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Current Update on Air Pollution or Quality and Meteorological Variables: A Review and Bibliometric Analysis

Merita Gidarjati[1*], Muhammad Ma'arij Harfadli [2], Toru Matsumoto [3]

[1]*Graduate Program in Environmental Systems, Graduate School of Environmental Engineering, University of Kitakyushu. ORCID: 0009-0004-0443-0240*

[2]*Graduate Program in Environmental Systems, Graduate School of Environmental Engineering, University of Kitakyushu. ORCID:* 0000-0001-7179-7668

[3]*Faculty of Environmental Engineering, University of Kitakyushu. ORCID: 0000-0002-3191-2681*

ABSTRACT. The study aims to investigate the existing understanding of air pollution and meteorological variables, with the goal of identifying and assessing research patterns, areas where research is lacking, and variables that are important for air pollution research. The Scopus Database is utilized as a data source, specifically searching for literature published in the last 10 years using keywords "Air pollution" or "Air quality" and "Meteorological variables". The study utilizes VOSviewer software to examine the data, emphasizing noteworthy trends in research on air pollution and climatic factors. The study produced a map and analysis of the expansion in scholarly publication concerning the above themes and it identified four significant clusters. The study also identified statistical models, tools, and sophisticated modeling methodologies utilized for both subjects. The analysis focuses on current patterns, areas of study that need attention, and factors that influence air pollution research. It offers a valuable understanding of the relationship between air pollution, meteorological variables, and their impact on public health. This study enhances our comprehension of the complexity of air pollution and meteorological factors, underscoring the significance of data-driven analysis, modeling methodologies, and interdisciplinary approaches in tackling environmental concerns.

Keywords: Air Pollution, Air Quality, Meteorological Variables

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1. INTRODUCTION

The World Resources Institute once again ranked Jakarta as the most polluted city in the world in November 2023. At the same time, the poor air quality has put the health of its citizens at risk. The majority of the population in Southeast Asia resides in the areas where air pollution levels surpass the clean air guidelines set by the World Health Organization's (WHO). Most of the source of air pollution come from vehicles, power plants and industrial emissions. According to the 2023 World Air Quality Report, only seven countries managed to meet the WHO $PM_{2.5}$ annual guideline (annual average of 5 μg/m3 or less). The countries listed in the report are Australia, Estonia, Finland, Grenada, Iceland, Mauritius, and New Zealand. The report also indicated that climate conditions and transboundary haze were significant contributors in Southeast Asia, where $PM_{2.5}$ concentrations increased across almost all countries in the region [1].

Air pollution is a crucial environmental concern that has unfortunate effects on human health, ecosystems, and climate change [2] [3]. There are plenty of studies that have investigated the relationship between air pollution or air quality and meteorological variables such as temperature, humidity, wind speed, radiation, etc. [4] [5] [6] [7]. Understanding the complex interactions between air pollution, air quality, and meteorological variables is important for effective air quality management and policy development.

Bibliometric analysis refers to the application of statistical techniques to published literature in order to analyze publication patterns over time and get valuable insights on prominent scientists, nations, and organizations. Bibliometrics is a valuable tool for visualizing the literature and conducting quantitative analysis of developments and growth in scientific publications [8]. Multiple bibliometric studies on air pollution have been published [9] [10] [11] [12] [13] [14] [15]. These studies demonstrate the growing interest in bibliometric analysis of air pollution research, which helps to identify key trends, hotspots, and areas of focus in the field. Several publications have also been published on meteorological variables [16] [17].

Evaluating research output is a crucial process for showcasing the impact and cooperation of a country or region in a specific field. Hence, the objective of this study was to examine internationally published literature on air pollution and meteorological variables. This study will contribute to the field of air pollution research by identifying emerging focus areas and research gaps that may have been largely overlooked. The study will include a variety of relevant research articles, conference papers, and other scientific publications. Additionally, to acquire diverse publication attributes, such as types of publications, subject categories, institutions or affiliations, countries, year trends, and content analysis of keywords, abstracts, and article titles. However, the search limits are for English publications only.

