Exposure Assessment of Biomass Burning: A Scoping Review on Current and Emerging Approaches

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Abstract

Biomass burning is the main source of air pollution in many countries and has been strongly linked to many morbid and mortal health outcomes. This scoping review aims to explore the current and emerging approaches linking health and air pollution from biomass burning. A literature search through PubMed was conducted to identify studies linking health and air pollution from biomass burning through the use of air quality data collection methods. A total of 197 studies were initially found, but after screening, only 57 studies were included. The most common methodology employed for air quality data was through atmospheric transport models (specifically GEOS-Chem) (59.65%), followed by remote sensing through satellite imaging (50.88%), then by direct site monitors (33.33%). A single approach was used by 56.14%, while the rest employed a blended approach (43.86%), likely due to the inherent limitations of each data collection method, necessitating supplementary or novel approaches. However, the bulk of existing literature uses methods that are calibrated for the global north (75.44%), leaving behind the global south, which bears the brunt of air pollution health impacts due to its socioeconomic and geographic vulnerabilities, worsened by climate change. There is a need to recalibrate or validate these models to increase the reliability of results for the global south, as well as explore the possibility of further developing these air pollution modeling initiatives to not only contribute to surveillance, but directly further policy development and public health programming (i.e., the creation of early warning systems).

Key words: agricultural burning, air pollution modeling, biomass burning, health, public health, vegetation burning

1. Introduction

1.1 Background and Context

In recent decades, there has been a noticeable spike in the incidence of biomass burning and open burning on a global scale. It is the largest source of black carbon globally at 42% (Yao *et al*., 2023). Central to this surge is the compounding influence of climate change (Adams and Kanaroglou, 2016; Albertson *et al*., 2010; Reddington *et al*., 2021). Biomass burning in agricultural settings, often used as a traditional land management or agricultural practice, has intensified in response to changing climate conditions, especially in tropical regions, causing serious air quality issues in East Asia (Adrianto *et al*., 2019; Johnson *et al*., 2020; Sheldon and Sankaran, 2017). Farmers, particularly in regions with subsistence agriculture, resort to controlled burning to clear fields, eliminate pests and enhance soil fertility (Reddington *et al*., 2021).

As climate change amplifies droughts and extends the fire season, these controlled burns can quickly escalate into widespread burning, engulfing vast tracts of land, homes and infrastructure, necessitating mass evacuations and overwhelming firefighting efforts. High temperatures, dry conditions, increased lightning strikes and other extreme weather events increase the vulnerability of forests (>200 hectares) to large fires and the frequency of these fires (Gaboriau *et al*., 2023). Such wildfires result in a cascading array of public health consequences, from acute injuries and respiratory illnesses to long-term mental health impacts stemming from trauma and displacement.

Biomass burning, including forest fires, wildfires, agricultural fires, residential energy production and waste burning, is the main source of air pollution in several countries like Canada, Africa, South America, Australia, Europe and Southeast Asia. Humans are responsible for about "90% of biomass burning with only a small percentage of natural fires contributing to the total amount of vegetation burned" (Chen *et al*., 2017; Karanasiou *et al*., 2021). In Southeast Asia, the practice of biomass burning is widely used for both occupational and non-occupational functions, most especially in rural areas (Amnuaylojaroen and Parasin, 2023). In Indonesia, agricultural burning destroyed almost a quarter of the country's forests in 20 years (Sheldon and Sankaran, 2017).

However, practical use of biomass burning has also led to a significant rise in vegetation fires across multiple Southeast Asian countries. From 2000 to 2010, Myanmar and Laos for instance experienced an increase in fire hotspots by 471% and 2383%, respectively, according to a study by Amnuaylojaroen and Parasin (2023). The same study noted that Vietnam also experienced a significant increase of 777.2% from 2000 to 2020, while Thailand demonstrated a relatively stable number of fire hotspots, even experiencing a small decrease of 10% from 2010 to 2020. A peak increase in these emissions seems to occur early each year in Southeast Asia (Khodmanee and Amnuaylojaroen, 2021; Amnuaylojaroen *et al*., 2023).

Regardless of the source, biomass burning has become a significant cause of air pollution, with global, regional and local impacts on air quality and public health. Airborne particulate matter (PM) and ground-level ozone have been largely demonstrated as key contributors to the global burden of mortality and disease (Sorek-Hamer *et al*., 2020; Vohra *et al*., 2021). In 2019, 4.2 million premature deaths were attributed to ambient outdoor air pollution, with 89% of these coming from the Southeast Asia and Western Pacific regions (World Health Organization, 2022).

Previous reviews have reported positive associations between wildfire smoke exposure and respiratory health effects, specifically exacerbations of asthma and chronic obstructive pulmonary disease (Adrianto *et al*., 2019; Albertson *et al*., 2010; Johnson *et al*., 2020; Oliveri *et al*., 2017). There is also a growing body of research linking ambient air pollution to cardiovascular health outcomes (Johnson *et al*., 2020; Karanasiou *et al*., 2021). Certain demographic groups, including children, the elderly and individuals with pre-existing health conditions, have been found to be particularly vulnerable to the negative effects of air pollution (Albertson *et al*., 2010; Karanasiou *et al*., 2021).

1.2 Rationale for the Scoping Review

Air pollution modeling has emerged as an indispensable tool in predicting and estimating public health outcomes attributable to biomass burning, especially within the changing landscape of climate trends. These models offer the capacity to delineate the dispersion of pollutants, assess exposure levels and project the spatial and temporal distribution of health impacts. Exposure assessments for PM have been limited by the availability of ground monitoring stations; hence, technology has led to the innovation of methods of estimating air pollution using atmospheric, chemical and satellite modeling to more accurately depict temporal and spatial variations, demonstrate historical associations, and predict future health outcomes (Johns *et al*., 2012; Sorek-Hamer *et al*., 2020). However, it is disconcerting to note that such modeling endeavors have been predominantly concentrated in the global north, often neglecting regions disproportionately affected by vegetation or wildfires in the global south.

