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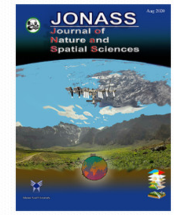

Analysis of Climate Change and Air Pollution Using GEE in a Beijing and Mumbai

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Background and objective: Urban areas worldwide are increasingly grappling with the impacts of pollution and climate change. This study investigates the spatiotemporal variations of environmental and climatic factors in Mumbai and Beijing. The primary objective is to analyze the influence of these factors on urban air quality and to provide insights into the effectiveness of pollution control measures in these rapidly evolving cities..

Materials and methods: The study utilized remote sensing data from Sentinel-5P, and Sentinel-2 satellites, as well as Global Satellite Mapping of Precipitation - Product 5P (GSMaP-5P) and Sentinel-3A images, accessed through Google Earth Engine (GEE). Data on SO_2, NO_2, and CH_4 concentrations were extracted and analyzed alongside 2-meter temperature, wind speed, NDVI, and precipitation patterns. Statistical analyses were performed to assess temporal trends and spatial distributions of these variables, with a focus on identifying correlations between pollutant levels and climatic factors.

Results and conclusion: In Mumbai, elevated concentrations of SO_2, NO_2, and CH_4 were observed, particularly in industrial and central areas, reflecting ongoing pollution challenges. NDVI data showed decreased vegetation cover, exacerbating urban heat island effects. Beijing, however, showed a significant reduction in SO_2 and NO_2 levels, attributed to stringent emission controls. CH_4 concentrations in Beijing also decreased over time, indicating successful mitigation efforts. Climatic data revealed consistently high temperatures and stable wind patterns in Mumbai, contrasting with Beijing's more variable temperatures and higher wind speeds. Precipitation patterns in Mumbai demonstrated high variability, while Beijing experienced decreasing total precipitation. The study underscores the effectiveness of pollution control measures in Beijing and highlights the ongoing need for improved air quality management strategies in Mumbai. These findings provide valuable insights for urban environmental policy and pollution control in rapidly urbanizing regions.

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1. Introduction

Air pollution and climate change are interrelated global environmental challenges that significantly impact human health, ecosystems, and the overall quality of life. These issues have become a major concern in modern society, as they are directly linked to economic development, urbanization, and industrial activities. Air pollution, in particular, has been recognized as a severe threat, especially in densely populated and rapidly industrializing cities such as Beijing and Mumbai. It not only affects the health of millions of residents but also has profound implications for regional climate systems, biodiversity, and environmental sustainability (Xu et al., 2021).

As a result, understanding the dynamics of air pollutants and their interactions with climatic factors is crucial for developing effective mitigation strategies. One of the most advanced tools available for monitoring atmospheric pollution is the Sentinel-5 Precursor (S5P) satellite, which was successfully launched on October 13, 2017, from Plesetsk in northern Russia. This satellite is equipped with the Tropospheric Monitoring Instrument (TROPOMI), a state-of-the-art sensor designed to measure various atmospheric gases, including nitrogen dioxide (NO_2), sulfur dioxide (SO_2), methane (CH_4), and carbon monoxide (CO). These trace gases are major pollutants, resulting from incomplete combustion processes, such as traffic emissions, industrial production, and biomass burning. Carbon monoxide (CO), for instance, is primarily removed from the atmosphere through chemical reactions with hydroxyl radicals (OH), highlighting the complex interactions within the atmospheric system (Kleipoolet al., 2018).

The TROPOMI sensor, with its high spatial resolution and wide swath width, provides unprecedented capabilities for observing atmospheric pollutants on a global scale. Its data is critical for understanding temporal and spatial variations in air quality, as well as for assessing the effectiveness of environmental policies and regulations. The use of satellite data, combined with advanced computational platforms like Google Earth Engine (GEE), allows for comprehensive analysis and visualization of pollutant trends across different regions and time periods. GEE provides a cloud-based platform for geospatial analysis, enabling researchers to analyze large datasets, such as those provided by the Sentinel-5P (S5P) satellite, with greater efficiency and accuracy (Kazemi Garajeh et al., 2023).

This combination of remote sensing technology and cloud computing facilitates real-time monitoring and assessment of air pollution and its drivers, including climatic factors like temperature and wind speed (Tabunschik et al., 2023). In this paper, we focus on two of the most heavily polluted and rapidly growing industrial cities in the world: Beijing and Mumbai. Both cities are facing severe challenges related to air quality and climate change due to their high population densities, industrial activities, and urban expansion (Halder et al., 2023). Previous studies have shown that these cities experience significant variations in pollutant concentrations, including NO_2, SO_2, and CH_4, which are major contributors to poor air quality (Zheng et al., 2023). For example, research has indicated varying trends of NO_2 and SO_2 in different regions, reflecting diverse sources and environmental regulations (Krotkov et al., 2016).

The complex interplay between local emission sources, meteorological conditions, and regional climate variability necessitates a more nuanced understanding of air quality dynamics in these urban environments. The Sentinel-5P (S5P) satellite's TROPOMI instrument has demonstrated high performance in monitoring these pollutants, providing valuable data for assessing air quality trends and identifying hotspots of pollution (Van Geffen et al., 2022). In this study, we leverage TROPOMI's high-resolution measurements to examine the temporal variability of NO_2, SO_2, and CH_4 in Beijing and Mumbai.

Additionally, we investigate the influence of climatic factors, such as temperature and wind speed, on the distribution and concentration of these pollutants. Understanding the relationship between meteorological conditions and air pollution is essential for predicting future scenarios under different climate change pathways and for informing policy decisions aimed at reducing pollution levels (He et al., 2017). Our study uses meteorological data—including temperature, wind speed, relative humidity, and precipitation—with TROPOMI-derived pollutant concentrations. This approach improves the accuracy of predictions for NO_2, SO_2, and CH_4 levels, providing a more comprehensive understanding of air quality dynamics in these cities. Previous research has highlighted the importance of incorporating meteorological variables into air quality models to enhance their predictive capabilities (Giovannini et al., 2020). By using advanced analytical techniques and robust datasets, our study aims to provide new insights into the factors driving air pollution and to identify potential mitigation strategies.

Kazemi Garajeh et al. (2023) investigated the effectiveness of Sentinel-5 air pollution (AP) products and the GEE platform for monitoring key air pollutants—carbon monoxide (CO), (NO_2), SO_2, and ozone (O_3)—in Arak city, Iran, over the years 2018 and 2019. The study aimed to evaluate the suitability of these tools for mapping and monitoring air pollution sources in a developing country where public health risks from air pollution are rising. The research involved processing Sentinel-5 satellite images using the GEE platform to identify areas affected by pollution on a monthly, seasonal, and annual basis. JavaScript coding in the GEE platform was used to extract data for the four pollutants. The study implemented cloud filtering techniques to refine the images and defined average filters to produce comprehensive annual maps for both years. The model's performance was assessed using ground-truth data from the Environmental Organization of Central Province. The findings indicated that Sentinel-5 data, when combined with GEE's automated processing, provided accurate estimates of annual CO, NO_2, SO_2, and O_3 levels, with root mean square errors (RMSE) of 0.13, 2.58, 4.62, and 2.36 for 2018, and 0.17, 2.41, 4.31, and 4.60 for 2019, respectively. Seasonal estimates also showed good accuracy, with RMSE values for 2018 of 0.09 for CO, 5.39 for NO_2, 0.70 for SO_2, and 7.81 for O_3, and for 2019 of 0.12 for CO, 4.99 for NO_2, 1.33 for SO_2, and 1.27 for O_3. The study concluded that Sentinel-5 data, when paired with GEE's automated methods, offers a superior approach to traditional pollution monitoring stations by providing spatially distributed and accurate air quality data.

Gharibvand et al. (2023) investigated the impact of the COVID-19 lockdown on air pollution levels, specifically focusing on NO_2 and ozone (O_3) in the industrial cities of Arak and Tehran, Iran. The study compared pollutant levels during the lockdown period from November 19 to December 05, 2020, with the same period in 2019. Using Sentinel-5P data, the researchers analyzed changes in NO_2 and O_3 levels while accounting for the effects of climatic factors such as rain and wind. The results revealed a reduction in NO_2 and O_3 concentrations during the 2020 lockdown compared to 2019: NO_2 decreased by 3.5% and 20.97% in Tehran and Arak, respectively, while O_3 levels fell by 6.8% and 5.67%. These decreases are attributed to reduced transportation and industrial activities during the lockdown. The study suggests that similar measures could be beneficial for pollution control in non-pandemic conditions.

