

Article

Air Quality Monitoring in Two South African Townships: Modelling Spatial and Temporal Trends in O₃ and CO Hotspots

Aluwani Innocent Muneri , Benett Siyabonga Madonsela  and Thabang Maphanga * Department of Environmental and Occupational Studies, Faculty of Applied Sciences,
Cape Peninsula University of Technology, Cape Town 8000, South Africa

* Correspondence: maphangat@cput.ac.za

Abstract

Air quality is a key priority in environmental policy agendas worldwide, yet rapid urban growth in developing countries disproportionately affects urban air quality. In sub-Saharan Africa, the spatial and temporal dynamics of key pollutants remain underexplored. This knowledge gap limits the ability to understand how pollution hotspots emerge, how they shift over time, and how they interact with the broader planetary processes such as climate change. This study analysed the spatial distribution of ozone (O₃) and carbon monoxide (CO) hotspots in Diepkloof and Klieprivier townships, Johannesburg, South Africa, using data from 2019 to 2023 obtained from air quality monitoring stations. Spatial patterns were mapped using Inverse Distance Weighting (IDW) interpolation in a Geographic Information System (GIS), and meteorological influences were assessed through multiple linear regression. Results showed distinct spatial trends: Diepkloof experienced a decrease in O₃ from 23 ppb to 16 ppb, whereas Klieprivier remained stable but exhibited marked seasonal variation, peaking at 30 ppb in spring. Wind speed, wind direction, and humidity were significant predictors ($p < 0.05$) of both CO and O₃. In Klieprivier, meteorological factors explained 54.2% of O₃ variability, with temperature being the strongest predictor. These findings provide valuable insight into pollutant behaviour in urban townships and highlight the importance of integrating spatial analysis with meteorological modelling for targeted air quality management.



Academic Editor: Susan Prescott

Received: 19 June 2025

Revised: 18 August 2025

Accepted: 20 August 2025

Published: 31 October 2025

Citation: Muneri, A.I.; Madonsela, B.S.; Maphanga, T. Air Quality Monitoring in Two South African Townships: Modelling Spatial and Temporal Trends in O₃ and CO Hotspots. *Challenges* **2025**, *16*, 52. <https://doi.org/10.3390/challe16040052>

Copyright: © 2025 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

Keywords: air pollution; ozone; carbon monoxide; spatial analysis; urban air quality

1. Introduction

Air pollution is a significant planetary health issue that poses an environmental management challenge and has a direct impact on the health of human populations, climate stability, and ecosystem integrity. This is problematic given that is a global challenge affecting both developed and developing countries, with urban areas particularly vulnerable due to rapid population growth, urbanization, and increased emissions from transportation, industry, and residential activities [1]. These emissions contribute to environmental degradation, global warming, and adverse health impacts. Among the pollutants of concern, O₃ and CO are recognized by the World Health Organization as two of the six “classic” air pollutants due to their serious public health effects and roles in atmospheric processes [2]. Surface-level O₃ is linked to respiratory illnesses and approximately 1.2 million adult deaths annually [3], while CO poses risks to cardiovascular and neurological health.

Air quality monitoring stations remain the accurate means of measuring pollutant concentrations, yet their limited spatial coverage can miss local variability [4,5]. Previous

studies have emphasized the importance of optimizing sensor placement and improving spatial representativeness to accurately capture pollution patterns [5,6]. However, many high-emission, densely populated areas, especially in developing regions, remain under-monitored, leading to gaps in pollution assessment and management [7,8].

Despite advancements in air pollution monitoring and modelling globally, existing studies often suffer from several limitations, especially in developing regions. Many rely on sparse monitoring networks that lack sufficient spatial resolution to capture localized pollution variability, particularly within informal settlements and rapidly changing urban landscapes [9,10]. Additionally, previous research focuses on broad regional or national scales, neglecting the fine-scale spatial and temporal dynamics critical for effective local exposure assessment and intervention planning [11,12]. Moreover, few studies integrate meteorological factors with spatial interpolation methods to elucidate the drivers behind pollutant variability over extended periods. This is especially true for African urban contexts, where industrialization, traffic emissions, and biomass combustion coexist, yet detailed longitudinal analyses remain scarce [13,14]. Consequently, these gaps limit understanding of pollution hotspots, temporal trends, and the interplay between environmental and meteorological influences, restricting the effectiveness of air quality management policies in vulnerable urban townships.

Geographic Information Systems (GISs) and spatial interpolation methods offer valuable tools for mapping pollutant distributions and addressing these coverage gaps [12]. They allow the integration of environmental and meteorological data to model pollutant variability, even in areas with limited monitoring [13]. While studies in Europe and North America have applied spatial regression models to assess pollutant variation and long-term trends [14,15], research in African cities, including Johannesburg, remains scarce [16]. This knowledge gap limits the ability to understand how pollution hotspots emerge, how they shift over time, and how they interact with broader planetary processes such as climate change. Moreover, communities in the informal settlements of urban areas frequently experience greater levels of exposure due to their close proximity to industrial zones and high traffic density; this is problematic since the air pollution is linked with social determinants of health.

Similarly, Diepkloof and Klieprivier were selected for this study due to their proximity to industrial zones, high traffic density, and biomass combustion in informal settlements factors likely to influence O₃ and CO levels. This study analyses five years of monitoring station data to examine the spatial and temporal variability of these pollutants, identify hotspots, and evaluate meteorological influences. The findings aim to inform personal exposure assessments, guide air quality management strategies, and assist policymakers in optimizing monitoring networks for urban townships.

Despite global advances in air pollution monitoring and spatial modelling, there remains a lack of detailed, long-term spatial and temporal analyses of ozone and carbon monoxide in rapidly urbanizing African townships. This knowledge gap hinders effective exposure assessment and targeted air quality management in vulnerable communities. By conducting a five-year study (2019–2023) combining Geographic Information Systems-based spatial interpolation with statistical modelling of meteorological factors, this research provides critical insights into pollution hotspots and temporal trends in Diepkloof and Klieprivier. This addresses the gap in localized air quality data and supports evidence-based policymaking for sustainable urban environmental health.

2. Methodology

2.1. Study Area

This study was conducted in Diepkloof and Klieprivier, which are found in the Johannesburg metropolitan area, as shown in Figure 1. Diepkloof is situated at approximately $26^{\circ}15'14''$ S $27^{\circ}56'02''$ E, 15 km southwest of Johannesburg Central Business District (CBD); this is one of the oldest townships of South Africa, and it is mostly known for its mixture of industrial zones such as the Orlando Power station (Twin towers), Adendorf machinery Mart, SASKO Aerton Bakery, and the congested vehicle traffic from the M79 highway and N17 road. This is an urban residential area that has high concentration of informal settlements [17]. It is bounded by four major roads and covers an area of 250,218 km², divided into six zones with a population density of approximately 9800 people according to census 2011 [18,19]. Diepkloof is 16.36 km away from the mine which could affect the quality of air for people living in this township. Klieprivier is found on the southern periphery of Johannesburg at $26^{\circ}21'18''$ S $28^{\circ}04'52''$ E; it is approximately 25 km away from Johannesburg CBD and 31.24 km away from Diepkloof. The same as Diepkloof, it is also affected by congested vehicle traffic from major roads. While the area is less urbanized compared to Diepkloof, it consists of a mix of both rural and peri-urban characteristics, with land use dominated by agricultural activities, such as dairy farms. Based on the 2011 census data, Klieprivier in Gauteng province had a population of 179 residents across seventy households, covering an area of 10.34 km², resulting in a low population density of approximately 17.3 people per km². The air quality might be affected by the nearby mine and the airport in Vaal [20].

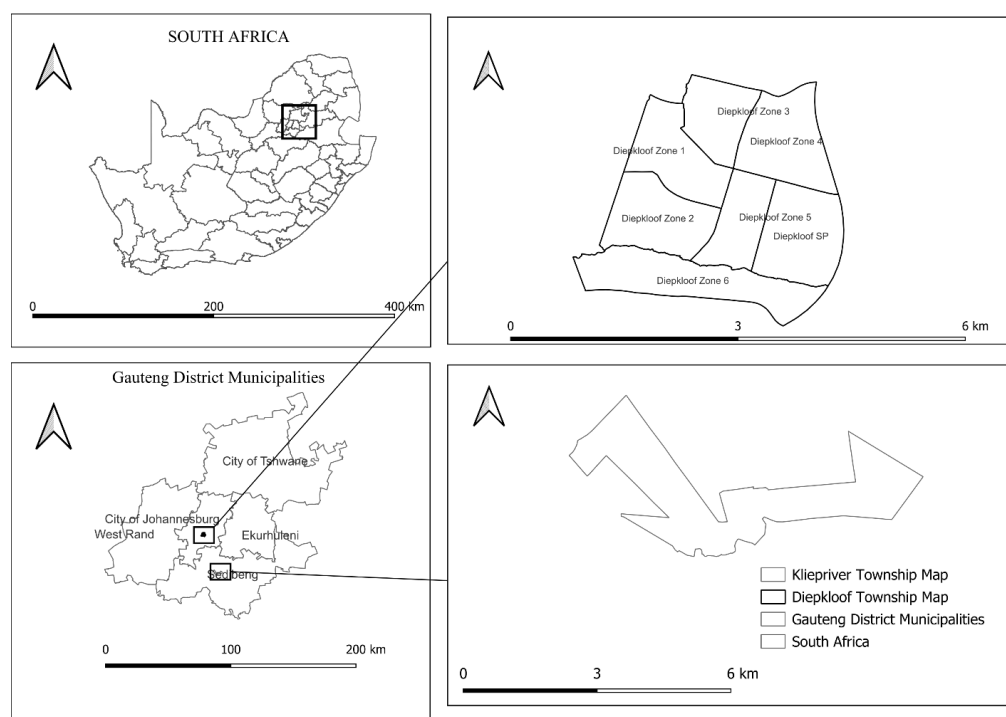


Figure 1. Map showing the location of Diepkloof and Klieprivier townships in Johannesburg, South Africa.

Both townships experience a climate of warm summers, with average temperatures of 25 °C, and mild winters, with a temperature average of 12 °C, which influences the meteorological conditions and the pollutants' dispersion pattern. Supplementary Figure S2 displays the average summer and winter temperatures for both Diepkloof and Klieprivier. Despite global advances in air pollution monitoring and spatial modelling, there remains a

significant lack of detailed, long-term spatial and temporal analyses of ozone and carbon monoxide in rapidly urbanizing African townships. This knowledge gap hinders effective exposure assessment and targeted air quality management in vulnerable communities. By conducting a five-year study (2019–2023) combining Geographic Information Systems-based spatial interpolation with statistical modelling of meteorological factors, this research provides critical insights into pollution hotspots and temporal trends in Diepkloof and Klieprivier. This addresses the gap in localized air quality data and supports evidence-based policymaking for sustainable urban environmental health.

2.1.1. Air Quality Data

Five years of air quality data for CO and O₃ was requested from the South African Air Quality Information System (SAAQIS) (<https://saaqis.environment.gov.za/>). This website is operated by the Department of Environmental Affairs, and it provides real-time air quality data. The study period was five years, from 2019 to 2023. A 24 h average was used to measure all the pollutants from the monitoring stations in Diepkloof and Klieprivier. The data collected provided a picture of the areas that have high industrial activities and vehicular emissions. Purposive sampling was used in this study through the selection of two monitoring stations amongst other stations that are found within the city of Johannesburg. The selected stations were within a 20 km radius from the Johannesburg CBD; this radius ensured that the selected stations capture both urban and peri-urban emission characteristics of Klieprivier that are relevant to the study area while maintaining the proximity to emission sources like industrial activities, traffic-dense zones, and household combustion areas [21,22].

