

Evaluating Air Pollution in South African Priority Areas: A Qualitative Comparison of Satellite and In-Situ Data

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Abstract

Validating satellite data is essential to ensure its accuracy, reliability, and practical applicability. Such validation underpins scientific research, operational use, and informed policymaking by confirming that space-based measurements reflect real-world conditions. This is typically achieved by comparing satellite observations with ground-based measurements or established reference standards. Without thorough validation, data integrity is compromised, which can negatively affect decisions and economic outcomes. In this study, we validated data from the Sentinel-5P TROPospheric Monitoring Instrument (TROPOMI) by comparing it with ground-based measurements from the South African Air Quality Information System (SAAQIS). The analysis focused on three monitoring stations—Kliprivier, Lephalale, and Middelburg—over the course of 2022. The pollutants examined include sulfur dioxide (SO₂), nitrogen dioxide (NO₂), and carbon monoxide (CO). The results indicate that CO was the predominant pollutant across all sites, particularly in industrial areas. The study also found that satellite data generally overestimated pollution levels, especially during the winter months, emphasizing the importance of robust ground-based validation. Additionally, data quality challenges such as gaps and temporal misalignments affected the accuracy of both satellite and ground datasets. Lastly, the study shows the discrepancy between the ground-based instruments in South Africa and the TROPOMI, and it suggests how these instruments can be incorporated to provide a better understanding of the air quality.

Keywords: TROPOMI; SAAQIS; sulfur dioxide; nitrogen dioxide; air quality



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1. Introduction

Air quality monitoring has become a global priority, especially in developing countries, because of the elevated concentrations of atmospheric pollutants resulting from rapid urbanization, transportation, industrialization, and energy production [1,2]. The main concern is the escalating impact of key emissions, such as sulfur dioxide (SO₂), nitrogen dioxide (NO₂), and carbon monoxide (CO) on public health and the environment. High concentrations of these gases in the atmosphere, particularly SO₂ and NO₂, present multifaceted health issues, including respiratory and cardiovascular diseases [3,4]. Though rarely investigated compared to the other two gases, studies also revealed that elevated

CO levels are associated with neurological and heart diseases [5]. Additionally, increased atmospheric concentrations are linked to soil and water quality deterioration as the primary contributor to the formation of acid rain [6]. Therefore, it is important to continuously monitor the spatiotemporal distribution of these pollutants to understand the air quality trends and their potential impacts on the above-mentioned sectors [7].

Air pollution monitoring stations are the most widely used method for measuring air quality [8]. However, due to their high installation and maintenance costs, these stations are typically installed at a limited number of locations, mostly in high-traffic areas, and can only capture pollution levels in their immediate surroundings [8,9]. While these ground-based measurements provide accurate and temporally discrete data, they are often subject to significant errors and may produce unrepresentative spatial patterns [10]. Furthermore, the limited spatiotemporal coverage of these stations makes it difficult to model complex air pollution parameters such as the pollutant sources, movement pathways, and chemical characteristics of individual pollutants [11]. This challenge is particularly evident in developing countries like South Africa (SA), where research resources and infrastructure often compete with other pressing priorities related to societal well-being, such as alleviating poverty. As a result, the technical condition of the ground station network is gradually deteriorating, compromising the quality of the obtained measurements [12], for example, the spatial distribution of the South African Air Quality Information System (SAAQIS) monitoring stations concentrated in the economically active provinces, mainly Gauteng, Mpumalanga, Limpopo, KwaZulu-Natal, and Western Cape. While the high-precision measurements from these stations provide valuable insights into local air quality, their sparse distribution across the country limits their ability to provide comprehensive data for national-scale monitoring. Consequently, there is a growing need to explore alternative air quality monitoring approaches that provide a high spatial and temporal resolution while maintaining measurement accuracy.

Satellite-based remote sensing (RS) techniques have emerged as powerful tools for monitoring changes in environmental and atmospheric conditions over the past few decades. Unlike the ground-based stations, the RS approach overcomes challenges associated with spatial coverage and often comes at minimal or no cost, simplifying air pollution monitoring efforts. The application of RS technology in air pollution monitoring gained traction over the past few decades, dating back to the early 1970s. The focus was on investigating how satellite instruments—GEOS, Landsat, and the Advanced Very High Resolution Radiometer (AVHRR)—originally developed for monitoring surface and meteorological conditions, can be applied to detect certain air pollutants, particularly nitrogen dioxide (NO₂) and particulate matter (PM), over oceans and during volcanic eruptions on a global scale [13]. The introduction of NASA's Nimbus 7 satellite in 1978 marked the beginning of satellites devoted to tracking tropospheric gases. Equipped with the Total Ozone Mapping Spectrometer (TOMS) instrument, Nimbus 7 was designed to monitor the tropospheric ozone (O₃) and was decommissioned in 2007 [14].

