Received: 15 May 2023 | Revised: 9 October 2023 | Accepted: 27 October 2023

DOI: 10.1002/met.2161

Meteorological Applications Open Access
Science and Technology for Weather and Climate
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REVIEW

Low-cost air quality monitoring networks for long-term field campaigns: A review

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Abstract

The application of low-cost air quality monitoring networks has substantially grown over the last few years, following the technological advances in the production of cheap and portable air pollution sensors, thus potentially greatly increasing the limited spatial information on air quality conditions provided by traditional stations. However, the use of low-cost air quality sensors still presents many limitations, mostly related to the reliability of their measurements. Despite the increasing number of papers focusing on these issues, some of the challenges connected to the use of low-cost air quality sensors are still poorly investigated and understood, considering in particular those related to long-term applications of low-cost air quality networks and their integration within the reference air quality monitoring system. The present review aims at filling this gap, by analysing the characteristics of low-cost air quality monitoring networks that were run across long-term field campaigns, including their geographical location, the pollutants monitored, the type and number of stations employed, and the length of the field campaign, with a particular attention on assessing the aims for their deployment and on the evaluation of their integration within official air quality monitoring networks. Moreover, a critical analysis of the most insightful suggestions and recommendations delivered in the literature, as well as of the relevant critical issues, is presented, highlighting still open research areas and outlining future challenges.

KEYWORDS

air quality, field campaign, low-cost sensor, monitoring network, review

1 | INTRODUCTION

Air pollution, considering both particulate matter and gas-phase pollutants, continues to be a massive health issue worldwide associated with millions of deaths (World Health Organization, 2021). Over the past decade, a huge amount of material has been published on low-cost (LC) air quality sensors, that is, sensors that are low in cost, small in size, and fast in response (few seconds to few minutes) (Idrees & Zheng, 2020). This is consistent with a shift in the air pollution monitoring paradigm that is no longer exclusive of government organizations

(Morawska et al., 2018; Snyder et al., 2013). Among citizen science actions, academic research, and commercial projects, a large number of LC networks monitoring different atmospheric pollutants has been deployed, all leveraging the technological advances that allow the production of cheap programmable microcontrollers and inexpensive miniaturized air pollution sensors. The challenge for these LC sensors is that they try to mimic highly accurate and expensive reference air quality stations (Schäfer et al., 2021). The keystone of this revolution in atmospheric monitoring lies in the trade-off between cost and precision. LC sensors cannot quantify airborne pollutants with the same precision as high-cost reference instruments, and currently remain not suitable to replace them (Bílek et al., 2021). Even the current legislation, however, does not require they do so: LC monitors are subject to a different regime than the reference monitors, so that a less demanding accuracy is required for their measurements (called "indicative" rather than "regulatory"). For example, the European Union directive 2008/50/EC prescribes that, while the maximum allowed uncertainty for regulatory measurements is 15% for gaseous pollutants and 25% for particulate matters $PM_{2.5}$ and PM_{10}, for LC measurements, it is 25% for carbon monoxide (CO), nitrogen oxides (NO_x), nitrogen dioxide (NO_2) and sulphur dioxide (SO_2), 30% for ozone (O_3), and 50% for $PM_{2.5}$ and PM_{10}.

As opposed to reference monitors, LC sensors can be deployed in a greater number, with less infrastructural investments and constraints (Mead et al., 2013). If the accuracy of the LC sensors is reasonable, then wider LC networks could complement the sparser ones from regulatory agencies, yielding new information about air quality with a higher spatiotemporal coverage. These LC networks, if allowed to operate for an extensive timespan, would be able to reveal information about air pollution, temporal trends, hotspots and eventually source-apportionment, that sparser networks would not be able to detect (Castell et al., 2017).

Despite the huge literature body published to date on LC sensor applications, some of the related research challenges are still poorly investigated and understood, and there is a lack of critical surveys assessing the state of the art (Concas et al., 2021). Most of the published reviews focused on the analysis of the behaviour of LC sensors during the calibration/validation processes (e.g., Alfano et al., 2020; Borrego et al., 2016; Delaine et al., 2019; Karagulian et al., 2019; McKercher et al., 2017; Rai et al., 2017), often highlighting the use of advanced statistical techniques (e.g., machine-learning algorithms) to improve their performance (e.g., Concas et al., 2021; Liang, 2021; Maag et al., 2018; Narayana et al., 2022). A number of reviews also described the characteristics of LC sensors/monitors for measuring particulate matter (e.g., Lung et al., 2022; Snyder et al., 2013; Yi et al., 2015) or gaseous pollutants (e.g., Baron & Saffell, 2017; Spinelle et al., 2017), or focused on crowd-sourced air quality studies (Thompson, 2016). Other reviews offered an overview of the relevant applications involving LC sensors or monitors (e.g., Clements et al., 2017; Kumar et al., 2015), or of the advances reached in their implemented technology (Idrees & Zheng, 2020; Mao et al., 2019; Morawska et al., 2018). On the other hand, an important aspect not adequately explored in the literature is the state of the art on the application of LC sensors for long-term monitoring and their integration within official air quality networks. This is a particularly relevant topic, since it considers the evolution of LC sensors from an innovative technology used for test and pilot applications to a consolidated technique which can provide a valuable support to traditional air quality monitoring. With the objective of filling this gap, the present review aims at taking a step forward by analysing the characteristics of already established LC air quality monitoring networks (i.e., those integrating stations that have already passed the calibration/validation processes) that were run across "long-term" (at least 3-month long) field campaigns, with an eye on detecting critical issues, deficiencies, or inconsistencies that emerged in the studies reviewed. All issues related to LC sensor calibration/validation processes are beyond the scope of the present review, and have, therefore, not been addressed. In particular, concerning (either currently ongoing or disabled) LC air quality monitoring networks, the aim of this work is to review the existing literature in order to: (i) identify the main aims lying behind their use; (ii) investigate their main characteristics as well as those of their monitoring campaigns; (iii) assess if they are/were integrated into the local official air quality monitoring framework; (iv) consolidate the most insightful suggestions and recommendations delivered by the scientific literature about their optimal deployment; (v) analyse still open research issues and outline possible future challenges.

