

INVESTIGATING URBAN ENVIRONMENTAL SHIFTS IN HYDERABAD AND BANGALORE CITIES IN INDIA DURING THE COVID-19 LOCKDOWN

K. S. ARUNAB¹, ANEESH MATHEW^{2*}

¹*Junior Research Fellow, Department of Civil Engineering, National Institute of Technology, Tiruchirappalli, 620015, Tamil Nadu, India.*

²*Assistant Professor, Department of Civil Engineering, National Institute of Technology, Tiruchirappalli, 620015, Tamil Nadu, India.*

**Corresponding author email: aneesh52006@gmail.com; aneesh@nitt.edu*

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ABSTRACT

This study investigates the complex dynamics of air quality and the Urban Heat Island (UHI) effect in urban region and rural region of Hyderabad and Bangalore pre-lockdown, lockdown, and post-lockdown during the COVID-19 pandemic. Employing advanced spatial and temporal analyses, including spatio-temporal maps, box plots, independent samples t-test, ANOVA, and post-hoc analysis, the study meticulously examines the distribution and temporal changes in key pollutants. In Bangalore, carbon monoxide (CO) levels exhibited a significant urban-rural disparity, with urban areas experiencing higher concentrations during the pre-lockdown period. However, an intriguing shift occurred during the lockdown, with CO levels decreasing in urban areas while increasing in rural areas. Formaldehyde (HCHO) and Aerosol Optical Depth (AOD) levels displayed a consistent urban-rural gradient, significantly higher in urban areas. Notably, both HCHO and AOD levels decreased in regions both rural and urban during the lockdown, indicating a notable impact of reduced anthropogenic activities. Nitrogen dioxide (NO₂) levels, a critical indicator of vehicular emissions, showed a substantial reduction during the lockdown in both urban and rural environments. Ozone (O₃) levels, on the other hand, increased post-lockdown, revealing a complex interplay of factors influencing air quality. Sulfur dioxide (SO₂) levels, typically associated with industrial emissions, exhibited lower concentrations in urban areas during the lockdown. The UHI effect, manifested through elevated Land Surface Temperature (LST) in urban regions, demonstrated a significant reduction during the lockdown, aligning with decreased anthropogenic heat sources. In Hyderabad, CO levels were consistently higher in urban areas, reaching a peak during the lockdown, indicative of localized emissions. HCHO and AOD levels followed a similar pattern to Bangalore, with a significant urban-rural gradient. NO₂ levels experienced a substantial reduction during the lockdown, consistent with a decrease in vehicular activities. O₃ levels showed an interesting urban-rural dichotomy, with increases in urban areas post-lockdown and higher concentrations in rural areas during the lockdown. SO₂ levels did not exhibit a consistent urban-rural gradient, indicating diverse emission sources. LST in urban areas demonstrated a significant reduction during the lockdown, suggesting a moderation of the UHI effect. This research provides a meticulous examination of the complex interplay between lockdown measures, pollutant

concentrations, and the UHI effect in two distinct urban environments. These findings provide important insights that may be used for urban planning strategies and environmental management in the context of global pandemics and emphasize the need for sustainable approaches to mitigate air quality challenges in urban regions.

Keywords: Spatio-temporal analysis; COVID-19 lockdown; Urban Heat Island effect; Urban environment; Air pollution

INTRODUCTION

Climate stands out as one of the paramount environmental variables influencing our habitats and daily lives (Naresh & Mathew, 2026). Biodiversity decline is attributed to multiple factors, with climatic change emerging as a key contributor, leading to modifications in various urban land covers (Varma *et al.*, 2025; Muraharirao & Chinthu, 2026). The onset of the pandemic (COVID-19) in 2019 triggered an unparalleled worldwide reaction, resulting in the adoption of extensive lockdown measures as the main approach for reducing the spread of the virus (Coccia, 2020; Jallu *et al.*, 2022). These lockdown measures, characterized by stringent restrictions on movement and economic activities, have had profound and multifaceted effects on urban environments worldwide. Cities, already complex ecosystems, witnessed significant shifts in various dimensions, including air quality, noise levels, transportation patterns, and socio-economic dynamics (Dantas *et al.*, 2020; Arunab & Mathew, 2023). As cities, already intricate ecosystems, grapple with the challenges posed by the pandemic, understanding the interplay of these factors becomes imperative for informed urban planning.

These lockdowns, characterized by reduced human activities and limited industrial operations, have inadvertently presented an exceptional opportunity to examine the influence of altered urban dynamics on environmental factors such as the Urban Heat Island (UHI) effect and atmospheric pollution (Taha, 1997; Mathew *et al.*, 2024). The UHI effect, which is increased by urbanisation and activities carried out by humans, is a factor that contributes to higher temperatures in urban regions with regard to their rural surrounds. With reduced vehicular emissions and industrial output during lockdowns, there are opportunities available for reducing the impact of the UHI (Santamouris, 2015; Arunab & Mathew, 2024). As a conspicuous human-induced climate modification, UHIs have been a subject of extensive global research. Additionally, the lockdowns have led to a marked decrease in anthropogenic activities, offering a rare glimpse into the direct impact on atmospheric quality. This study seeks to thoroughly investigate the impact of COVID-19 lockdowns on the UHI effect and air pollution in urban areas, providing insights into possible options for sustainable urban development. Concurrently, the lockdowns have led to an extensive decrease in anthropogenic sources of air pollutants, providing a unique window to investigate the impact on the quality of the air (Meda & Mathew, 2022).

Numerous studies have examined how atmospheric quality and meteorological factors influence the transmission dynamics of COVID-19 (Coccia, 2020; Dantas *et al.*, 2020; Orak & Ozdemir, 2021; Srivastava, 2021; Bashir *et al.*, 2020). Bao & Zhang (2020) demonstrated a 7.80 % decline in the air quality index, with average reductions of 6.76 % for Sulfur dioxide (SO₂), 4.58 % for Carbon monoxide (CO), 13.66 % for PM₁₀, 24.67% for Nitrogen dioxide (NO₂), and 5.93 % for PM_{2.5} in 44 Chinese cities due to the implementation of lockdown measures. Dantas *et al.* (2020) assessed the impact of partial lockdown measures in Rio de Janeiro during the COVID-19 pandemic on atmospheric quality, comparing concentrations of various pollutants with 2019 values and pre-lockdown weeks. CO levels

exhibited the significant reductions, correlated with decreased vehicular emissions, while variations in nitrogen dioxide and particulate matter concentrations were observed, influenced by factors like meteorological conditions and changes in vehicular flux. Orak & Ozdemir (2021) utilized SO₂ and PM₁₀ monitoring data to examine how COVID-19 lockdowns affected ambient atmospheric pollution and human mobility in 81 Turkish cities. PM₁₀ and SO₂ concentrations dropped significantly in April 2020, with 67 % and 59 % of cities having lower levels than five years earlier. The study emphasized the correlation between specific mobility patterns, such as Workplaces mobility, Transit, and Restaurant, Café, and air pollution, providing valuable insights for a broader understanding of the air quality implications during the COVID-19. A significant reduction in NO₂ emissions in the early months of 2020. Additionally, a separate study conducted in the United States by Berman and Ebisu (2020) demonstrated a notable decrease in NO₂ (25.5 %) and PM_{2.5} (11.3 %) levels during the COVID-19.

An alternate research group conducted an analysis of the atmospheric quality impacts in São Paulo, revealing significant drops of 77.3 %, 54.3 %, and 54.3 % for NO, NO₂, and CO, respectively, in comparison to the five-year monthly mean. Urban areas witnessed a rise of about 30% in ozone concentrations (Nakada & Urban, 2020). During the initial lockdown phase that took place in Kazakhstan between the middle of March and the middle of April, there was a decrease of 21 %, 49 %, and 35 % in the concentrations of NO₂, PM_{2.5}, and CO, respectively. This was in comparison to the averages on corresponding days in 2018 to 2019 (Kerimray *et al.*, 2020). After a three-week lockdown in India from March 24 to April 14, 2020, PM_{2.5} and PM₁₀ levels dropped by nearly 50 %, while NO₂ (52.68 %) and CO (30.35 %) concentrations dropped (Mahato *et al.*, 2020). In 2020, Giani *et al.* (2020) found that COVID-19 lockdown interventions reduced fine PM_{2.5}, with decreases of 29.7 % over China and 17.1 % over Europe. In Salé City, Morocco, substantial reductions of (SO₂) 49 %, (PM₁₀) 75 %, and (NO₂) 96 % were observed (Otmami *et al.*, 2020). A research conducted in the United Arab Emirates examined the levels of NO₂, Aerosol Optical Depth (AOD), and Surface Urban Heat Island Intensity (SUHI) throughout lockdown periods. The study found that there was a decrease of 23.7 % (NO₂), 3.7 % (AOD), and 19.2 % (SUHI) compared to the corresponding period in 2019 (Alqasemi *et al.*, 2021). These investigations predominantly concentrate on the initial lockdown phase between March and April 2020, with a predominant focus on mobility data in existing literature for exploring the spread of COVID-19 in societies (Chang, 2020). Tobias *et al.* (2020) observed significant reductions of 19 % (CO), 51 % (NO₂), 31 % (SO₂), and 45 % (PM₁₀), during the lockdown, within a month, over Barcelona, Spain. The substantial decrease in these greenhouse gas levels could potentially influence the spatio-temporal characteristics, such as intensity and spatial extent, of urban heat islands (UHIs).

In previous investigations, several studies, such as those conducted by Roshan *et al.* (2021) in Tehran, Mukherjee & Debnath (2020) in New Delhi, and Kenawy *et al.* (2021) in major cities across the Middle East, have consistently demonstrated an important decline in UHIs effect. El Kenawy *et al.* (2021) noted a distinct trend during the lockdown phase, decreasing the mean nighttime SUHI intensity, while the daytime SUHI mean intensity exhibited either a rise or a marginal decline across the surveyed locations. Notably, megacities such as Tehran, Ankara, and Istanbul, alongside Gulf metropolitans like Kuwait, Dubai, and Muscat, displayed abnormal increments in the daytime SUHI intensity, surpassing 2 °C. The lockdown significantly contributed to reducing the mean surface temperature in Hyderabad, New Delhi, and Mumbai. The extent of temperature reduction varied across these cities, approximately measuring 1.9 °C, 5 °C, and 0.26 °C, respectively. This discrepancy in magnitude may be attributed to the improved atmospheric quality, potentially offsetting the

UHI effect, and variations in city-specific activities, including industrial operations, emergency transportation, and agriculture (Jallu *et al.*, 2022). Liu *et al.* (2022) found that the implementation of COVID-19 lockdown measures resulted in a decrease in the severity of both canopy and surface UHI effects throughout China. The decrease in surface UHI intensity averaged 0.23 K during the night and 0.25 K during the day, while canopy UHI intensity exhibited a reduction of 0.39 K during the night and 0.42 K during the day. At different times of day, the COVID-19 lockdown affected the UHI intensity.

