Temporal Analysis of Changes in Anthropogenic Emissions and Urban Heat Islands during COVID-19 Restrictions in Gauteng Province, South Africa

Special Issue:

Special Issue on COVID-19 Aerosol Drivers, Impacts and Mitigation (XVII)

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ABSTRACT

Anthropogenic emissions are significant drivers of temperature rises in major urban areas across the globe. Waste heat and exhaust emissions from motor vehicles and industrial combustion cause the warming of cities, resulting in microclimates' changes. Recently, national lockdown regulations restricting movement and socio-economic activities to curb the spread of a novel COVID-19 and the associated deaths have been implemented in various countries worldwide. Consequently, these unprecedented restrictions resulted in reductions in traffic volumes and industrial activities in most urban areas across the world. Thus, it was hypothesised that these reductions in traffic congestion and industrial activities in cities would reduce both air pollutants and thermal radiation. Using multisource data from Sentinel-5P, MERRA-2, and MODIS, this study assessed the short-term trends in emissions and land surface temperature in South Africa's economic hub, i.e., Gauteng Province. Mann-Kendall (MK) and Sequential Mann-Kendall (SQMK) trend analysis were used to characterise trends in CO, SO₂, SO₄, long-wave radiation (LWR), and land surface temperature (LST) at periods corresponding to various lockdown restrictions. The results showed a significant decline in atmospheric pollutants at Level-5 lockdown restrictions, followed by an abrupt increase as the regulations were eased to Level-4 lockdown. Similarly, LST and surface urban heat island (SUHI) reduced when compared to the previous year. Therefore, the lockdown restrictions provided an experimental scenario in which pollutants could be drastically reduced, thus accentuated the human impact on microclimates.

Keywords: Lockdown, COVID-19, Emissions, Nitrogen dioxide, Sentinel-5P

1 INTRODUCTION

Anthropogenic emissions and air pollution are significant drivers of temperature rises in major urban areas worldwide (Taha, 1997; Ryu and Baik, 2012; Ma *et al.*, 2017). Waste heat and exhaust emissions from motor vehicles and industrial combustion cause warming of cities resulting in changes in microclimates urban areas (Schiano-Phan *et al.*, 2015; Soltani and Sharifi, 2017). The marked increase in urban temperature compared to the neighbouring non-urban areas is known as the urban heat island effect (Oke, 1982; Gallo *et al.*, 1993). Several factors are known to impact the urban heat island. These include anthropogenic heat, air pollution, surface geometry, thermal characteristics of urban artificial fabrics, surface geometry, reduced evaporation, increased heat storage, increased net radiation, reduced convection and surface waterproofing (Grimmond, 2007; Shahmohamadi *et al.*, 2011; Soltani and Sharifi, 2017). Emission of Carbon dioxide, water vapour, and particulates into the atmosphere warms ambient air in urban environments through the reduction of incident flux of short-wave radiation and re-emission of long-wave infrared radiation from the urban surface and subsequent absorption of long-wave radiation from the urban surface (Ramanathan and Feng, 2009). A combination of air pollution and anthropogenic

OPEN ACCESS

Received: July 24, 2020

Revised: May 5, 2021

Accepted: May 26, 2021

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Publisher:

Taiwan Association for Aerosol Research

ISSN: 1680-8584 print

ISSN: 2071-1409 online

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heat produced by human activities due to transportation, human metabolism, heating, and cooling affect urban temperature conditions through the heat transfer processes that influence the formation of urban heat islands. The complex interaction of anthropogenic heat with the environment are succinctly simplified by Oke (1988).

The Urban Heat Island (UHI) phenomena have been analysed in many cities globally and constitute of three main segments classified as canopy UHI, boundary-layer UHI, and surface UHI (Azevedo *et al.*, 2016). Specifically, the surface UHIs (SUHIs) are commonly studied for UHIs as they can be detected by land surface temperature (LST) measurements from satellites. It directly affects the air temperature in the canopy layer by energy exchange. Anthropogenic factors such as industrial heat emissions, heating, transport, or air conditioning are recorded to affect surface UHI significantly (Wang *et al.*, 2018; Shi *et al.*, 2019). These elevated urban temperatures have detrimental effects on human health and energy consumption from increased indoor air conditioning (Priyadarsini, 2009; Shahmohamadi *et al.*, 2011; Arifwidodo and Chandrasiri, 2015). It is well recorded that high temperature causes heat stress and increases the risks of dehydration, heatstroke, and hyperthermia associated with heatwaves (Hifumi *et al.*, 2018; Leyk *et al.*, 2019). Studies reveal that during favourable weather conditions, i.e., no cloud cover and stable wind conditions, urban temperatures tend to be more elevated by at least 6 to 11°C compared to the rural sites (Suomi, 2018) (<https://www.britannica.com/science/urban-climate>). The utility of the earth observation satellites to efficiently measure atmospheric aerosols and land surface parameters that influence UHI formation has been widely used in a multitude of UHI studies.

