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# Community-based and low-cost air quality monitoring: a global bibliometric analysis

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Air pollution is one of the most significant environmental challenges of recent years, and monitoring it through accessible, cost-effective methods is crucial to protecting public health. This study presents a comprehensive bibliometric analysis of the scientific literature at the intersection of citizen science, low-cost sensor technologies, and air quality monitoring, during the period 1996–2026. The study aims to systematically map the intellectual structure, thematic evolution, collaboration patterns, and future trends of this interdisciplinary field. A total of 2571 scientific publications from the Web of Science Core Collection and Scopus databases were analyzed using the bibliometrix package in R and VOSviewer software. Performance analysis, science mapping, co-citation networks, keyword co-occurrence analysis, and thematic evolution mapping were conducted. The field is rapidly developing with an annual growth rate of 15.27%. A total of 9642 authors and 978 scientific sources were identified. The USA is the most prolific country with 519 publications. The most frequently used keywords were LCS (559), air quality (432), and air pollution (349). The keyword clustering identified four main thematic clusters: sensor technologies and monitoring infrastructure; measurement and calibration; particulate matter (PM) characterization using machine learning; and citizen engagement and environmental equity. The international collaboration rate is 22.29%, and this rate is lower in developing countries and regions, such as Africa and South America, which remain significantly underrepresented. Community-based, low-cost air quality monitoring is one of the most dynamic subfields of environmental health research. Sensor calibration and data quality standardization remain the most critical research issues in the field. Capacity building in developing countries, strengthening the environmental justice dimension, and developing AI-assisted calibration methods are suggested as priority topics for future research.

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### Environmental significance

This bibliometric analysis provides a comprehensive overview of nearly three decades of research on community-based and low-cost air quality monitoring, highlighting key trends, influential studies, and emerging themes. By mapping the global research landscape, this work identifies critical knowledge gaps and future directions for citizen science-driven air quality monitoring, which is essential for addressing environmental justice and public health challenges in both developed and developing regions.

## 1. Introduction

Air pollution is one of the most dangerous environmental problems worldwide, adversely affecting the quality of life for millions of people.[1] According to the World Health Organization (WHO) 2021 report, approximately 7 million people die each year from diseases related to air pollution. It exposes billions to health risks.[2] The fact that this risk is substantially higher, particularly in developing countries, underscores the seriousness of the socioeconomic dimension of air pollution. The effects of air pollution on human health are diverse and serious. Respiratory diseases, early development of asthma, and decreased lung function are observed in children. On the contrary, there is an increased risk of cardiovascular diseases, hypertension, and heart attacks in adults.[3,4] An increase in cancer incidence, particularly pulmonary cancer and bladder cancer, is recorded. Air pollution leads to significant socioeconomic consequences, including economic losses, increased medical costs, and reduced employee productivity. Also, it impacts educational activities and further shortens already low life expectancy.[4,5]

Traditional air quality monitoring systems provide highly accurate measurements, but have significant limitations. Reference-level monitoring stations typically cost hundreds of thousands of dollars. They require complex technical maintenance and cannot cover large geographic areas with sufficient spatial resolution.[6] For example, many developing countries

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have only a few dozen monitoring stations across their entire national territory. It is impossible to detect air quality variability in urban, industrial, and rural microenvironments.[7] The lack of spatial resolution leads to the invisibility of disadvantaged communities, especially those most exposed to air pollution.

The evolution of air quality monitoring technology has undergone rapid and innovative transformations over the last century. Beginning with manual sampling and gravimetric methods in the early twentieth century, the process gained much momentum in the 1970s and 1980s with the establishment of automated continuous monitoring systems. Developed countries have created comprehensive monitoring networks. However, these networks have been limited to a small number of locations and have proven insufficient in capturing the spatial variability within cities due to their high costs. Since the 2010s, rapid advancements in technologies such as micro-electromechanical systems (MEMS), electrochemical sensors, and optical particle counters have led to the emergence of low-cost sensors (LCS).[8,9] This new option extensively uses sensor-based systems for air quality monitoring.[10–14]

The proliferation of LCS has accelerated the integration of the citizen science movement into air quality research. Citizen science is a participatory research approach that enables non-professional individuals to actively participate in scientific research processes.[15] In relation to air quality, citizen science projects allow communities to measure air pollution in their surroundings, share data, and contribute evidence-based information to environmental policies. For example, the PurpleAir network uses tens of thousands of low-cost $PM_{2.5}$ sensors worldwide to measure air quality. These measurements are presented visually with a real-time air quality map.[16] The CITI-SENSE project in Europe has supported public participation by establishing smart citizen observatories.[17] On the other hand, the AirCasting platform, established in America, facilitates community-based data collection using mobile and fixed sensors.[18] As a result of these projects, the spatial and temporal resolution of air quality data has been significantly increased.

Low-cost sensor technologies have played a significant role not only in outdoor air quality monitoring but also in the development of indoor air quality research. Given that people spend approximately 80–90% of their time indoors, monitoring exposure to pollutants such as volatile organic compounds (VOCs), particulate matter (PM), carbon dioxide ($CO_2$), and formaldehyde is of paramount importance.[19] The affordable and compact design of low-cost sensors has made it possible to conduct large-scale indoor monitoring campaigns in residences, schools, offices, and public spaces.[20,21] Furthermore, IoT-based low-cost sensor systems integrated with citizen science approaches have been successfully implemented, particularly in school settings, to increase students' awareness of air quality.[22] These developments have expanded the scope of air quality research beyond traditional outdoor fixed station networks, enabling research on personal exposure assessment and the health effects of indoor pollutants with unprecedented spatial and temporal resolution.[23]

However, the proliferation of LCS has brought with it some problems. For example, these sensors are significantly affected by environmental and meteorological factors such as temperature and humidity.[24] Also, calibration processes are also complex. Inconsistencies between sensors and performance degradation over time are commonly observed.[25] To address these inconsistencies and improve sensor resolution, machine learning-based calibration models have been shown to significantly improve sensor accuracy. However, the generalizability of these models across different geographical and climatic conditions remains under investigation.[26] Therefore, data quality assurance remains one of the most urgent issues in air pollution research. Therefore, the Environmental Protection Agency (EPA)'s efforts to standardize performance evaluation criteria for LCS are important steps.[27]

Bibliometric analysis, which examines scientific publications using comprehensive quantitative methods,[28,29] is an effective and valuable tool for understanding the development trends, intellectual structure, and subject-specific development of a research area. Bibliometric studies conducted using

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modern software such as Bibliometrix, VOSviewer, and CiteSpace help to create detailed scientific maps of research areas, identify key actors and leading organizations, and predict future research directions.[30–32] Bibliometric analysis not only provides quantitative data and statistics but also helps visualize how scientific knowledge flows, how collaboration is organized among researchers and institutions, and how ideas are exchanged. This approach and methodology have been successfully applied and found valuable in management science, librarianship, business, education, medicine, and many other academic disciplines. For example, to examine the status of Machine Learning (ML) applications in air pollution research, a bibliometric analysis was conducted using 2962 articles published between 1990 and 2021.[33] Similarly, a bibliometric analysis examined research performance on ambient air quality monitoring and management in South Africa between 2010 and 2021.[34] Although bibliometric methods have been increasingly applied across diverse environmental disciplines, including groundwater research[35] and natural hazard studies,[36] a comprehensive bibliometric analysis integrating both WoS and Scopus databases to map the intersection of citizen science, low-cost sensor technologies, and air quality monitoring has not yet been conducted. This study aims to fill this important research gap.

Most current bibliometric studies focus on traditional air pollution monitoring approaches or specific types of pollutants. Recent research highlights the rapid growth of low-cost sensor technologies and their applications in community-based monitoring networks.[37] They also analyzed the citizen science dimension by focusing on "low-cost sensors" using a single database,[38] by focusing only on Artificial Intelligence (AI) applications,[39] by focusing only on ML,[40] or by considering only urban areas.[41] This gap represents a significant deficiency in mapping both technological advancements and community participation dynamics. Furthermore, existing studies generally use a single database (WoS or Scopus), and an integrated analysis of both would provide a more comprehensive perspective. The main objective of this research is to conduct a comprehensive bibliometric analysis of the scientific literature on community-based, low-cost air quality monitoring published between 1996 and 2026. This study focuses on five fundamental questions to provide a clearer and more holistic overview of the field. First, it examines how scientific output in this field has changed over time and the direction of its growth trends. Second, it identifies the most productive countries, institutions, and journals and evaluates the structure of international collaboration networks. Third, it analyzes the field's thematic structure and keyword clusters to reveal how research topics have evolved. Fourth, it identifies the most impactful studies and prominent researchers in the field. Finally, it presents a framework for the future development of the field based on current trends. The answers to these questions aim to help researchers better understand the current body of knowledge in the field and to assist policymakers in developing scientifically evidence-based decisions.