This offered a broad industrial, residential, and urban area coverage. The dataset consists of daily averages of CO and O₃ over a period of five years, which amounts to more than 18,250 observations. This dataset allowed for spatial and temporal analysis of pollutant trends. In this study, the data collected from the monitoring stations were consistent and continuous daily measurements of CO and O₃ from 2019 to 2021.

2.1.2. Meteorological Data

A five-year dataset (2019–2023) of meteorological parameters such as wind speed, wind direction, temperature, humidity, and rainfall were requested from the South African Weather Service. These parameters are crucial for understanding the dispersion and transportation of CO and O₃ in Diepkloof and Klieprivier townships. Air quality data and meteorological data were both aligned to obtain exact modelling of the atmospheric influence on pollutant concentrations.

2.2. Data Analysis

For spatial analysis, GIS tools such as QGIS were used to interpolate pollutant concentrations across Diepkloof and Klieprivier. Spatial interpolation techniques such as IDW were applied to create continuous surface maps that visualize pollutant concentration gradients. IDW is a spatial interpolation method which assumes that points on a map that are closer together are more alike than those that are further apart [23]. It is a good technique for this study as it helps to estimate the values of locations that do not have data; however, their spatial distribution is required. By using known measurement, IDW can predict the unknown location's measurements. It assigns higher weights to points that are nearby and then calculates the predicted values based on the average of the weighted neighbouring measurements. IDW is used in air pollution studies to estimate the concentration of pollutants in areas where monitoring stations are sparse [24].

On the other hand, Ordinary Kriging, which is a geostatistical interpolation method, was used to create continuous surface maps that visualize pollutant concentration gradients.

This method was implemented in QGIS 3.22 using default semi-variogram parameters, and it provides the predictions and measures the uncertainty of those predictions [25]. By integrating both methods, we can easily compare their outputs, which ensures reliability and robustness of spatial interpolation. This approach minimizes biasedness that might occur when only one method is used [26]. Kriging is a geostatistics interpolation method that calculates the distance and degree of variation between the points that are known when estimating values of unknown points [27]. Both IDW and Kriging methods were evaluated using cross-validation techniques calculating error metrics, such as Root Mean Square Error and Mean Absolute Error. The cross-validation results indicated that Kriging generally yielded lower RMSE and MAE values, reflecting higher prediction accuracy and better modelling of spatial variability, especially in areas with high pollution variability. Conversely, IDW demonstrated competitive performance in locations with sparser data and smaller datasets, producing smooth and reliable concentration surfaces. By integrating both interpolation methods, this study balances the strengths of each approach, namely Kriging's superior uncertainty quantification and IDW's effectiveness with limited data, thereby minimizing bias and improving the robustness of pollutant distribution mapping.

Kriging is one of the top-performing methods in pollution studies, mostly in studies where variables are affected by local meteorological and emission sources [28]. IDW and Kriging were selected because of their accuracy in different air pollution studies. IDW was chosen for its ability to manage small datasets and the ability to produce smooth pollutant concentration maps, while Kriging's strength is in modelling spatial variability in the data. Different studies have successfully utilized IDW and Kriging in air pollution research. Ref. [29] modelled NO₂ and PM_{2.5} concentrations in an urban area, demonstrating how effective IDW is when it comes to generating spatial predictions that are dependable.

Ref. [30] IDW and Kriging were compared, and Kriging outperformed IDW in certain areas that had high variability in pollutant levels. Ref. [7] predicted CO hotspots in industrial areas using Kriging, which highlighted how it is suitable for analysing how meteorological patterns influence pollution pattern. Kriging was successfully implemented to model the dispersion of O₃; it was found to provide the most accurate and reliable estimates among interpolation methods after reviewing different techniques for interpolation, and it was concluded that IDW is best in small-scale environmental studies, whereas Kriging can cover large-scale areas because of its ability to quantify uncertainty [19,22,28]. As a result of limited spatial representativeness due to lack of air quality monitoring stations in Diepkloof and Klieprivier, IDW was selected because it is effective to estimate pollutant concentrations, while Kriging was chosen because it can quantify spatial uncertainty and improve prediction accuracy; through the integration of both these techniques, we ensure that bias is minimized while improving reliability of pollutant distribution maps.

Ref. [31] Moran's I statistics calculates the degree of spatial clustering of different pollutant levels. Because of its ability to quantify the degree of spatial clustering of pollutant levels, it was also used to determine the spatial patterns of pollutants whether they are randomly distributed or not. It also identified any spatial dependencies between CO and O₃ concentrations. The Getis-Ord Gi statistic is a spatial statistic that finds clusters of high and low values in a dataset; it calculates the z- score and p-value for each grid cell and compares sum of values [1,4,7]. It was used to find statistically significant hotspots where pollutant concentrations were higher than those in surrounding areas. This combination of methods ensured the exact mapping of areas with elevated pollutant concentrations.

The calculation of Moran's I statistic (Equation (1)) and its expected value and variance (Equations (4) and (5)) follow the formulation by [32,33], which are widely used to quantify spatial autocorrelation in environmental data. The Moran's I statistics for spatial autocorrelations is given as

$$I = (n/S_0) * (\sum_{i=1}^n \sum_{j=1}^n w_{i,j} z_i z_j) / (\sum_{i=1}^n z_i^2) \quad (1)$$

where z_i is the deviation of an attribute for feature i from its mean ($x_i - \bar{X}$), $w_{i,j}$ is the spatial weight between feature i and j , n is equal to the total number of features, and S_0 is the aggregate of all the spatial weights:

$$S_0 = \sum_{i=1}^n \sum_{j=1}^n w_{i,j} \quad (2)$$

The zI-score for the statistic is computed as

$$zI = (I - E[I]) / \sqrt{V[I]} \quad (3)$$

where

$$E[I] = -1/(n - 1) \quad (4)$$

$$V[I] = E[I^2] - E[I]^2 \quad (5)$$

A time series was used for calculating and analysing a sequence of data points collected over a period. It was also used to decompose pollutant concentration data into different trends, seasonal variations, and residual fluctuations, which are useful in identifying long-term trends, seasonal patterns, and any anomalies in the concentration of CO and O₃. To explore the relationship between pollutant hotspots and environmental factors such as proximity to industrial zones, traffic density, and meteorological conditions, correlation and regression were calculated and analysed. Ref. [34] defined correlation as a statistical measure that calculates how two or more variables are linearly related; it examines the relationships between pollutant levels, the proximity to industries, the traffic densities, and meteorological conditions. Ref. [35] defined regression as a statistical measure that determines how strong the relationship is between a dependent variable and independent variables. In this study, multiple linear regression was used to identify key drivers of CO and O₃ pollution, including temperature, humidity, rainfall, and wind speed. These models provided insights into the key drivers of O₃ and CO pollution in Diepkloof and Klieprivier. Missing data were addressed using linear interpolation for short gaps, while longer missing periods were excluded to maintain data integrity. Outliers were identified using the interquartile range (IQR) method and were further examined before excluding values deemed as measurement errors or physically implausible. This pre-processing step ensured the robustness and reliability of our spatial and statistical analyses. All statistical investigations were conducted using the Statistical Package for the Social Sciences (IBM SPSS Statistics) software version V30.0, with statistical significance set at $p < 0.05$. Results were presented with 95% confidence intervals, ensuring the robustness of the findings.

3. Results

3.1. Spatial Distribution of CO and O₃

Figure 2A–E depict the spatial distribution of CO across Diepkloof township from 2019 to 2023. In Figure 2A, CO concentration in 2019 ranged from a low of 94 ppb to a high of 1206 ppb. In 2020, Diepkloof recorded a low concentration of 187 ppb and a high concentration of 1300 ppb. These high concentrations were seen in Zone 1 and parts of Zones 2, 3, and 4. Zone 6 depicted low concentrations, while a moderate concentration was observed in Zones 5 and 6, which can be estimated around 500 ppb. These moderate levels could result from lower emission sources and the availability of open spaces in Zone 5. In 2021 and 2022, the concentration pattern did not change; Zone 1 and other parts of Zones 3 and 4 were depicted as hotspots shown by the red colour in the maps, with the concentrations ranging from a low of 126 ppb to a high of 1135 ppb. Figure 2E depicts concentrations for the year 2023; there was a decrease in the concentrations of CO, with the

levels ranging from a low of 39 ppb to a high of 987 ppb. Hotspots areas also diminished in part of Zone 2 and are only visible in portions of Zones 1, 3, and 4. This decrease in CO concentrations could be a result of the adopted practices of cleaner energy use and the Just Energy Transition (JET), which was implemented in August 2022 [36].