Thermal space-borne data from sensors such as Landsat Thematic Mapper (TM), Landsat Enhanced TM (ETM+), Landsat 8 Thermal Infrared Sensor (TIRS), ASTER, Advanced Very High-Resolution Radiometer (AVHRR), and Moderate Resolution Imaging Spectroradiometer (MODIS) have been widely used to retrieve LST (Zha *et al.*, 2003; Chen *et al.*, 2006; Liu and Zhang, 2011; Tsou *et al.*, 2017). Thermal Infrared measurements from optical satellites are often constrained by cloud cover and low temporal resolution. Modern microwave space-borne instruments can provide near-surface air temperature at a high temporal frequency and penetrate through the cloud cover. Before its demise in October 2011, the Advanced Microwave Scanning Radiometer-Earth observing system (AMSR-E) onboard the Aqua satellite collected measurements on the land surface and boundary layer (Gao *et al.*, 2007; Zhao *et al.*, 2017). Sentinel-5P from the European Commission's Copernicus program and long-term missions such as MODIS are invaluable for measuring atmospheric and surface parameters that influence the UHI. Sentinel-5P has been limitedly explored for characterising atmospheric pollutants. In contrast, MODIS remains the main sensor for frequent thermal infrared measurements, suitable for studying short-term changes.

A global pandemic is known as coronavirus disease 2019 (COVID-19) started from Wuhan, China, in December 2019 has affected many countries internationally (Harapan *et al.*, 2020). It is widely accepted that the COVID-19 pandemic is possibly the worst global public health crisis since the influenza pandemic in 1918 (Beach *et al.*, 2020). The infectious nature of the COVID-19 and the associated high death rates forced most governments globally to institute lockdowns that control the rapid spread of this deadly disease (Haldar and Sethi, 2020). The lockdown measures resulted in various levels of restrictions on movement, trade, transport, and mining operations and industries' closures for periods ranging from a few weeks to several months. Governments' unprecedented control measures resulted in low traffic volumes and low industrial combustion in most urban areas in some countries, thus resulting in a reduction in both air pollution and anthropogenic heat (Metya *et al.*, 2020; Jain and Sharma, 2020). Therefore, this study's objective was to assess the trends of air pollution in the Gauteng Province, Republic of South Africa (RSA) over the lockdown period and the subsequent changes in urban temperature using multisource data. Specifically, Sentinel-5P was used to assess the temporal trends in atmospheric pollutants such as NO₂, SO₄, and CO, while MODIS data were used to assess LST and surface urban heat islands (SUHI) in Gauteng province.

2 STUDY AREA

South Africa (30.56°S, 22.94°E) has nine provinces with widely varying landscapes (Fairbanks *et al.*, 2000), with the Gauteng province (26.27°S, 28.11°E) having the smallest land area.

However, Gauteng province has the biggest provincial economy generating over a third of South Africa's gross domestic product (GDP). As can be expected, Gauteng is also the most populated among other provinces, constituting more than 26% (i.e., 15,488,137) of South Africa's population. It is divided into three metropolitan municipalities; the City of Ekurhuleni, City of Johannesburg, and City of Tshwane Metropolitan Municipalities and two district municipalities, which are further subdivided into six local municipalities (see Fig. 1). Compared to other provinces (not shown in Fig. 1), Gauteng has more built-up area (consisting of impervious surfaces such as buildings, mines, and quarries). However, it also has large areas of cultivated lands and grasslands.