The following rationale has been used in the organization of this review article. The methodology of the paper research, including the relevant literature collected, the automatic search query, and the inclusion and exclusion criteria, is introduced in Section 2. Section 3 presents an overview of the LC network applications found in the literature, detailing geographical distribution, campaign timespan, pollutants monitored and sensor technology used, all supported by a quantitative analysis, while these results are discussed in Section 4, focusing on strong and weak points of LC sensor networks. In the concluding Section 5, remarks are made on the insights gathered in the previous sections, providing

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indications on possible future directions to overcome the current limitations hindering the widespread diffusion of LC sensor networks.

2 | MATERIALS AND METHODS

Following the definition adopted by McKercher et al. (2017), it is useful to distinguish the term "sensor," standing for the measuring component, from "monitor" or "station," referring to the whole monitoring system, consisting of one or several sensors and communication/data components.

The procedure implemented to address the paper selection was a two-stage one, including (i) an automatic query via a search engine, and (ii) a manual selection/filtering based on specific inclusion/exclusion criteria. The automatic paper search was conducted using the Web of Science (WoS) search engine by entering a set of keywords in order to accommodate as much material as possible. The query's keywords were various spellings of terms like "sensor network," "low-cost," "inexpensive," "air quality," "pollutant," "open-source," etc. The query was restricted to the English language and included original research studies classified as articles, books, or book chapters and reviews. No filter was set on the publication year, so that all papers ever published on the subject were considered. Full details on the query run on WoS are provided in Table 1.

This literature body was then subjected to a manual filter based on a number of selection criteria. As detailed in Table 2, only papers focusing on real-case applications performed by deploying outdoor-operating and fixed (stationary) LC air quality monitoring stations, that integrate sensors already calibrated and validated, were

TABLE 1 Details of the paper automatic search.

Indexing database	Web of Science (WoS)
Query equation	(TS = ((sensor network*) AND (low-cost OR lowcost OR low cost OR opensource OR open source OR inexpensive) AND (air-quality OR air quality OR pollution OR pollutant*))) AND LANGUAGE: (English) AND DOCUMENT TYPES: (Article OR Book OR Book Chapter OR Review)
Query timespan	All years
Query indexes	SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, BKCI-S, BKCI-SSH, ESCI, CCR-EXPANDED, IC.
Running date	10/06/2022
Results found	684

TABLE 2 Criteria set for the paper manual selection.

Item	Condition	Comments
General		
Type of study	Real-case application based on measured data	For example, merely theoretical studies only reporting methodologies, recommendations, guidelines, etc., are not considered
Application	Combination of monitoring network, campaign duration and pollutant(s)	The same network measuring different pollutants or across different periods results in a different application
Sensor/station		
Environment	Outdoor	
Position	Fixed (stationary)	For example, mobile sensing is not considered
Pollutants	No filters applied	
Sensor technology	Aerosol Photometer (AP) Electrochemical (EC) Gas-sensitive semiconductor (GSS) Light scattering (LS) Metal oxide semiconductor (MOS)	For particulates, nephelometers and optical particle counters (OPC) are grouped into light scattering (LS)
Calibration and validation	✓	Only calibrated and validated sensors are considered
Network of low-cost stations		
Size	Number of stations ≥3	
Deployment time span	Number of days ≥90	At least one season should be covered during the campaign
Field application of validated stations	✓	Only field operated networks are considered

selected. No filter was set on the monitored air pollutants, which can be either gas- or particle-phase pollutants. In this review, a "network of LC stations" was defined as an array of at least three LC stations deployed over a homogeneous area, fully incorporating the remarks by Morawska et al. (2018) that a large number of monitors and locations does not necessarily constitute a network unless they are linked together or transmit information to a central location. As for the deployment timespan, only networks being operative for at least 90 consecutive days (3 months) were considered. An "application" was considered any combination of monitoring network, campaign duration, and pollutant(s) monitored, so that any variation of either campaign duration or pollutants—even relating to the same geographically referred network—resulted in a different application. Noteworthy, papers solely dealing with sensor calibration and/or validation without conducting an actual monitoring campaign were excluded. The results presented in Section 3 are based on the quantitative analysis of the 77 papers selected with this procedure, focusing on different network characteristics, namely: (i) geographical location; (ii) pollutants monitored; (iii) sensor technology; (iv) network size and campaign timespan; (v) possible integration with official air quality networks. In addition, an analysis of the main aims lying behind the deployment of the LC networks and a critical discussion on the most insightful recommendations delivered by the authors were also addressed.

3 | RESULTS

3.1 | Overview on the selected studies

A total of 684 research papers were initially retrieved after applying the query equation on WoS on 10 June 2022 (Table 1). The second step of the procedure, conducted by applying the filtering criteria set out in Table 2, ultimately returned a total of 77 studies, which constitute the definitive body of literature reviewed. The full list of such studies, also detailing the geographical location of the networks, is presented in Table S1, while the same list reporting the main characteristics of the reviewed networks is presented in Table S2.

Overall, the studies span from 2014 to 2022. A closer look at their publication year (Figure S1), however, reveals that only a few studies were published in the earlier years. Only since 2019, the long-term application of LC air quality monitoring networks has become a quite popular topic within the scientific community, with 17–22 publications per year, a figure that should expectedly be matched or even exceeded at the end of 2022.

3.2 | Aims for network deployment

The body of literature reviewed was first investigated in order to detect the different aims—selected among the most relevant ones—lying behind the deployment of LC air quality monitoring networks (Figure 1). The results indicated that increasing the spatiotemporal resolution of the monitoring campaign was by far the prevailing aim (63.6%), while assessing sensor monitoring accuracy and testing calibration techniques or models were also frequently pursued (41.6% and 33.8%, respectively). Within about 30% of the papers, network deployment was performed in order to integrate or assimilate LC measurements within other monitors or numerical/statistical models, analyse specific pollution episodes or processes, or detect patterns or location of emission sources. A further reported aim (24.7%) was assessing sensor monitoring durability.

