International Journal of Engineering and Geosciences

https://dergipark.org.tr/en/pub/ijeg

e-ISSN 2548-0960

A five-year Study Using Sentinel-5P Data Observing Seasonal Dynamics and Long-term Trends of Atmospheric Pollutants

Hossam Aldeen Anwer *[1], **Abubakr Hassan** [2], **Abdelrahim Elhag** [3]

[1] *Karary University, Faculty of Surveying Engineering, Sudan, hossamanwe234@gmail.com*
[2] *Karary University, Faculty of Surveying Engineering, Sudan, bakhas@my.swjtu.edu.cn*
[3] *Sudan University of Science and Technology, School of Surveying, Sudan, rasilna@hotmail.com*

Cite this study: Anwer, H. A., Hassan, A., & Elhag, A. (2025). A five-year study using Sentinel-5P data observing seasonal dynamics and long-term trends of atmospheric pollutants. International Journal of Engineering and Geosciences, 10 (2), 262-271.

https://doi.org/10.26833/ijeg.1587122

Keywords
Air pollution
Sentinel-5P
Seasonal variation
Particulate Matter (PM2.5)
Google Earth Engine (GEE)

Research Article

Received:18.11.2024
Revised: 05.01.2025
Accepted:17.01.2025
Published:01.07.2025

Abstract

Air pollution is an escalating concern for both environmental sustainability and public health, exacerbated by urbanization and industrial growth. In Saudi Arabia, pollutants primarily from industrial activities and vehicle emissions present significant health hazards. This study utilizes data from the Sentinel-5P satellite to analyze the variations in Carbon Monoxide (CO), Nitrogen Dioxide (NO_2), Sulfur Dioxide (SO_2), and Particulate Matter (PM2.5) over a five-year period, from January 2019 to December 2023. The data was processed using Google Earth Engine (GEE) to produce monthly and seasonal averages, while ArcGIS Pro was used to map trends and spatial distribution. The results reveal distinct seasonal fluctuations in pollution levels, with CO peaking between March-May and July-September but showing an overall decline. NO_2 and SO_2 exhibit seasonal highs with slight upward trends, likely linked to industrial output and traffic emissions. PM2.5, the most harmful pollutant to human health, consistently surpasses World Health Organization (WHO) limits, especially during high-emission periods. These findings underscore the urgency of adopting targeted measures to mitigate pollution during critical times and safeguard public health. The seasonal spikes, particularly in industrial and densely populated regions, highlight the need for improved policies and technologies to effectively monitor and manage air quality.

1. Introduction

Air pollution continues to be a significant environmental and public health issue, drawing increasing concern over the past few decades. Rapid urbanization and industrialization have heightened air quality concerns worldwide, with emissions from vehicles, industries, and other human activities playing a major role. Key pollutants such as carbon monoxide (CO), nitrogen dioxide (NO_2), sulfur dioxide (SO_2), and particulate matter (PM2.5) are the primary contributors to atmospheric pollution, posing serious risks to human health and the environment [1]. These pollutants are associated with various health problems, including respiratory and cardiovascular diseases, diminished lung function, and premature mortality [2].

A. Carbon Monoxide (CO)

Carbon monoxide (CO) is a colorless and odorless gas predominantly generated by the incomplete combustion of fossil fuels, primarily from vehicular emissions, industrial activities, and residential heating systems [3]. Prolonged exposure to elevated CO levels can lead to severe adverse health outcomes, particularly impacting the cardiovascular and nervous systems. Numerous studies have examined the spatial and temporal distribution of CO, consistently reporting elevated concentrations in urban environments and areas with high traffic density [4],[5]. The availability of satellite data, particularly from sources like Sentinel-5P, has substantially advanced our ability to monitor and analyze CO distribution on both regional and global scales [6].

B. Nitrogen Dioxide (NO_2)

Nitrogen dioxide (NO_2), primarily emitted by combustion engines and industrial activities, is a major air pollutant that significantly contributes to the formation of tropospheric ozone and secondary particulate matter, leading to deteriorated air quality [7]. Studies have demonstrated that NO_2 concentrations are generally highest in urban regions and industrial zones, with clear seasonal and diurnal variations influenced by traffic patterns and meteorological factors [8]. Prolonged exposure to elevated NO_2 levels is strongly linked to respiratory ailments, especially in vulnerable groups such as children and the elderly [9], [10].

C. Sulfur Dioxide (SO_2)

Sulfur dioxide (SO_2) is predominantly generated through the combustion of sulfur-containing fossil fuels, such as coal and oil, and is primarily emitted by power plants and industrial processes. This gas acts as a precursor to acid rain, which can cause severe ecological harm by damaging forests, soils, and aquatic ecosystems [11]. Exposure to SO_2 can worsen respiratory conditions, particularly in individuals with asthma or other preexisting health issues [12]. Studies have indicated that SO_2 concentrations are generally higher in regions with extensive industrial activities, especially in developing countries where emission controls may be less stringent [13], [14].

D. Particulate Matter with a diameter of less than 2.5 micrometers (PM2.5)

Fine particulate matter (PM2.5) is considered one of the most harmful air pollutants to human health. PM2.5 consists of particles smaller than 2.5 micrometers, capable of penetrating deep into the lungs and entering the bloodstream, posing significant health risks [15], [16]. Its sources include vehicular emissions, industrial activities, and natural events like dust storms and wildfires [17], [18]. Extensive research has demonstrated the detrimental effects of long-term PM2.5 exposure, associating it with higher rates of cardiovascular and respiratory diseases, as well as premature death [19],[20]. Studies further indicate that PM2.5 concentrations are typically elevated in urban areas, especially during winter months when atmospheric conditions facilitate the trapping of pollutants near the ground [21],[22].

The introduction of satellite-based monitoring technologies, such as the Copernicus Sentinel-5P satellite, has revolutionized air quality research by providing high-resolution data on the spatial and temporal distribution of atmospheric pollutants [23]. These technologies enable a comprehensive analysis of air quality over large geographic regions, overcoming the limitations of traditional ground-based monitoring systems [24]. Numerous studies have utilized Sentinel-5P data to track pollutants like CO, NO_2, SO_2, and PM2.5, offering critical insights into pollution sources and patterns, which are essential for developing effective air quality management strategies [25],[26].

