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Review Article

Analysis of Human Activities and Deforestation Impact on Air Quality: a Paper Review

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Abstract

This paper discusses the relationship between changes in human activities and deforestation with the condition of pollutant concentration parameters in an area using the Google Earth engine (GEE) method. By applying the Systematic Literature Review method, it is expected to provide an explanation of changes in pollutant conditions, such as concentration patterns of CO, NO_2, SO_2, O_3, HCHO, PM2.5, and PM10 as a result of changes in human activity and deforestation. Human activity patterns may change due to certain events or rules that force humans to follow them. A clear example is the lockdown event during the Covid-19 pandemic that resulted in restrictions on human activities, especially outdoor activities. Similarly, deforestation is the process of significant reduction of forest area through tree felling, forest burning, or other land use changes that result in loss of tree cover and alter forest ecosystems. Both of these events impact the environment and air quality in the region, such as affecting air pollution concentrations. In various studies, changes in human activities and deforestation have been shown to have a significant relationship and influence on air quality concentration parameters in a region.

Keywords: Air Quality; Human Activity; Deforestation; Google Earth Engine

1. Introduction

Lockdown events implemented in response to the Covid-19 pandemic have significantly altered human activity patterns around the world. They have led to a decrease in transport, industrial and commercial activities, which in turn can affect the environment and air quality (Faisal & Jaelani, 2023; Fayaz, 2023; Matci et al., 2022; Wang et al., 2022). Meanwhile, deforestation associated with forest fires is a serious concern in the context of climate change and ecosystem balance (Murmu et al., 2022; Viedra & Sukojo, 2023).

While lockdown policies can reduce industrial and transport emissions, continued deforestation can have the opposite effect on air quality. Forest fires release not only greenhouse gases but also particulates that can negatively affect human health (Arikan & Yildiz, 2023). Therefore, in-depth studies of air quality changes in regions experiencing lockdown and deforestation events are crucial.

This research utilises the advanced technology of Sentinel-5 satellite imagery that can provide high-precision data on gas and particulate concentrations in the atmosphere. Google Earth Engine will be the main tool to process and analyse this data in an efficient and structured way (Kazemi Garajeh et al., 2023). The combination of these two technologies allowed the authors to identify and understand the direct impact of lockdown and deforestation events on air quality (Rabiei-Dastjerdi et al., 2022; Singh et al., 2022).

Air quality analysis in this context involves measuring concentrations of air pollutants such as Nitrogen Dioxide, Sulphur Dioxide, Ozone, Particulates and other polluting gases. By comparing data before and during the lockdown period, as well as integrating deforestation information, this research seeks to reveal the joint impact of these two factors on air quality in a region (Dhar, 2023; Gharibvand et al., 2023). By combining information from Sentinel-5 satellite imagery and analyses using Google Earth Engine, this research seeks to contribute to a complex understanding of the relationship between changes in human activity, deforestation and air quality (Rahaman et al., 2023; Singh et al., 2022).

As such, the findings of this review paper are expected to provide a more detailed and granular insight into the complex interaction relationship between lockdown events, deforestation, and air quality changes. For instance, during the 2020 lockdown in Jakarta, a notable 21% reduction in nitrogen dioxide (NO_2) levels was observed, followed by a subsequent increase after restrictions were lifted, illustrating the temporary nature of air quality improvements driven by human activity reductions (Faisal & Jaelani, 2023). The implications of this research are urgent, as ongoing deforestation in regions such as the Amazon and Kalimantan not only exacerbates global warming but also leads to deteriorating air quality, posing significant health risks to local populations (Viedra and Sukojo, 2023). Therefore, the study's contributions are critical, both for advancing scientific understanding and for forming more effective and immediate policies related to air quality management and environmental sustainability, particularly in regions where deforestation and human activity are in constant flux. The implications of this research not only include contributions to scientific understanding, but can also provide a foundation for the formulation of more effective policies related to air quality management and environmental sustainability.

The main purpose of this review paper is to dig deeper into the dynamics of air quality changes during the lockdown period and the impact of deforestation in certain areas based on the articles that have been reviewed. By using the Systematic Literature Review method in collecting and analysing research articles, it is expected that the results obtained will be maximised in providing a comprehensive and in-depth understanding related to the research topic being studied.

2. Methods

2.1. Systematic literature review (SLR)

In this review paper, Systematic Literature Review (SLR) method was used to collect and analyse articles and publications related to the relationship of human activity change and deforestation to air quality using the Google Earth Engine method (Dhar, 2023; Gharibvand et al., 2023). This approach involves a systematic search across multiple databases to identify articles relevant to the research topic (Kazemi Garajeh et al., 2023; Singh et al., 2022). The use of appropriate keywords, such as "Air Quality", "Deforestation", and "Google Earth Engine", was used to narrow down the search. The corresponding set of articles was then analysed in detail using VOSviewer software to gain a comprehensive understanding of the impacts of changing human activities and deforestation on air quality.

