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RESEARCH

Factors influencing spatiotemporal variability of NO_2 concentration in urban area: a GIS and remote sensing–based approach

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Abstract The growing global attention on urban air quality underscores the need to understand the spatiotemporal dynamics of nitrogen dioxide (NO_2) and its environmental and anthropogenic factors, particularly in cities like Dhaka (Gazipur), Bangladesh, which suffers from some of the world's worst air quality. This study analysed NO_2 concentrations in Gazipur from 2019 to 2022 using Sentinel-5P TROPOMI data on the Google Earth Engine (GEE) platform. Correlations and regression analysis were done between NO_2 levels and various environmental factors, including land surface temperature (LST), normalized difference vegetation index (NDVI), land use and land cover (LULC), population density, road density, settlement density, and industry density. The results reveal significant seasonal variations. The highest annual mean NO_2 concentration (3.1×10^{-4} mol/ m^2)was recorded for winter 2021, and the lowest (1.1×10^{-4} mol/m^2) was for monsoon 2022. The study demonstrates a significant positive correlation between NO_2 concentrations and LST (0.47), road density (0.55), settlement density (0.44), and industrial density (0.35) and a negative correlation with NDVI (−0.4). Regression analysis revealed that NO_2 concentrations were positively associated with land surface temperature (LST; $\beta=0.02$, $R^2=0.22$), road density ($\beta=0.002$, $R^2=0.30$), settlement density ($\beta=0.002$, $R^2=0.19$), and industrial density ($\beta=0.007$, $R^2=0.12$), while a negative association was observed with NDVI ($\beta=-0.28$, $R^2=0.16$). This research offers critical insights for policymakers and urban planners, advocating for enhanced green infrastructure, stringent emission controls, and sustainable urban development strategies to mitigate air pollution in Gazipur. Our methodological approach and findings contribute to the broader discourse on urban air quality management in developing countries.

Keywords NO_2 · Concentration · Urban air quality · Spatiotemporal patterns · GIS · Gazipur-Dhaka

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Introduction

In tackling the global air pollution situation, diverse programs and policies at the international, regional, and local scales have been put in place aimed at fostering environmental sustainability and enhancing overall well-being (Melamed et al., 2016). Despite these efforts, air pollution persists as the fourth leading cause of premature death globally (Health Effects Institute, 2020) and remains the most substantial external threat to human life expectancy (Greenstone & Hasenkopf, 2023). Shockingly, it contributes to an annual toll of 6.67 million premature deaths (Health Effects Institute, 2020), with nitrogen dioxide (NO_2), an ambient air pollutant, playing a pivotal role among others (Song et al., 2023). NO_2 exerts adverse effects on both human health (Song et al., 2023) and the ecological environment (L. Li & Wu, 2021). It serves as a crucial precursor for anthropogenic ozone (O_3) and urban smog. This gaseous pollutant is a key player in the formation of other pollutants, such as nitric acid (HNO_3), fine particulate matter ($PM_{2.5}$), and nitro-polycyclic aromatic hydrocarbons (nitro-PAHs) (L. Li & Wu, 2021). A global analysis in 2019 found that 81% of cities exceeded WHO standards for NO_2, contributing to 2.7% of all mortalities that year (Song et al., 2023). Existing epidemiological evidence firmly establishes the link between ambient NO_2 exposure and an increased risk of adverse health outcomes (Stieb et al., 2021). Inhaling of increased NO_2 level can lead to throat and upper respiratory tract inflammation, resulting in breathing difficulties, throat spasms, and lung fluid accumulation (DoE, 2018). Additionally, it diminishes blood oxygen-carrying capacity, causing symptoms like headaches, fatigue, and dizziness (DoE, 2018). Recent research also indicates a positive correlation between atmospheric NO_2 levels and susceptibility to COVID-19 infection (Amoroso et al., 2022; Zhu et al., 2020). Long-term exposure to NO_2 poses significant health risks, including cardiovascular disease, lung cancer, and other potentially fatal respiratory conditions (Atkinson et al., 2018). Recognizing the severity, the World Health Organization (WHO) and the US Environmental Protection Agency (US EPA) designate NO_2 as a key indicator of outdoor air pollution (Islam et al., 2022; Melamed et al., 2016). Also, the WHO has reduced the ambient NO_2 annual mean limit from 40 to 10 $\mu g/m^3$ in the latest air quality guideline (WHO, 2021). This yellowish-orange to reddish-brown gaseous pollutant with a pungent, irritating odour (DoE, 2018), exhibits a brief atmospheric photochemical longevity, ranging from 2 to 5 h during the daytime in summer to 12 to 24-h during winter, which indicates spatiotemporal variability based on emission sources (Goldberg et al., 2021; Islam et al., 2022). Worldwide population-weighted nitrogen dioxide (NO_2) estimates, spanning from 1996 to 2012, reveal a yearly decline of 4.7% in the USA and Canada, 2.5% in Western Europe, and a notable increase of around 6.7% in East Asia and major Indian cities (Geddes et al., 2016; Singh et al., 2023). The observed trends in NO_2 concentration are highly influenced by various spatiotemporal (Singh et al., 2023) and anthropogenic factors (Ambade, 2018; Chawala et al., 2023; Jamal et al., 2024). However, obtaining an accurate estimate of NO_2 remains a challenge in many developing nations like Bangladesh (Bechle et al., 2013; Islam et al., 2022) due to the high costs associated with establishing and maintaining monitoring stations (Rabiei-Dastjerdi et al., 2022). Advanced remote sensing (RS) (Bechle et al., 2013; Islam et al., 2022) and geographic information system (GIS) (Ashwini & Sil, 2022; Chawala et al., 2023) technologies play a crucial role in addressing this gap, enabling scientists to monitor atmospheric NO_2 and study its determinants effectively (Bechle et al., 2013; Islam et al., 2022). The most recent tropospheric vertical column of NO_2 data from the European Space Agency's Sentinel 5P, also known as the TROPOMI (Copernicus Sentinel-5P (processed by ESA), 2021), offers a reliable estimate of NO_2 emission values in comparison with on-site data recordings (Goldberg et al., 2021; Islam et al., 2022). In recent literature, diverse factors including the NDVI, LULC patterns, and LST have been explored, using GEE-based RS (Ashwini & Sil, 2022; Rahaman et al., 2023); on the other hand, road density, industry density, and settlement density have been investigated, using GIS platforms to quantify and understand the variations in NO_2 levels (Ashwini & Sil, 2022; Grzybowski et al., 2023). Gazipur City, part of the Greater Dhaka Division, experiences some of the worst air quality in Bangladesh, as highlighted by recent studies (Basak et al., 2023; Uddin et al., 2023). Its rapid urbanization, significant industrial activity, and dense transportation networks make it a critical area for investigating NO_2 pollution. The city's industrial prominence is evident, with 2633 registered

factories and approximately 500 unregistered ones, totalling around 3133 factories (DIFE) (Prothom Alo, 2024). Additionally, Gazipur is a major brick-production hub, with an estimated 148 brick kilns contributing to NO_2 emissions (Khan et al., 2023). The influx of rural migrants has intensified demands for transportation, housing, and industrial expansion, further contributing to NO_2 levels. The city's diverse land use, ranging from dense industrial zones to mixed-use urban areas and patches of greenery, offers a unique opportunity to analyse factors influencing NO_2 variability such as, land use and land coverage (LULC), industrial density, road density, settlement density, land surface temperature (LST), and vegetation cover (measured using the normalized difference vegetation index, NDVI). Understanding the interplay between these variables and NO_2 concentrations will provide insights for policymakers to implement targeted control measures. Findings will not only benefit Gazipur but also serve as a model for addressing NO_2 pollution in other rapidly urbanizing regions, particularly in South Asia and other low- and middle-income countries. Despite limited studies on NO_2 pollution in Bangladesh (Islam et al., 2022; Mukta et al., 2020; Hasan et al., 2018; Rahaman et al., 2023; Rana et al., 2021), several researchers have employed GIS and RS techniques to measure and analyse NO_2 concentration (Islam et al., 2022; Rahaman et al., 2023; Rana et al., 2021), yet there remains a need to address crucial factors (NDVI, LULC, LST, road density, industry density, and settlement density) to comprehensively grasp the variability of NO_2 concentration levels, using RS and GIS techniques. Although studies on NO2 pollution in Bangladesh remain limited (Islam et al., 2022; Mukta et al., 2020; Rabbi, 2018; Rahaman et al., 2023; Rana et al., 2021), several researchers have utilized GIS and remote sensing (RS) techniques to assess NO_2 concentrations and understand their spatial and temporal variability (Islam et al., 2022; Rahaman et al., 2023; Rana et al., 2021). For instance, one study analysed TROPOMI satellite data from 2018 and 2019 across Bangladesh, examining the relationship between NO_2 levels, climatic conditions, and anthropogenic factors. The study reported a mean NO_2 concentration of 0.9×10^{-4} mol/m^2, identifying Dhaka as having the highest levels, with the south-eastern corner, including Gazipur, highlighted as an area of concern. It also found that regions with high vegetation cover, low population density, and minimal industrial activity exhibited lower NO_2 concentrations (Islam et al., 2022). Another study investigated the spatiotemporal trends of NO2 pollution and the influence of factors such as land surface temperature (LST), normalized difference vegetation index (NDVI), and enhanced vegetation index (EVI) in Dhaka and Delhi from 2019 to 2021. The findings indicated that Dhaka faced worse conditions than Delhi, with significant vegetation loss and concurrent increases in both LST and NO_2 levels (Rahaman et al., 2023). These studies, while insightful, have not fully explored the interplay of specific factors—such as road density, settlement patterns, industrial density, and land-use dynamics—that influence NO_2 variability at localized scales, particularly in Gazipur. To address the research gaps, the present study aims to: (1) investigate the spatiotemporal distribution of NO_2 concentration in urban areas like Gazipur city, using RS and GIS techniques, and (2) identify the factors that influence the variation in NO_2 concentration.