## 2. Materials and methods

### 2.1 Data sources and search strategy

This bibliometric study uses data from the Web of Science (WoS) Core Collection and Scopus databases.[28,42] These two databases are among the most comprehensive and reliable sources of international scientific publications, covering a wide range of disciplines. The Web of Science Core Collection contains millions of articles that have indexed since 1990, including those in the social sciences and the arts and humanities. Scopus has covered a wide range of publications since 1996 and provides detailed information on articles published thereafter. The combined use of these two databases provides the most complete and balanced picture of the research area. The search strategy was designed based on the intersection of two main groups of concepts. The first group consists of terms representing community-based and participatory monitoring approaches: "citizen science", "community-based monitoring", "participatory monitoring", "crowdsourc*", and "low-cost sensor*". The second group consists of terms related to air quality: "air quality", "air pollution", "atmospheric pollution", and "ambient air". Searches were performed using the TS (Topic Search) field in WoS and the TITLE-ABS-KEY field in Scopus. For Web of Science, the TS (Topic Search) field was used, which searches titles, abstracts, author keywords, and KeyWords Plus: TS=("citizen science" OR "community-based monitoring" OR "participatory monitoring" OR "crowdsourc*" OR "low-cost sensor*" OR "low cost sensor*") AND TS=("air quality" OR "air pollution" OR "atmospheric pollution" OR "ambient air")

This search yielded 1878 records. No year restriction was applied, covering all publications from 1996 to 2026. Records were downloaded in BibTeX format with Full Record and Cited References selected. Due to the WoS platform's 500-record download limit for BibTeX format, the export was conducted in four separate batches.

For Scopus, the TITLE-ABS-KEY field was used, which searches titles, abstracts, and author keywords: TITLE-ABS-KEY ("citizen science" OR "community-based monitoring" OR "participatory monitoring" OR "crowdsourc*" OR "low-cost sensor*" OR "low cost sensor*") AND TITLE-ABS-KEY ("air quality" OR "air pollution" OR "atmospheric pollution" OR "ambient air"). This search yielded 2352 records. Again, no year restriction was applied. All citation information, bibliographical information, abstract, and keywords fields were selected, and records were exported in BibTeX format in a single download. The search was conducted in January 2026. Records from both databases were merged using the convert2df () function of the bibliometrix R package. During the merging process, DOI numbers served as the primary matching criterion for duplicate detection; for records lacking DOI information, a title–year–author triplet was used for matching. Priority was given to WoS records, and only Scopus records not found in WoS were added to the dataset. A total of 659 duplicate records were identified and removed. The final dataset comprised 2571 unique scientific publications. On the other hand, resources such as Google

Scholar and IEEE Xplore were not examined in this study. Although Google Scholar offers free access and broad coverage, it was not preferred for bibliographic analysis due to indexing ambiguities and the lack of control over data quality. Data were exported in BibTeX and processed using the bibliometrix package in R statistical software. Before analysis, records were excluded if they were incomplete, lacked author information, or lacked publication dates.

### 2.2 Bibliometric analysis methods

Bibliometric analyses were performed using the R programming bibliometrix package.[43] This R package systematically analyzes the relationships between publications, authors, citations, and scientific concepts using mathematical and statistical methods. Also, Co-citation analysis is a fundamental technique that reveals the intellectual connections between frequently co-cited articles.[44] Bibliometrix is an open-source package specifically designed for creating comprehensive science maps and includes tools for performance analysis, science mapping, network analysis, and summary analysis. VOSviewer (version 1.6.20) software was used as a complement for network visualizations.[32] VOSviewer can produce efficient maps for visualizing large-scale bibliometric networks. The keyword co-occurrence network and the inter-country cooperation network were created with VOSviewer. Thematic clusters were determined using the Louvain clustering algorithm in network analysis. The applications used and analyzed in this study are summarized in detail under the following headings:

**2.2.1 Performance analysis.** Firstly, the general bibliometric profile and characteristics of the dataset were extracted. This profile includes key indicators such as the total number of publications, the number of authors, the average number of publications per author, the co-authorship index, the number of publication sources, the average number of citations, and the *h*-index.[45] At that time, time-series analysis of the number of publications per year was conducted. After that, trends and growth rates were quantified. The most productive authors, institutions, and countries were identified and ranked; for this purpose, productivity indicators, including the total number of publications, average number of citations, *h*-index, and *m*-index, were calculated.

**2.2.2 Science maps.** Various science maps and network graphs were created to understand the intellectual and scientific structure of the research area. Co-citation analysis was systematically performed to identify frequently cited articles and the thematic clusters they formed.[44] Co-authorship network analysis reveals collaboration relationships and network connections among authors and institutions.[46] Keyword co-occurrence analysis reveals the relationships between frequently used keywords and identifies themes. The thematic map classifies the keywords into four categories: engine areas, basic themes, niche areas, and emerging themes, representing the various themes of the research.

**2.2.3 Network Analysis and Visualization.** All networks (co-authorship, keyword co-occurrence, *etc.*) are professionally visualized in R packages. In network analysis, node size is determined by the total number of publications or citations; edge thickness is determined by the strength and frequency of collaboration between authors or sources. Color coding indicates thematic clusters or temporal changes, facilitating analysis. These visualizations facilitate understanding of the structure and dynamics of the research areas.

## 3. Results

### 3.1 General bibliometric profile

The analysis identified 2571 scientific publications from 1996 to 2026. These publications have appeared in 978 different scientific sources (journals, conference proceedings, *etc.*). A total of 9642 authors contributed, with an average of 5.95 authors per publication. 155 publications, representing 6% of the total publications, were single-authored. The rate of international co-authorship was 22.29%. The average number of citations per publication was 17.57. The annual growth rate was 15.27%, reflecting the field's dynamic development. Table 1 summarizes the bibliometric analysis of publications (1996–2026).

Research articles constitute the largest share by publication type, with 1687 (65.6%). This is followed by conference papers (361, 14.0%), conference proceedings (251, 9.8%), and review articles (123, 4.8%). The relatively low proportion of review articles suggests that the field is still in its early stages of maturation. Researchers are focusing on primary data-generating studies. The 24% share of conference proceedings and articles together reflects the field's application-oriented nature and technology-development dimension.

### 3.2 Annual publication trends

Fig. 1 shows the annual scientific output graph. Although the dataset covers the full period 1996–2026, Fig. 1 shows annual output from 2005 to 2025 for clarity. The period prior to 2005 contained only sporadic publications (4 documents total between 1996 and 2004). When examining the field's chronological development, three distinct periods can be seen. The

Table 1 Summary of bibliometric analysis of publications (1996–2026)

| Description | Results |
|---|---|
| Timespan | 1996–2026 |
| Sources (count) | 978 |
| Documents (count) | 2571 |
| Annual growth rate (%) | 15.27 |
| Document average age (years) | 4.4 |
| Average citations per document (count) | 17.57 |
| Average citations per year per document (count/doc) | 2.613 |
| Authors (count) | 9642 |
| Author appearances (count) | 15 291 |
| Authors of single-authored documents (count) | 105 |
| Single-authored documents (count) | 155 |
| Documents per author (ratio) | 0.267 |
| Co-authors per document (ratio) | 5.95 |
| International co-authorships (%) | 22.29 |
| Keywords plus (ID) (count) | 5703 |
| Author's keywords (DE) (count) | 5201 |

first period, the pioneering period (2005–2012), is characterized by low and irregular publication numbers. Annual output during this period ranged from 1 to 5 publications, with no publications recorded in 2007. During this period, air quality monitoring was largely based on traditional reference stations, and low-cost sensor technologies were still in their infancy. Although the concept of citizen science was increasingly recognized in environmental science, its applications in air quality were quite limited. The second period, the growth period (2013–2018), shows a marked increase in publication numbers: 8 in 2013, 30 in 2014, 30 in 2015, 47 in 2016, 99 in 2017, and 138 in 2018. Two key developments may trigger this acceleration. Firstly, there is the increasing prevalence of open-source hardware platforms like Arduino and Raspberry Pi, and the release of affordable sensor modules from companies such as Shinyei, Alphasense, and Plantower. The second is published in science in 2014 and discusses the future of citizen science.[47] This work strengthened the scientific legitimacy of citizen science and attracted researchers from different disciplines to the field. The third period, the maturation and explosion period (2019–2026), is characterized by exponential growth: 175 in 2019, 270 in 2020, 269 in 2021, 328 in 2022, 322 in 2023, 369 in 2024, and 389 in 2025. The COVID-19 pandemic may affected this period in two ways: it accelerated research documenting improvements in urban air quality using low-cost sensor networks during lockdowns. Also, it raised awareness of the role of community-based monitoring in responding to urgent environmental health crises. The widespread adoption of artificial intelligence and ML-based calibration methods has sparked a new wave of research since 2022.