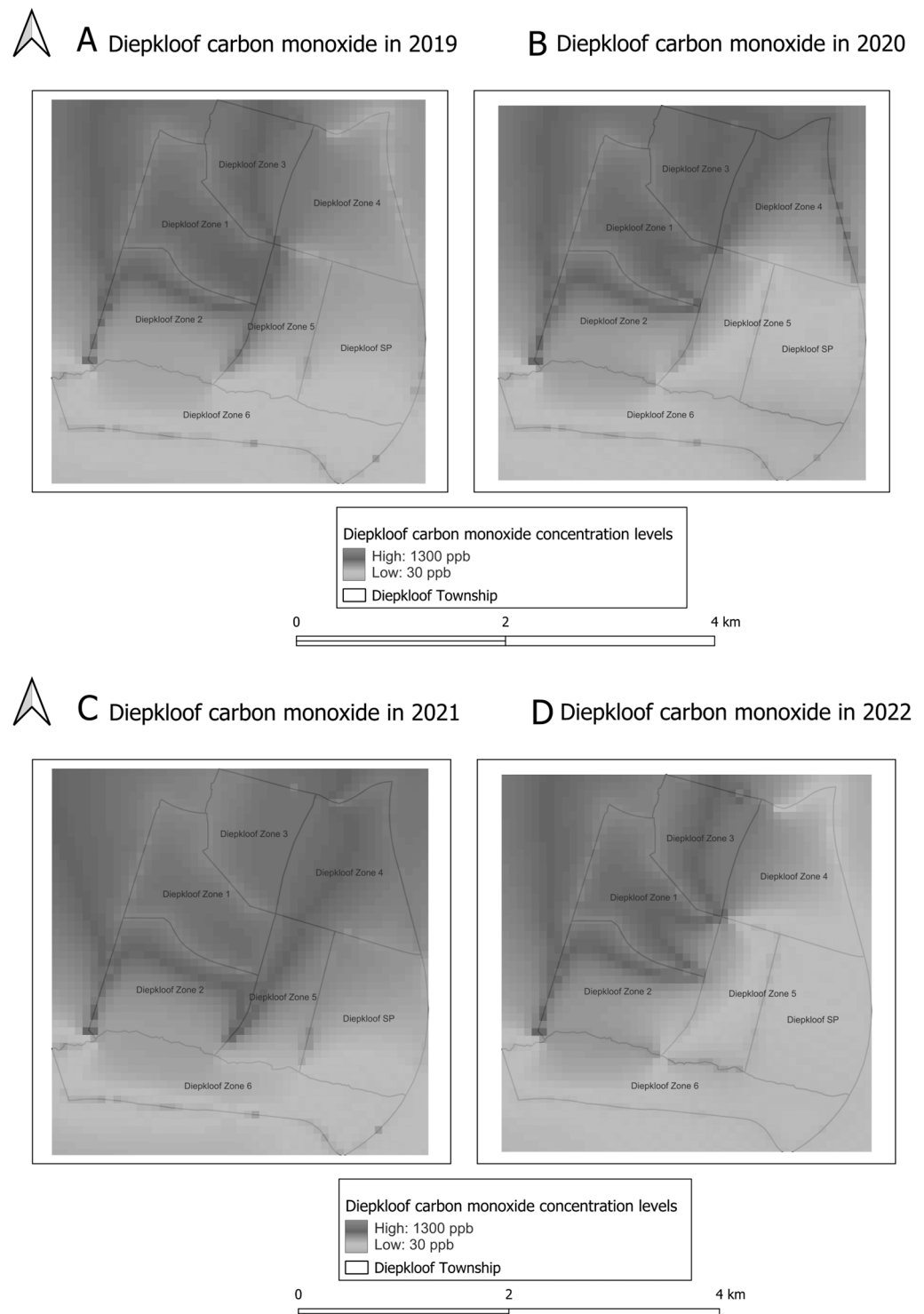


Figure 2. *Cont.*

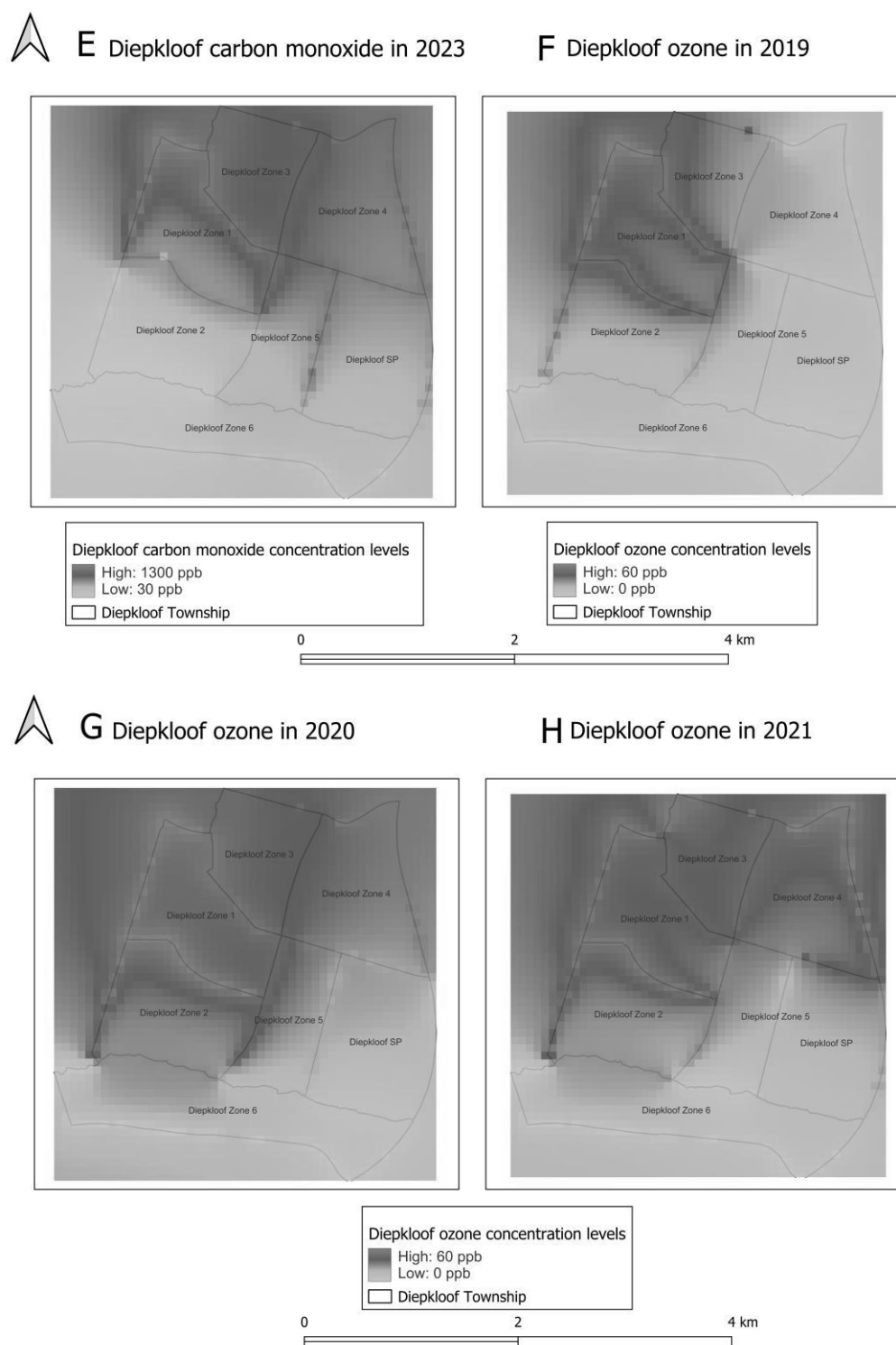


Figure 2. Cont.

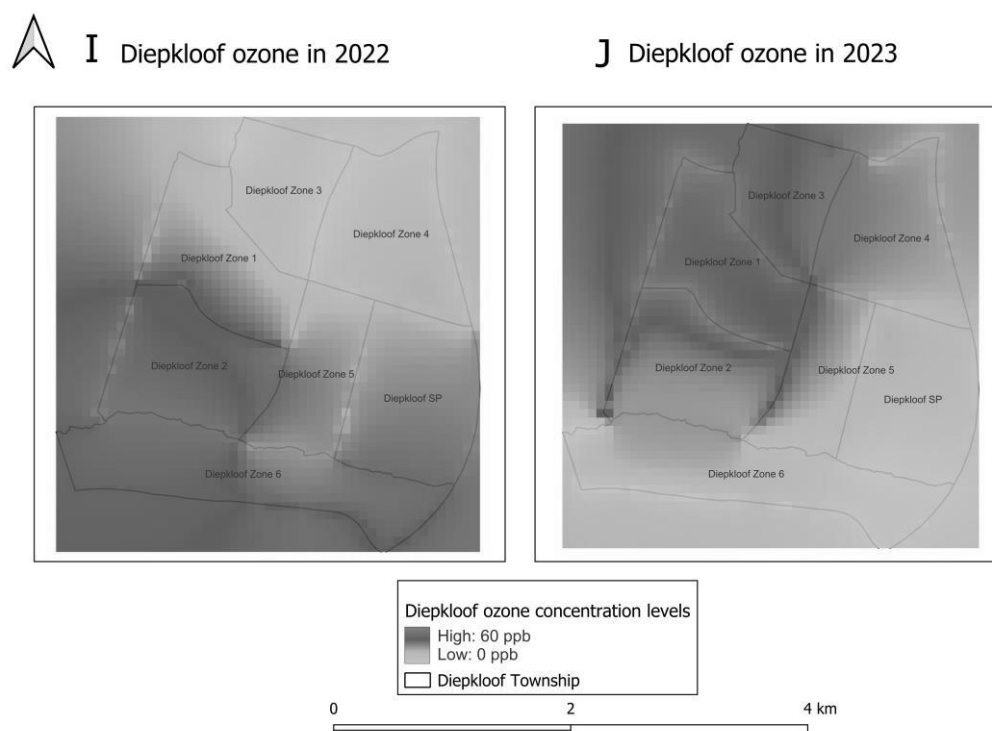


Figure 2. Carbon monoxide spatial distribution map for Diepkloof (A–E) and ozone spatial distribution map for Diepkloof (F–J) 2019 to 2023.

Overall, maps from 2019 to 2023 indicate that high concentrations of CO, which are represented by red, are consistent in Zones 1, 2, and 3. This could result from the proximity of identified hotspots to sources of emissions, such as the Orlando Power Station (Twin Towers), which are located at approximately 1.49 km from hotspots. Other emission sources around hotspots include the Bara taxi rank and Chris Hani Baragwaneth hospital, which could contribute to elevated levels of CO in this area. These concentrations are higher compared to those reported in other studies conducted in different regions of South Africa. For example, a study conducted in the urban area of Tshwane found an annual mean CO concentration of 630 ppb [37].

Figure 2F–J depict the spatial distribution of O₃ concentrations across Diepkloof township from 2019 to 2023. In Figure 3F,G, the concentrations of 2019 and 2020 ranged from a low of 3 ppb to a high of 49 ppb, with 2019 showing a large portion of areas that have lower concentrations compared to other years, whereas Zone 1 and parts of Zones 2 and 3 were identified as hotspots. From 2020 to 2023, the area was dominated by higher concentrations, which could result from high traffic volumes from the M17 highway, the Bara taxi rank, and the surrounding industries. In Figure 2H, representing the year 2021, the concentrations of O₃ ranged from a low of 5 ppb to a high of 47 ppb. In this year, most parts of Zone 1 to Zone 4 were depicted as hotspots shown by the red colour on the map; while Zone 6 displayed lower concentrations, a substantial portion of Diepkloof was characterized by high O₃ levels. The shift observed in O₃ concentration patterns between the years 2021 and 2022 was attributed to the aftermath of the COVID-19 lockdown period. This resulted from reduced human activities in 2020 and early 2021. As the restrictions eased in late 2021 into 2022, human activities could have caused an increase in ozone levels in the area. This is evident in global observations showing that post-lockdown air pollution levels started to increase [38].

Figure 2I depicts the concentration of O₃ in 2022, with the levels of concentration ranging from a low of 5 ppb to a high of 56 ppb. Zone 2 is a consistent hotspot alongside

portions of Zones 5 and 6. By the year 2023, as shown in Figure 2J, few O₃ hotspots had diminished; high concentrations are still visible in most parts of Zones 1, 2, 3, and 4. Approximately 70% of Diepkloof in 2023 was covered by high concentrations, while only 30% depicted lower concentrations.

The reduction in hotspots in the small portions of Diepkloof could be linked to the emission control by the Department of Environmental Affairs and the adoption of cleaner energy sources altogether, with increased public awareness. Meteorological conditions such as increased rainfall, which has resulted in flooding in most of the places, may contribute to dispersing ozone pollutants, resulting in lower concentrations in some parts of Diepkloof.

In 2020, Figure 3G depicts an increase in CO concentrations, which ranged from a low of 150 ppb to a high of 1564 ppb. Points 1, 4, and 8 remained consistent hotspots. Approximately 60% of Klieprivier displayed low–moderate CO concentrations, while 40% displayed high concentrations. The rise in CO levels during this period might be linked to increased industrial activities and higher traffic volumes. By 2023, as depicted in Figure 3I, CO concentrations ranged from 100 ppb to 1389 ppb. There is a clear spatial pattern which includes Points 1, 4, and 8, which are consistent hotspots throughout the years. Overall, the variation in CO concentrations across Klieprivier from 2019 to 2023 can be linked to the influence of factors such as traffic emissions, urban development, and the effectiveness of local air quality management practices. Local household combustion may also be a contributing factor.