3 METHODS

3.1 Atmospheric Emissions

The Copernicus Sentinel-5P (Precursor) satellite was launched on October 13 2017, by the European Space Agency (ESA). The TROPospheric Monitoring Instrument (TROPOMI) is an onboard sensor Sentinel-5P, which monitors the density of several atmospheric gases, aerosols, and cloud distributions that affect air quality and climate (Veefkind *et al.*, 2012; Omrani *et al.*, 2020). TROPOMI has full global coverage each day with an improved resolution of $(3.5 \times 7 \text{ km}^2)$, which is 13 times better than the Ozone Monitoring Instrument (Theys *et al.*, 2019). The comparison of these two instruments shows that the high spatial resolution of TROPOMI observations is adequate to monitor polluting emission sources at a city level (Ialongo *et al.*, 2020). The algorithms for sulfur dioxide (SO_2) retrieval are described by Theys *et al.* (2017). TROPOMI is operated in a non-scanning push-broom configuration, with an instantaneous field of view of 108° and a measurement period of about 1 s (Ialongo *et al.*, 2020). Furthermore, TROPOMI has more spectral

Fig. 1. Map of the Republic of South Africa showing the location of the nine provinces and the study area (Gauteng Province) is indicated by a red rectangle. Map of the Gauteng province showing the municipal boundaries and land cover.

bands than previous sensors. It has ultraviolet and visible in the range (270–500 nm), near-infrared in the range (675–77 nm), and short-wave infrared in the range (2305–2385 nm). A wide variety of these spectral bands allows TROPOMI to measure a broader range of atmospheric trace gases such as nitrogen dioxide (NO₂), ozone (O₃), sulfur dioxide (SO₂), methane (CH₄), and carbon monoxide (CO) (Omrani *et al.*, 2020). For TROPOMI, quality-control has been performed before the analysis. A flag, namely quality assurance value (qa_value), for each ground pixel indicates the status and quality of the retrieval result, ranging from 0 (no output) to 1 (<http://www.tropomi.eu/documents/level-2>). Furthermore, when the TROPOMI OFFL level 2 tropospheric columns were compared with multi-axis DOAS (MAX-DOAS) data at 14 sites, it was found that TROPOMI tropospheric columns have a median negative bias of less than 50% (Zhao *et al.*, 2020). In this study, the focus is on the SO₂, and CO OFFL level 2 tropospheric columns.

The nitrogen oxide (NO₂) tropospheric column density datasets are retrieved from the Ozone Monitoring Instrument (OMI). OMI uses hyperspectral imaging in a push-broom mode to observe solar backscatter radiation in the visible and ultraviolet. It is a nadir-viewing, wide-field-imaging UV and visible spectrometer designed to monitor ozone and other atmospheric species including aerosols. It can also distinguish between aerosol types, such as smoke, dust, and sulfates, and can further measure key air quality components such as NO₂, SO₂ and Bromine oxide (BrO) to name a few. A detailed description of OMI is discussed by Levelt *et al.* (2016). In this study, the focus is on the NO₂ tropospheric column datasets.

The sulfate (SO₄) data were retrieved from the Modern-Era Retrospective analysis for Research and Applications, Version 2 (MERRA-2). MERRA-2 was introduced to replace and extend the original MERRA dataset (Rienecker *et al.*, 2008; Rienecker *et al.*, 2011), which ended in February 2016. It is produced using version 5.12.4 of the GEOS DAS. Gridded data are released at a 0.625° longitude × 0.5° latitude resolution on 72 sigma–pressure hybrid layers between the surface and 0.01 hPa. The bottom 32 layers are terrain following, while remaining model layers from 164 to 0.01 hPa are constant pressure surfaces (Wargan *et al.*, 2017). MERRA-2 assimilates bias-corrected AOD from the Moderate Resolution Imaging Spectroradiometer (MODIS) and the Advanced Very High-Resolution Radiometer instruments (Buchard *et al.*, 2017; Randles *et al.*, 2017). More details on MERRA-2 can be found in Gelaro *et al.* (2017). Additionally, data for surface absorbed long-wave radiation was retrieved from MERRA-2.

3.2 Land Surface Temperature (LST) and Surface Urban Heat Island (SUHI)

Land Surface Temperature (LST) was derived from the Moderate Resolution Imaging Spectroradiometer (MODIS). Specifically, the MODIS 8-day Land Surface Temperature and Emissivity (MOD11.006) product from February 01 to May 31, 2019, and 2020, i.e., characterising the reference and Covid-19 years, respectively, were averaged over the study area for further analysis. MODIS LST product (i.e., MOD11A2.006) is an 8-day average of MOD11A1 LST in a grid of 1200 × 1200 km. Further details can be found in Wan (2014). In this study, day-time LST was used to characterize LST at periods: 01 February–26 March (i.e., before lockdown), 27 March–30 April (i.e., during Level-5 lockdown) and May 01–31 May (during Level-4 lockdown) (see Table 1 for description of various lockdown levels).