The study will concentrate on examining the current understanding of how air pollution and meteorological variables related. The study also aims to identify and evaluate research trends, research gaps and variables for air pollution research in the Scopus database using VOSviewer software that researches air pollution and meteorological variables influential.

2. MATERIALS AND METHODS

2.1 Data Collection and Screening

Data sources in this study are taken using the Scopus Database. From previous research, Scopus was selected to obtain information from digital libraries and offer various queries through institutional subscriptions [18]. The keywords used in this study are **"**Air pollution**"** or "Air quality" and **"**Meteorological variables**"**. The data used was the literature published over the last 10 years, from 2014 to 2024. The article selection or screening process for this study took several stages that can be seen in the flow chart image (Figure 1). Stage 1 involves the identification of papers with the keywords above, with a total of 1,576 articles analyzed. After applying Stage 2 filtering based on the publication year, we acquired a total of 996 documents as the results. After applying stage 3 filtering, which includes criteria such as document kind (article, conference paper, and book chapter), publishing stage, and English language, a total of 907 items were eligible articles.

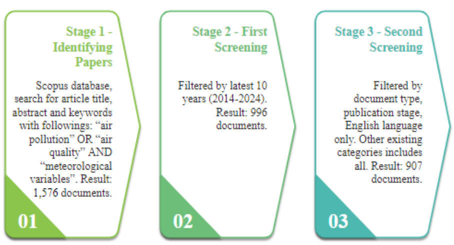

Fig. 1. Flow diagram for article selection process

2.2 Data Analysis

Documents selected in the Scopus database of 907 articles are then downloaded in the csv format and included in the qualitative content analysis using VOSviewer software. The term "keyword" in bibliographic metadata typically serves indexing purposes, containing important information from scientific work [19] [20]. Furthermore, VOSviewer is used to illustrate trends in the form of bibliometrics [21], i.e., publication maps with keywords or terms (term co-occurrence maps) will form a network (co-citation) that is connected based on related research. The more links there are between keywords or terms, the stronger the relationship between them. In this study, for network visualizaiton and overlay analysis, bibliometric data was analyzed using a binary approach for text data and a fractional approach for bibliographic data. The analysis aimed to provide a qualitative understanding of air pollution research trends, gaps, and variables through visual representation and network connections between keywords or terms.

3. RESULTS AND DISCUSSION

In this section, the bibliometric analysis results are discussed based on research trends, research gap, and variables for air pollution research.

3.1 Research Trends

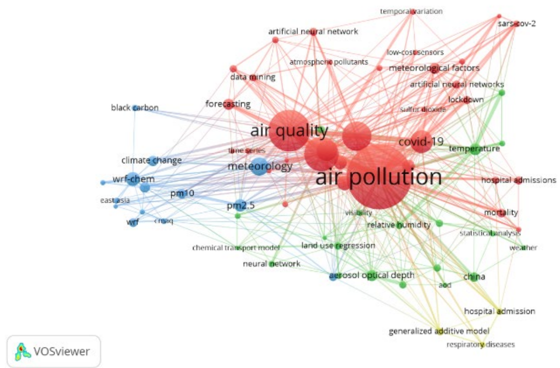

Fig. 2. Map of research cluster

As demonstrated in Figure 2, there are four clusters formed based on the co-occurrence of keywords. The first cluster is entitled Air Pollution and Health Impact: Analyzing Meteorological and Pollutant Data. This cluster focuses on the intersection of air pollution, meteorological variables, and their impacts on public health. It covers a comprehensive range of topics related to air quality and pollutants, including particulate matter ($PM_{2.5}$ and PM_{10}), nitrogen dioxide (NO_2), ozone (O_3), sulfur dioxide (SO_2), and general air pollutants. The emphasis is on understanding how these pollutants, along with various meteorological factors such as temperature and atmospheric boundary layers, affect health outcomes like morbidity, mortality, and hospital admissions [22] [23].