Since then, the development of sensors devoted to detecting tropospheric gases has increased rapidly. Sensors such as the European Remote Sensing 2 (ERS2) satellite (GOME-2), ENVISAT, Ozone Monitoring Instrument (OMI), Tropospheric Emission Spectrometer (TES), and the TERRA (MODIS, MOPITT, MISR) instruments were developed for the continuous detection of key atmospheric pollutants at improved spatial scales. Among these sensors is the development of the latest Sentinel-5P as part of the European Space Agency's (ESA's) Copernicus program, which is aimed at continuously improving environmental monitoring and assessment through an extensive, global, and high-quality Earth Observation capability [14]. The Tropospheric Monitoring Instrument (TROPOMI) sensor aboard the Sentinel-5P satellite plays an important role in global air quality assessment, providing

high-resolution daily measurements of numerous major atmospheric pollutants, including sulfur dioxide (SO₂), carbon monoxide (CO), O₃, methane (CH₄), formaldehyde (HCHO), and NO₂ [15].

Several studies investigated the potential of Sentinel-5P in monitoring key air pollutants. Hasaan et al. [16] argued that Sentinel-5P can be a viable tool for tracking air quality. Their study used Sentinel-5P to retrieve CO and PM_{2.5} over the Nile Delta in Egypt and developed a PM_{2.5} and CO vulnerability index. Similar results were demonstrated in other studies for different pollutants; for example, Sameh et al. [17] used Sentinel-5P data to assess seasonal air pollution variations, mainly on NO₂, SO₂, and CO emissions over Cairo City in Egypt, and the study showed presentable results with a high concentration of these pollutants observed over dense built-up environments. In South Africa, Sentinel-5P capabilities have been investigated to calculate the air quality index (AQI) derived from multiple pollutant gases [18]. Other studies included the detection of different gases such as the assessment of NO₂ [19]; trend analysis of emissions from coal-fired power stations [20]; trend analysis of SO₂, sulphates (SO₄), and NO₂ variations [21]; assessment of fine particulate matter (PM_{2.5}) levels [22]; and assessment of seasonal variations in methane emissions [23]. The results from all these studies consistently demonstrate that Sentinel-5P has a significant potential for the enhanced assessment and continuous monitoring of tropospheric gases at regional scales.

However, like any other spaceborne satellite instrument, the accuracy of TROPOMI measurements is subject to various uncertainties, including retrieval errors, cloud interference, and limitations in detecting near-surface concentrations. Therefore, it is necessary to compare TROPOMI measurements with other data from airborne sensors and ground-based instruments where the distance between the pollutant source and the sensor is reduced, thus minimizing atmospheric interference and other possible errors [24]. Unmanned Aerial Vehicle (UAV) systems are emerging as adaptable platforms for collecting air pollutant data across a wide range of environments, including remote areas [25]. When equipped with advanced sensor systems, UAVs provide a significant advantage in real-time air pollution monitoring. Past studies demonstrated the applicability of low-cost sensors for monitoring emissions like NO₂, O₃, SO₂, PM_{2.5}, PM_{1.0}, CO, and black carbon, and the results obtained were highly correlated with the stationary monitoring stations [26,27]. However, Lambey and Prasad [26] argued that in addition to the technical difficulties presented by the UAV technologies, policies and laws that vary for each country present a major drawback to the global application of UAVs in air quality monitoring [26]. So far, only data from ground stations is accessible for calibrating and validating satellite data. In this context, the present study compares measurements from the TROPOMI instrument with ground-based observations from selected SAAQIS stations in South Africa. The primary objective is to evaluate the level of agreement between these datasets. The underlying hypothesis is that TROPOMI measurements adequately represent ground-based observations and can therefore serve as an effective tool for air quality monitoring.

By definition, statistical approaches involve the application of quantitative techniques to analyze data, identify patterns, and establish trends through rigorous mathematical modeling. In contrast, observational approaches emphasize the systematic documentation and description of phenomena as they occur naturally, without experimental manipulation. This study employs an observational approach. One key advantage of this method is its ability to effectively identify emerging trends, generate preliminary hypotheses, and detect potential correlations, thereby providing a foundational basis for subsequent controlled or statistically driven investigations.