The averaged LST per lockdown period was used to compute the surface urban heat island (SUHI) intensity respectively. SUHI is calculated as a difference in LST between the urban (i.e., built-up) and rural (i.e., peripheral green spaces). For each pixel, SUHI intensity was calculated as follows:

$$SUHI \text{ intensity} = LST_{urban} - \overline{LST}_{rural} \quad (1)$$

Table 1. Lockdown levels in South Africa during the global pandemic.

Lockdown level	Duration of lockdown	Number of days	Determination of levels
5	27 March 2020–30 April 2020	35	High COVID-19 spread with a low health system readiness
4	01 May 2020–31 May 2020	31	Moderate to a high COVID-19 spread with a low to moderate health system readiness

where, LST_{urban} is the pixel-wise land surface temperature (LST) and $\overline{LST}_{rural}$ is the mean LST over surrounding green spaces at the study area (Estoque and Murayama, 2017). The $\overline{LST}_{rural}$ was extracted based on the 2018 National Land Cover (NLC) data from the South African Department of Environmental Affairs (accessible from: https://egis.environment.gov.za/sa_national_land_cover_datasets). LST over Water bodies was excluded.

Furthermore, the spectral discrimination index (SDI, Eq. (1)) was used to determine the degree of observed differences between 2020 (i.e., COVID-19) and 2019 (i.e., reference) years.

$$SDI = \frac{|\mu_1 - \mu_2|}{\sigma_1 + \sigma_2} \quad (2)$$

where μ_1 and μ_2 denote the mean LST for 2020 (i.e., COVID-19 year) and 2019 (i.e., reference year), while σ_1 and σ_2 denote standard deviations for 2020 and 2019, respectively. SDI values greater than 1 indicate a higher degree of difference between the COVID-19 year (2020) and reference year (2019), while a value lower than 1 indicates no difference. Previously, the SDI has been used for spectral separability between different images and vegetation types (Kganyago *et al.*, 2018).

3.3 M-K and SQMK Trend Analysis

The non-parametric Mann-Kendall (MK) test is generally used to detect monotonic trends in a series of environmental data, climate data, and hydrological data (Mann, 1945; Abghari *et al.*, 2013; Pohlert, 2018). The MK test has several advantages, such as (1) its low sensitivity to abrupt breaks due to inhomogeneous time series (Tabari *et al.*, 2011) and (2) its ability to consider the data distribution and cope with the outliers (Sonali and Kumar, 2013; Şen, 2017; Nashwan and Shahid, 2019). The MK test steps are presented in Appendix 2.

The Sequential Mann-Kendall (SQMK) test proposed by Sneyers (1991) is used for determining the approximate period of the beginning of a significant trend (Sneyers, 1997; Kganyago and Shikwambana, 2019). This test sets up two series, a progressive $u(t)$ and a retrograde (backward) series $u'(t)$. If they cross each other and diverge beyond the specific threshold value, then there is a statistically significant trend. The point where they cross each other indicates the approximate period at which the trend begins (Mosmann *et al.*, 2004). The threshold values used in this study are ± 1.96 ($p = 0.05$), with the crossing point indicating the change point for trends. The SQMK test steps are presented in Appendix 3.

4 RESULTS AND DISCUSSION

4.1 NO₂ Observations over RSA and Gauteng Province

Fig. 2 shows the distribution of NO₂ over RSA before and during the lockdown. Before the lockdown (see Fig. 2(a)), high NO₂ tropospheric column values ranging from 7×10^{15} to 9×10^{15} mol cm⁻² are observed in the Gauteng, Mpumalanga, and Limpopo provinces. These high values of NO₂ can be attributed to both (1) emissions from the coal-powered stations for electricity generation and (2) motor vehicle emissions which make a substantial contribution to the boundary layer concentrations of NO₂, especially upwind from the power stations. These areas have been reported as the hotspots of NO₂ in RSA (Shikwambana *et al.*, 2020). Shikwambana *et al.* (2020) further describe the dispersion of NO₂ during various seasons. During Level-5 of the lockdown (see Fig. 2(b)), there is a slight reduction in the NO₂ distribution over RSA hotspots; however, the Gauteng province has a notable decrease in the NO₂ distribution and tropospheric column values ranging from 4×10^{15} to 5×10^{15} mol.cm⁻²). This decrease could be due to lesser demand for electricity due to the closure of industries and mines. Therefore, not all power stations were operating at full capacity. Furthermore, the reduction of motor vehicle emissions also had a large impact in the detection of lesser NO₂.