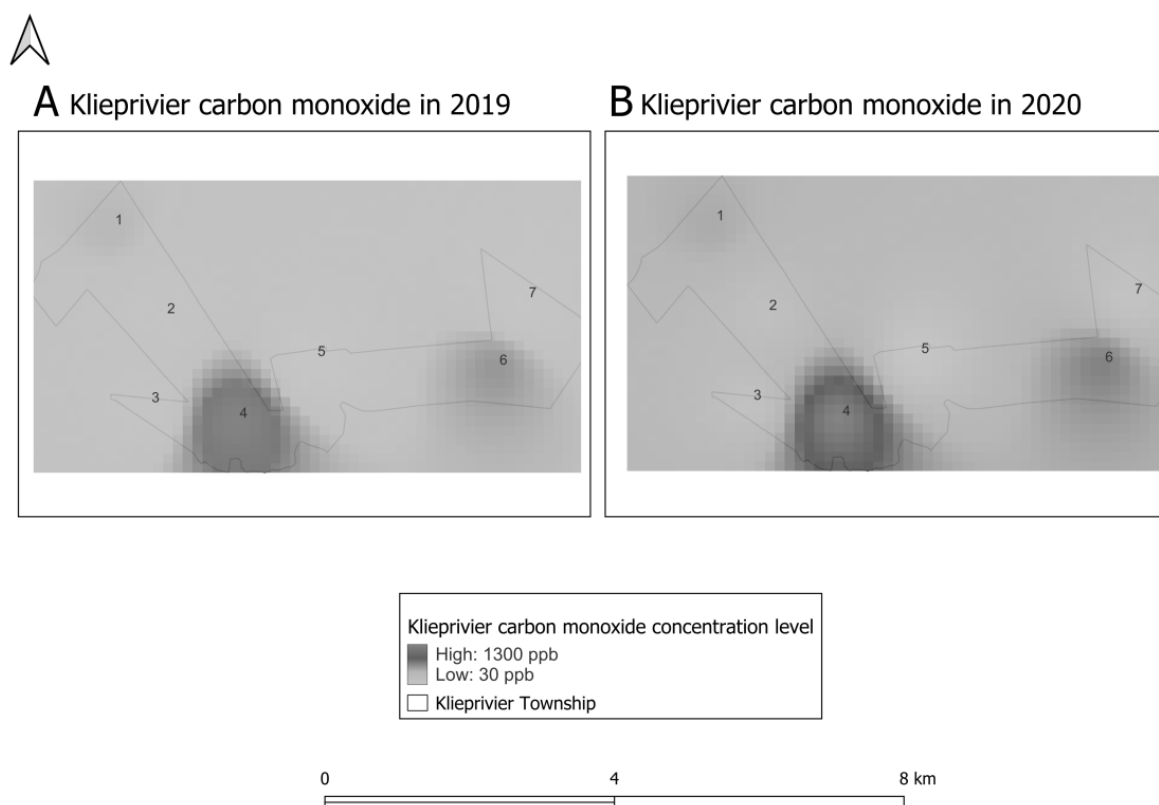


Figure 3. *Cont.*

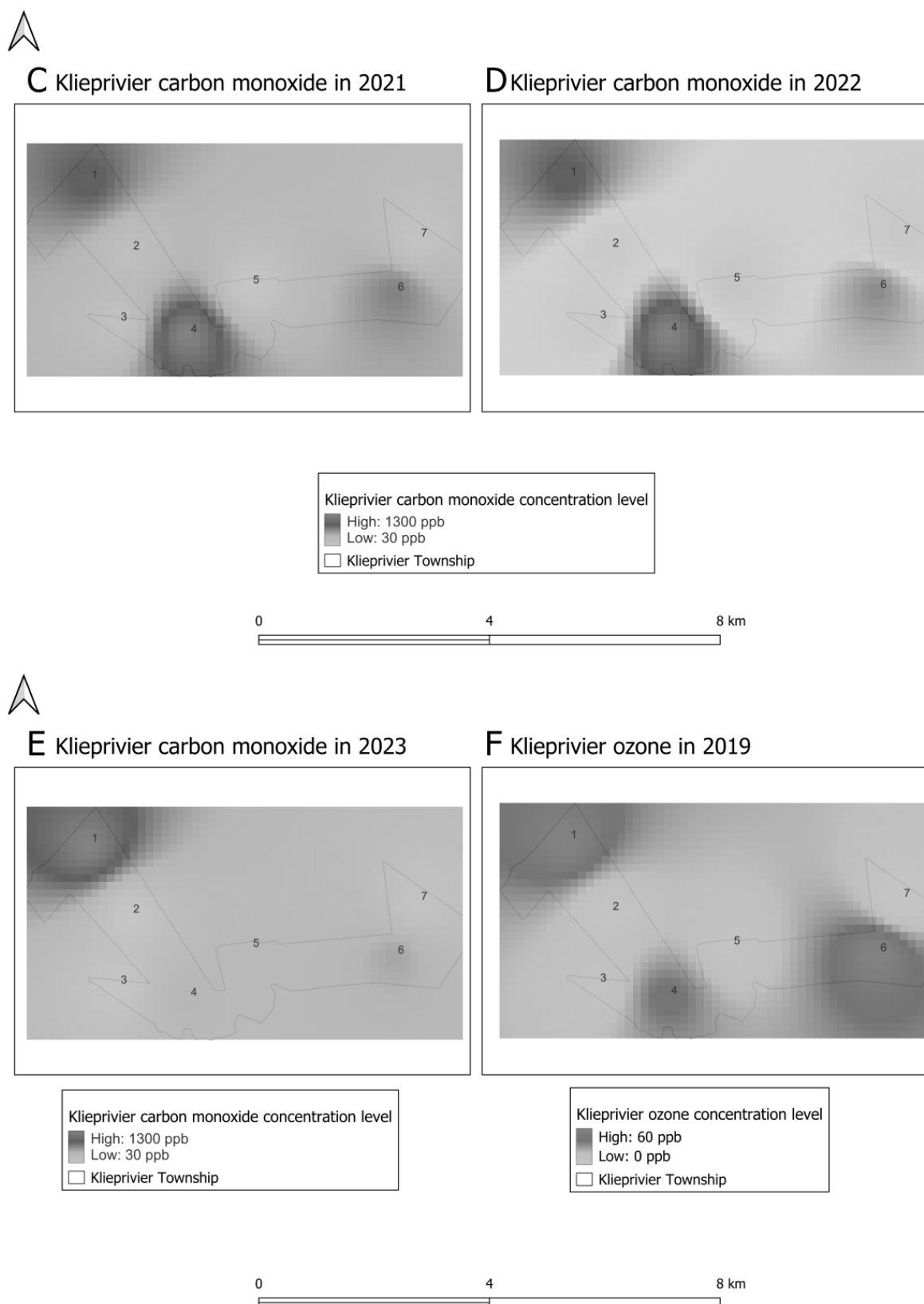


Figure 3. Cont.

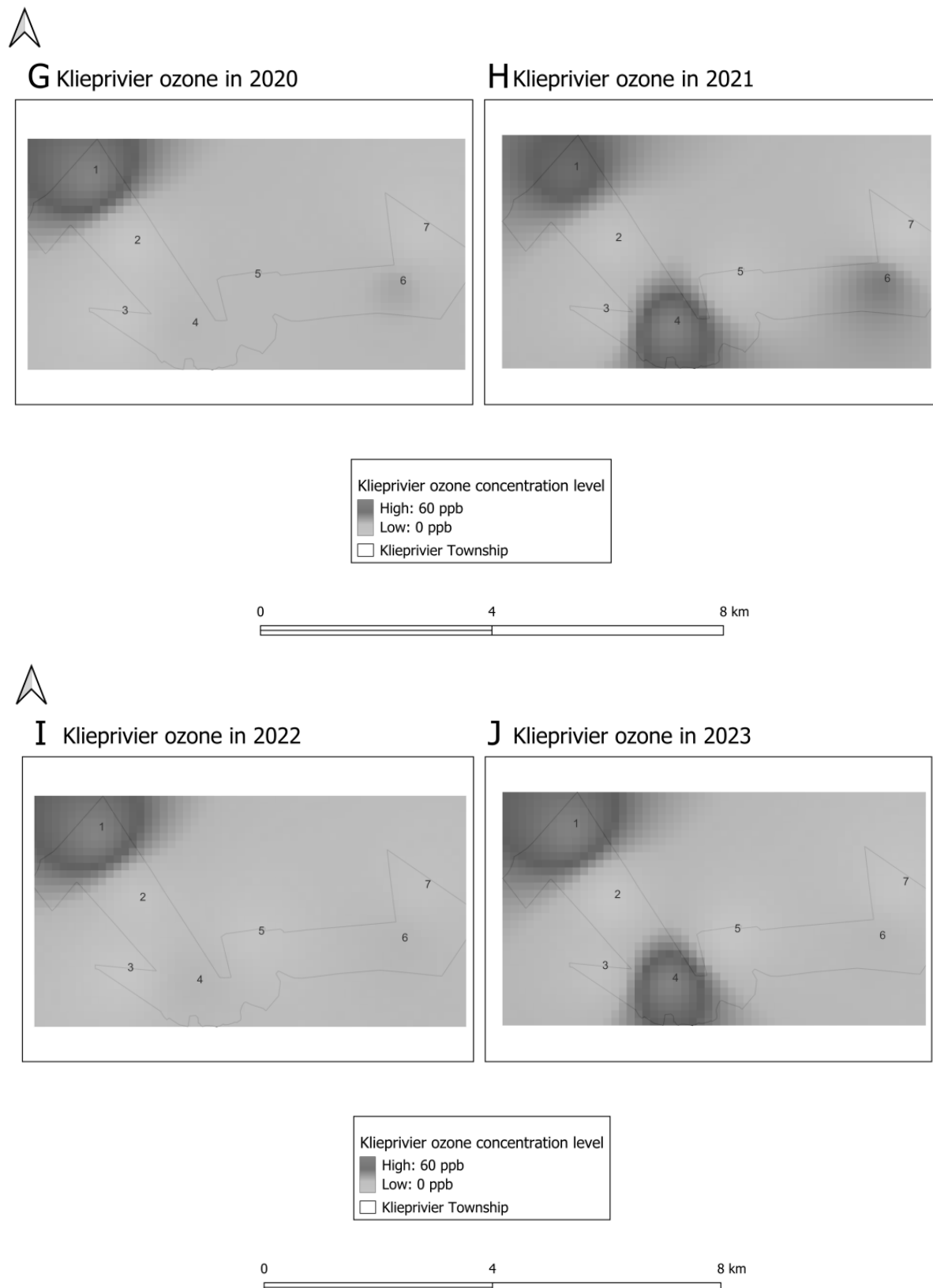


Figure 3. Carbon monoxide spatial distribution map for Klieprivier (A–E) and ozone spatial distribution map for Klieprivier (F–J) 2019 to 2023.

Figure 3A–E depict the spatial distribution of CO concentration across Klieprivier township from 2019 to 2023. In Figure 3A, the concentration of CO in 2019 ranged from a low of 103 ppb to a high of 1300 ppb. High concentrations were displayed at Points 4 and 6,

which were identified as hotspots and depicted in red. Approximately 80% of Klieprivier depicted low concentrations of CO, while the remaining 20% displayed high concentrations. High concentrations of pollutants are often linked to proximity to industrial areas, vehicular emissions, and fossil fuel combustion [38,39]. Conversely, areas with lower pollution levels are characterized by lower population densities and fewer industrial activities [7,13,40].

In 2020, as depicted in Figure 3B, CO concentrations ranged from a low of 103 ppb to a high of 1277 ppb. Point 4 was displayed as a primary hotspot, while Points 1 and 8 displayed moderate concentrations. Only a small part of Klieprivier displayed low concentration values. The hotspot at Point 4 could be attributed to nearby industrial operations or increased traffic flow, while moderate concentrations at Point 1 and 6 could be linked to emissions from local areas, such as household combustion. Figure 3C presents CO concentrations for 2021, which ranged from 199 ppb to 1121 ppb. Point 4 remained consistent hotspots, with Points 1 and 6 being partial hotspots from 2020. The overall concentration pattern resembles that of 2020; however, there is a slight increase in high concentrations and hotspots. This increase could be linked to emissions and increased industrial activities; alternatively, this increase in concentration could be linked to the easing of lockdown restriction post the COVID-19 lockdown.