Network Visualization using VOSviewer refers to a method of visualizing relationships, connections, and patterns in large datasets, particularly those involving bibliometric analysis (e.g., analyzing citations or co-occurrences in academic literature). VOSviewer is a specialized software tool designed for creating and interpreting such visualizations, often in the context of systematic literature reviews or scientific mapping (Van Eck & Waltman, 2010). In the paper, this method is used to show relationships between articles, keywords, and themes that are relevant to the study of air quality, human activities, and deforestation. Key data such as research data, methodology used, and research results, were extracted from relevant articles to support this paper. The following is the result of using VOSviewer (Figure 1).

Figure 1. Network visualization based VOSviewer
Source: (Processing, 2024)

2.2. Research question

Through a search in the Scopus database using the keywords "Air Quality" and "Deforestation" 426 articles were found. Furthermore, searching with the keywords "Air Quality" and "Google Earth Engine" resulted in 81 articles, while searching with the keywords "Deforestation" and "Google Earth Engine" resulted in 190 articles. In total, around 697 articles were found through searching with these keywords.

Table 1. Keyword search in Scopus database

Search by keywords	Scopus Database
"Air Quality" AND "Deforestation"	426
"Air Quality" AND "Google Earth Engine"	81
"Deforestation" AND "Google Earth Engine"	190
TOTAL	697

(Source: Processing, 2024)

Search results in the Scopus database are filtered through the PRISMA diagram flow to produce articles that will be used as review material. The following is a series of PRISMA diagram stages that describe the article filter process (Table 1). The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) diagram is a standardized flowchart that outlines the process of identifying, screening, and selecting studies for inclusion in a systematic review. It is an essential tool for ensuring transparency and reproducibility in systematic reviews by providing a clear visual representation of how the final set of studies was selected from an initial pool of research articles (Moher et al., 2009; Page et al., 2021).

This PRISMA diagram reflects the process of filtering and selecting articles based on certain steps in the research sequence. Initially, studies were identified by searching the Scopus Index database, which resulted in 697 articles. From these articles, duplicates articles (24 articles) were removed, leaving 673 studies. Next, articles that did not use Google Earth Engine were excluded, leaving 426 studies. Next, articles that did not address air quality were removed, reducing the number of studies to 236. Then, articles that did not address deforestation were excluded, resulting in 155 remaining studies. Of these, 84 articles were excluded after looking at their abstracts, leaving 71 articles, and after a thorough review, 49 articles were excluded again, leaving 22 articles.

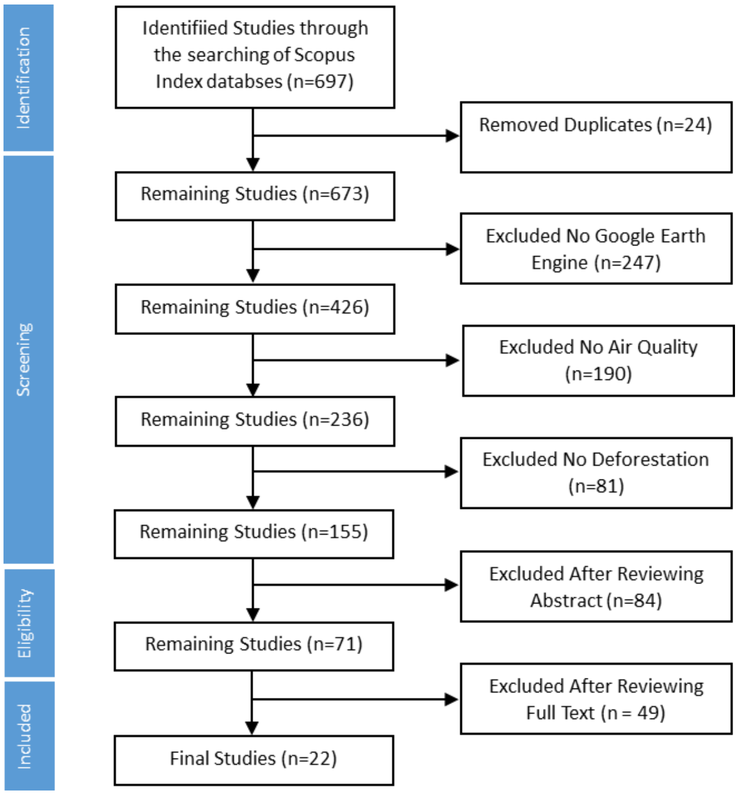

Figure 2. PRISMA Diagram of Article Filter Process
Source: (Processing, 2024)

Finally, after a full selection stage, 22 studies fulfilled the final criteria and were considered the final studies to be used in the research. This PRISMA diagram provides a clear picture of the process of screening and selecting studies that fulfil the research objectives and criteria. Below is a graph of the year of publication of the 22 reviewed articles (Fig 3). Based on 22 articles that have been reviewed, 13 articles were published in 2023.Then in 2022 there were 8 articles. While in 2024 there was only 1 article.