Moreover, the power stations also used the lockdown period for maintenance; thus, only a few generating units were operating. A move to the Level-4 lockdown (see Fig. 2(c)) saw a steady increase in the NO₂ tropospheric column values (back to the 8×10^{15} and 9×10^{15} mol cm⁻² range)

Fig. 2. NO₂ tropospheric column and distribution (a) before the lockdown, (b) during the lockdown Level 5 and (c) during the lockdown Level 4 over RSA observed by OMI.

and more extensive distribution of NO₂ in the hotspot areas. The increase in the NO₂ column density is due to the increase in generation units' operation as electricity consumption increased in Level-4, as seen in the Energy Transition in South Africa-The Power Sector in 2020 report.

Fig. 2 clearly shows that Gauteng is amongst the leading provinces in terms of NO₂ distribution and total column density. Therefore, the NO₂ distribution and total column density over the Gauteng Province's municipal boundaries, before and during the lockdown, are analysed further (see Fig. 3). Gauteng has Before the lockdown (see Fig. 3(a)), high (0.00013 mol m⁻²) to moderate (0.00010 mol m⁻² and 0.000078 mol m⁻²) column density values are observed in Johannesburg, Ekurhuleni, Mid-Vaal and Emfuleni, and southern parts of Tshwane. In Johannesburg, Ekurhuleni and Tshwane, the primary source of NO₂ is motor vehicle emissions, especially during high traffic peak periods. In the Mid-Vaal and Emfuleni areas, the primary source of NO₂ is industrial and processing activities. These are industrial areas comprise of coal-fired power stations and chemical producing companies.

During Level-5 of the lockdown, there is a noticeable decline in the NO₂ total column densities values in Johannesburg, Ekurhuleni and Tshwane. An approximate decline of 31% of NO₂ in these areas is observed. This reduction is due to the decrease in motor vehicles on the road, closure of some factories, a drop in the coal-fired power station's operations, and the chemical producing companies. Most companies were dormant during 35 days of the Level-5 lockdown, with most people restricted to their homes. This has resulted in fewer vehicles on the road. However, during the 31 days of the Level-4 lockdown, an increase in the NO₂ total column density values is observed (see Fig. 3(c)). Level-4 regulations allowed for more mobility and the opening of some

Fig. 3. NO₂ tropospheric column and distribution (a) before the lockdown, (b) during the lockdown Level 5 and (c) during the lockdown Level 4 over the Gauteng Province observed by OMI.

economically strategic companies. This led to the re-opening of most industries, thus increased mobility. Consequently, the number of vehicles on the road increased, thus increasing the emissions of NO₂. Moreover, the re-opening of industries and their near full capacity operations led to more emissions.

4.2 SO₂ Observations over RSA and Gauteng Province

Fig. 4 shows the distribution of SO₂ over RSA before and during the lockdown. Before the lockdown (see Fig. 4(a)), SO₂ hotspots are observed in the Limpopo, Mpumalanga, and Gauteng provinces. The primary sources of SO₂ in these areas are coal-fired power stations (Pretorius *et al.*, 2015; Girmay and Chikobvu, 2017; Shikwambana *et al.*, 2020). Other sources of SO₂ include the processing, manufacturing, mining, and smelter industries. Motor vehicle emissions also have a small SO₂ contribution to the local total SO₂ density (Pierson *et al.*, 1978; Yasar *et al.*, 2013). Extensive distribution of SO₂ is observed from the hotspot areas. However, during the Level-5 lockdown period, a slight decrease in the distribution of SO₂ is observed. This indicates lesser emissions of SO₂ due to (1) a decrease in electricity production resulting from a lesser demand for electricity by the manufacturing, mining, smelters, and processing industries. (2) Lesser motor vehicles on the road also slightly contribute to the lower SO₂, as observed. With the easing of the regulations from Level-5 to Level-4, an uneven distribution of SO₂ is observed in most RSA. The sudden increase in the SO₂ distribution is mainly due to the full operations of the coal-fired power stations and industries' resumption to their full capacities. This resulted in an increase in SO₂ loading in the atmosphere. Interestingly, regions in RSA known to have less SO₂ densities (namely,

Fig. 4. SO₂ total column density and distribution (a) before the lockdown, (b) during the lockdown Level 5 and (c) during the lockdown Level 4 over RSA.

the Western Cape and Eastern Cape provinces) suddenly experienced larger densities of SO₂. The more stable condition of the atmosphere in the May period and the massive injection of SO₂ in the atmosphere could be the main reason for the rapid dispersion of SO₂ countrywide (Shikwambana *et al.*, 2020).