From an equity standpoint, the burden of increasing biomass burning is disproportionately shouldered by disadvantaged and marginalized communities. Anthropogenic activities in agriculturally-producing countries and ideal tropical weather conditions have shaped fire-prone land conditions, especially in Africa and Southeast Asia (Liu *et al*., 2015; Reddington *et al*., 2021; Ren *et al*., 2021; Taylor, 2010). Climate change threatens to extend and increase the severity of biomass burning through prolonged droughts, increased greenhouse gas emissions and other instabilities in ecosystems (i.e., changes in biodiversity, decreased soil fertility) (Reddington *et al*., 2021; Taylor, 2010). Similarly, marginalized populations living in wildfire-prone regions, often with limited access to resources and infrastructure, are at a greater disadvantage. Their ability to evacuate safely, access healthcare or recover from the aftermath of wildfires is severely constrained (Liu *et al*., 2015; Thomas *et al*., 2022). In fact, the annual mortality in low- to middle-income countries is predicted to increase by more than 100% by 2060 (Holloway *et al*., 2021).

This stark geographical disparity in air pollution modeling has not only hindered a comprehensive understanding of public health impacts but also contributed to knowledge gaps in assessing the consequences of biomass burning on marginalized communities. Consequently, these communities remain disproportionately vulnerable, with inadequate data and resources to address the impending threats posed by both biomass burning and climate change. This scoping review aims to explore the current and emerging approaches for assessing exposure to biomass burning and its use in establishing associations to public health outcomes. A clearer understanding of the advantages and disadvantages of these approaches in predicting specific health outcomes and public health impacts would benefit the research designs of future studies on atmospheric modeling and possible early warning systems.

2. Methodology

A literature search through PubMed was conducted using the following terms: “biomass burning,” “forest fire,” “vegetation fire” and “wildfire.” This was used in combination with the terms “public health,” “health,” “morbidity” and “mortality.” To link the study to air pollution and modeling, the terms “air pollution,” “air quality,” “atmospheric modeling,” “model” and “modeling” were also used to gather studies that explored the connection between biomass burning, air pollution and public health impacts (both long- and short-term), through the use of atmospheric modeling methods. Any articles that did not attempt to establish links between health and air pollution from biomass burning through the use of atmospheric modeling methods were excluded (i.e., systematic reviews, guidelines, perspectives, other scoping reviews). After appropriate selection, the following data were extracted from the articles: authors, location, year conducted, health impact measured and atmospheric modeling technique used.

The database search identified 197 papers. We then excluded five duplicates (i.e., papers identified by more than one search). We eliminated papers that did not meet the inclusion criteria by first screening the titles (42 papers excluded), by examining abstracts (72 papers excluded), and then by examining the full articles (21 papers excluded) (Fig. 1). The final review included 57 studies of human health impacts of biomass burning, which can be found in Annex 1.

3. Results and Discussion

3.1 Descriptive Statistics

The three main categories of air quality data collection included direct site monitors, satellite imaging (i.e., remote sensing) and air quality models (i.e., chemical transport models). More than half of these studies used a single approach (32/57 studies, 56.14%), while the rest employed a blended approach (25/57 studies, 43.86%), using at least two of the three data collection methods. Among the three, the majority of our reviewed articles (33/57 studies, 57.89%) used chemical transport models for their data collection, the most popular specific model being GEOS-Chem (Goddard Earth Observing System-Chemistry), followed by WRF-Chem (Weather Research and Forecasting-Chemistry). After chemical transport models, the next most commonly used data source was satellite imaging (30/57 studies, 52.63%), most popularly through MODIS (Moderate Resolution Imaging Spectroradiometer). The least commonly used data source was direct station monitors (20/57, 35.08%).

There were 43 countries and regions included in this review. The studies spanned the continents of North America, South America, Europe, Asia and Australia and emphasized the health impacts of air pollution in densely populated urban regions, industrial zones and areas prone to wildfires. The focus of the studies was on areas in the global north in 75.44% of the studies (43/57 studies), with 39.53% focusing on the USA (17/43 studies), with California, then Colorado being the most studied states. This is likely due to richness of research infrastructure, funding opportunities, data availability, diverse range of