Tabunschik et al. (2023) conducted an assessment of atmospheric pollutant concentrations using advanced geoinformation research methods, incorporating Sentinel-5 satellite imagery, the GEE platform, and ArcGIS 10.8 software. The study focuses on analyzing the spatial distributions of various pollutants—including NO_2, SO_2, formaldehyde (HCHO), carbon monoxide (CO), and CH_4—within the basins of the Zapadnyy Bulganak, Alma, Kacha, Belbek, and Chernaya rivers on the north-western slope of the Crimean Mountains. The research compares the average annual and monthly pollutant concentrations for each catchment area. The GEE platform is employed to extract annual and monthly average rasters of these pollutants, while ArcGIS is used for enhanced data visualization and detailed analytical processing. Background concentrations within protected natural areas are calculated, and a complex index of atmospheric pollution is constructed by comparing the spatial and temporal distribution of pollutants with these background concentrations. The study highlights the variability of NO_2 concentrations through regression analysis, with a coefficient of determination ($R > 0.85$) indicating a robust assessment of emission fields based on spatial and temporal heterogeneity. The significance of this study lies in its innovative approach to using Sentinel-5 satellite imagery to evaluate air quality and pollution in regions with sparse observational networks. The findings emphasize the importance of this research for understanding air pollution impacts on human health and ecosystems, particularly in the river basins of the Crimean Mountains.

Halder et al. (2023) examined the impact of climatic conditions and anthropogenic activities on air quality and human health by monitoring key air pollutants using Sentinel-5P satellite data and the GEE platform from 2018 to 2021. This study highlights the influence of human activities—such as urban expansion, transportation development, and industrial work—on climate change and global warming, which in turn affects the concentration of air pollutants. The study focuses on three critical pollutants: NO_2, carbon monoxide (CO), and aerosol optical depth (AOD). It was found that NO_2 levels varied significantly due to anthropogenic activities, with high concentrations recorded in Kolkata and Delhi. Specifically, the Air Quality Index (AQI) in Kolkata and Delhi showed substantial fluctuations between 2018 and 2021, with NO_2 levels reaching as high as 102 in 2018 in Kolkata and 107 in 2021 in Delhi. The CO concentrations also displayed noticeable variations, particularly between different months, indicating significant changes in air quality over time. The research underscores that the AQI was notably high in 2020 and 2021, while it was relatively lower in 2018 and 2019. The study also revealed high AOD values in Uttar Pradesh in 2020, suggesting elevated levels of particulate matter. These findings emphasize the need for continuous air quality monitoring and management to address the adverse effects of air pollution and climate change, which are crucial for ensuring the health of the planet and its inhabitants.

Zheng et al. (2023) examined the impact of climate change on air quality in Peninsular Malaysia by analyzing ground-based observations of temperature, precipitation, relative humidity, wind speed, and concentrations of particulate matter (PM10), ozone (O_3), CO, NO_2, and SO_2 from 2000 to 2019. The study utilized Pearson correlation and canonical correlation analysis (CCA) to explore the relationships between climatic variables and air quality, and to predict future air quality changes under different warming scenarios. The findings indicated that Peninsular Malaysia experienced increased temperatures (+4.2%), decreased relative humidity (−4.5%), and more variable precipitation over the study period. Air pollution worsened with notable increases in PM10 (+16.4%), O_3 (+39.5%), and NO_2 (+2.1%), while SO_2 (−53.6%) and CO (−20.6%) concentrations decreased. Monthly variations showed bimodal patterns for PM10 and O_3 corresponding to monsoon transitions. The CCA results revealed strong correlations between air quality factors and meteorological variables, with CO, O_3, and PM10 closely interacting with temperature. The study predicts that air quality in Peninsular Malaysia is likely to deteriorate under future warming conditions.

There is a notable gap in the current research regarding the combined impact of climatic factors, such as temperature, precipitation, and wind speed, along with specific air pollutants, on urban air quality over time in major industrial cities like Beijing and Mumbai. While previous studies have often focused on isolated aspects of either air pollution or climate change, comprehensive analyses that integrate both environmental and meteorological variables remain limited. This study addresses this gap by using high-resolution satellite data from multiple sources, including the Tropospheric Monitoring Instrument (TROPOMI) sensor aboard the Sentinel-5P (S5P) satellite for air pollutants (NO_2, SO_2, CH_4), Sentinel-2 for the NDVI, Sentinel-3A for land surface temperature (LST), and the GSMaP-5P satellite for precipitation. These datasets are analyzed through the cloud-based geospatial analysis platform, GEE.

In this study, GEE models were employed to investigate the temporal and spatial distribution of NO_2, SO_2, and CH_4 in relation to meteorological data, such as temperature, precipitation, and wind speed, to enhance the understanding of pollution dynamics in Beijing and Mumbai. This approach allows for a more precise analysis of the temporal variability of air pollutants and their correlation with climatic factors, thereby providing insights into their interactions. The study is based on two primary hypotheses:

1. Climatic variables, particularly temperature and precipitation, significantly influence the concentrations of NO_2, SO_2, and CH_4 and, consequently, the trends in urban air quality.

2. There is an inverse relationship between Normalized Difference Vegetation Index (NDVI) (as a proxy for vegetation health) and the concentration of these pollutants, suggesting that areas with higher vegetation cover have lower levels of air pollution.

This research has three primary objectives:

1. To monitor and assess the spatial and temporal variability of air quality indicators (NO_2, SO_2, CH_4) in Beijing and Mumbai using TROPOMI satellite data.

2. To evaluate the impact of climatic factors such as temperature, precipitation, and wind speed on pollution levels.

3. To provide a comprehensive understanding of the interaction between climatic factors and air pollutants, as well as the role of vegetation in these urban environments.

Unlike previous studies, this research integrates advanced remote sensing technology with cloud-based geospatial analysis and machine learning models to provide a holistic view of air quality management. The findings of this study are expected to offer valuable insights for policy makers and urban planners, aiding in the development of more effective strategies for air pollution mitigation and climate change adaptation in highly polluted cities like Beijing and Mumbai.

2. Material and Methods

2.1. Study Area

Beijing is the capital of the People's Republic of China and one of the most populous cities globally, serving as the country's political, cultural, and educational center. With a population of approximately 22 million people, Beijing is the second most populous city in China, following Shanghai (Wang et al., 2019). Geographically, Beijing is located in northern China, bordered by Hebei Province to the north, west, and south, and Tianjin Municipality to the southeast. The city's climate is characterized by hot, humid summers and cold, dry winters, which are typical of a monsoon-influenced humid continental climate. Summers, from June to August, are also the rainy season, accounting for nearly 75% of the annual precipitation. Winters are dry and cold, while spring and autumn are short and cool. The city's air quality has been a significant concern in recent years due to rapid urbanization, industrial activities, and a high population density, which contribute to substantial emissions of pollutants such as NO_2 and particulate matter (PM) (Wei et al., 2023).

Mumbai, the capital of Maharashtra, is the most populous city in India and serves as the financial, commercial, and entertainment hub of the country. With a population of about 20 million (as of 2018) and an area of 603 square kilometers, Mumbai is among the four largest and most densely populated cities in India, and one of the top six most populous cities globally (Kadam & Thakur , 2020). Located on the west coast of India along the Arabian Sea, Mumbai has a tropical climate characterized by hot and humid conditions throughout the year. The city experiences three primary seasons: a hot and humid summer, a monsoon season with heavy rainfall, and a mild winter. The monsoon, from June to September, brings substantial rainfall, often leading to flooding and waterlogging in various parts of the city (Mohanty et al., 2023). Due to its high population density, rapid urban development, and industrial growth, Mumbai also faces severe air quality issues, with significant emissions of pollutants like SO_2 and carbon monoxide (CO) (Gupta, 2024).

The Digital Elevation Model (DEM) for both Beijing and Mumbai, providing a comparative visualization of their topography (Fig.1). The two cities, despite being geographically distant, share similar challenges related to rapid urbanization, population growth, and air pollution. Both cities are focal points for studying the impacts of air quality and climate change on urban environments, making them ideal study areas for understanding urban air pollution dynamics and the effects of various climatic and anthropogenic factors.

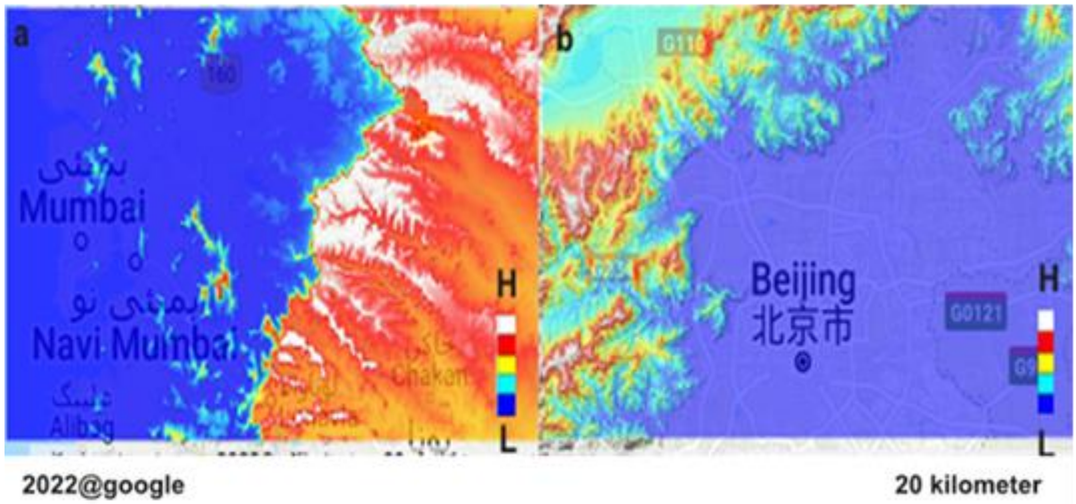

Fig. 1 – Digital Elevation Model (a) Mumbaei; (b) Beijing

2.2. Data Collection and Research Methods

2.2.1. Overview of Data Sources

The primary data sources for this study are satellite-based measurements obtained from various missions that provide high-resolution observations of atmospheric and climatic variables. These data sources include the Sentinel-5 Precursor (S5P) mission for atmospheric pollutants, the GSMaP-5P mission for precipitation data, Sentinel-2 for vegetation indices, and Sentinel-3A for LST. Each of these datasets is critical for understanding the interplay between air quality and climatic factors in the study areas.