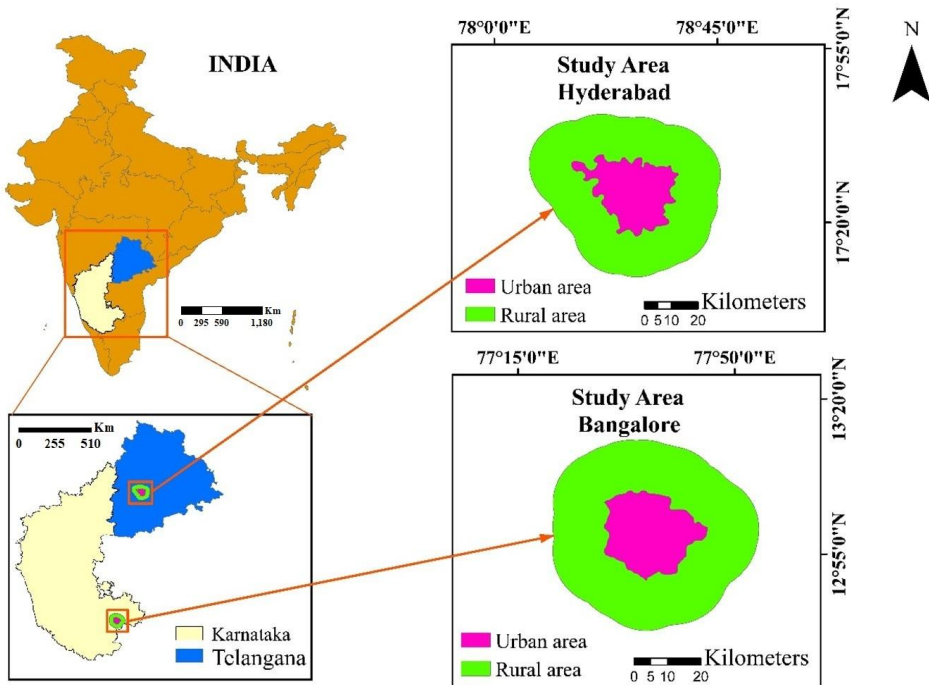
While preliminary, previous studies have offered valuable insights; however, a comprehensive examination of both surface UHI and atmospheric pollution, particularly in the context of the unprecedented reduction in human activities during the COVID-19 lockdown in Indian cities like Bangalore and Hyderabad, remains largely unexplored. Bangalore and Hyderabad regions are relatively young metropolitan cities that have experienced rapid, recent urbanization driven primarily by economic growth rather than long-established heavy industry. Their development trajectories are comparable, yet distinct, allowing for meaningful analytical comparison. Unlike older Indian megacities with entrenched industrial emissions and complex legacy pollution sources, these cities represent emerging urban systems where changes in activity levels can be more clearly linked to variations in air quality. The sudden halt in development provides a unique analytical setting to examine how emerging urban systems respond to sharp reductions in emissions, helping to isolate the influence of urban growth on pollution dynamics and to understand baseline and transitional air-quality behavior in rapidly developing cities. Three key questions necessitate investigation: (a) the extent of UHI variability during lockdown periods; (b) distinctions in variations between surface UHI and air pollution during lockdown periods; and (c) the large-scale spatio-temporal patterns characterizing UHI variations and air pollution during lockdown periods. As cities are complex ecosystems with intricate relationships between anthropogenic activities and environmental dynamics, understanding the repercussions of the COVID-19 lockdowns on the UHI effect and air pollution is crucial for informing sustainable urban development strategies. This study aims to comprehensively explore these impacts, drawing on global trends and case studies, to provide valuable insights into the intersection of public health, urban planning, and environmental sustainability in the post-pandemic era.

STUDY AREAS

Bangalore and Hyderabad are prominent cities located on the Indian region, both situated on the peninsular plateau. Based on Köppen's climatic classification, Bangalore experiences a semi-arid climate, while Hyderabad has a tropical wet and dry climate. Bangalore finds its place within the Indian state Karnataka, positioned at coordinates 77° 34' 50.31" E and 12° 58' 20.79" N. The temperature in Bangalore fluctuates from 14.60°C to 32.80 °C across the months, with an annual average settling at 22.9 °C. The city receives an average annual rainfall of approximately 960 mm. On the other hand, Hyderabad is nestled in the Indian state Telangana, located at coordinates 78° 29' 30.06" E and 17° 23' 13.70" N. Its temperature ranges from 21.80 °C to 37.80 °C throughout the year, with an annual average of 25.9 °C. Hyderabad witnesses an annual mean precipitation of about 745 mm. This geographical position of study areas is depicted in Fig. 1. The 2011 MODIS annual land cover type image (MCD12Q1, which has a 500 m spatial resolution) was used to create the urban area polygons for Bangalore and Hyderabad. A buffer of 12 km (half of the maximum extent of the urban area) has been added to the boundary of the urban area polygon to delineate the boundary of study areas. The buffer was selected such that the study area includes sufficient

rural/suburban areas and satellite towns of the city. A study area of 2630 km² and 3130 km² is opted for Bangalore and Hyderabad respectively. Bangalore and Hyderabad were selected because both are rapidly growing inland metropolitan cities of southern India with comparable urban expansion patterns but distinct climatic, land-surface, and emission characteristics. Bangalore has a relatively moderate semi-arid climate and service-sector-dominated urban structure, whereas Hyderabad has a warmer tropical wet-and-dry climate with mixed urban, industrial, and peri-urban emission influences. This contrast provides a useful basis to examine whether lockdown-induced changes in air pollution and UHI behaviour were uniform or controlled by city-specific environmental and emission factors.

Fig. 1: Study areas – Bangalore and Hyderabad.

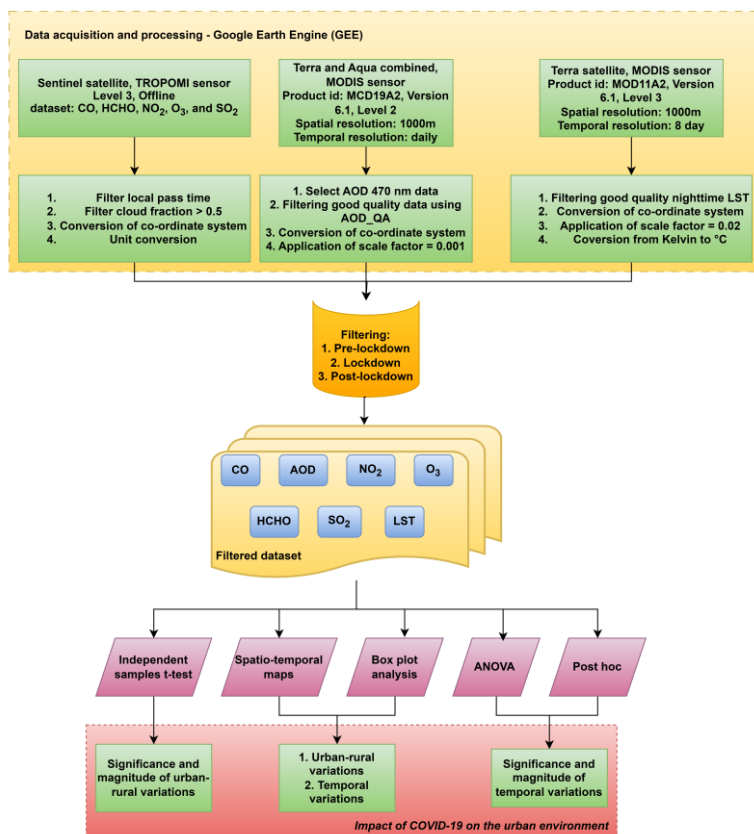


METHODOLOGY

The methodology used in the present study is illustrated in Fig. 2. Satellite data acquisition, processing, and filtering were performed using Google Earth Engine (GEE). Sentinel-5P TROPOspheric Monitoring Instrument (TROPOMI) Level 3 data were used to obtain CO, HCHO, NO₂, O₃, and SO₂, applying local overpass filtering, cloud fraction filtering (>0.5 removed), coordinate transformation, and unit conversion. AOD at 470 nm was derived from the Moderate Resolution Imaging Spectroradiometer (MODIS) Terra and Aqua combined product (MCD19A2, Version 6.1), where quality assurance filtering (AOD_QA), reprojection, and a scale factor of 0.001 were applied. Nighttime LST was obtained from MODIS Terra (MOD11A2, Version 6.1), with quality filtering, reprojection, application of a 0.02 scale factor, and conversion from Kelvin to °C. All datasets were categorized into

pre-lockdown, lockdown, and post-lockdown periods to generate a filtered dataset comprising CO, AOD, NO₂, O₃, HCHO, SO₂, and LST. The data during April and May months of - 2019 is labelled as the pre-lockdown dataset, 2020 is labelled as the lockdown dataset, and 2021 is labelled as the post-lockdown dataset. To provide a nuanced assessment of the influence of COVID-19 on the atmospheric quality, the thermal environment and spatio-temporal maps of the filtered data, statistical analysis on the filtered data, and quantitative assessments such as ANOVA analysis, the independent samples t-test, and the post hoc test on the filtered data was carried out. The spatio-temporal maps (using ArcGIS) and the statistical analysis (using Statistical Package for the Social Sciences (SPSS) software) is carried out to assess the pollutant and LST gradient in the urban-non-urban setting, and its variation over the years. The magnitude and significance of the pollutant and LST gradient in the urban-non-urban setting is assessed using the independent samples t-test. The independent sample t-test also ranks the urban-rural gradient of pollutants and LST, which aids in the comparative analysis of the urban and rural regions. The significance and magnitude of the temporal variations in air quality and LST is assessed using the ANOVA and post hoc analysis. The rise or fall of the pollutant concentration level before or pre-lockdown, during the lockdown, and after or post-lockdown in the study area and the urban-rural settings is also estimated using the ANOVA and post hoc analysis.

Fig. 2: Flowchart of the methodology.



Data used:

Current research uses satellite derived pollutants (SO₂, NO₂, O₃, CO, aerosols, and HCHO) and LST to assess COVID-19's impacts on UHI and air pollutant concentrations. The impact of COVID-19 is analysed by employing comparative analysis technique. Table 1 presents the dataset utilized along with its associated details. The data obtained from TROPOMI and MODIS sources were applied to compile information on pollutants on a seasonal and annual basis (Veefkind *et al.*, 2012; Wan & Li, 2008; Ghasempour *et al.*, 2021; Lyapustin *et al.*, 2018).

Table 1: Atmospheric Pollutants, LST and AOD datasets.

Dataset	Sensor	Band/Product
O ₃	TROPOMI	O ₃ _column_number_density
SO ₂		SO ₂ _column_number_density
HCHO		tropospheric_HCHO_column_number_density
CO		CO_column_number_density
NO ₂		tropospheric_NO ₂ _column_number_density
AOD (Aerosols)	MODIS	MCD19A2/Optical_Depth_047
LST		MOD11A2/ LST_Night_1km

Independent samples t-test

It is used to compare rural and urban pollutants levels in this investigation. The determination of key statistical parameters such as standard deviation (Equation 1), t-value (Equation 2), and degrees of freedom (Equation 3) were used.

$$\text{Standard deviation, } S = \sqrt{\frac{\sum(X_1 - \bar{X}_1)^2 + \sum(X_2 - \bar{X}_2)^2}{n_1 + n_2 - 2}} \quad (1)$$

$$\text{t-value} = \frac{\bar{X}_1 - \bar{X}_2}{S} \sqrt{\frac{n_1 n_2}{n_1 + n_2}} \quad (2)$$

$$\text{Degrees of freedom} = n_1 + n_2 - 2 \quad (3)$$

Where,

X = individual data point of a group

$\bar{X}$ = mean of a particular group

n = number of observations in a group

Analysis of variance (ANOVA)

The ANOVA (Analysis of Variance) analysis encompasses a range of statistical measures, including significance levels, mean square, F-value, and sum of squares, offering a thorough assessment of variations in pollutant levels across various time periods. Post-Hoc study quantifies the variations by assessing mean pollutant levels between time periods, and significance and standard errors.

The basic equation used in the analysis are provided in equations 4 to 11.

$$\text{Sum of Squares between, } SS_{\text{between}} = \sum n_j (\bar{X}_j - \bar{X})^2 \quad (4)$$

Where

$\bar{X}_j$ is a group mean

$\bar{X}$ is the overall mean

n_j is the sample size per group

$$df_{\text{between}} = m - 1 \quad (5)$$

Where, m is the number of groups.

$$\text{Mean Square between, } MS_{\text{between}} = \frac{SS_{\text{between}}}{df_{\text{between}}} \quad (6)$$

$$\text{Sum of Squares, } SS_{\text{within}} = \sum (X_i - \bar{X}_j)^2 \quad (7)$$

Where

$\bar{X}_j$ denotes a group mean

X_i denotes an individual observation

For n independent observations and m groups,

$$df_{\text{within}} = n - m \quad (8)$$

$$\text{Mean Square within, } MS_{\text{within}} = \frac{SS_{\text{within}}}{df_{\text{within}}} \quad (9)$$

$$F - \text{statistic, } F = \frac{MS_{\text{between}}}{MS_{\text{within}}} \quad (10)$$

$$\text{Effect size, } \eta^2 = \frac{SS_{\text{between}}}{SS_{\text{between}} + SS_{\text{within}}} \quad (11)$$