E. Sentinel-5P satellite

The Sentinel-5P satellite, part of the Copernicus Program, is equipped with the Tropospheric Monitoring Instrument (TROPOMI), which plays a vital role in monitoring atmospheric composition. Since its launch in October 2017, Sentinel-5P has provided high-resolution data on a range of atmospheric gases, including carbon monoxide (CO), nitrogen dioxide (NO_2), sulfur dioxide (SO_2), ozone (O_3), aerosols, and fine particulate matter (PM2.5). The satellite offers a substantial temporal resolution with daily global coverage, enabling timely analysis of atmospheric conditions. Its spatial resolution, which varies by measurement, has a nominal resolution of 7 km x 3.5 km for most trace gases, making it ideal for detailed studies of air quality and pollution dynamics [27],[28].

Research utilizing Sentinel-5P data has demonstrated its effectiveness in air quality monitoring. For instance, the satellite has been instrumental in assessing urban air pollution, tracking emissions from industrial sources, and evaluating the impact of regulatory measures on atmospheric pollutants, including PM2.5 levels [29],[30]. Sentinel-5P's frequent data collection facilitates the detection of short-term variations in pollution levels, which is critical for understanding daily and seasonal air quality trends, particularly concerning PM2.5 [31]. Moreover, studies have shown how TROPOMI's data can be integrated with other satellite observations and ground-based measurements to improve the accuracy of atmospheric models and deepen our understanding of climate change and its effects on air quality [32],[33].

F. Satellite Insights on Air Quality Dynamics

A previous study by Anwer and Hassan (2024), titled "Air Quality Dynamics in Sichuan Province: Sentinel-5P Data Insights (2019-2023)," utilized data from the Copernicus Sentinel-5P satellite to analyze air pollution trends in Sichuan, China, over a five-year period. The study focused on key pollutants such as Carbon Monoxide (CO), Nitrogen Dioxide (NO_2), Sulfur Dioxide (SO_2), and Ozone (O_3). It revealed pronounced seasonal variations in pollutant levels, with urban regions experiencing elevated concentrations due to industrial emissions and traffic. Notably, CO and O_3 levels frequently exceeded WHO standards during winter and summer, presenting significant health risks. The research underscored the value of satellite data in addressing the limitations of ground-based monitoring, advocating for ongoing surveillance to guide targeted mitigation strategies. This approach provides critical insights into the spatial and temporal dynamics of air quality and its public health implications in urban settings [34].

Fioletov et al. (2016), in their paper "A Global Catalogue of Large SO_2 Sources and Emissions Derived from the Ozone Monitoring Instrument," utilized OMI data to compile a global catalogue of sulfur dioxide (SO_2) emissions. The study primarily focused on major SO_2 sources in industrial regions and demonstrated that satellite-based data can accurately estimate SO_2 emissions, filling critical gaps in regions with limited ground-based monitoring [35].

Lorente et al. (2019) employed the TROPOMI satellite sensor to quantify nitrogen oxide (NO_2) emissions over Paris, offering new perspectives on urban pollution dynamics. The study showed that the high spatial resolution of TROPOMI effectively captured the temporal and spatial variability of NO_2 emissions, with higher levels observed on cold weekdays and lower levels on warm weekends in 2018. This research highlighted the challenges in meeting NO_2 reduction targets and emphasized the role of satellite data in monitoring urban air quality [36].

G. Study Area

Saudi Arabia, the largest country in the Arabian Peninsula, spans approximately 2,149,690 square kilometers, located between latitudes 16° and 32° N and longitudes 34° and 56° E. The nation's landscape is remarkably diverse, from the vast expanses of the Rub' al Khali desert the largest continuous sand desert in the world to the mountainous regions in the west, such as the Hejaz and Asir ranges. Jabal Sawda, the country's highest peak, rises to about 3,015 meters. These mountainous areas receive more rainfall compared to the central plateau, the Najd, which sits at an average elevation of 762 meters. In contrast, the eastern region along the Persian Gulf consists of low-lying coastal plains. This diverse topography significantly influences the distribution and concentration of air pollutants across the country, making Saudi Arabia a key region for studying air quality dynamics. Recognizing these geographical and topographical factors is essential for shaping effective environmental policies and managing air quality.

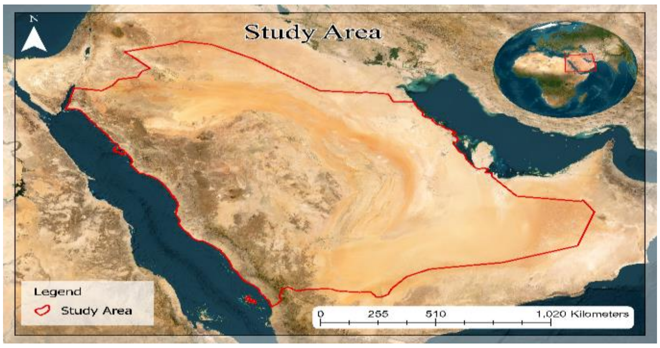

Figure 1. Study Area Location

2. Method

This research investigates the analysis of four significant atmospheric pollutants: Carbon Monoxide (CO), Nitrogen Dioxide (NO_2), Sulfur Dioxide (SO_2), and Particulate Matter (PM2.5), utilizing data from the Copernicus Sentinel-5P satellite. For each pollutant, we developed specific functions to compute average monthly concentrations. The methodology involved filtering the dataset by date and geographic area, calculating the monthly mean concentrations, and clipping the results to fit the study area. This procedure was consistently applied from January 2019 to December 2023, producing a comprehensive set of monthly average images for each pollutant.