2. Study Area

Figure 1 displays three ground-based monitoring stations operated by SAAQIS, located in Lephalale (Limpopo province), Kliprivier (Gauteng province), and Middelburg (Mpumalanga province). Lephalale, situated at 23.6° S and 28° E, spans approximately 66.94 km^2 . It is an industrialized rural municipality known for coal mining and energy production [28], with a climate marked by hot summers and dry winters, and annual temperatures ranging from 7°C to 32°C [29]. Kliprivier is located at 26.3° S and 28° E within the Midvaal Local Municipality, with an average annual temperature ranging from 16°C to 20°C , sitting at an elevation of around 1445 m [30]. Middelburg, positioned at 25.5° S and 29.3° E in Mpumalanga Province, is a mining town characterized by warm summers and winter temperatures ranging from -3°C to 20°C , with summer temperatures between 12°C and 29°C [31].

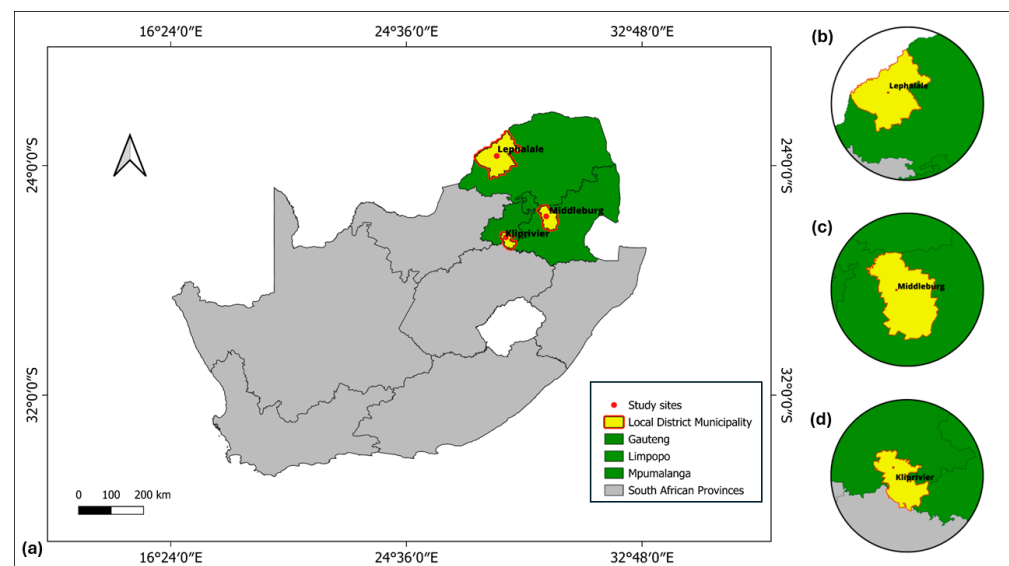


Figure 1. (a) A study area map of South Africa showing the three selected sites monitored by SAAQIS at (b) Lephalale, (c) Middelburg, and (d) Kliprivier.

3. Data and Methods

3.1. SAAQIS

The ground truth data for this study is obtained from the South African Air Quality Information System (SAAQIS), managed by the South African Weather Service (SAWS) [32]. SAAQIS offers near real-time and historical air quality data for multiple locations across South Africa. The dataset includes measurements of major atmospheric pollutants such as $\text{PM}_{2.5}$, SO_2 , O_3 , NO_2 , and CO , along with meteorological variables like temperature, wind speed, and wind direction, which help in understanding pollutant dispersion. This study specifically focuses on three key pollutants, NO_2 , SO_2 , and CO , with a temporal resolution of one day. Further information about SAAQIS can be found in Gwaze and Mashele [32].

3.2. TROPOMI

The satellite-based air quality data used in this study is sourced from the Tropospheric Monitoring Instrument (TROPOMI) aboard the Sentinel-5 Precursor (Sentinel-5P), which has been operational since its launch in 2017 [33]. TROPOMI is a hyperspectral spectrometer designed for global air quality monitoring, capturing data across the ultraviolet-visible (UV-VIS, 267–499 nm), near-infrared (NIR, 661–786 nm), and shortwave-infrared (SWIR, 2300–2389 nm) spectral ranges [34]. With a high spatial resolution of approximately $3.5 \times 7 \text{ km}$ and a swath width of 2600 km, it enables the detailed monitoring of various

atmospheric pollutants, including NO₂, SO₂, O₃, CH₄, formaldehyde (HCHO), and CO [34]. TROPOMI also provides aerosol optical depth (AOD) data, which is vital for understanding the impacts of aerosols on air quality and climate [35].