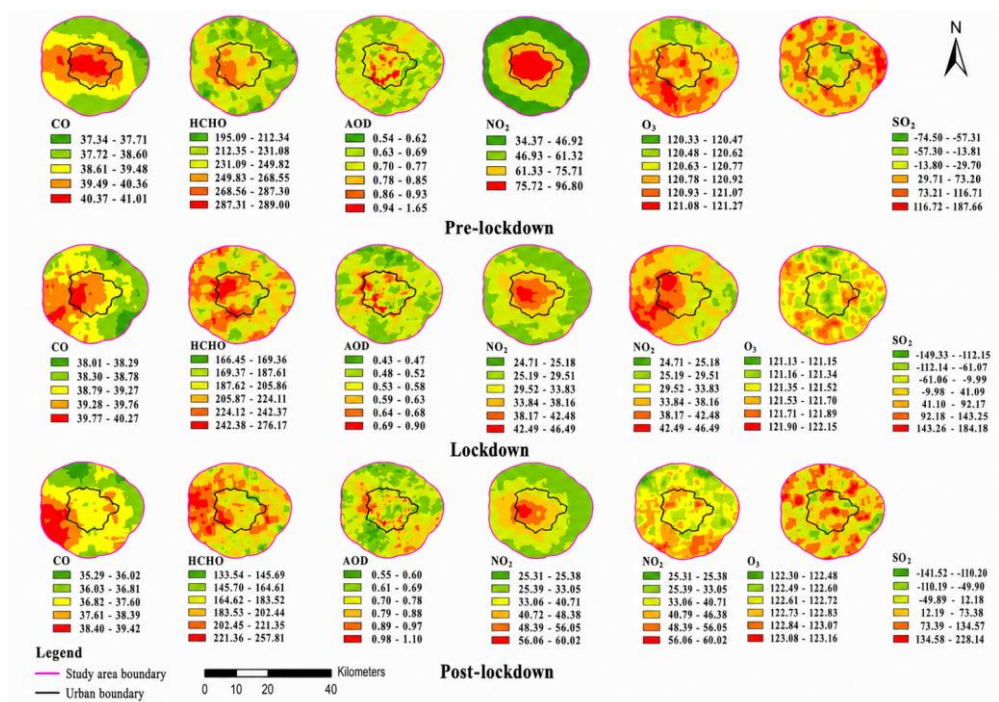
RESULTS AND DISCUSSION

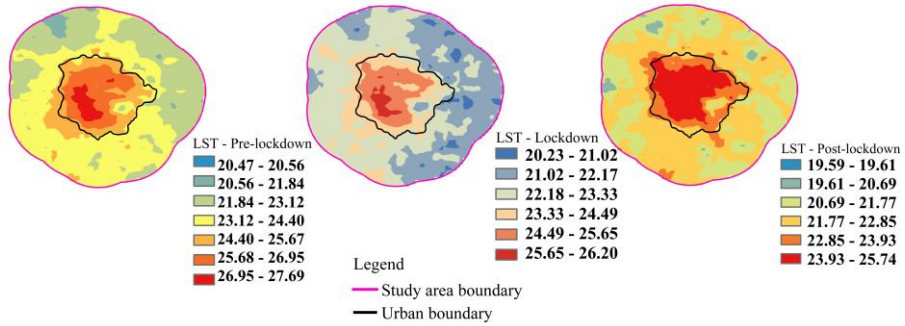
Spatio-temporal pollutant distribution:

The spatio-temporal pollutant maps showing the pollutant levels and the LST is shown in Fig. 3. For most pollutants (NO_2 , AOD, HCHO), urban concentrations are consistently higher than rural areas, confirming dominant anthropogenic sources within the urban region of Bangalore. Rural regions generally show lower and more dispersed pollution levels. The lockdown period narrows the urban–rural gap for several pollutants, especially AOD, NO_2 and CO. LST consistently remains higher within the urban boundary, reinforcing the UHI effects. Collectively, the spatial patterns confirm that COVID-19 lockdown measures had a measurable but temporary impact on Bangalore's air quality, while the UHI effect remained structurally embedded due to land cover and built-up characteristics.

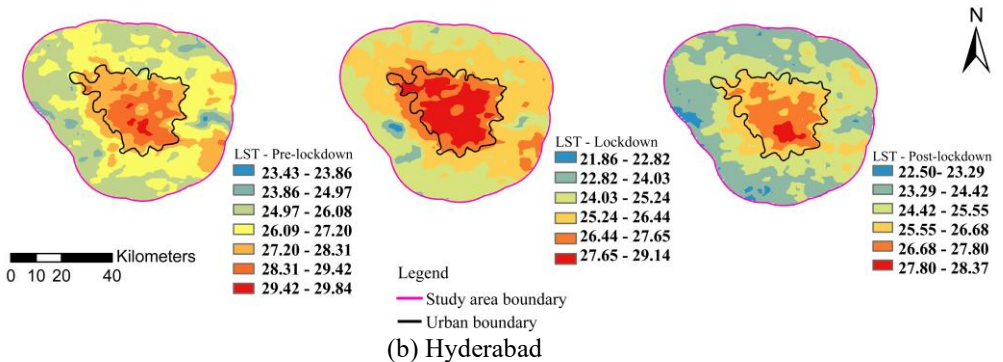
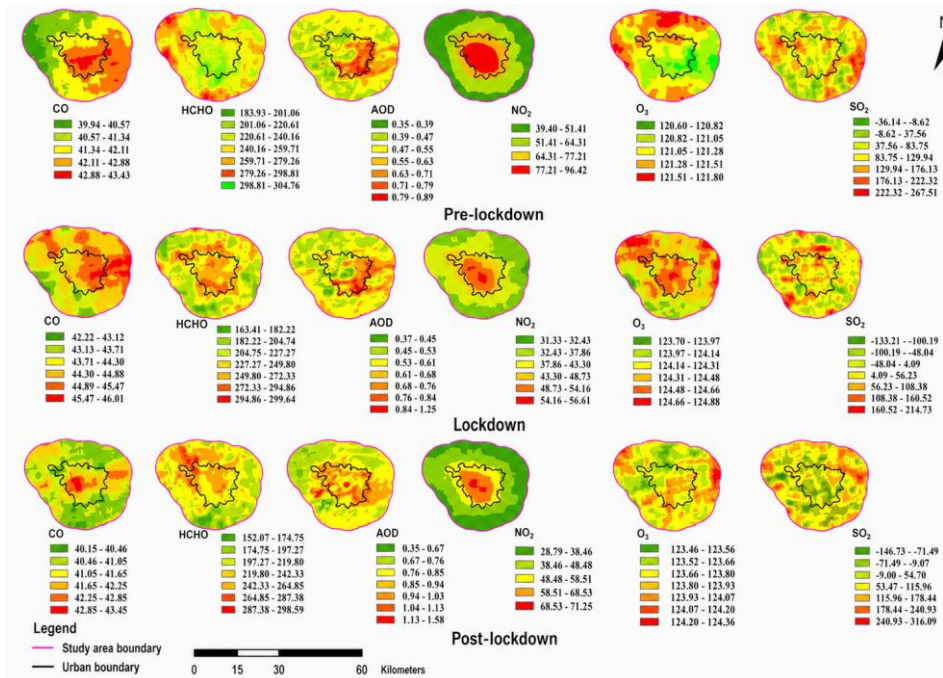
The spatio-temporal maps reveal urban–rural contrasts and temporal changes in both LST and air pollution across Hyderabad during the pre-lockdown, lockdown, and post-lockdown periods. In all phases, the urban core consistently exhibited higher LST and greater pollutant concentrations (especially CO, NO_2 , and AOD) than the surrounding rural areas, reflecting dense built-up surfaces, traffic, and industrial activity. Collectively, the spatial patterns confirm that COVID-19 lockdown measures had a measurable but temporary impact on Hyderabad's air quality, while the UHI effect remained structurally embedded due to land cover and built-up characteristics.

Fig. 3: Spatio-temporal pollutant –HCHO ($\mu\text{mol}/\text{m}^2$), SO_2 ($\mu\text{mol}/\text{m}^2$), CO (mmol/m^2), AOD, O_3 (mmol/m^2), and NO_2 ($\mu\text{mol}/\text{m}^2$) maps showing the pollutant levels and the LST in (a) Bangalore and (b) Hyderabad.





