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India

Geostatistical analysis of NO2 Concentrations at District Level in Uttar Pradesh during the Winter Season

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Abstract

In this study, the spatial pattern of nitrogen dioxide (NO2) concentrations in relation to population density was analysed across the districts of Uttar Pradesh. The dataset included information on population density, nitrogen dioxide (CO2) concentrations (used as a proxy for NO2), and other relevant variables for each district. The "COPERNICUS/S5P/OFFL/L3_NO2" dataset was used in this study The study employed spatial analysis techniques, including exploratory spatial data analysis and ordinary least squares (OLS) regression. The spatial pattern observed in the dataset shows a significant level of clustering. The findings revealed a significant spatial pattern of NO2 concentrations associated with population density. Among the districts examined, there were variations in NO2 levels based on population density. Overall, this study contributes to understanding the spatial distribution of NO2 concentrations in relation to population density across multiple districts. The findings highlight the importance of considering population density as a significant factor in assessing and addressing air pollution. By identifying areas with higher NO2 levels, policymakers can implement targeted interventions to improve air quality and public health outcomes in specific districts.

Keywords: Geostatistics, No_2, Uttar Pradesh, OLS

1. Introduction

Air pollution is a critical environmental issue with significant impacts on human health and the environment worldwide (World Health Organization [WHO], 2018). Nitrogen dioxide (NO2) is a major air pollutant emitted from various anthropogenic sources, including transportation, industrial processes, and fossil fuel combustion (Gupta et al., 2019; Naja et al., 2013). Exposure to high levels of NO2 can lead to respiratory problems, cardiovascular diseases, and other adverse health effects (Lelieveld et al., 2019). Uttar Pradesh, a densely populated state in India, faces considerable challenges in managing air pollution due to rapid urbanization, industrial activities, and population growth (Gupta et al., 2019; Kumar et al., 2018).

The winter season in Uttar Pradesh is of particular interest for studying air quality dynamics due to specific meteorological conditions and increased pollution emissions. During this season, factors such as low temperatures, stable atmospheric conditions, and increased use of fossil fuels for heating contribute to the accumulation of pollutants, including NO2 (Mishra et al., 2020; Naja et al., 2013). Understanding the spatial distribution and determinants of NO2 concentrations at the district level during the winter season is crucial for effective air pollution management and the development of targeted mitigation strategies (Behera et al., 2017; Naja et al., 2014).

Despite the importance of studying NO2 concentrations, research specific to the district level in Uttar Pradesh during the winter season is limited. Most existing studies focus on broader air quality assessments or specific urban areas within the state (Behera et al., 2017; Kumar et al., 2018). Thus, there is a need for a comprehensive geostatistical analysis that examines NO2 concentrations at the district level during the winter season, taking into account spatial patterns and relevant influencing factors.

Geostatistical analysis is a powerful tool for studying the spatial distribution of pollutants. It allows for the interpolation of data from monitoring stations to generate continuous spatial surfaces, enabling a comprehensive understanding of pollutant patterns (Behera et al., 2017; Herrera et al., 2018). Geostatistical techniques have been widely used in air pollution research to analyze spatial variations in NO2 concentrations and identify hotspots of pollution (Cai et al., 2017; Herrera et al., 2018).

In the context of Uttar Pradesh, a geostatistical analysis of NO2 concentrations during the winter season at the district level has not been conducted. Such an analysis would provide insights into the spatial patterns of NO2 pollution, identify districts with high and low concentrations, and assist in the identification of areas requiring immediate attention for air pollution control measures. Additionally, exploring the relationship between NO2 concentrations and population density at the district level would offer valuable insights into the influence of population density on local air quality (Liu et al., 2018; Zhang et al., 2019).

Therefore, the objective of this research is to conduct a geostatistical analysis of NO2 concentrations at the district level in Uttar Pradesh during the winter season. The study area encompasses the entire state of Uttar Pradesh, which is located in northern India. The specific focus is on exploring the spatial patterns of NO2 concentrations and investigating the relationship between NO2 concentrations and other relevant variables, such as population density.