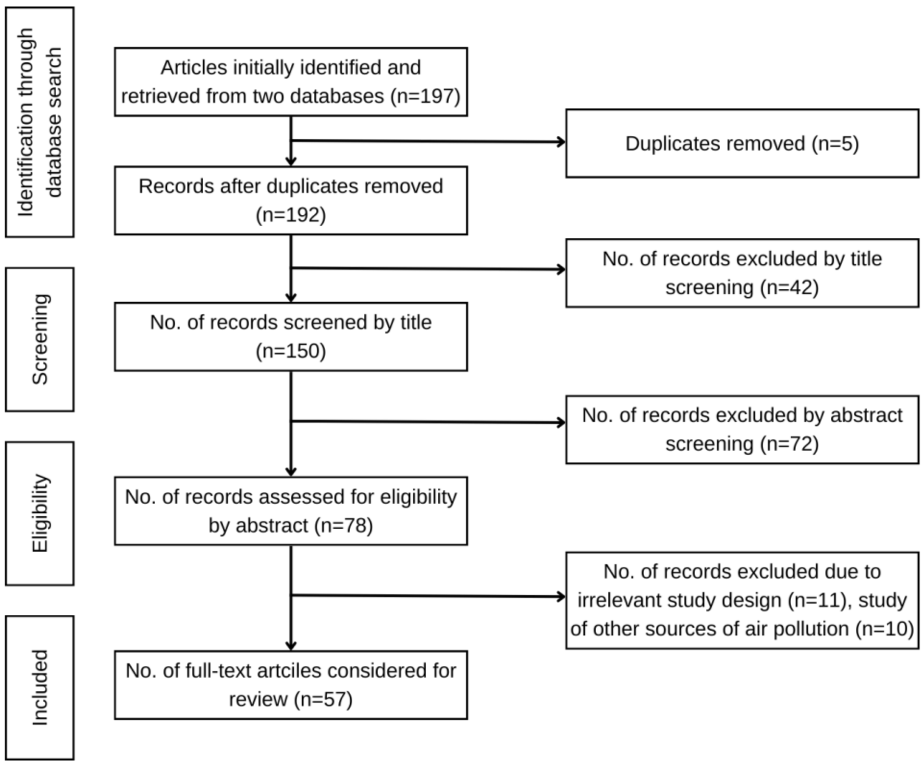

Fig. 1 Article selection process following PRISMA.

geographic and environmental settings, and collaborative research culture. Meanwhile, the Pacific region, particularly Southeast Asia, was not extensively represented in the studies, with only 14 out of the 57 (24.56%) articles focusing on countries considered part of the global south. This is likely due to limited research resources, absence of comprehensive air quality monitoring networks (save for Thailand where station monitors are abundant) (Cândido Da Silva *et al*., 2014; Mueller *et al*., 2021; Othman *et al*., 2022; Pothirat, *et al*. 2021), and lack of collaborative opportunities and partnerships. Additionally, only four articles out of the 19 (7.02%) that employed direct monitors were also focused on countries considered in the global south. The results from the different modeling methods used can be seen in Fig. 2, alongside the geographical distribution of these studies in Fig. 3.

3.2 Station Monitoring

Station monitoring is widely considered the gold standard for air quality information in most developed countries. This involves the use of devices that directly detect air quality within their vicinity. Station monitoring offers the advantage of directly measuring highly accurate data at a more local level, allowing for long-term and reliable data for air quality (Holloway *et al*., 2021; Xie *et al*., 2017). The disadvantage of station monitoring is that it is limited by the number and placement of the stations, as well as the quality of the measuring devices themselves. They are often sparsely distributed over urban areas due to high initial and maintenance costs, thereby limiting possible areas for real-time mapping and assessment. This is especially true in rural areas where vegetation and open burning usually occurs (Adams and Kanaroglou, 2016; Holloway *et al*., 2021; Mueller *et al*., 2021; Xie *et al*., 2017). The density of monitoring stations

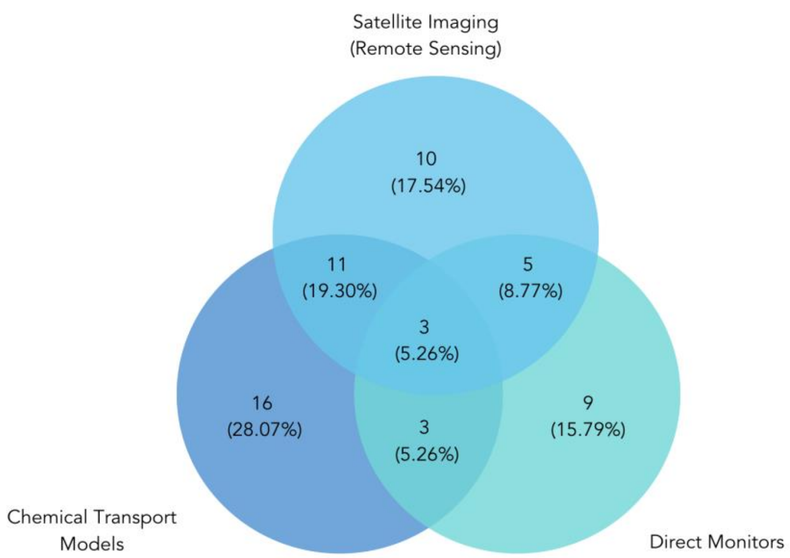

Fig. 2 Venn diagram of air quality modelling methods.

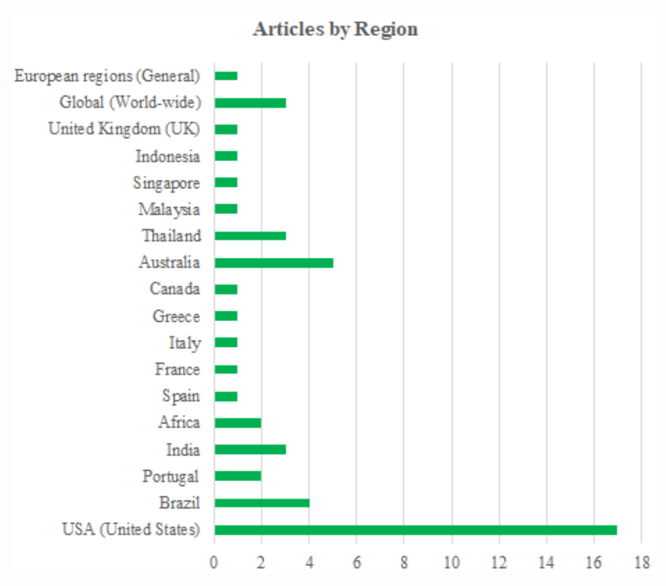

Fig. 3 Articles by region/location.

may also greatly vary. For example, in the USA, there are thousands of monitoring stations for various atmospheric measurements, yet only 20% of US counties have at least one monitor (Holloway *et al*., 2021). Globally, more than half (60%) of all countries have no regular PM2.5 monitoring, and only 10% of all countries have more than three monitors per million inhabitants (Martin *et al*., 2019). The spatial representativeness of air quality monitoring stations may also vary significantly (220 to 4500km^2), highlighting the need for qualitative and ad hoc assessments to understand the limitations and complexity of the results (Mueller *et al*., 2021; Piersanti *et al*., 2015).