The Sentinel-5P satellite, launched on 13 October 2017, is equipped with the Tropospheric Monitoring Instrument (TROPOMI), which offers global daily coverage of trace gases such as NO_2, SO_2, and CH_4 with high spatial resolution (7x7 km). The GSMaP-5P system integrates precipitation data from GSMaP with atmospheric measurements from Sentinel-5P, providing valuable insights into the relationship between rainfall patterns and air pollutant concentrations.

The Sentinel-2 mission, part of the Copernicus program, provides high-resolution multispectral imagery suitable for calculating the NDVI, which is used to assess vegetation health and land cover. Sentinel-3A provides data on LST, critical for examining heat distribution and its impact on atmospheric conditions.

Data from these satellites are processed through the GEE platform, a cloud-based geospatial analysis service that facilitates large-scale environmental monitoring and data processing (Gorelick et al., 2017). GEE provides access to extensive historical and real-time datasets and supports the processing of satellite imagery for extracting relevant climatic and atmospheric variables.

Additionally, wind rose diagrams have been employed to analyze the spatial distribution and prevailing directions of wind speed across the study regions. The wind rose diagrams offer valuable insights into the variability of wind patterns and their potential impact on the dispersion of pollutants and climatic conditions. By visualizing the frequency and intensity of wind directions, these diagrams help to contextualize the effects of wind on air quality and precipitation patterns, complementing the satellite data and providing a comprehensive understanding of the atmospheric dynamics in Mumbai and Beijing. Initially, this paper provides a comprehensive overview of the study, followed by a detailed flowchart illustrating the workflow and methodological approach employed in the research (Fig.2).

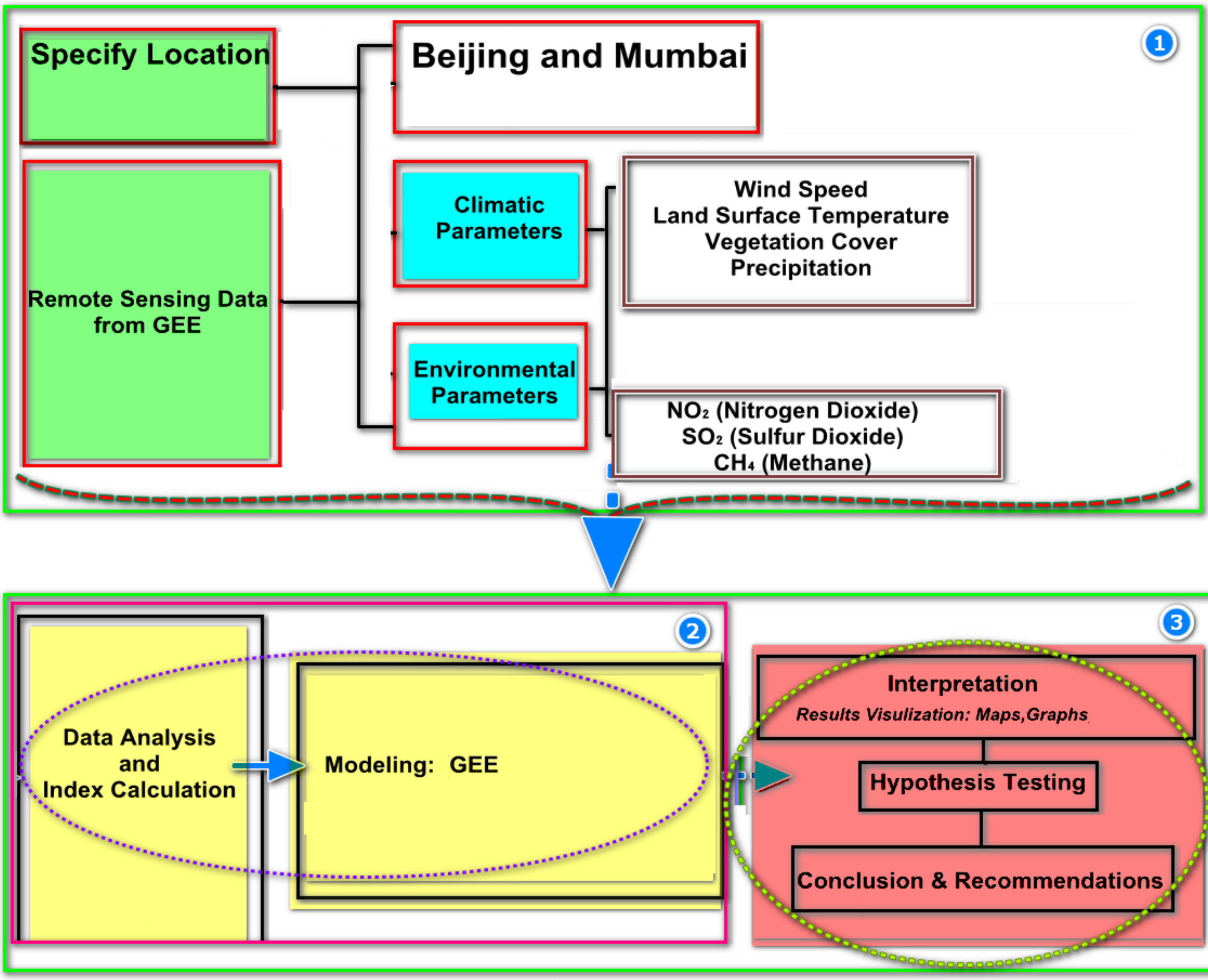

Fig.2 - Workflow Diagram of the Research Methodology

2.2.2. Data Acquisition

The data acquisition process involved several steps to ensure comprehensive coverage and accuracy:

1. Selection of Study Areas: The focus of the study is on Beijing and Mumbai, two major industrialized and highly populated cities with significant air quality challenges. The selection of these cities is based on their representative nature in terms of urbanization, industrial activities, and climatic conditions.

2. Data Retrieval:

Atmospheric Pollutants (NO_2, SO_2, CH_4): Data for these pollutants were retrieved from the Sentinel-5P TROPOMI mission.

Precipitation: Precipitation data was obtained from the GSMaP-5P system, which provides high temporal and spatial resolution measurements suitable for detailed analysis.

LST: Temperature data was extracted from the Sentinel-3A mission, which offers accurate LST data that helps in understanding surface heat patterns.

NDVI: NDVI data was obtained from Sentinel-2 imagery, providing critical information on vegetation cover and health.

Wind Speed: Wind speed data was retrieved from ERA5, a comprehensive dataset available on GEE.

2.3. Data Acquisition and Processing

2.3.1. Data Processing

Data processing was conducted using the GEE platform, which offers powerful tools for analyzing large datasets. The following steps were performed:

1. Data Preprocessing:

Cloud Masking: Satellite images with cloud cover were filtered using cloud masks to ensure data accuracy. The GEE platform provides cloud masking algorithms to enhance the quality of the retrieved images.

Data Calibration: Calibration of the TROPOMI data was performed to correct for instrumental and atmospheric effects, ensuring that the measurements reflect accurate concentrations of NO2, SO2, and CH4.

2. Extraction of Time Series:

Tropospheric NO_2, SO_2, and CH_4: Time series data were extracted by applying the TROPOMI sensor’s specific algorithms. These measurements reflect the atmospheric concentrations of these pollutants.

Precipitation: Precipitation data was extracted to assess rainfall patterns and their impact on atmospheric conditions.

LST from Sentinel-3A: Temperature data was extracted to analyze the thermal properties and their correlation with air pollutants.

NDVI (Sentinel-2): NDVI data, which provides insights into vegetation health and land cover, were also extracted from the GEE platform.

3. Data Integration:

The various datasets were integrated to create a comprehensive dataset encompassing all relevant climatic and atmospheric parameters. This integration was essential for performing detailed analyses and investigations.

2.3.2. Data Analysis

1. Statistical Analysis:

Temporal Analysis: Trends and patterns in the concentrations of NO_2, SO_2, CH_4, precipitation, NDVI, and temperature were analyzed over time to identify significant changes and seasonal variations.