Materials and methods

A flowchart-based depiction of the complete methodological process of the study is available in Fig. S1.

Study area

The present study focuses on Gazipur, a rapidly urbanizing area located in the north-eastern region of Dhaka, Bangladesh (Arifeen et al., 2021). Gazipur district lies centrally in Bangladesh, between latitudes 23°53′ and 24°20′N and longitudes 90°9′ and 90°42′E, covering an area of 321 square kilometres (Fig. 1). The Gazipur city has a population of approximately six million and a total road length of around 1552 km (Abdullah et al., 2019). Gazipur's proximity to Dhaka has transformed it into a major hub for employment and commerce, contributing significantly to the country's gross domestic product (GDP). Notably, 65% of Bangladesh's garment factories are situated in this region (Oeurng et al., 2016). Consequently, people from surrounding districts, particularly rural areas, are migrating to Gazipur. This rapid urbanization, along with an increase in vehicles and industrial activities, has led to a substantial rise in NO_2 levels in the area (Uddin et al., 2023).

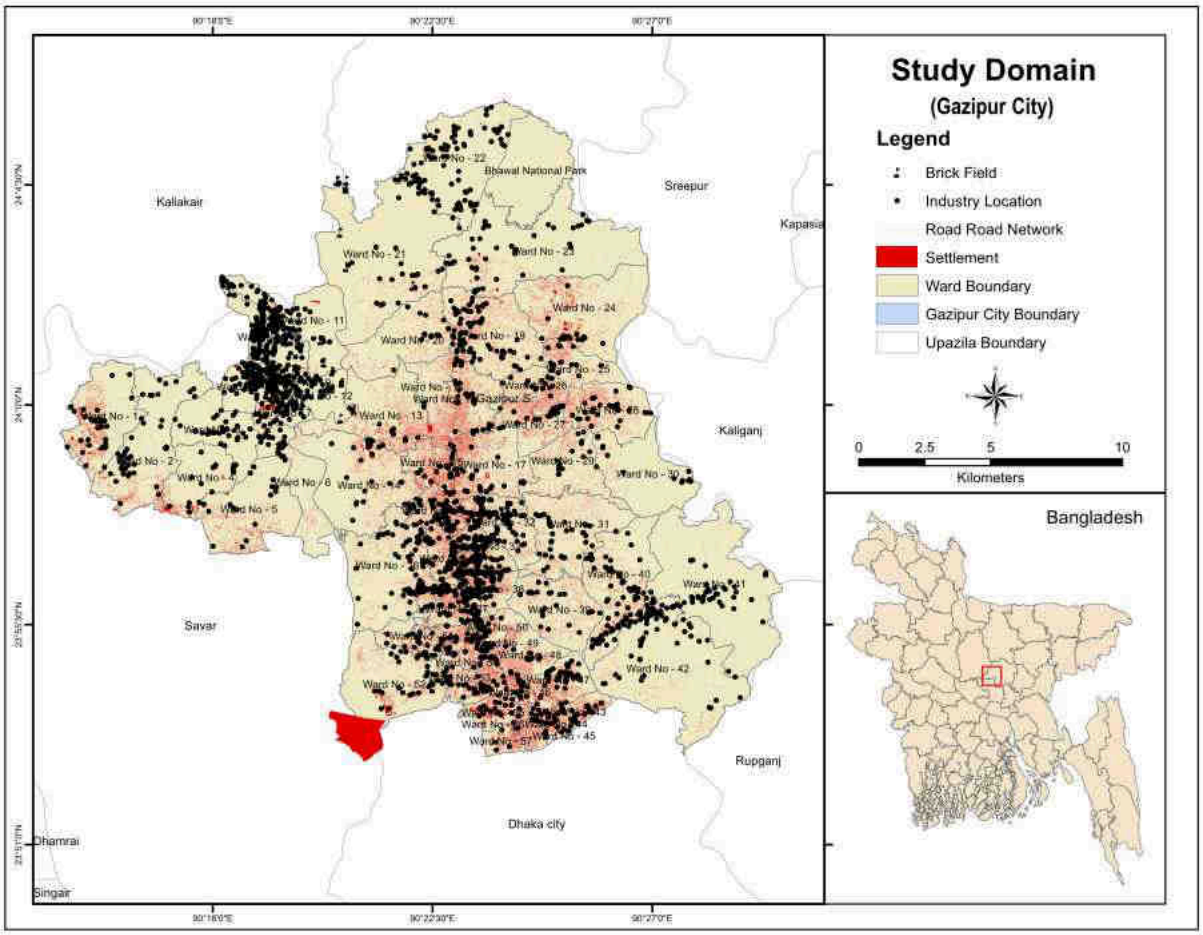


Fig. 1 The study area in Gazipur City

Data description

In this study, we utilized Sentinel 5P TROPOMI satellite NO_2 concentration data from 2019 to 2022, along with various environmental variables including population density, LST intensity, NDVI, LULC, road density, settlement density, and industry density for the year 2022. Detailed information about these datasets is provided in Table 1. Furthermore, thematic maps illustrating the 2022 data for Gazipur City, including population density, LST intensity, NDVI, LULC, road density, settlement density, and industry density, are presented in Fig. 6.

Methods

Numerous studies have effectively utilized the GEE platform to analyse factors such as LULC, LST, NDVI, population density, road density, settlement density, and industry density. This study focuses on the following analyses: (1) the spatiotemporal distribution of NO_2 concentration using satellite images, with seasonal and monthly statistics extracted for the years 2019 and 2022, and (2) the comparison of Sentinel 5P TROPOMI NO_2 values with seven environmental variables (LST, NDVI, LULC, population density, road density, settlement density, and industry density) in Gazipur city.

Table 1 Geospatial dataset with their different attributes used in the study domain

Data used	Data type	Special resolution	Temporal resolution	Dataset provider	Dataset availability	Range/units
Sentinel 5P TROPOMI NO_2	**Raster Data**	**1000 m**	**Daily**	**European Union/ESA/Copernicus**	**2018 to present**	**mol/m^2**
Sentinel 2A Dynamics (LULC) [32]	**Raster Data**	**10 m**	**6 Days**	**European Space Agency**	**2017 to present**	**Square meter grid**
LST	**Raster Data**	**1000 m**	**Daily**	**MODIS**	**2000 to present**	**K**
NDVI	**Raster Data**	**30 m**	**16 Days**	**Landsat 8**	**2013 to present**	**Square meter grid**
Human Modification	**Raster Data**	**1000 m**	**5-Year interval**	**Conservation Science Partners**	**February 2016**	**km^2**
Road Network	**Vector Data**	**100 m**	**Random**	**European Union/ESA/Copernicus**	**2018 to present**	**km**
Settlement	**Vector Data**	**Point values**	**Yearly**	**OpenStreetMap**	**2004 to present**	**Point**
Industry	**Vector Data**	**Point**	**Daily**	**OpenStreetMap**	**2004 to Present**	**Point**
Precipitation	**Raster Data**	**5566 m**	**Daily**	**CHIRPS (Climate Hazards Center)**	**1981 to present**	**mm/d**

The study leverages free image collections from TROPOMI, MODIS, Dynamic World, and Global World instruments available in the GEE datasets, along with road, settlement, and industry data from the OpenStreetMap (OSM) platform. GEE and OSM are open-source geospatial analysis platforms that allow users to visualize and analyse changes, map trends, and quantify differences in Earth's environment.

Gazipur City was divided into 356 grids, each with a size of 1×1 square km, based on NO_2 concentration. Environmental variable's values for each grid were extracted based on NO_2 concentration points. The study computed and processed the NO_2 concentration, along with all the seven environmental parameters for each grid.

NO_2 concentration data

The impacts of air pollution can be assessed using different methods, including ground-based, ship-based, and satellite-based monitoring. Satellite-based monitoring stands out for its extensive spatial and temporal coverage, offering comprehensive global and regional insights into air pollution (Gao et al., 2023). This study uses satellite-based observation for the spatiotemporal distribution of NO_2 concentration. The Sentinel 5P TROPOMI is an on-board satellite system used to measure NO_2 concentrations (Prunet et al., 2020). NO2 concentration data from TROPOMI, spanning January 2019 to December 2022, were acquired daily through the GEE platform (Harper et al., 2021). Daily tropospheric NO2 vertical column concentration data from TROPOMI version 1 level 3, featuring a spatial resolution of 1×1 square km, were sourced from GEE platform (X. Li et al., 2023). For the analysis, a JavaScript program was created in GEE to access, process, and display the data from the image collections. The scripts utilized in this study are available in supplementary material Algorithm S1. During this phase, the chosen images undergo the following processing steps:

(a) filtering the imaging time for the clipped region of interest (Gazipur City); (b) eliminating cloudy pixels using a condition on TROPOMI, MODIS, and Landsat-based products and selecting the highest quality satellite data; (c) extracting daily images by mosaicking overlapping scenes across the entire study area; (d) extracting hourly pixel values for AOD (Aerosol Optical Depth) and NO2 column density from

the relevant images; and (e) computing monthly and seasonal images by averaging the daily images to create spatiotemporal maps and to analyse the relationship between environmental variables from January 2019 to December 2022.