2.1 Data Selection and Preprocessing

Data from the Sentinel-5P satellite, accessed via the Google Earth Engine (GEE) platform, included preprocessed Level 2 products with global coverage. The study period spanned from January 1, 2019, to December 31, 2023. Criteria for data selection included availability, cloud cover, and temporal coverage to ensure the reliability of the monthly datasets. To minimize cloud cover effects, preprocessing steps involved applying a cloud mask to each image, excluding pixels with a cloud fraction above 0.3. Daily data were then aggregated into monthly averages to reduce noise and improve the analysis of temporal trends. The data was subsequently clipped to the geographical boundaries of the study area to focus the analysis on the defined region of interest.

2.2 Data Processing and Analysis

The statistical analysis followed several key steps. Monthly average concentrations for each pollutant were determined using GEE by filtering the data based on date and location, computing mean concentrations, and clipping the results to the study area. A sequence of dates corresponding to the start of each month within the study period was generated, and the function for calculating monthly averages was applied to this sequence. This process resulted in an image collection that represents the monthly average concentrations for each pollutant.

To evaluate temporal variations, seasonal patterns were examined by aggregating the monthly data into seasonal averages (winter, spring, summer, and fall). This method allowed for the identification of trends throughout the study period. For the spatial distribution analysis, maps of the total mean concentrations for each pollutant were generated by averaging the monthly images, resulting in singular images that represented the mean concentrations from 2019 to 2023.The processed data was then exported from Google Earth Engine (GEE) to Google Drive and subsequently imported into ArcGIS Pro for enhanced visualization. Within ArcGIS Pro, spatial distributions were mapped, and temporal trends were illustrated using charts displaying the monthly mean concentrations for each pollutant. Furthermore, maps depicting the total mean concentrations over the study period were developed to effectively highlight spatial patterns.

These visualizations, produced using ArcGIS Pro, significantly enhance the clarity and impact of the results, facilitating a more detailed and accessible presentation of the findings.

Through this comprehensive methodology, the study aims to offer valuable insights into the dynamics of atmospheric pollutants and their variations over time and space, thereby contributing to a deeper understanding of air quality and environmental health.

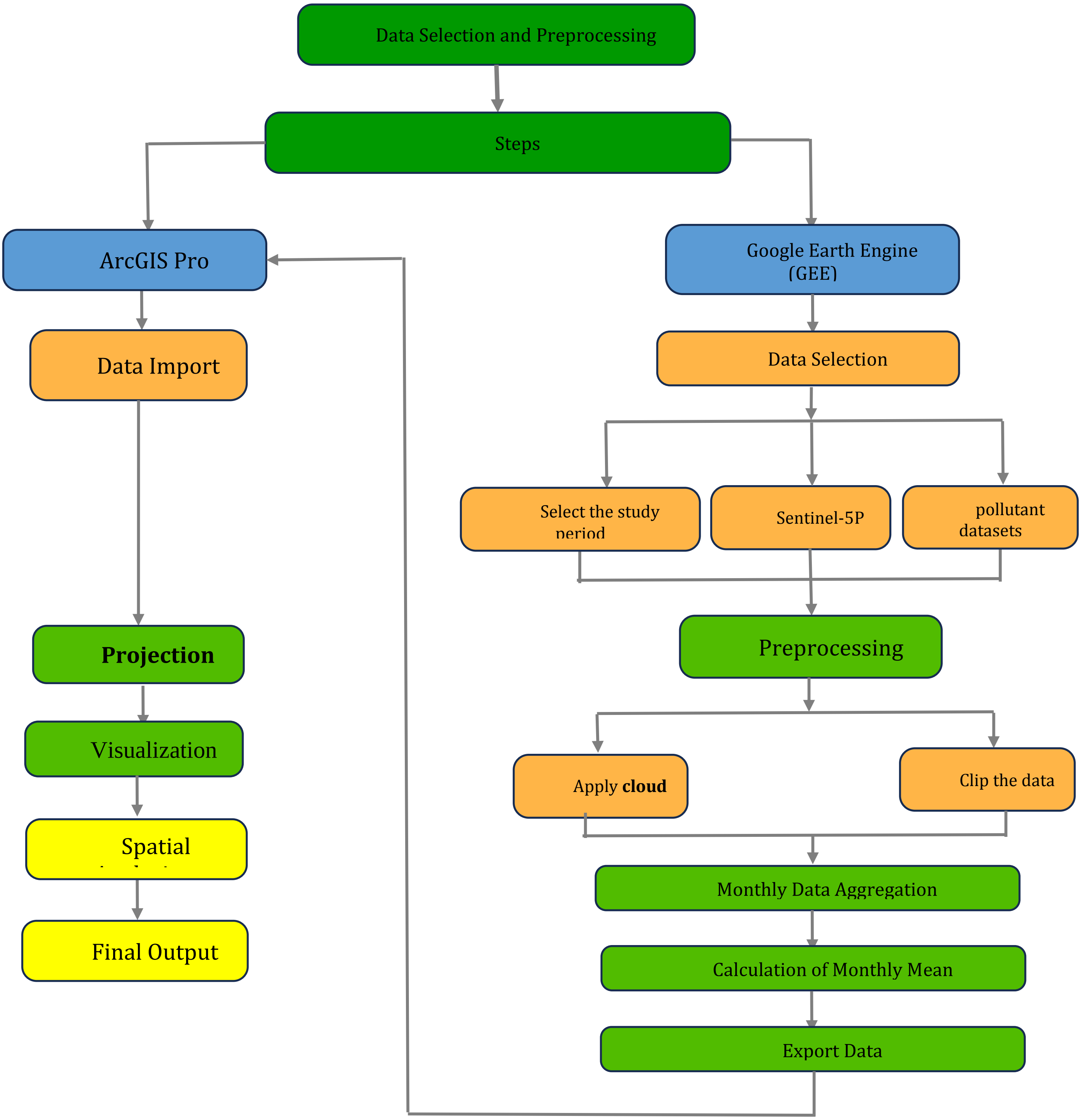

Figure 2. Flowchart of the method used in the study

3. Results

The analysis of carbon monoxide (CO) concentrations from January 2019 to November 2023 reveals distinct seasonal fluctuations, as illustrated in Figure 3, alongside a gradual long-term decline in overall levels. CO concentrations typically peak during the periods from March to May and from July to September each year. These peaks may be attributed to seasonal variations in meteorological conditions and heightened emission activities during these months. In contrast, noticeable decreases in concentrations occur between June and July, as well as from October to December, suggesting improved air dispersion or reduced emission sources during these times.