(a) Bangalore



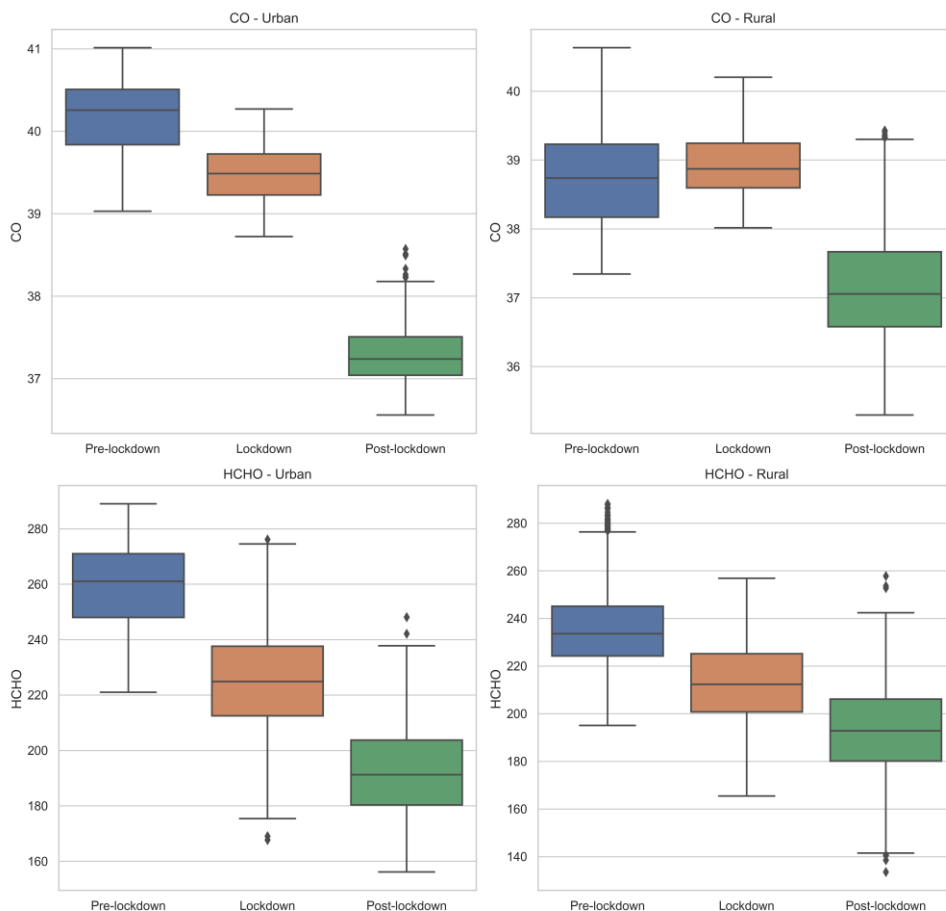
(b) Hyderabad

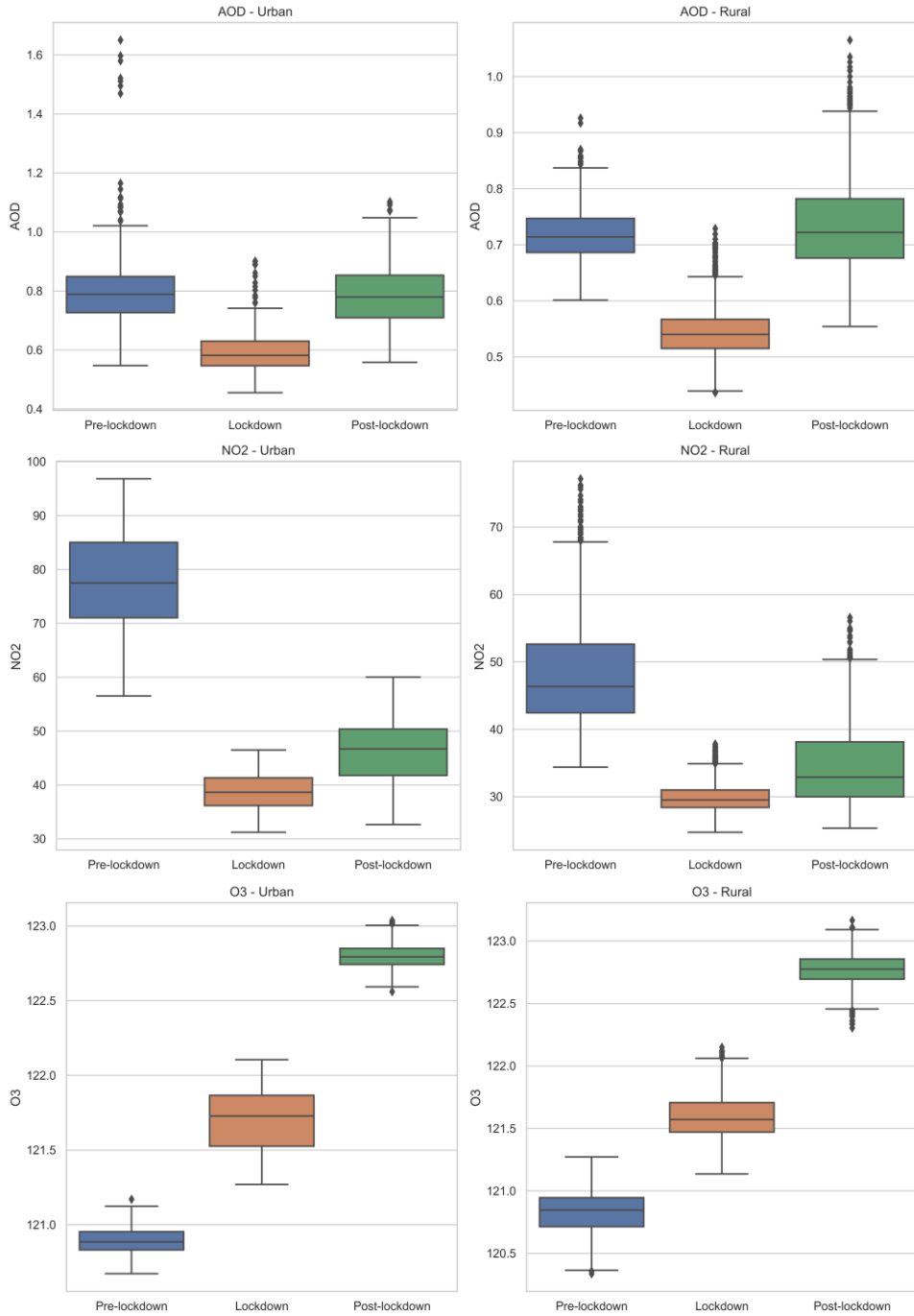
The box plots highlighting the distribution of the pollutant concentrations and LST in the urban region and rural region in the study areas are shown in the Fig. 4. For Bangalore, Fig. 4(a) shows clear urban–rural and temporal variations in pollutant concentrations, LST, and UHI index. In the urban region, CO decreased from 40.175 mmol/m² during pre-lockdown to 39.483 mmol/m² during lockdown and further to 37.313 mmol/m² post-lockdown. In contrast, rural CO slightly increased from 38.755 mmol/m² to 38.918 mmol/m² during lockdown before decreasing to 37.187 mmol/m² post-lockdown. HCHO declined consistently in both regions, with urban values decreasing from 259.692 µmol/m² to 225.493 µmol/m² and 193.302 µmol/m², while rural values decreased from 235.618 µmol/m² to 212.379 µmol/m² and 192.922 µmol/m² during the same periods. AOD decreased during lockdown in both urban and rural areas, from 0.803 to 0.592 and from 0.718 to 0.545, respectively, followed by post-lockdown recovery. NO₂ showed the strongest reduction, especially in urban areas, where it declined from 77.784 µmol/m² pre-lockdown to 38.760 µmol/m² during lockdown, before increasing to 46.551 µmol/m² post-lockdown. Rural NO₂ followed a similar trend, decreasing from 48.230 µmol/m² to 29.909 µmol/m² during lockdown and increasing to 34.483 µmol/m² post-lockdown. In contrast, O₃ increased continuously in both urban and rural areas, from 120.895 mmol/m² to 121.704 mmol/m² and 122.799 mmol/m² in urban areas, and from 120.832 mmol/m² to 121.595 mmol/m² and 122.774 mmol/m² in rural areas. SO₂ showed large variability, with urban SO₂ decreasing from 24.910 µmol/m² to 3.066 µmol/m² during lockdown and then increasing to 45.075 µmol/m² post-lockdown, while rural SO₂ decreased from 58.157 µmol/m² to 18.688 µmol/m² and then increased to 42.216 µmol/m². LST remained consistently higher in urban areas than rural areas. Urban LST decreased from 25.732 °C to 24.371 °C and 23.965 °C, while rural LST decreased from 23.267 °C to 22.354 °C and 21.899 °C. The UHI index was also higher in urban areas, decreasing from 0.729 to 0.693 during lockdown and slightly increasing to 0.711 post-lockdown. Overall, Bangalore showed a clear lockdown-related reduction in most pollutants and thermal indicators, while O₃ showed a continuous increasing pattern.

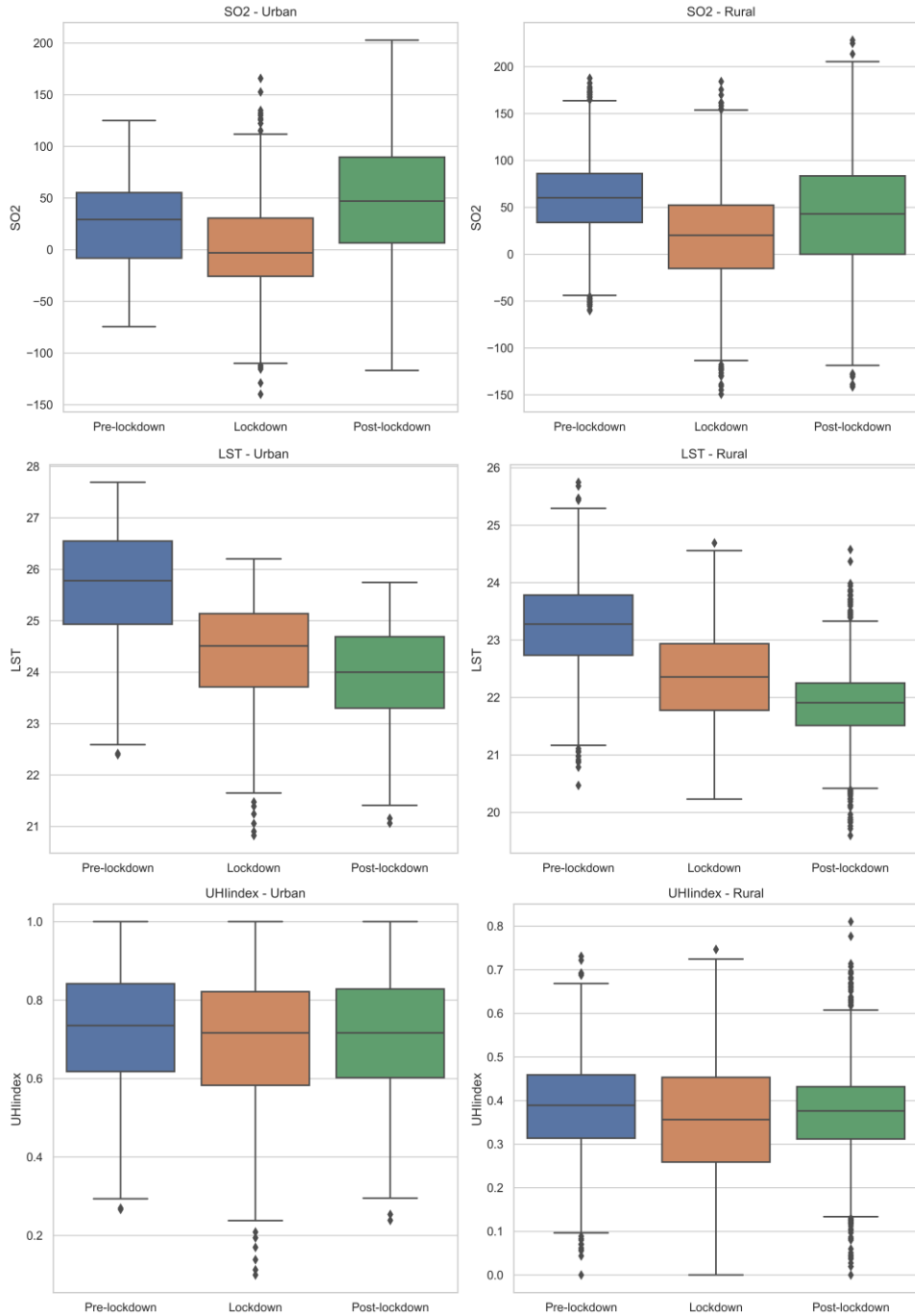
For Hyderabad, Fig. 4(b) indicates a mixed pollutant and thermal response across the pre-lockdown, lockdown, and post-lockdown periods. CO increased during lockdown in both regions, with urban CO rising from 42.345 mmol/m² to 44.842 mmol/m² before decreasing to 41.776 mmol/m² post-lockdown. Rural CO followed the same pattern, increasing from 41.570 mmol/m² to 44.530 mmol/m² during lockdown and then decreasing to 41.252 mmol/m² post-lockdown. HCHO showed a declining trend, with urban values decreasing from 262.947 µmol/m² to 258.724 µmol/m² and 242.937 µmol/m², while rural values decreased from 246.581 µmol/m² to 233.335 µmol/m² and 227.995 µmol/m². AOD increased across the study periods, rising from 0.648 to 0.686 and 0.983 in urban areas, and from 0.579 to 0.640 and 0.882 in rural areas. NO₂ showed a strong lockdown-related decrease, with urban NO₂ declining from 78.242 µmol/m² to 48.667 µmol/m², followed by an increase to 59.036 µmol/m² post-lockdown. Rural NO₂ also decreased from 52.692 µmol/m² to 38.528 µmol/m² during lockdown and slightly increased to 39.519 µmol/m² post-lockdown. O₃ increased sharply during lockdown, with urban values rising from 121.262 mmol/m² to 124.501 mmol/m² before decreasing slightly to 123.880 mmol/m² post-lockdown. Rural O₃ showed a similar pattern, increasing from 121.141 mmol/m² to 124.376 mmol/m² and then decreasing slightly to 123.865 mmol/m². SO₂ decreased markedly during lockdown, from 109.604 µmol/m² to 42.737 µmol/m² in urban areas and from 106.185 µmol/m² to 26.989 µmol/m² in rural areas, before increasing post-lockdown to 59.814 µmol/m² and 91.108 µmol/m², respectively. LST remained higher in urban areas than rural areas, with urban LST decreasing from 28.245 °C to 27.667 °C and 26.702 °C, while rural LST decreased from 26.235 °C to 25.375 °C and 24.552 °C. The UHI index increased during

lockdown in both regions, from 0.751 to 0.797 in urban areas and from 0.437 to 0.482 in rural areas, before decreasing post-lockdown. Overall, Hyderabad showed reductions in NO_2 , HCHO , SO_2 , and LST during lockdown, whereas CO , AOD, O_3 , and UHI index increased, indicating a more complex and mixed environmental response compared with Bangalore.

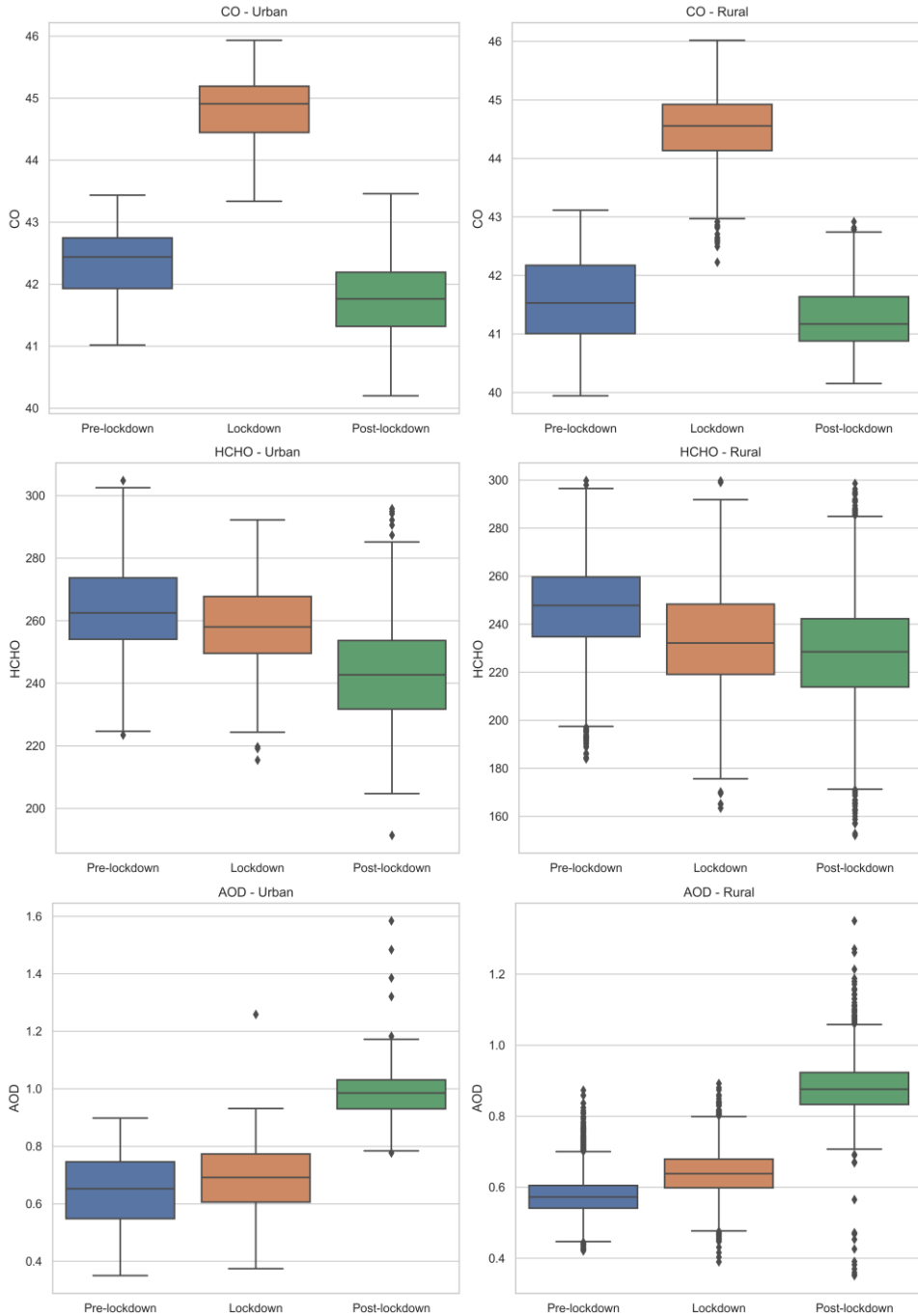
Fig. 4: Box plots highlighting the distribution of the pollutant - O_3 , SO_2 , NO_2 , AOD, HCHO , and CO concentrations and LST in the urban and rural regions in (a) Bangalore and (b) Hyderabad.