3.3 | Geographical location

The geographical location of the LC air quality monitoring network applications reported in the selected papers is graphically presented in Figure 2 and summarized in Table 3. The analysis only refers to those applications explicitly reporting information about countries and continents where the networks were deployed, which overall summed up to $N = 87$. The majority of the applications were performed in Europe (37.9%) and America (36.8%), while a lower fraction was found in Asia (12.6%), Oceania (8%), and Africa (4.6%). The detailed locations in Europe are shown in Figure S2. At the country level, the absolute highest number of applications was found in the USA ($N = 28$), sharing about 1/3 (32.2%) of the total applications (Figure S3). Dramatically outranked, Australia, China, Italy, and UK ($N = 5$, 5.7%) trail in this table, while a total of 13 countries (14.9%) only returned a single application (1.1%). At city or regional level, the

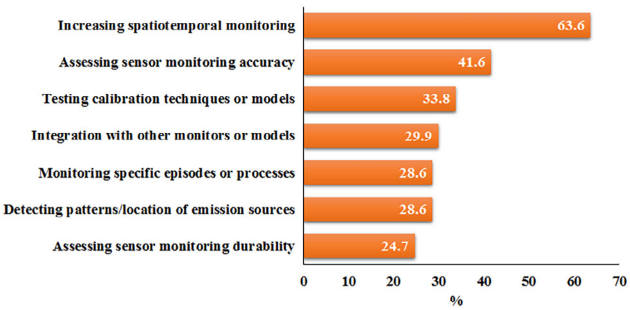

FIGURE 1 Main aims for network deployment pursued within the selected papers.

FIGURE 2 Geographical location, sorted by number of applications, of the low-cost air quality monitoring networks described within the selected papers.

highest number of applications was again addressed in the USA (Figure S3), such as in Los Angeles ($N = 7$), Pittsburgh (6) and Imperial County (4), while 3 applications are reported from Barcelona (Spain) and Sydney (Australia, Figure 2). Indeed, considering applications relating to the same location, it should be noted that the same network was often used for different applications.

3.4 | Monitored pollutants

As shown in Figure 3, most of the examined studies (62.3%) reported network applications measuring a single pollutant, while fewer studies reported networks investigating two (20.8%), three (7.8%), or more (9.1%) pollutants.

Figure 4 shows the share of the pollutants investigated within all the network applications ($N = 136$) reported in the selected papers. The majority of such applications ($N = 56$, 41.2%) focused on measuring $PM_{2.5}$, while a lower attention was paid to PM_{10} ($N = 18$, 13.2%), and particularly PM_1 ($N = 3$, 2.2%) and black carbon (BC) ($N = 1$, 0.7%). As for gas-phase pollutants, quite comparable shares were found for NO_2 (14.7%), O_3 (11.8%), and CO (10.3%), while nitrogen monoxide (NO) was only measured within 4.4% of the applications. SO_2 ($N = 2$, 1.5%) was rarely measured, while no applications on volatile organic compounds (VOCs) were found.

3.5 | Sensor technology

The analysis of sensor technology was addressed by separating sensors aimed at measuring gaseous pollutants from those measuring particle pollutants. As for the former, about 2/3 (67.6%) used the electrochemical (EC) technology, while metal oxide semiconductors (MOS, 18.9%) and gas-sensitive semiconductors (GSS, 13.5%) were less frequently applied (Figure 5). As for the particulates, all pollutants were measured by implementing light scattering (LS) technology.

3.6 | Network and campaign characteristics

To assess network characteristics, the number of stations and the duration of the related monitoring campaign were analysed. Since various papers included multinetwork applications, the number of stations and the corresponding duration have been disaggregated by monitoring network (Table S2). Overall, a total of 111 networks deploying a total of 7734 stations were found. Looking at the total number of stations deployed within the monitoring networks (Figure 6), the latter are mainly constituted by 3–10 stations (46.8%), while a comparable fraction (45%) accounts for networks including 10–100 stations. Networks deploying a number of stations between 100 and 500 sum up to 6.3%, while two papers

Continent	No. applications (%)	Country	No. applications (%)
Africa	4 (4.6)	Malawi	1 (1.1)
		Rwanda	1 (1.1)
		Togo	1 (1.1)
		Uganda	1 (1.1)
America	32 (36.8)	Canada	1 (1.1)
		Chile	2 (2.3)
		Colombia	1 (1.1)
		USA	28 (32.2)
Asia	11 (12.6)	China	5 (5.7)
		India	1 (1.1)
		Israel	1 (1.1)
		Malaysia	1 (1.1)
		Russia	1 (1.1)
		Taiwan	2 (2.3)
Europe	33 (37.9)	Austria	1 (1.1)
		Czech Republic	2 (2.3)
		Finland	1 (1.1)
		Greece	4 (4.6)
		Italy	5 (5.7)
		Netherlands	3 (3.4)
		Norway	2 (2.3)
		Poland	2 (2.3)
		Serbia	2 (2.3)
		Slovenia	1 (1.1)
		Spain	3 (3.4)
		Switzerland	2 (2.3)
		UK	5 (5.7)
Oceania	7 (8.0)	Australia	5 (5.7)
		New Zealand	2 (2.3)
Total			87 (100.0)

TABLE 3 Share by continent and country of the low-cost air quality network applications reported within the selected papers.

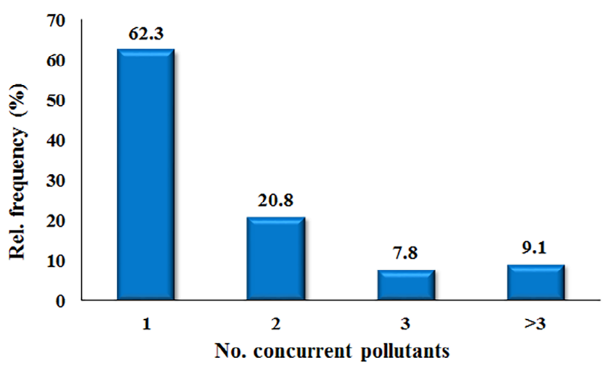

FIGURE 3 Number of pollutants concurrently measured within the selected papers.

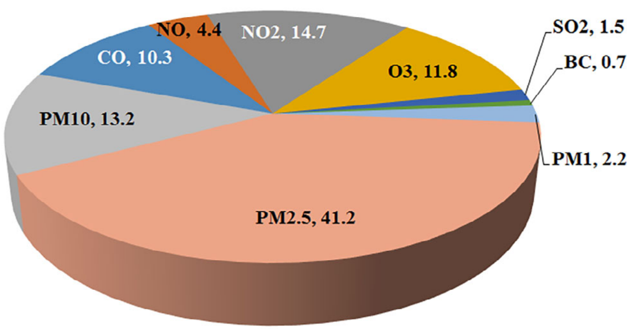

FIGURE 4 Share (%) of air pollutants measured within the analysed applications.

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(1.8%) report network applications even involving some 2000–3000 stations.