Spatial Analysis: Spatial distribution maps of the pollutants and climatic variables were generated to visualize the geographical extent and intensity of pollution in Beijing and Mumbai.

2. Comparative Analysis:

City Comparison: The study compared air quality and climatic conditions between Beijing and Mumbai to highlight differences and similarities in pollution patterns and their drivers.

2.4. Investigation of Relationships

1. Parameter Interactions:

The study investigated the interactions between different atmospheric and climatic parameters to understand how changes in one parameter might influence others. For instance, the impact of temperature changes on NO_2 and SO_2 levels was analyzed.

2. Model Validation:

The findings were validated using ground-based measurements and other available data sources to ensure the accuracy and reliability of the satellite-derived information.

3. Implications for Air Quality Management:

The results were interpreted to provide insights into the implications for air quality management and policy-making in Beijing and Mumbai. Recommendations were made based on the observed relationships and trends.

This comprehensive methodology ensures a thorough analysis of the air quality and climatic factors affecting Beijing and Mumbai, providing valuable insights into pollution dynamics and their drivers.

3. Results

3.1. Spatial and Temporal Analysis of NO_2, SO_2, and CH_4 Concentrations in Beijing and Mumbai (February to March 2022)

This section aims to provide a detailed understanding of the spatiotemporal distribution of NO_2, SO_2, and CH_4 concentrations in Beijing and Mumbai, which can serve as a basis for effective urban air quality management strategies. The results are depicted in Fig. 3, which provides visual representations of the concentration maps for these pollutants across both cities (Fig. 3).

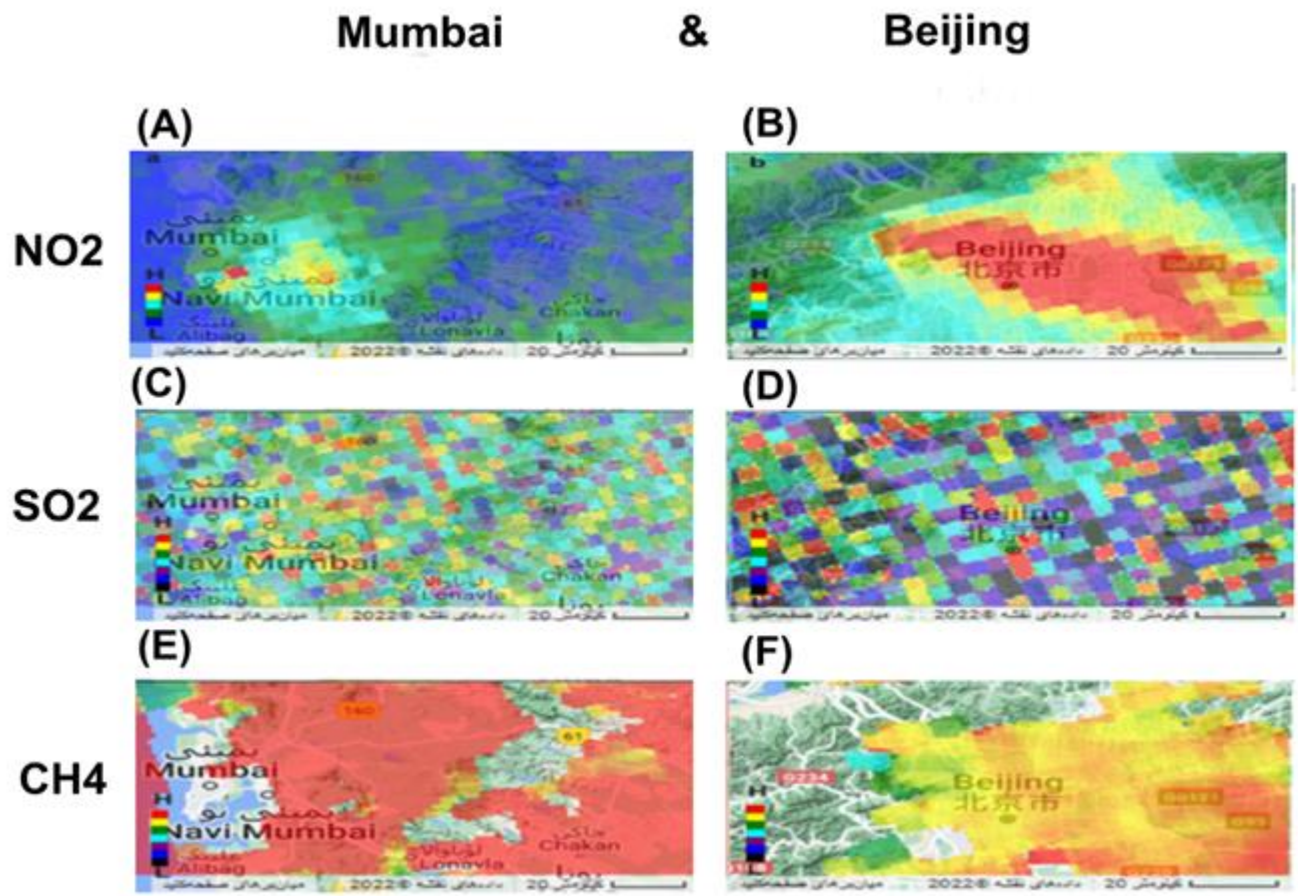

Fig. 3 – Spatial Distribution and Temporal Variation of (A & B: NO_2), (C & D: SO_2), and (E & F: CH_4) Column Concentrations in Beijing and Mumbai from February to March 2022

3.1.1. Spatial Distribution of NO_2, SO_2, and CH_4 Concentrations in Beijing and Mumbai (February to March 2022)

The spatial distribution of NO_2, SO_2, and CH_4 concentrations in Beijing and Mumbai from February to March 2022 reveals notable patterns and variations in air quality across the two cities. The analysis highlights distinct spatial and temporal characteristics of these pollutants, which are crucial for understanding their environmental and health impacts.

NO_2: In Mumbai (Panel A), NO_2 concentrations are notably higher in the city center, where red patches indicate the highest concentrations. There are also high levels in the western outskirts, marked by yellow patches. The overall distribution and concentration of NO_2 are quite high, indicating substantial emissions likely stemming from urban activities and traffic. In Beijing (Panel B), NO_2 also shows extensive coverage across the entire city, with the highest concentrations seen in the central areas, highlighted by red patches. The city's outskirts similarly show elevated NO_2 levels, suggesting widespread pollution from various urban and industrial sources.

SO_2: In Mumbai (Panel C), SO_2 is spatially distributed throughout the city; however, the central areas exhibit higher concentrations, marked by red and yellow patches. This pattern indicates a concentration of SO_2 emissions likely originating from industrial activities in the city center. In Beijing (Panel D), SO_2 concentrations are also spread across the city, but the distribution appears more uniform, indicating a consistent presence of SO_2 emissions across the city without significant localized peaks.

CH_4: In Mumbai (Panel E), CH_4 concentrations cover the entire city, with particularly high concentrations and focus, shown in red patches. This suggests significant CH_4 emissions throughout the city, potentially from sources such as organic waste and industrial activities. In Beijing (Panel F), CH_4 similarly covers the whole city with high concentrations but shows a mix of red and yellow patches. However, compared to Mumbai, the CH_4 concentration in Beijing is slightly lower, which might indicate different sources and emission intensities between the two cities.

General Observations: The spatial distribution of these pollutants indicates that both cities experience high levels of NO_2, SO_2, and CH_4 emissions. The concentration patterns suggest that local emission sources, such as industrial zones, vehicular traffic, and waste management activities, play significant roles in air quality variations. Temporal variations during the study period also reflect fluctuations in pollutant levels, often peaking during specific times linked to urban and industrial activities.

3.1.2. Temporal Variation in NO_2, SO_2, and CH_4 Concentrations (February to March 20)

This section examines the temporal variation in concentrations of NO_2, SO_2, and CH_4 over the period from February to March 2022 in Beijing and Mumbai. The analysis focuses on identifying significant patterns of increase or decrease in pollutant levels and associating these trends with potential influencing factors such as weather conditions, industrial operations, and daily human activities. For instance, the concentration of NO_2, primarily emitted from vehicles and industrial processes, may peak during weekdays when traffic is heavier and industrial activities are at their peak, while lower levels may be observed during weekends due to reduced economic activities. Similarly, SO_2 levels could vary in response to operational shifts in power plants and factories, reflecting changes in energy production and consumption patterns. CH_4 concentrations, often related to organic waste management and natural gas leaks, may also show fluctuations depending on temperature, wind speed, and other meteorological factors affecting its dispersion and concentration. By analyzing these temporal variations, this section provides a comprehensive understanding of how urban air quality is dynamically influenced by both anthropogenic and environmental factors, highlighting periods that may require targeted interventions to mitigate pollution.