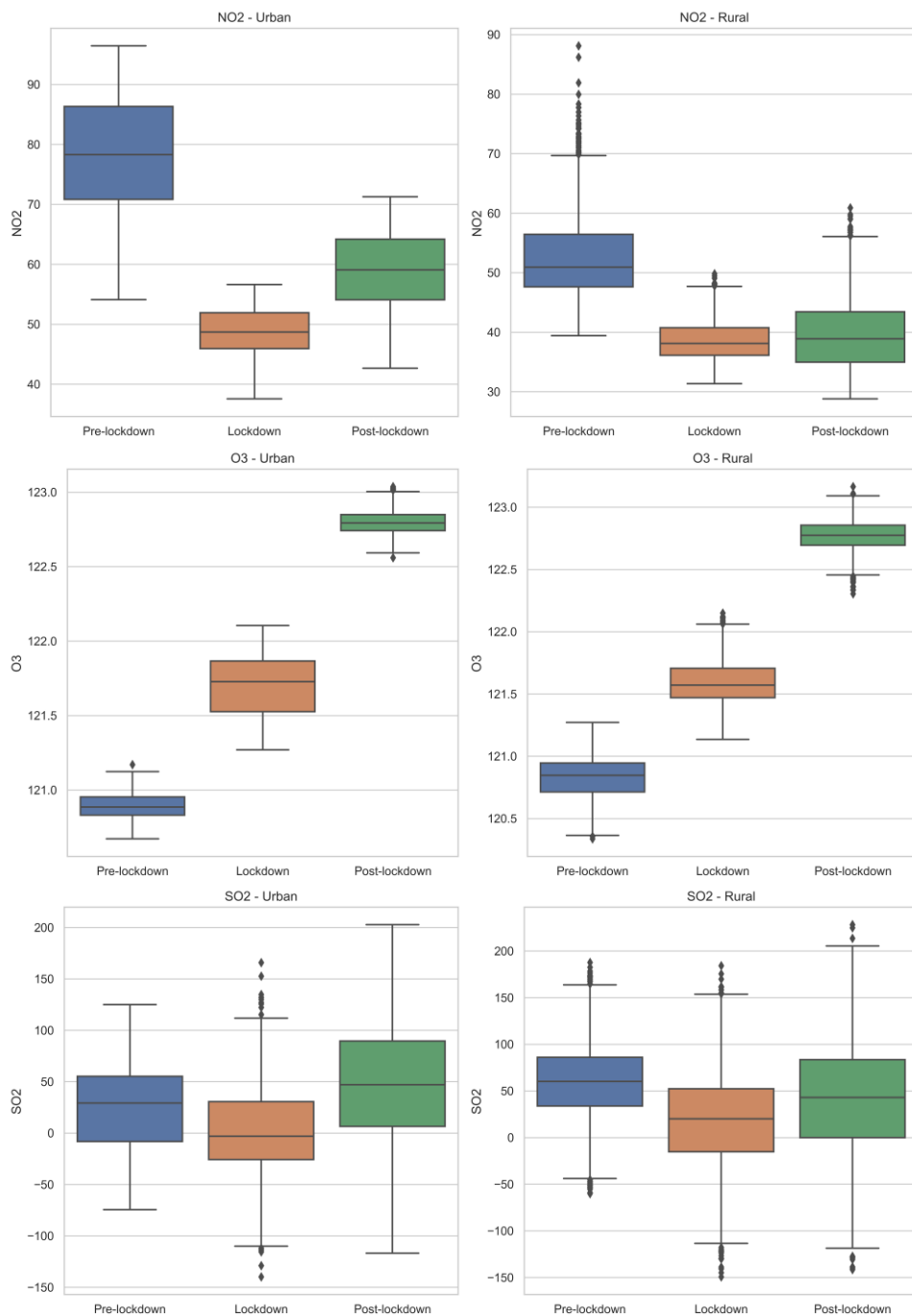


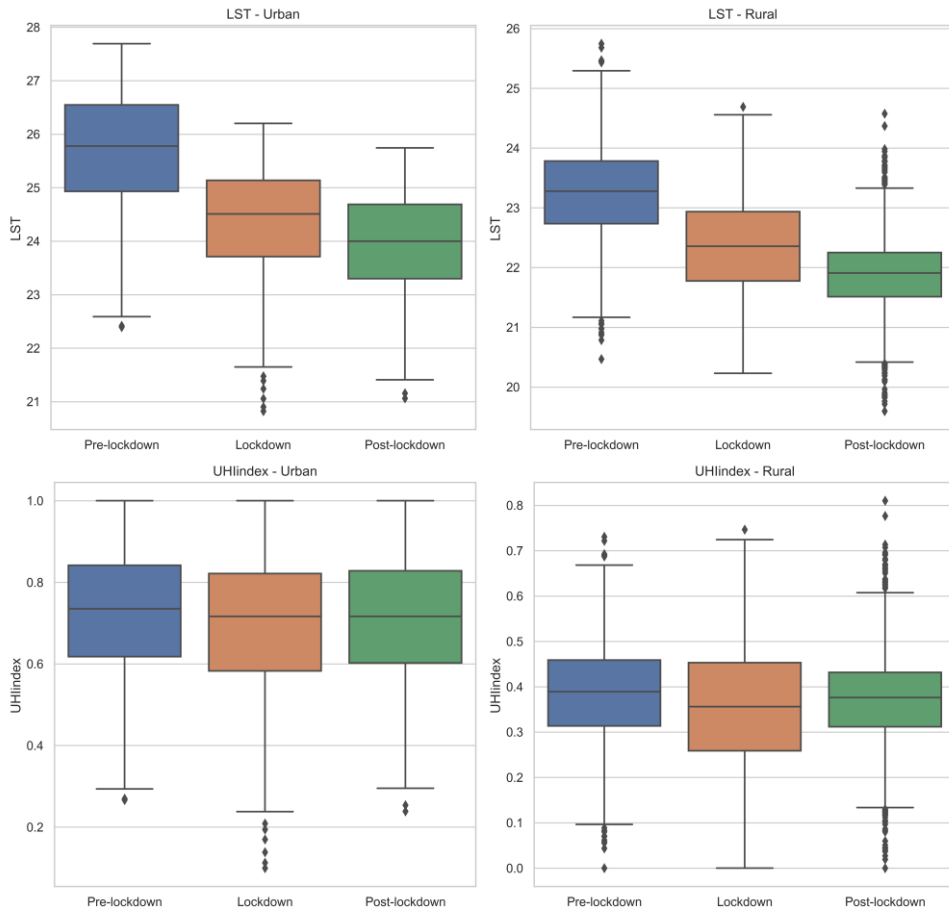




(a) Bangalore







(b) Hyderabad

The standard deviation and mean of the pollutants and LST in the current study areas are provided in Table 2.

Table 2: Standard deviation and mean of the LST and pollutants in Bangalore and Hyderabad.

			Pre-lockdown		Lockdown		Post-lockdown	
City	Parameter	Region/ Area	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation
Bangalore	CO	Urban	40.175	0.461	39.483	0.357	37.313	0.357
		Rural	38.755	0.714	38.918	0.45	37.187	0.86
	HCHO	Urban	259.692	14.718	225.493	21.006	193.302	17.315
		Rural	235.618	16.281	212.379	16.38	192.922	19.208
	AOD	Urban	0.803	0.131	0.592	0.07	0.787	0.106
		Rural	0.718	0.044	0.545	0.044	0.733	0.083

	NO ₂	Urban	77.784	9.429	38.76	3.284	46.551	6.131
		Rural	48.23	7.704	29.909	2.184	34.483	5.853
	O ₃	Urban	120.895	0.096	121.704	0.191	122.799	0.086
		Rural	120.832	0.157	121.595	0.175	122.774	0.125
	SO ₂	Urban	24.91	42.663	3.066	49.916	45.075	60.193
		Rural	58.157	40.887	18.688	50.66	42.216	61.165
	LST	Urban	25.732	1.012	24.371	1.015	23.965	0.945
		Rural	23.267	0.742	22.354	0.769	21.899	0.606
Hyderabad	UHI _{index}	Urban	0.729	0.14	0.693	0.17	0.711	0.154
		Rural	0.387	0.103	0.356	0.129	0.375	0.099
	CO	Urban	42.345	0.524	44.842	0.488	41.776	0.686
		Rural	41.57	0.74	44.53	0.59	41.252	0.519
	HCHO	Urban	262.947	14.635	258.724	13.281	242.937	15.652
		Rural	246.581	19.152	233.335	21.355	227.995	22.895
	AOD	Urban	0.648	0.112	0.686	0.112	0.983	0.077
		Rural	0.579	0.062	0.64	0.064	0.882	0.082
	NO ₂	Urban	78.242	9.745	48.667	4.076	59.036	6.446
		Rural	52.692	7.064	38.528	3.401	39.519	6.067
	O ₃	Urban	121.262	0.202	124.501	0.113	123.88	0.111
		Rural	121.141	0.228	124.376	0.175	123.865	0.141
	SO ₂	Urban	109.604	37.003	42.737	40.964	59.814	52.726
		Rural	106.185	48.029	26.989	53.937	91.108	62.883
	LST	Urban	28.245	0.732	27.667	0.659	26.702	0.725
		Rural	26.235	0.761	25.375	0.795	24.552	0.711
	UHI _{index}	Urban	0.751	0.114	0.797	0.091	0.716	0.124
		Rural	0.437	0.119	0.482	0.109	0.349	0.121

In Bangalore, HCHO levels exhibited a decreasing trend in urban areas from pre-lockdown to post-lockdown, with a similar pattern observed in rural areas but with some variability. The urban-rural disparity in HCHO levels was more pronounced throughout the pre-lockdown phase. The CO levels exhibited a decreasing trend in urban areas from pre-lockdown to post-lockdown and in the rural areas, it increased during the pre-lockdown to lockdown period and then decreased. Aerosols, SO₂ and NO₂ experienced a clear reduction in both urban region and rural region during the lockdown, followed by a partial recovery post-lockdown. Urban areas consistently exhibited higher aerosols, and NO₂ levels compared to rural areas across all periods. NO₂ levels reductions in the rural areas were less pronounced compared to the urban areas. O₃ levels increased from the pre-lockdown to

post-lockdown period in both urban region and rural region, with minor fluctuations. LST consistently showed higher values in urban regions compared to rural regions across all periods, with a slight decline from the pre-lockdown to post-lockdown phase. UHI_{index} in urban and rural areas decreased during the lockdown and showed a subsequent increase post-lockdown.