Concerning the timespan of the monitoring campaigns involving the reviewed networks (Figure 7), the analysis reveals that the campaigns were mostly carried out for a period of 6–12 months (37.8%). Shorter (3–6 months) or longer (12–24 months) field campaigns are also rather common, with percentages of 27.0% and 24.3%, respectively. About 10% of the field campaigns lasted between 2 and 3 years, while even longer applications are quite rare (0.9%). The average campaign duration slightly exceeds 1 year (393 days).

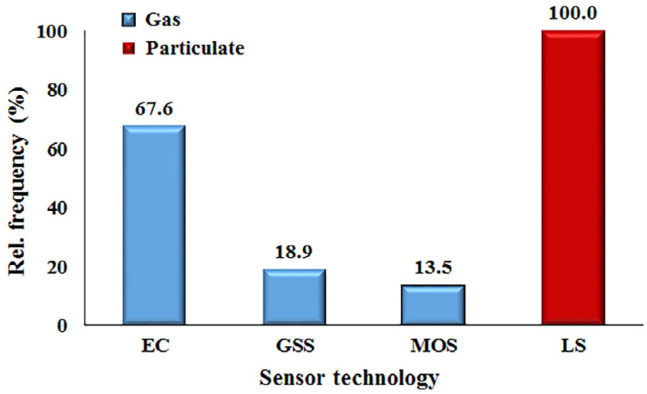

FIGURE 5 Sensor technology by pollutant type ($N_{gas} = 37$; $N_{part} = 58$) used within the analysed applications.

3.7 | Networks integrated into the local regulatory framework

Only a small fraction of LC monitoring networks (17.1%) proved to be integrated into the local official air quality framework. However, if considering the number of stations belonging to such integrated LC networks, that is, the number of single integrated stations, this figure dramatically increases to 68.9%, that is, 5325 over 7734. This may be seen in Figure 6, showing that high frequencies occur for the largest bins: for example, integration involves about 1/3 of the LC networks including between

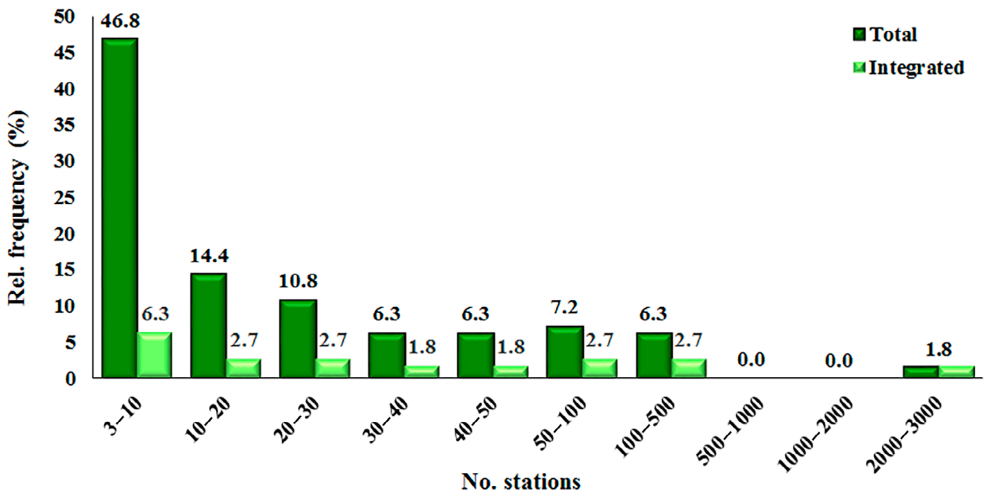

FIGURE 6 Number of stations deployed in the low-cost monitoring networks within the selected papers, sorted by their total number and those integrated into official regulatory networks.

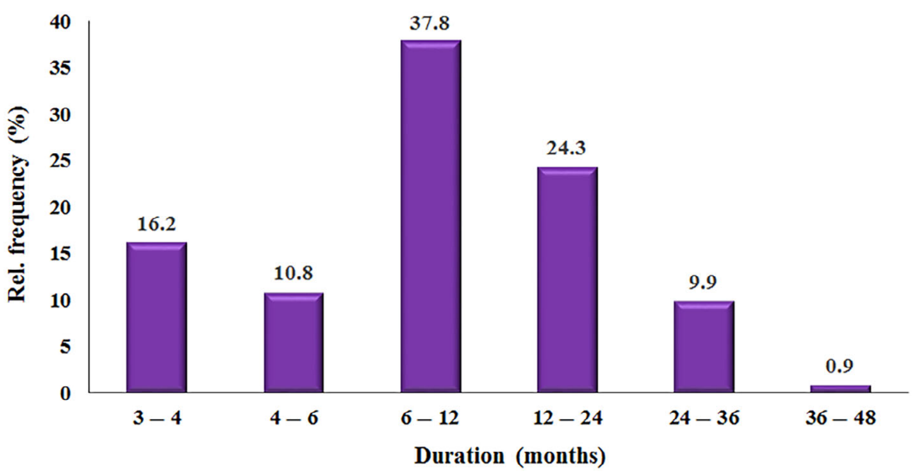

FIGURE 7 Duration of the network field campaigns described in the selected papers.

50 and 500 stations, and all the networks including between 2000 and 3000 stations.

3.8 | Main recommendations delivered

The analysis of the reviewed scientific papers also allowed identifying a number of recommendations delivered by the Authors following the development and deployment of the LC air quality monitoring networks. These recommendations have been selected among those of broader/general relevance, thus excluding those focusing on minor/local issues, so that a total of seven was eventually consolidated (Figure 8). Urging deployment of dense LC sensor networks, resulting in higher efficiency in capturing the whole spatial and temporal air pollution variability than sparse reference monitoring networks is the predominant recommendation, delivered in over 3/4 (75.3%) of the analysed literature. A second issue is the need to perform in-situ sensor calibration, especially by comparing LC sensor measurements against those from official reference stations, which was indicated within 46.8% of the selected papers. Further recommendations include integration of LC stations into reference networks and/or assimilation into models (31.2%), investigation of emission patterns and source locations (31.2%), detection and understanding of the seasonal/weather factors affecting sensor measurements (28.6%), indication about the best calibration techniques or models (23.4%), and need to create protocols for sensor maintenance (16.9%). The statistics also showed that in 13% of the papers only one such recommendation was delivered, while two recommendations were delivered by 39% of the papers. More generous with advice and suggestions (4) were 9.1% of the papers, and even more (5) 6.5% of the papers.