Normalized difference vegetation index (NDVI)

To calculate NDVI, the raw scenes from USGS Landsat 8 Collection 1 Tier 1 and real-time data were utilized. A custom script was employed on the GEE platform to derive NDVI values from the Landsat 8 dataset composite, with a 30-m spatial resolution and a temporal resolution of 16 days. NDVI, which ranges from − 1 to + 1, quantifies the earth's vegetation cover. Negative values indicate non-vegetated surfaces, a value of 0 denotes minimal vegetation, and a value of 1 signifies dense vegetation (Ashwini & Sil, 2022). Equation 1, presented below, illustrates the calculation of NDVI, while Algorithm S2 provides the NDVI extraction code.

$$NDVI = (NIR - RED) / (NIR + RED) \quad (1)$$

In this formula, "RED" refers to the red reflectance, and "NIR" refers to the near infrared reflectance.

Land surface temperature (LST)

LST images from the MOD11A1 dataset, obtained by the MODIS sensor on the Terra satellite, were utilized. This dataset offers daily LST data with a 1x1 km grid resolution, available in both day and night temperature bands (Suthar et al., 2024). For this study, only daytime satellite imagery was considered. The LST, derived from the difference between outgoing thermal radiation and surface temperature, was calculated using the GEE platform.

The calculation involves several steps, starting with:

$$LST = (K2 / In\ (K1/radiance) + 1) - 273.15 \quad (2)$$

(Algorithm S3)

where K1 and K2 are calibration constants specific to the MODIS sensor and thermal infrared bands.

ArcGIS Pro software was employed to convert the pixel/grid data of Gazipur city into a point vector grid. The final output was then used to create and visualize the LST map, providing insights into the LST patterns in the Gazipur city area.

Land use land cover (LULC) classification

This research utilizes the 2022 Sentinel-2 Dynamic World LULC satellite dataset to illustrate these land use changes. The land is classified into six categories: built-up areas, water bodies, trees, grasslands, flooded vegetation, cropland, and shrubland or bare land (Agarwal & Kumar, 2022). The images in the Dynamic World collection correspond to specific Sentinel-2 L1C asset (AlgorithmS4) For instance, the image "COPERNICUS/S2/20160711T084022_20160711T084751_T35PKT" matches the dynamic world image "GOOGLE/DYNAMICWORLD/V1/20160711T084022_20160711T084751_T35PKT". All probability bands in these images, except the "label" band, collectively sum to one.

Grided population density

To explore the interactions with LST, NDVI, LULC, settlement density, road density, and NO2 concentration, the Global Human Modification (GHM) data or population density information was utilized. The Gridded Population of the World, version 4 (GPWv4), offers a comparative analysis of human population density (Suthar et al., 2023). This dataset employs a proportional allocation gridding algorithm to distribute the population into 30 arc-second grid cells, covering approximately 13.5 million administrative units worldwide. The GHM data for the years 2005, 2010, 2015, and 2020 are available for download. For this study, the 2020 data was obtained through the GEE platform (Algorithm S5) from the following website: https://csp-inc.org/ (CSP, 2024).

Industry, road, and settlement density

Data for industry, settlements, and roads were sourced from the OSM portal (https://www.openstreetmap.org) (OpenStreetMap contributors, 2024). The dataset includes point features for industry and settlements, and polyline features for roads. To analyse density, we used ArcMap commands specifically designed for point density (for industry and settlements) and line density (for roads). The spatial resolution of the dataset is 100 m. The density calculation process involves

measuring the quantity of features per unit area within a specified radius around each cell. This method enables the assessment of the density of linear features across different regions. ArcGIS 10.8 software facilitates the conversion of polygons to points and subsequently calculates point densities, which are then categorized by height, settlement type, and settlement classification.

Kernel density analysis

The kernel density tool is utilized to determine the concentration of features within a specific area. This analysis can be applied to both point and line features, providing an index that represents the intensity of influence that certain factors have on their surroundings (Mitchell, 1999). In this study, three environmental variables are examined using kernel density analysis with ArcGIS 10.8 software: road network (line feature), settlements (point feature), and industry (point feature). Firstly, the road network data, initially a line feature, is converted into a kernel density distribution. This conversion produces a weighted value based on the density of the road network, highlighting areas with higher road concentrations. Secondly, the settlement and industry data, originally point features, are converted into kernel point densities. This process focuses on the distribution patterns of settlements and industries within the Gazipur city area. The results of this analysis provide detailed density maps for both settlements and industries, fulfilling the study's requirements.

Data analysis

This study analysed the relationship between NO_2 levels and various environmental factors, including NDVI, LST, LULC, population density, industry density, road density, and settlement density, in Gazipur City.

Data for NO2 concentrations and each environmental parameter (NDVI, LST, LULC, population density, industry density, road density, and settlement density) were extracted, cleaned, and checked for missing values to ensure a complete and reliable dataset. NO_2 concentrations from 356 grid cells covering Gazipur City were used in regression analysis. A univariate regression model was applied to assess the impact of each factor on NO2 concentrations. For variables with monthly data (NDVI and LST), regression was performed by categorizing the representative year 2022 into four seasons: winter (December–February), pre-monsoon (March-May), monsoon (June–August), and post-monsoon (September–November). For other variables, regression was conducted yearly. To satisfy the assumption of normality for the dependent variable, NO2 concentrations were log-transformed before analysis. Scatter plots were created to visualize the relationships between NO_2 levels and each environmental factor.

Correlation analysis was performed to further evaluate the strength and direction of associations between NO_2 concentrations and the selected environmental variables.

Data sorting and cleaning were conducted using Microsoft Excel, while regression and correlation analyses were performed using R and Python programming languages.

Ground versus satellite data

A correlation analysis was conducted to evaluate the agreement between satellite-derived monthly NO_2 concentrations and ground-level continuous air quality monitoring station data from Gazipur city for 2022. The analysis yielded a coefficient of determination ($R^2 = 0.73$), indicating a strong correlation between the two datasets (Fig S2). This result supports the use of tropospheric NO_2 measurements as a reliable proxy for ambient NO_2 levels.

Final visualization

The spatiotemporal distribution maps of NO2 concentrations, along with other environmental variable maps, were created using ArcGIS 10.8 software. The methodology to summarize the study results for the entire Gazipur City area included: (i) mapping the spatiotemporal distribution of NO2 concentrations across the city, (ii) developing a JavaScript program in GEE to calculate and visualize the average NO_2 concentrations on a monthly and seasonal basis, and (iii) comparing and analysing satellite-based NO_2 data with various environmental variables.

Result and discussion

The study analyses NO2 levels from 2019 to 2022, highlighting trends over different seasons and months. It examines how NO_2 concentrations relate to environmental factors such as LST, LULC, NDVI, and the density of populations, settlements, roads, and industries. The findings demonstrate the impact of these factors on NO_2 levels through correlation and regression analysis. The summary statistics for NO2 concentrations and environmental parameters for a representative year 2022 are provided in Table S1.

Spatial and temporal variation of NO_2 concentration

The NO_2 seasonal concentrations exhibited fluctuations over four consecutive years (2019–2022), as illustrated in Fig. 2 (Table S2). The seasonal shifts in NO_2 concentration are further demonstrated with the use of geospatial mapping for each investigated years in Fig. 3. Additionally, the monthly variations in NO2 concentrations are provided in Table S3. The findings revealed a diverse pattern of NO_2 concentration across the studied years. In 2019, mean NO_2 concentration showed almost similar levels during post-monsoon (2.5×10^{-4} mol/m^2), pre-monsoon (2.3×10^{-4} mol/m^2), and winter (2.2×10^{-4} mol/m^2) seasons; on the other hand, monsoon recorded the minimum concentration (1.4×10^{-4} mol/m^2). In 2020, the pre-monsoon season exhibited the highest average NO_2 concentration (2.9×10^{-4} mol/m^2), with winter and post-monsoon showing comparable levels (2.0×10^{-4} mol/m^2 and 2.3×10^{-4} mol/m^2, respectively), and monsoon recording the lowest average (1.5×10^{-4} mol/m^2). The winter of 2021 marked the peak mean NO_2 concentration (3.1×10^{-4} mol/m^2) of all the studied years, with post-monsoon, pre-monsoon, and monsoon seasons following with concentrations of 2.1×10^{-4} mol/m^2, 1.2×10^{-4} mol/m^2, and 1.7×10^{-4} mol/m^2, respectively. Winter 2022 nearly matched the highest average NO_2 concentration (3.0×10^{-4} mol/m^2) that was observed across all study years with other three seasons following a descending trend: post-monsoon (2.0×10^{-4} mol/m^2) > pre-monsoon (1.8×10^{-4} mol/m^2) > monsoon (1.1×10^{-4} mol/m^2).

