and noise pollution levels (Tang and Wang, 2007; Shu et al., 2014; Weber et al., 2014; Tenailleau et al., 2016). This includes building heights and density. Façade materials have not been included in the reviewed studies, although building materials play an important role, as well, in noise propagation (Lyon, 1974; Van Renterghem et al., 2013). Some form of information on buildings' attributes has been used in all modelling studies (Table 1) (70%, Fig. S4) but it was ignored in most measuring campaigns (19%). In a few instances, buildings' information was not available in the study.

In terms of air pollutants dispersion, building layout leads to the development of a street canyon vortex – which traps pollutants thereby – resulting in increased air pollution concentrations (Huang et al., 2014). Hence, in-canyon vortex dynamics (e.g. vortex orientation) and the characteristics of pollutant dispersion are strongly dependent on the roof shapes and ambient building structures (Xie et al., 2005).

Urban sound propagation is influenced by the reflection with surfaces (e.g. building façades, roofs etc.), diffraction from edges as from building roofs and scattering from rough surfaces as irregular building façades (Hornikx, 2016). The author further reported that at microscale (local or street-scale), the effect of individual buildings and surfaces are more important as a typical microscale is the sound field within a street or at a square. Based on Hornikx's finding, buildings act as screens and reduce noise much more than air pollution. Foraster et al. (2011) studied the effect of building density on air-noise correlation in Girona (Spain) and found that the locations with continuous buildings on both side of the road "2 sided built" had higher air pollution (NO_2)-noise ($L_{Aeq,24h}$) levels as compared to the locations with "isolated houses". Similarly, Shu et al. (2014) also accounted building layout near freeways as one of the major factors affecting air and noise pollution correlation.

9. Meteorology

Meteorological parameters such as wind speed, wind direction (Weber, 2009; King et al., 2016), air temperature (King et al., 2016) or temperature gradient/stability (Zhang et al., 2018) also have a significant influence on the degree of correlation between air and noise pollution. Concerning air pollution, wind speed (above 1.5–2.0 m/s, Berkowicz et al., 1997) and wind direction together with street geometry may lead to the formation of a street canyon vortex (King et al., 2016). Consequently, air pollutants concentrations are increased on the leeward side as compared to the windward side of the street (Manning et al., 2000). An overview of various wind flow regimes as function of building (length-to-depth ratio) and urban canyon (depth-to-width ratio) geometries (Oke, 1988) is shown in Fig. 8. Lower air temperature may result in increased concentrations of air pollutants (e.g. ultrafine particles) (Xu et al., 2016).

Sound propagation is faster along the wind direction and slower against the wind (Penton et al., 2002). Also, air temperature gradients are capable to refract outdoor sound waves (e.g., road traffic) either towards or away from the ground. Fig. 9 shows the effect of wind and air temperature on sound propagation.

Weber (2009) studied the spatio-temporal covariation of urban air and noise pollution in Essen (Germany). The authors reported a positive correlation between both stressors in 10 of 12 measurements. Weber's work indicated that meteorology has a greater influence on air pollution as compared to noise. Can et al. (2011) performed principal component analysis (PCA) to study the correlation of ultrafine particles (UFP) and noise in a street canyon in Antwerp (Belgium). Pollution components i.e., particles from 20 nm to 200 nm (total particle number), NOx concentrations, L_{50} and $L_{2kHz\,-\,125kHz}$ were grouped with similar meteorological conditions (e.g. wind speed). PCA in Can's work revealed that there was a stronger influence of meteorological conditions on airborne pollutants variation.