4 | DISCUSSION

4.1 | Aims and findings

The analysis of the papers selected for this review confirms, as highlighted by various Authors (e.g., Clements et al., 2017; Concas et al., 2021; Lung et al., 2022; Morawska et al., 2018), that the main purpose for running LC air quality sensor networks is to increase the spatiotemporal resolution of air pollution monitoring (Figure 1), useful for peak event identification or to link pollution levels to people's exposure. Due to the high granularity of their collected data, dense LC networks are able to capture pollution hotspots (Bi et al., 2020a), while the high-time resolution of LC measurements allow data to be categorized by time of day, season, and meteorological condition, helping to better understand the role played by different factors such as emission sources, land cover, built environment, and human behaviour (Eilenberg et al., 2020; Zimmerman et al., 2020). Moreover, the higher flexibility and ease of deployment of LC monitors allow them to be used for evaluating the impact on air quality of singular particular activities or events, which cannot be usually monitored with regulatory networks.

Several interesting findings were achieved within the reviewed papers, demonstrating the potentiality of LC networks to greatly expand the air quality monitoring

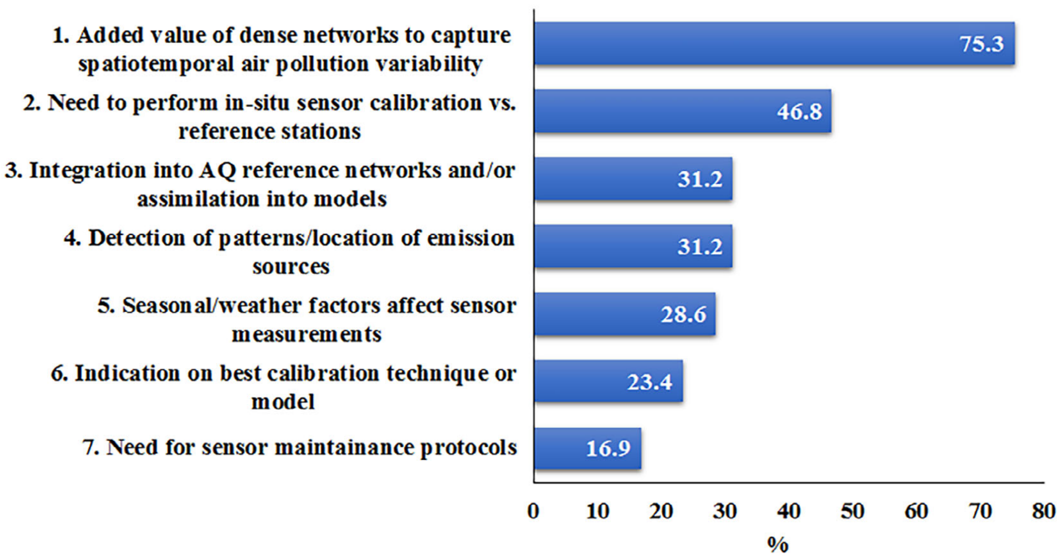

FIGURE 8 Main recommendations delivered in the selected papers.

capability. LC networks allowed, for example, investigating ship emissions in harbour areas (Jayaratne et al., 2020; Merico et al., 2019), identifying restaurants as an important local contributor to $PM_{2.5}$ concentrations (Eilenberg et al., 2020; Kosmopoulos et al., 2022), finding that local sources are responsible for only a fraction (30%) of the total $PM_{2.5}$ in the urban core while the rest is transported from other areas (Kosmopoulos et al., 2022), identifying the best hours to practice physical activities in the open air (Nieckarz & Zoladz, 2020), improving air pollution monitoring during special events (Chao et al., 2021; Kuhn et al., 2021), and evaluating the impact on air quality of the Covid-19 pandemic (Chadwick et al., 2021; Davidović et al., 2021; Mohd Nadzir et al., 2021; Mousavi & Wu, 2021), forest fires (Stavroulas et al., 2020), fireworks (Petäjä et al., 2021), a stone quarry (Molho et al., 2019) and a volcano (Whitty et al., 2020).

4.2 | Geographical location

The implementation of LC networks would be important especially in low-income countries, where regulatory air quality networks do not exist or are sparse. Many African countries, for example, have among the highest estimated annual average PM concentrations, yet they are also among those with the lowest number of regulatory PM monitoring stations per capita (Malings et al., 2020). Conversely, confirming outcomes from other Authors (e.g., Liang, 2021), air pollution hotspots such as India, Central China, Southeast Asia, Africa, South America, and Eastern Europe have not received much attention within research applications (Table 3 and Figure 2). Furthermore, the spatial distribution of networks deployed in developed countries is also highly heterogeneous. For example, sites in the USA tend to cluster in the coastal regions, while the midwestern regions display a large vacancy (Figure S3). China exhibits a similar pattern, as more developed provinces and several key cities (e.g., Beijing, Shanghai, and Xi'an) have received higher attention (Figure 2).

A contribution towards the spreading of LC networks and the homogenization of their geographical distribution could be given by the growth of commercial initiatives (e.g., Bi et al., 2020b; Collier-Oxandale et al., 2022). However, the practical use of their measurements is still hindered by their reliability, which can be affected by malfunctions or biases due to environmental conditions or non-conventional positioning (Miskell et al., 2017), also considering that LC sensors composing these networks may be operated by citizens without particular technical expertise. As will be highlighted in Section 4.5, special post-processing approaches should be developed to assure sufficient data quality (Mousavi & Wu, 2021).