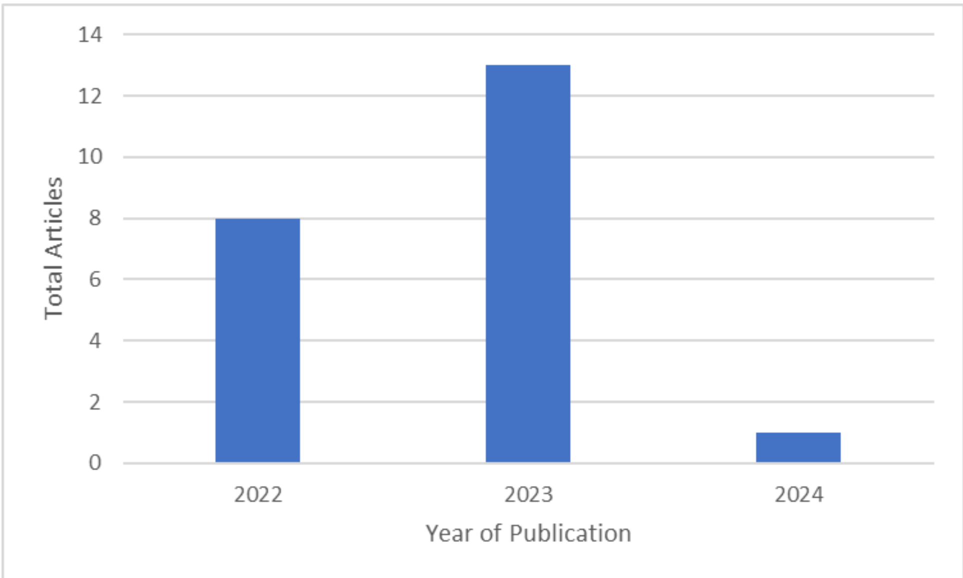

Figure 3. Chart of Year of Article Publication
Source: (Processing, 2024)

3. Result and Discussion

3.1. Pollution Concentration Monitoring using Sentinel-5 Satellite Imagery and Analysis using Google Earth Engine (GEE)

According to Garajeh, et al (2023) the use of Sentinel-5 satellite image data and processing and analysis using GEE is effective in mapping and monitoring air pollution. In their research, Garajeh et al. monitored time-based concentrations of air pollutants such as carbon monoxide (CO), nitrogen dioxide (NO_2), sulfur dioxide (SO_2), and ozone (O_3) processed using GEE. The results showed a strong correlation between satellite data and measurements at direct observation stations. Chinnasamy et al (2023) and Rabiei-Dastjerdi et al (2022) also said that remote sensing data from Sentinel-5 satellite imagery can be used for air quality analysis and monitoring using high spatial and temporal resolution.

Monitoring the concentration of pollutants NO_2, SO_2, CO, HCHO, O_3, and Absorbing Aerosol Index (AAI) using Sentinel-5 satellite image data and processing it using GEE has also been done by Davybida (2023) and Mehrabi, et al (2023) to analyse the impact of air pollution from the Russia-Ukraine war. The result was an increase in pollutant concentrations in the region, especially major cities in Ukraine.

Sentinel-5P satellite imagery and the Google Earth Engine platform are also useful for monitoring air quality in tourism areas (Sunarta & Saifulloh, 2022). Data processing, data extraction, and data visualisation can be done using Google Earth Engine. Data processing methods using GEE can produce accurate and spatially distributed data for air pollution mapping. Monitoring the concentration of key pollutants such as NO_2, SO_2, CO, HCHO, O_3, and AAI using Sentinel-5 satellite data and processing it through Google Earth Engine is essential for managing air quality, protecting public health, and responding to environmental threats. This approach provides a powerful, scalable, and efficient means of obtaining real-time, global data on air pollutants, allowing researchers and policymakers to make informed decisions on environmental management and pollution control.