### 3.3 Source analysis

The journal with the highest number of publications was Sensors (158 publications, $h$-index = 32), followed by Atmosphere (128, $h = 20$) and Atmospheric Environment (71, $h = 24$). Sensors' leading position reflects the dominant role of low-cost sensor technologies in the field. Its open-access policy may also enhance its publication attractiveness. Although Atmospheric Environment has a relatively low number of publications, its high $h$-index suggests that its studies have a higher citation impact. Science of the Total Environment (69, $h = 26$), Atmospheric Measurement Techniques (57, $h = 25$), and Aerosol and Air Quality Research (50, $h = 15$) are among other important sources. Table 2 shows that journals have a high citation impact despite relatively few publications, indicating a strong scientific influence.

Bradford Law analysis revealed that only three journals are located in the core region (Zone 1): Sensors, Atmosphere, and Atmospheric Environment. These three journals account for approximately one-third of the total publication volume. Zone 2 includes journals such as Science of the Total Environment, Environmental Science and Technology, Aerosol and Air Quality Research, and Environmental Pollution. This distribution demonstrates a strong concentration of journals within the field. The concentration of core journals across both sensor technologies (Sensors) and atmospheric sciences (Atmosphere,

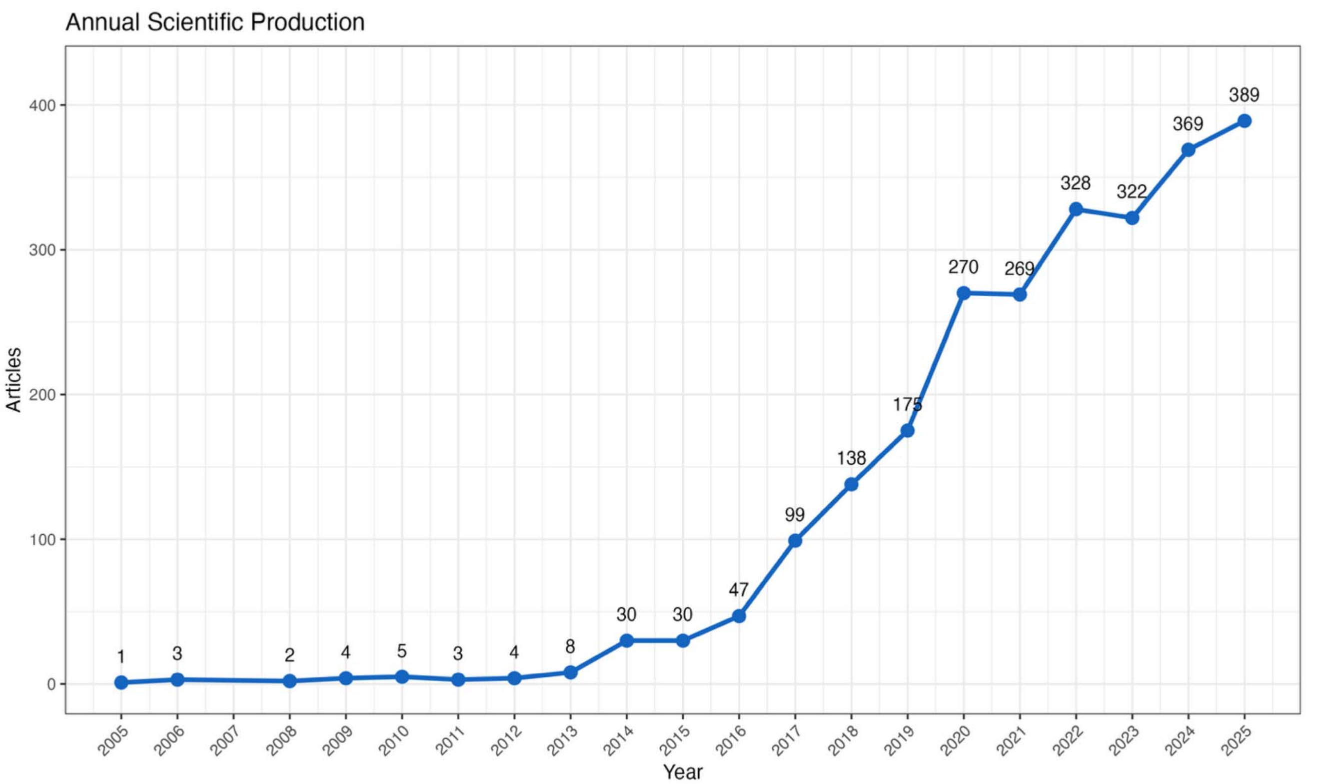


Fig. 1 Annual scientific output (2005–2025).

Table 2 Journal-level bibliometric indicators and publication performance for community-based and low-cost air quality monitoring research

| Source | Number of articles published | h_index | Total_Citations |
|---|---|---|---|
| Sensors | 158 | 32 | 3685 |
| Atmosphere | 128 | 20 | 1871 |
| Atmospheric environment | 71 | 24 | 1876 |
| Science of the total environment | 69 | 26 | 2144 |
| Atmospheric measurement techniques | 57 | 25 | 3022 |
| Aerosol and air quality research | 50 | 15 | 949 |
| International journal of environmental research and public health | 40 | 19 | 977 |
| Building and environment | 32 | 14 | 586 |
| Environmental pollution | 32 | 17 | 1706 |
| Environment international | 30 | 20 | 3193 |
| Environmental monitoring and assessment | 30 | 12 | 568 |
| Atmospheric pollution research | 27 | 8 | 186 |
| Environmental science & technology | 27 | 14 | 690 |
| Environmental research | 24 | 14 | 937 |
| Sustainability | 22 | 10 | 323 |

Atmospheric Environment) confirms the field's interdisciplinary nature, bridging engineering and environmental science.

### 3.4 Country and international cooperation analysis

Country-level productivity was analyzed by the relevant author's country (Fig. 2), while citation analysis was performed across the countries of all contributing authors (Table 3). This distinction is important because, when authors from different countries contribute, a single publication may be counted under more than one country in citation analysis. Country-based analysis shows that the US is the clear leader with 519 publications. The US is followed by China (202), Italy (165), the United Kingdom (161), and India (115). This US dominance can be explained by the EPA's performance evaluation programs for low-cost sensors, National Science Foundation (NSF) funding, and the tradition of university-community collaboration. China's second-place ranking is consistent with its motivation to seek innovative solutions to chronic air pollution problems. The strong presence of European countries (Italy, the United Kingdom, Germany, and Spain) demonstrates that the EU's Horizon programs and Clean Air policies support the research.

The analysis of Single Country Publications (SCP) and Multi-Country Publications (MCP) reveals the research profiles of countries. The US has an MCP rate of 17.3%, slightly below the global average (22.29%). The UK has one of the highest MCP rates at 41%, reflecting the openness of British research institutions to international collaboration. India's relatively low MCP rate (19.1%) indicates that research is mostly conducted at the national level. In contrast, China's MCP rate (28.2%) is above the global average (22.29%), suggesting a moderate level of international engagement; however, given its high publication volume, a significant portion of Chinese research still relies on domestic collaboration networks. The generally low MCP rates of developing countries point to structural inequalities in access to and funding of international research networks. From a citation analysis perspective, the US ranks first with 69 523 citations and an average of 101.64 citations per document. The UK is second with 25 915 citations and an average of 101.63 citations per document, almost on par with the US. The high citation rate for UK publications can be attributed to publishing in high-impact factor journals, choosing open access, or an innovative approach. China received a total of 19 724 citations and averaged 76.45 citations per document; this relatively low average suggests that high publication volume lowers the citation rate. High citation-*per*-document rates in smaller countries like Australia and Norway reflect specialization in these fields.