10. The role of GIS in air-noise exposures

GIS-based tools and techniques prevailed in many of the studies (Table 1) and, thereof, this section describes the most common of

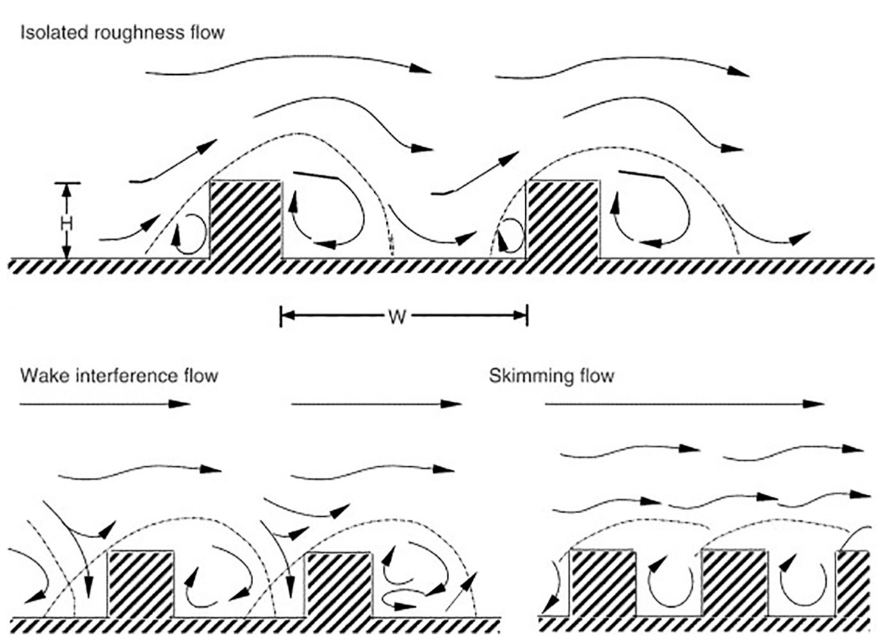

Fig. 8. An overview of the perpendicular wind flow regimes in urban street canyons.
(Image adapted from Oke (1988) and reproduced with permission.)

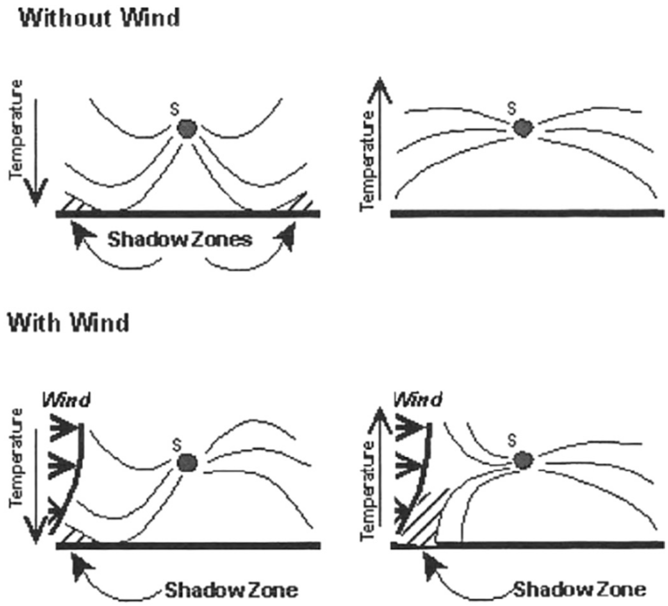

Fig. 9. The schematic representation of wind and air temperature gradients on sound propagation.
(Adapted from ISO-9613-1 (1993).)

them and what their role is on improving the understanding of air and noise pollution combined exposures.

GIS is a powerful computer based mapping and analysis tool which permits spatial linking of different types of data (e.g. residential addresses, environmental exposure levels, demographic information) (Croner et al., 1996; Vine et al., 1997). At least half of the identified studies (Table 1) made use of a specific GIS tool. While, others (21%) used GIS-based maps, local/regional GIS databases and/or GIS programming to assess/model exposure to air and noise pollution. However, many studies (30%) have probably used a GIS tool/technique but no further details are given in the publications. Table 3 lists the GIS tools used in our identified studies. The following paragraph provides more details on each of them.