3.1.3. Comparative Analysis Between Beijing and Mumbai

This section provides a comparative analysis of the concentration levels and patterns of NO_2, SO_2, and CH_4 between Beijing and Mumbai. It highlights the key differences and similarities observed in the spatial and temporal distributions of these pollutants. For example, while both cities exhibit high NO_2 concentrations in their central areas, Beijing tends to show a more extensive spread across its urban and suburban regions, potentially due to its larger geographical size and higher industrial density. Conversely, Mumbai may have more localized hotspots of SO_2 around its central areas, indicating concentrated industrial activities or power plants. The comparison also considers factors like population density, vehicular emissions, industrial operations, and meteorological conditions such as wind patterns and temperature, which can significantly influence pollutant dispersion and concentration levels. By exploring these differences and similarities, the study offers insights into how varying urban dynamics and environmental contexts impact air quality in major industrial cities.

3.1.4. Implications of the Findings on Urban Air Quality Management

This section discusses the implications of the observed concentrations and spatial-temporal patterns of NO_2, SO_2, and CH_4 for urban air quality management in Beijing and Mumbai. The findings underscore the need for city-specific strategies to address pollution sources effectively. For instance, in Beijing, where NO_2 and SO_2 levels are widespread, policies might focus on transitioning to cleaner energy sources, improving industrial emissions standards, and enhancing public transportation to reduce vehicular pollution. In Mumbai, where CH_4 levels are significantly influenced by organic waste management and agricultural activities, strategies could include better waste management practices, the promotion of biogas as a renewable energy source, and stricter regulations on agricultural burning practices. The study recommends continuous monitoring using satellite-based remote sensing and ground-based measurements to provide comprehensive data for policymakers. Future directions may involve integrating advanced machine learning models for predictive air quality assessments and expanding monitoring to include other emerging pollutants to create a more holistic urban air quality management framework.

3.2. Spatial Distribution of NDVI in Mumbai and Beijing

The spatial distribution of the NDVI in Mumbai and Beijing reveals distinct patterns of vegetation cover in these urban environments (Fig.4). In Mumbai (Panel A), the western outskirts of the city show almost no vegetation cover, indicated by red patches, which suggests the presence of highly urbanized or industrial areas devoid of significant green cover. In contrast, other parts of Mumbai exhibit scattered vegetation cover, which is relatively sparse, suggesting fragmented and less dense vegetation across the urban landscape. These patterns could be attributed to the city's rapid urban expansion, land use practices, and environmental management policies that have resulted in limited green spaces in certain areas.

In Beijing (Panel B), the NDVI map shows a stronger and more concentrated vegetation cover in the western parts of the city, stretching from the northwest to the southwest, indicated by greener patches. This suggests a more preserved natural or managed vegetation area, potentially due to the presence of mountains, parks, or planned green belts in these regions. On the other hand, the central parts of Beijing, similar to Mumbai’s outskirts, exhibit very low NDVI values, indicating a lack of vegetation cover. This could be due to the dense urban infrastructure, road networks, and limited green spaces in the heart of the city, reflecting different urban planning and development approaches compared to other parts of the city.

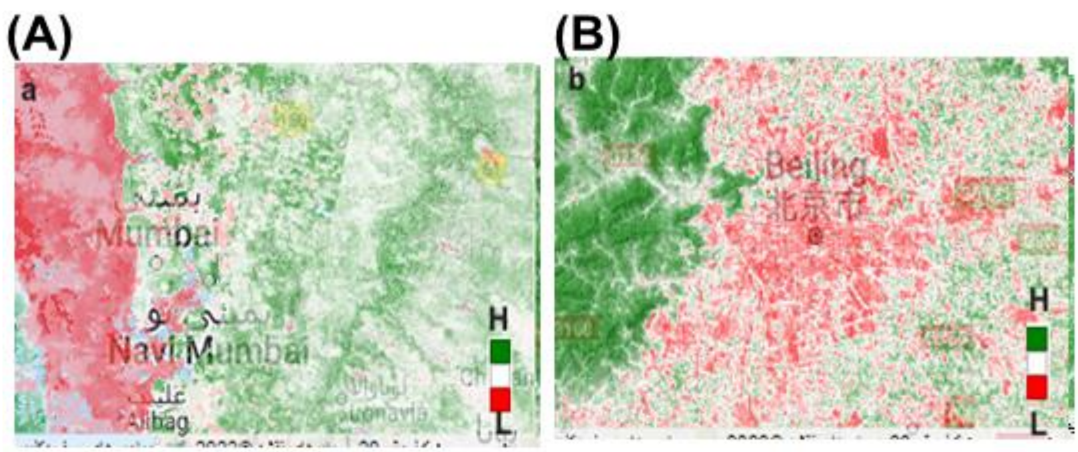

Fig. 4 – NDVI Variation of (A : Beijing and B: Mumbai) from February to March 2022

3.2.1. Temporal Variation of Vegetation Cover in Urban Areas

Analyzing the temporal variation of NDVI in both cities provides insights into seasonal changes, vegetation health, and growth dynamics. NDVI values tend to vary across different seasons due to climatic factors such as temperature, rainfall, and human activities like agriculture, urban expansion, and maintenance of green spaces. For instance, higher NDVI values could be observed in the monsoon season in Mumbai due to increased rainfall promoting vegetation growth, whereas, during drier months, NDVI values might drop, reflecting stress on vegetation cover. In contrast, Beijing may exhibit distinct seasonal variations where vegetation in the western parts could flourish in spring and summer due to favorable weather conditions, while dropping significantly in the winter due to harsher climatic conditions and potential snow cover. The temporal analysis of NDVI helps in understanding these dynamics and their implications for urban planning, climate resilience, and ecological management.

3.2.2. Comparative Analysis of NDVI Patterns Between Mumbai and Beijing

Comparing the NDVI patterns between Mumbai and Beijing highlights both similarities and differences in urban vegetation distribution and density. While Mumbai shows scattered and sparse vegetation primarily concentrated away from the western outskirts, Beijing’s green cover is more concentrated in the western regions, and the city center is almost devoid of vegetation. These differences may be influenced by several factors, including urban planning policies, geographical conditions, environmental conservation efforts, and socio-economic dynamics. For example, the stronger vegetation cover in Beijing's western regions could be due to deliberate urban planning efforts to maintain green belts and public parks, while the fragmented vegetation in Mumbai might result from organic urban sprawl and differential land use practices. Understanding these comparative dynamics is crucial for city planners and policymakers to develop effective urban greening strategies and improve the overall ecological health of these cities.

3.2.3. Implications for Urban Environmental Management

The observed spatial and temporal patterns of NDVI in Mumbai and Beijing have significant implications for urban environmental management and sustainable development strategies. The lack of vegetation in key urban areas, such as the central parts of both cities, underscores the need for enhanced green infrastructure, such as urban parks, rooftop gardens, and green corridors, to mitigate the urban heat island effect, improve air quality, and promote biodiversity. Moreover, the findings suggest that strategic urban planning should incorporate climate-resilient vegetation management practices to enhance the ecological sustainability of these cities. Recommendations include targeted reforestation efforts, the creation of green belts, and policies aimed at preserving existing vegetation. Future studies should also explore the socio-economic benefits of increasing urban green cover, such as improved public health, recreational spaces, and potential contributions to climate change adaptation.

3.2.4. Discussion: Drivers of Vegetation Patterns and Policy Recommendations

The discussion integrates the findings from the spatial and temporal analysis of NDVI with broader urban ecological and planning perspectives. Key drivers influencing vegetation patterns in Mumbai and Beijing are identified, including urbanization rates, climate variability, socio-economic factors, and local governance. The differences in vegetation patterns between the two cities suggest that while natural factors play a significant role, urban policy and management practices are equally crucial in shaping these patterns. To improve urban vegetation and ecological resilience, both cities could benefit from adopting more integrated urban planning approaches that prioritize green infrastructure and climate-adaptive strategies. Policy recommendations include implementing stringent land-use regulations, incentivizing urban greening initiatives, and enhancing community involvement in maintaining and expanding urban green spaces. Such measures could contribute to more sustainable and livable urban environments in the face of rapid urbanization and climate challenges.

3.3. Analysis of Temporal and Spatial Graphs of Pollutant Concentrations in Mumbai and Beijing

This section presents an analysis of the temporal and spatial graphs related to the concentrations of key air pollutants, including NO_2, SO_2, and CH_4, in two major industrial cities: Mumbai (A) and Beijing (B) (Fig. 5). These graphs illustrate the temporal changes and spatial patterns of these pollutants over different periods, enabling a precise comparison between the two cities. Since these pollutants are directly influenced by industrial activities, transportation, and weather conditions, a detailed analysis of the graphs can provide a better understanding of the distribution and concentration of these pollutants, as well as their variations over time. This section discusses the key differences and similarities in the concentration patterns of these pollutants in Mumbai and Beijing, and the findings can offer valuable insights for air quality management and environmental policy-making in these regions.