In the context of the COVID-19 pandemic, this cluster examines the correlation between air pollution and the spread and severity of the disease. It discusses how increased levels of atmospheric pollutants can exacerbate respiratory diseases such as asthma, leading to higher mortality and morbidity rates [24]. It highlights the role of advanced prediction and modeling techniques, such as machine learning, artificial neural networks (ANN), and data mining, in forecasting air quality and its health impacts [25]. The influence of lockdowns during the pandemic and their effects on air quality and pollution levels is also explored [26]. Additionally, the cluster includes discussions on temporal variation studies and the use of low-cost sensors for air quality monitoring and management.

The second cluster describes Meteorological Parameters and Public Health: Insights and Implications. This cluster examines the relationship between meteorological parameters and public health outcomes. It includes studies on the health effects on relative humidity, wind speed, and visibility [27] [28]. It also covers the use of land use regression, MODIS (Moderate Resolution Imaging Spectroradiometer) data, and statistical analysis to understand surface ozone, aerosol, and weather patterns [29]. The cluster also stress how important chemical transport models (CTMs) and aerosol optical depth (AOD) are in studying the atmosphere. These models figure out the levels of exposure and health risks that come with different weather situations [30] [31]. The research explores how varying meteorological conditions can modify pollutant concentrations, thus impacting public health epidemiology. This cluster focuses on the role of weather in driving air quality trends and its implications for public health policies.

Further, the third cluster explains Advanced Air Quality Modeling and Atmospheric Studies. This cluster is dedicated to advanced air quality modeling and the study of atmospheric processes. It includes topics such as meteorology, $PM_{2.5}$, PM_{10}, black carbon, and tropospheric ozone. The cluster features the use of models like WRF-Chem (Weather Research and Forecasting model coupled with Chemistry), CMAQ (Community Multiscale Air Quality model), and WRF (Weather Research and Forecasting) to simulate air quality and atmospheric circulation [32] [33]. These models are utilized to predict pollutant behavior, understand the effects of climate change on air quality, and devise effective management strategies, especially in highly polluted regions like East Asia [34] [35]. The cluster highlights the integration of climate models with air quality simulations to provide a comprehensive assessment of air pollution's impact on human health and the environment, particularly focusing on fine particulate matter ($PM_{2.5}$) and its sources.

The fourth cluster portrays Statistical Methods in Assessing Health Outcomes from Air Pollution. This cluster focuses on applying statistical methods to evaluate the health outcomes associated with air pollution. It includes the use of generalized additive models and other statistical tools to analyze hospital admissions and respiratory diseases [36] [37]. The cluster provides insights into how statistical analysis can help in understanding the correlation between air quality and health outcomes, guiding public health interventions and policies [38] [39]. The focus is on understanding the epidemiological aspects of air pollution and its direct effects on public health by using statistical modeling to decipher complex datasets [40]. By identifying key trends and correlations, the research in this cluster aims to inform better regulatory measures and health guidelines to mitigate the adverse effects of air pollution on vulnerable populations.