To retrieve atmospheric gas concentrations, TROPOMI uses advanced retrieval algorithms. For trace gases such as NO₂, SO₂, and HCHO, the Differential Optical Absorption Spectroscopy (DOAS) algorithm is used to identify specific absorption features in the UV-visible spectrum [36]. These features allow for the extraction of slant column densities (SCDs), which are then converted to vertical column densities (VCDs) using air mass factors that consider the observation geometry [37]. For infrared-absorbing gases like CO and CH₄, the optimal estimation (OE) method is applied. This technique uses inverse modeling to adjust atmospheric profiles based on observed spectra, allowing for accurate gas concentration retrieval [38]. Further refinements in the retrieval process, including corrections for cloud cover and surface reflectivity, help minimize uncertainties. The integration of these methods ensures that TROPOMI provides high-quality, timely data critical for air quality assessment and environmental research.

3.3. Calculation of the Concentration

This study compares satellite-derived pollutant concentrations from TROPOMI with ground-based air quality measurements to evaluate their correlation and accuracy. TROPOMI provides tropospheric column densities of pollutants in mol/m², whereas ground-based pollutant concentrations obtained through SAAQIS are reported in µg/m³ and ppm. Since satellite observations represent the total column densities rather than near-ground concentrations, a conversion process is required to estimate the surface-level pollutant concentrations. The near-ground concentration value can be estimated using Equation (1) [39],

$$C = \frac{C_{col}}{H} \cdot M \cdot A \quad (1)$$

where C_{col} is the pollutant column content (mol/m²), M is the molar mass (g/mol), A is a conversion factor for the concentration, and H is expressed in (m). Furthermore, H is assumed to be the planetary boundary layer height (PBLH) and varies between the three sites. H has no resolution. It is the height between ground and the PBLH, as that is where most of the pollutants reside. H can be retrieved from the Cloud-Aerosol Transport System (CATS) satellite. The TROPOMI overpass time is around 12 UTC over these stations.

4. Results and Discussion

4.1. Pollutant Type and Area Comparison

Figure 2 presents a time series of daily NO₂, SO₂, and CO concentrations retrieved from TROPOMI at the various study sites for the year 2022. High NO₂ concentrations are observed in the Lephalale and Middelburg areas, while low NO₂ concentrations are noted in the Kliprivier area (see Figure 2a). The elevated NO₂ concentrations in Lephalale and Middelburg primarily originate from coal-fired power stations [20], whereas the low NO₂ concentrations in Kliprivier are mainly attributed to domestic combustion and vehicle emissions [40]. In 2006, South Africa proposed NO₂ standards of 200 µg·m⁻³ for the highest daily average and 40 µg·m⁻³ for the annual average [41]. All study areas comply with these standards.

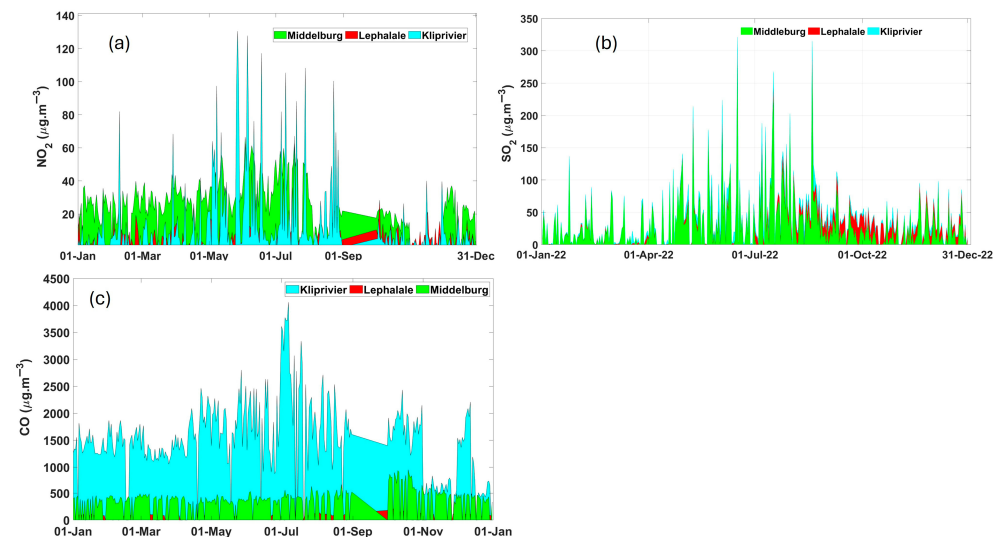


Figure 2. Comparison of (a) NO_2 , (b) SO_2 , and (c) CO pollutant concentrations in the Kliprivier, Lephale, and Middleburg areas.