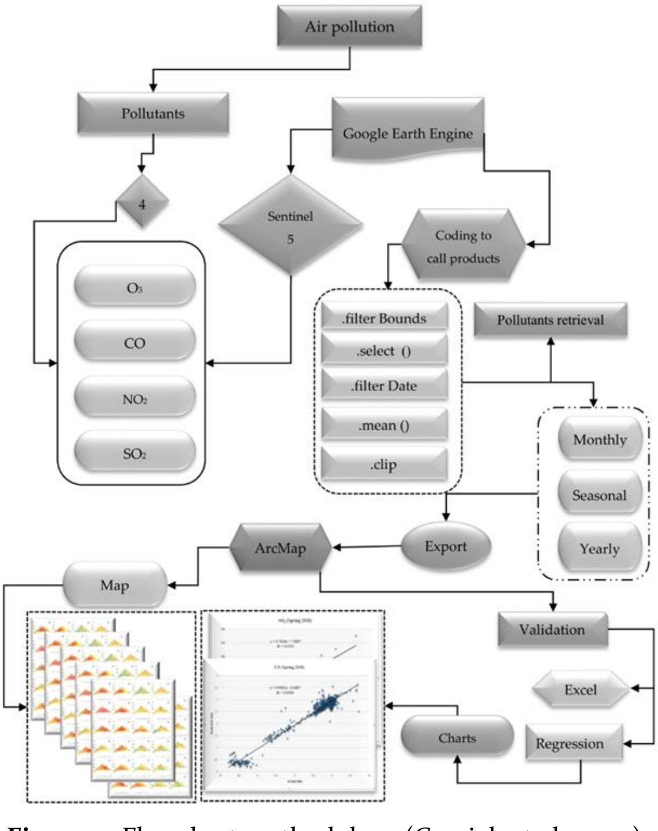

Figure 4. Flowchart methodology (Garajeh et al., 2023)

The diagram illustrates a comprehensive workflow for monitoring air pollution using Sentinel-5 satellite data and Google Earth Engine (GEE). It begins by identifying key pollutants, including Ozone

(O_3), Carbon Monoxide (CO), Nitrogen Dioxide (NO_2), and Sulfur Dioxide (SO_2). The data is retrieved from the Sentinel-5 satellite and processed using GEE, where specific coding functions such as .filterBounds, .select(), .filterDate, .mean(), and .clip() are employed to extract relevant information about the pollutants over specified time periods (monthly, seasonal, yearly). The processed data is then exported to tools like ArcMap for spatial analysis, allowing for the creation of maps and charts that visualize the spatial distribution and temporal trends of the pollutants. Validation steps compare satellite measurements with ground data, while regression analysis is performed to explore relationships between pollutant levels and other factors. This workflow provides valuable insights into air quality, essential for informing policy decisions and managing environmental health effectively.

3.2. Impact of Changes in Human Activities Due to Covid-19 on Pollutant Concentrations

The COVID-19 lockdown has had a significant impact on air quality in 16 metropolitan areas in China. Based on the analysis of data from TROPOMI's Sentinel-5P obtained through the GEE platform, it was found that NO2 concentrations decreased significantly in different types of cities during the lockdown period (Wang et al., 2022; Xing et al., 2022). Similarly, Wang et al. and Xing et al. Gharibvand et al. (2023) also conducted a study in Iran using GEE, the results of which showed a decrease in NO2 concentration by 3.5% and O3 by 6.8% in Tehran, as well as a decrease in NO2 concentration by 20.97% and O3 by 5.67% in Arak during the lockdown period compared to the same period in 2019. This decrease can be attributed to the reduction in transport and industrial and socio-economic activities due to the lockdown measures.

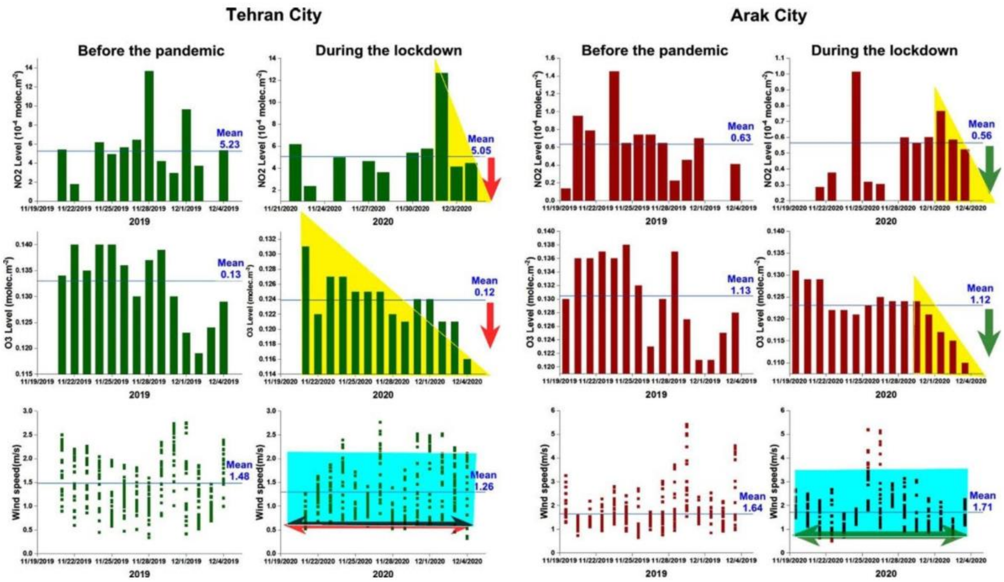

Figure 5. NO2 and O3 Concentrations before the Pandemic and During Lockdown in Tehran City and Arak City, Iran