During 2019, average NO_2 levels were substantially higher in the pre-monsoon and post-monsoon seasons by 4.3% and 12% respectively, compared with winter. In 2020, this trend continued with NO_2 concentrations as 31% higher in the pre-monsoon season and 4.8% higher in the post-monsoon season compared with winter. Elevated NO_2 levels during

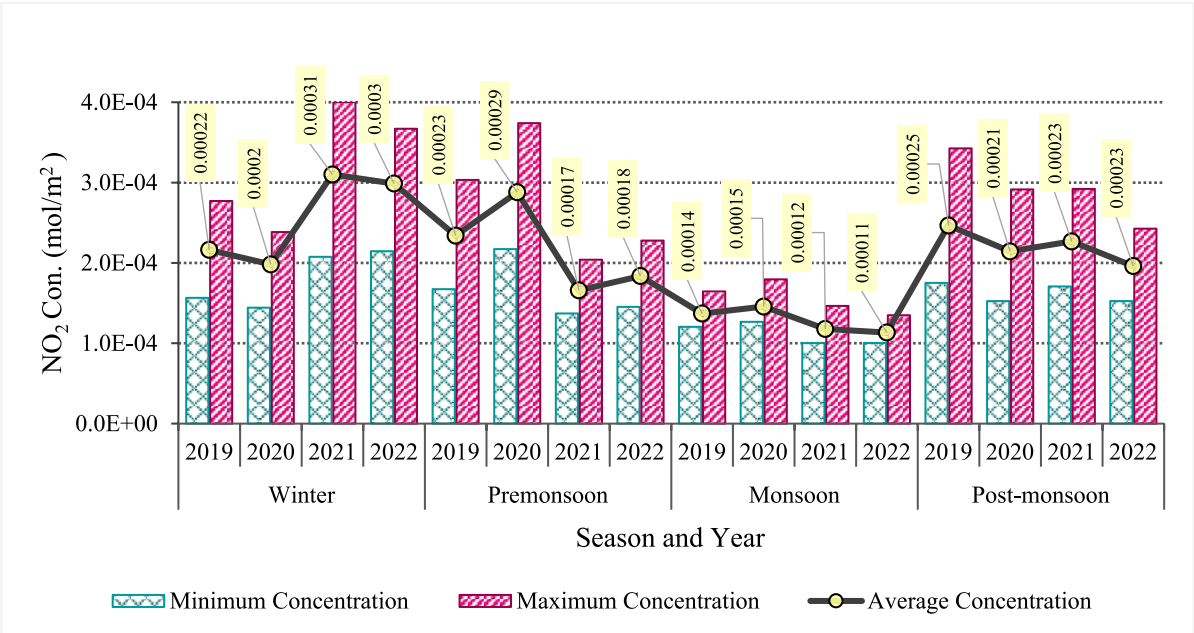


Fig. 2 Seasonal variation of NO_2 concentration at Gazipur City over the study period

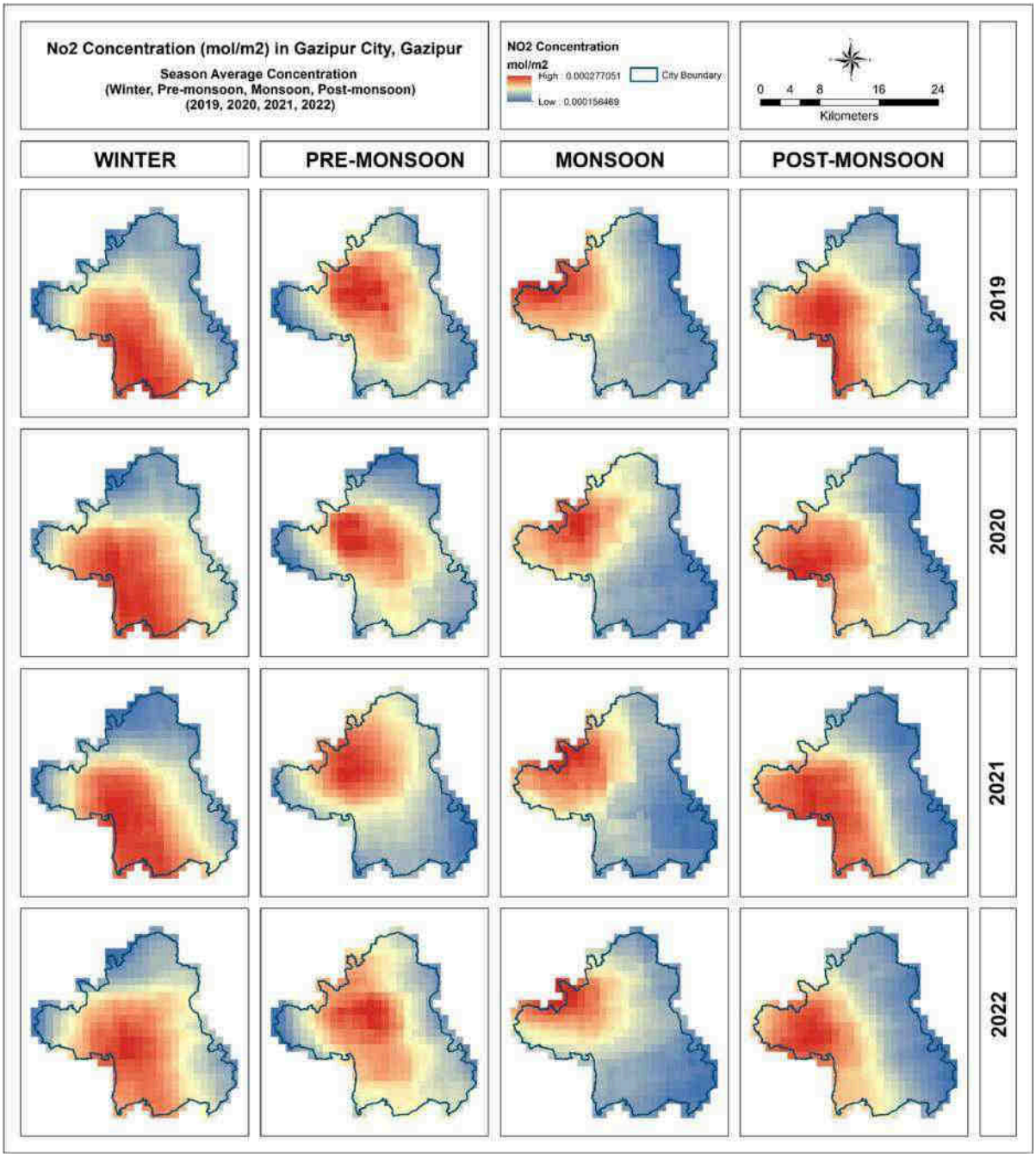


Fig. 3 Seasonal distribution NO2 concentration in Gazipur City from 2019 to 2022: **a** winter, **b** pre-monsoon, **c** monsoon, **d** post-monsoon

the dry pre-monsoon and post-monsoon periods are commonly observed across Bangladesh, including Gazipur and Dhaka (Azad & Kitada, 1998; Islam et al., 2022; Mukta et al., 2020). This pattern is consistent with trends in the Indo-Gangetic Plain, where Bangladesh is geographically located. For example, a study using Google Earth Engine data from 2005 to 2019 across five Indian states and two

union territories reported the highest NO_2 concentrations ($3.82 \pm 0.98 \times 10^{15}$ mol/cm^2) during the post-monsoon season (Chawala et al., 2023). For the years 2020 and 2022, our study found that winter recorded the highest NO_2 levels, with average concentrations of 0.00031 and 0.0003 mol/m^2, respectively. Similarly, a study on Dhaka using TROPOMI data from 2019 to 2021 reported that winter consistently had the highest NO_2 concentrations, showing an annual increase of 0.05 mol/m^2. Previous research in Dhaka has also consistently identified winter as the season with the highest NO_2 pollution (Azad & Kitada, 1998; Rahaman et al., 2023; R. R. Rahman & Kabir, 2023), attributing this to various sources, including vehicular emissions, biomass fuel burning, industrial activities, and brick kilns (DoE, 2018).