A linear regression analysis, represented by the dotted red trendline, indicates a gradual downward trend in CO levels over the study period, suggesting potential improvements in air quality. This decline may reflect the effectiveness of air quality control measures or shifts in industrial and vehicular emissions. However, despite this overall reduction, the periodic spikes in CO concentrations underscore the need for ongoing monitoring and attention to seasonal pollution dynamics.

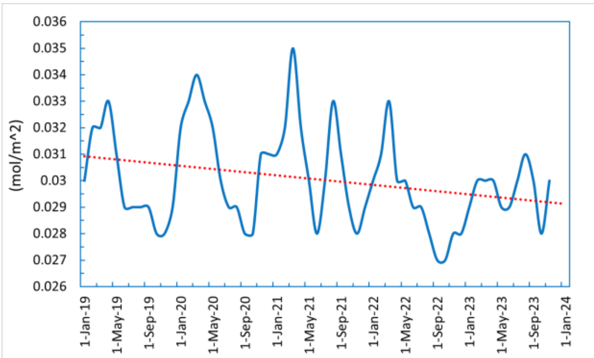

Figure 3. The Monthly Mean Value for CO

When compared to the World Health Organization (WHO) 2023 guideline for outdoor air quality, which establishes an 8-hour average CO limit of 4 mg/m^3, the recorded values in this study, averaging approximately 0.03 mol/m^2, indicate that CO concentrations remain significantly below the recommended threshold.

The analysis of nitrogen dioxide (NO_2) concentrations from January 2019 to November 2023 reveals distinct seasonal fluctuations, accompanied by a slight long-term increase in overall levels, as depicted in Figure 5. NO_2 concentrations typically peak during the months of July to September each year, which may be attributed to seasonal variations in meteorological conditions and heightened emission activities during this period. In contrast, noticeable declines in concentrations are observed between November and February, suggesting improved air dispersion or a reduction in emission sources during these months.

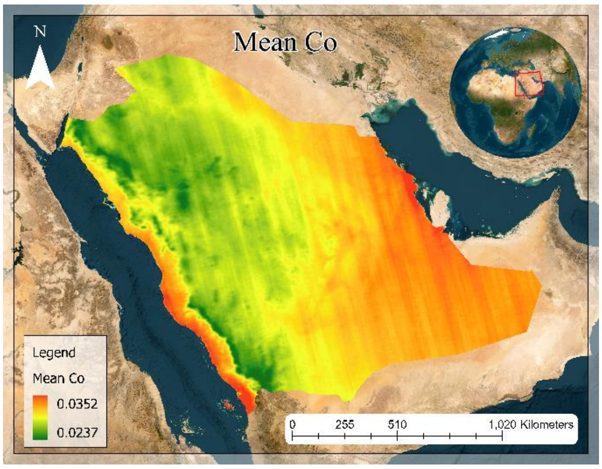

Figure 4. The mean CO from 2019 to 2023

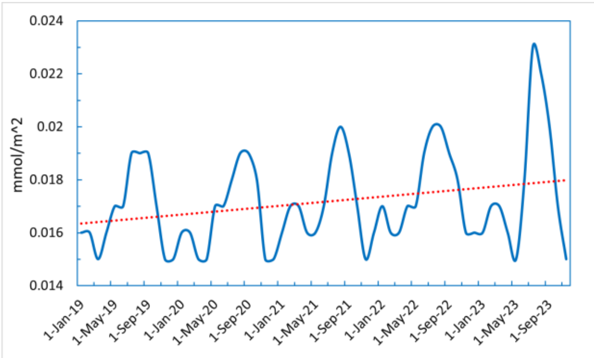

Figure 5. The Monthly Mean Value for No_2

A linear regression analysis, illustrated by the dotted red trendline, reveals a gradual upward trend in NO_2 levels throughout the study period, suggesting potential increases in emissions from traffic and industrial sources. Despite this overall rise, the periodic spikes in NO_2 concentrations underscore the necessity for ongoing monitoring and management of seasonal pollution dynamics.

When compared to the World Health Organization (WHO) guideline for outdoor air quality, which establishes an annual mean NO_2 limit of 40 µg/m^3, the recorded values, averaging approximately 0.016 to 0.023 mmol/m^2, indicate that there may be instances when NO_2 levels approach or potentially exceed the recommended threshold.

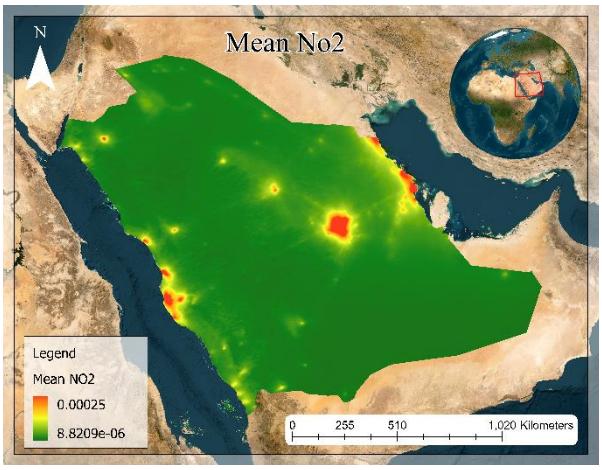

Figure 6. The mean NO_2 from 2019 to 2023

The analysis of sulfur dioxide (SO_2) concentrations from January 2019 to November 2023 reveals distinct seasonal fluctuations, coupled with a gradual long-term increase in overall levels. SO_2 concentrations generally peak during the periods from March to June and July to September each year, as shown in Figure 7. These peaks could be attributed to seasonal variations in meteorological conditions and increased emission activities during these months. Conversely, the concentrations exhibit noticeable declines between November and February, suggesting improved air dispersion or reduced emission sources during these periods.