Source: (Gharibvand et al., 2023)

The results of research conducted by Morozova et al (2023) and Dhar (2023) also show that there was a decrease in the concentration of air pollutants in major Russian and Indian cities during the lockdown period compared to the period before and after the pandemic. The decrease was particularly significant for nitrogen dioxide (NO2), with an average decrease in concentration in 2020 of 30.7% compared to 2019. The maximum decrease was recorded in Moscow at 41% of 2019 levels, Podolsk, and New Moscow (34% and 29%). However, five cities recorded higher pollution levels compared to 2019, namely Tomsk, Novokuznetsk, Stavropol, Kemerovo, and Volzhsky. After the lifting of the lockdown, air pollution levels increased again, suggesting that the improvement in air quality during the lockdown was temporary without long-term intervention to reduce emissions.

Faisal and Jaelani (2023) revealed that the decrease in Nitrogen Dioxide (NO_2) concentration during the COVID-19 social restriction period in Jakarta. Analysis using Sentinel-5P satellite imagery showed that NO_2 decreased by 21% in 2020 compared to the previous year. However, in 2021, NO_2 increased by 23% compared to the previous year. In addition, this study also found a correlation between changes in community mobility and changes in NO_2 concentrations. Mobility data from Google Mobility Reports showed that a decrease in mobility in the residence and workplace categories correlated with a decrease in NO_2 concentrations. The largest decrease in NO_2 occurred at the beginning of the implementation of social restrictions from April to May 2020, as well as during the emergency PPKM period from July to August 2021. The results of this study can be used to evaluate the effectiveness of social distancing policies in reducing NO_2 levels and improving air quality. The decrease in NO_2 concentrations that occurred during the social distancing period indicates that the policy can have a positive impact on the environment. However, it should be noted that the increase in NO_2 concentration in 2021 indicates the need for further efforts in air pollution control.

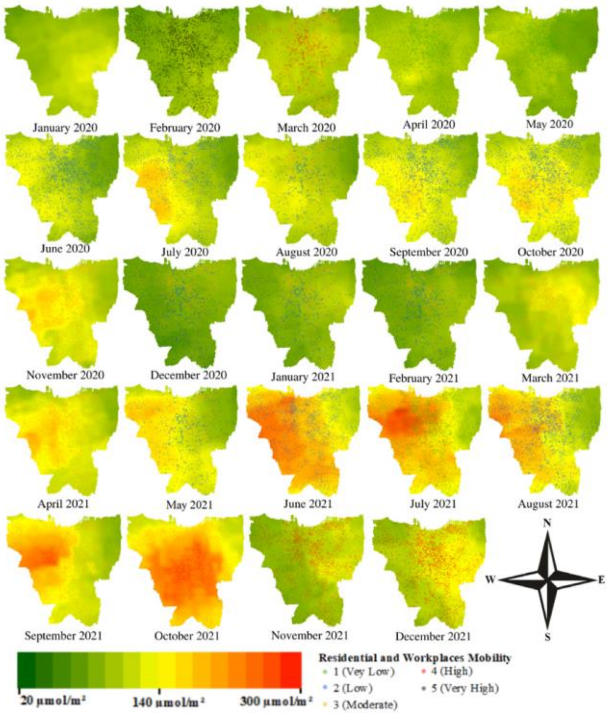

Figure 6. Visualisation of NO_2 from January 2020 to December 2021
Source: (Faisal & Jaelani, 2023)

Halder, et al (2023) explained that anthropogenic activities such as industrialisation, transportation, and urbanisation are the main factors for increasing air pollution in India. The COVID-19 lockdown temporarily reduced the concentrations of air pollutants, indicating the role of human activities in reducing air quality concentrations. The concentrations of NO_2, CO, and Aerosol Optical Depth (AOD) increased from 2018 to 2021, except during the 2020 lockdown. The same research also conducted by Sunarta and Saifulloh (2022) also stated that NO_2 concentrations decreased in March-April 2020 when activity restrictions (lockdown) were carried out. Then NO_2 concentrations increased again after the lockdown policy was enforced, where outdoor activities were allowed again even though under limited circumstances. Not only due to anthropogenic activities, meteorological factors such as temperature, wind speed and direction, and rainfall also affect AOD values (Dhital et al., 2022; Meng et al., 2024).

Further analysis revealed that lockdowns implemented during the COVID-19 pandemic had a significant impact on reducing air pollution levels. Decreases and changes in NO_2, $PM_{2.5}$, and PM_{10} concentrations were observed in many countries from the beginning to the middle of the second quarter of 2020 (15 May 2020), indicating the positive impact of lockdown policies on the environment. Although the lockdown had negative impacts on economic growth, such as increasing the unemployment rate and affecting the welfare index, one of the positive impacts was the decrease in air pollution in most regions of the world. This decrease was observed not only in Iran but also in some neighbouring countries and around the world, which shows that the lockdown policy can be an effective tool to temporarily reduce air pollution (Fayaz, 2023).