Out of the years examined, the monsoon season consistently recorded the lowest average NO_2 levels, reaching a minimum of 0.00011 mol/m^2 in 2022. During the monsoon season, wet scavenging reduces the influence of long-range pollution, making local sources, such as industrial areas, the primary contributors to NO_2 levels (Chawala et al., 2023; Islam et al., 2022). In Gazipur City, the northwestern region, dominated by industries (Fig. 6h and i), emerges as the main source of NO_2 pollution during this period, significantly affecting the overall seasonal pollution levels. Our findings for the monsoon season is consistent with previous research findings(Hoque, 2020; M. M. Rahman et al., 2019; Shobnom et al., 2023) and low TROPOMI-NO_2 during the monsoon period is likely attributed to heavy precipitation, strong winds and high humidity (Priya & Iqbal, 2023). The distribution of mean NO_2 concentration varied throughout the studied years, and this shows fluctuations between months with higher and lower pollution levels (Fig. 4), consistent with seasonal changes. The spatial distribution patterns of NO_2 concentration also support the similar monthly variations as shown in Fig. 5. For instances, during winter 2022, NO_2 pollution peaks due to colder temperatures, low wind speeds, and stagnant atmospheric conditions that trap pollutants. The primary sources include industrial and vehicular emissions, along with biomass burning in densely populated areas. Pollution hotspots are concentrated in central, south-eastern, southwestern, and northeaster regions. The wind direction is predominantly from the north or northwest, but calm winds contribute to pollutant accumulation (Begum & Hopke, 2018). December marks the rise in NO2 levels, peaking in January, and slightly declining in February as temperatures begin to rise. During the post-monsoon months of 2022 (Fig. 5), NO_2 distribution patterns differ. The dominant wind direction shifts to the northeast, accompanied by

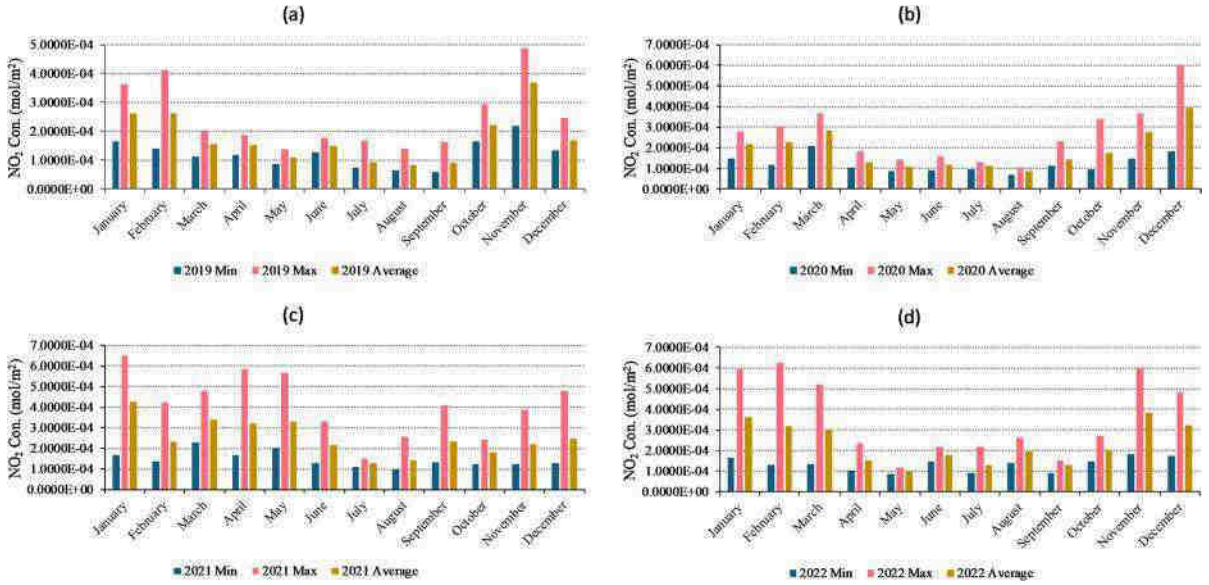


Fig. 4 Month-wise temporal distribution NO2 concentration in Gazipur City: **a** year 2019, **b** year 2020, **c** year 2021, **d** year 2022

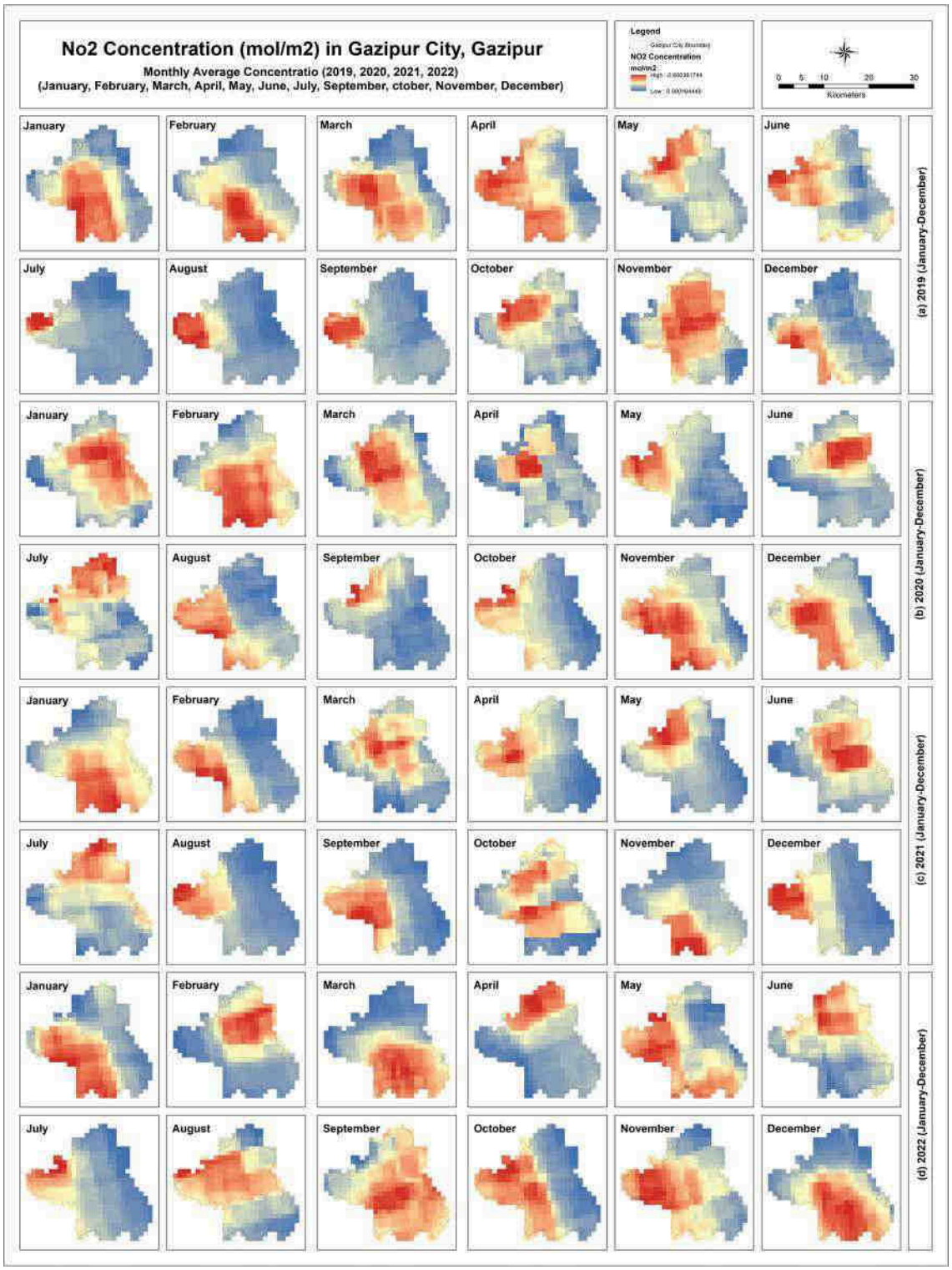


Fig. 5 Month-wise spatial distribution NO2 concentration in Gazipur City: **a** year 2019, **b** year 2020, **c** year 2021, **d** year 2022