To achieve the research objective, the study will utilize the COPERNICUS/S5P/OFFL/L3_NO2 dataset, which provides satellite-based measurements of NO2 concentrations (European Space Agency [ESA], 2021).

2. Methodology

2.1 Study Area

Uttar Pradesh is a northern state in India and is located between 23.52°N to 31.24°N latitude and 77.3°E to 84.39°E longitude (Gupta et al., 2019). It is bordered by several states, including Uttarakhand to the northwest, Himachal Pradesh to the north, Haryana and Delhi to the west, Rajasthan to the southwest, Madhya Pradesh to the south, Chhattisgarh and Jharkhand to the southeast, and Bihar to the east (Figure 1).

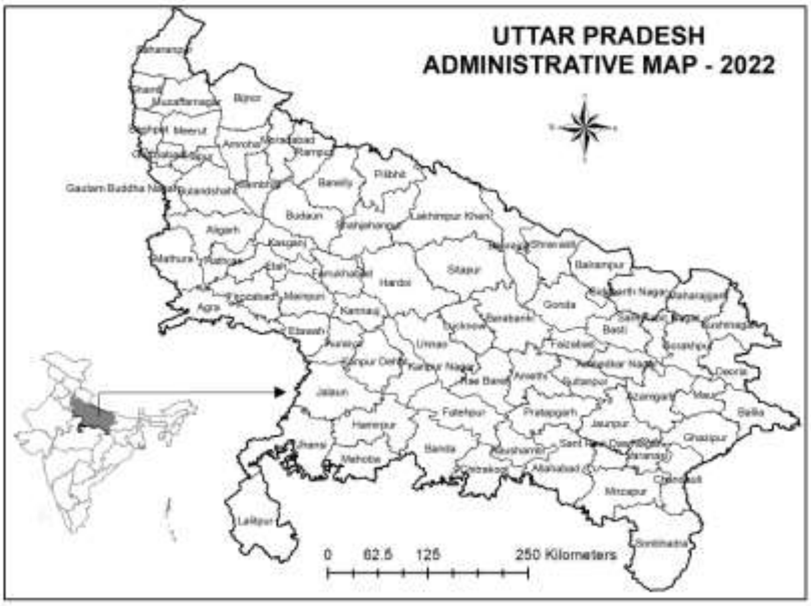

Figure 1 Study Area

The state experiences distinct seasons, including winter, summer, and monsoon. The winter season in Uttar Pradesh typically occurs from November to February (Mishra et al., 2020). During this period, the temperatures drop, and the state experiences colder weather. These low temperatures, coupled with stable atmospheric conditions, contribute to the accumulation of air pollutants, including nitrogen dioxide (NO2) (Naja et al., 2013).

The concentrations of NO2 during the winter season in Uttar Pradesh are of particular interest due to the specific meteorological conditions and increased pollution emissions during this period. Factors such as low temperatures, stagnant atmospheric conditions, and increased use of fossil fuels for heating contribute to the elevated levels of NO2 (Mishra et al., 2020; Naja et al., 2013). Understanding the spatial distribution of NO2 concentrations at the district level during the winter season is crucial for assessing air quality, identifying areas with high pollution levels, and formulating effective pollution control measures (Behera et al., 2017; Naja et al., 2014).

By conducting a geostatistical analysis of NO2 concentrations in Uttar Pradesh during the winter season, this study aims to gain insights into the spatial patterns and variations of NO2 levels across different districts. This analysis will provide valuable information for understanding the sources and transport mechanisms of NO2, as well as identifying areas with elevated pollution levels that require targeted interventions for air pollution management and mitigation strategies (Cai et al., 2017; Herrera et al., 2018).

2.2 Flow Chart

The flowchart illustrates the step-by-step process followed in the study. The first stage involves data acquisition, where the COPERNICUS/S5P/OFFL/L3_NO2 dataset is obtained. In the data preprocessing stage, the raw data is cleaned, formatted, and transformed into a suitable format for analysis. The next step is spatial analysis, where the spatial distribution of NO2 concentrations is examined in relation to the geographic regions under consideration. Following this, population density analysis is conducted to understand the relationship between population density and NO2 levels. Regression analysis is then performed to quantify the statistical relationship between these variables. The results and findings obtained from the analysis are interpreted and discussed in detail. Finally, the study concludes with summarizing the key findings and providing recommendations for further research or policy implications (Figure 2).