Multiple articles incorporate the use of station monitors as their source of air quality data. For example, Othman *et al*. (2022) described in detail the use of an AS-LUNG V.2 outdoor sensing device, which can measure particulate matter levels, CO_2, temperature and relative humidity. Mueller *et al*. (2021) on the other hand utilized ground monitors to assign exposure and noted limited spatial accuracy in capturing differences within smaller subdivisions of its area of interest in Thailand. Portable devices have been increasing in popularity for their relatively low cost and high spatial and temporal resolution, but rely on standardized data collection under different weather conditions (Xie *et al*., 2017). Data quality relies on the consistency of the mobile monitoring unit, i.e., an outfitted industrial van with pollution monitors, a GPS device and a laptop. Data collection is also limited by interrupted data and the logistical inability to cover all areas simultaneously (Xie *et al*., 2017). Leveraging mobile air pollution monitoring techniques may be complimentary to areas with limited monitors (Adams and Kanaroglou, 2016).

Open-source monitoring data are also available through resources like OpenAQ (OpenAQ, n.d.), which aim to provide free access to air quality data for analysis that may lead to advocacies. Studies like Sannigrahi *et al*. (2022) utilized OpenAQ to determine the effects of forest fires on the west coast of the United States on the incidence COVID-19. OpenAQ station density varies by region, however, being concentrated mostly in the United States, Europe and Japan as of writing, possibly limiting its use for many countries, especially those of the global south.

3.3 Chemical Transport Models

Chemical transport models (CTMs) are a class of numerical models used in air pollution modeling to simulate the dispersion, transport and chemical transformation of air pollutants in the atmosphere. They estimate coverage of air pollution concentrations by combining emissions, pollutant transport, chemical reactions and physical processes (e.g., deposition) in the atmosphere in space and time (Koman *et al*., 2022). The advantages of CTMs are that they aggregate data from various sources such as satellite measurements and ground-based observations into their simulations, providing a potentially more holistic picture of multiple datasets. Additionally, this modeling technique is popular for its powerful ability to perform long-term simulations and demonstrate the temporal evolution of the atmospheric composition (Monge-Sanz and Chipperfield, 2006). The disadvantage of CTMs is that they require significantly intensive computational demands, especially when running at high spatial and temporal resolutions. CTMs may also be limited by lack of input, as described by Magzamen *et al*. (2021), where the lack of in situ monitors in mountains and plains has limited the scope of potential study. CTMs also operate under certain assumptions, potentially resulting in data that might be considered oversimplified or with spatial and temporal uncertainties. Burke *et al*. (2021) mention that CTMs provide an alternative approach to linking local pollution concentrations to specific fire activities, aside from those of satellite imaging and direct monitors. However, they also mentioned that model-related assumptions and uncertainties may lead to dramatic discrepancies (either overestimation or underestimation) in downstream exposure estimates. Hence, CTMs are typically cross-referenced and validated with data either from satellite imaging or ground-based monitors, as is the case in Wu, *et al*. (2023) and Crippa, *et al*. (2016). Very often CTMs are used in conjunction with other data sources for air pollution.

Close proximity of the studied locations with densely populated urban areas may affect CTMs, as urban smoke emissions may have similar emission footprints to those of biomass burning (Le *et al*., 2022; Wu *et al*., 2023). The vertical distribution of emissions, secondary chemical reactions and the confounding effect of other pollutants such as ozone and nitrogen dioxide contribute to the limitations of CTMs (Bachwenkizi *et al*., 2021; Kollanus *et al*., 2017; Wu *et al*., 2023). Certain strategies and methods, including kriging and land-use regression, may be employed to adjust the model's raw output and increase the accuracy of the model (Valari *et al*., 2011). Subsequent performance model evaluation in a study by Ballesteros-Gonzales *et al*. (2020) found that overpredictions and underpredictions were apparent for various meteorological conditions (i.e., wind speed, humidity) and air pollutant concentrations (i.e., ozone, carbon dioxide) by as much as twice the actual measurement. Despite the potential for inaccuracies, CTMs remain an indispensable tool in the assessment of air quality. These models are also regularly updated to enhance their performance and accuracy over time.

There are several CTM models. These include GEOS-Chem (Goddard Earth Observing System-Chemistry) and WRF-Chem (Weather Research and Forecasting-Chemistry), both of which use a variety of inputs including satellite, ground-based and other meteorological datasets to simulate the transport of gases and aerosols in the atmosphere. GEOS-Chem in particular includes data about oxidant-aerosol chemistry and reanalysis meteorology from NASA's Global Modeling and Assimilation Office (GMAO). Datasets and regional inventories come from all areas where these are available to the USA, including Europe, Asia and Africa, allowing for regional simulations that allow a better match to the population's spatial distribution (Bachwenkizi *et al*., 2021; Chen *et al*., 2021; Linares *et al*., 2018; Vohra *et al*., 2021; Wu *et al*., 2023).

WRF-Chem was employed by Crippa *et al*. (2016) in their study to determine the relationship between wildfires and mortality in equatorial Asia, noting that the model was able to capture the temporal and spatial variability within Singapore and Sumatra when compared to the data collection at local monitoring stations. One study (Ballesteros-González *et al*., 2020) employed WRF-Chem to assess the effects of open biomass burning on pollutant concentration and estimate potential health impacts associated with wildfires in northern South America. Higher spatial horizontal-grid resolutions might be advantageous in difficult topographical and highly mountainous locations like the northern Andes, they observed, in order to capture the spatial variability of air pollution particles over smaller areas.