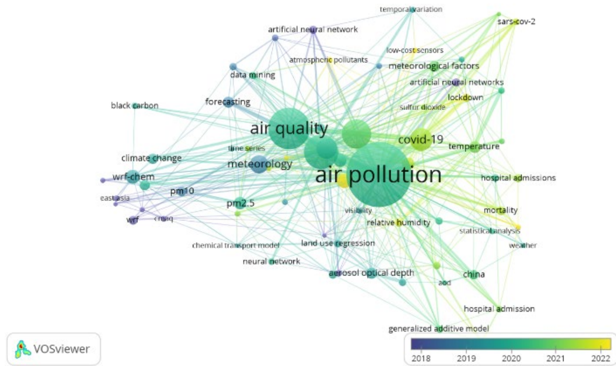

Fig. 3. Overlay Map of Research Year

As demonstrated in Figure 3, there is a relationship among labels (topics), clusters (thematic groupings), the weight of occurrences (frequency or emphasis), and the year of publication. Emerging focus in the first cluster is air pollution (weight 195), air quality (weight 103), and particulate matter (weight 80). They were the most frequently occurring topics, particularly around 2020. This period coincides with increased global awareness of air pollution and its health impacts, likely influenced by the COVID-19 pandemic. Further, COVID-19 Impact labels such as COVID-19 (weight 44), sars-cov-2/severe acute respiratory syndrome coronavirus 2 (weight 8), and related terms like lockdown (weight 11) showed a significant increase in 2020 and 2021, reflecting research into how the pandemic influenced air quality and public health.

The next research trend in the second cluster has shown topics such as temperature (weight 18), humidity (weight 8), and relative humidity (weight 9). These topics have gained attention, especially in 2020 and 2021. This indicates a growing interest in understanding how weather and climate factors impact air quality and health. Terms such as public health (weight 10) and epidemiology (weight 8), which highlight an increasing focus on the intersection of environmental science and public health, also raise the issue of public health integration.

Several terms such as WRF-chem (weight 22), CMAQ (weight 7), and chemical transport model (weight 5) indicate that advanced modeling is a frequently raised issue by researchers in the third cluster. This topic shows a steady increase, with significant research activity around 2019. This indicates advancements in using sophisticated models to study air quality. Climate Change and Pollutants is an interesting topic. Topics like climate change (weight 15), $PM_{2.5}$ (weight 20), and black carbon (weight 8) reflect ongoing concerns and research into how these factors influence atmospheric conditions and public health.

The fourth cluster concentrates on statistical analysis of fundamental topics pertaining to the years 2017-2018. The use of methods like generalized additive model (weight 10) and statistical analysis (weight 7) points to a robust approach in assessing the health impacts of air pollution. Health Implications: In the context of air pollution, labels like hospital admission (weight 8) and respiratory diseases (weight 7) underscore the direct health consequences under investigation.

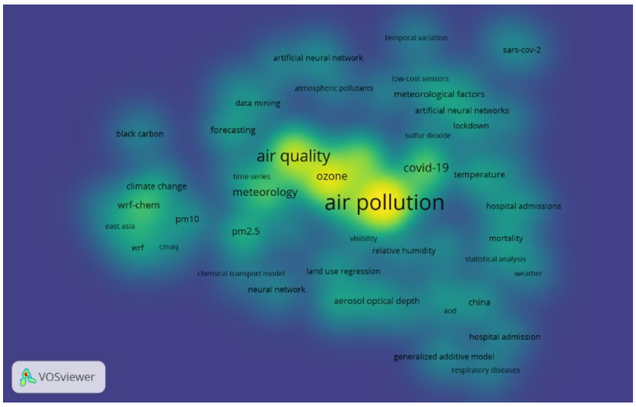

Fig. 4. Research Density Map

The density analysis of the research data revealed concentrated periods of intense study, particularly around 2020 and 2021, which were largely driven by the global impact of the COVID-19 pandemic. The first cluster, which focused on air pollution and health impacts, demonstrated the highest density, with significant emphasis on topics such as air pollution, air quality, and particulate matter. During these years, this cluster also demonstrated increased research on the effects of COVID-19, machine learning, and meteorological variables. The second cluster which covers meteorological parameters and public health, also showed notable density in 2019 and 2020, highlighting the integration of weather factors and public health studies. The third cluster, focused on air quality modeling and atmospheric studies, exhibited dense occurrences in 2019, reflecting advancements in modeling techniques and climate change research. The fourth cluster, dealing with statistical methods and health outcomes, exhibited increased density in 2020 and 2021, emphasizing the application of statistical analysis to health impacts related to air pollution. The overall density trends indicate key periods of research intensity and the evolving focus areas within the field.