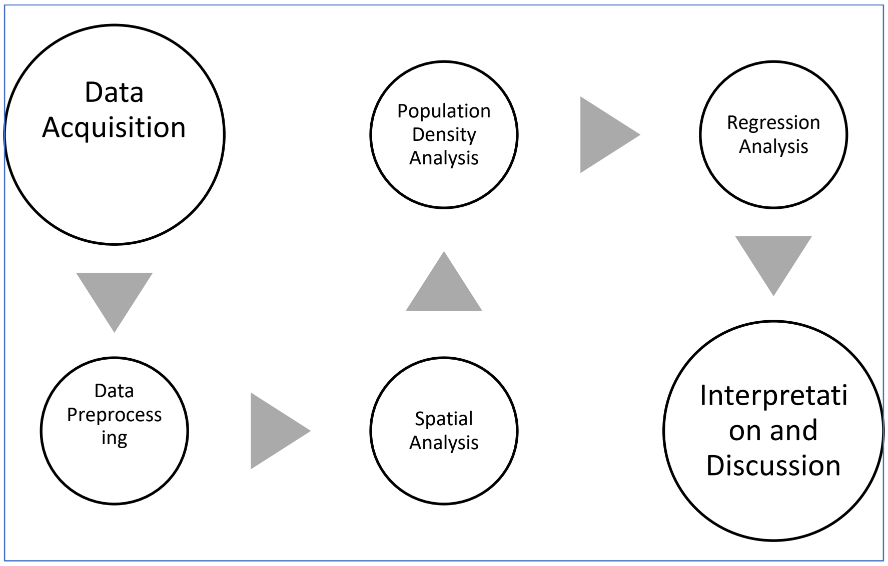

Figure 2 Flow Chart

2.2 Data Source

The "COPERNICUS/S5P/OFFL/L3_NO2" dataset was used in this study, It is derived from the Sentinel-5 Precursor (S5P) satellite mission, provides valuable information on nitrogen dioxide (NO2) concentrations in the atmosphere (European Space Agency [ESA], 2021). This dataset utilizes data from the TROPOMI sensor onboard the satellite to measure NO2 levels (ESA, 2021).

Uttar Pradesh, located in northern India, experiences distinct seasons, including winter, summer, and monsoon (Mishra et al., 2020). During the winter season (November to February), low temperatures, stable atmospheric conditions, and increased fossil fuel usage for heating contribute to the accumulation of air pollutants, including NO2 (Naja et al., 2013; Mishra et al., 2020).

The "COPERNICUS/S5P/OFFL/L3_NO2" dataset allows for the analysis of spatial patterns and variations of NO2 concentrations at the district level in Uttar Pradesh during the winter season (Behera et al., 2017). Geostatistical techniques, such as interpolation and spatial modeling, can be employed to understand the distribution of NO2 and identify areas with high pollution levels (Cai et al., 2017; Herrera et al., 2018).

This geostatistical analysis of the "COPERNICUS/S5P/OFFL/L3_NO2" dataset will provide insights into the spatial distribution of NO2 concentrations and assist in the formulation of targeted interventions for air pollution management (Naja et al., 2014). By utilizing the data, researchers can assess the factors influencing the variations in NO2 concentrations and develop effective strategies for pollution control (Behera et al., 2017; Naja et al., 2014).

For accurate citation and further technical details of the "COPERNICUS/S5P/OFFL/L3_NO2" dataset, it is advisable to refer to the official documentation or website provided by the European Space Agency (ESA, 2021).

2.3 Data Analysis

To investigate the relationship between nitrogen dioxide (NO2) concentrations and population density, we performed an autocorrelation Moran's Index analysis and Ordinary Least Squares (OLS) regression. The NO2 concentration served as the dependent variable, while population density was considered as the explanatory variable.