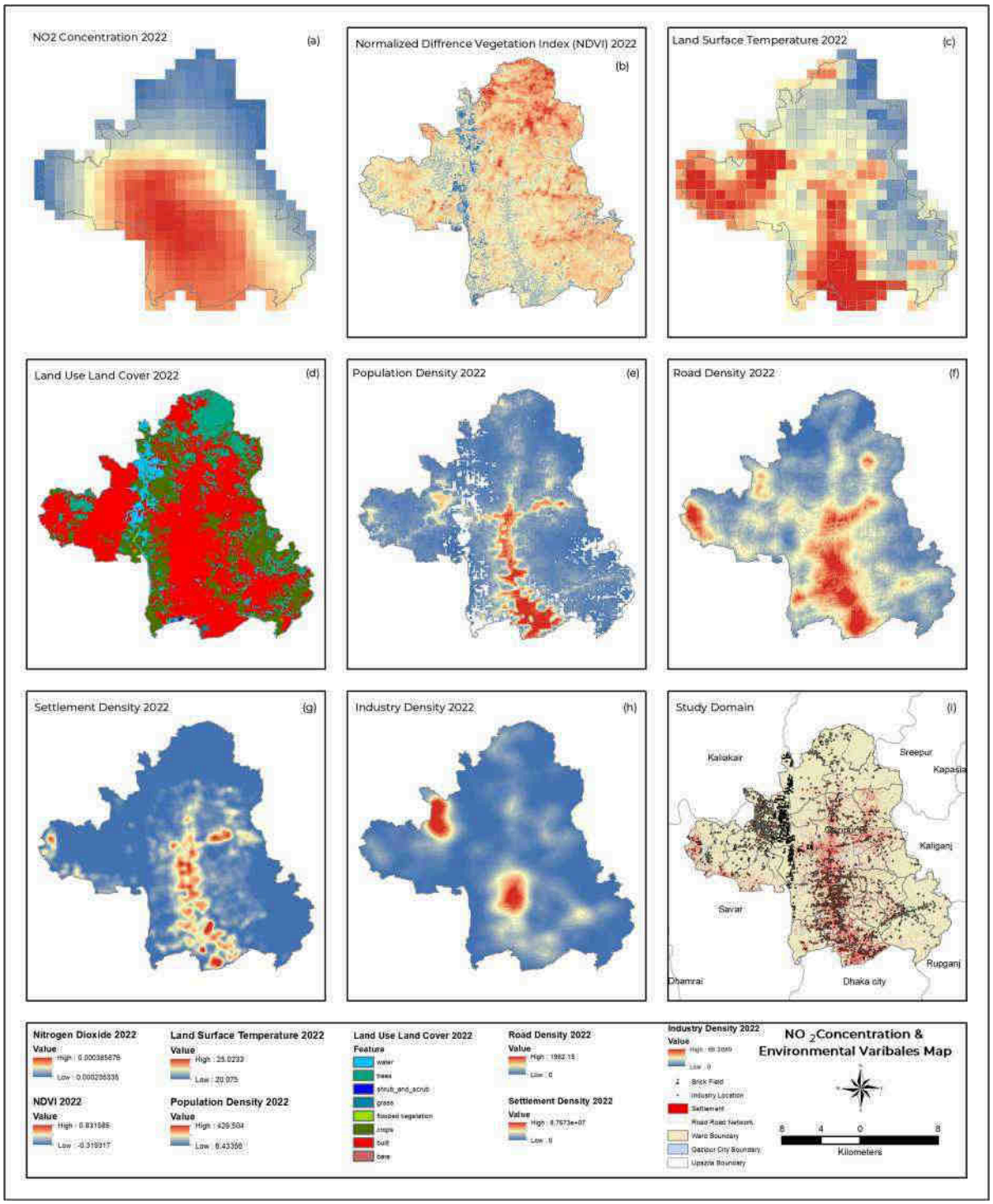


Fig. 6 **a** Nitrogen dioxide (NO_2) map 2022, **b** normalized difference vegetation index (NDVI) map 2022, **c** land surface temperature (LST) map 2022, **d** land use land cover map 2022, **e** population density map 2022, **f** road density map 2022, **g** settlement density map 2022, **h** industry density map 2022, and i study domain overview

reduced wind speeds and precipitation (Begum & Hopke, 2018). These conditions, combined with emissions from traffic, industries, and brick kilns, significantly contribute to the overall pollution levels during this period. During the pre-monsoon months, higher temperatures and stronger atmospheric turbulence enhance pollutant dispersion, resulting in a different NO_2 distribution pattern. Industrial and vehicular emissions remain key contributors, particularly in densely populated and industrial areas. Late pre-monsoon rains in April and May further reduce NO_2 levels through wet scavenging. The prevailing south-westerly winds (Begum et al., 2014) during this period disperse pollutants toward the northeast, creating broader and less localized pollution patterns. The precipitation map for the years 2019 to 2022 are available in Fig. S4. In 2019 (Fig. 4a), the highest average NO_2 concentration occurred in November (3.7×10^{-4} mol/m^2), the last month of the post-monsoon season, followed by January and February of the winter season with the second highest mean concentration (2.6×10^{-4} mol/m^2). During the pre-monsoon months of March, April, and May, as well as extension to the moth of June (1.5×10^{-4} mol/m^2), concentrations fluctuated between 1.1×10^{-4} mol/m^2 and 1.6×10^{-4} mol/m^2. The latter part of the monsoon season, July, and August displayed the lowest mean NO_2 concentration levels at 0.9×10^{-4} mol/m^2. In 2020 (Fig. 4b), December, the onset of winter, saw the highest mean NO_2 concentration at (3.9×10^{-4} mol/m^2), whereas August, marking the end of the monsoon, had the lowest at (0.9×10^{-4} mol/m^2). As it shown in 2021 (Fig. 4c) and 2022 (Fig. 4d), the lowest concentrations were in August (1.4×10^{-4} mol/m^2) and July (1.3×10^{-4} mol/m^2) respectively, with the peak levels recorded in January 2021 (4.3×10^{-4} mol/m^2) and November 2022 (3.8×10^{-4} mol/m^2). The analysis reveals a consistent increase in NO_2 levels from November to March across all studied years. Starting in August 2019, NO_2 concentrations showed a significant upward trend, peaking with a 35.7% rise by 2021. Over the period from July 2019 to July 2022, NO_2 levels increased by 30.7%. These findings align with those of Islam et al., who reported the highest mean NO_2concentration in November 2018 across Bangladesh, with the greatest value (5.03×10^{-4} mol/m^2) observed in the central region, including Dhaka (Gazipur) (Islam et al., 2022). This rise in pollution is primarily due to rapid unchecked urbanization and heavy loss of vegetation (Rahaman et al., 2023). The average NO_2 concentrations across four seasons are detailed in Table S2 and Fig. 2. The combined influence of environmental and anthropogenic factors on NO_2 concentrations was evaluated using regression and correlation analyses. Table S4 presents the results of the regression analysis, highlighting the relationships between NO_2 concentrations and environmental factors such as NDVI and LST, as well as anthropogenic factors including population density, industry density, road density, settlement density, and LULC. The analysis incorporates seasonal trends for NDVI and LST and annual trends for the other factors for the year 2022.

Vegetation scenario (NDVI) and NO_2 concentration

Table S1 (Fig S3) exhibits a moderate negative correlation ($r=-0.4$, $P<0.01$) with NDVI and NO_2 concentrations, indicating that areas with greater vegetation cover tend to have lower NO_2 levels. Further season-wise regression analysis (Table S4, Fig. 7a) reveals NDVI consistently exhibited a negative association with NO_2 concentrations across all seasons. The strongest negative effect ($\beta=-0.28$) was observed in winter and post-monsoon seasons, with modest explanatory power ($R^2=0.042$ and $R^2=0.012$, respectively). During the monsoon season, although the relationship remained negative ($\beta=-0.18$), it explained slightly more variability in NO_2 levels ($R^2=0.064$). These findings underscore the critical role of vegetation in mitigating NO_2 pollution. Similar results have been reported in the literature; for instance, Kumari et al. (2021) found a negative correlation between NO_2 and vegetation index, estimating that a unit increase in vegetation index could reduce NO_2 concentrations by 35.68% (Kumari et al., 2021). Expanding green spaces, such as parks, gardens, and urban trees, in city planning could serve as an effective strategy for NO_2 pollution mitigation (Ali et al., 2024). Increased greenery would not only lower NO_2 levels but also reduce the disease burden associated with NO_2 pollution, regardless of city size (Suthar et al., 2023).

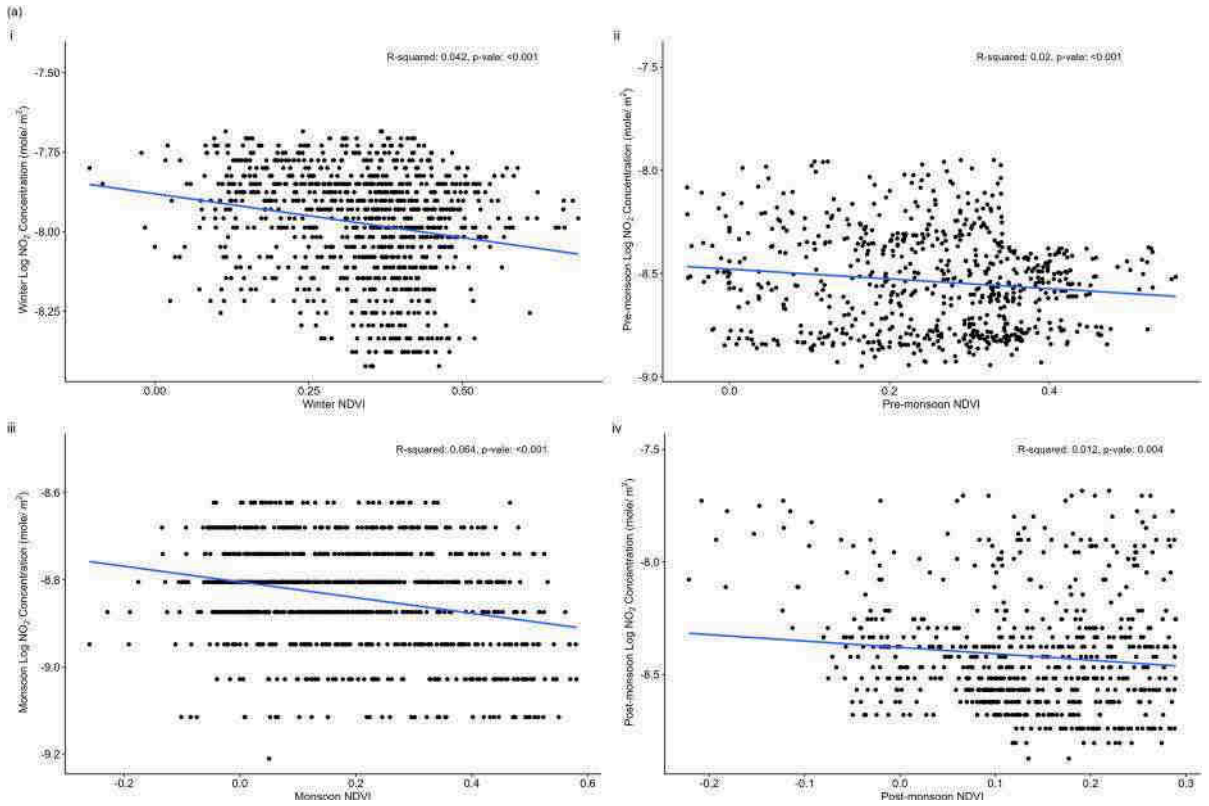


Fig. 7 **a** Grid-based analysis of extracted monthly averaged NO_2 concentrations correlated with seasonal normalized difference vegetation ndex (NDVI) using scatter plots for the year 2022: (i) winter, (ii) pre-monsoon, (iii) monsoon, and (iv) post-monsoon. **b** Grid-based analysis of extracted monthly averaged NO_2 concentration correlated with seasonal land surface temperature (LST) for the year 2022: (i) winter, (ii) pre-monsoon, (iii) monsoon, and (iv) post-monsoon. **c** Grid-based analysis of extracted annual averaged NO_2 concentration correlated with environmental parameters for the year 2022: (i) scatter plot of NO_2 concentration with population density. (ii) Scatter plot of NO_2 concentration with industry density. (iii) Scatter plot of NO_2 Concentration with settlement density. (iv) Scatter plot of NO_2 concentration with land use and land coverage (LULC). (v) Scatter plot of NO_2 concentration with road density