3.2 Research Gap

This subchapter will discuss the research gaps based on the VOSviewer analysis results. Table 1 shows the relationship value of each of the lowest labels in each cluster. The total link strength and total occurrences reflect this relationship. The closer a label is to research center, the smaller its relationship value is. This means that these labels can become problems or gaps in research.

Table 1 The value of the weight of total link strength and occurrences

Label	Total link strength	Occurrences
coronavirus	17	5
aerosol	13	5
chemical transport model	12	5
morbidity	15	6
sulfur dioxide	11	6
wind speed	14	7
modeling	13	7
cmaq	13	7
statistical analysis	12	7
temporal variation	11	7
random forest	11	7
sars-cov-2	20	8
humidity	20	8
hospital admission	15	8
prediction	13	8
relative humidity	24	9
land use regression	22	9
data mining	19	9
neural networks	15	9
modis	14	9

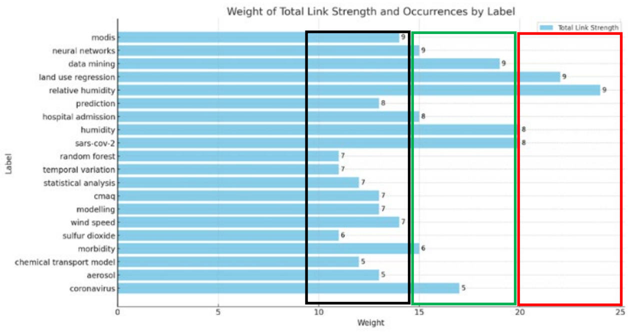

Fig. 5. Research Gap on Air Pollution based on the weight of total link strength and occurrences in each cluster from VOSviewer result. The biggest gap or highest weight is inside red box, the moderate one is inside the green box and the smallest gap or lowest weight is inside the black box.

The bar chart provides a visual representation of lowest weight of total link strength and occurrences for various research labels. This chart can be used to identify potential research gaps and areas that may require more focus. Figure 5 shows that relative humidity, land use regression, sars-cov-2, and humidity have high connectivity but relatively few studies. More frequent and diverse studies in these areas could fill this gap. Researchers have consistently studied neural networks, hospital admission, and coronavirus, and data mining, but additional research could enhance understanding, particularly in the context of air pollution and health. Modes, prediction, temporal variation, statistical analysis, CMAQ, modeling, wind speed, sulfur dioxide, chemical transport models, aerosols, and random forests are terms that have received less emphasis in research, showing potential for new discoveries and wider study.

3.3. Variables for Air Pollution Research

To identify the important variables for air pollution modeling from the data of VOSviewer, the observation can focus on the labels associated with high weights of occurrences and total link strength. These labels often represent key variables and factors frequently studied and considered crucial in the context of air pollution modeling. The following are the variables in Table 2.