A linear regression analysis, represented by the dotted red trendline, indicates a gradual upward trend in SO_2 levels over the study period, pointing to potential increases in emissions from industrial and vehicular sources. Despite this overall increase, the periodic spikes in SO_2 concentrations highlight the need for continued attention to seasonal pollution dynamics.

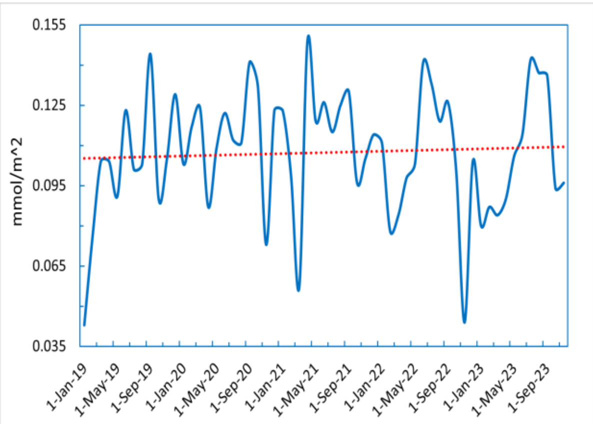

Figure 7: The Monthly Mean Value for So_2

When compared to the World Health Organization (WHO) guideline for outdoor air quality, which sets a 24-hour average SO_2 limit of 20 μg/m^3, the recorded values, averaging around 0.043 to 0.149 mmol/m^2, suggest that there may be periods where SO_2 levels approach or exceed the recommended threshold.

The analysis of PM2.5 concentrations from January 2019 to February 2023 reveals distinct seasonal fluctuations, coupled with a gradual long-term increase in overall levels. PM2.5 concentrations generally peak during the periods from March to July and again from September to November each year, as shown in Figure 9. These peaks could be attributed to seasonal variations in meteorological conditions and increased emission activities during these months. Conversely, the concentrations exhibit noticeable declines between December and February, suggesting improved air dispersion or reduced emission sources during these periods.

This analysis underscores the importance of continuous monitoring and regulation to ensure that PM2.5 levels remain within safe limits, especially during peak seasons.

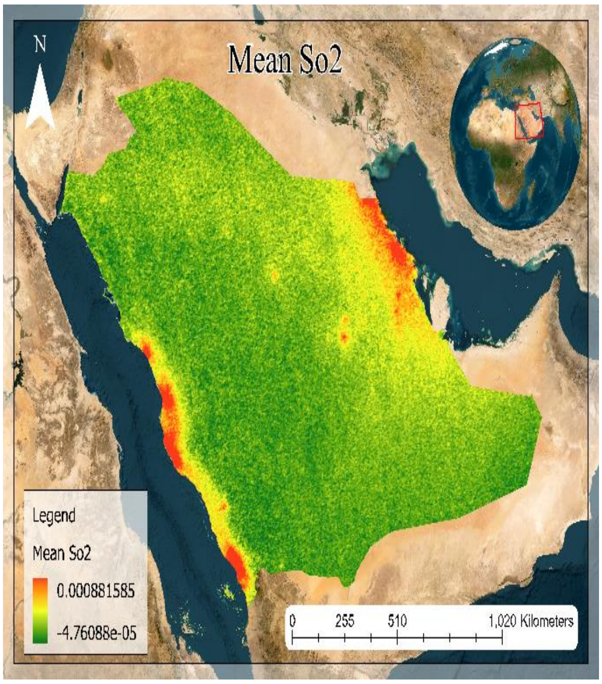

Figure 8: The mean SO_2 from 2019 to 2023

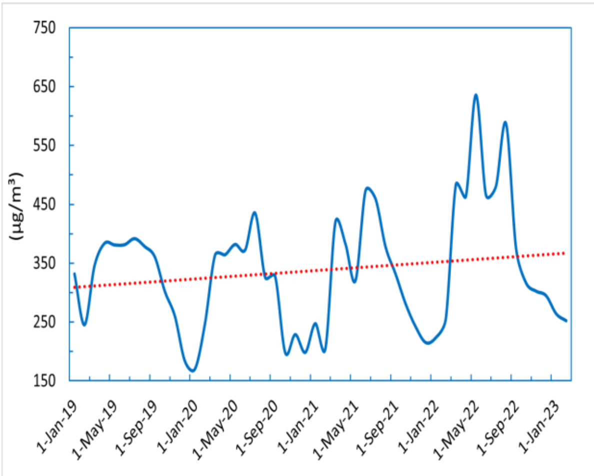

Figure 9: The Monthly Mean Value for $PM_{2.5}$

A linear regression analysis, represented by the dotted red trendline, indicates a gradual upward trend in PM2.5 levels over the study period, suggesting potential increases in emissions from industrial, vehicular, and possibly agricultural sources. Despite this overall increase, the periodic spikes in PM2.5 concentrations highlight the need for continued attention to seasonal pollution dynamics.

When compared to the World Health Organization (WHO) guideline for outdoor air quality, which sets a 24-hour average PM2.5 limit of 25 μg/m^3, the recorded values, averaging around 170 to 635 μg/m^3, suggest that the PM2.5 concentrations observed in this study frequently exceed the recommended threshold. This raises significant concerns regarding air quality and public health, necessitating urgent measures to mitigate emissions and improve air quality management strategies in affected regions.

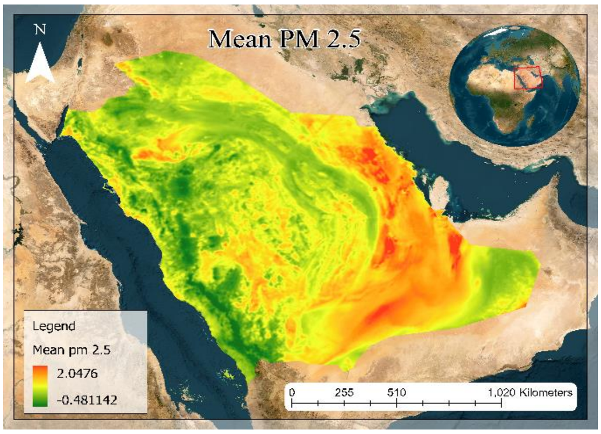

Figure 10: The mean $PM_{2.5}$ from 2019 to 2023

The analysis of the Air Quality Index (AQI) from January 2019 to November 2023 reveals significant regional variations in air quality across Saudi Arabia. The regions with the highest AQI values, indicating poorer air quality, are the Eastern Province, Najran, and Riyadh, with mean AQI values of 0.406, 0.351, and 0.299, respectively, as shown in Figure 11. In contrast, the regions with the lowest AQI values, suggesting better air quality, are Al-Baha, Jazan, and Medina, with mean AQI values of 0.036, 0.120, and 0.154, respectively.