3.3. Impact of Deforestation Forest Burning on Pollutant Concentration

Based on research conducted by Arikan and Yildiz (2023), it was found that during forest fires, there was a significant increase in carbon monoxide (CO) and ultraviolet aerosol index (UVAI) values. This suggests that forest fires have a direct impact on air quality, by increasing the concentration of certain pollutants in the atmosphere. Further analyses show that the gases released during forest fires have a significant correlation with data obtained from local area air quality stations. This suggests that forest fires contribute to the rise and fall of air quality in the region. This is in line with research conducted by Singh, et al (2022) which states that significant increases in air pollutant concentrations, with an increase of approximately 272% for carbon monoxide and 45% for nitrogen oxides. This shows the significant impact of forest fires on air quality in the affected areas.

Rahaman, et al (2023) conducted a study to analyse the relationship between NO_2 concentrations with land surface temperature (LST) and vegetation density in Delhi and Dhaka in 2019-2021. The results showed that there was a negative correlation between NO_2 concentration and vegetation density (NDVI and EVI) and positive with LST. The value of NO_2 concentration in Delhi decreased, while it increased in Dhaka in 2019-2021. Dhaka's LST increased and vegetation density decreased. This caused the increase of NO_2 in Dhaka region. The same research conducted by Viedra and Sukojo (2023), stated that there was an increase in the annual average nitrogen dioxide concentration in East Kalimantan from 172,283 $\mu g/m^3$ in July 2018 - June 2019 to 173,040 $\mu g/m^3$ in July 2019 - June 2020. The main sources of sulphur dioxide (SO_2) gas are coal-fired power plants, fossil fuels and volcanic activity. Meanwhile, NO_2 is produced from fuel combustion processes, including motor vehicle emissions, heavy equipment such as mining vehicles, and power plants.

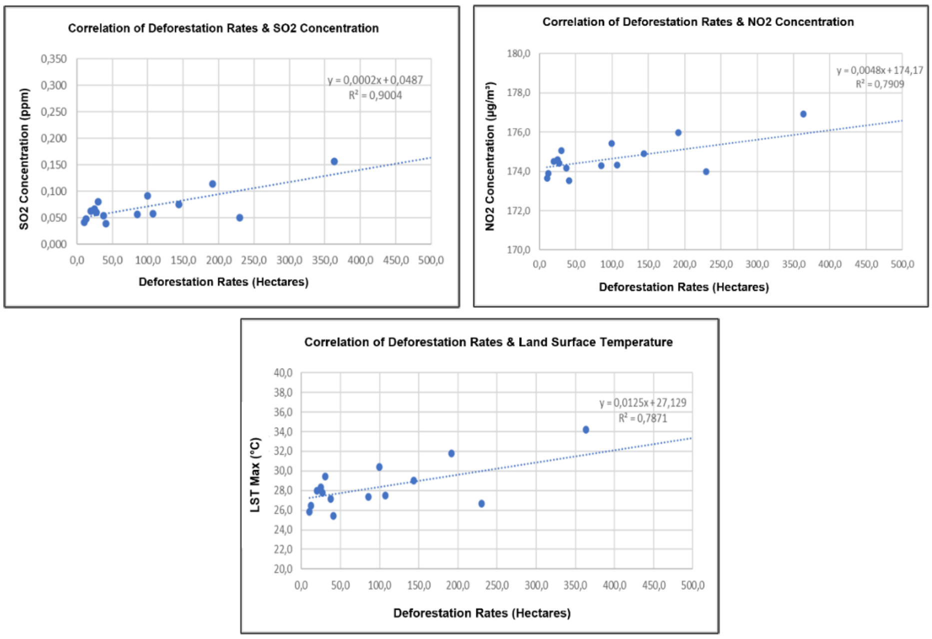

Figure 7. Correlation Diagram between Deforestation and SO_2, NO_2 and LST
Source: (Viedra & Sukojo, 2023)

Murmu, et al (2022) also stated that there was a correlation between forest fire incidence and air pollutant concentrations in the Western Himalayan region. This correlation varied across regions and pollutant types. Nitrogen Dioxide (NO_2) showed a moderate correlation with fire incidence, while Formaldehyde (HCHO) showed a moderate to high correlation in all studied regions.