The distribution of SO₂ over the Gauteng Province before and during the lockdown is shown in Fig. 5. Before the lockdown restrictions, large values of the total column density (0.0004 mol m⁻² and 0.00034 mol m⁻²) are observed in the central, eastern and southern parts of the Gauteng Province (see Fig. 5(a)). These are the regions with high emissions of SO₂ from (1) the coal-fired power station in the south of Gauteng and (2) high traffic congestion in the central and eastern parts of Gauteng. However, after the Level-5 lockdown restrictions (see Fig. 5(b)), a noticeable drop in the SO₂ column density (0.00011–0.00017 mol m⁻²) is observed in these hotspot areas, especially in the central and eastern parts of Gauteng. This is mainly from the reduction in traffic congestion. In southern Gauteng, the slight decrease in SO₂ distribution was due to the limited operation of the coal-fired power stations. Upon the introduction of the Level-4 lockdown, large values of the SO₂ column density (0.0004 mol m⁻²) are observed in the entire Gauteng Province (see Fig. 5(c)). The meteorological conditions in this period are suspected of having aided the dispersion of SO₂ in the region (Shikwambana *et al.*, 2020). More importantly, the recommencement of mobility (i.e., motor vehicles), the coal-fired power station's full operations, and industries increased the SO₂ load in the atmosphere.

4.3 CO Observations over RSA and Gauteng Province

Fig. 6 shows the distribution of CO over RSA before and during the lockdown, indicating large CO distributions and high CO column density values (0.026 mol m⁻²) in the north-eastern parts of RSA (Limpopo Province). High CO column density values (0.03 mol m⁻²) are also observed at the RSA and Zimbabwe border. This may be due to exhaust vehicle emissions (mainly from trucks) that pass the Beitbridge Border daily, i.e., one of the busiest borders in Southern Africa. This

Fig. 5. SO₂ total column density and distribution (a) before the lockdown, (b) during the lockdown Level 5 and (c) during the lockdown Level 4 over the Gauteng Province.

Fig. 6. CO total column density and distribution (a) before the lockdown, (b) during the lockdown Level 5 and (c) during the lockdown Level 4 over RSA.

results in a large injection of CO into the atmosphere. The Lebombo Border between RSA and Mozambique also sees large amounts of CO for the same reason. Because of its high traffic congestions and industries, the Gauteng Province also shows high amounts of CO column density. The interior, southern and western parts of RSA have lesser amounts of CO column density values ($0.0023 \text{ mol m}^{-2}$). This is primarily because of the absence of high traffic congestions and fewer operational industries. During the Level-5 lockdown (see Fig. 6(b)), these areas saw a further drop of $\sim 17\%$ in CO column density. Similar results are observed in the Gauteng Province and the borders of Zimbabwe and Mozambique. The decrease in CO emissions was due to the limited cross border movements imposed by the RSA government. Only limited trucks carrying goods regarded as essential were allowed to cross the borders. The easing of restrictions to Level-4 lockdown (see Fig. 6(c)) allowed for more trucks across the border and a country as a whole. Nevertheless, this does not have a significant impact on the CO column density across the country. No significant changes are observed in the Level-4 and Level-5 CO distributions.

The Gauteng Province CO distribution before and during the lockdown is seen in Fig. 7. Before the lockdown (see Fig. 7(a)), high CO column density values (0.026 mol m^{-2}) are observed in Johannesburg, Ekurhuleni, and Tshwane municipalities. These are urban areas with high traffic congestions. Therefore, high values of CO in these are mainly from exhaust vehicle emissions. Moreover, industries and informal settlements might also contribute to the high CO column density (Shikwambana and Tsoeleng, 2020). During the Level-5 lockdown (see Fig. 7(b)), most of Gauteng had a $\sim 14\%$ decrease in CO column density. This is due to lesser vehicles on the road and many industries' closing due to the RSA lockdown regulations. With the easing of the lockdown regulations to Level-4, a slight increase in CO distribution is observed (see Fig. 7(c)). This CO could be from an increase in the number of vehicles on the road and partial openings of Gauteng industries.

Fig. 7. CO total column density and distribution (a) before the lockdown, (b) during the lockdown Level 5 and (c) during the lockdown Level 4 over the Gauteng Province.