4.3 | Sensors and technology

One of the most widely recognized issues affecting LC sensors, also highlighted in many of the reviewed papers, is that they suffer from the interference of various environmental factors, mostly air temperature and relative humidity (Barcelo-Ordinas et al., 2019; Bi et al., 2020a; Broday et al., 2017; Liu et al., 2020; Mueller et al., 2017; Petäjä et al., 2021; Stavroulas et al., 2020). In addition, it is well known that LC sensors are prone to cross-sensitivities with other ambient pollutants (Bart et al., 2014; Concas et al., 2021; Rai et al., 2017). For example, O_3 EC sensors undergo redox reactions in the presence of NO_2, while NO has been observed to interfere with NO_2 (Mead et al., 2013). Furthermore, $PM_{2.5}$ sensors give different responses to different types of aerosol (Castell et al., 2017), and thus to different aerosol sources, for example, fresh traffic emissions, aged traffic emissions, industrial emission sources, marine aerosol, and urban background (Liu et al., 2020). In measuring gaseous pollutants, EC sensors are generally preferred over GSS and MOS (Figure 5), mainly because they consume less power and are less impacted by higher humidity and temperature, while, conversely, they have a shorter lifespan (Narayana et al., 2022). The great popularity of LS sensors in PM monitoring (Figure 5) is due to their very low cost, limited power consumption, and low maintenance efforts (Concas et al., 2021), while their recognized disadvantages include the failure to detect very small particles (Koehler & Peters, 2015; Morawska et al., 2018; Rai et al., 2017) and sensitivity to temperature and humidity (Narayana et al., 2022). LS is actually an umbrella term that encompasses multiple measurement technologies. Nephelometers, for example, measure the light scattered by multiple particles entering the instrument and relate scattered-light intensity to aerosol mass concentration (Sorensen et al., 2011). Optical Particle Counters (OPCs), instead, are more sophisticated instruments able to detect light scattering due to single particles. OPCs can actually determine number concentration and aerosol size distribution (Kulkarni et al., 2011). Nevertheless, this distinction was often not considered by the examined papers, simply identifying these instruments as "light-scattering," and partly hindering the interpretation of the results. Different LS technologies are also differently affected by changes in aerosol and environmental properties (Hagan & Kroll, 2020), but these differences were often not taken into account in the reviewed papers, due to the confounding factors detailed above.

4.4 | Campaign timespan

In agreement with the findings reported by Concas et al. (2021), only 35.1% of the reviewed applications lasted for more than one year (Figure 7), highlighting that in most cases, LC networks are still used for test applications or specific projects and are not part of long-term efforts aiming at routinely monitoring air quality conditions. Short monitoring activities do not allow for a complete evaluation of the performance of LC monitors, since it is well known that one of the most important weaknesses affecting this kind of sensors is the tendency to present long-term drifts. Field campaigns longer than one year should be run in order to capture seasonal phenomena and the effects of different weather patterns, allowing for a better characterization of the long-term performance of these sensors, that in many cases is still not well understood (Castell et al., 2017; Liu et al., 2020). Furthermore, periods shorter than one year prevent the LC measured pollutant concentrations from being compared against reference yearly air quality limit values.

4.5 | Network management

LC sensor lifecycle management with minimal need for manual intervention is a critical issue for continuous long-term operation, considering in particular the procedures to continuously assure data quality (Concas et al., 2021). A common approach to guarantee long-term data quality is to periodically calibrate LC sensors against reference measurements as well as to periodically check sensitivity and uncertainty associated with sensor technology. In this regard, different papers highlight that the choice of the calibration period strongly affects the sensor performance. Sufficiently long calibration periods should be used, in order to explore a wide range of meteorological conditions and pollutant concentrations. In particular, it is crucial that the calibration period covers all the environmental conditions expected during the operational deployment (Kim et al., 2022; Ratingen et al., 2021; Wei et al., 2020). However, sensor calibration next to reference sites is time consuming (Mueller et al., 2017) and can represent a major obstacle to their widespread deployment (Broday et al., 2017). Moreover, this approach does not guarantee continuous data collection. For this reason, in situ and on the fly calibration methods have been recently developed, mainly exploiting machine learning techniques (Bagkis et al., 2022; Considine et al., 2021). Near-real-time calibration approaches can also be used to continuously monitor sensor performance over time, for the early detection of sensor failure or progressive data quality degradation (Mueller et al., 2017). In this regard, it would be important to develop standardized tools and procedures aiming at timely identifying low-quality data, allowing for the continuous determination of the reliability of LC network measurements (Collier-Oxandale et al., 2022). A strategy also recommended in different works to improve the reliability of LC network data is not to deploy LC sensors individually, as co-location of multiple sensors providing redundancy allows for the detection of faults/outliers and ensures full data coverage (Bart et al., 2014; Bulot et al., 2019).

4.6 | Integration into official networks

As highlighted by Collier-Oxandale et al. (2022), regulatory agencies are now beginning to explore the possibility to integrate LC monitors into official networks, but the documented implementations still appear to be limited. In fact, even if, within the reviewed applications, over 2/3 (68.9%) of the deployed LC stations proved to be integrated into official networks, this score mostly involved a few networks with a large number of stations (Figure 6), which expectedly are the networks most suitable to be integrated. However, different studies have proven that the permanent integration of LC monitors into official networks is beneficial for increasing the spatial and temporal resolutions of air pollutant monitoring (Liu et al., 2020), allowing the achievement of novel insights with respect to traditional networks (Petäjä et al., 2021), as highlighted in Section 4.1. Moreover, dense LC networks can be useful for addressing current limitations in the spatial coverage of government air monitoring, to provide real-time warnings of high pollution episodes to vulnerable populations (Seto et al., 2019). For example, within a 5-month LC monitoring campaign in the Imperial Valley (CA, USA), more than 50% of $PM_{2.5}$ critical episodes identified by the 38 community stations were not observed by the government monitors (English et al., 2020; Seto et al., 2019).

The integration between LC and regulatory networks can be beneficial also for improving the quality of LC sensor data, if reference measurements are used as trusted proxies (Bi et al., 2020b; Davidović et al., 2021; Weissert et al., 2020). For example, the integration of data from regulatory stations and LC sensors allowed the US Environmental Protection Agency (EPA) to develop quality control procedures to correct and operationally use data from LC networks (Collier-Oxandale et al., 2022). In this regard, the approach proposed in different studies is to build a hierarchical network, in which a limited number of high-quality, regulatory-grade measurement sites provide trusted information to calibrate and correct LC sensors, which, in turn, allow for increasing the spatial

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and temporal resolutions of the network and for capturing details, that, otherwise, would not have been seen by the official stations alone (Weissert et al., 2020).