Figures 2J and 3F–I depict the spatial distribution of O₃ concentrations across Klieprivier township from 2019 to 2023. In Figure 3F, the concentration of O₃ ranged from a low of 6 ppb to a high of 47 ppb; high concentrations were displayed at Points 1, 4, and 6, which are hotspots depicted in red. In 2020, as depicted by Figure 3G, O₃ concentrations ranged from a low of 8 ppb to a high of 38 ppb. Point 1 is the only hotspot present depicted by a red colour, with Points 4 and 6 showing moderate concentrations, while Points 2, 3, and 7 show average to moderate concentrations. Figure 3H presents O₃ concentration for 2021, with a low concentration of 7 ppb and a high of 49 ppb, Points 1, 4, and 6 are hotspots depicted by a red colour. Conversely, Points 2, 3, 5, and 7 display low concentrations displayed by a yellow-green colour.

Figure 3I shows the concentrations for Klieprivier in 2022; the concentrations ranged from a low of 6 ppb to a high of 54 ppb, and Point 1 remained a consistent hotspot. Conversely, Points 2, 3, 5, and 7 are consistent with low concentrations of O₃. There is a clear pattern of decreasing in concentration from 2020 to 2022, which could be linked to the adoption of clean energy policies by industries and public awareness about the consequences of fuel combustion. In Figure 3J, the concentration of O₃ is displayed with a slight increase in high concentration, with a low of 6 ppb and a high of 53 ppb. The distribution pattern continues from 2020, with Point 1 being a consistent hotspot and Point 4 remaining a partial hotspot, thereby resembling the pattern of 2020. Points 2, 3, 5, and 7 were covered in low concentrations, covering most of the area with lower concentrations for 2023. These O₃ concentrations in Diepkloof and Klieprivier are within the standard set by the South African National Ambient Air Quality Standards (NAAQS) of 61 ppb.

3.2. Temporal Trends of Carbon Monoxide (CO) and Ozone (O₃)

Temporal Trends for Carbon Monoxide (CO) in Diepkloof and Klieprivier

Figure 4A,B show the annual trends of CO and O₃ concentrations for both townships from 2019 to 2023. The results shows that Klieprivier recorded higher level of CO in 2022 (631 ppb) and 2020 (581 ppb) contrary to 2021, which recorded a lower level of 497 ppb. This temporal variation can be attributed to the lockdown period during COVID-19 during which there were minimal activities taking place. Moreover, the temporal variation in ozone has seen a sharp decline during COVID-19 period and post-COVID-19, a downward trend is observed in both Diepkloof and Klieprivier. Klieprivier maintained a decreasing

trend for CO concentrations, ending at 531 ppb in 2023 compared to its initial level of in 2019 (581 ppb).

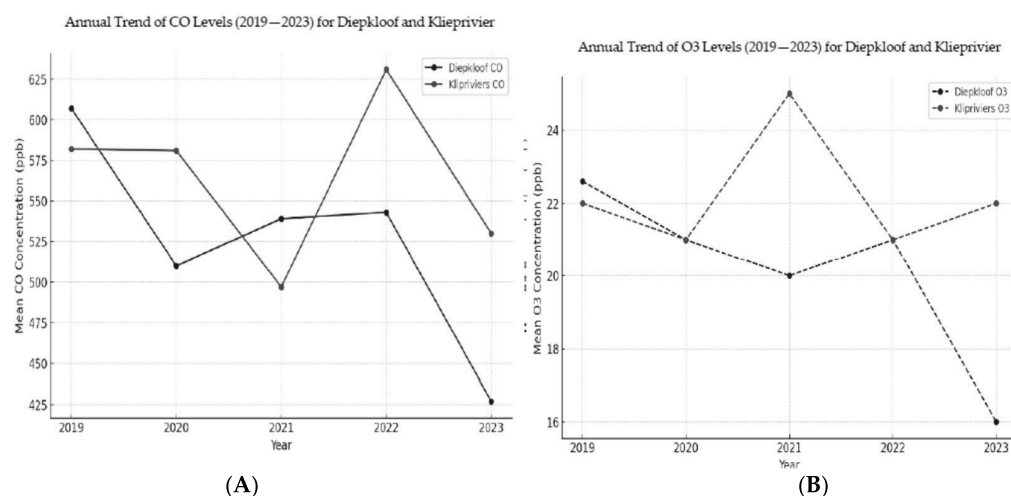


Figure 4. Diepkloof and Klieprivier annual trends (A,B) and seasonal trends (S1) (2019–2023).

Supplementary Figure S1A,B present the seasonal analyses of CO and O₃ concentrations in Diepkloof and Klieprivier from 2019 to 2023. Both Diepkloof and Klieprivier recorded the lowest concentration in summer (411 ppb and 432 ppb). In both townships, CO concentrations increased during the autumn and winter. Diepkloof showed an increase to 532 ppb in autumn and 651 ppb in winter. These seasonal increases could be attributed to temperature inversions which happens in colder months, trapping pollutants near the ground [41]. Fuel combustion, which increases in winter, can also contribute to elevated levels of pollutants [42]. However, the concentration of both townships declined in spring to 487 ppb in Klieprivier and 503 ppb in Diepkloof, which could be attributed to a decrease in household combustion as temperatures rise in warm seasons [43].

For O₃, Diepkloof depicted the lowest concentration of 17 ppb in both summer and autumn. While Klieprivier showed higher concentrations of 30 ppb in spring and 25 ppb in summer, this difference suggests that Klieprivier experiences greater photochemical activity during summer compared to Diepkloof. In winter, O₃ concentrations increased to 20 ppb in Diepkloof and decreased slightly to 17 ppb in Klieprivier; this could be due to higher NO_x levels from combustion [44]. Higher NO_x levels in Diepkloof might be based on NO_x being a key precursor for O₃ formation through photochemical reactions. It is assumed that Diepkloof, being a more densely populated township with higher traffic volumes and combustion-related activities, could contribute to high NO_x emissions. Also, the type of fuel combustion processes, such as older vehicle engines and residential fuel use, could influence NO_x levels. The highest concentrations of O₃ for both townships were recorded in spring, with a peak of 26 ppb in Diepkloof and 30 ppb in Klieprivier. These increases could be due to the increased photochemical reactions combined with emissions from industrial and agricultural activities that are found in these townships.

Higher levels in spring could be because of increased precipitation and cloud cover during summer which may reduce sunlight intensity, which will limit the photochemical reactions necessary for the formation of O₃. Klieprivier recorded higher seasonal concentrations of both CO and O₃ compared to Diepkloof; this could be the influence of the industries and agricultural activities that are found in Klieprivier (Supplementary Figure S1). The seasonal trend shows that elevated levels of CO were recorded in winter in both townships because of combustion that occurs in this season, while spring had peak concentrations of O₃ due to increased temperatures, which catalyze photochemical reactions.

In contrast to studies conducted in Gauteng and Mpumalanga, where O₃ levels in Mpumalanga exceeded the South African 8-hour ozone standard of 61 ppb, the 8 h mean O₃ concentration in Tshwane was 17 ppb, which complied with the National Ambient Air Quality Standards (NAAQS). Another study conducted in Cape Town found the highest O₃ concentrations at the remote Cape Point site and the lowest at the suburban site of Goodwood [22,45,46].

3.3. Correlation Analysis of CO, O₃, and Meteorological Parameters

Correlation Between Diepkloof's CO and Meteorological Parameters

Table 1A shows the relationship between O₃ levels in Diepkloof and different meteorological parameters. There is a weak positive correlation between O₃ and temperature, and the relationship is statistically significant ($r = 0.292$, $p < 0.001$). This indicates that higher temperatures may enhance the formation of O₃; however, the weak correlation suggests that temperature alone is not a strong predictor. There is a moderate positive correlation between O₃ and wind speed ($r = 0.329$, $p < 0.001$), implying that increased wind speeds might contribute to O₃ formation, though other factors may also play a role. Both humidity and wind speed display statistically significant relationships ($p < 0.001$), with humidity showing a weak negative correlation ($r = -0.312$) and wind speed showing a moderate positive correlation ($r = 0.329$). Rain shows a very weak negative correlation ($r = -0.046$, $p = 0.620$), showing little to no linear relationship between rainfall and O₃ levels.

Table 1B shows the Pearson correlation between CO levels in Diepkloof and different meteorological parameters. The correlation between CO and temperature is weak and negative ($r = -0.224$, $p < 0.001$), meaning that when temperature increases, CO levels tend to decrease, though the weak correlation suggests other factors are more influential. CO and wind speed show a weak negative correlation ($r = -0.229$, $p < 0.001$), showing that as wind speed increases, CO levels decrease due to dispersion. CO and humidity display a weak negative correlation ($r = -0.267$, $p < 0.001$), suggesting that higher humidity may contribute to lower CO concentrations.

There is a weak positive correlation between CO and wind direction ($r = 0.083$, $p = 0.353$), and the relationship is not statistically significant, suggesting that wind direction has little to no linear effect on CO levels. Lastly, there is a weak negative correlation between CO and rain ($r = -0.058$, $p = 0.547$), showing no significant relationship. Although wind speed, humidity, and wind direction show statistical significance at $p < 0.05$, their weak correlation values suggest they explain only a small fraction of the variability in CO levels, meaning they may not be strong predictors.

Table 1C shows the relationship between O₃ levels in Klieprivier and different meteorological parameters. Temperature has a strong positive correlation with O₃ ($r = 0.662$, $p < 0.001$), suggesting that higher temperatures significantly contribute to O₃ formation. Wind speed also has a moderate positive correlation that is statistically significant ($r = 0.342$, $p < 0.001$), showing that wind speed plays a role in O₃ dynamics. Humidity has a weak negative correlation ($r = -0.225$, $p = 0.003$), suggesting a slight inverse relationship. Wind direction has a weak positive correlation ($r = 0.077$, $p = 0.387$), which is not statistically significant. Lastly, rain has shown a weak negative correlation that is statistically significant ($r = -0.133$, $p < 0.001$), implying that rainfall might slightly reduce O₃ concentrations.

Table 1D demonstrates the relationship between CO levels and various meteorological parameters in Klieprivier. A moderate and statistically significant negative correlation occurs between temperature and CO levels ($r = -0.465$, $p < 0.001$ *), implying that higher temperatures are associated with lower CO concentrations. There is a weak to moderate negative correlation between wind speed and CO levels ($r = -0.265$, $p < 0.001$ *), suggesting that wind plays a role in dispersing CO, though its influence is limited. This suggests that

these factors may play a secondary role in influencing CO levels rather than being primary predictors. It is important to note that although several correlations between meteorological parameters and pollutant levels are statistically significant ($p < 0.05$), many exhibit weak correlation coefficients ($r < 0.3$). Such weak correlations indicate these factors explain only a small fraction of the variability in pollutant concentrations. Therefore, caution is warranted in interpreting these relationships, as pollutant dynamics are influenced by a complex interplay of multiple factors beyond the linear associations detected here.