4.4 LST and Surface Urban Heat Islands

Fig. 8 shows the LST results for Gauteng Province and its surroundings for 2020 (i.e., COVID-19 year) and 2019 (i.e., reference year) and the LST differences between these years. Specifically, LST was averaged over various periods: 01 February–26 March, 27 March–30 April, and 01–31 May, characterising periods before lockdown, during Level-5 lockdown and Level-4 lockdown, respectively. Generally, the results show that the LST for COVID-19 year, i.e., 2020, was slightly higher than the reference year, i.e., 2019, depicted by widely distributed LST differences around 0.7°C over the study area (see Table 2), especially before the lockdown restrictions (i.e., 01 February–26 March) and during Level-5 lockdown (27 March–30 April). However, the results also show fewer areas showing the lower LST between the years. In particular, the eastern part of the province (i.e., east of Tshwane and Lesedi) shows lower LST (i.e., the difference of around –3.7°C) during Level-5 lockdown. These areas correspond to cultivated and grassland land covers

Fig. 8. LST over the Gauteng Province before and during the lockdown and LST differences between COVID-19 year (2019) and reference year (2019).

Table 2. Descriptive statistics for LST at periods: February 01–March 26; March 27–April 30; and May 01–May 31.

LST (C)	Mean	S.D.	Min.	Max.
Reference year (2019)				
01 Feb–26 March	29.82	1.72	23.48	36.36
27 March–30 April	25.33	1.24	20.30	29.85
01 May–31 May	24.35	1.29	18.15	28.55
COVID-19 year (2020)				
01 Feb–26 March	29.78	1.75	23.49	35.58
27 March–30 April	25.07	1.29	19.43	29.91
01 May–31 May	21.97	1.12	16.79	25.80

(see Fig. 1). On the other hand, markedly low LST values in 2020 relative to 2019 are observed during Level-4 lockdown across the study area. However, the northern part of the study area (i.e., Tshwane) has higher LST than other areas. This area is characterized by Forested land, grasslands, and built-up areas (see Fig. 1) as well as the rapid proliferation of informal settlements. It is anticipated that the land clearance in the construction of settlements may have resulted in the observed high LST values during the 01–30 May period. Feng *et al.* (2019) found that bare soil is an intense heat source, thus agrees with our results. Moreover, previous studies (Luyssaert *et al.*, 2014; Fu and Weng, 2016; Ravanelli *et al.*, 2018) note that LST is closely related to land-use patterns and configuration, coverage, and landscape structure. Nevertheless, the SDI results indicate no significant difference between 2020 (i.e., COVID-19) and 2019 (i.e., reference year) for all dates considered, i.e., 01 February–26 March (i.e., SDI = −0.01); 27 March–30 April (i.e., SDI = −0.1); and 01 May–31 May (i.e., SDI = −0.99), respectively.

The surface urban heat island (SUHI) intensity (Fig. 9) indicates high intensity ($\sim 3^{\circ}\text{C}$) in northern Gauteng province (i.e., Tshwane), driven by a myriad of factors including Urban expansion due to proliferation of informal settlements and agricultural land clearance. The areas in the middle and southern interior of the province such as Johannesburg, Ekurhuleni, Emfuleni and Midvaal also exhibit high SUHI intensity. These areas are mainly built-up, characterized by commercial and residential buildings and mining areas. Comparatively and in agreement with LST results, the SUHI intensity during 01 February–26 March period is more or less similar to the reference year (i.e., 2019), while it is lower (i.e., $\sim -3^{\circ}\text{C}$) in the eastern part of the province (i.e., east of Tswane and Lesedi) during Level-5 lockdown (i.e., 27 March–30 April) and most of the interior during Level-4 lockdown (01–31 May). As shown earlier the decline in electricity production, minimal industry operations, and lesser motor vehicles on the road are responsible for the decrease in emissions (NO_2 and CO) in the province. These emissions are known to cause anthropogenic heating, which substantially raises the temperatures. However, there was no evidence of the influence of these emissions on LST and SUHI in this study. Therefore, this aspect as well as other

Fig. 9. Surface urban heat island (SUHI) intensity before (01 February–26 March), during Level-5 lockdown (27 March–30 April) and level-4 (01–31 May).

influencing factors of SUHI and LST such as land-use patterns and topography need to be investigated further in the future, to reveal the effect of COVID-19 Lockdown emission reductions on anthropogenic heating. The observed slight decline in LST and SUHI, in this study, is mainly attributed to the expected drop in temperature from February to May due to a change in season (i.e., from summer to autumn).

4.5 Trend analysis of SO₄, LWR and LST

Mann-Kendall (M-K) trend test is applied to determine whether there is a significant trend in the surface absorbed long-wave radiation (LWR) and sulfate (SO₄) concentration in Gauteng Province (see Table 3). The null hypothesis (H₀) that there is no significant trend in the LWR and SO₄ at 95% confidence level ($\alpha = 0.05$) was tested. The LWR results show a significant increasing trend for 2018 and decreasing significant trends for 2019 and 2020. SO₄ results show significantly decreasing trends for 2018–2020.