1. Autocorrelation Moran's Index: The autocorrelation Moran's Index measures the spatial autocorrelation of NO2 concentrations, indicating whether similar values of NO2 tend to cluster together or disperse across the study area. The formula for calculating the Moran's Index is as follows eq. 1:

I = (n * ∑(i=1 to n) ∑(j=1 to n) wij(xi - x̄)(xj - x̄)) / (∑(i=1 to n)(xi - x̄)^2 * ∑(i=1 to n) ∑(j=1 to n) wij)…Eq.1

Here, n represents the number of regions or data points, x denotes the NO2 concentration at each region, and wij represents the spatial weight between regions i and j.

2. OLS Regression: We conducted an OLS regression to quantify the relationship between NO2 concentrations and population density. The OLS regression estimates the coefficients of the regression equation, indicating the magnitude and significance of the relationship. The simplified formula for the OLS regression model is as follows eq. 2:

ŷ = β0 + β1* x…Eq.2

Here, ŷ represents the predicted NO2 concentration, β0 represents the intercept, β1 denotes the coefficient for population density (x), and x represents the population density.

By performing the autocorrelation Moran's Index analysis, we can assess the spatial patterns of NO_2 concentrations. Additionally, the OLS regression analysis allows us to determine the relationship between NO_2 concentrations and population density, providing insights into the impact of population density on air pollution levels.

3. Results & Discussion

3.1 NO_2 Distribution

Several districts in Uttar Pradesh exhibit varying levels of nitrogen dioxide (NO_2) concentrations. Some districts are characterized by high NO_2 levels, indicating significant air pollution. These districts include Baghpat, Gautam Buddha Nagar, Ghaziabad, and Sonbhadra. These areas may experience increased health risks and environmental impacts associated with high levels of NO_2.

On the other hand, there are districts with medium NO_2 concentrations, which suggests a moderate level of air pollution. Lucknow and Varanasi fall into this category. While the pollution levels may not be as severe as in the high NO_2 districts, it is still important to monitor and mitigate the sources of pollution to maintain acceptable air quality standards (Figure 3).