Ref. [30] conducted a study in Tehran which supports this observation, showing that CO levels are higher in colder months and decrease as the temperature increases due to warm conditions catalysing photochemical reactions that reduce CO concentrations. Ref. [47] conducted a study in Port Harcourt that highlights the role of wind speed in reducing CO concentrations during wet seasons, aligning with the observed negative correlation between wind speed and CO due to increased dispersion mechanisms.

Table 1. Pearson correlation relationship between CO, O₃, and meteorological parameters in Diepkloof O₃ (A), CO (B) with Klieprivier O₃ (C) and CO (D). The double asterisk (**) almost always means $p < 0.01$, while the single asterisk (*) typically means $p < 0.05$.

		(A) Diepkloof O ₃ (ppb)	(B) Diepkloof CO (ppb)			(C) Klieprivier O ₃ (ppb)	(D) Klieprivier CO (ppb)
Diepkloof Temperature	Pearson Cor-relation	0.292 **	−0.224 **	Klieprivier Temperature	Pearson Cor-relation	0.662 **	−0.465 **
	Sig. (2-tailed)	<0.001	<0.001		Sig. (2-tailed)	<0.001	<0.001
Diepkloof Wind Speed	Pearson Cor-relation	0.329 **	−0.229 **	Klieprivier Wind Speed	Pearson Cor-relation	0.342 **	−0.265 **
	Sig. (2-tailed)	<0.001	<0.001		Sig. (2-tailed)	<0.001	<0.001
Diepkloof Humidity	Pearson Cor-relation	−0.312 **	−0.267 **	Klieprivier Humidity	Pearson Cor-relation	−0.225 **	−0.211 **
	Sig. (2-tailed)	<0.001	<0.001		Sig. (2-tailed)	<0.001	<0.001
Diepkloof Wind Direction	Pearson Cor-relation	0.238 **	0.083 **	Klieprivier Wind Direction	Pearson Cor-relation	0.077 **	−0.029
	Sig. (2-tailed)	<0.001	<0.001		Sig. (2-tailed)	0.001	0.212
Diepkloof Rainfall	Pearson Cor-relation	−0.046	−0.058 *	Klieprivier Rainfall	Pearson Cor-relation	0.017	−0.126 **
	Sig. (2-tailed)	0.050	0.013		Sig. (2-tailed)	0.480	<0.001

Table 2A displays the regression models for CO in Diepkloof; there is a weak positive relationship between CO and meteorological parameters shown by an R-value of 0.193, and there is a slight variation of 3.7% in CO concentrations that can be explained by meteorological conditions ($R^2 = 0.037$). The ANOVA test for CO in Diepkloof showed that the model is statistically significant ($p = 0.004$). Table 2C displays the Klieprivier CO model, which yielded a weak to moderate positive relationship with R-value of 0.396. Only 15.6% ($R^2 = 0.156$) of the variability in CO levels can be ascribed to meteorological parameters in Table 2C. The relationship between CO level and meteorological parameters in Klieprivier is statistically significant with a p -value < 0.001 .

The low R^2 values observed in the CO regression models (e.g., 3.7% in Diepkloof and 15.6% in Klieprivier) indicate that meteorological variables explain only a small fraction of the variability in CO concentrations. This suggests that other factors such as local emission sources, traffic patterns, and biomass burning likely have a stronger influence on CO levels. Such low explanatory power is common in air pollution modelling due to the complex

interplay of multiple variables affecting pollutant concentrations. Therefore, while the statistically significant relationships highlight the role of meteorological conditions, caution is needed when interpreting these models, and further studies incorporating additional variables and source apportionment methods are recommended to better understand CO dynamics in these urban townships.

Table 2B depicts the Diepkloof O₃ regression model; an R-value of 0.6574 indicates that there is a moderate positive relationship between O₃ levels and meteorological parameters. The R² value of 0.329 indicates that only 32.9% of the variability in O₃ concentrations can be ascribed to meteorological parameters. Table 2D shows that the relationship between O₃ and meteorological parameters in Klieprivier is statistically significant with ($R = 0.577$, $p < 0.001$).

To evaluate model assumptions, we examined the standardized residuals for each regression model (Figure 5). The histogram displays the regression model for CO in Diepkloof; the model suggests that CO levels in Diepkloof are normally distributed. Table 1 displays the regression model for O₃ in Diepkloof, which suggests that residuals for O₃ levels are normally distributed. Similarly, Table 1 shows the histogram for Klieprivier CO and O₃ levels. Both models suggest that CO and O₃ levels in Klieprivier are normally distributed. All the ANOVA results showed a p -value of less than 0.005, which indicated that the regression models are statistically significant, meaning that, overall, meteorological parameters have a significant effect on CO and O₃ concentrations in both townships. From the regression models, O₃ is better predicted by meteorological parameters than CO. There is a similar trend that is displayed by both locations: the R and R-square values for O₃ at Diepkloof and Klieprivier are close to each other, and the same applies to the R and R-squared values for CO.

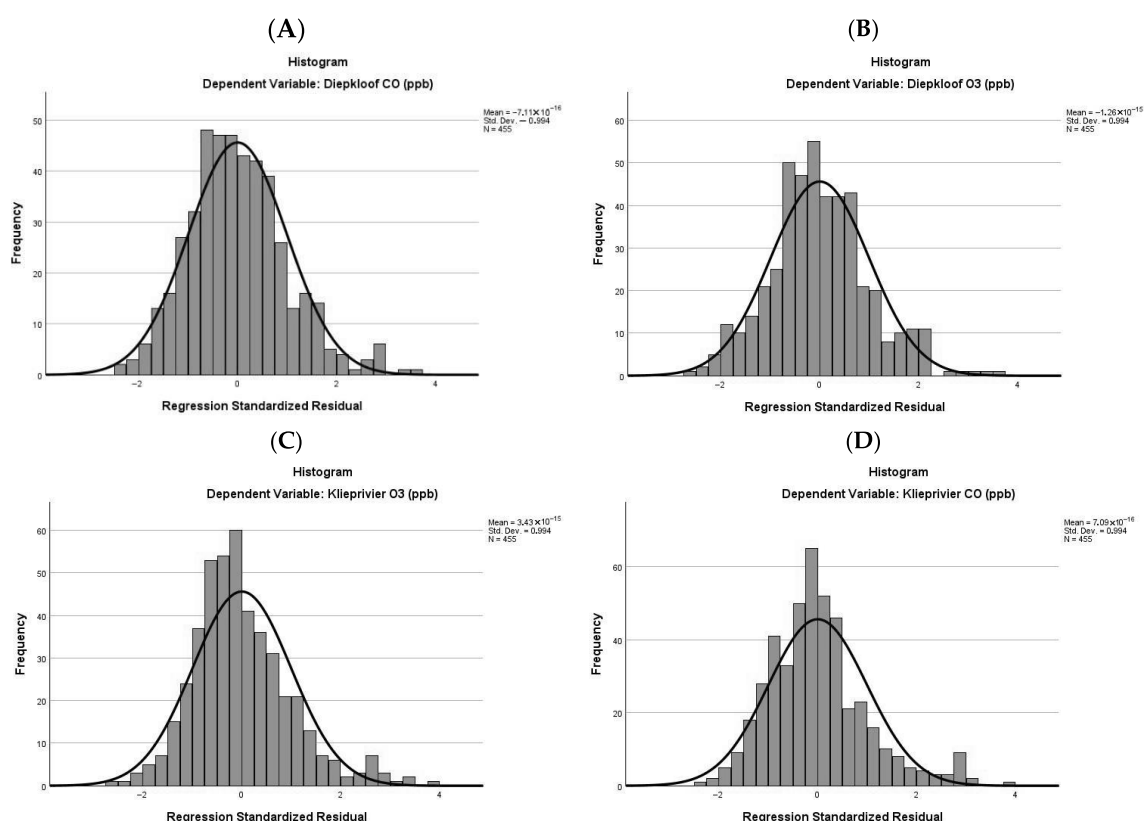


Figure 5. Regression standardized residual histograms for pollutant concentration models: (A) Diepkloof CO, (B) Diepkloof O₃, (C) Klieprivier O₃, and (D) Klieprivier CO.

4. Discussion

This study analysed the spatial and temporal distribution of CO and O₃ in Diepkloof and Klieprivier townships, revealing distinct pollutant hotspots and varying trends over time. In Diepkloof, CO hotspots shifted between zones during the study period, likely reflecting changes in emissions from industrial activities, household combustion, and vehicular traffic. Conversely, CO hotspots in Klieprivier remained stable, suggesting consistent local emissions primarily from household combustion. Higher CO levels near sources such as the Orlando Power Station, Bara taxi rank, and Chris Hani Baragwaneth Hospital reinforce the influence of proximity to emission sources on pollutant concentrations.

These findings are consistent with [48], who reported persistent O₃ and CO pollution exceeding South African National Ambient Air Quality Standards in Johannesburg, with notable temporal peaks linked to traffic emissions and photochemical activity. Ref. [49] similarly documented comparable O₃ concentration ranges across rural South African provinces, emphasizing spatial variability across urban and rural contexts. Furthermore, Ref. [29] highlighted the role of urbanization and industrialization in shifting pollution hotspots, supporting our observation of dynamic CO distribution patterns in Diepkloof. Collectively, these comparisons underscore the critical importance of localized, long-term monitoring to capture unique pollution dynamics in rapidly urbanizing areas [50].

Temporal analysis indicated a declining trend in O₃ concentrations in both townships, with seasonal peaks during warmer months likely driven by photochemical production under elevated temperatures and solar radiation, which aligns with previous studies [51–54]. In contrast, CO exhibited an increasing trend in Diepkloof and relatively stable levels in Klieprivier, likely reflecting differing local emission sources and patterns. These observations highlight the complex interplay between emission sources and meteorological factors in shaping pollutant dynamics.

Meteorological parameters were significant predictors of pollutant variability. Temperature strongly influenced O₃ formation, particularly in Klieprivier, which is consistent with established photochemical reaction theory [41]. For CO, however, regression models explained only a limited portion of variability (e.g., $R^2 = 0.037$ in Diepkloof), suggesting that meteorological factors alone are insufficient to fully capture CO dynamics. This low explanatory power may stem from omitted variables such as traffic volume, fuel usage, and industrial activities, as well as constraints related to spatial resolution and uneven monitoring station distribution. Future studies should aim to incorporate these factors to enhance model robustness.

The use of GIS and statistical modelling effectively identified pollution hotspots and spatial patterns, confirming the utility of these tools for environmental management. Nonetheless, capturing the full complexity of urban air pollution remains challenging, particularly considering local factors unique to Johannesburg townships, such as informal settlements and widespread biomass combustion elements less frequently accounted for in studies from Europe and North America [15,35,38,47,51]. From a planetary health perspective, these findings illustrate how local environmental exposures intersect with broader social determinants of health; thus, residents in townships often face higher exposure due to inequitable urban planning, reliance on polluting fuels, and limited access to healthcare.

South Africa's air quality regulations under the National Environmental Management Air Quality Act aim to reduce pollutant emissions, yet some evidence indicates limited progress in certain regions [55,56]. While the observed decline in O₃ may reflect reduced precursor emissions as seen in other industrialized settings [52,57,58], the increasing CO trend highlights persistent local emission challenges that require targeted mitigation. This study advances understanding of pollutant distributions and drivers in Johannesburg

townships; however, it also reveals model limitations and local complexities that warrant comprehensive data collection and inclusion of additional emission sources in future analyses. Integrating meteorological forecasting within air quality management frameworks could enhance prediction and mitigation strategies moving forward.