A comprehensive analysis of international cooperation reveals an asymmetrical relationship between the global South and the global North (Table 4). Developed countries generally act as technology providers and methodologists, while developing countries serve primarily as field implementation areas. This asymmetry reflects power imbalances in knowledge production processes and highlights the need to develop equitable research partnerships. Research groups, particularly in Sub-Saharan Africa, the underdeveloped regions of Southeast Asia, and Central America, remain on the periphery of the international collaboration network. Given that these regions house populations most affected by air pollution, the societal consequences of research capacity inequality are quite serious. Institutional analysis shows that the University of Washington (94 publications) is the leading institution. This is followed by the University of Utah (90), the University of Colorado (69), the Indian Institute of Technology (IIT) (67), and Peking University (52). The dominance of US universities is consistent with the strong environmental research infrastructure and community-based research tradition in that country. The strong presence of IIT demonstrates the scale of the academic response to India's air pollution crisis. The three-field plot (Fig. 3) illustrates the relationships between the most productive institutions (left), countries (center), and publication sources (right). The diagram shows that US-based institutions such as the University of Washington, the University of Utah, and the University of Colorado predominantly publish in Sensors, Atmospheric Measurement Techniques, and Atmospheric Environment. The

 

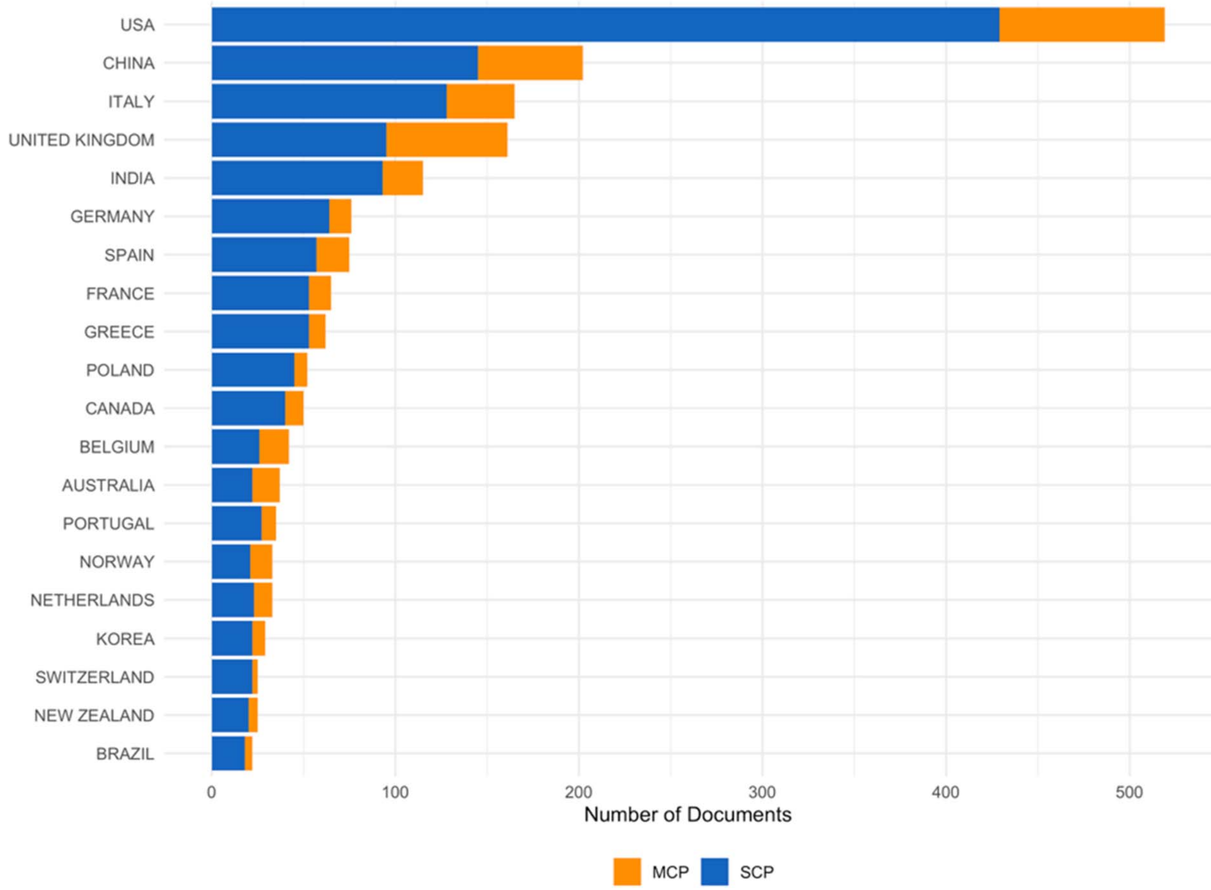


Fig. 2 The distribution of countries of the top 20 authors who have written the most articles on community-based and low-cost air quality monitoring research is shown separately as single-country publications (SCP) and multi-country publications (MCP).

Table 3 Scientific output, citation impact, and publication timeline of the most productive countries in community-based and low-cost air quality monitoring research; total number of publications, total number of citations, average number of citations per document, and the year of first and last publication

| Country | Articles | Total_Citations | Average_Article_Citations | First publication | Last publication |
|---|---|---|---|---|---|
| USA | 684 | 69 523 | 101.64 | 2001 | 2026 |
| United Kingdom | 255 | 25 915 | 101.63 | 2003 | 2026 |
| China | 258 | 19 724 | 76.45 | 2014 | 2026 |
| Italy | 226 | 10 983 | 48.6 | 2009 | 2026 |
| Australia | 65 | 10 394 | 159.91 | 2013 | 2025 |
| France | 103 | 6039 | 58.63 | 2013 | 2026 |
| Norway | 59 | 5554 | 94.14 | 2014 | 2026 |
| India | 172 | 4648 | 27.02 | 2015 | 2026 |
| Spain | 117 | 4606 | 39.37 | 2014 | 2026 |
| Netherlands | 62 | 4438 | 71.58 | 2009 | 2026 |
| Germany | 115 | 4292 | 37.32 | 2006 | 2026 |
| Greece | 87 | 3837 | 44.1 | 2015 | 2026 |
| Switzerland | 50 | 3584 | 71.68 | 2012 | 2026 |
| Belgium | 68 | 3178 | 46.74 | 2010 | 2026 |
| New Zealand | 32 | 3048 | 95.25 | 2017 | 2025 |
| Canada | 78 | 2739 | 35.12 | 2015 | 2026 |
| Finland | 36 | 2726 | 75.72 | 2015 | 2025 |
| Poland | 66 | 2266 | 34.33 | 2016 | 2026 |
| Serbia | 23 | 1932 | 84 | 2014 | 2025 |
| Portugal | 50 | 1931 | 38.62 | 2010 | 2026 |

Table 4 Most Productive Institutions

| Affiliation | Articles |
|---|---|
| University of Washington | 94 |
| University of Utah | 90 |
| University of Colorado | 69 |
| Indian Institute of technology | 67 |
| University of Birmingham | 65 |
| University of California, Berkeley | 61 |
| University of Surrey | 59 |
| University of Cambridge | 53 |
| Colorado State university | 52 |
| Carnegie Mellon university | 51 |

Indian Institute of Technology shows strong connections to Sensors, Aerosol, and Air Quality Research. UK institutions, particularly the Universities of Birmingham, Cambridge, and Surrey, contribute significantly to Environment International, Environmental Pollution, and Building and Environment".

Analysis of the cross-country cooperation network (Fig. 4) shows that the strongest cooperation links are formed by the US-UK, US-China, and US-Germany axes. The intra-European cooperation network is quite extensive, reflecting the unifying effect of EU framework programmes. African and South American countries occupy an peripheral position in the cooperation network, and greater integration of these regions into the field is critical for increasing global air quality monitoring capacity. Notably, countries such as Portugal, Poland, Indonesia, Finland, Austria, Colombia, and Czech Republic appear isolated in the network, indicating limited international collaboration ties and reinforcing the need for capacity building in these regions.

### 3.5 Keyword and theme analysis

Keyword analysis reveals the basic themes and concepts that community-based and low-cost air quality monitoring research focuses on. The most frequently used keywords are ranked visually in a lollipop graph in Fig. 5. The author's keyword analysis clearly reveals the field's thematic focus The most frequently used author keywords are: LCS (559 occurrences), air quality (432), air pollution (349), citizen science (289), PM (281), low-cost sensor (205), $PM_{2.5}$ (163), ML (147), calibration (143), and air quality monitoring (138). This distribution underscores the field's technology-driven nature, with low-cost sensor technology and air quality assessment as dominant research themes, while the prominence of citizen science highlights the growing role of participatory approaches.