Other types of CTMs include the Community Multiscale Air Quality Modeling System (CMAQ) employed by Stowell *et al*. (2019) and Zou *et al*. (2022). This is a photochemical transport model for estimating fire-specific air pollution concentrations and is able to include and distinguish all categories of PM sources. The modeling system uses a three-dimensional grid-based model resulting in raster data grid cells over the studied area. One study (Koman *et al*., 2022), however, observed that CMAQ would be useful in exposure assessments for aging health outcomes due to the model's ability to separate wildfire PM2.5 from other sources of biomass burning in both monitored and unmonitored locations, though overestimation of the severity of wildfire impacts may occur in juxtaposition to the data collected by routine surface monitors. Other CTMs in use are the Atmospheric Dispersion Modelling System (ADMS), developed by the Cambridge Environmental Research Consultants (Le *et al*., 2022), and the SILAM model employed by Kollanus *et al*. (2017). The study by Kollanus (2017) in particular noted that the model underestimated the observed PM levels as it omitted wind-blown dust, secondary organic aerosols and aerosol-bound water in its simulations.

3.4 Satellite-data-based Modeling

Satellite-based modeling and data collection is an approach to air pollution modeling that leverages remote sensing data from Earth-observing satellites to monitor, analyze and model air quality and atmospheric conditions. This modeling technique measures aerosol optical depth (AOD) and other markers of particulate loading in the atmosphere instead of detecting PM2.5 directly (Holloway *et al*., 2021). This approach offers several advantages, as it provides a wealth of information on a regional to global scale (NASA, n.d.; Sohrabinia and Khorshiddoust, 2007). They are spatially consistent and may have high temporal resolution and data coverage, complementing the spatial gaps in traditional surface monitor networks (Holloway *et al*., 2021; Mijling and Van Der A, 2012). Satellite sensor sensitivity, however, varies. The quality and granularity of the data also depend on the satellite technology involved. Spatial resolutions may vary between ~1 to ~50 km and temporal data coverage from hourly to once a day or every few days, depending on whether polar-orbiting or geospatial satellite technology is used (Holloway *et al*., 2021).

Unlike ground monitoring stations, satellite-retrieved data offer more reliable, consistent information regardless of local conditions at a more affordable price, making it a better option in low- to middle-income countries (Sohrabinia and Khorshiddoust, 2007). They can demonstrate dynamic changes even over the last few decades as well as show the regional and intercontinental conditions downwind of transported pollution (Holloway *et al*., 2021; Sorek-Hamer *et al*., 2020). Plume monitoring can link fire activity to receptor regions, proving it an invaluable source of information for both short-term air-quality forecasting and early warning disaster response (Burke *et al*., 2021; Holloway *et al*., 2021; Sorek-Hamer *et al*., 2020).

The most popular satellite imaging device is MODIS, which is attached to NASA's Terra and Aqua satellites launched in 1999 and 2002, respectively. MODIS captures data in 36 spectral bands, covering a wide range of wavelengths from visible to thermal infrared (NASA, n.d.). It has moderate spatial resolution (hence the name "Moderate Resolution Imaging Spectroradiometer"), allowing it to provide detailed observations of the Earth's surface and atmosphere on a global scale. The instrument is capable of collecting data on a daily basis, making it valuable for studying Earth's dynamic processes and changes over time (NASA, n.d.; Sorek-Hamer *et al*., 2020). Other satellite retrieving technology includes NASA's Fire Information for Resource Management System (FIRMS) which uses data from MODIS (Sheldon and Sankaran, 2017), and Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2) (Wani *et al*., 2021).

The most significant constraint of satellite data for health applications is the lack of surface-level information and individual-level information (Holloway *et al*., 2021; Sorek-Hamer *et al*., 2020). Kollanus *et al*. (2017), who used a blended method for his study, noted that satellite modeling approaches were limited by uncertainties in diurnal variations in fire intensity and challenges in observing small vegetation fires. They were unable precisely to measure smoke density or separate smoke higher in vertical transmission and thus found it difficult to link to exposure-health response relationships alone (Burke *et al*., 2021). Conversely, Holloway *et al*. (2021) noted that newer satellite technology has been able to detect emissions from single power plants or industrial facilities and these will likely be further improved to be able to detect individual fires in the near future. Mueller, *et al*. (2021) utilized NASA's Visible Infra-red Imaging Radiometer Suite sensor on the daily number of fires in Thailand, measuring both PM10 and O_3, in addition to ground-monitoring data. They noted the inability to distinguish effects on the measured health outcome of low birth weight between exposure levels of either chemical. They are also limited by the long-term changes in satellite functionality, resulting in challenges in establishing connections between satellite trends and ground monitoring stations (Holloway *et al*., 2021).

3.5 Blended Models

Blended models use a combination of different methods to determine air pollution characteristics and data sources. Given the large uncertainties in air pollution data arising from the limitations of a single method, the application of a blended model may significantly enhance the accuracy and reliability of the data collected (Johnson *et al*., 2020; Pennington *et al*., 2019). One study (Jegasothy *et al*., 2023) for example used MODIS (satellite imaging) to estimate PM2.5 emitted by bushfires. They did a two-stage study where they first measured PM2.5 from monitoring sites to check for air quality, then visually confirmed any measurements exceeding the 95th percentile through MODIS if the source was indeed from bushfires, albeit with the potential for false negatives if the smoke produced was too thin. Magzamen *et al*. (2021) similarly used satellite imaging to determine the presence of smoke plumes while using surface monitors for actual PM2.5 measurements.

Another emerging approach is the use of all the previous models in conjunction with machine learning for improved accuracy. Reid *et al*. (2015) employed a unique approach of combining CTMs with outputs from satellite imaging and meteorological data used in conjunction with gradient-boosted machine learning to provide accurate predictions of out-of-sample air pollution concentrations. O'Neill *et al*. (2021) and Zou *et al*. (2022) used a similar approach, using multiple data sources (CTM with satellite imaging) while applying three machine-learning approaches that similarly improved predictions when compared to surface monitors. The addition of machine learning however will likely require even more computational power than CTMs alone.