The SQMK test is further applied to the SO₄ concentration for the period 2018–2020 (for the months, February–May only) over Gauteng Province. The trend of the SO₄ concentration for the three years is shown in Fig. 10(a). In the 2018 period, the highest peak concentration of SO₄ is observed in the early days of April, and a subsequent stable decrease in SO₄ concentration until May is observed. On the other hand, in the March–May 2019 period, a steady trend with less variations is observed. However, during the lockdown period of April–May 2020, a decreasing trend in SO₄ concentration is observed. The main emissions of SO₄ include coal-fired power stations (Shikwambana and Sivakumar, 2019), diesel-powered light-duty vehicles (Truex *et al.*, 1980), and diesel-powered machinery. Therefore, the decline in SO₄ concentration during the Level-5 and Level-4 lockdown in Gauteng (see Fig. 10(b)) can be attributed to a drop in the operation of the coal power station (due to less electricity demand) and a reduction in motor vehicles on the road.

The SQMK test on the LST does not show any significant trend (see Fig. 11(a)). Therefore, based on this result, it is difficult to determine the behaviour of LST during the lockdown period. In

Table 3. M-K test results for LWR and SO₄ over three years, i.e., 2018, 2019, and 2020. Positive M-K τ value indicates an increasing trend, while the negative values indicate a decreasing trend.

Parameter	Longwave Radiation (LWR)		SO ₄	
	Tau (τ)	p -value	Tau (τ)	p -value
2018	0.857	0.004434	−0.296	< 2.22e-16
2019	−0.285	< 2.22e-16	−0.273	< 2.22e-16
2020	−0.284	< 2.22e-16	−0.284	< 2.22e-16

Fig. 10. Sequential Mann-Kendall trend for SO₄ during (a) 2018–2020 and (b) 2020.

Fig. 11. Sequential Mann-Kendall trend during for the period 2018–2020 for (a) LST and (b) LWR.

contrast, LWR shows a decreasing trend during the lockdown period (see Fig. 11(b)), which agrees with Table 2. However, this type of decrease is also seen in the years 2018 and 2019. This seasonal decrease in LWR is due to various factors such as Earth's skin temperature, surface emissivity, atmospheric temperature, water vapour profile, and cloud cover. Therefore, a quantitative study is required to determine the effect of the lockdown on the LWR.

5 CONCLUSIONS

Globally, the COVID-19 pandemic has adversely impacted socio-economic activities. The spread of the disease has left many destitute, especially in Africa. The lockdown restrictions in many African countries, including RSA, has led to many companies permanently closing down due to financial difficulties. Nevertheless, the slowing down of the economic activities in RSA has led to an improvement in air quality. During the Level-5 lockdown, most industries and mines were closed. The number of motor vehicles on the road reduced, and the coal-fired power stations' operations were reduced drastically due to a lack of electricity demand by industries. Indeed, the nation-wide lockdown restrictions have positively impacted air quality, human health, and the environment. Atmospheric gases such as SO_2 , NO_2 , and CO are toxic, especially to human populations living in cities where there are vast sources. Therefore, as observed in this study, the lockdown restrictions have led to a brief decline in emissions, highlighting the effect of human activities on the environment.

Moreover, LST and SUHI from MODIS showed slight reductions over some parts of the province during period consistent with the imposed lockdown regulations. It is, however, not clear whether the observed reductions in SO_2 , NO_2 , and CO emissions were the cause of the decline in LST and SUHI, as the period under study coincides with normal cooling as seasons change. Therefore, this aspect needs a more in-depth analysis in future studies. Overall, the results in this study provide insights into the effect of policy changes on emissions and the potential in reducing the effect on micro-climates and related human health risks.

ACKNOWLEDGMENTS

The authors wish to thank the South African National Space Agency and the University of the Witwatersrand for their support in this study. We gratefully acknowledge ESA for the Sentinel-5 P/TROPOMI products. We acknowledge the GES-DISC Interactive Online Visualization and Analysis Infrastructure (Giovanni) for providing us with the MERRA-2 and OMI data. The authors

would also like to thank the National Aeronautics and Space Administration (NASA) for their support in LST data.

DISCLAIMER

The authors declare that there are no financial and personal interests that influenced the results and work presented in the manuscript.

SUPPLEMENTARY MATERIAL

Supplementary material for this article can be found in the online version at <https://doi.org/10.4209/aaqr.200437>

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