SO_2 concentrations across the three sites show little variation (see Figure 2b). However, the Lephale site exhibits some variability during certain periods, notably in June, September, and October. The main sources of SO_2 in Lephale are the Matimba and Medupi coal-fired power stations [29], while SO_2 in the Kliprivier area originates from residential fuel burning, industrialized urban areas, and coal-fired power stations (Sangeetha et al. [42]). According to the Government Gazette No. 28899, 9 June 2006 [41], the South African standard for SO_2 is a maximum 24 h average of $125 \mu\text{g}\cdot\text{m}^{-3}$. On winter days, Middleburg and Kliprivier exceed this limit, with some days recording concentrations above $150 \mu\text{g}\cdot\text{m}^{-3}$.

An interesting trend in CO concentrations is observed across all three sites (see Figure 2c). The primary sources of CO in these areas include industrial, mining, residential, agricultural, and transportation sectors [20,42,43]. However, a late winter/early spring peak in open biomass burning leads to elevated CO concentrations exceeding $2000 \mu\text{g}\cdot\text{m}^{-3}$ [44]. This increase is observed at all three sites.

Figure 3 shows the concentrations of three gaseous pollutants at the three study sites. CO is the dominant gas across all sites, with lower concentrations of SO_2 and NO_2 . Kliprivier has the highest CO concentration, ranging between 2500 and $4000 \mu\text{g}\cdot\text{m}^{-3}$ during the mid-winter to early spring season. Overall, Kliprivier exhibits CO concentrations exceeding $1000 \mu\text{g}\cdot\text{m}^{-3}$, driven by the industrial activities prevalent in the area. Kliprivier is located in the Vaal Triangle, an industrialized region known for high levels of air pollution due to industrial activities and power generation [22,44–46]. On 21 April 2006, the Vaal region was declared a priority area [47] due to excessive emissions of toxic and hazardous pollutants into the atmosphere. A comparison of the three study areas indicates that the Kliprivier region is of serious concern.

Lephale, located in the Waterberg-Bojanala Priority Area, is primarily affected by mining and industrial activities, which contribute significantly to total emissions. The results of this study show that CO is the dominant gas, with a maximum concentration of approximately $700 \mu\text{g}\cdot\text{m}^{-3}$, while SO_2 and NO_2 concentrations do not exceed $50 \mu\text{g}\cdot\text{m}^{-3}$. These findings align with a baseline study by the Department of Fisheries, Forestry and Environment (DFFE) of South Africa, which indicated that (1) motor vehicle emissions, associated with SO_2 and CO, are confined to urban areas; (2) industrial activities contribute to scheduled and unscheduled process-related emissions and power generation; and (3) mining activities are sources of particulate matter, asbestos fibres, heavy metals, and odors [48].

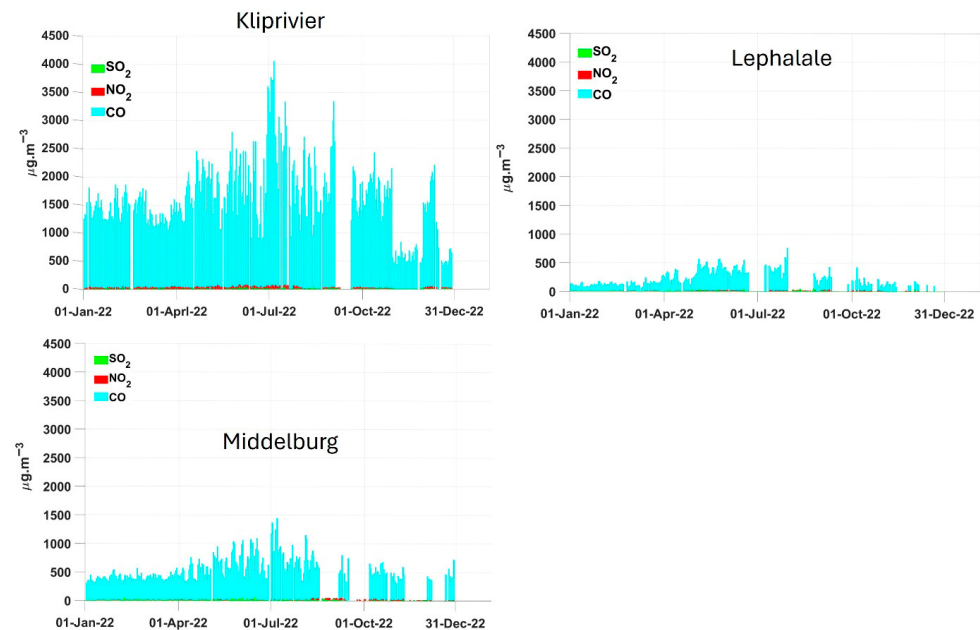


Figure 3. Comparison of NO₂, SO₂, and CO pollutant concentrations in Kliprivier, Lephalale, and Middelburg.