4. Conclusions and Recommendations

The objective of our review was to provide a concise overview of the available resources used when exploring the link between air pollution produced from biomass burning and its potential impact on public health. Our study revealed that air pollution caused by biomass burning can be observed and studied through a diverse array of data sources and modeling approaches. From chemical (atmospheric) transport models to satellite observations, many researchers employ various techniques—usually in combination—to understand the complex dynamics of pollutants released during biomass burning events. Broadly categorized, the three main methods of quantifying and collecting air quality data are through direct site/station monitors, satellite data and air quality models (i.e., CTMs), each with its own strengths and weaknesses. In our findings, the use of combinations or blended approaches have been the prevailing method for collecting air pollution data. It is likely that the inherent limitations of each data collection method necessitate supplementary approaches, and also pave the way for the birth of novel techniques, as in the case of machine-learning algorithms that improve the accuracy of existing approaches. Both the traditional and the novel approaches would benefit from qualitative and ad hoc assessments to grasp their limitations and the complexity of their results, especially when used to make generalizations for real-life scenarios that could potentially impact public health policy later on.

While certain data collection methods may be impractical for many regions—particularly that of monitoring stations, which are limited mostly to resource-abundant countries—alternative and free methods are available through the use of NASA's satellite imaging as well as through simulations, as seen in CTMs. These advancements will hopefully alleviate the need for such stations to provide quality evidence when linking air pollution to negative health impacts. While the emergence of machine learning holds significant promise to improving the accuracy of these methods when compared to direct local measurements of air quality seen in monitoring stations, the bulk of existing literature uses air pollution modeling methods that are calibrated for the global north, leaving behind the global south, which suffers from more frequent biomass burning and bears the brunt of air pollution health impacts due to climate change. Additionally, most modeling methods were developed for the primary purpose of surveillance and not necessarily directly considered for policy development or public health programming. These technological advancements can potentially be leveraged to create systems that can communicate risks in a timely manner. Recalibration or validation of these models is needed to increase the reliability of the results for the global south, as well as to explore the possibility of further developing these air pollution modeling initiatives to create early warning systems, especially in the global south, where monitoring stations are fewer and further in between.

It is likely that our study was limited in terms of true deep technical understanding of the various data collection methods employed by the various reviewed articles, potentially missing out on the nuanced strengths and weaknesses of each method. However, it is not within our objective to delve into the technical aspects of each method, but to inform the reader of potential avenues for data collection for future studies. Moreover, the addition of health impact assessments adds another layer of complexity to these studies, and we hope that our review may potentially reveal potential health impacts that may have been overlooked and require further investigation.

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Annex 1 Full list of publications included in the study.

Study	Location	Study duration	Health Outcome	Data Collection Method
Ademu, *et al.*, 2022	California, USA	February 1 – December 31, 2020	Confirmed COVID-19 cases	Station monitoring
Alman, *et al.*, 2016	Colorado, USA	June 5 – July 6, 2012	Respiratory and cardiovascular emergency department visits	Weather Research and Forecasting Model with Chemistry (WRF-Chem); Model for Ozone and Related chemical Tracers (MOZART-4); National Center for Environmental Protection's North American Mesoscale Forecast System (NCEP/NAM); NCAR Fire Inventory (FINN); SMARTFIRE framework; EPA surface network
Augusto, *et al.*, 2020	Portugal	October 2017	Mortality	Satellite imaging using the Navy Aerosol Analysis and Prediction System (NAAPS) Station monitoring (52 fixed air quality monitoring stations)
Bachwenkizi, *et al.*, 2021	15 African countries	2005 – 2015	Infant mortality	Chemical transport model (GEOS-Chem); Satellite monitoring; Ground based observations
Ballesteros-Gonzales, *et al.*, 2020, 2020	Northern South America	February 2010 – February 2018	All-cause mortality Cardiovascular and respiratory mortality Chronic Obstructive Pulmonary Disease (COPD) Respiratory emergency visits	Chemical transport model using Weather Research and Forecasting Model coupled with Chemistry (WRF-Chem)
Chakrabarti, *et al.*, 2019	India	September 2013 – February 2014	Seeking treatment for Acute Respiratory Infection	Moderate-Resolution Imaging Spectroradiometer (MODIS)
Chen, *et al.*, 2021	749 cities in 43 countries and regions, globally	2000 – 2016	All-cause mortality Cardiovascular mortality Respiratory mortality	Chemical transport model (GEOS-Chem)
Cobelo, *et al.*, 2023	Brazil	2003 – 2018	Mortality	Fire Information for Resource Management System (FIRMS) provided by NASA; Copernicus Atmosphere Monitoring Service (CAMS); Meteorological variables from the ERA-Interim model; Pixel-based classification of Landsat satellite images by MapBiomas
Crippa, *et al.*, 2016	Equatorial Asia	September 1 – December 2015	All-cause Mortality	Weather Research and Forecasting model (version 3.5) with Chemistry (WRF-Chem)
Da Silva, *et al.*, 2014	Mato Grosso, Brazil	July 1, 2004 – December 31, 2005	Low birth weight at term	Coupled Aerosol and Trace Gas Transport Model to the Brazilian Developments of the Regional Atmospheric Modeling System (CATT-BRAMS Model) and Center for Weather Forecasting and Climate Studies of the National Institute for Space Research (INPE-CPTEC)
Fadadu, *et al.*, 2021	San Francisco, USA	November 2018	Weekly clinic visit counts for AD or itch	Station monitoring and satellite-based smoke plume density scores rom the Bay Area Air Quality Management District
Faustini, *et al.*, 2019	10 southern European cities in Spain, France, Italy and Greece	2003 – 2010	Natural mortality Cardiovascular mortality Respiratory mortality	Navy Aerosol Analysis and Prediction System (NAAPS) model; Satellite measurements and fire-related smoke plumes
Ford, *et al.*, 2018	Contiguous United States (without Hawaii)	early 21st century (2000–2010) midcentury (2040–2050) late century (2090–2099)	All-cause mortality	Community Atmospheric Model v4 with an interactive gas-aerosol scheme (CAM-Chem); Community Earth System Model (CESM); Community Land Model (CLM) v4.5