In Hyderabad, CO levels exhibited an overall increase during the lockdown, followed by a subsequent decrease post-lockdown in both urban and rural regions. HCHO levels decreased from the pre-lockdown to post-lockdown phase in the urban region and rural region. Aerosol levels increased during the lockdown and decreased during the post-lockdown in the urban region and rural region. NO₂ and SO₂ levels decreased during the lockdown in both urban and rural regions and increased throughout the post-lockdown phase. O₃ levels experienced an increase during the lockdown and a subsequent decrease post-lockdown in both settings. LST showed a slight decrease from the pre-lockdown period to the post-lockdown phase. Urban areas consistently reported higher LST values. UHI_{index} increased during the lockdown and decreased post-lockdown in both the settings. Table 3 presents the results of the independent samples t-test, which examines the urban-rural gradient of pollutants and LST in the research locations.

Table 3: An independent samples t-test was used to examine the urban and rural gradient of pollutants and LST in Bangalore and Hyderabad.

City	Parameter	t	Significance		Mean Difference	Std. Error Difference	Time period
			One-Sided p	Two-Sided p			
Bangalore	CO	44.199	.000	.000	1.420	.032	Pre-lockdown
	HCHO	31.469	<.001	<.001	24.074	.765	
	LST	64.074	.000	.000	2.466	.038	
	UHI _{index}	64.066	.000	.000	.342	.005	
	NO ₂	76.400	.000	.000	29.554	.387	
	O ₃	9.037	<.001	<.001	.064	.007	
	AOD	25.352	<.001	<.001	.085	.003	
	SO ₂	-16.835	<.001	<.001	-33.247	1.975	Lockdown
	CO	27.268	<.001	<.001	.565	.021	
	HCHO	15.737	<.001	<.001	13.115	.833	
	LST	51.115	.000	.000	2.017	.039	
	UHI _{index}	51.111	.000	.000	.338	.007	
	NO ₂	75.610	.000	.000	8.851	.117	
	O ₃	12.834	<.001	<.001	.109	.009	
	AOD	19.774	<.001	<.001	.048	.002	
	SO ₂	-6.460	<.001	<.001	-15.621	2.418	Post-lockdown
	CO	3.361	<.001	<.001	.126	.038	
	HCHO	.421	.337	.674	.380	.902	
	LST	62.764	.000	.000	2.067	.033	
	UHI _{index}	62.767	.000	.000	.336	.005	
	NO ₂	42.649	<.001	<.001	12.068	.283	
	O ₃	4.434	<.001	<.001	.025	.006	
	AOD	12.688	<.001	<.001	.054	.004	
	SO ₂	.979	.164	.327	2.859	2.919	
Hyderabad	CO	25.591	<.001	<.001	.775	.030	Pre-lockdown
	HCHO	20.690	<.001	<.001	16.366	.791	
	LST	61.663	.000	.000	2.010	.033	
	UHI _{index}	61.663	.000	.000	.314	.005	
	NO ₂	76.986	.000	.000	25.550	.332	

	O ₃	12.523	<.001	<.001	.121	.010	
	AOD	21.134	<.001	<.001	.069	.003	
	SO ₂	1.722	.043	.085	3.419	1.986	
	CO	12.680	<.001	<.001	.312	.025	Lockdown
	HCHO	29.437	<.001	<.001	25.388	.862	
	LST	68.959	.000	.000	2.291	.033	
	UHI _{index}	68.962	.000	.000	.315	.005	
	NO ₂	66.168	.000	.000	10.139	.153	
	O ₃	17.685	<.001	<.001	.126	.007	
	AOD	13.749	<.001	<.001	.045	.003	
	SO ₂	7.074	<.001	<.001	15.747	2.226	
	CO	21.819	<.001	<.001	.524	.024	
	HCHO	16.010	<.001	<.001	14.942	.933	Post-lockdown
	LST	69.729	.000	.000	2.150	.031	
	UHI _{index}	69.729	.000	.000	.367	.005	
	NO ₂	73.553	.000	.000	19.517	.265	
	O ₃	2.488	.006	.013	.015	.006	
	AOD	28.818	<.001	<.001	.101	.004	
	SO ₂	-11.892	<.001	<.001	-31.294	2.631	

In Bangalore:

Throughout the pre-lockdown phase, the urban-rural gradient in the pollutant levels is in the order - NO₂, CO, HCHO, AOD, and O₃ with the urban areas reporting higher pollutant concentrations. SO₂ reports lower concentration in the urban regions compared to the rural regions throughout the pre-lockdown and lockdown phase. Throughout the post-lockdown, HCHO and SO₂ doesn't exhibit a significant urban-rural gradient. During the lockdown period, the urban-rural gradient in the pollutant levels is in the order - NO₂, CO, AOD, HCHO, and O₃ with the urban areas reporting higher pollutant concentrations. During the post-lockdown period, the urban-rural gradient in the pollutant levels is in the order - NO₂, AOD, O₃, and CO, with the urban areas reporting higher pollutant concentrations. Compared to the pre-lockdown, during the lockdown, there is a reduction in urban-rural pollutant gradient and is in the order NO₂, SO₂, HCHO, CO, and AOD. Interestingly, compared to the pre-lockdown phase, during the lockdown phase, there is a rise in urban-rural pollutant gradient of O₃ concentrations.

In Hyderabad:

Throughout the pre-lockdown phase, the urban-rural gradient in the pollutant levels is in the order - NO₂, CO, AOD, HCHO, and O₃, with the urban areas reporting higher pollutant concentrations. SO₂ doesn't exhibit a significant urban-rural gradient during the pre-lockdown period and O₃ doesn't exhibit a significant urban-rural gradient post-lockdown phase. Throughout the lockdown phase, the urban-rural gradient in the pollutant levels is in the order - NO₂, HCHO, O₃, AOD, CO, and SO₂, with the urban areas reporting higher pollutant concentrations. Throughout the post-lockdown phase, the urban-rural gradient in the pollutant levels is in the order - NO₂, AOD, CO, HCHO, and SO₂, with the urban areas reporting higher pollutant concentrations. Compared to the pre-lockdown phase, throughout the lockdown phase, there is a reduction in urban-rural pollutant gradient and is in the order NO₂, CO, and AOD. Interestingly, compared to the pre-lockdown phase, throughout the lockdown phase, there is a rise in urban-rural pollutant gradient of HCHO, and O₃ concentrations.

Both cities show a general reduction in urban-rural pollutant gradients during the lockdown, with a consistent decrease in NO₂, CO, and AOD concentrations. Bangalore experiences an unexpected rise in the urban-rural gradient of O₃ concentrations during the lockdown, while Hyderabad sees an increase in the urban-rural gradient of HCHO, and O₃.

The ANOVA analysis of the LST and for the entire study areas is provided in Table 4. The ANOVA demonstrates that LST and pollutant concentrations varied significantly in both study locations.

Table 4: ANOVA analysis of the LST and pollutants for the entire Bangalore and Hyderabad study areas.

City	Parameter	Sum of Squares	Mean Square	F	Sig.
Bangalore	CO	6024.895	3012.447	5538.650	.000
	HCHO	3064983.969	1532491.984	4447.042	.000
	LST	2989.161	1494.581	1089.889	.000
	UHI _{index}	1.443	.721	21.829	<.001
	NO ₂	752234.159	376117.079	3995.061	.000
	O ₃	5153.560	2576.780	110485.149	.000
	AOD	62.315	31.158	5419.633	.000
	SO ₂	1909499.279	954749.639	349.912	<.001
Hyderabad	CO	20713.903	10356.951	24161.911	.000
	HCHO	596965.137	298482.569	646.000	<.001
	LST	4521.801	2260.901	1724.808	.000
	UHI _{index}	25.294	12.647	404.316	<.001
	NO ₂	567598.967	283799.484	2895.172	.000
	O ₃	19881.338	9940.669	297444.023	.000
	AOD	179.724	89.862	12953.866	.000
	SO ₂	10286962.936	5143481.468	1776.175	.000

Table 5 shows the post hoc LST and pollutant analysis for the entire study regions.

Table 5: Post hoc analysis of the LST and pollutants for the entire Bangalore and Hyderabad study areas.

City	Parameter	(I) Year	(J) Year	Mean Difference (I-J)	Std. Error	Sig.
Bangalore	CO	Lockdown	Pre-lockdown	-0.008	0.019	0.962
			Post-lockdown	1.820	0.018	.000
	HCHO		Pre-lockdown	-25.442	0.5	<.001
			Post-lockdown	22.016	0.502	<.001
	LST		Pre-lockdown	-1.002	0.033	<.001
			Post-lockdown	.446	0.03	<.001
	UHI _{index}		Pre-lockdown	-.032	0.005	<.001
			Post-lockdown	-.019	0.005	<.001

	NO ₂		Pre-lockdown	-22.481	0.287	.000
			Post-lockdown	-5.220	0.168	.000
	O ₃		Pre-lockdown	.773	0.005	.000
			Post-lockdown	-1.162	0.004	.000
	AOD		Pre-lockdown	-.181	0.002	.000
			Post-lockdown	-.190	0.002	.000
	SO ₂		Pre-lockdown	-35.928	1.282	.000
			Post-lockdown	-27.242	1.524	.000
Hyderabad	CO	Lockdown	Pre-lockdown	2.866	0.017	<.001
			Post-lockdown	3.235	0.015	<.001
	HCHO		Pre-lockdown	-11.404	0.517	<.001
			Post-lockdown	7.472	0.552	<.001
	LST		Pre-lockdown	-.802	0.028	<.001
			Post-lockdown	.852	0.029	<.001
	UHI _{index}		Pre-lockdown	.045	0.004	<.001
			Post-lockdown	.122	0.004	<.001
	NO ₂		Pre-lockdown	-17.309	0.243	0
			Post-lockdown	-2.905	0.198	0
	O ₃		Pre-lockdown	3.236	0.005	<.001
			Post-lockdown	.533	0.004	<.001
	AOD		Pre-lockdown	.056	0.002	<.001
			Post-lockdown	-.253	0.002	<.001
	SO ₂		Pre-lockdown	-76.680	1.207	<.001
			Post-lockdown	-54.519	1.41	<.001

In Bangalore:

Pollutant levels for AOD, HCHO, SO₂, and NO₂ reduced over the whole investigation region during the lockdown phase, as compared to the pre-lockdown phase. Conversely, the concentration of O₃ increased during the lockdown phase compared to the pre-lockdown phase. Additionally, LST decreased across the entire study area throughout the lockdown phase compared to the pre-lockdown phase. Subsequently, during the post-lockdown phase, CO and HCHO values decreased in comparison to the lockdown phase. Additionally, the LST also decreased. However, NO₂, O₃, AOD, and SO₂ increased during the post-lockdown phase compared to the lockdown phase.

In Hyderabad:

Across the entire study area, levels of pollutants such as HCHO, NO₂, and SO₂ decreased during the lockdown phase compared to the pre-lockdown phase. However, concentrations of CO, O₃, and AOD increased during the lockdown phase compared to the pre-lockdown phase. Additionally, LST decreased across the entire study area throughout the lockdown phase compared to the pre-lockdown phase. Subsequently, throughout the post-lockdown phase, CO and HCHO values decreased compared to the lockdown phase. Additionally, the LST also decreased. However, NO₂, AOD, O₃, and SO₂ increased during the post-lockdown phase compared to the lockdown phase.

The ANOVA analysis of the LST and pollutants for the urban area in the study areas is provided in Table 6.

Table 6: ANOVA analysis of the LST and pollutants for the Bangalore and Hyderabad urban areas.

City	Parameter	Sum of Squares	Mean Square	F	Sig.
Bangalore	CO	2434.112	1217.056	7815.136	.000
	HCHO	1203672.393	601836.197	1885.316	.000
	LST	935.460	467.730	475.765	<.001
	UHI _{index}	.345	.173	7.171	<.001
	NO ₂	465750.912	232875.456	5089.304	.000
	O ₃	996.992	498.496	28261.707	.000
	AOD	15.036	7.518	682.269	<.001
	SO ₂	482027.966	241013.983	91.121	<.001
Hyderabad	CO	3586.004	1793.002	5477.099	.000
	HCHO	149956.532	74978.266	353.917	<.001
	LST	818.896	409.448	820.759	<.001
	UHI _{index}	2.230	1.115	91.453	<.001
	NO ₂	303547.534	151773.767	2973.329	.000
	O ₃	3984.515	1992.257	90562.083	.000
	AOD	45.472	22.736	2210.732	.000
	SO ₂	1627023.688	813511.844	418.809	<.001

The post hoc analysis of the LST and pollutants for the urban area in both the study areas is provided in Table 7.

Table 7: Post hoc LST and pollutant analysis for Bangalore and Hyderabad urban areas.