Table 8. Correlation between Pulutan Concentration and 4 Forest Fire Regions (Murmu et al., 2022)

		HCHO	CO	AI	NO2	SO2
KUMAON	2019	0.5	0.6	0.5	0.5	0.0
	2020	0.2	0.2	0.2	0.2	0.2
	2021	0.2	0.3	0.4	0.3	0.1
GARHWAL	2019	0.6	0.5	0.3	0.5	-0.1
	2020	0.1	0.0	-0.1	0.2	0.4
	2021	0.2	0.3	0.3	0.2	0.0
HIMACHAL PRADESH	2019	0.5	0.3	0.2	0.5	-0.1
	2020	0.2	0.1	0.1	0.4	0.3
	2021	0.0	0.2	0.2	0.1	-0.1
JAMMU AND KASHMIR	2019	0.4	0.3	-0.1	0.5	-0.1
	2020	0.3	0.2	0.1	0.4	-0.2
	2021	0.3	0.3	-0.1	0.3	0.0

Based on research conducted by Matci, et al (2022), there is a significant correlation between several meteorological parameters and air pollutants. For example, the relationship between SO_2 and temperature, NO_2 and temperature, and O_3 and CH_4. This shows that meteorological conditions also affect the concentration and distribution of air pollutants.

3.4. Relationship Between Human Activity, Deforestation, and Air Quality

This article elucidates the significant relationship between changes in human activity, deforestation, and air quality. Firstly, changes in human activities, particularly during lockdown periods, have a substantial impact on air quality. The restrictions imposed to limit human mobility led to a measurable decrease in pollutant concentrations such as CO, NO_2, SO_2, O_3, HCHO, $PM_{2.5}$, and PM_{10}. These findings support the discussion on how levels of human activity directly influence air quality. Additionally, the article highlights the negative impact of deforestation, specifically due to forest burning, on air quality. The increase in pollutant concentrations following deforestation activities demonstrates the complex relationship between land use changes and the exacerbation of air pollution. Deforestation leads to the loss of forest vegetation, which serves as a carbon storage mechanism and pollutant absorber, resulting in higher pollutant levels in affected areas.

In this context, both the article and the broader discussion emphasize the urgent need for effective policies to manage air quality and promote environmental sustainability. The findings underscore the necessity for regulatory frameworks that can mitigate the impacts of human activities and deforestation on air quality, making a compelling case for action. Furthermore, the article calls for further research into the long-term effects of the interactions between human activities and environmental changes, such as deforestation, on air quality, aligning with the discussion aimed at better understanding these relationships. Therefore, this article provides empirical evidence that supports the discussion on how changes in human activity and deforestation impact air quality, while also emphasizing the need for effective environmental policies and ongoing research in this field.

4. Conclusions

Based on the reviewed articles related to the relationship between changes in human activity, deforestation, and air quality, it can be concluded that the interplay between lockdown-induced changes in human activity and deforestation caused by forest burning significantly impacts air quality concentration parameters. Specifically, pollutants such as CO, NO_2, SO_2, O_3, HCHO, $PM_{2.5}$, and PM_{10} showed decreased concentrations following the enforcement of regulations limiting human activities, compared to periods before and after these regulations. Conversely, deforestation activities, particularly those resulting from forest fires, lead to increased concentrations of these pollutants relative to pre-fire levels. The loss of forest vegetation, which serves as a crucial carbon storage mechanism, further exacerbates pollutant concentrations in affected areas. This review emphasizes the urgent need for effective policies addressing environmental sustainability and air quality management, especially in regions experiencing rapid industrialization and urbanization. Future studies should also explore the long-term effects of these interactions and consider the potential of satellite monitoring technologies to deepen our understanding of air pollution dynamics. Ultimately, the insights gained from this research provide a foundation for informed decision-making in environmental policy and highlight the necessity for collective action to mitigate air quality deterioration.

Despite limitations in conducting direct field research, the use of remote sensing techniques and data processing and analysis using Google Earth Engine-based web applications can be very useful for air quality management, especially in identifying the impacts of human activity restrictions and deforestation. The results of some of these studies not only provide an in-depth understanding of the spatial distribution of air quality, but also provide a basis for the development of air pollution control policies and strategies. The data generated can be taken into consideration for stakeholders to take appropriate actions to address air quality pollution issues, in line with efforts to maintain and improve air quality in the relevant region.

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References

Arikan, D., & Yildiz, F., 2023. Investigation of antalya forest fire's impact on air quality by satellite images using google earth engine. Remote Sensing Applications: Society and Environment, 29.

Chinnasamy, P., Shah, Z., & Shahid, S., 2023. Impact of lockdown on air quality during covid-19 Pandemic: a case study of India. Journal of the Indian Society of Remote Sensing, 51, 103–120.

Davybida, L. I., 2023. Air quality impacts of war detected from the sentinel-5p satellite over Ukraine. IOP Conference Series: Earth and Environmental Science, 1254.

Dhar, S. B., 2023. A comparative study of air quality between pre and post COVID-19 periods in India. Environment, Development and Sustainability.

Dhital, N. B., Bhattarai, D. R., Sapkota, R. P., Rijal, K., Byanju, R. M., & Yang, H. H., 2022. Comparing the change in air quality during the COVID-19 lockdown between dry and wet seasons in Nepal. Aerosol and Air Quality Research, 22.