LST condition and NO_2 concentration

A moderate positive correlation ($r=0.47$, $P<0.01$) was observed between LST and NO_2 concentrations for the year 2022 (Table S1, Fig S3), indicating that higher surface temperatures are associated with elevated NO_2 levels. This aligns with a 2006 study in China that reported a similar positive correlation between LST and NO_2 (Weng & Yang, 2006). A positive association was observed during winter ($\beta=0.02$) and pre-monsoon seasons ($\beta=0.03$), suggesting higher NO_2 during these periods (Table S4, Fig. 7b). In contrast, a negative association was found during the monsoon season ($\beta=-0.01$, $R^2=0.039$), reflecting seasonal atmospheric dynamics, such as increased rainfall and humidity reducing NO_2 levels. The post-monsoon season exhibited the strongest positive correlation ($\beta=0.06$, $R^2=0.089$), likely due to reduced rainfall and persistent emissions during this period. These findings are consistent with studies reporting that high temperatures are often observed in regions with dense populations, intense industrial activity, and extensive urban infrastructure (Ali et al., 2024)—conditions prevalent in Gazipur, which are precursors to significant NO_2 pollution. A study of Dhaka from 2019 to 2021 also found a positive relationship between LST and NO_2 concentrations (Rahaman et al., 2023). Similarly, research conducted in Bengaluru, India, from 2018 to 2022 identified a strong association ($R^2=0.87$ to 0.91) between LST, air pollutants, and meteorological parameters, particularly during the winter season (Suthar et al., 2023).

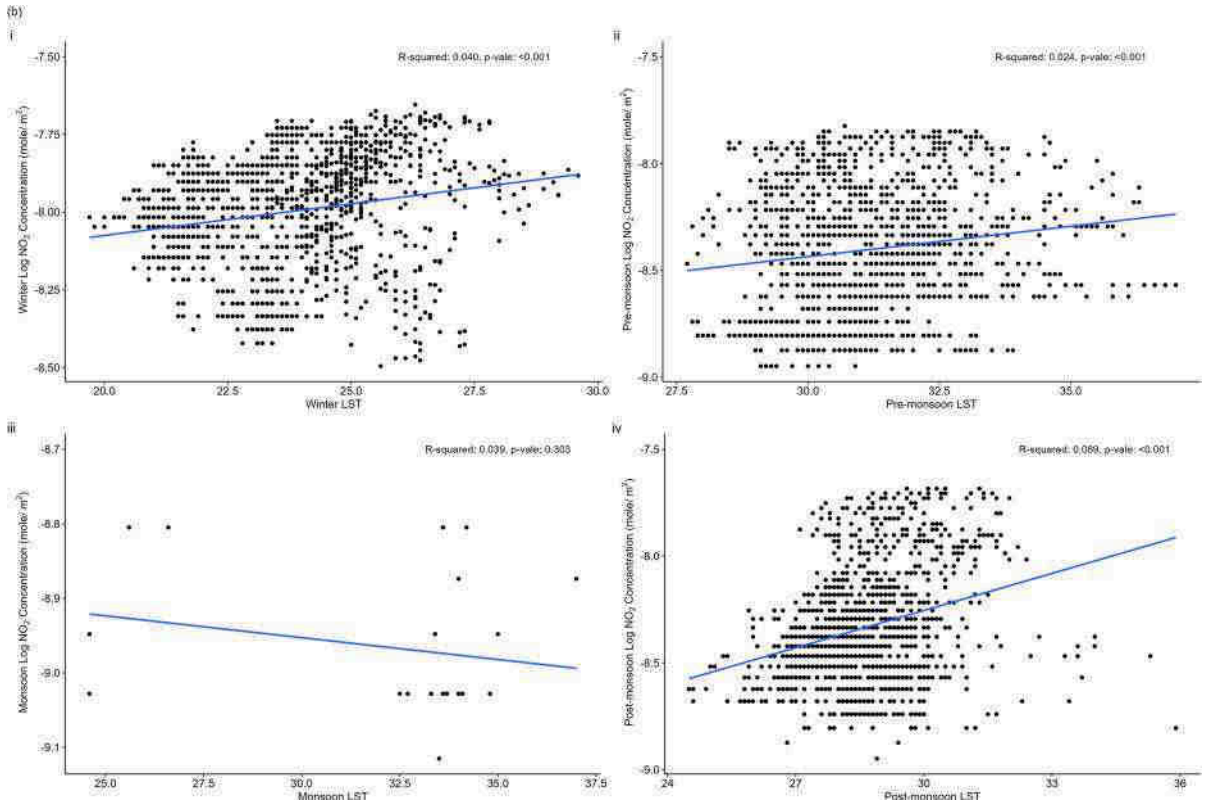


Fig. 7 (continued)

Population density and NO_2 concentration

This study investigates how population migration and movements impacts nitrogen dioxide (NO_2) levels in the Gazipur City region amid significant demographic shifts as illustrated in Fig. 6e and Fig. 7ci. The detailed analysis reveals a correlation coefficient of 0.4, which indicates a positive association between NO_2 concentrations and population density. Areas experiencing substantial population mobility show higher NO_2 levels, likely due to increased motor vehicle usage and subsequent NO_2 emissions. Conversely, regions with lower population mobility tend to have lower NO_2 concentrations. Furthermore, population density was positively associated with NO_2 concentrations ($\beta = 0.0008$), explaining 17% of the variation in NO_2 concentration ($R^2 = 0.170$) (Table S4). This result aligns with findings from Islam et al. (2022) and Ryu et al. (2019), which also reported a positive relationship between NO_2 concentrations and population density.

Industry density and NO_2 concentration

This study assessed the relationship between industrial density and NO_2 levels in Gazipur City. The findings reveal that areas with a greater concentration of industrial facilities consistently show higher NO_2 levels. Specifically, the correlation coefficient of 0.35, as shown in Table S1 (Fig S3), indicates a positive relationship between the number of industries and the increase in NO_2 levels. The found result aligns with prior research, which suggests a significant impact of industrial activities on air quality (Jiang et al., 2021; Leffel et al., 2022).

Additionally, although the influence appears modest, the coefficient of determination (0.02) depicted in Fig. 7cii, confirms that industrial density does affect NO_2 levels during the study period. The finding points to industrial emissions as a likely contributor to increased NO_2 levels in the surrounding regions. This finding aligns with a 2022 nationwide study in Bangladesh, which also observed a similar association

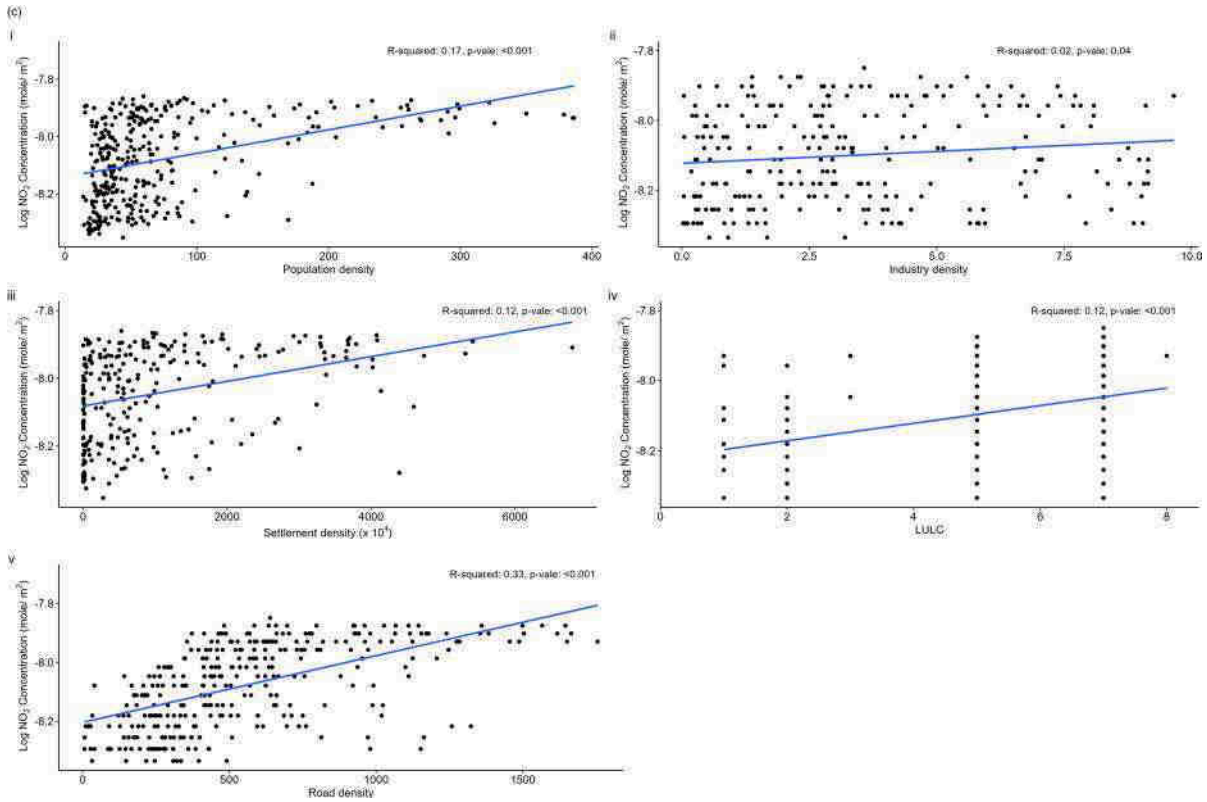


Fig. 7 (continued)