City	Parameter	(I) Year	(J) Year	Mean Difference (I-J)	Std. Error	Sig.
Bangalore	CO	Lockdown	Pre-lockdown	-.691	0.025	<.001
			Post-lockdown	2.170	0.022	<.001
	HCHO		Pre-lockdown	-34.199	1.098	<.001
			Post-lockdown	32.192	1.165	<.001
	LST		Pre-lockdown	-1.361	0.061	<.001
			Post-lockdown	.406	0.059	<.001
	UHI _{index}		Pre-lockdown	-.036	0.009	<.001
			Post-lockdown	-0.017	0.01	0.21
	NO ₂		Pre-lockdown	-39.024	0.427	.000
			Post-lockdown	-7.790	0.298	<.001
	O ₃		Pre-lockdown	.809	0.009	.000
			Post-lockdown	-1.095	0.009	.000
	AOD		Pre-lockdown	-.211	0.006	<.001
			Post-lockdown	-.194	0.005	<.001
SO ₂	Pre-lockdown	-21.844	2.81	<.001		
	Post-lockdown	-42.009	3.347	<.001		
Hyderabad	CO	Lockdown	Pre-lockdown	2.497	0.028	.000
			Post-lockdown	3.066	0.032	<.001
	HCHO		Pre-lockdown	-4.223	0.761	.000
			Post-lockdown	15.787	0.791	.000
	LST		Pre-lockdown	-.578	0.038	.000
			Post-lockdown	.965	0.038	.000
	UHI _{index}		Pre-lockdown	.046	0.006	.000
			Post-lockdown	.081	0.006	.000
	NO ₂		Pre-lockdown	-29.575	0.407	<.001

	O ₃		Post-lockdown	-10.369	0.294	<.001
			Pre-lockdown	3.240	0.009	<.001
			Post-lockdown	.622	0.006	.000
			Pre-lockdown	.038	0.006	.000
	AOD		Post-lockdown	-.297	0.005	<.001
			Pre-lockdown	-66.867	2.126	.000
	SO ₂		Post-lockdown	-17.077	2.572	.000
			Pre-lockdown			

In Bangalore:

In the urban area, pollutant levels including CO, HCHO, NO₂, AOD, and SO₂ decreased throughout the lockdown phase compared to the pre-lockdown phase. However, O₃ concentrations increased throughout the lockdown phase compared to the pre-lockdown period. Additionally, both LST and UHI_{index} decreased during the lockdown period compared to the pre-lockdown period. During the post-lockdown period, CO and HCHO values decreased compared to the lockdown phase, as did LST. However, NO₂, SO₂, O₃, and AOD, increased during the post-lockdown period compared to the lockdown phase. No significant difference in the UHI_{index} was observed between the lockdown and post-lockdown phases.

In Hyderabad:

In the urban area, levels of pollutants such as SO₂, NO₂, and HCHO declined throughout the lockdown phase compared to the pre-lockdown phase. Conversely, concentrations of CO, O₃, and AOD increased throughout the lockdown phase compared to the pre-lockdown phase. Moreover, there was a decrease in LST during the lockdown phase in contrast to the pre-lockdown phase. However, the UHI_{index} exhibited an increase during the lockdown phase compared to the pre-lockdown phase. Subsequently, during the post-lockdown phase, both CO and HCHO values decreased compared to the lockdown phase, alongside reductions in LST and the UHI_{index}. Nevertheless, NO₂, AOD, SO₂, and O₃ showed an increase during the post-lockdown period compared to the lockdown phase.

The ANOVA analysis of the LST and pollutants for the rural area in the study areas is provided in Table 8. The ANOVA analysis displays that there is a substantial difference in the LST and pollutant concentration in the rural area of both the study areas.

Table 8: ANOVA analysis of the pollutants and LST for the Bangalore and Hyderabad rural areas.

City	Parameter	Sum of Squares	Mean Square	F	Sig.
Bangalore	CO	3968.258	1984.129	4098.572	.000
	HCHO	1984009.036	992004.518	3298.250	.000
	LST	2106.530	1053.265	2093.453	.000
	UHI _{index}	1.104	.552	44.932	<.001
	NO ₂	394788.841	197394.421	6018.859	.000
	O ₃	4158.121	2079.060	87927.300	.000
	AOD	47.640	23.820	6626.571	.000

	SO ₂	1711898.947	855949.474	321.809	<.001
Hyderabad	CO	17185.510	8592.755	22118.651	.000
	HCHO	481439.958	240719.979	536.103	<.001
	LST	3724.125	1862.062	3252.573	.000
	UHI _{index}	24.043	12.021	884.711	.000
	NO ₂	328756.337	164378.169	5017.973	.000
	O ₃	15901.051	7950.525	231949.382	.000
	AOD	135.087	67.543	13700.703	.000
	SO ₂	9298299.355	4649149.677	1520.938	.000

The post hoc analysis of the LST and pollutants for the rural area in both the study areas is provided in Table 9.

Table 9: Post hoc analysis of the LST and pollutants for the Bangalore and Hyderabad rural areas.

City	Parameter	(I) Year	(J) Year	Mean Difference (I-J)	Std. Error	Sig.
Bangalore	CO	Lockdown	Pre-lockdown	.163	0.018	.000
			Post-lockdown	1.731	0.021	.000
	HCHO		Pre-lockdown	-23.239	0.496	.000
			Post-lockdown	19.457	0.542	.000
	LST		Pre-lockdown	-.912	0.023	.000
			Post-lockdown	.456	0.021	.000
	UHI _{index}		Pre-lockdown	-.032	0.004	.000
			Post-lockdown	-.019	0.003	.000
	NO ₂		Pre-lockdown	-18.321	0.172	<.001
			Post-lockdown	-4.574	0.134	<.001
	O ₃		Pre-lockdown	.763	0.005	.000
			Post-lockdown	-1.179	0.005	.000
	AOD		Pre-lockdown	-.173	0.001	.000
			Post-lockdown	-.189	0.002	.000
	SO ₂		Pre-lockdown	-39.470	1.397	.000

			Post-lockdown	-23.529	1.705	.000
Hyderabad	CO	Lockdown	Pre-lockdown	2.960	0.018	.000
			Post-lockdown	3.278	0.015	.000
	HCHO		Pre-lockdown	-13.245	0.559	.000
			Post-lockdown	5.340	0.611	.000
	LST		Pre-lockdown	-.859	0.021	.000
			Post-lockdown	.824	0.021	.000
	UHI _{index}		Pre-lockdown	.045	0.003	.000
			Post-lockdown	.133	0.003	.000
	NO ₂		Pre-lockdown	-14.164	0.153	.000
			Post-lockdown	-.991	0.136	.000
	O ₃		Pre-lockdown	3.235	0.006	.000
			Post-lockdown	.510	0.004	.000
	AOD		Pre-lockdown	.061	0.002	.000
			Post-lockdown	-.242	0.002	.000
	SO ₂		Pre-lockdown	-79.196	1.409	.000
			Post-lockdown	-64.118	1.616	.000

In Bangalore:

In the rural area, levels of pollutants such as HCHO, NO₂, AOD, and SO₂ decreased during the lockdown phase compared to the pre-lockdown phase. However, concentrations of CO and O₃ increased during the lockdown phase compared to the pre-lockdown phase. Additionally, both LST and UHI_{index} decreased during the lockdown phase compared to the pre-lockdown phase. Subsequently, throughout the post-lockdown phase, both CO and HCHO values decreased compared to the lockdown phase, as did LST. However, NO₂, AOD, O₃, and SO₂ showed an increase throughout the post-lockdown phase compared to the lockdown phase. Moreover, the UHI_{index} increased throughout the post-lockdown phase compared to the lockdown phase.

In Hyderabad:

In the rural area, levels of pollutants such as HCHO, SO₂, and NO₂ decreased during the lockdown phase compared to the pre-lockdown phase. However, concentrations of CO, O₃, and AOD increased during the lockdown phase compared to the pre-lockdown period. Additionally, LST decreased during the lockdown period compared to the pre-lockdown phase. However, the UHI_{index} increased during the lockdown phase compared to the pre-lockdown phase. Subsequently, throughout the post-lockdown phase, values for CO,

HCHO, and O_3 decreased compared to the lockdown phase, as did LST and the UHI_{index} . However, NO_2 , AOD, and SO_2 increased during the post-lockdown phase compared to the lockdown phase.

DISCUSSION

The spatio-temporal maps of the study areas depicted the pollution distribution, the key features of the statistical distribution of the pollutant levels in the urban region and rural region was visualized using the box plots, the gradient in the pollutant concentration and the significance of the gradient was analysed using the difference in the pollutant concentration, and the independent samples t-test in the study areas were quantified and its significance was measured using the ANOVA and post-hoc analysis to provide a complete overview of the pollutant distribution and changes. The key findings from this analysis are:

In Bangalore:

Urban regions have considerably higher concentrations of CO_2 than rural regions. The highest mean difference was observed to be 1.420 mmol/m^2 (pre-lockdown). A significant change in the CO levels throughout the lockdown, pre-lockdown, and post-lockdown phase was observed. The CO levels in the urban areas were observed to be decreasing from the pre-lockdown to post-lockdown. In the rural areas, CO levels increased from pre-lockdown to lockdown and then increased.

The concentration of HCHO is considerably greater in urban regions as compared to rural regions. The highest mean difference was observed to be $24.074 \text{ } \mu\text{mol/m}^2$ (pre-lockdown). A significant change in the HCHO levels throughout the lockdown, pre-lockdown, and post-lockdown period was observed. The HCHO levels in the urban and rural areas were observed to be decreasing from the pre-lockdown to post-lockdown.

The levels of AOD in urban regions are considerably greater in comparison to those in rural regions. The highest mean difference was observed to be 0.085 (pre-lockdown). A significant change in the AOD levels throughout the lockdown, pre-lockdown, and post-lockdown period was observed. The AOD levels in the urban and rural areas were noticed to be lesser in the lockdown phase.

The levels of NO_2 in urban regions are considerably greater in comparison to those in rural regions. The highest mean difference was observed to be $29.554 \text{ } \mu\text{mol/m}^2$ (during pre-lockdown period). A significant change in the NO_2 levels throughout the lockdown, pre-lockdown, and post-lockdown period was observed. The NO_2 levels in the urban and rural areas were found to be lower in the lockdown phase.

The levels of O_3 in urban regions are considerably greater in comparison to those in rural regions. The highest mean difference was observed to be 0.109 mmol/m^2 (lockdown). A significant change in the O_3 levels throughout the lockdown, pre-lockdown, and post-lockdown period was observed. The O_3 levels in the urban and rural areas were observed to be increasing from the pre-lockdown to post-lockdown.

The levels of SO_2 in rural regions are considerably greater in comparison to those in urban regions. The highest mean difference was observed to be $33.247 \text{ } \mu\text{mol/m}^2$ (during pre-lockdown period). A significant change in the SO_2 levels during the pre-lockdown, lockdown and post-lockdown period was observed. The SO_2 levels in the urban and rural areas were observed to be lower in the lockdown period.

During the pre-lockdown phase, the urban-rural gradient in pollution concentration is in the order - NO_2 , CO, HCHO, AOD, and O_3 , NO_2 having the largest gradient and O_3 has the

least gradient. During the lockdown period, the urban-rural gradient in pollution concentration is in the order - NO₂, CO, AOD, HCHO, and O₃, NO₂ having the largest gradient and O₃ has the least gradient. During the post-lockdown phase, the urban-rural gradient in pollution concentration is in the order - NO₂, AOD, O₃, and CO, NO₂ having the largest gradient and CO has the least gradient. Compared to the pre-lockdown phase, during the lockdown phase, there is a reduction in urban-rural pollutant gradient and is in the order NO₂, SO₂, HCHO, CO, and AOD. Interestingly, compared to the pre-lockdown phase, during the lockdown phase, there is a rise in urban-rural pollutant gradient of O₃ concentrations.

The LST in urban regions is considerably greater than that of rural regions. The highest mean difference was observed to be 2.466 °C (pre-lockdown). A significant change in the LST throughout the pre-lockdown, lockdown and post-lockdown phase was observed. The LST in the urban and rural areas were observed to be decreasing from the pre-lockdown to post-lockdown.

The UHI effects are found to be higher in the urban regions compared to the rural regions. The UHI effects are found to be lower in the lockdown phase.

In Hyderabad:

The levels of CO in urban regions are considerably greater in comparison to those in rural regions. The highest mean difference was observed to be 0.775 mmol/m² (pre-lockdown). A significant change in the CO levels throughout the lockdown, pre-lockdown, and post-lockdown period was observed. The CO levels were found to be highest during the lockdown phase.