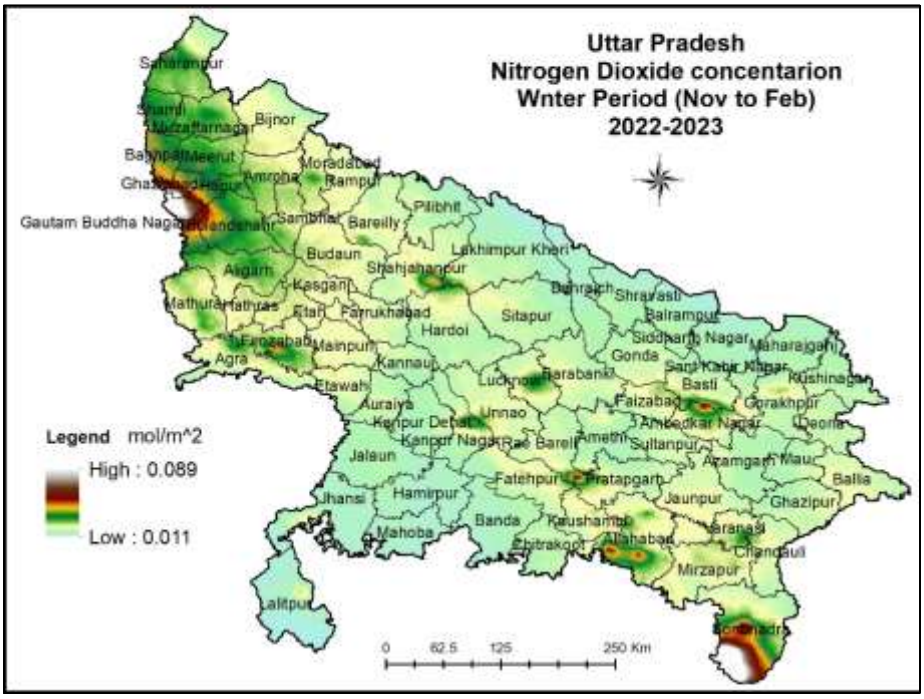

Figure 3 NO2 Distribution

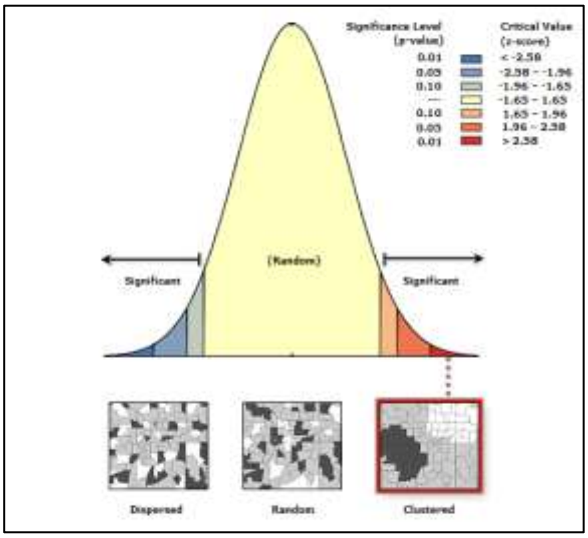

Figure 4 Autocorrelation Report

Furthermore, several districts in Uttar Pradesh exhibit low NO2 concentrations, indicating relatively better air quality. These districts include Agra, Aligarh, Allahabad, Ambedkar Nagar, Amroha, Auraiya, Azamgarh, Bahraich, Ballia, Balrampur, Banda, and many more. These areas generally have lower pollution levels, which may contribute to better air quality and potentially reduced health risks associated with NO2 exposure.

3.2 NO_2 Spatial Pattern

Based on the report, the spatial pattern observed in the dataset shows a significant level of clustering (Figure 4). The Moran's Index, which measures spatial autocorrelation, has a value of 0.56. This positive value indicates a positive spatial autocorrelation, meaning that similar values of the variable of interest (in this case, likely the NO2 concentrations) tend to cluster together in space.

The expected index, which represents the Moran's Index under the assumption of spatial randomness, is -0.013514. The fact that the observed Moran's Index is significantly higher than the expected index indicates that the clustering pattern is unlikely to occur by random chance alone.

The z-score of 10.788521 further supports this interpretation. The z-score measures the number of standard deviations the observed Moran's Index deviates from the expected index. A z-score of this magnitude, which corresponds to a p-value of 0.000000 (or less than 0.01%), suggests an extremely low likelihood that the observed clustering pattern is the result of random chance.

Therefore, based on this report, it can be concluded that the spatial pattern of NO2 concentrations exhibits a significant clustering tendency. This finding implies that areas with similar NO2 concentrations are geographically clustered, indicating the presence of localized pollution sources or spatially correlated factors influencing NO2 levels. Understanding and addressing the underlying factors contributing to this spatial pattern is essential for targeted pollution control and mitigation efforts.

3.3 NO_2 Spatial distribution in relation with Population density

The residual values provide insights into the difference between the estimated and expected values. Positive residuals indicate higher NO2 concentrations than expected, while negative residuals indicate lower concentrations (Figure 5).