(Islam et al., 2022). Furthermore, a 2006 study conducted in Hamilton, Canada, reported significant NO_2 pollution near industrial zones (Sahsuvaroglu et al., 2006). These results underscore the urgent need for effective pollution control measures and regulatory interventions in regions with high industrial activity to mitigate air quality deterioration. For instance, shifting industries 500 m away from their current positions could potentially reduce the average monthly NO_2 concentration in Mirpur—a heavily polluted area in Dhaka—by 46% (Islam et al., 2022).

Road density and NO_2 concentration

This study reveals a moderately strong correlation (0.55) between road density and NO2 concentrations, as detailed in S1 Table S1 (Fig S3). This suggests that areas with more roads tend to have higher levels of NO2, likely due to vehicle emissions. This pattern is supported by similar findings in other research (CARSLAW, 2005; Zheng et al., 2009), which confirm the link between road networks and air pollution. Additionally, a spatial map presented in Fig. 6f visually illustrates this relationship across the study area. Further analysis, shown in Fig. 7cv, reveals that road density accounts for approximately 33% ($R^2 = 0.33$) of the variation in NO2 levels, which indicate a moderate influence of roads on NO2 concentration.

These findings are crucial for urban planners, environmental managers, and policymakers. The findings highlight the need for improved transportation and fuel standards, as well as thoughtful urban planning. By addressing these factors, we can mitigate the adverse effects of road density on air quality and public health. This evidence strongly supports the importance of strategic settlement planning to reduce the negative impact of road networks on NO2 pollution.

Settlement density and NO_2 concentration

In this investigation, the researchers explore the relationship between building density and nitrogen dioxide

(NO_2) levels in Gazipur City, considering the studied years. The analysis reveals a moderate correlation coefficient of 0.44 between settlement density and NO_2 concentrations (Table S1, Fig. S3). The results indicate that settlement density has a moderate influence ($R^2 = 0.12$) on NO_2 concentration levels in the current study (Fig. 7ciii). Overall, the findings of this study suggest that higher settlement density corresponds to increased population movement, reduced vegetation, more commuting roads, and consequently, higher settlement density leads higher NO_2 concentrations (Erbertseder et al., 2023; Reinmann et al., 2016).

Land use land cover classification and NO_2 concentration

In this study, the researchers explored how different types of land uses influence the levels of NO_2. The land was categorised into six groups: settlements, vegetation, water bodies, bare land, farm fields, and others, as part of the LULC classification. The analysis of this study demonstrated a moderate relationship between the types of land use and NO2 concentrations, with a correlation coefficient of 0.37 (Table S1, Fig. S3) and an R^2 value of 0.12 (Fig. 7civ). This suggests that as the land use changes, the levels of NO2 also vary moderately. Interestingly, this research found that NO2 levels were consistently low in areas of reduced settlement, vegetation, agricultural fields, and near water bodies (Fig. 6d). In contrast, higher concentrations of NO2 are usually observed in industrial and urban areas due to denser human activities (Erbertseder et al., 2023).

This pattern underscores the impact of human development and land use on environmental quality, particularly air pollution levels. The findings can help guide urban planning and public health initiatives to better manage and mitigate NO2 pollution in various environments.

Conclusion

This study explored the changing levels of tropospheric vertical column NO_2 concentration in Gazipur city from January 2019 to December 2022, utilizing TROPOMI satellite data that were analysed through the GEE platform. The researchers investigated the influences of environmental factors on NO_2 concentrations, using regression analysis, and map visualizations. Gazipur is experiencing significant environmental challenges due to high levels of NO_2, unstable LST, and transformations in land use and cover. These issues, combined with increasing population density and expanding road networks, are leading to heavy vegetation loss and eventually reshaping the urban landscape. The findings of the present study underscore the link between monthly and seasonal fluctuations in NO_2 concentrations and environmental variables. The analysis provided insights into the spatial and temporal patterns of NO_2 concentration, with a focus on its spatial relationships with LST, NDVI, road density, settlement density, LULC, industrial activity, and population density. To address the high NO_2 levels and associated environmental challenges in Gazipur City, this study recommends several strategic measures. Given that industrial emissions are a major source of NO_2 pollution, relocating high-polluting industries, such as brick kilns, away from residential areas is imperative. Regular emission monitoring and incentivizing industries to adopt green technologies should also be prioritized. Additionally, the study highlights the significant role of vegetation in reducing NO_2 concentrations and strongly advocates for the creation of green belts, the establishment of urban green spaces, and the conservation of existing greenery to mitigate pollution. Vehicular emissions are another major contributor to NO_2 pollution in Gazipur and the Greater Dhaka area. Phasing out outdated and unfit vehicles, while promoting the adoption of hybrid and electric vehicles, should be a top priority. Public awareness campaigns can further support these efforts by encouraging eco-friendly behaviours such as using LPG for cooking, adopting e-cooking appliances, and utilizing sustainable modes of transportation. Finally, to enhance scientific understanding and policy-making, establishing additional ground-based air quality monitoring stations to complement satellite data is essential. Making the data publicly accessible will improve the management and resolution of air quality issues.

Strength and limitations

The present study is one of the first in the Gazipur Dhaka region, explores the changing patterns of NO_2 levels and their causes, using advanced geographic and remote sensing techniques. The methods used in this study are scientific, and the findings are pioneering and trustworthy. However, to fully appreciate the

implications of these findings, especially for policy-making, it is important to acknowledge some limitations of the study.

Firstly, Bangladesh currently has only 11 air monitoring stations with only one station allocated for Gazipur City, which is too few for detailed satellite-based studies. Since 2019, the S5P satellite has been providing data with a resolution of 1×1 square kilometres. This resolution is not fine enough for analysing small areas effectively. However, the study found a strong agreement between the satellite and ground-level monitoring station data allowing it to use satellite data as a proxy for the ground level NO_2 concentration. This approach is well-established and widely accepted within the scientific community. A potential concern arises from the difference in measurement units, as Sentinel-5P reports NO_2 concentrations as total or tropospheric columns in mol/m^2, whereas surface NO_2 levels are commonly expressed in $\mu g/m^3$. However, this study primarily focuses on analysing spatial and temporal trends and exploring the relationships between NO_2 concentrations and environmental factors. Therefore, the variation in units does not undermine the reliability or relevance of our findings, especially considering the strong correlation observed between satellite-derived and ground-based data.

Second, due to the limited availability of ground-based monitoring in Gazipur City, the study relied on satellite data to explore the relationship between road traffic and NO_2 levels. While this approach provides a comprehensive view of NO_2 pollution, it does not enable pinpointing specific emission sources. Moreover, while Sentinel-5P offers daily NO_2 data, other relevant variables, such as those related to meteorological conditions, lack similar temporal resolution.

Lastly, incorporating additional meteorological factors such as wind speed, humidity, and precipitation could have offered a deeper understanding of how NO_2 levels fluctuate over time and space. Despite these challenges, the study offers valuable insights into NO_2 pollution patterns, particularly by providing an estimate of atmospheric NO_2 levels in an area with limited or no ground-based monitoring stations. This contribution is of significant interest to scientists and policymakers, as it enhances the understanding of NO_2 dynamics concerning its environmental and anthropogenic factors in regions where traditional monitoring infrastructure is lacking.

Abbreviations NO_2: Nitrogen dioxide; NDVI: Normalized difference vegetation index; LULC: Land use land cover; LST: Land surface temperature; GEE: Google Earth Engine; OSM: OpenStreetMap; MODIS: Moderate resolution imaging spectroradiometer; CSP: Conservation Science Partners

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Author contribution Al Jubaer: Formal analysis, Methodology, Software, Visualization, Writing—Original Draft; Rakib Hossain: Formal analysis, Visualization, Writing—Original Draft, Writing – reviewing & editing; Md. Shakhaoat Hossain: Supervision, Validation, Conceptualization; Afzal Ahmed: Super Vision, Funding acquisition;

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Data availability The datasets utilized to derive the findings of this study are available upon request.

Declarations

Competing interests The authors declare no competing interests.

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