Keyword co-occurrence network analysis revealed four main thematic clusters (Fig. 6). The first cluster (red), focusing on sensor technologies and air quality monitoring infrastructure, includes the keywords low-cost sensors, air quality, sensors, indoor air quality, air quality monitoring, environmental monitoring, sensor calibration, Internet of Things, smart cities, and wireless sensor networks. This cluster forms the technological and infrastructural backbone of the field. The second cluster (purple), focusing on measurement and calibration, brings together the keywords monitoring, calibration, sensor, pollution measurement, sensor networks, and low-cost. This cluster reflects ongoing efforts to improve measurement accuracy and standardization. The third cluster (green), relating to PM characterization, covers $PM_{2.5}$, $PM_{10}$, LCS, and ML, highlighting the convergence of air pollutant measurement with data-driven analytical approaches. The fourth cluster (blue), focusing on citizen engagement and environmental equity, includes citizen science, air pollution, environmental justice, crowdsourcing, exposure, and exposure assessment. This cluster reflects the application of participatory monitoring to social inequality and public health issues. The shift towards green-colored keywords such as low-cost sensors, air quality, PM, citizen science, and calibration reflects the rapid growth of these core topics during the 2016–2020 period. Newest

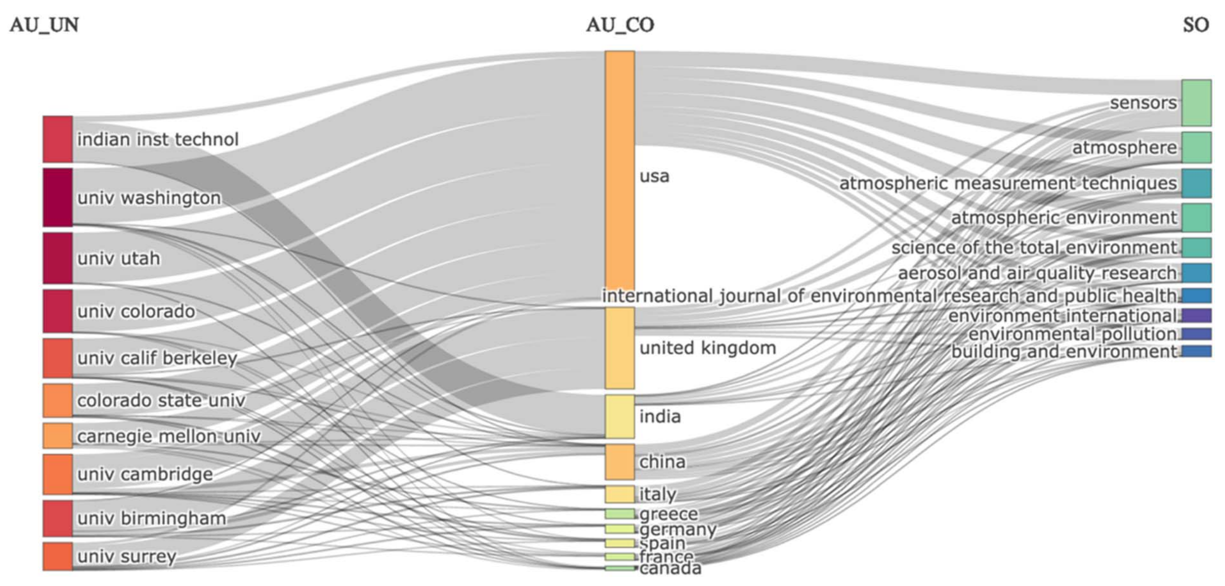


Fig. 3 A three-zone diagram visualizing the relationships and flows between institutions, countries, and publication sources.

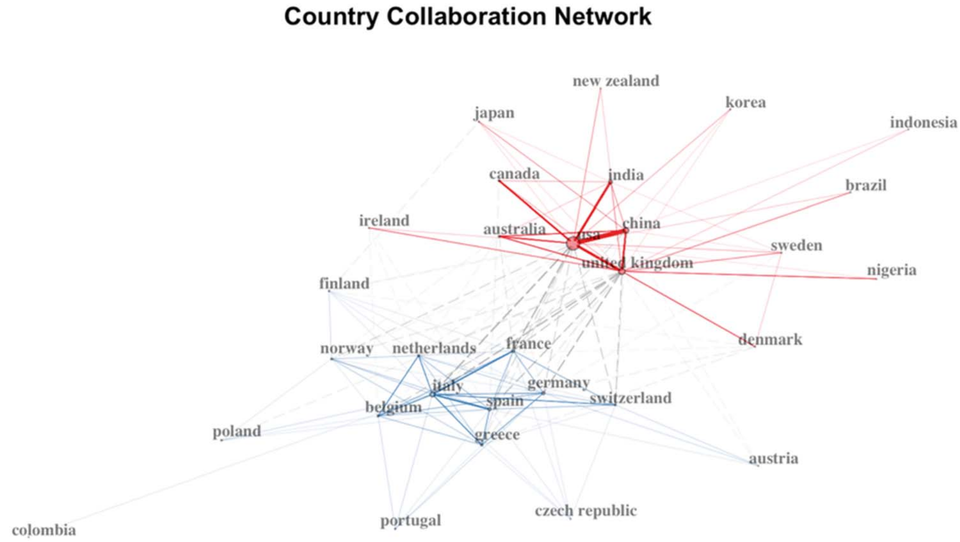


Fig. 4 Network of cooperation between countries.

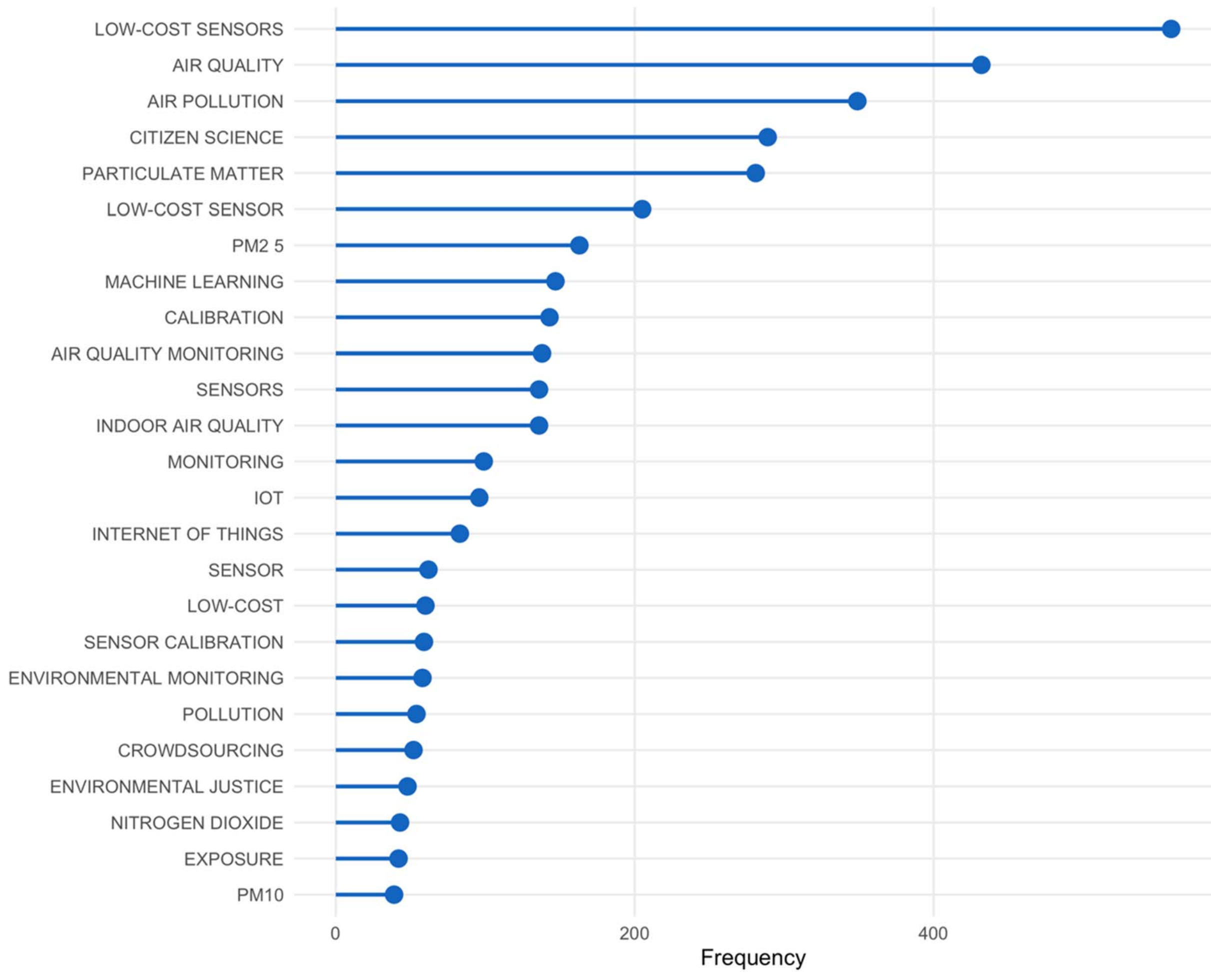


Fig. 5 Graph of most frequently used keywords (Top 20).