Faisal, M., & Jaelani, L. M., 2023. Spatio-temporal analysis of nitrogen dioxide (NO2) from sentinel-5p imageries using google earth engine changes during the COVID-19 social restriction policy in Jakarta. Natural Hazards Research, 3, 344–352.

Fayaz, M., 2023. The lock-down effects of COVID-19 on the air pollution indices in Iran and its neighbors. Modeling Earth Systems and Environment, 9, 669–675.

Gharibvand, L. K., Jamali, A. A., & Amiri, F., 2023. Changes in NO2 and O3 levels due to the pandemic lockdown in the industrial cities of Tehran and Arak, Iran using sentinel 5p images, google earth engine (GEE) and statistical analysis. Stochastic Environmental Research and Risk Assessment, 37, 2023–2034.

Halder, B., Ahmadianfar, I., Heddam, S., Mussa, Z. H., Goliatt, L., Tan, M. L., Sa'adi, Z., Al-Khafaji, Z., Al-Ansari, N., Jawad, A. H., & Yaseen, Z. M., 2023. Machine learning-based country-level annual air pollutants exploration using sentinel-5p and google earth engine. Scientific Reports, 13.

Kazemi Garajeh, M., Laneve, G., Rezaei, H., Sadeghnejad, M., Mohamadzadeh, N., & Salmani, B., 2023. Monitoring trends of CO, NO2, SO2, and O3 pollutants using time-series sentinel-5 images based on google earth engine. Pollutants, 3, 255–279.

Matci, D. K., Kaplan, G., & Avdan, U., 2022. Changes in air quality over different land covers associated with COVID-19 in Turkey aided by GEE. Environmental Monitoring and Assessment, 194.

Mehrabi, M., Scaioni, M., & Previtali, M., 2023. Air quality monitoring in Ukraine during 2022 military conflict using sentinel-5p imagery. Air Quality, Atmosphere and Health.

Meng, H., Bai, G., & Wang, L., 2024. Analysis of the spatial and temporal distribution characteristics of AOD in typical industrial cities in northwest China and the influence of meteorological factors. Atmospheric Pollution Research, 15.

Moher, D., Liberati, A., Tetzlaff, J., Altman, D. G., , & PRISMA Group., 2009. Preferred reporting items for systematic reviews and meta-analyses: The PRISMA Statement. Annals of Internal Medicine, 151, 264–269 W64.

Morozova, A., Sizov, O., Elagin, P., Lobzhanidze, N., Fedash, A., & Mironova, M., 2023. Evaluation of the Impact of COVID-19 restrictions on air pollution in Russia's largest cities. Atmosphere, 14.

Murmu, M., Roy, A., Karnatak, H. C., & Chauhan, P., 2022. Impact of forest fire emissions on air quality over western himalaya region. International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives, 43, 1153–1160.

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., ... Moher, D., 2021. The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. The British Medical Journal, 372, n71.

Rabiei-Dastjerdi, H., Mohammadi, S., Saber, M., Amini, S., & McArdle, G., 2022. Spatiotemporal analysis of NO2 production using TROPOMI time-series images and google earth engine in a middle eastern country. Remote Sensing, 14.

Rahaman, S. N., Ahmed, S. M. M., Zeyad, M., & Zim, A. H., 2023. Effect of vegetation and land surface temperature on NO2 concentration: a google earth engine-based remote sensing approach. Urban Climate, 47.

Singh, S., Singh, H., Sharma, V., Shrivastava, V., Kumar, P., Kanga, S., Sahu, N., Meraj, G., Farooq, M., & Singh, S. K., 2022. Impact of forest fires on air quality in Wolgan Valley, New South Wales, Australia—a mapping and monitoring study using google earth engine. Forests, 13.

Sunarta, I. N., & Saifulloh, M., 2022. Spatial variation of no2 levels during the COVID-19 pandemic in the Bali tourism area. Geographia Technica, 17, 140–149.

Viedra, G. G. Z., & Sukojo, B. M., 2023. Analysis of the effect of deforestation rates on air pollution concentration and land surface temperature using landsat-8 imagery with google earth engine (case study: east kalimantan province, 2019-2020). IOP Conference Series: Earth and Environmental Science, 1127.

Van Eck, N. J., & Waltman, L. 2010. Software Survey: VOSviewer, a computer rogram for bibliometric mapping. Scientometrics, 84, 523-538.

Wang, S., Chu, H., Gong, C., Wang, P., Wu, F., & Zhao, C., 2022. The effects of COVID-19 lockdown on air pollutant concentrations across China: a google earth engine-based analysis. International Journal of Environmental Research and Public Health, 19.

Xing, H., Zhu, L., Chen, B., Niu, J., Li, X., Feng, Y., & Fang, W., 2022. Spatial and temporal changes analysis of air quality before and after the COVID-19 in Shandong province, China. Earth Science Informatics, 15, 863–876.