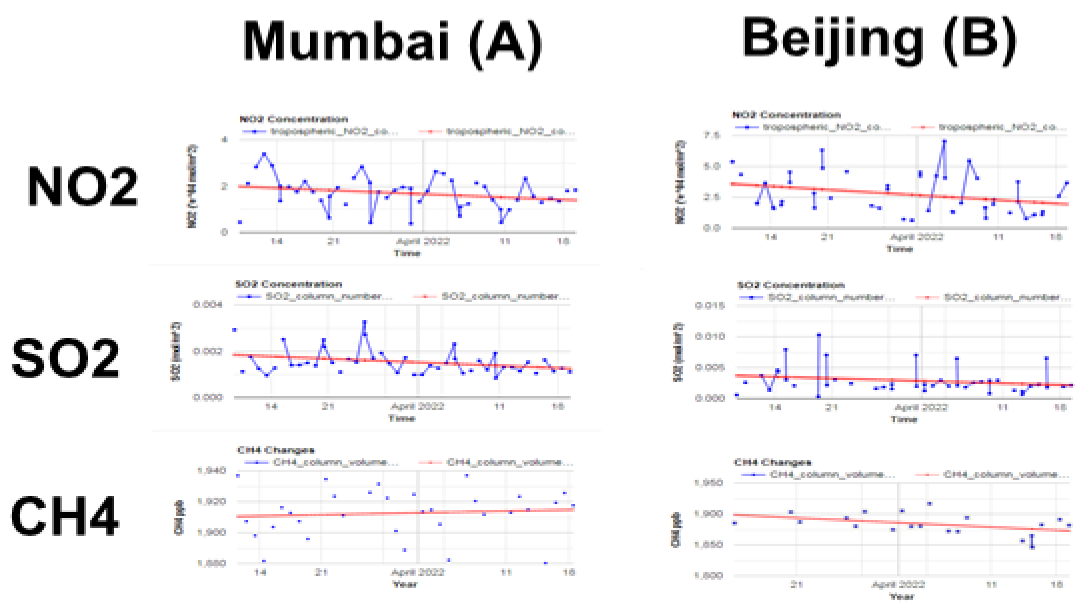

Fig.5 - Temporal and Spatial Distribution of NO_2, SO_2, and CH_4 Concentrations in Mumbai and Beijing from February to March 2022

3.3.1. Nitrogen Dioxide (NO_2) Concentration Graphs:

The NO_2 concentration graphs reveal distinct patterns in Mumbai and Beijing. In Mumbai, the initial concentration of NO_2 begins around 4 units and shows a gradual decrease over the study period. This downward trend suggests a steady reduction in NO_2 levels, which may be attributed to improved air quality measures or changes in industrial activity. However, the concentration remains more localized, with higher levels detected in specific areas of the city. This localization indicates that certain sources, such as traffic or industrial emissions, may continue to contribute significantly to NO_2 pollution.

In contrast, Beijing exhibits a more fluctuating trend in NO_2 concentrations, with noticeable increases and decreases throughout the period. This variability suggests that NO_2 levels in Beijing are influenced by a range of factors, including seasonal changes and fluctuating industrial emissions. Unlike Mumbai, NO_2 in Beijing is more evenly dispersed across the city, indicating a broader distribution of pollution sources. The more widespread distribution could reflect differences in urban density, industrial practices, and emission control measures between the two cities.

The difference in NO_2 concentration patterns between Mumbai and Beijing highlights the impact of local pollution sources and urban management strategies. Mumbai's localized NO_2 hotspots suggest targeted pollution sources, potentially related to traffic or specific industrial areas. In contrast, Beijing's broader distribution and variability may indicate a more complex interplay of multiple emission sources and changing regulatory environments. These insights can guide targeted air quality management strategies tailored to each city's unique pollution profile.

3.3.2. Sulfur Dioxide (SO_2) Concentration Graphs:

The SO_2 concentration graphs for Mumbai show a general decreasing trend over time, though there are periods with slight increases. This trend suggests a gradual improvement in air quality, likely due to interventions or reductions in sulfur emissions from key sources such as power plants or industrial facilities. The graph also indicates that SO_2 concentrations are more concentrated in specific areas of Mumbai, suggesting persistent emission sources in these regions.

In Beijing, SO_2 levels remain relatively stable throughout the period, with occasional localized spikes. This stable pattern reflects a more uniform distribution of SO_2 across the city, although temporary increases in specific areas may be linked to localized industrial activities or other short-term factors. The consistency in SO_2 levels across Beijing contrasts with Mumbai's more variable pattern, pointing to different emission dynamics and control measures.

The SO_2 concentration patterns underscore the effectiveness of pollution control measures and the impact of industrial activity on air quality. Mumbai's concentrated SO_2 emissions suggest ongoing challenges in specific areas, while Beijing's stable distribution highlights broader regulatory successes but with localized exceptions. These findings emphasize the need for continued monitoring and targeted interventions in areas with persistent SO_2 emissions to further improve air quality.

3.3.3. Methane (CH_4) Concentration Graphs:

The CH_4 concentration graphs illustrate an overall increasing trend in Mumbai, with fluctuating values across different areas of the city. This suggests that CH_4 emissions are driven by various localized sources, such as waste management and transportation, resulting in a moderate but uneven distribution of CH_4 concentrations. The lack of spatial consistency indicates intermittent sources contributing to the overall rise in CH_4 levels.

Conversely, Beijing shows a decreasing trend in CH_4 concentrations over the study period. The graph indicates that CH_4 levels are less dispersed and more concentrated in specific areas of the city. This spatial clustering could be due to targeted emission controls or reduced activity in specific sectors contributing to CH_4 emissions. The decreasing trend in Beijing suggests that emission reduction strategies may be having a measurable impact.

The contrasting trends in CH_4 concentrations between Mumbai and Beijing highlight differences in emission sources and control effectiveness. Mumbai's increasing and scattered CH_4 levels suggest ongoing challenges with managing CH_4 emissions from diverse sources. Beijing's decreasing trend and localized concentrations indicate successful emission reduction efforts or shifts in industrial practices. These results underscore the importance of tailored emission control strategies to address the specific sources and distribution patterns of CH_4 in urban environments.

3.4. Analysis of Temporal and Spatial Graphs of Climatic Variables (Temprature 2m, Wind Speed, Total Precipitation) in Mumbai and Beijing

Understanding the dynamics of climatic variables such as temperature, wind speed, and total precipitation is crucial for assessing their impact on urban environments. The analysis of these variables provides valuable insights into how they influence air quality, weather patterns, and overall environmental conditions. In this section, we present a detailed examination of the temporal and spatial variations of temperature at 2 meters, wind speed, and total precipitation in Mumbai and Beijing (Fig. 6).

The following graphs (Fig. 6) illustrate the fluctuations and distribution of these climatic factors over time in both cities. By examining these graphs, we aim to uncover patterns and trends that reflect the interplay between climatic conditions and urban pollution dynamics. The temporal analysis reveals how these variables change over time, while the spatial analysis highlights their distribution across different areas of each city.

These insights are essential for understanding how climatic factors contribute to variations in air quality and other environmental conditions. The subsequent analysis will explore the implications of these trends and their potential impact on urban planning and pollution management strategies.

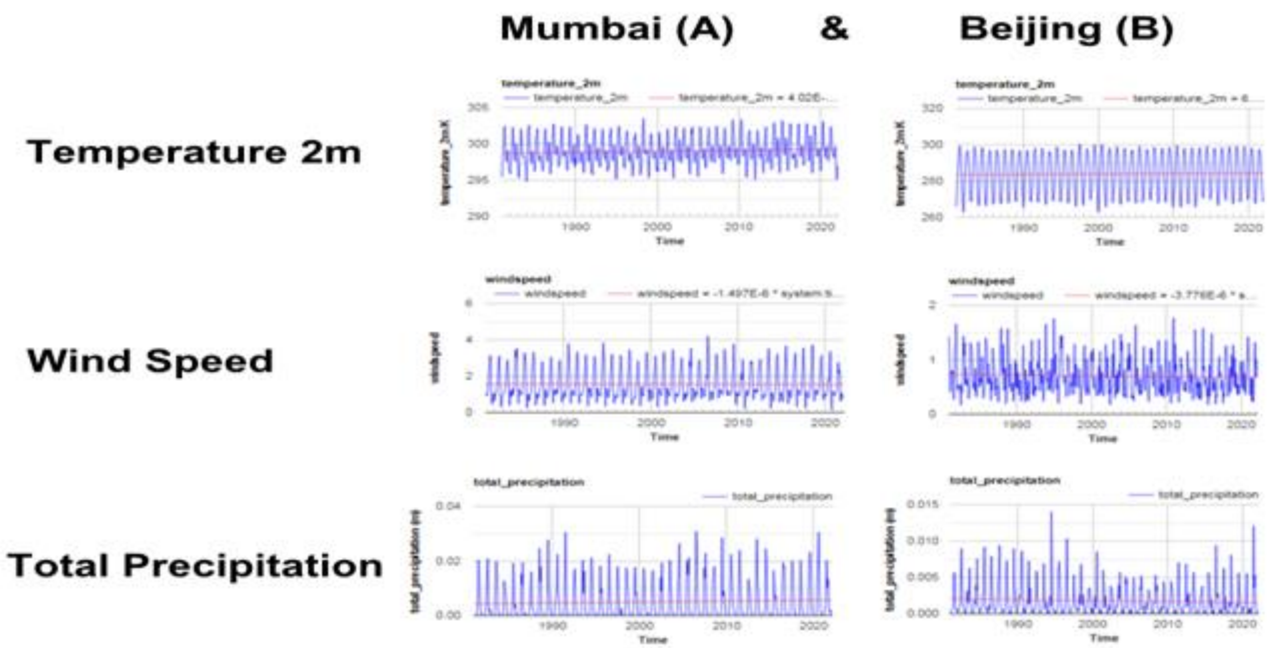

Fig.6 - Temporal and Spatial Distribution of Climatic Variables (Temprature 2m, Wind Speed, Total Precipitation) in Mumbai and Beijing from February to March 2022.