The levels of HCHO in urban regions are considerably greater in comparison to those in rural regions. The highest mean difference was observed to be 25.388 µmol/m² (during lockdown period). A significant change in the HCHO levels throughout the lockdown, pre-lockdown, and post-lockdown period was observed. The HCHO levels in the urban and rural areas were observed to be decreasing from the pre-lockdown to post-lockdown.

The levels of AOD in urban regions are considerably greater in comparison to those in rural regions. The highest mean difference was observed to be 0.101 (post-lockdown). A significant change in the AOD levels throughout the lockdown, pre-lockdown, and post-lockdown period was observed. The AOD levels in the urban and rural areas were observed to be increasing from the pre-lockdown to post-lockdown phase.

The levels of NO₂ in urban regions are considerably greater in comparison to those in rural regions. The highest mean difference was observed to be 25.550 µmol/m² (pre-lockdown). A significant change in the NO₂ levels throughout the lockdown, pre-lockdown, and post-lockdown period was observed. The NO₂ levels in the urban and rural areas were observed to be lower in the lockdown phase.

The levels of O₃ in urban regions are considerably greater in comparison to those in rural regions. The highest mean difference was observed to be 0.126 mmol/m² (during lockdown period). A significant change in the O₃ levels throughout the lockdown, pre-lockdown, and post-lockdown period was observed. The O₃ levels in the urban areas were observed to be increasing from the pre-lockdown to post-lockdown. The O₃ levels in the rural areas were observed to be higher in the lockdown phase.

A consistent significant urban-rural gradient in the SO₂ levels were not observed in the current investigation. A significant change in the SO₂ levels during the lockdown, pre-lockdown, and post-lockdown period was observed. The SO₂ levels in the urban and rural areas were observed to be lower in the lockdown phase.

During the pre-lockdown phase, the urban-rural gradient in pollution concentration is in the order - NO₂, CO, AOD, HCHO, and O₃, NO₂ having the largest gradient and O₃ has the

least gradient. During the lockdown period, the urban-rural gradient in pollution concentration is in the order - NO₂, HCHO, O₃, AOD, CO, and SO₂, NO₂ having the largest gradient and SO₂ has the least gradient. During the post-lockdown period, the urban-rural gradient in pollution concentration is in the order - NO₂, AOD, CO, HCHO, and SO₂, NO₂ having the largest gradient and SO₂ has the least gradient. Compared to the pre-lockdown phase, during the lockdown, there is a reduction in urban-rural pollutant gradient and is in the order NO₂, CO, and AOD. Interestingly, compared to the pre-lockdown, during the lockdown, there is a rise in urban-rural pollutant gradient of HCHO, and O₃ concentrations.

The levels of LST in urban regions are considerably greater in comparison to those in rural regions. The highest mean difference was observed to be 2.291 °C (lockdown). A significant change in the LST throughout the lockdown, pre-lockdown, and post-lockdown period was observed. The LST in the urban and rural areas were observed to be decreasing from the pre-lockdown to post-lockdown.

The UHI effects are found to be higher in the urban regions compared to the rural regions. The UHI effects are found to be higher in the lockdown period.

Generally, for both the study areas, NO₂, CO, and AOD shows the highest significant urban-rural pollutant gradient level. The comparative results reveal that the environmental response to lockdown was not uniform between the two cities. Bangalore exhibited a more consistent reduction in CO, HCHO, AOD, NO₂, SO₂, LST, and UHI index during lockdown, suggesting that reduced traffic, industrial activity, and anthropogenic heat release had a direct moderating effect on its urban environment. Similar reductions in traffic-related pollutants and urban thermal intensity during lockdown have also been reported in previous studies (Alqasemi *et al.*, 2021; Liu *et al.*, 2022; Sicard *et al.*, 2020). The stronger reduction observed in Bangalore may also be related to its relatively greater vegetation influence, moderate climatic setting, and service-sector-dominated urban structure, where lockdown restrictions directly reduced mobility and commercial activity. In contrast, Hyderabad showed reductions in NO₂, HCHO, SO₂, and LST, but CO, AOD, O₃, and UHI index increased during the lockdown period. This indicates that Hyderabad's warmer background climate and mixed urban-industrial-peri-urban setting may have supported higher or more persistent CO, AOD, and O₃ levels during lockdown. Similar studies have reported that lockdown-related pollutant changes vary across cities depending on local emission sources, meteorology, land use, and atmospheric chemistry (Biswal *et al.*, 2021; Biswas *et al.*, 2021; Parida *et al.*, 2021). The increase in O₃ during lockdown may be associated with reduced NO titration and altered photochemical reactions under lower NO₂ conditions, as observed in other urban lockdown studies (Dantas *et al.*, 2020; Nakada & Urban, 2020; Sicard *et al.*, 2020). Thus, the comparison demonstrates that lockdown-induced environmental changes are strongly city-specific, and similar restrictions can produce different pollutant and thermal responses depending on local emission structure, land cover, meteorology, and climatic setting.

Compared with earlier lockdown-related studies, the present study provides a more integrated interpretation by jointly analysing air pollutants, LST, UHI index, and urban-rural gradients for two rapidly growing Indian metropolitan cities. Previous studies over India reported substantial reductions in NO₂, HCHO, SO₂, and aerosols during the lockdown period, mainly due to reduced vehicular movement, industrial activity, and other anthropogenic emissions (Biswas *et al.*, 2021; Biswal & Ayantika, 2021). Similarly, Parida *et al.* (2021) observed that lockdown restrictions influenced aerosol loading, LST, and urban heat conditions across Indian cities, while Jallu *et al.* (2022) reported that lockdown-induced changes in surface urban heat intensity varied according to land use/land cover conditions. In comparison, the present study shows that Bangalore and Hyderabad did not respond in the

same way, even though both are rapidly growing southern Indian cities. Bangalore showed a more consistent reduction in pollutants, LST, and UHI index during lockdown, whereas Hyderabad showed a mixed response, with increases in CO, AOD, O₃, and UHI index. This difference indicates that lockdown-induced environmental improvement is not controlled only by reduced emissions, but also by local emission structure, land-cover composition, background meteorology, and atmospheric chemistry. The observed increase in O₃ during lockdown is also consistent with Sicard *et al.* (2020), who reported that reduced NO emissions can weaken NO titration and enhance urban ozone formation. Therefore, the significance of this study lies in demonstrating that air-quality improvement and UHI reduction during temporary activity restrictions are city-specific, and that urban environmental management should adopt multi-pollutant, land-cover-sensitive, and city-specific mitigation strategies rather than applying a single generalized approach. Recent Indian urban air-quality studies also show that pollutant behaviour is strongly controlled by local emissions, meteorology, and city-specific conditions. Suhas *et al.* (2025), for example, analysed PM_{2.5} and PM₁₀ in Ghaziabad and found frequent exceedance of permissible limits, strong winter pollution enhancement, and good predictive performance using XGBoost. Although the present study focuses on satellite-derived pollutants, LST, and UHI response during lockdown, these findings support our interpretation that air-quality changes cannot be generalized across cities and require location-specific assessment.

In the wake of the COVID-19 pandemic, studies exploring the interplay between lockdown measures, air quality dynamics, and UHIs have gained significant traction (Alqasemi *et al.*, 2021; Kerimray *et al.*, 2020; Dantas *et al.*, 2020). Recent research has underscored the complex relationship between anthropogenic activities, pollutant concentrations, and urban environmental conditions. The findings of these studies contribute to our understanding of how temporary restrictions on human mobility and economic activities impact air quality and urban heat patterns. Numerous studies have examined the impact of COVID-19 lockdowns on air quality in urban areas. For instance, research conducted by Sicard *et al.* (2020) in major cities across Europe found significant reductions in NO₂ and particulate matter (PM) concentrations during lockdown periods. Similarly, studies in India by Sharma *et al.* (2020) observed substantial declines in air pollutant levels, attributed to reduced industrial activities and vehicular emissions during lockdowns. The findings from these studies underscore the importance of sustainable urban development and environmental management practices. Urban planning strategies that prioritize green infrastructure, sustainable transportation, and efficient land use can mitigate the effects of urban heat islands and improve air quality (Arunab & Mathew, 2024). Moreover, The COVID-19 pandemic has shown that temporary interventions, such as lockdowns, to offer insights into the feasibility and efficacy of long-term air quality improvement measures (Bao & Zhang, 2020).

This research meticulously examines the complex interplay between air quality, the UHI effect, and lockdown measures in Bangalore and Hyderabad. The findings echo recent studies (Meda & Mathew, 2022; He *et al.*, 2020; Kang *et al.*, 2022; Chang *et al.*, 2022). Consistent with other research, significant reductions in traffic-related NO₂ emissions were observed during the lockdown in both cities, highlighting the substantial contribution of vehicles to air quality concerns (He *et al.*, 2020). The rise of CO in rural areas of Bangalore during lockdown suggests potential local emission sources like biomass burning, aligning with research by Singh & Chauhan (2020). Conversely, Hyderabad's CO peak might indicate localized industrial or waste-related emissions. The decline of pollutants like formaldehyde (HCHO), often associated with industrial processes, and AOD, linked to human activities, in both cities during lockdown strengthens the connection between human actions and air quality.

The observed decrease in LST in urban areas during lockdowns aligns with findings by Kang *et al.* (2022). This suggests that decreased anthropogenic heat sources like traffic and industrial activity can moderate the UHI effect. Long-term UHI studies in Indian cities support our finding that urban thermal conditions are strongly controlled by land cover and urban expansion. Gadekar *et al.* (2025) reported increasing nighttime LST and UHI trends in Coimbatore, indicating that UHI effects are structurally linked to built-up growth, vegetation loss, and impervious surfaces, and cannot be fully reversed by short-term reductions in human activity. This study emphasizes the need for sustainable urban planning strategies that prioritize green spaces, public transport infrastructure, and cleaner energy sources, aligning with the growing focus on creating "green cities" to improve air quality and mitigate the UHI effect (Huang *et al.*, 2018). It also strengthens the case for stricter emission regulations and the promotion of electric vehicles for long-term air quality improvement. The study underscores the complex interplay of various pollutants, highlighting the need for a multi-pollutant approach that addresses diverse emission sources for effective air quality management.

Overall, the research on the relationship between COVID-19 lockdowns, air quality dynamics, and UHIs provides valuable insights for policymakers and urban planners. By integrating these findings into urban development strategies, cities can mitigate the adverse effects of air pollution and climate change, promoting healthier and more sustainable urban environments.

CONCLUSIONS

The spatio-temporal analysis conducted in this study provides valuable insights into the variations in air pollution and associated environmental factors in Bangalore and Hyderabad. Key findings reveal important disparities in pollutant concentrations between urban region and rural region, with distinct trends observed across various parameters.

In Bangalore, CO levels exhibited a substantial urban-rural gradient, being significantly higher in urban areas compared to rural areas, with a mean difference of 1.420 mmol/m² throughout the pre-lockdown phase. However, a positive outcome of the lockdown is evident, as CO levels in urban areas decreased from pre-lockdown to post-lockdown, highlighting the positive impact of reduced anthropogenic activities. Conversely, rural areas experienced an initial increase in CO levels during the lockdown, followed by a subsequent rise. HCHO levels displayed a similar urban-rural gradient, with higher concentrations in urban areas. Notably, the lockdown led to a decrease in HCHO levels in both urban and rural areas. AOD levels exhibited a significant decrease in urban areas during the lockdown phase. NO₂ levels, another major urban pollutant, followed a similar trend with a significant reduction in urban areas during the lockdown. O₃ levels, typically higher in urban areas, increased during the lockdown, indicating a potential shift in atmospheric chemistry.

In Hyderabad, CO levels displayed an urban-rural gradient, with significantly higher concentrations in urban areas throughout the pre-lockdown phase. The highest mean difference was observed to be 0.775 mmol/m². Similar to Bangalore, CO levels were highest during the lockdown phase, emphasizing the impact of reduced restrictions on vehicular emissions. HCHO levels, higher in urban areas, decreased during the lockdown, aligning with reduced anthropogenic activities. AOD levels in urban areas increased during the post-lockdown period, suggesting a gradual resumption of industrial and vehicular activities. NO₂ levels, typically higher in urban areas, experienced a significant reduction during the lockdown. O₃ levels displayed a marked increase in urban areas during the lockdown,

indicating a complex interplay of atmospheric factors. Surprisingly, a consistent urban-rural gradient in SO₂ levels was not observed.

Overall, the study underscores the effectiveness of the lockdown measures in mitigating certain air pollutants in both cities, with variations influenced by specific local conditions and activities. The findings contribute to our understanding of the dynamic relationship between lockdown measures, air quality, and urban-rural pollutant gradients, paving the way for targeted environmental interventions and policies.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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