4.7 | Integration with other observing techniques or model simulation tools

While the integration of LC networks into the official monitoring framework still appears to be limited, the reviewed papers highlighted that measurements from LC monitors are often used in combination with other observation techniques or modelling tools to expand air quality monitoring capabilities, for example, merging LC sensor data with satellite measurements or assimilating them into dispersion models (Figure 1). Integration of data from several sources, including LC networks, is a desirable strategy to optimally exploit the strong points of the different techniques, while limiting their weaknesses, in a data fusion perspective (Ferrer-Cid et al., 2020). For example, denser monitoring networks, such as those integrating several LC stations, improve the accuracy and robustness of surface $PM_{2.5}$ estimates from satellites, providing better estimates than those achieved by using the nearest surface monitor alone (Malings et al., 2020). Particularly in developing countries, combining satellite-based air quality monitoring and ground-based LC sensors could efficiently cope with the lack of traditional reference ground-based air quality monitoring. On the other hand, merging satellite, reference, and LC stations can improve the spatial resolution and extension of pollution maps (Bi et al., 2020a, 2020b; Li et al., 2020; Lin et al., 2020). Furthermore, land use regression models can help to extend the spatial information provided by LC monitors over points not covered by the network (Masiol et al., 2019).

4.8 | Delivered recommendations

Conforming to the critical viewpoint taken by Concas et al. (2021) within their review, a number of critical issues have been detected in the recommendations returned by the reviewed papers. Following the analysis addressed in Section 3.8, it can be concluded that the two most popular recommendations are also the most obvious to deliver (Figure 8). As for recommendation #2, however, Morawska et al. (2018) pointed out that many research studies did not conduct any sensor/monitor testing, but only relied on the manufacturer's information for the application of the sensors. Surprisingly, recommendation #1 is the sole recommendation delivered by 10.4% of the papers. These results give an idea of a certain limitation in the variety of advice delivered by the reviewed articles, and that not many studies provide actual and constructive guidelines on the use of LC networks. Furthermore, several research issues still remain open and worth fully addressing, as will be discussed in the next Section.

5 | CONCLUDING REMARKS AND RECOMMENDATIONS FOR FUTURE DIRECTIONS

The present review of literature studies focusing on long-term LC sensor networks highlighted that in recent years, the scientific interest on this topic has substantially grown, with an increasing number of publications presenting a wide range of applications in different countries. However, the analysis of these papers also revealed that several limitations are still present, considering both their geographical diffusion and the purpose of the applications, which in many cases are connected to isolated research projects and remain at a demonstration level, without a real integration of LC monitors in reference air quality observing networks.

Considering the geographical distribution, results showed that most applications are displaced over developed countries (Table 3 and Figure 2), whereas, by contrast, developing countries are those that would actually require a higher monitoring coverage with LC networks, since, on the one hand, they are hotspots for generally higher pollution levels, and, on the other hand, they suffer from a low number of official stations, due to their limited resources (Coker et al., 2021). In this regard, LC sensor networks, suitably integrated with regulatory-grade stations, would be a strategic asset for planning and establishing robust and cost-effective air quality monitoring networks in low- and middle-income countries, as also highlighted by Gulia et al. (2020b) and Munir et al. (2019b).

The portability of LC sensors makes them ideal devices for improving the monitoring capabilities also in remote or hard-to-access regions worldwide, such as, for example, the Arctic (Carotenuto et al., 2020), or the open sea (e.g., on buoys), that is, where the lack of NO emissions consuming O_3 and the rather low mixing height are expected to result in O_3 summer concentration peaks, that are generally unknown. Furthermore, the portability of LC sensors makes them a much more affordable solution than mobile air quality monitoring campaigns, often carried out by government agencies to tackle specific air pollution issues.

As mentioned above, this review also highlighted that in most cases, LC networks are still implemented only for test applications, with a few documented cases of a complete integration into the official network to improve the air quality monitoring capability on a permanent basis. In this regard, according to various authors (e.g., Schäfer et al., 2021), the development by official environmental authorities of certifications on LC air quality sensors/monitors would be particularly helpful to support the systematic use of LC sensors. For example, protocols clearly dictating the optimal placement of LC stations within the urban infrastructure (elevation from the ground, clearance from nearby buildings, distance from roads, etc.) are still missing (Concas et al., 2021). On the other hand, the level of information delivered by the selected papers often lacks some relevant features, such as the type of sensors/stations deployed. On the contrary, protocols should be agreed by governmental authorities on classifying LC stations based on the deployment environment (urban, roadside, outskirt, rural, etc.) or the predominant emission source (traffic, industry, residential activities, agricultural activities, etc.), as shown, for example, by Idrees and Zheng (2020). In addition, there are currently no standardized protocols defining the number of nodes to be placed within a network to achieve sufficient coverage of any environmental pollutant (Morawska et al., 2018). Furthermore, in many of the reviewed papers, there was also a lack of information regarding the positioning of the stations, the effective duration of the campaigns and, in certain cases, even the number of nodes in the network. Due to all these issues, organizational frameworks linking LC measurements to those from the official air quality networks are still missing (Schäfer et al., 2021). A connected aspect often hindering the integration of LC sensor networks into the official air quality monitoring framework is the lack of standardized procedures/algorithms for sensor calibration. Therefore, in this regard, a decisive step for the widespread integration of LC monitors into official air quality networks will be the development and use of algorithms allowing the real time and on the fly calibration of LC sensors, which can guarantee continuous monitoring with adequate data quality.

A first step towards a harmonized combination of LC network data and classic air quality mapping methods in Europe has been recently promoted in the framework of FAIRMODE (Forum for Air quality Modeling, https://fairmode.jrc.ec.europa.eu/Activity/CT6), an initiative launched by the European Commission Joint Research Centre (JRC) for exchanging best practices about the integration of calibrated LC sensor data with the official measurements. In this context, several European research groups are working on a benchmarking exercise assimilating data from 1500 $PM_{2.5}$ LC sensors and exploring different methodologies.

The diffusion of LC sensor networks is also potentially connected with the engagement of the local community, which can be directly involved in air quality monitoring programs. This can be beneficial for the sustainable management of the LC sensor network, since citizens can ease the time-consuming effort of maintaining a large number of monitors (Becnel et al., 2019), providing that a minimum technical training is provided, in order to avoid measurement errors due to the incorrect operation of the stations. Moreover, the participatory approach is crucial for raising awareness on air quality issues, for example, involving schools or citizens' organizations in projects related to the installation and management of LC sensor networks, which can foster individual virtuous actions to reduce emissions.