5. Future Studies

Future research can build upon this study by incorporating higher-resolution temporal data to better understand short-term variations in pollutant levels, with a focus on peak traffic hours and seasonal changes. Expanding the geographical scope to include more townships in Johannesburg and other South African cities can provide a broader understanding of urban air pollution patterns. Additionally, integrating more advanced spatial modelling techniques, such as machine learning-based approaches, could enhance the accuracy of hotspot detection and pollutant dispersion patterns. Further studies could also explore the health impacts of long-term exposure to CO and O₃ in these communities, using epidemiological data to strengthen the link between pollution levels and public health outcomes. Investigating existing regulatory measures and public awareness initiatives can guide policymakers in developing more targeted interventions. Collaboration with local communities to gather qualitative data on household combustion practices could also offer deeper insights into emission sources, enabling the design of tailored mitigation strategies.

5.1. Recommendation of the Study

Based on the findings of this study, these recommendations are proposed to address air pollution challenges in urban townships like Diepkloof and Klieprivier.

Emission regulations for industrial facilities should be strict, especially for industries that are near residential zones, where measures such as the implementation of cleaner production technologies and the transformation to low emission energy can reduce CO hotspots that are linked to industrial, vehicle, and household activities. There is a need to provide affordable alternatives to biomass fuels, with a focus on congested urban areas where a large percentage of residents rely on fuelwood combustion for cooking and heating, alternatives such as the introduction of clean cooking technologies and subsidizing electricity, which will accommodate people in informal settlements so that they can use electricity for cooking and heating their homes.

Vehicular traffic has adverse effects on air pollution of urban areas; there is a need to manage these traffic contestations to reduce emissions in areas that have high density, such as near the Bara taxi rank, promoting the use of public transportation where the government subsidizes public transport, such as trains and buses, and developing strategies to mitigate and regulate vehicle emissions. This goes hand in hand with developing a framework to reduce O₃ precursors such as NO_x and VOCs through the introduction of strict vehicle standards and emission caps for the industries. If these recommendations are implemented, policymakers and stakeholders can address and improve environmental and health challenges that are caused by air pollution in urban areas, which will benefit the public. Addressing health risks that are presented by these pollutants requires refined health monitoring, community health programs, and effective emergency responses. Urban planning should prioritize expanding in green infrastructures and managing traffic emissions; industrial pollutants should be regulated, and ventilation friendly designs should be promoted. Policy recommendations such as promoting strict air quality standards should be implemented. Environmental and health considerations should be integrated into urban health policies, and communities should also engage in decision-making. These measures can mitigate air pollution impacts and foster sustainable urban environments.

5.2. Study Limitations

This study acknowledges limitations that may influence the interpretation of its findings. The uneven distribution of air quality monitoring stations in Diepkloof and Klieprivier may have introduced spatial biases, as areas without monitoring coverage might present different pollution levels that were not captured. Moreover, this study relied on secondary data from SAAQIS, and SAWS also poses limitations such as data with gaps, which could affect the robustness of the analysis. The spatial and statistical models (QGIS and SPSS) used have assumptions that may overlook certain local factors influencing pollutant concentrations. The use of daily or averaged meteorological data, rather than higher-resolution datasets, may have concealed short-term variations affecting pollutant dispersion. Furthermore, the study focused solely on O₃ and CO, excluding other influential pollutants such as nitrogen dioxide (NO₂) and particulate matter (PM_{2.5}).

6. Conclusions

This study investigated the spatio-temporal distribution of CO and O₃ in Diepkloof and Klieprivier townships, emphasizing pollutant hotspots, temporal trends, and the influence of meteorological parameters using GIS and statistical modelling. Results revealed shifting CO hotspots in Diepkloof associated with urbanization, traffic, and industrial emissions, while CO levels in Klieprivier remained relatively stable with seasonal peaks in winter. O₃ concentrations showed a declining trend from 2019 to 2023, with higher levels during spring and summer driven by photochemical reactions influenced by temperature. Temperature and wind speed were identified as key meteorological factors affecting pollutant variability and dispersion. Despite these insights, the study has limitations that should be considered. The regression models, particularly for CO, explained only a small fraction of pollutant variability, indicating that important emission sources and factors such as traffic intensity, biomass burning, and local industrial activities were not fully captured. Furthermore, the uneven spatial distribution and limited number of air quality monitoring stations restricted the ability to comprehensively characterize pollutant patterns, especially in less-monitored areas. These limitations highlight the need for expanded and localized air quality monitoring networks, particularly in rapidly urbanizing townships, to improve spatial representativeness and data quality. Additionally, integrating meteorological forecasting into air quality management could enhance real-time prediction and mitigation strategies, such as targeted traffic or industrial emission controls. Overall, this study contributes valuable information to air quality research in South African townships and underscores the importance of incorporating broader emission data and improving monitoring infrastructure to support effective environmental and public health interventions. From a planetary health perspective, these findings reveal how urban air pollution not only threatens respiratory and cardiovascular health locally but also contributes to global climate challenges. Therefore, protecting human health and reducing emissions that are driving climate change are goals that can be achieved by addressing the air quality in the townships. As African cities continue to urbanize rapidly, integrating planetary health principles into policies can ensure that cleaner air, healthier communities, and climate resilience are pursued together.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/challe16040052/s1>, Supplementary data—trends over time. Figure S1. (A) seasonal analysis of O₃ levels in Diepkloof and Klieprivier. (B) Seasonal analysis of CO levels in Diepkloof and Klieprivier townships. Figure S2. The average temperatures for (A) Diepkloof summer, (B) Klieprivier summer (C) Diepkloof winter and (D) Klieprivier winter.

Author Contributions: Conceptualization, A.I.M., B.S.M. and T.M.; methodology, A.I.M. and T.M.; software, A.I.M.; validation, B.S.M.; formal analysis, A.I.M.; investigation, A.I.M.; writing—original draft, A.I.M.; writing—review and editing, B.S.M. and T.M.; visualization, T.M.; supervision, B.S.M. and T.M. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: All data analysed during this study are available from <https://saaqis.environment.gov.za/>.

Acknowledgments: Special thanks to Michyle Magerman from the Centre for Postgraduate Studies (CPUT) for assisting with the licensing for the IBM SPSS software. The author also acknowledges Vishanth Singh for providing Statistics South Africa data and Christian Hamann from the Gauteng City Region Observatory for supplying geographic shape files for Diepkloof and Klieprivier. Appreciation is also extended to the South African Weather Services for their provision of meteorological data used in this research.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Priya, M.G.; Jayalakshmi, S. Assessment of air pollution modelling using spatial interpolation techniques. *Asian Rev. Civ. Eng.* **2018**, *7*, 1–6.
2. Olaniyan, T.; Jeebhay, M.; Rössli, M.; Naidoo, R.; Baatjies, R.; Künzil, N.; Tsai, M.; Davey, M.; de Hoogh, K.; Berman, D.; et al. A prospective cohort study on ambient air pollution and respiratory morbidities including childhood asthma in adolescents from the western Cape Province: Study protocol. *BMC Public Health* **2017**, *17*, 712. [CrossRef] [PubMed]
3. Naidoo, R.N.; Robins, T.G.; Batterman, S.; Mentz, G.; Jack, C. Ambient pollution and respiratory outcomes among schoolchildren in Durban, South Africa. *S. Afr. J. Child Health* **2013**, *7*, 127–134. [CrossRef]
4. Malley, C.S.; Henze, D.K.; Kuynlenstierna, J.C.; Vallack, H.W.; Davila, Y.; Anenberg, S.C.; Turner, M.C.; Ashmore, M.R. Updated global estimates of respiratory mortality in adults ≥ 30 years of age attributable to long-term ozone exposure. *Environ. Health Perspect.* **2017**, *125*, 087021. [CrossRef]
5. World Health Organization. *The World Health Report 2000: Health Systems: Improving Performance*; World Health Organization: Geneva, Switzerland, 2000.
6. Filonchik, M.; Yan, H.; Li, X. Temporal and spatial variation of particulate matter and its correlation with other criteria of air pollutants in Lanzhou, China, in spring-summer periods. *Atmos. Pollut. Res.* **2018**, *9*, 1100–1110. [CrossRef]
7. Zhang, B.; Zhang, Y.; Zhang, K.; Zhang, Y.; Ji, Y.; Zhu, B.; Liang, Z.; Wang, H.; Ge, X. Machine learning assesses drivers of PM_{2.5} air pollution trend in the Tibetan Plateau from 2015 to 2022. *Sci. Total Environ.* **2023**, *878*, 163189. [CrossRef]
8. Reames, T.G.; Bravo, M.A. People, place and pollution: Investigating relationships between air quality perceptions, health concerns, exposure, and individual-and area-level characteristics. *Environ. Int.* **2019**, *122*, 244–255. [CrossRef]
9. Joseph, M.; Wang, F.; Wang, L. GIS-based assessment of urban environmental quality in Port-au-Prince, Haiti. *Habitat Int.* **2014**, *41*, 33–40. [CrossRef]
10. Wells, B.; Dolwick, P.; Eder, B.; Evangelista, M.; Foley, K.; Mannshardt, E.; Misenis, C.; Weishampel, A. Improved estimation of trends in US ozone concentrations adjusted for interannual variability in meteorological conditions. *Atmos. Environ.* **2021**, *248*, 118234. [CrossRef]
11. Madonsela, B.S.; Maphanga, T.; Malakane, K.C.; Phungela, T.T.; Gqomfa, B.; Grangxabe, S.; Thamaga, H.K.; Hajji, L.; Lekata, S.; Karmaoui, A.; et al. The Influence of Outdoor Exposure Concentrations on Indoor Air Quality in Rudimentary Designed Household Structures: Mpumalanga Province, South Africa. *Pollution* **2024**, *10*, 466–480.
12. Isinkalar, K.; Isinkalar, O.; Koc, I.; Cobanoglu, H.; Canturk, U. Accumulation analysis and overall measurement to represent airborne toxic metals with passive tree bark biomonitoring technique in urban areas. *Environ. Monit. Assess.* **2024**, *196*, 689. [CrossRef] [PubMed]
13. Jafarigol, F.; Yousefi, S.; Darvishi Omrani, A.; Rashidi, Y.; Buonanno, G.; Stabile, L.; Sabanov, S.; Amouei Torkmahalleh, M. The relative contributions of traffic and non-traffic sources in ultrafine particle formations in Tehran mega city. *Sci. Rep.* **2024**, *14*, 10399.
14. Alaran, A.J.; O’Sullivan, N.; Tatah, L.; Sserunjogi, R.; Okello, G. Air pollution (PM_{2.5}) and its meteorology predictors in Kampala and Jinja cities, in Uganda. *Environ. Sci. Atmos.* **2024**, *4*, 1145–1156. [CrossRef]
15. Ko, D.; Park, S. Investigating the Correlation between Air Pollution and Housing Prices in Seoul, South Korea: Application of Explainable Artificial Intelligence in Random Forest Machine Learning. *Sustainability* **2024**, *16*, 4453. [CrossRef]