3.4.1. Temporal and Spatial Analysis of 2-Meter Temperature Trends in Mumbai and Beijing (1990-2020)

The analysis of 2-meter temperature trends from 1990 to 2020 for Mumbai and Beijing reveals distinct patterns reflective of each city's climatic characteristics (Fig.6). In Mumbai, the graph illustrates a consistent trend in 2-meter temperatures over the years, with a generally high-temperature range. This indicates a persistently warm climate in Mumbai throughout the observed period. The high temperatures are notably stable and continuous, suggesting a consistent urban heat island effect and minimal variability in temperature extremes. This steady high-temperature trend may be attributed to Mumbai's geographical location and urbanization factors, which contribute to its consistently warm climate. Conversely, Beijing's 2-meter temperature data from 1990 to 2020 show lower temperatures compared to Mumbai, indicating a cooler climate overall. The temperature variability in Beijing is less pronounced, with lower extremes and a more moderate range. This lower temperature trend suggests a different climatic influence, likely related to Beijing's geographical location, seasonal variations, and differing urbanization patterns. The reduced intensity of high temperatures in Beijing may also reflect effective urban planning and environmental management strategies aimed at mitigating the urban heat island effect.

The observed temperature trends highlight significant climatic differences between Mumbai and Beijing. Mumbai's consistently high temperatures underscore the impact of its tropical climate and dense urbanization, which contribute to sustained high-temperature levels. This consistency in high temperatures may also reflect challenges in managing urban heat and the need for strategies to address heat-related issues in such a hot and densely populated city. In contrast, Beijing's cooler temperatures and lower variability suggest a more temperate climate influenced by its latitude and seasonal changes. The relatively lower temperature extremes could indicate effective urban cooling measures and a less pronounced urban heat island effect compared to Mumbai. However, the data also points to the need for continued monitoring and management of temperature extremes to ensure that Beijing can adapt to any future climatic shifts. Overall, these temperature patterns provide valuable insights into the climatic conditions of Mumbai and Beijing, informing urban planning, climate adaptation strategies, and policy development aimed at managing temperature extremes and improving urban living conditions.

3.4.2. Temporal and Spatial Analysis of Wind Speed Trends in Mumbai and Beijing (1990-2020)

The analysis of wind speed trends from 1990 to 2020 provides valuable insights into the climatic dynamics of Mumbai and Beijing (Fig.6). For Mumbai, the wind speed graph shows a generally stable trend over the observed period, with some fluctuations. This stability indicates that while the average wind speeds have remained consistent, there have been intermittent periods where wind speeds increased beyond the typical range. These variations might be linked to specific meteorological events or seasonal changes, but the overall trend suggests that Mumbai experiences relatively moderate and stable wind conditions (Fig.6). In contrast, Beijing exhibits a higher average wind speed compared to Mumbai during the same period. The graph reveals that wind speeds in Beijing are generally more intense and have experienced greater variability. This higher intensity and variability in wind speeds could be attributed to Beijing's geographical setting, which is influenced by factors such as regional wind patterns, topography, and seasonal atmospheric conditions. The increased wind speed in Beijing may also reflect its location in a more exposed or open region compared to Mumbai, leading to stronger and more variable wind conditions (Fig.6).

The wind speed trends underscore notable climatic differences between Mumbai and Beijing. Mumbai's stable wind conditions, despite occasional fluctuations, suggest a relatively calm and consistent wind environment. This stability could have implications for air quality management and urban planning, as steady wind speeds might contribute to the dispersion of pollutants more predictably compared to areas with higher variability. On the other hand, Beijing's higher average wind speeds and greater variability indicate a more dynamic and turbulent wind environment. The stronger and more variable winds in Beijing may influence various aspects of urban life, including air quality, energy consumption, and infrastructure resilience. Higher wind speeds can enhance the dispersion of air pollutants but may also present challenges related to wind-induced damage or increased energy needs for heating and cooling. Overall, these wind speed patterns offer crucial insights into the climatic conditions of Mumbai and Beijing. Understanding these trends helps inform strategies for managing environmental impacts, optimizing urban planning, and adapting to the varying wind conditions in each city.

3.4.3. Temporal and Spatial Analysis of Total Precipitation Trends in Mumbai and Beijing (1990-2020)

The examination of total precipitation trends from 1990 to 2020 reveals distinct patterns for Mumbai and Beijing (Fig.6). In Mumbai, the precipitation graph shows variability with some fluctuations throughout the observed period. Overall, the precipitation levels exhibit a stable trend, with occasional increases and decreases. The maximum precipitation recorded in Mumbai during this period did not exceed 0.03 units, indicating relatively modest variations in total rainfall. This stability suggests a consistent climatic pattern with predictable seasonal changes and minor deviations in precipitation levels (Fig.6). Conversely, Beijing demonstrates a decreasing trend in total precipitation over the same period. Despite this overall decline, the intensity of rainfall in Beijing has been higher compared to Mumbai. The graph indicates that while Beijing's total precipitation has been reducing, the rainfall events have been more intense, reflecting a different climatic dynamic. This trend may be influenced by changing atmospheric conditions, urbanization effects, or shifts in regional climate patterns (Fig.6).

The precipitation trends highlight important climatic differences between Mumbai and Beijing. Mumbai's stable precipitation levels, despite occasional fluctuations, indicate a relatively predictable and consistent rainfall pattern. This stability could be beneficial for water resource management and agricultural planning, as it suggests a more regular distribution of rainfall over time. In contrast, Beijing's decreasing trend in total precipitation, coupled with higher intensity rainfall events, suggests a shift in climatic conditions that may impact water availability and flood risk. The reduction in overall precipitation could be associated with broader climatic changes or urbanization effects, while the increased intensity of rainfall events may exacerbate flooding or impact infrastructure resilience. These precipitation patterns offer valuable insights into the climatic behavior of Mumbai and Beijing, informing strategies for water management, flood control, and urban planning. Understanding these trends helps in adapting to changing precipitation patterns and mitigating the impacts of extreme weather events in each city.

3.5. Wind rose

The wind rose diagrams for Mumbai and Beijing reveal significant differences in wind patterns between the two cities (Fig.7). In Mumbai, the wind predominantly blows from the Northen area and southwest, with moderate speeds throughout the year, contributing to the dispersion of air pollutants primarily towards the inland areas. In contrast, Beijing experiences winds from the West, with low variable directional pattern. These wind dynamics play a crucial role in the spatial distribution of air pollutants, influencing the concentration and spread of pollutants like NO_2 and SO_2. The distinct wind patterns in each city suggest a direct impact on local air quality management strategies.