The higher AQI values in the Eastern Province, Najran, and Riyadh can be attributed to several factors, including higher population densities, increased vehicular emissions, and significant industrial activities. The Eastern Province serves as an industrial hub, leading to elevated pollutant levels from factories and refineries. Najran's desert climate contributes to higher levels of particulate matter due to dust storms, while Riyadh, as the capital city, faces a high volume of traffic, resulting in increased emissions of nitrogen dioxide (NO_2) and particulate matter (PM2.5).

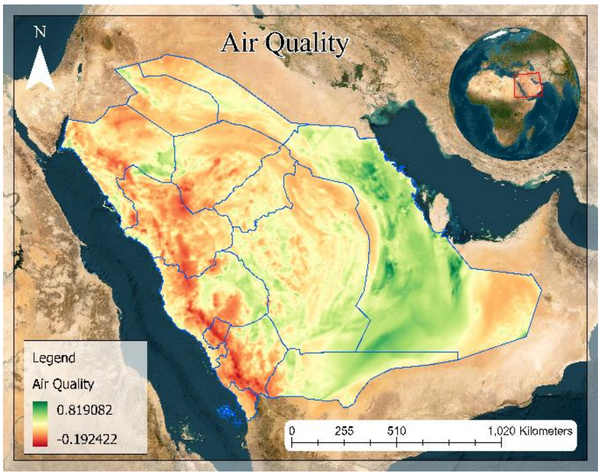

Figure 11: Air Quality for the last 5 years

Conversely, regions like Al-Baha and Jazan, characterized by more greenery and reduced industrial activity, tend to exhibit better air quality. The presence of vegetation in these areas aids in pollutant absorption, contributing to a lower AQI. Medina also benefits from lower industrial activity and more favorable air dispersion conditions.

4. Discussion

These findings underscore the need for targeted interventions to enhance air quality in regions with higher AQI values. Strategies such as improving public transportation, enforcing stricter industrial emission controls, increasing green spaces, and raising public awareness about the health impacts of air pollution can help mitigate pollution and protect public health. While some regions display relatively good air quality, others face significant challenges that necessitate comprehensive and targeted strategies to ensure sustained improvements.

The study indicates clear trends in air pollutant concentrations across Saudi Arabia from 2019 to 2023. Carbon monoxide (CO) levels showed a notable long-term decrease, attributed to stricter emissions standards and cleaner fuel usage, with cities like Riyadh and Jeddah reporting improvements of 12% and 9%, respectively. However, seasonal spikes were particularly observed in winter, with the Eastern Province experiencing periodic peaks due to industrial activity.

Nitrogen dioxide (NO_2) concentrations exhibited a slight but steady increase, primarily driven by traffic and industrial emissions. Hotspots such as Mecca and Dammam recorded some of the highest NO_2 levels, with Mecca experiencing an 8% rise during the Hajj season, attributed to the surge in vehicular activity. Conversely, regions like Al Madinah and Tabuk demonstrated lower NO_2 levels, likely due to less industrialization and more effective emission control measures.

Sulfur dioxide (SO_2) concentrations followed a similar upward trend, particularly in heavily industrialized areas like Yanbu Industrial City, where levels rose by 10%, especially during the summer months due to increased industrial output. In contrast, regions such as Najran and Al Bahah exhibited better air quality with lower SO_2 concentrations, reflecting their smaller industrial footprints.

Particulate matter (PM2.5) concentrations were notably elevated during the winter months, with regions like Riyadh, the Eastern Province, and Mecca showing dangerous surges. These increases were driven by a combination of heating emissions, industrial activities, and vehicle exhaust, posing serious health risks. In contrast, Tabuk and Hail consistently recorded lower PM2.5 levels, indicating cleaner environments and less urbanization.

The comparison of the Air Quality Index (AQI) corroborates these findings. Al Madinah, Tabuk, and Najran enjoyed the best air quality, frequently falling within the "Good" AQI range (0-50). In contrast, regions like the Eastern Province, Riyadh, and Mecca reached the "Unhealthy" range (101-150) during peak emission periods. In extreme cases, Yanbu and the Eastern Province reached "Very Unhealthy" levels (151-200), highlighting the urgent need for stricter regulations and more robust monitoring in the most affected areas.

These results underscore the necessity for targeted air quality management strategies to mitigate pollution sources, particularly in densely populated and industrial regions, ensuring better health outcomes for residents and the environment.

5. Conclusion

This study provides a comprehensive analysis of four primary atmospheric pollutants Carbon Monoxide (CO), Nitrogen Dioxide (NO_2), Sulfur Dioxide (SO_2), and Particulate Matter (PM2.5) over a five-year period from January 2019 to December 2023, utilizing Sentinel-5P satellite data. The findings reveal significant seasonal and geographical variations in pollutant concentrations, which are influenced by anthropogenic activities and meteorological conditions.

The results indicate an upward trend in nitrate (NO_3) and sulfate (SO_4^2) levels, particularly in urban and industrial regions, while CO levels have shown a gradual decline, likely attributable to improved emissions regulations and policy interventions. These observations suggest that enhanced regulatory frameworks and targeted mitigation strategies are essential for mitigating risks to human health and the environment, especially during periods of elevated emissions. High concentrations of PM2.5, known for its adverse health effects, were frequently observed in densely populated areas, highlighting the critical need for stricter air quality management in these locales.