Table 2 Variables for air pollution

Category	Variable	Description
Meteorological Variables	Humidity	The amount of water vapor present in the air.
	Wind Speed	The rate at which air is moving horizontally past a given point.
	Relative Humidity	The ratio of the amount of water vapor present in the air to the maximum amount that the air could hold at that temperature.
Pollutants	Sulfur Dioxide	A colourless gas with a pungent odour, primarily emitted from burning fossil fuels.
	Black Carbon	Fine particulate matter consisting of black carbon particles, primarily emitted from incomplete combustion of fossil fuels and biomass.
	Particulate Matter ($PM_{2.5}$ & PM_{10})	Fine particles suspended in the air, with diameters of 2.5 micrometres or smaller ($PM_{2.5}$) and 10 micrometres or smaller (PM_{10}).
	Ozone	A gas molecule composed of three oxygen atoms, often formed through chemical reactions between nitrogen oxides and volatile organic compounds in the presence of sunlight.
Health Impact Indicators	Morbidity	The incidence of disease within a population.
	Hospital Admission	The number of individuals admitted to hospitals due to health issues, often related to air pollution exposure.
	Respiratory Diseases	Disorders affecting the lungs and respiratory system, including conditions such as asthma, bronchitis, and chronic obstructive pulmonary disease (COPD).
Modeling and Analytical Methods	Machine Learning	A field of artificial intelligence that enables computer systems to learn from data and make predictions or decisions without being explicitly programmed.
	Neural Networks	Computational models inspired by the structure and functioning of the human brain, capable of learning complex patterns and relationships from data.
	Random Forest	A machine learning algorithm consisting of multiple decision trees, used for classification and regression tasks.
	Statistical Analysis	Techniques for analysing and interpreting data to uncover patterns, trends, and relationships, often used for hypothesis testing and inference.
	Generalized Additive Model	A statistical model used to explore relationships between predictors and a response variable, allowing for nonlinear and nonparametric relationships.
Data Sources and Tools	MODIS (Moderate Resolution Imaging Spectroradiometer)	in the Earth's environment, including air quality parameters.
	CMAQ (Community Multiscale Air Quality model)	A computational tool used for simulating air quality at regional and local scales, integrating meteorological, emission, and chemical transport processes.
	WRF-Chem (Weather Research and Forecasting model coupled with Chemistry)	A numerical weather prediction model coupled with a chemistry module, used for simulating atmospheric composition and air quality.
Temporal Factors	Temporal Variation	Changes in air pollution levels and other variables over time, influenced by factors such as diurnal patterns, seasonal

		variations, and long-term trends.
	Time Series Analysis	Statistical methods for analysing sequential data collected at regular intervals over time, used to identify patterns, trends, and anomalies.

4. CONCLUSIONS

The results of the bibliometric analysis reveal insightful patterns of air pollution and meteorological variables research. The study explores research trends related to air pollution and meteorological variables. Four clusters were identified based on keyword co-occurrence, covering various aspects such as air pollution, health impacts, meteorological parameters, and advanced air quality modeling. The clusters delve into topics like air quality, particulate matter, nitrogen dioxide, ozone, sulfur dioxide, health outcomes, statistical analysis, and modeling techniques. Significant research activity was noted around 2019-2021, particularly influenced by the COVID-19 pandemic. Emphasis was placed on machine learning, artificial neural networks, statistical methods, and models like WRF-Chem and CMAQ in studying air quality and health impacts. The research gaps identified may include areas where further investigation is needed to enhance understanding, prediction, and management of air pollution and its impacts on public health. Specific gaps in the literature could involve novel methodologies, emerging pollutants, understudied health outcomes, or unexplored interactions between air pollutants and meteorological factors. The study identified emerging focus areas in air pollution research, including the impact of climate change on air quality, statistical methods for assessing health outcomes, and advancements in air quality modeling. Notable topics such as climate change, $PM_{2.5}$, black carbon, statistical analysis, and health implications were emphasized in the clusters.

The findings from this study have several important implications. The identification of key research clusters suggests that future air quality management strategies must account for the increasing role of climate change and its interaction with air pollution. Policymakers and environmental agencies can use this insight to develop more targeted interventions that incorporate both meteorological variables and machine learning models to predict and mitigate air quality issues. This study also highlights the importance of incorporating advanced statistical techniques to improve the understanding of health outcomes related to air pollution, which can guide public health policies and urban planning in high-pollution areas.

Future research in the field of air pollution and meteorological variables could focus on several key areas. Firstly, there is a need for further investigation into the impact of climate change on air quality, particularly considering the evolving environmental conditions and their effects on pollutant levels. Additionally, exploring the application of advanced statistical methods in assessing health outcomes related to air pollution could provide valuable insights into the effectiveness of different analytical approaches. Furthermore, future studies could delve into the integration of machine learning techniques with meteorological data to enhance predictive models for air quality monitoring and forecasting. Lastly, examining the long-term trends and patterns in air pollution, especially in relation to changing meteorological variables, could offer a comprehensive understanding of the dynamics between atmospheric conditions and pollutant concentrations.

In summary, this work provides a foundation for continued advancements in the fields of air quality and meteorological research, with significant potential to inform both science and policy on global level.

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