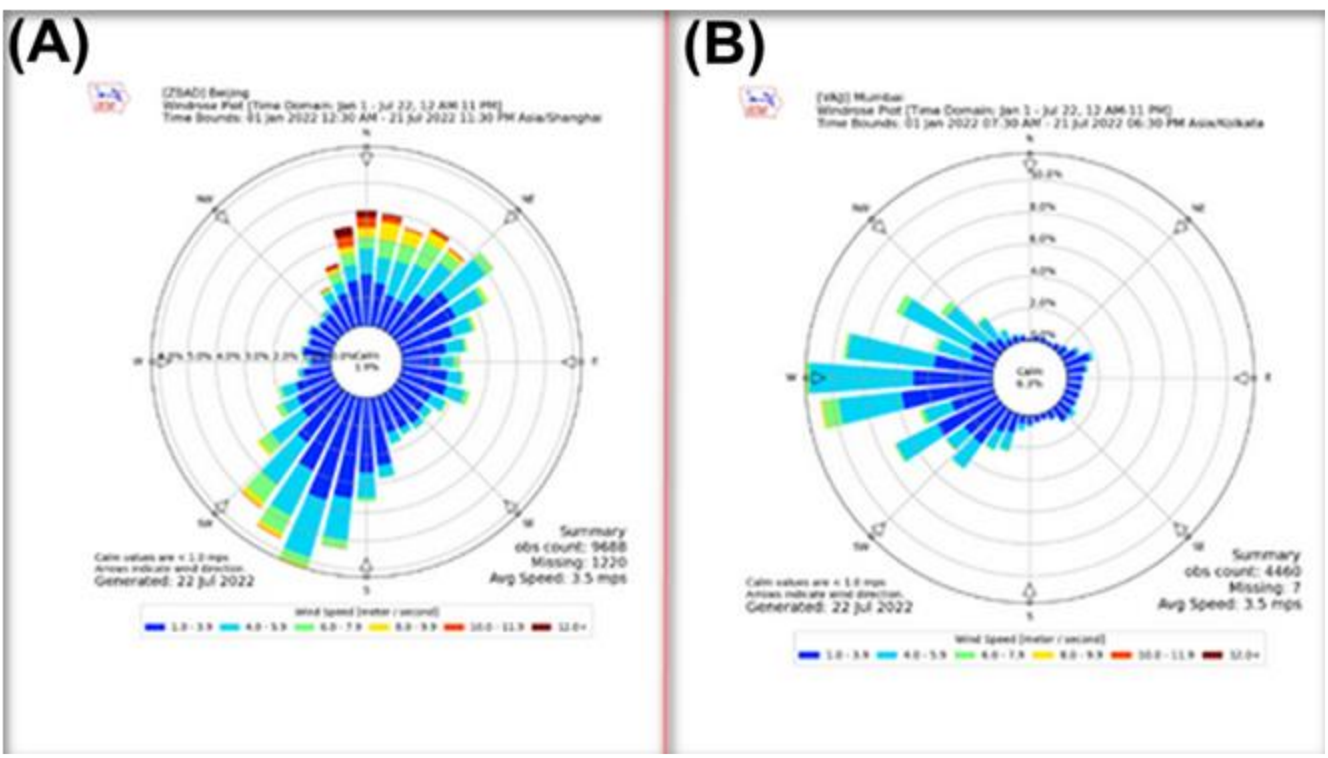

Fig.7-Wind rose chart for Mumbai (A) and Beijing (B)

4. Discussion

In this study, we have analyzed the spatial and temporal variations of SO_2 and NO_2, as well as CH_4 concentrations and climatic variables such as NDVI, temperature, wind speed, and precipitation in Mumbai and Beijing. By comparing these findings with existing research, we gain a comprehensive understanding of urban pollution dynamics and their implications for environmental management.

Our findings indicate a significant rise in SO_2 and NO_2 levels in Mumbai, with more pronounced increases observed in central and industrial areas. This aligns with the work of Sharma et al. (2024), who documented high pollutant concentrations in rapidly urbanizing areas of Indian cities due to industrial and vehicular emissions. Conversely, Beijing shows a notable reduction in both SO_2 and NO_2 concentrations over time, particularly in the north and central parts of the city. This trend supports the results of Wang et al. (2023), who attributed improvements in Beijing's air quality to stringent emission controls and policy measures. The significant drop in NO_2 levels observed in Beijing, in particular, underscores the effectiveness of recent air quality regulations.

The analysis of CH_4 concentrations reveals an increasing trend in Mumbai, with substantial variability across different city areas. This finding is consistent with the observations of Aithal et al. (2018), who identified CH_4 emissions from waste management and transportation as major contributors in urban settings. On the other hand, Beijing shows a decreasing trend in CH_4 concentrations, which might be indicative of successful emission reduction strategies or decreased activity in key emission sources. This trend corroborates the study by Gao et al. (2020), who reported effective mitigation measures and emission controls in Beijing leading to reduced CH_4 levels.

The examination of NDVI trends reveals a significant decline in vegetation cover in Mumbai, particularly in areas affected by higher temperatures and increased pollution levels. This reduction in NDVI highlights the detrimental effects of urbanization and environmental degradation on green spaces, consistent with the findings of Shahfahad et al. (2021), who observed similar patterns of vegetation loss in rapidly urbanizing regions. Conversely, Beijing exhibits a relatively stable and high NDVI, suggesting effective management of urban green spaces and environmental policies that preserve vegetation cover. This stability aligns with the research of Huang et al. (2021), who noted that strategic urban planning and green space initiatives contribute to maintaining higher vegetation indices. The contrasting NDVI trends between Mumbai and Beijing underscore the varying impacts of urban development and environmental management practices on urban vegetation.

The examination of 2-meter temperature trends reveals consistently high temperatures in Mumbai, reflecting the urban heat island effect exacerbated by extensive urbanization (Sharma et al., 2024). This finding is in line with the research of Shahfahad et al. (2021), who documented persistent high temperatures in tropical cities due to the combined effects of urban expansion and climatic conditions. Beijing, in contrast, shows lower and more variable temperatures, which can be attributed to its temperate climate and effective urban planning strategies (Cheng et al., 2016). The comparative analysis of wind speed indicates that Mumbai experiences relatively stable wind conditions, while Beijing shows higher variability. This aligns with the findings of Zha et al. (2021), who noted that wind patterns play a critical role in pollutant dispersion and air quality management.

Mumbai's precipitation patterns demonstrate high variability with some intense events, while Beijing shows a decreasing trend in total precipitation but with more intense rainfall events. These observations are consistent with the results of Liu et al. (2021) and Rahaman (2021), who highlighted similar trends in precipitation in tropical and temperate urban environments. The stable yet variable precipitation in Mumbai contrasts with the decreasing trend in Beijing, which suggests shifts in climatic conditions or changes in regional weather patterns (Huang et al., 2023).

The wind rose diagrams reveal distinct wind patterns affecting pollutant dispersion. In Mumbai, winds predominantly blow from northern and southwestern directions, contributing to the dispersion of pollutants towards inland areas. This finding supports the work of Fattah et al. (2023), who observed similar wind patterns in South Asian cities influencing air quality. In Beijing, prevailing winds from the west lead to higher pollutant levels in specific areas, aligning with the observations of Kim et al. (2016), who discussed the impact of wind patterns on urban air quality in East Asian cities.

The first hypothesis, that climatic variables—particularly temperature and precipitation—significantly influence the concentrations of NO_2, SO_2, and CH_4, is supported by the findings. In Mumbai, the consistently high temperatures and variable precipitation patterns were associated with elevated concentrations of these pollutants, particularly in industrial areas. Conversely, Beijing's more variable temperatures and decreasing precipitation correlated with reduced pollution levels, indicating that climatic factors indeed play a critical role in shaping urban air quality. This observation aligns with previous studies that emphasize the importance of climatic conditions in influencing pollutant dispersion and accumulation (Wu et al., 2022).

The second hypothesis, proposing an inverse relationship between NDVI and pollutant concentrations, is also corroborated by the results. In Mumbai, areas with lower vegetation cover, as indicated by reduced NDVI values, exhibited higher levels of air pollution, exacerbating the urban heat island effect. Meanwhile, Beijing's relatively stable NDVI and extensive green spaces contributed to lower pollutant levels, demonstrating the mitigating effects of vegetation on air quality. These findings further highlight the role of vegetation in regulating pollution and its potential in urban environmental management (Ferrini et al., 2020).

Our study highlights the complex interplay between pollution levels, climatic factors, and urban dynamics in Mumbai and Beijing. The comparative analysis with previous research underscores the effectiveness of emission reduction strategies in Beijing and the ongoing challenges faced by Mumbai in managing urban pollution. The insights gained from this study are crucial for developing targeted environmental management strategies and improving air quality in rapidly urbanizing cities. Future research should continue to explore the interactions between these factors and their implications for sustainable urban development and environmental health.

4. 5. Conclusion

Our study sheds light on the intricate relationship between SO_2, NO_2, and CH_4 concentrations, and it clarifies the impact of these pollutants on the environmental dynamics in Mumbai and Beijing. Through the analysis of various parameters including pollutant concentrations, temperature at 2 meters, wind speed, and total precipitation, we have uncovered significant insights into the spatial and temporal patterns influencing air quality in these two distinct cities. The utilization of remote sensing data through GEE has proven to be instrumental in this analysis, providing reliable and comprehensive information for our study.

Our findings reveal that Mumbai experiences a generally high and increasing trend in SO_2 and NO_2 concentrations, with fluctuations indicating diverse local sources. The analysis of CH_4 concentrations further highlights the challenges in managing emissions from varied sources. In contrast, Beijing shows a decreasing trend in SO_2 and NO_2, suggesting successful emission reduction efforts. The spatial clustering of CH_4 concentrations in Beijing points to targeted control measures and reduced activity in specific sectors.

The temporal and spatial analysis of climatic variables such as temperature, wind speed, and precipitation provides additional context to these pollutant patterns. Mumbai's consistently high temperatures and stable wind conditions contrast with Beijing's cooler temperatures and more variable wind patterns. The precipitation trends also indicate differing climatic influences between the two cities, with Mumbai showing stable precipitation levels and Beijing experiencing decreasing overall precipitation but more intense rainfall events.

These results underscore the importance of tailored pollution control strategies and effective urban planning to address the unique environmental challenges faced by each city. By understanding the interplay between pollutants and climatic factors, we can better inform strategies for improving air quality and adapting to changing environmental conditions.

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Authors Contributions (author contributed to the manuscript)

Code availability (Not applicable)

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