16. Fazel-Rastgar, F.; Sivakumar, V.; Rostami, M.; Fallah, B. Study on associated effects of extreme drought and heatwave on air quality in South Africa during october 2022. *Bull. Atmos. Sci. Technol.* **2025**, *6*, 14. [CrossRef]
17. Khan, J.; Kakosimos, K.; Raaschou-Nielsen, O.; Brandt, J.; Jensen, S.S.; Ellermann, T.; Ketzel, M. Development and performance evaluation of new AirGIS—a GIS based air pollution and human exposure modelling system. *Atmos. Environ.* **2019**, *198*, 102–121. [CrossRef]
18. Ndletyana, O.; Madonsela, B.S.; Maphanga, T. Spatial Distribution of PM₁₀ and NO₂ in Ambient Air Quality in Cape Town CBD, South Africa. *Nat. Environ. Pollut. Technol.* **2023**, *22*, 1–13. [CrossRef]
19. Weng, Q.; Yang, S. Urban air pollution patterns, land use, and thermal landscape: An examination of the linkage using GIS. *Environ. Monit. Assess.* **2006**, *117*, 463–489. [CrossRef]
20. Kazemi Garajeh, M.; Laneve, G.; Rezaei, H.; Sadeghnejad, M.; Mohamadzadeh, N.; Salmani, B. Monitoring trends of CO, NO₂, SO₂, and O₃ pollutants using time-series sentinel-5 images based on google earth engine. *Pollutants* **2023**, *3*, 255–279. [CrossRef]
21. Meij, R.; Te Winkel, B. The emissions and environmental impact of PM₁₀ and trace elements from a modern coal-fired power plant equipped with ESP and wet FGD. *Fuel Process. Technol.* **2004**, *85*, 641–656. [CrossRef]
22. Harrison, S.P.; Kutzbach, J.E.; Liu, Z.; Bartlein, P.J.; Otto-Bliesner, B.; Muhs, D.; Prentice, I.C.; Thompson, R.S. Mid-Holocene climates of the Americas: A dynamical response to changed seasonality. *Clim. Dyn.* **2003**, *20*, 663–688. [CrossRef]
23. Jasim, A.K.; Walli, H.A. Analysis of hotspots and inverse distance weighting (IDW) of polluted habitats using ArcGIS Pro.: A case study in the sea of Najaf and surrounding terrestrial area. In *IOP Conference Series: Earth and Environmental Science*; IOP Publishing: Bristol, UK, 2023; Volume 1215, p. 012005.
24. Li, J.; Heap, A.D. Spatial interpolation methods applied in the environmental sciences: A review. *Environ. Model. Softw.* **2014**, *53*, 173–189. [CrossRef]
25. Farzaneh, A.; Pawar, N.; Portela, C.M.; Hopkins, J.B. Sequential metamaterials with alternating Poisson’s ratios. *Nat. Commun.* **2022**, *13*, 1041. [CrossRef] [PubMed]
26. Mobarakeh, M.S.; Jazi, M.D.; Rahmani, A.M. Direction based method for representing and querying fuzzy regions. *Multimed. Tools Appl.* **2024**, *83*, 60365–60392. [CrossRef]
27. Mustafa, A.; Szydlowski, M.; Veysipanah, M.; Hameed, H.M. GIS-based hydrodynamic modeling for urban flood mitigation in fast-growing regions: A case study of Erbil, Kurdistan Region of Iraq. *Sci. Rep.* **2023**, *13*, 8935. [CrossRef]
28. Wang, X.; Zhang, C.; Wang, C.; Liu, G.; Wang, H. GIS-based for prediction and prevention of environmental geological disaster susceptibility: From a perspective of sustainable development. *Ecotoxicol. Environ. Saf.* **2021**, *226*, 112881. [CrossRef] [PubMed]
29. Jubaer, A.; Hossain, R.; Ahmed, A.; Hossain, M.S. Factors influencing spatiotemporal variability of NO₂ concentration in urban area: A GIS and remote sensing-based approach. *Environ. Monit. Assess.* **2025**, *197*, 167. [CrossRef]
30. Masroor, K.; Fanaei, F.; Yousefi, S.; Raeesi, M.; Abbaslou, H.; Shahsavani, A.; Hadei, M. Spatial modelling of PM_{2.5} concentrations in Tehran using Kriging and inverse distance weighting (IDW) methods. *J. Air Pollut. Health* **2020**, *5*, 89–96. [CrossRef]
31. Afolayan, A.; Easa, S.M.; Abiola, O.S.; Alayaki, F.M.; Folorunso, O. GIS-based spatial analysis of accident hotspots: A Nigerian case study. *Infrastructures* **2022**, *7*, 103. [CrossRef]
32. Moran, P.A.P. Notes on Continuous Stochastic Phenomena. *Biometrika* **1950**, *37*, 17–23. [CrossRef]
33. Anselin, L. Local Indicators of Spatial Association—LISA. *Geogr. Anal.* **1995**, *27*, 93–115. [CrossRef]
34. Hassan, A.H. Correlation Analysis—Types, Methods, and Examples. *J. Appl. Stat. Methods* **2024**, *14*, 245–259.
35. Montgomery, D.C.; Peck, E.A.; Vining, G.G. *Introduction to Linear Regression Analysis*; John Wiley & Sons: Hoboken, NJ, USA, 2021.
36. Presidency of South Africa. South Africa’s Just Energy Transition Investment Plan 2023–2027. 2022. Available online: [https://www.stateofthenation.gov.za/assets/downloads/climate/SAs_Just%20Energy%20Transition%20Investment%20Plan%20\(JET%20IP\)%202023-2027.pdf](https://www.stateofthenation.gov.za/assets/downloads/climate/SAs_Just%20Energy%20Transition%20Investment%20Plan%20(JET%20IP)%202023-2027.pdf) (accessed on 20 April 2025).
37. Morakinyo, O.M.; Mukhola, M.S.; Mokgobu, M.I. Ambient gaseous pollutants in an urban area in South Africa: Levels and potential human health risk. *Atmosphere* **2020**, *11*, 751. [CrossRef]
38. Zhang, Z.; Xue, T.; Jin, X. Effects of meteorological conditions and air pollution on COVID-19 transmission: Evidence from 219 Chinese cities. *Sci. Total Environ.* **2020**, *741*, 140244. [CrossRef]
39. Eregowda, T.; Chatterjee, P.; Pawar, D.S. Impact of lockdown associated with COVID19 on air quality and emissions from transportation sector: Case study in selected Indian metropolitan cities. *Environ. Syst. Decis.* **2021**, *41*, 401–412. [CrossRef]
40. Zheng, B.; Cheng, J.; Geng, G.; Wang, X.; Li, M.; Shi, Q.; Qi, J.; Lei, Y.; Zhang, Q.; He, K. Mapping anthropogenic emissions in China at 1 km spatial resolution and its application in air quality modeling. *Sci. Bull.* **2021**, *66*, 612–620. [CrossRef]
41. Seinfeld, J.H.; Pandis, S.N. *Atmospheric Chemistry and Physics: From Air Pollution to Climate Change*; John Wiley & Sons: Hoboken, NJ, USA, 2016.
42. Madzivhandila, T.; Maledi, N.; Fazluddin, S. Characterization of particulate matter in the process of manufacturing titanium metal powder. In Proceedings of the 22nd International Conference on Data Science for Air Quality Monitoring, Cape Town, South Africa, 16–17 April 2020.
43. Government of South Africa. *National Household Energy Strategy*; Department of Energy: Washington, DC, USA, 2019.

44. de Souza, A.; de Oliveira-Júnior, J.F.; Cardoso, K.R.; Gautam, S. Impact of vehicular emissions on ozone levels: A comprehensive study of nitric oxide and ozone interactions in urban areas. *Geosyst. Geoenviron.* **2025**, *4*, 100348. [CrossRef]
45. Laban, T.L.; Van Zyl, P.G.; Beukes, J.P.; Vakkari, V.; Jaars, K.; Borduas-Dedekind, N.; Josipovic, M.; Thompson, A.M.; Kulmala, M.; Laakso, L. Seasonal influences on surface ozone variability in continental South Africa and implications for air quality. *Atmos. Chem. Phys.* **2018**, *18*, 15491–15514. [CrossRef] [PubMed]
46. Nzotungicimpaye, C.M.; Abiodun, B.J.; Steyn, D.G. Tropospheric ozone and its regional transport over Cape Town. *Atmos. Environ.* **2014**, *87*, 228–238. [CrossRef]
47. Henry, R.C.; Mohan, S.; Yazdani, S. Estimating potential air quality impact of airports on children attending the surrounding schools. *Atmos. Environ.* **2019**, *212*, 128–135. [CrossRef]
48. Borduas-Dedekind, N.; Naidoo, M.; Zhu, B.; Geddes, J.; M Garland, R. Tropospheric ozone (O₃) pollution in johannesburg, south africa: Exceedances, diurnal cycles, seasonality, O_x chemistry and O₃ production rate. *Clean Air J.* **2023**, *33*, 1–6. [CrossRef]
49. Ngoasheng, M.; Beukes, J.P.; van Zyl, P.G.; Swartz, J.S.; Loate, V.; Krisjan, P.; Mpambani, S.; Kulmala, M.; Vakkari, V.; Laakso, L. Assessing, SO₂, NO₂ and O₃ in rural areas of the North West Province. *Clean Air J.* **2021**, *31*, 1–4. [CrossRef]
50. Martins, H. Urban compaction or dispersion? An air quality modelling study. *Atmos. Environ.* **2012**, *54*, 60–72. [CrossRef]
51. Venter, A.D.; Beukes, J.P.; Van Zyl, P.G.; Tiitta, P.; Josipovic, M.; Pienaar, J.J.; Laakso, L.; Vakkari, V.; Laakso, H.; Kulmala, M. An air quality assessment in the industrialised western Bushveld Igneous Complex, South Africa. *S. Afr. J. Sci.* **2012**, *108*, 1–10. [CrossRef]
52. Ohyama, H.; Kawakami, S.; Uchino, O.; Sakai, T.; Morino, I.; Nagai, T.; Shiomi, K.; Sakashita, M.; Akaho, T.; Okumura, H.; et al. Seasonal variation of the O₃–CO correlation derived from remote sensing measurements over western Japan. *Atmos. Environ.* **2016**, *147*, 344–354. [CrossRef]
53. Plocoste, T.; Calif, R. Spectral observations of PM₁₀ fluctuations in the Hilbert space. In *Functional Calculus*; Shah, K., Okutmustur, B., Eds.; IntechOpen: London, UK, 2019; pp. 1–3, ISBN 1838800077.
54. Bu, X.; Xie, Z.; Liu, J.; Wei, L.; Wang, X.; Chen, M.; Ren, H. Global PM_{2.5}-attributable health burden from 1990 to 2017: Estimates from the Global Burden of disease study 2017. *Environ. Res.* **2021**, *197*, 111123. [CrossRef]
55. Tshehla, C.; Wright, C.Y. 15 Years after the national environmental management air quality Act: Is legislation failing to reduce air pollution in South Africa? *S. Afr. J. Sci.* **2019**, *115*, 1–4. [CrossRef]
56. Allu, S.K.; Srinivasan, S.; Maddala, R.K.; Reddy, A.; Anupoju, G.R. Seasonal ground level ozone prediction using multiple linear regression (MLR) model. *Model. Earth Syst. Environ.* **2020**, *6*, 1981–1989. [CrossRef]
57. Wan, Z.; Yang, C.; Wang, X.; Xue, Y.; Zhao, J.; Cui, J.; Guo, Q.; Hua, H.; Sun, H.; Chen, D.; et al. Spatial and temporal differentiation of air quality and its influence factors in 16 cities in Shandong Province from 2019 to 2020. *RSC Sustain.* **2024**, *2*, 1528–1542. [CrossRef]
58. Madonsela, B.S. A meta-analysis of particulate matter and nitrogen dioxide air quality monitoring associated with the burden of disease in sub-Saharan Africa. *J. Air Waste Manag. Assoc.* **2023**, *73*, 737–749. [CrossRef]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.