Middelburg, part of the Highveld Priority Area, is influenced by power generation, coal mining, metallurgical operations, and the petrochemical industry. The CO concentration in Middelburg is 1400 µg/m³, which is double the level recorded in Lephalale at 700 µg/m³; this is for the period of the overpass of the satellite. This difference is attributed to more frequent and intense biomass burning in the Highveld Priority Area [19,49,50] compared to the Waterberg-Bojanala Priority Area. Biomass burning includes activities such as veld fires (grass fires), agricultural waste burning, and the use of biomass for fuel. SO₂ is the second most dominant pollutant after CO in this area, primarily released from coal-fired power stations and other industrial activities, with concentrations below 50 µg·m⁻³.

4.2. Satellite (TROPOMI) Versus Ground-Based (SAAQIS) Measurements

The validation of satellite-derived products is essential to assess their accuracy and precision. From an end-user perspective, validation and uncertainty assessments are critical for satellite data products [51]. Reliable, long-term datasets and products require validation to ensure their continued provision and utility. Overreliance on satellite data without knowledge of their error propagation in a specific setting or advanced modeling may inflate pollution estimates, potentially misleading policy or public health decisions.

Figure 4 compares TROPOMI and SAAQIS (ground-based) measurements for NO₂, SO₂, and CO in the Kliprivier area. For NO₂ (Figure 4a), satellite and ground-based measurements show good agreement in most months, except during winter, when satellite data overestimate NO₂ concentrations. In June, NO₂ concentrations reach approximately 180 µg m⁻³, reflecting the satellite sensor's measurement during its overpass, which is not necessarily inaccurate. For SO₂ (Figure 4b), satellite and ground measurements consistently disagree, with satellite data significantly overestimating concentrations, particularly in winter. CO measurements show some agreement in summer; however, like NO₂ and SO₂, satellite data overestimate concentrations in winter. Several factors may contribute to these overestimations: (1) TROPOMI's coarse spatial resolution may blur localized pollution sources, leading to overestimation in areas with uneven pollutant distribution; (2) algorithmic errors or assumptions may inflate concentration estimates; and (3) satellite measurements capture pollutants across the entire atmospheric column, including those at

higher altitudes that do not impact ground-level air quality. Furthermore, satellites capture data at fixed intervals, whereas ground sensors typically record continuously, leading to a temporal mismatch that can overlook brief events, such as rapid air quality shifts. Additionally, cloud cover, atmospheric interference, or terrain can obstruct or skew satellite measurements, resulting in inaccuracies.

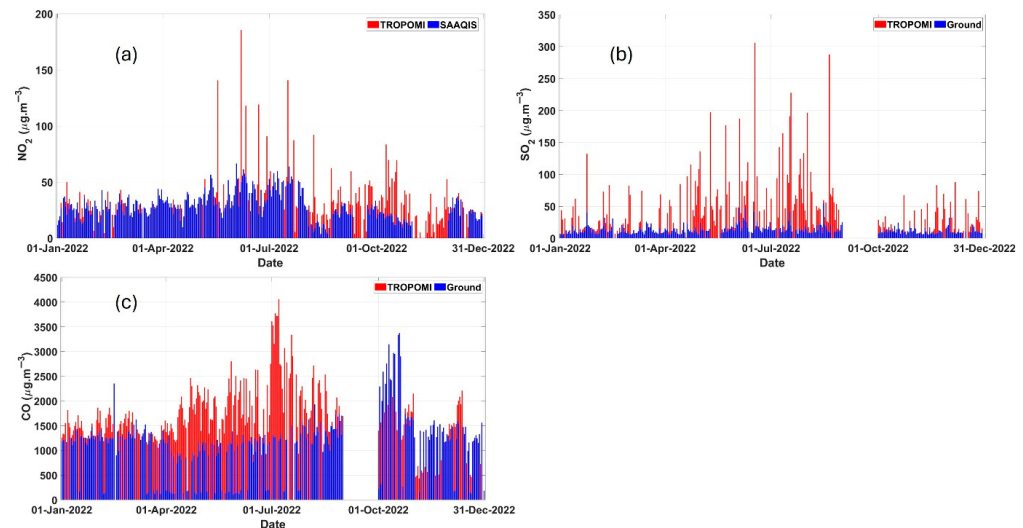


Figure 4. Comparison of (a) NO_2 , (b) SO_2 , and (c) CO pollutant concentrations in Kliprivier.