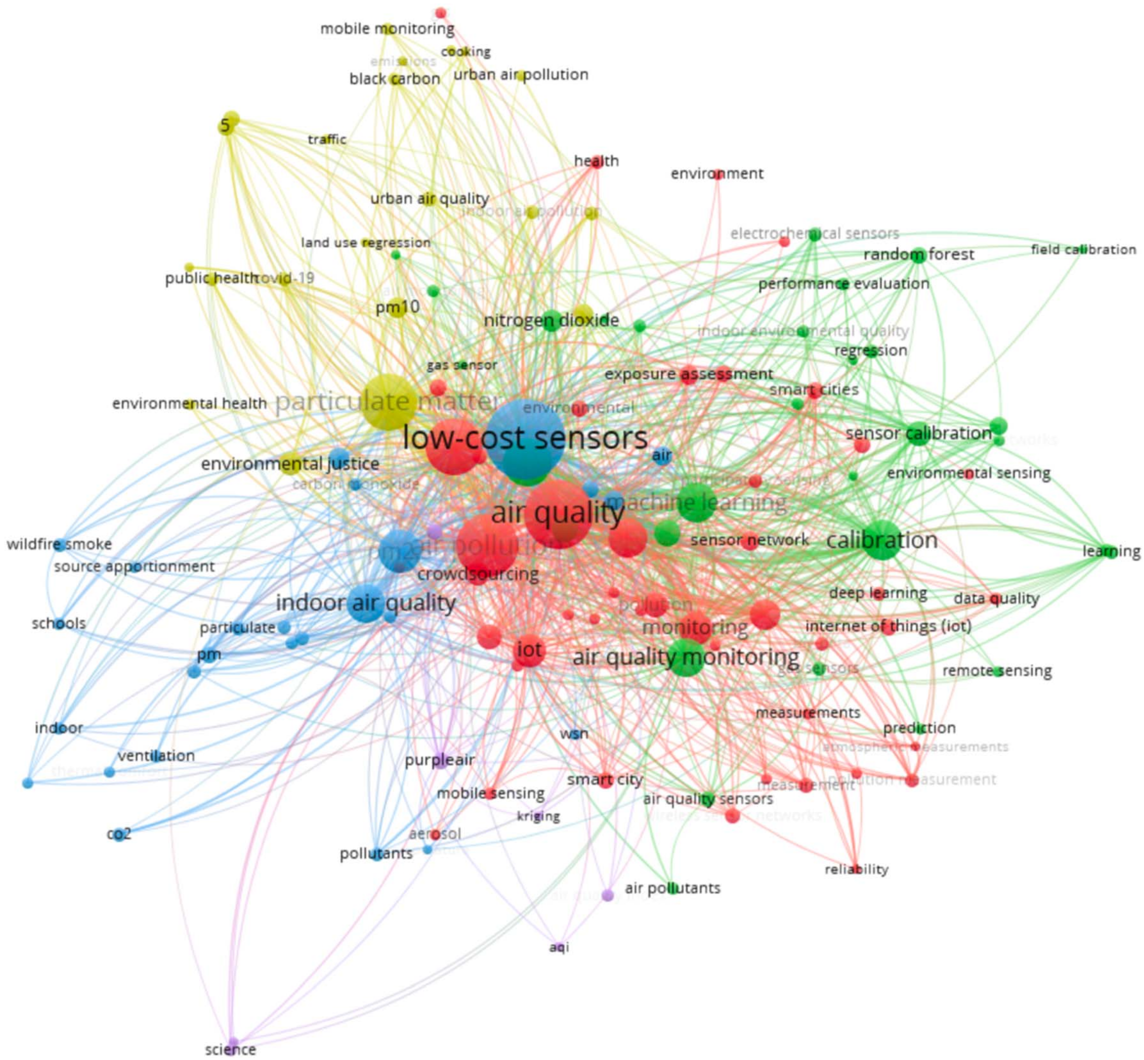


Fig. 6 A keyword co-occurrence network showing relationships and thematic clusters between low-cost sensors and key concepts in air quality monitoring.

keywords appearing in yellow-green include deep learning, randomized forests, ML, field calibration, performance evaluation, and smart cities, indicating the field's continued shift towards advanced analytics methods and urban-scale monitoring applications.

Word cloud and tree map visualizations illustrate the relative importance of keywords (Fig. 7 and 8). Lifecycle control systems constitute the dominant theme, accounting for 14.2% of the total keyword space. Air quality and air pollution rank second and third, at 11% and 8.9%, respectively. Citizen science (7.3%), PM (7.1%), and low-cost sensors (5.2%) make up the next tier, while emerging topics such as machine learning (3.7%), and the Internet of Things (IoT) (2.1%) reflect the increasing integration of data science and digital technologies into the field.

Thematic map analysis allows classification of the field into four structures: engine themes (high density and high centrality), basic themes (high centrality and low density), niche themes (high density and low centrality), and emerging or disappearing themes (low density and low centrality). The engine theme quadrant includes machine learning, demonstrating its high centrality and density within the field. Low-cost sensors and air pollution are positioned as key themes with high centrality but low density, serving as core and outward-facing issues within the area. Indoor air quality is identified as a niche theme with high density but low centrality, indicating intensive research by specialized groups. Nitrogen dioxide is located in the emerging or declining themes quadrant, suggesting it is a newly developing or declining research area. Topics such as indoor air quality and personal exposure have been identified as niche themes and are being intensively studied by specialized research groups. Emerging or disappearing themes, located in the lower-left quadrant with low density and low centrality, represent topics that are either newly developing or losing research momentum (Fig. 9). Citizen science and community engagement are among the field's basic themes and serve as its outward-facing gateway. A temporal analysis of trending topics (Fig. 10) reveals the field's thematic evolution. In the early period (before 2013), only sporadic


Fig. 7 A word cloud showing the most frequently used terms in low-cost sensors and air quality research.

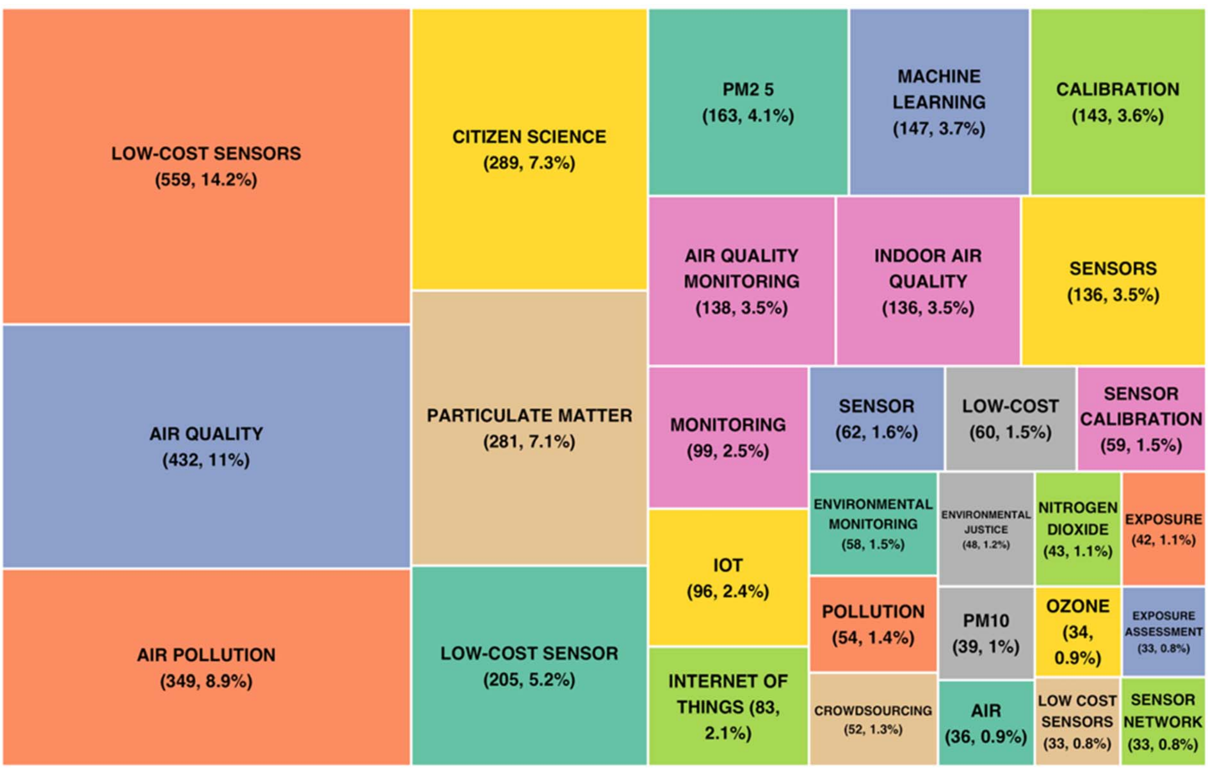


Fig. 8 Treemap of key terms in low-cost sensor and air quality monitoring research.