ArcGIS was the most frequently used GIS tool (Table 3). It is commercial software for working with maps and geographic information; a leading geospatial software (Dowell and McClellan, 2017) – routinely used for air and/or noise pollution exposure assessment studies (e.g. Casey et al., 2017; Ghosh et al., 2017). In addition to proprietary software, several freely available (open source) GIS tools are also present (e.g. Kulawiak et al., 2010; Jeong et al., 2012; Neteler et al., 2012; Steiniger and Hunter, 2013). Furthermore, Ibrahim and Ludin (2015) reported that open-source GIS tools have significant capability to extend GIS-based analyses through optimized handling of datasets and sharing of information. Among such open-source tools, we identified QGIS, PostgreSQL/PostGIS, Geospatial Data Abstraction Library (GDAL), although they are still only rarely used.

Data management and handling is of the first and most common uses of GIS tools. Moreover, in field campaigns, data acquisition via GPS and GIS tools can assure and control the data quality. Also, they can greatly enhance exposure studies in terms of definition of sources and routes, and the overall exposure assessment process (Nuckols et al., 2004). In this context, GIS is flexible on selecting of spatial scale of the study area i.e. size (Stroh et al., 2005) and resolution (Fecht et al., 2016).

A specific example where GIS could enhance data management is sharing and harmonization of input and epidemiological data like detailed traffic datasets (see Section 7) and health observations. Some authors have even pointed towards data pooling from established cohort studies to investigate health effects of both stressors (Cai et al., 2015). Using harmonized data, similar source description could also be helpful in effective implementation of air and noise pollution mapping in e.g. EU member states. By providing a mean of capturing and linking spatial data within a single geographical structure, GIS should help to improve data integration and consistency (Briggs, 2005).

In addition, GIS offers powerful algorithms for the data processing and visualization in pollution studies. Briggs (2005) presented a comprehensive classification of such approaches and their procedures. In our study, we adapted this classification and noted the procedures applied in the reviewed literature (Table 4). The main approaches are spatial interpolation and dynamic simulations. One of the several spatial interpolation procedures is regression mapping. It makes use of data available from monitoring stations or campaigns to estimate pollution levels at other (unsampled) sites. It has often been tested and applied in Europe (Aguilera et al., 2015) and worldwide (Jerrett et al., 2005b), and appears to give reasonable results (Briggs, 2005; Gulliver et al., 2011). In our identified studies, Apparicio et al. (2016) used spatial-regression to study cyclists' exposure to air and noise pollution in Montreal (Canada). The authors indicated spatial-regression, being a spatial-lag model (Anselin and Rey, 2014), suits well to associate levels of air-noise exposure to the levels observed during the time lead and lag intervals of measurement campaign. Regression mapping in space and time, however, is more suitable for studies based on long term exposure to pollution (Gulliver et al., 2011). Other spatial interpolation procedures like Kriging and Inverse-Distance Weighting (IDW) are used frequently in solely air pollution studies (Garcia et al., 2016) or noise pollution studies (Tsai et al., 2009; Vienneau et al., 2009), have not been applied in the combined stressors studies (of Table 1).

Another approach i.e. dynamic simulation is the integration of the deterministic (i.e. dispersion/propagation) algorithms with GIS tools to model temporal patterns of pollution. The advantage of this technique lies in the efficient integration of the related information (e.g. meteorology, land use), the validation of the results, and the post-processing of the outcomes (Briggs, 2005). More details on the deterministic models have been provided earlier and in related literature (Jerrett et al., 2005a). A large number of our identified studies employed dynamic simulations (e.g. Huang et al., 2013; Tenailleau et al., 2016).

GIS, however – like any other tool – is also subjected to some limitations. That is, GIS-based exposure models need to be validated and often require specific input datasets. These and other underlying limitations such as inaccuracies in spatial extent, crude assumptions, errors and inaccuracies in digital maps etc. must be considered and thoroughly analyzed in order to achieve reliable exposure estimates.

Table 3
The distribution of our selected studies on the basis of frequently used GIS tools.