Figure 5 presents a comparison between TROPOMI and SAAQIS measurements for NO_2 , SO_2 , and CO concentrations in the Lephalale area. A prominent feature of this dataset is the presence of significant data gaps in both satellite and ground-based observations, which complicates direct comparisons and validation efforts. Notably, data are missing for the period between August and September, limiting the ability to analyze trends during the spring season. For the period from January to March, concentrations of NO_2 , SO_2 , and CO show relatively good agreement between the two sensors (see Figure 5a–c). However, from April through December, substantial inconsistencies emerge. These data gaps, along with variability in the reported concentrations, raise concerns about the reliability of both sensing systems. Wright et al. [52] also showed that gaps in the SAAQIS data have disadvantages affecting the accuracy of the data. Overall, the 2022 Lephalale dataset appears unreliable, casting doubt on the accuracy of the measured pollutant levels. These findings underscore the importance of rigorous validation efforts, particularly when ground-based data—typically used as the reference standard—may also be inaccurate. There is a clear need for the development of new methods and techniques to validate satellite observations in the absence of dependable ground truth data.

Figure 6 presents a comparison between TROPOMI and SAAQIS measurements of NO_2 , SO_2 , and CO concentrations in the Middelburg area. As with the data shown in Figure 5, a significant gap between August and September limits the analysis of trends during the spring season. For NO_2 (see Figure 6a), satellite and ground measurements generally agree from January to May, although there are isolated instances where TROPOMI overestimates concentrations. The highest NO_2 value, around $80 \mu\text{g}\cdot\text{m}^{-3}$, is observed in March. Similar to trends in Kliprivier and Lephalale, elevated NO_2 levels are recorded during the autumn and winter months, with the highest estimated concentration reaching approximately $130 \mu\text{g}\cdot\text{m}^{-3}$, indicating a pattern of overestimation by the satellite during these periods. For SO_2 and CO concentrations (Figure 6b,c), the satellite and ground-based data show overall good agreement. However, occasional underestimations by the satellite

are noted. Such underestimations are important to acknowledge, as they can lead to inaccurate assessments of air quality and public health risks.

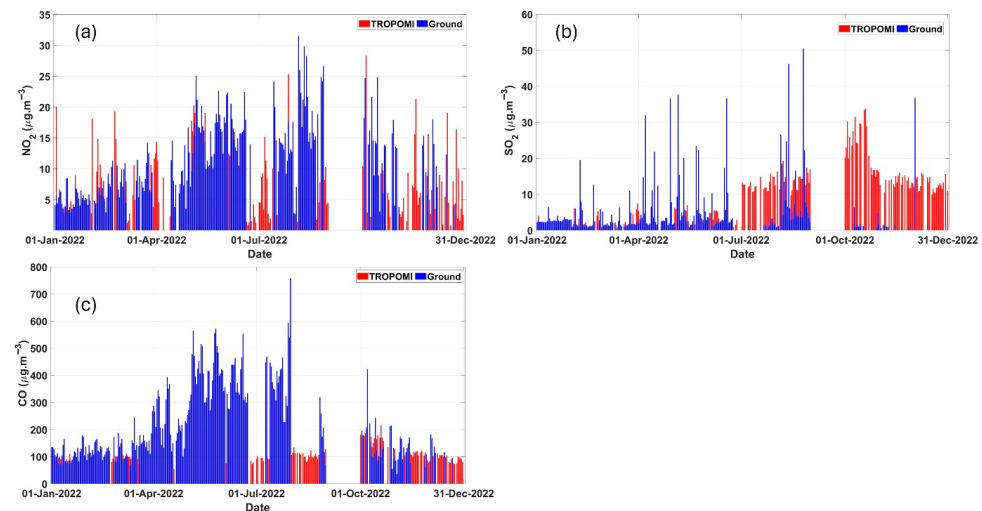


Figure 5. Comparison of (a) NO_2 , (b) SO_2 , and (c) CO pollutant concentrations in Lephalale.