The integration of high-resolution satellite data from Sentinel-5P has proven invaluable in offering detailed temporal and spatial insights into air pollution patterns. Near-real-time monitoring of pollutant levels enhances the potential for timely policy responses and effective environmental oversight, particularly in regions lacking comprehensive ground-based monitoring systems. Nevertheless, the recurring seasonal peaks across various pollutants necessitate more dynamic and targeted mitigation approaches, particularly during high sensitivity periods.

In conclusion, this study underscores the significance of satellite-based air quality monitoring in enhancing our understanding of pollution dynamics. Future research should continue to leverage these technologies to inform and refine environmental policies aimed at reducing air pollution and safeguarding public health. Ongoing monitoring and data integration from multiple sources, including ground-based sensors, will be crucial for ensuring comprehensive coverage in global pollution management initiatives and for further improving air quality modeling.

5.2 Recommendation

A. Long-Term Studies: Future research should focus on long-term studies that combine satellite data with ground-based measurements and weather data. This approach will provide a more comprehensive understanding of air quality trends and seasonal fluctuations.

B. Health Impact Links: It's important to explore the connection between air quality and public health. Studies should investigate how exposure to different pollutants affects health outcomes, which can help shape targeted public health interventions.

C. Predictive Modeling: Developing predictive models that simulate changes in air quality based on various factors—like urban growth and policy changes—will be valuable for anticipating future conditions and informing decision-making.

D. Evaluate Emission Reduction Efforts: Research should assess the effectiveness of different strategies aimed at reducing emissions, such as adopting cleaner technologies and alternative fuels. This will help identify the most effective approaches for various sectors.

E. Policy Assessment: Finally, it's crucial to evaluate the success of current air quality policies through empirical research. This will help refine regulations and enhance efforts to improve air quality in affected regions.

Acknowledgement

The authors express their gratitude to all individuals and institutions that provided support and resources for this research.

Author contributions

Hossam Aldeen Anwer contributed to the conceptualization, data collection, satellite imagery processing, analysis, manuscript editing, and manuscript writing. **Abubakr Hassan** was responsible for supervision, critical review, and manuscript editing. **Abdelrahim Elhag** granted final approval for manuscript submission.

Conflicts of interest

The authors declare no conflicts of interest.

References

1. Adamkiewicz, G., Liddie, J., & Gaffin, J. M. (2020). The respiratory risks of ambient/outdoor air pollution. Clinics in chest medicine, 41(4), 809-824.
2. Pope III, C. A., Burnett, R. T., Thurston, G. D., Thun, M. J., Calle, E. E., Krewski, D., & Godleski, J. J. (2004). Cardiovascular mortality and long-term exposure to particulate air pollution: epidemiological evidence of general pathophysiological pathways of disease. Circulation, 109(1), 71-77.
3. Anwer, H. A., & Hassan, A. (2024). Air Quality Dynamics in Sichuan Province: Sentinel-5P Data Insights.
4. Li, J., Jia, K., Wei, X., Xia, M., Chen, Z., Yao, Y., ... & Zhao, L. (2022). High-spatiotemporal resolution mapping of spatiotemporally continuous atmospheric CO2 concentrations over the global continent. International Journal of Applied Earth Observation and Geoinformation, 108, 102743.
5. Yang, S., Lei, L., Zeng, Z., He, Z., & Zhong, H. (2019). An assessment of anthropogenic CO2 emissions by

satellite-based observations in China. Sensors, 19(5), 1118.