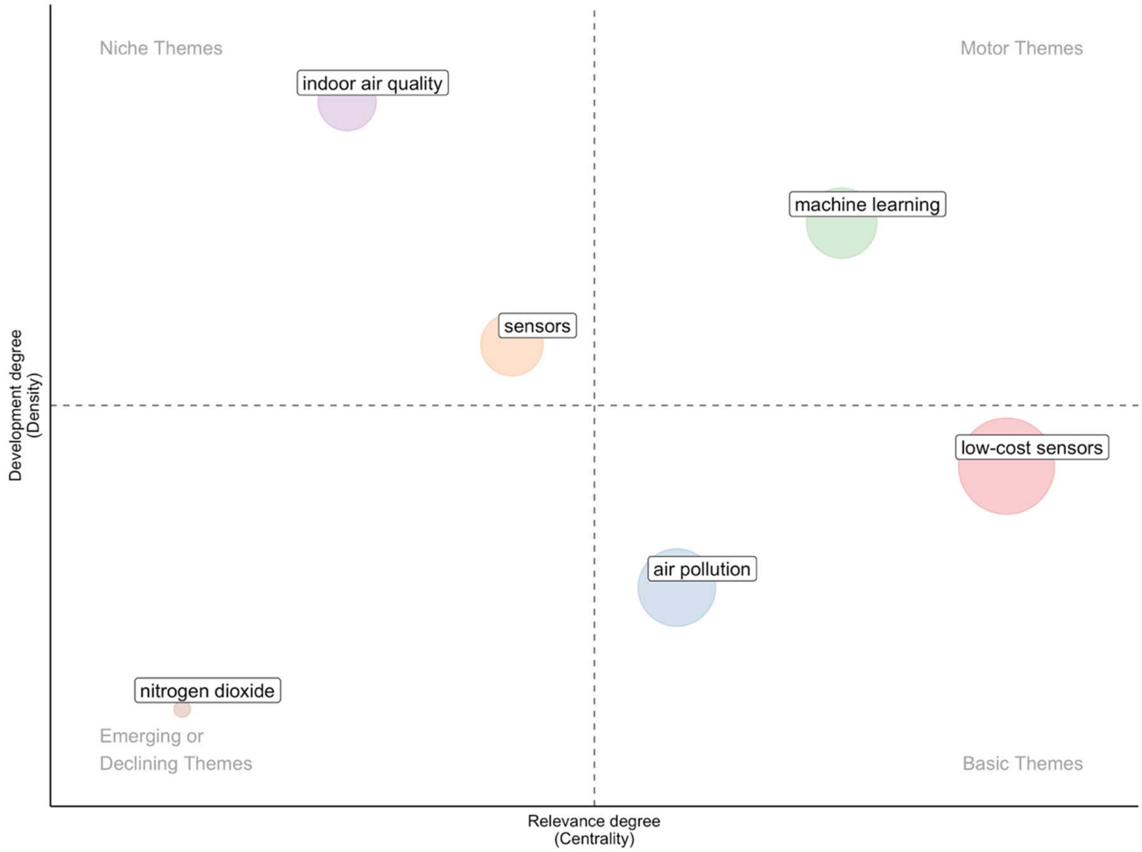


Fig. 9 Thematic map analysis.

occurrences of air quality, air pollution, and citizen science were observed. Between 2014 and 2018, LCS and citizen science gained significant momentum alongside calibration and $PM_{2.5}$. LCS has been the dominant trending keyword, with the highest publication frequency since 2019, while ML, indoor air quality, and air quality monitoring have emerged as rapidly growing topics, reflecting the field's shift toward data-driven approaches and broader environmental monitoring applications. This evolution demonstrates a shift in the field from a purely measurement-focused structure to one centered on data science and societal impact.

Cross-analysis across thematic clusters and countries reveals differing national research priorities. The US and UK dominate across all thematic areas, reflecting their overall leadership in the field. However, notable patterns of specialization emerge: China and India demonstrate a technology-driven research approach with a strong focus on calibration and machine learning, while European countries such as Italy, the Netherlands, Spain, and Belgium are particularly active in citizen science, reflecting the impact of EU-funded participatory monitoring programs. Indoor air quality research is led by the US and UK, with significant contributions from India, the Netherlands, and China. Poland shows a distinct concentration on air pollution studies relative to overall publication volume. These patterns indicate that fundamental themes such as low-cost sensors are addressed universally, engine themes such as machine learning are driven by technologically advanced countries, and niche themes such as indoor air quality are pursued by research groups specializing in various geographic contexts.

## 4. Discussions

This comprehensive bibliometric analysis reveals the overall structure, development trends, and thematic characteristics of community-based and low-cost sensor-based air quality monitoring research. When findings are systematically evaluated across multiple dimensions, they help us understand both the field's strengths and critical gaps.

One of the most striking features of the field is its rapid growth, particularly after 2017. An annual growth rate of 15.27% indicates that the field is still in an active expansion phase rather than in a maturation phase. The significant increase in the number of publications since 2017 can be explained by the commercial proliferation of low-cost sensor technologies (especially PurpleAir, Alphasense, and Plantower-based devices), the increasing funding policies of the US EPA and the European Union for citizen science projects, and the widespread use of open data platforms (such as OpenAQ and Sensor.Community). The increased interest in indoor air quality during the pandemic after 2020 has also been a significant factor supporting this growth.

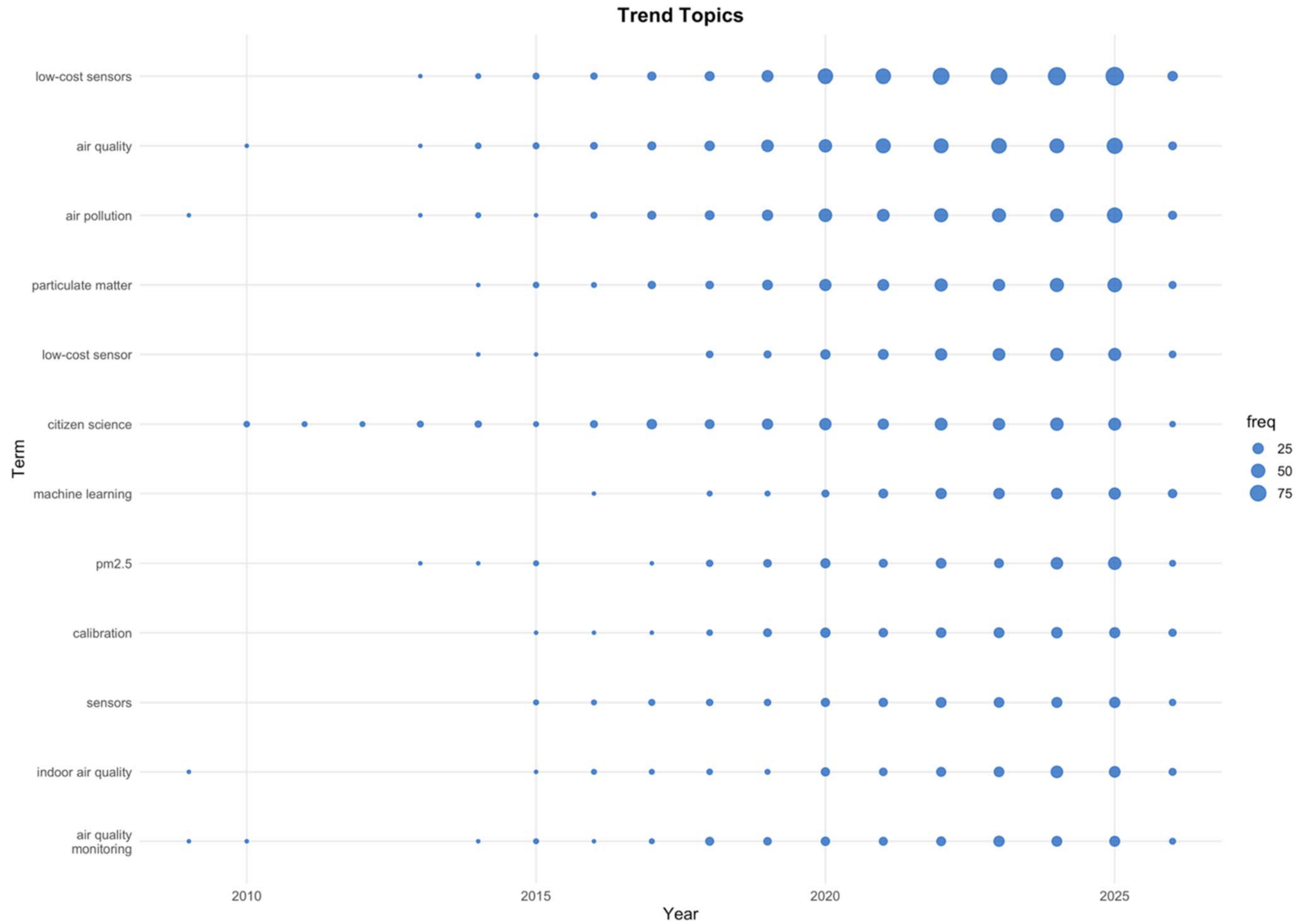


Fig. 10 Temporal analysis of trending topics.