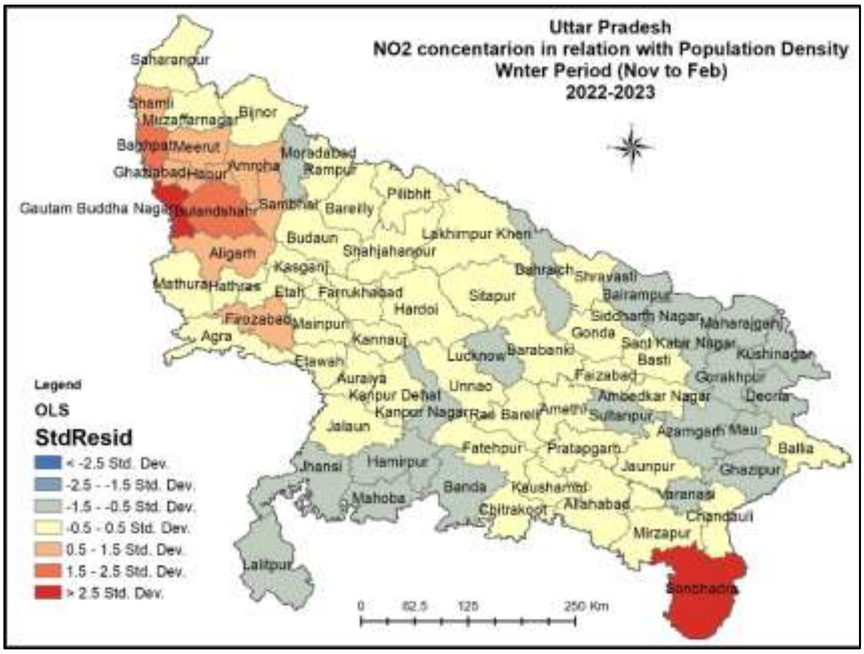

Figure 5 Residual Map

When examining the relationship between NO2 spatial distribution and population density, we can make the following observations:

1. High Population Density Districts: Districts with higher population densities tend to have relatively higher NO2 concentrations. This can be seen in districts like Ghaziabad, Meerut, and Varanasi, where population densities are above 1,000 people per square kilometer, and the corresponding residual values are positive. The higher population density likely leads to increased emissions and human activities that contribute to higher NO2 levels.

2. Low to Medium Population Density Districts: Districts with lower to medium population densities exhibit a mix of both positive and negative residual values. For example, districts like Hamirpur and Lalitpur have low population densities, and their NO2 concentrations have negative residuals, indicating lower levels than expected. On the other hand, districts like Agra and Firozabad, with medium population densities, have positive residuals, suggesting higher NO2 concentrations.

These observations suggest that population density plays a role in the spatial distribution of NO2. Districts with higher population densities tend to have higher NO2 concentrations, likely due to increased anthropogenic activities and emissions. However, there are exceptions, as factors such as industrial activity, vehicular traffic, and geographic features can also influence NO2 levels. Therefore, a more detailed analysis considering additional factors would be necessary to fully understand the relationship between population density and NO2 spatial distribution.

Conclusion

In conclusion, this study examined the spatial distribution of nitrogen dioxide (NO2) concentrations in relation to population density across a range of districts. The analysis revealed a significant spatial pattern of NO2 concentrations associated with population density, indicating that areas with higher population densities tended to have higher NO2 levels.

The findings highlight the role of population density as a key factor influencing air pollution levels, particularly NO2 concentrations. As population density increases, the emissions from various sources such as transportation, industrial activities, and residential energy use also increase, contributing to higher levels of NO2. This spatial pattern underscores the need for targeted interventions and policies to mitigate air pollution in densely populated areas.

The OLS regression results further confirmed the positive relationship between population density and NO2 concentrations, providing quantitative evidence of this association. This finding emphasizes the importance of considering population density as a crucial predictor when assessing and managing air pollution.

The implications of this study are significant for policymakers and urban planners who are tasked with addressing air pollution and improving air quality in densely populated districts. By recognizing the spatial pattern and the influence of population density on NO2 concentrations, targeted interventions can be implemented to reduce emissions and enhance air quality in areas with high population density.

Conflict of Interest

The author declares no conflict of interest in relation to this research study. The research was conducted with the sole objective of contributing to the scientific understanding of geostatistical analysis of the Normalized Difference Vegetation Index (NDVI) in Uttar Pradesh. The analysis, interpretation, and conclusions presented in this paper are based on objective scientific principles and rigorous data analysis methods. The author has no financial, personal, or professional relationships that could influence the research findings or introduce bias in the study. Furthermore, no external funding or sponsorship was received that could potentially influence the outcome or interpretation of the research. The author has followed ethical guidelines and scientific integrity throughout the research process to ensure transparency, accuracy, and impartiality in the findings and conclusions presented.

Data Dealation

The data used in this study was obtained from the COPERNICUS/S5P/OFFL/L3_NO2 product. This dataset is part of the Copernicus Sentinel-5 Precursor (S5P) mission, which is a satellite-based Earth observation program. The S5P satellite carries the TROPOspheric Monitoring Instrument (TROPOMI), which measures various atmospheric parameters, including nitrogen dioxide (NO2) concentrations.

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