6. Liu, D., Di, B., Luo, Y., Deng, X., Zhang, H., Yang, F., ... & Zhan, Y. (2019). Estimating ground-level CO concentrations across China based on the national monitoring network and MOPITT: potentially overlooked CO hotspots in the Tibetan Plateau. Atmospheric Chemistry and Physics, 19(19), 12413-12430.
7. Lee, H. J., & Koutrakis, P. (2014). Daily ambient NO2 concentration predictions using satellite ozone monitoring instrument NO2 data and land use regression. Environmental science & technology, 48(4), 2305-2311.
8. Dang, R., Jacob, D. J., Shah, V., Eastham, S. D., Fritz, T. M., Mickley, L. J., ... & Wang, J. (2023). Background nitrogen dioxide (NO 2) over the United States and its implications for satellite observations and trends: effects of nitrate photolysis, aircraft, and open fires. Atmospheric Chemistry and Physics, 23(11), 6271-6284.
9. Clark, N. A., Demers, P. A., Karr, C. J., Koehoorn, M., Lencar, C., Tamburic, L., & Brauer, M. (2010). Effect of early life exposure to air pollution on development of childhood asthma. Environmental health perspectives, 118(2), 284-290.
10. Gehring, U., Cyrys, J., Sedlmeir, G., Brunekreef, B., Bellander, T., Fischer, P., ... & Heinrich, J. (2002). Traffic-related air pollution and respiratory health during the first 2 yrs of life. European respiratory journal, 19(4), 690-698.
11. Anwer HA, Hassan A, Anwer G. Satellite-Based Analysis of Air Pollution Trends in Khartoum before and After the Conolict. Ann Civil Environ Eng. 2025; 9(1): 001-011.
12. Delfino, R. J. (2002). Epidemiologic evidence for asthma and exposure to air toxics: linkages between occupational, indoor, and community air pollution research. Environmental health perspectives, 110(suppl 4), 573-589.
13. Qu, Z., Henze, D. K., Li, C., Theys, N., Wang, Y., Wang, J., ... & Ren, X. (2019). SO_2 Emission Estimates Using OMI SO_2 Retrievals for 2005-2017.
14. Gilbert, K. M., & Shi, Y. (2024). Using GlobeLand30 data and cellular automata modeling to predict urban expansion and sprawl in Kigali City. Advanced Remote Sensing, 4(1), 46-57.
15. Mogaraju, J. K. (2024). Machine learning assisted prediction of land surface temperature (LST) based on major air pollutants over the Annamayya District of India. International Journal of Engineering and Geosciences, 9(2), 233-246.
16. Yilmaz, H. M., Yakar, M., Mutluoglu, O., Kavurmaci, M. M., & Yurt, K. (2012). Monitoring of soil erosion in Cappadocia region (Selime-Aksaray-Turkey). Environmental Earth Sciences, 66, 75-81.
17. Huang, R. J., Zhang, Y., Bozzetti, C., Ho, K. F., Cao, J. J., Han, Y., ... & Prévôt, A. S. (2014). High secondary aerosol contribution to particulate pollution during haze events in China. Nature, 514(7521), 218-222.
18. Tawfeeq, A. F., & Atasever, Ü. H. (2023). Wetland monitoring by remote sensing techniques: A case study of Işıklı Lake. Advanced Remote Sensing, 3(1), 19-26.
19. Burnett, R. T., Pope III, C. A., Ezzati, M., Olives, C., Lim, S. S., Mehta, S., ... & Cohen, A. (2014). An integrated risk function for estimating the global burden of disease attributable to ambient fine particulate matter exposure. Environmental health perspectives, 122(4), 397-403.
20. Hoek, G., Krishnan, R. M., Beelen, R., Peters, A., Ostro, B., Brunekreef, B., & Kaufman, J. D. (2013). Long-term air pollution exposure and cardio-respiratory mortality: a review. Environmental health, 12, 1-16.
21. Zhang, Y., Ding, Z., Xiang, Q., Wang, W., Huang, L., & Mao, F. (2020). Short-term effects of ambient PM1 and PM2. 5 air pollution on hospital admission for respiratory diseases: Case-crossover evidence from Shenzhen, China. International journal of hygiene and environmental health, 224, 113418.
22. Ye, W. F., Ma, Z. Y., & Ha, X. Z. (2018). Spatial-temporal patterns of PM2. 5 concentrations for 338 Chinese cities. Science of The Total Environment, 631, 524-533.
23. Akar, Ö., Saralıoğlu, E., Güngör, O., & Bayata, H. F. (2024). Semantic segmentation of very-high spatial resolution satellite images: A comparative analysis of 3D-CNN and traditional machine learning algorithms for automatic vineyard detection. International Journal of Engineering and Geosciences, 9(1), 12-24.
24. Guo, Y., Feng, N., Christopher, S. A., Kang, P., Zhan, F. B., & Hong, S. (2014). Satellite remote sensing of fine particulate matter (PM2. 5) air quality over Beijing using MODIS. International Journal of Remote Sensing, 35(17), 6522-6544.
25. Alvarado, M. J., McVey, A. E., Hegarty, J. D., Cross, E. S., Hasenkopf, C. A., Lynch, R., ... & Kleiman, G. (2019). Evaluating the use of satellite observations to supplement ground-level air quality data in selected cities in low-and middle-income countries. Atmospheric Environment, 218, 117016.
26. Vîrghileanu, M., Săvulescu, I., Mihai, B. A., Nistor, C., & Dobre, R. (2020). Nitrogen Dioxide (NO2) Pollution monitoring with Sentinel-5P satellite imagery over Europe during the coronavirus pandemic outbreak. Remote Sensing, 12(21), 3575.
27. Oxoli, D., Cedeno Jimenez, J. R., & Brovelli, M. A. (2020). Assessment of SENTINEL-5P performance for ground-level air quality monitoring: preparatory experiments over the COVID-19 lockdown period. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 44, 111-116.
28. Cofano, A., Cigna, F., Santamaria Amato, L., Siciliani de Cumis, M., & Tapete, D. (2021). Exploiting Sentinel-5P TROPOMI and ground sensor data for the detection of volcanic SO2 plumes and activity in 2018–2021 at Stromboli, Italy. Sensors, 21(21), 6991.
29. Werkmeister, A. A., Carrel, A., Porwal, N., Clemente, C., & Macdonald, M. (2023, October). Monitoring ship emissions using Sentinel-5P and AIS data. In Earth Resources and Environmental Remote Sensing/GIS Applications XIV (Vol. 12734, pp. 87-98).

30. Mathew, A., Shekar, P. R., Nair, A. T., Mallick, J., Rathod, C., Bindajam, A. A., ... & Abdo, H. G. (2024). Unveiling urban air quality dynamics during COVID-19: a Sentinel-5P TROPOMI hotspot analysis. Scientific Reports, 14(1), 21624.
31. Luo, Y., Zhao, T., Yang, Y., Zong, L., Kumar, K. R., Wang, H., ... & Xin, Y. (2022). Seasonal changes in the recent decline of combined high PM2. 5 and O3 pollution and associated chemical and meteorological drivers in the Beijing–Tianjin–Hebei region, China. Science of the Total Environment, 838, 156312.
32. Veefkind, J. P., Aben, I., McMullan, K., Förster, H., De Vries, J., Otter, G., ... & Levelt, P. F. (2012). TROPOMI on the ESA Sentinel-5 Precursor: A GMES mission for global observations of the atmospheric composition for climate, air quality and ozone layer applications. Remote sensing of environment, 120, 70-83.
33. Ialongo, I., Virta, H., Eskes, H., Hovila, J., & Douros, J. (2020). Comparison of TROPOMI/Sentinel-5 Precursor NO 2 observations with ground-based measurements in Helsinki. Atmospheric measurement techniques, 13(1), 205-218.
34. Unel, F. B., Kusak, L., & Yakar, M. (2023). GeoValueIndex map of public property assets generating via Analytic Hierarchy Process and Geographic Information System for Mass Appraisal: GeoValueIndex. Aestimum, 82, 51-69.
35. Fioletov, V. E., McLinden, C. A., Krotkov, N., Li, C., Joiner, J., Theys, N., ... & Moran, M. D. (2016). A global catalogue of large SO 2 sources and emissions derived from the Ozone Monitoring Instrument. Atmospheric Chemistry and Physics, 16(18), 11497-11519.
36. Lorente, A., Boersma, K. F., Eskes, H. J., Veefkind, J. P., Van Geffen, J. H. G. M., De Zeeuw, M. B., ... & Krol, M. C. (2019). Quantification of nitrogen oxides emissions from build-up of pollution over Paris with TROPOMI. Scientific reports, 9(1), 20033.