The geographic distribution analysis reveals a significant inequality in the field. The US is overwhelmingly dominant in both the number of corresponding authors (519 articles) and total citations. It is followed by China (202), Italy (165), the UK (161), and India (115). These five countries account for approximately half of all publications. On the other hand, the extremely low representation of Africa and South America, regions most affected by air pollution, in the research network is a striking and ironic finding. Considering that the primary purpose of LCS is to produce air quality data in regions lacking traditional monitoring infrastructure, this geographical disparity constitutes one of the most critical contradictions in the field. The international collaboration rate of 22.29% is consistent with previous findings showing that international collaboration networks tend to expand as scientific fields mature.[48] However, the concentration of these collaborations largely around the US-UK and US-China axes indicates that the Global South remains marginalized not only in research production but also in collaboration networks. Keyword and thematic analysis findings clearly reveal the field's thematic evolution. In a similar bibliometric study, 986 publications were analyzed and four main themes were identified: community-based monitoring, IoT integration, indoor air quality assessment, and advanced calibration techniques.[38] These themes largely overlap with the keyword-clustering analysis in our study. The dominance of the keywords “low-cost sensors” (559) and “air quality” (432) reflects the field's technology-oriented nature. On the other hand, the fourth-ranked keyword, “citizen science” (289), indicates that participatory approaches have become an integral part of the field. Trend analysis reveals that the field is evolving from a purely measurement-focused structure to one centered on data science and community impact. The rapid rise of the keywords ML, indoor air quality, and air quality monitoring after 2019 is concrete evidence of this transformation. This finding demonstrates that LCS are now positioned not only as data-collection tools but also as components of intelligent monitoring systems integrated with ML algorithms. Furthermore, LCS can be integrated into UAV platforms, enabling high-resolution mapping of pollutant spatial distributions.[33]

From a journal analysis perspective, Sensors, with 158 articles, is the most productive journal, consistent with the field's focus on sensor technology. However, the fact that Environment International Journal has the highest average citation count indicates that studies focusing on environmental impact and policy have a greater scientific impact in the field. According to established bibliometric frameworks, the density of publications in high-impact and internationally indexed journals is considered an indicator of a field's maturity and global integration.[28] The concentration of analyzed publications in high-impact journals such as Atmospheric Environment, Science of the Total Environment, and Environment International reflects the field's scientific maturity. One of the most significant challenges in the field is the calibration and data quality issues of low-cost sensors. The fact that the term "calibration" (143) is among the top ten in the keyword analysis also supports this finding. Similarly, the lack of unified performance metrics and cross-validation methods makes it difficult to compare calibration techniques of different low-cost sensor networks, while the absence of common protocols and standard definitions hinders data sharing and integration between systems.[49] The lack of standardization and variability in sensor performance across different environmental conditions continues to limit the usability of citizen science data in regulatory decision-making. Finally, it appears that the concepts of citizen science and LCS form a mutually reinforcing cycle. LCS enables citizens to participate in the scientific data production process, while citizen science projects drive the dissemination and development of sensor technologies. Citizen science approaches are also effective tools for identifying residential health risks, such as water quality, toxic substances, and noise beyond air quality, but integrating mechanisms to ensure data quality remains a critical need.[50] On the other hand, it has been shown that 90% of community-based air pollution research focuses on sensor performance evaluation, with only 10% aiming to translate research findings into policy action.[51] This indicates a significant gap in policy integration despite the field's technical maturity. This reciprocal relationship suggests that the field will progress towards greater community participation, improved data quality standards, and environmental justice practices in the future.

## 5. Limitations

While this study provides a comprehensive bibliometric analysis based on the Scopus and Web of Science databases, it is important to acknowledge that these traditional academic databases may not fully reflect all relevant knowledge production in the field of community-based and low-cost air quality monitoring. This is because the citizen science field, with its participatory and open nature, generates a significant grey literature and a set of non-traditional sources that fall outside the scope of traditional bibliometric analysis. For example, these include open-source software networks such as GitHub and the Python Package Index (PyPI), maker community platforms such as Autodesk Instructables, and citizen science project websites. Furthermore, government technical reports, such as the Advanced Air Sensors Guide, including those published by the EPA, may not be fully indexed in academic databases. Exclusion of these sources can create a bias toward formal academic output and potentially underrepresent grassroots innovation and community-driven monitoring initiatives.

## 6. Conclusion and recommendations

This comprehensive and systematic bibliometric analysis presents a detailed profile of community-based, low-cost air quality monitoring research from 1996 to 2026, based on 2571 documents from the WOS and Scopus databases.

The research field has experienced rapid and significant growth, particularly since 2017, with an annual growth rate of 15.27%, driven by the commercialization of low-cost sensor technologies and increased funding for citizen science initiatives. Examining the geographical distribution of the field, the United States dominates with 519 corresponding author publications, followed by China (202), Italy (165), the United Kingdom (161), and India (115); these five countries account for approximately half of the total publications. The international co-authorship rate is 22.29%, with the strongest collaboration axes established between the US and the UK, and the US and China; however, regions most affected by air pollution, such as Africa and South America, are significantly underrepresented in both research output and collaboration networks. The most prominent research themes are centered on low-cost sensors (559), air quality (432), air pollution (349), citizen science (289), and particulate matter (281), reflecting the technology-driven and participatory nature of the field. Temporal trend analysis reveals a significant shift in research focus, moving from purely measurement-centric studies to data science and societal impact; machine learning, indoor air quality, and air quality monitoring have emerged as rapidly growing areas since 2019. Citation analysis shows that the most influential studies in the field focus on sensor performance evaluation, calibration methodologies, and conceptual frameworks for citizen science and low-cost monitoring.

Researchers should prioritize bridging the gap between sensor performance evaluation and policy-relevant applications, as current literature remains heavily focused on technical validation rather than translating findings into actionable policy outcomes. Additionally, standardized calibration protocols and unified performance metrics should be developed to enable cross-comparison of different low-cost sensor networks and facilitate data integration across systems. Future studies should also address the geographic imbalance by expanding citizen science and low-cost sensor research to underrepresented regions, particularly in the Global South, where air pollution challenges are most severe yet monitoring infrastructure is most lacking. Furthermore, integrating LCS with emerging technologies such as ML, IoT platforms, and UAV-based monitoring should be explored to enhance spatial coverage and data quality.

Policymakers and funding agencies should increase financial support for citizen science air quality monitoring programs, establish regulatory frameworks for incorporating low-cost sensor data into official air quality management systems, and promote equitable sensor distribution to ensure environmental justice.

In conclusion, community-based and low-cost air quality monitoring research is a dynamic, rapidly evolving field with significant scientific and societal potential. The convergence of citizen science approaches with advancing sensor technologies creates a unique opportunity to democratize air quality data and empower communities worldwide. The future success of this field depends on effective collaboration among researchers, technology developers, communities, policymakers, and international partners to address the persistent challenges of data quality, standardization, and equitable access to monitoring resources. Also, future studies in this area should consider integrating unconventional data sources such as open-source repositories (GitHub, PyPI), generative community platforms, and citizen science project websites to overcome the inherent limitations of academic databases. Including government technical reports and grey literature through web scraping methods will provide a more holistic picture of knowledge production in this field.

## Consent to participate

All authors participated in the study.

## Consent for publication

The authors read and approved the final version of the manuscript.

## Author contributions

Conceptualization: EB; methodology: EB; formal analysis and investigation: EB; writing original draft preparation: EB, AD; review and editing: AD; supervision: AD.

## Conflicts of interest

The authors declare no competing interests.

## Data availability

The data presented in this study are available on request from the corresponding author.

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