Study	Location	Study duration	Health Outcome	Data Collection Method
Gao, *et al.*, 2023	UK Biobank subset	2004 – 2010	Mortality	Chemical transport model (GEOS-Chem) (version 12.0.0); Inverse Distance Weighted (IDW) method; Deep ensemble machine learning (DEML) framework
Goncalves, *et al.*, 2023	5 Brazilian Amazon states	2020 – 2021	COVID-19 morbidity, mortality, and severity	MOD043K (MYD043K) products; Nasa (LAADS DAAC), Collection v. 6.1 (C6); Non-linear prediction model and the higher-resolution MODIS AOD
Heaney, *et al.*, 2022	California, USA	2004 – 2009	Cardiorespiratory emergency hospital visits	Chemical transport model simulation (GEOS-Chem)
Hein, *et al.*, 2022	Indonesia	2013 – 2017	All-cause adult mortality Infant mortality Severe asthma attacks in children Asthma-related hospital admissions Respiratory hospital admissions Lost work days for the current labor force	Satellite remote sensing (MODIS); Chemical transport model simulation (GEOS-Chem)
Henderson. *et al.*, 2011	British Columbia, Canada	July 1 – September 30, 2003	Respiratory physician visits Asthma-specific visits Respiratory hospital admissions	PM10 TEOM instruments; Moderate Resolution Imaging Spectroradiometer (MODIS)
Ignotti, *et al.*, 2010	Brazilian Amazon	2004 – 2005	Hospitalization due to respiratory disease in children under five years old and Elderly people (over 64 years of age) Hospitalization due to childbirth	Coupled aerosol and trace gas transport model for the Brazilian development of the Regional Atmospheric Modeling System Model (CATT-BRAMS)
Jegasothy, *et al.*, 2023	Sydney, Australia	2019 – 2020	All-cause mortality	Satellite imagery; Monitoring stations using inverse-distance weighting and cross-referenced extreme days (95th percentile or above)
Johnson and Garcia-Menendez, 2020	North Carolina, USA	November 2016	Mortality and morbidity	U.S. Environmental Protection Agency's (U.S. EPA) Air Quality System for 172 monitors; Satellite-based Hybrid Single-Particle Lagrangian Integrated Trajectory (HYSPLIT); Weather Research and Forecasting model coupled with Chemistry (WRF-Chem)
Johnston *et al.*, (2007)	Darwin, Australia	Fire seasons of 2000, 2004, 2005	Respiratory Cardiovascular admissions	Rupprecht and Patashnick Tapered Element Oscillating Microbalance (TEOM) series 1400a
Johnston, *et al.*, 2012	Global	1997 – 2006	Mortality	MODIS (Satellite) GEOS-Chem (Chemical Transport Model)
Kollanus *et al.*, 2017	European regions (27 countries)	2005 and 2008	Mortality risk	Moderate Resolution Imaging Spectroradiometer (MODIS) satellite data; System for Integrated modeLling of Atmospheric coMposition (SILAM) chemical transport model
Landguth, *et al.*, 2020	Montana, USA	2009 – 2018	Influenza	Air quality monitoring stations; Satellite imagery via Moderate Resolution Imaging Spectroradiometer (MODIS)
Leibel, *et al.*, 2020	San Diego County, USA	December 7 – 16, 2017	Pediatric respiratory visits	Satellite imagery via Moderate Resolution Imaging Spectroradiometer (MODIS)
Li, *et al.*, 2023	Global (48 countries)	2003 – 2014	Acute respiratory illness symptoms in children under 5y	Chemical transport model (GEOS-Chem)
Linares, *et al.*, 2018	1 province in Spain	2004 – 2009	Provincial daily natural-cause mortality	NAAPS (Navy Aerosol Analysis and Prediction System) Global Aerosol Model (Atmospheric numerical); Geostationary satellite; Satellite imagery via Moderate Resolution Imaging Spectroradiometer (MODIS)
Magzamen, *et al.*, 2021	Colorado, USA	2010 – 2015	Cardiopulmonary hospitalizations and deaths	Environmental Protection Agency Air Quality System monitors for the western United States (kriged PM2.5 surface at a 15 × 15 km resolution); Satellite-based smoke plume estimates via National Oceanic and Atmospheric Administration's Hazard Mapping System
Mueller, *et al.*, 2021	Thailand	2015 – 2018	Low-birth weight (LBW) (<2500 g)	Ambient air pollutant data from ground-based monitors; Biomass burning from satellite remote sensing data (NASA's Visible Infra-red Imaging Radiometer Suite sensor)
Nguyen, *et al.*, 2021	Queensland, New South Wales, Victoria and South Australia	November 1, 2019 – January 8, 2020	Mortality Respiratory and cardiovascular diseases hospitalizations	Weather Research and Forecasting with Chemistry (WRF-Chem) model; Moderate Resolution Imaging Spectroradiometer (MODIS); Cloud-Aerosol Lidar and Infrared Pathfinder Satellite Observation (CALIPSO) satellites
O'Keefe, *et al* 2016	Victoria, Australia	Not specified	Morbidity and mortality	E-sampler Aerosol Monitor (MetOne Instruments Inc. Grants Pass OR)
O'Neill, *et al.*, 2021	Northern California, USA	October 8 – 20, 2017	Multiple-cause mortality	Regional modeling (WRF-CMAQ) with data fusion and three machine learning methods; GOES-16 Advanced Baseline Imaging (ABI); Visible Infrared Imaging Radiometer Suite (VIIRS); Moderate Resolution Imaging Spectroradiometer (MODIS); Fire Radiative Power (FRP); US Environmental Protection Agency (EPA) Air Quality System
Othman, *et al.*, 2022	Thailand, Malaysia	2019–2020	Deposition of Particles in Respiratory Tract	AS-LUNG V.2 Outdoor sensing device
Owili, *et al.*, 2017	54 countries in Africa	2000 – 2015	Under-five mortality Maternal mortality	Satellite imaging via Moderate Resolution Imaging Spectroradiometer (MODIS)
Pan, *et al.*, 2023	USA	April – October 2012, 2013, and 2014	Premature mortality	Fire inventory from NCAR (FINN); CMAQ model
Pennington, *et al.*, 2019	Atlanta, Georgia, USA	1998 – 2010	Respiratory emergency department visits	Receptor-based source apportionment methods (Chemical mass balance with organic molecular markers, Chemical mass balance with gas-based constraints, and Positive matrix factorization); Chemical transport model (Community Multiscale Air Quality [CMAQ]); Street monitor
Pothirat, *et al.*, 2021	Chiang Mai, Thailand	2016 – 2018	All-cause mortality	Single sampling station (located at center of municipal areas of Maung Chiang Mai district, Chiang Mai, Thailand)
Pullabhotla, *et al.*, 2023	Africa	2004 – 2018	Infant mortality	Satellite-derived burned area
Rappold, *et al.*, 2011	42 contiguous counties in eastern North Carolina, USA	June 1 – July 14, 2008	Asthma Chronic obstructive pulmonary disease Pneumonia and acute bronchitis Upper respiratory tract infections Heart failure Cardiac dysrhythmia Myocardial infarction	Geostationary operational environmental satellite instruments
Reddington, *et al.*, 2021	Southeast Asia (including Mainland Southeast Asia and south-eastern China)	2003 – 2015	All-cause mortality and morbidity	Global Model of Aerosol Processes (GLOMAP); Weather Research and Forecasting model coupled with Chemistry (WRF-Chem)