Sr. #	GIS tool	No. of studies	Availability	Link
1	ArcGIS (including ArcView/ArcInfo)	19	Commercial	https://www.arcgis.com
2	PostgreSQL	6	Open source	https://www.postgresql.org
3	PostGIS	6	Open source	http://postgis.net/
4	QGIS	1	Open source	https://www.qgis.org
5	GDAL	1	Open source	http://www.gdal.org/
6	MapInfo	1	Commercial	https://www.pitneybowes.com/us/location-intelligence/geographic-information-systems/mapinfo-pro.html

Table 4
A list of GIS-based approaches proposed for air-noise pollution combined exposures assessment.
(Adapted from Briggs (2005).)

Approach	Procedure	Method	Example
Spatial interpolation	Regression mapping	Pollutants' levels modelled using empirically derived regression model, developed on basis of "training" data set	Apparicio et al. (2016)
	Kriging	Pollutants' levels interpolated from monitored data, using ordinary or universal kriging	n.f.
	Inverse distance weighting (IDW)	Pollutants' levels interpolated from monitored data based on inverse-distance	n.f.
Dynamic simulation[a]	Modelling of air dispersion and/or noise propagation	Pollutants' levels estimated using models of dispersion/propagation pathways and rates	Dzhambov and Dimitrova (2016); Tenailleau et al. (2016)
	Exposure modelling	Exposures modelled on basis of time-weighted pollution levels in each (micro) environment occupied during the study period	Huang et al. (2013); King et al. (2016)

n.f.: not found in our studies.
[a] Modelling of time-varying patterns of pollutants (e.g., annual averages of NO_2 or L_{den}).

11. Conclusions

In this paper, studies related to air and noise pollution in relation with current practices of modelling and exposure assessment techniques have been reviewed.

This review addresses a modern research and societal challenge, i.e. the combined exposure assessment to air and noise pollution. It is the first time that this type of review has been conducted based on a comprehensive number of studies of both stressors. In addition, it identifies the employed techniques, the potential research gaps, and future tools to study this challenge.

One of the main challenges of this review was the large number of search hits, which made exclusion process necessary, and the difficulty to identify all the important information and parameters such as building geometry information, nature of traffic datasets etc.

Deterministic modelling is the most frequently used assessment technique for road traffic air-noise pollution exposure. It is equally suitable to study short-term and long-term exposure to both types of stressors. Whereas, stochastic modelling (e.g. LUR) is more suited for long-term exposure assessment. Concerning air pollution modelling tools, a large number of models has been employed while for noise modelling, most studies employ the same few commercial softwares.

Among the air pollution models we observed a larger variety compared to the applied noise pollution models. The majority of all used models are proprietary. However, open source or freeware tools are getting more popular. There exists no standard or harmonized tool in the scientific literature for modelling both exposures simultaneously.

Correlations between air-noise pollution vary significantly between studies (i.e. 0.05–0.74); this wide range, in general, can be explained by the usage of various types of exposure models, indicators and techniques. In addition, one cannot expect a perfect correlation between noise and air pollution since both stressors are affected by several other study parameters. For example, traffic attributes, e.g. traffic volume, travel speed and vehicle type, affect differently noise and air pollution.

Building attributes also play a key role in determining air-noise interaction but they affect noise more than air pollution. Inside street canyons, buildings tend to increase both types of pollution. At the same time buildings act as screens for pollution, but the reduction effect is much larger for noise than for air pollution. In contrast, meteorology has a greater influence on air pollution levels as compared to noise, although it is very important for both types of pollution.

Among the several employed tools and techniques, GIS appears to help on the integration of the specific tools and data. GIS has been used to retrieve and process input data, to perform calculations, and visualize results and outcomes. The preparation of harmonized input data with similar geographical structure of the two environmental stressors can accelerate investigations and policy making.

Thus, future studies could employ GIS approaches to combine harmonized data and validated models specifically to obtain address-level or personal reliable exposure estimates. Eventually, these will help to improve the understanding of health implications due to air and noise pollution, and finally, to reduce confounding between air and noise pollution health effects frequently reported in health studies.

Air and noise pollution propagate very differently in space and time and they are not necessarily highly correlated. Therefore, they should be modelled separately and cannot serve as proxy for each other. Separate modelling of air and noise pollution can be helpful to disentangle the independent health effects of the two stressors.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2018.03.374.

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