In perspective, the high spatiotemporal granularity of LC measurements could provide a valid contribution to air quality improvement policies. In the case of pollutants monitored daily such as PM, for example, the high temporal resolution of LC sensor measurements could support the introduction into air quality regulations of intra-daily limits in addition to the current daily ones. As shown, for example, in Brilli et al. (2021), this would dramatically increase the assessment of population exposure to PM levels, but also would foster a better understanding of the dynamics and location of the emission sources.

In selecting the monitored pollutants, LC stations tend to conform to official measurements, generally focusing on the pollutants regulated by air quality regulations (Figure 4). This is often forced by the fact that calibration and/or validation of LC sensors are performed against data collected by the official networks. However, even considering this issue, it would be desirable to include new pollutants. For example, LC sensors for measuring ultrafine PM ($PM_{0.1}$), that pose greater risk to human health, should be included (Kumar et al., 2015): instead, due to the current LC technology limitations (Morawska et al., 2018; Rai et al., 2017), this pollutant was never monitored in the papers analysed in this review (Figure 4). To thoroughly characterize the dynamics of secondary pollutants, it would be desirable to also measure the concentrations of their precursors, thus indirectly inferring on their emission rates. While measuring O_3 concentrations, for example, it would be helpful to also monitor the different VOC species leading to O_3 formation; likewise, monitoring of $PM_{2.5}$ concentrations should be complemented by that of, for example, NH_3 (Gualtieri et al., 2022). Unfortunately, neither VOC nor NH_3 were measured within the selected studies (Figure 4).

To achieve sufficiently comprehensive air quality monitoring, O_3 measurements should never be decoupled from those of NO and NO_2, and vice versa. Likewise, the various size fractions of total PM (PM_{10}, $PM_{2.5}$, and PM_1)

should always be measured altogether. By contrast, these goals were rarely pursued within the reviewed papers, where in only 7.8% of the applications, 3 pollutants were concurrently measured, and in only 9.1%, the observations involved more than 3 pollutants (Figure 3). Markedly, NO, NO_2, and O_3 were concurrently measured in 5.2% of the papers, $PM_{2.5}$ and PM_{10} in 22.1% of the papers, and all these five pollutants in 3.9% of the papers.

LC sensors are particularly suitable for providing real-time warnings of high pollution episodes to population (e.g., wildfires, waste burning, accidental contaminants release, leaks in natural gas pipelines, fireworks, for example, Li et al., 2021; Lu et al., 2021; Petäjä et al., 2021; Seto et al., 2019; Veiga et al., 2021), particularly as these episodes are sudden and fast evolving and the higher spatial density of LC sensor networks increases the possibility to detect them. To this aim, possible inclusion of other pollutants such as, for example, polycyclic aromatic hydrocarbons (PAHs), heavy metals, hydrogen sulphide (H_2S), benzene (C_6H_6), dioxins, and furans would greatly increase the application field of LC sensors. The same can be said to tackle odour nuisances, an issue citizen communities often complain about (Clements et al., 2017): in this case, detecting chemical markers in addition to H_2S remains a challenge.

The possible introduction of specific chemical species could efficiently serve for assessing the chemical speciation of ambient PM, thus possibly tracing its origin and assessing its source-apportionment. Unfortunately, only one out of the reviewed studies analysed BC concentrations (Figure 4), while other PM chemical components such as organic carbon or elemental carbon were completely overlooked. Another key species to be monitored could be levoglucosan, which is a recognized tracer for biomass burning (Massimi et al., 2020). Further monitored species could be hematite (Fe_2O_3), magnetite (Fe_3O_4), and metallic Fe, which are the dominant PM type originating from abrasion from train and rail wear (Font et al., 2019). When measuring PM, it is also important to have a clear understanding of the sensor's measurement methodology (e.g., light-scattering nephelometers vs. light-scattering OPCs), in order to properly take into account the various factors that will influence the measurements (Hagan & Kroll, 2020).

If LC stations are complemented with sensors (again LC) that measure wind speed and direction, they could turn out to be emission-monitoring tools, as pollutant emissions directly released from the source could be measured. Among the others, this could apply, for example, to quite understudied emission sources typical of Asia and developing countries, such as biomass and agriculture open burning, tailpipe emissions from various locally made vehicles, fuel combustion for cooking and street cooking, incense burning, open waste burning, and fuel combustion for brick manufacturing (Lung et al., 2022).

The widespread and systematic use of LC sensor networks has also the potentiality to provide a significant contribution towards filling various knowledge gaps in air quality-related issues, being capable of handling specific air pollution phenomena that traditional official monitoring networks are unable to. One of main application fields could be to assess population exposure to pollution at or nearby particularly sensitive places such as schools and hospitals or close to specific emission sources, for example, petrol stations, construction sites, mining quarries, etc. (Schäfer et al., 2021). Other LC sensor network applications might include monitoring of areas poorly or not covered at all by the official networks, like city parks, road tunnels, rural areas, etc., or optimizing the positioning of new regulatory stations (Feenstra et al., 2020).

In order to achieve these objectives, it appears crucial that future strategies aiming at improving air quality monitoring capabilities will take advantage of all the new opportunities provided by technological advancement, combining information coming from different sources, among which LC air quality monitoring networks undoubtedly present enormous potentiality, even if still largely not exploited.

AUTHOR CONTRIBUTIONS

F. Carotenuto: Conceptualization (equal); data curation (equal); formal analysis (equal); investigation (equal); methodology (equal); visualization (equal); writing – original draft (equal); writing – review and editing (equal). **A. Bisignano:** Conceptualization (equal); data curation (equal); formal analysis (equal); investigation (equal); methodology (equal); visualization (equal); writing – original draft (equal); writing – review and editing (equal). **L. Brilli:** Conceptualization (equal); data curation (equal); formal analysis (equal); investigation (equal); methodology (equal); visualization (equal); writing – original draft (equal); writing – review and editing (equal). **G. Gualtieri:** Conceptualization (equal); data curation (equal); formal analysis (equal); investigation (equal); methodology (equal); visualization (equal); writing – original draft (equal); writing – review and editing (equal). **L. Giovannini:** Conceptualization (equal); data curation (equal); formal analysis (equal); investigation (equal); methodology (equal); supervision (equal); visualization (equal); writing – original draft (equal); writing – review and editing (equal).

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Carotenuto, F., Bisignano, A., Brilli, L., Gualtieri, G., & Giovannini, L. (2023). Low-cost air quality monitoring networks for long-term field campaigns: A review. *Meteorological Applications*, *30*(6), e2161. https://doi.org/10.1002/met.2161