Study	Location	Study duration	Health Outcome	Data Collection Method
Reid, *et al.*, 2019	USA (California)	June – September 2008	All respiratory health outcomes (Asthma, COPD, Pneumonia, Acute Bronchitis, Acute Respiratory Infections)	Chemical transport model; Satellite; Machine Learning AI
Sannigrahi, *et al.*, 2022	West Coast of the USA	August 1 – October 30, 2020	Daily COVID-19 morbidity and mortality	OpenAQ platform (retrieved the latest and up-to-date air quality data from multiple sources such as government/institution air quality monitoring stations and low-cost open-air quality sensors)
Sheldon and Sankaran, 2017	Singapore	2010 – mid 2016	Acute upper respiratory tract infections Acute conjunctivitis Acute diarrhea Chickenpox	Satellite fire data using NASA's Fire Information for Resource Management System (FIRMS)
Stowell, *et al.*, 2019	Colorado, USA	May – August 2011-2014	Cardiorespiratory acute events	Community Multiscale Air Quality Modeling System (CMAQ) AOD Model (derived from Multi-angle Implementation of Atomospheric Correction (MMAIAC)
Viswanathan, *et al.*, 2006	San Diego, USA	September 28 – December 6, 2003	Hospital emergency room visits for asthma, respiratory problems, eye irritation, and smoke inhalation	Station monitoring
Vohra *et al.*, (2021)	Globe	2012	Global mortality	Chemical transport model (GEOS-Chem)
Wani, *et al.*, 2021	Himalayan region of India	2013 – 2017	Acute respiratory infections	Modern-Era Retrospective Analysis for Research and Applications, version 2 (MERRA-2)
Wu, *et al.*, 2022	Africa	2001 – 2014	Lifetime Cancer Risk	BaP inventory (based on GEOS-Chem), CanMETOP
Wu, *et al.*, 2023	510 immediate regions in Brazil	2000 – 2016	All-cause, cardiovascular, and respiratory mortality	Chemical transport model (GEOS-Chem); Global Fire Emissions Database (GFED); Ground monitored data and machine learning
Xu, *et al.*, 2023	Australia	2000 – 2008	Selected genetic markers (26 CpGs and 33 DMRs)	Satellite observations; Chemical transport models (GEOS-Chem); Ground-based observations
Xue, *et al.*, 2023	South Asia	2000 – 2014	Stillbirth	Chemical transport model simulations; Satellite observations
Ye, *et al.*, 2022	510 immediate regions in Brazil	2000 – 2015	All-cause mortality Cardiovascular mortality Respiratory mortality	Chemical transport model (GEOS-Chem)
Yin, 2023	Mainland Southeast Asia	1990 – 2019	Premature mortality	Satellite fire observations and emission inventories; Global Exposure Mortality Model (GEMM)
Zhang, *et al.*, 2023	USA	January 1, 1998 – December 31, 2016	Dementia	Spatiotemporal model Chemical transport model
Zhang, *et al.*, 2023	New South Wales, Australia	2015 – 2019	Preterm birth Term low birth weight Maternal medical conditions	Chemical transport model (GEOS-Chem) with Reanalysis meteorological data
Zou, *et al.*, 2019	Pacific Northwest	August – December 2017	Multiple-cause mortality	Satellite imaging (Multi-Angle Implementation of Atmospheric Correction satellite aerosol optical depth); U.S. Environmental Protection Agency AirNow; Weather Research and Forecasting (WRF) model version 3.7; Community Multiscale Air Quality (CMAQ) model

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