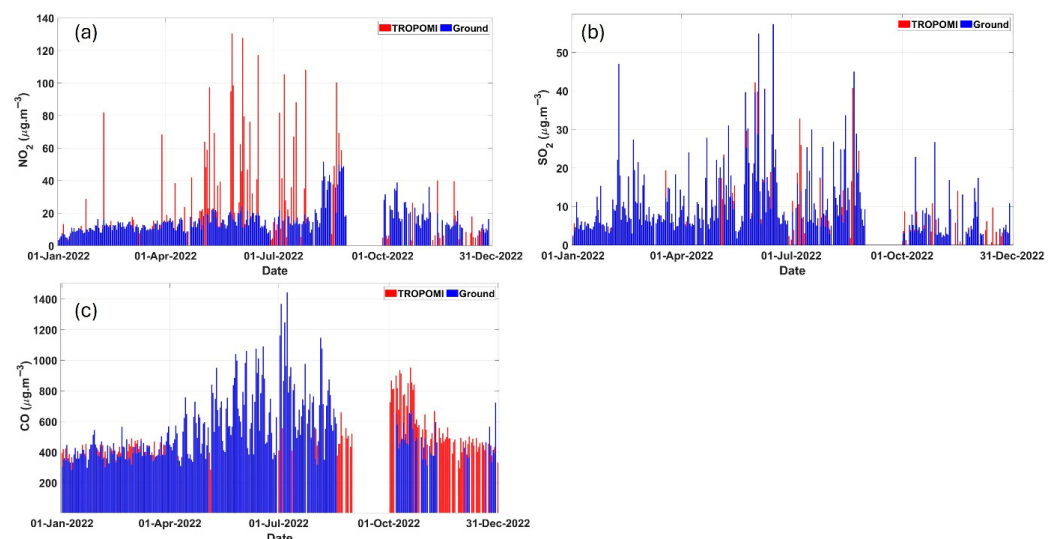


Figure 6. Comparison of (a) NO_2 , (b) SO_2 , and (c) CO pollutant concentrations in Middelburg.

5. Summary and Conclusions

The 2022 time series data for NO_2 , SO_2 , and CO concentrations across Lephalale, Middelburg, and Kliprivier reveal distinct patterns and sources of air pollution, as well as varying compliance with South African air quality standards. NO_2 levels, driven primarily by coal-fired power stations in Lephalale and Middelburg, remain within regulatory limits, while Kliprivier's lower concentrations reflect domestic and vehicular sources. SO_2 concentrations show limited variation, while Middelburg and Kliprivier exceed the 24 h standard during winter. CO concentrations, influenced by diverse industrial and biomass burning activities, exhibit a notable peak in October due to open biomass burning. These findings underscore the complex interplay of industrial, residential, and environmental factors shaping air quality in these regions, highlighting the need for targeted mitigation strategies to address exceedances and protect public health.

The results from Kliprivier, Lephalale, and Middelburg further highlight significant variations in gaseous pollutant concentrations, with CO dominating across all sites, particularly in the industrialized Kliprivier region, where concentrations reach $2500\text{--}4000\text{ }\mu\text{g}\cdot\text{m}^{-3}$.

Kliprivier's severe pollution, driven by industrial activities and power generation, underscores its status as a critical concern within the Vaal Triangle Priority Area. Lephalale and Middelburg, influenced by mining, industrial operations, and biomass burning, exhibit lower CO concentrations but still face challenges from SO₂ and NO₂ emissions. Comparisons between TROPOMI and SAAQIS measurements reveal inconsistencies, with satellite data often overestimating winter concentrations, and significant data gaps in Lephalale complicating validation efforts. These findings emphasize the critical need for the robust validation of satellite-derived data, integration of reliable ground measurements, and development of advanced methods to ensure accurate air quality assessments, ultimately informing effective policy and public health strategies in South Africa's priority areas.

The results show that while satellite-derived products offer valuable insights into atmospheric pollution patterns, their accuracy can vary significantly depending on the pollutant, season, and local environmental conditions. The comparison with ground-based data in the Kliprivier area highlights that although satellite data generally align with ground measurements for NO₂, and, to a lesser extent, CO during certain periods, they tend to overestimate concentrations, particularly in winter. This discrepancy underscores the importance of continued validation using ground-based observations and improved modeling techniques to refine satellite estimates. Without such validation, satellite data alone may misrepresent air quality trends, potentially leading to misguided policy decisions.

Lastly, the comparisons presented in Figures 5 and 6 reveal both the strengths and limitations of satellite-based air quality monitoring in regions like Lephalale and Middelburg. While periods of agreement between TROPOMI and SAAQIS data suggest the potential for reliable satellite measurements, significant data gaps and seasonal discrepancies—particularly in autumn and winter—highlight the challenges of relying solely on either data source. The unreliability of the 2022 Lephalale dataset, compounded by missing observations and inconsistencies, emphasizes the need for improved validation strategies, especially when ground-based data are incomplete or potentially inaccurate. The observations from Middelburg further stress that even when agreement is generally good, occasional over- or underestimations by satellites can lead to flawed interpretations of air quality.

Overall, variations in acquisition times between satellite overpasses and in-situ measurements contribute to misalignments in the data. To address this issue and ensure consistency, a carefully coordinated timing of both satellite and in-situ observations must be considered. This alignment in acquisition times can help minimize discrepancies and enhance the reliability of the comparison between the two datasets.

Wright et al. [52] concluded that continuous datasets with high capture rates are critical to assess long-term trends in air pollution levels, ensuring an understanding of the impact of the implemented policies. The findings of this study point to an urgent need for enhanced validation methods, improved sensor calibration, and robust data integration techniques to ensure the credibility and usability of satellite-derived air quality products.

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