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Predictive Modelling and Spatial Analysis of M3 Motorway-Induced Air Quality Impacts in Punjab

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Abstract

There is an increasing global concern about the potential environmental impacts of the continuous expansion of highways and transportation infrastructure, particularly regarding air quality. This research provides a comprehensive analysis of the effects of highway development, specifically the M3 Motorway, on air quality in the Punjab region by integrating innovative air impact prediction models and spatial analysis techniques. This research uses ground-based data from 2006 to 2022 and Remote Sensing data (Sentinel-5P and MODIS) from 2018 to 2022. The analysis is focused on the concentrations of key air pollutants, including sulfur dioxide (SO_2), nitrogen dioxide (NO_2), carbon monoxide (CO), methane (CH_4), aerosol optical depth (AOD), formaldehyde (HCHO), and ozone (O_3). The results revealed that SO_2 concentrations fluctuated noticeably, ranging from 0.08 to 0.26 µmol/m². Higher amounts were regularly noted in the Renala Khurd and Kabir Wala regions. Similarly, NO_2 values ranged from 78.65 to 97.54 µmol/m² in the Renala Khurd and Sahiwal regions. The concentrations of CO varied between 36.30 and 40.30 µmol/m², with higher values found in urban areas. The concentration of CH_4 was noted from 188058 to 1920961.12 µmol/m², reflecting the effects of industry and agricultural pollutants. Predictive modelling coupled with spatial analysis provides a thorough framework for evaluating the complex links between highway construction and air quality. This study helps to balance contemporary transportation networks and environmental stewardship by advancing a more nuanced knowledge of the environmental impact of highway developments in Punjab.

Keywords**:** Air quality; Predictive modeling; Environmental impacts; Spatial analysis; Punjab highways

1. Introduction

Poor air quality results in several health hazards, including chronic obstructive pulmonary disease, diabetes, and respiratory infections. Urban air quality plays a crucial role in the planning and design of emerging cities (Banerjee et al., 2018a, b). Many parts of northern India face various air pollution-related issues due to transportation and industrial sources. In Punjab, maximum personal travel and freight movement are reliant on the road network. The highest concentration of pollutants has been reported in regulating road networks (Adriano, 2001). The increased heavy vehicle load on highways also increases the formation of particulate matter in the atmosphere. Therefore, the major objective of this research work is to argue the need of the hour to address this crucial issue, to identify the pollutants affected by the highways in Punjab, and to shape the transport policy to tackle the increased level of air pollution (Brunekreef et al., 1997; Adam et al., 2015; Delfino et al., 2009; Su et al., 2009). The concentration of SO_2 and NO_2 along some highways in Punjab was taken for five years. The concentration of SO_2 and NO_2 was found to be more than standard. The methodology adopted for this research work is to identify and summarize the pollutants formed by roads and model the transport of these pollutants using computational fluid dynamics-based modeling. The predicted values from the model agree with the predicted values of the statistical model. Additionally, the limitations of the current study and the future direction have been summarized at the end of the current study. The predicted output of the present model can be utilized in urban planning and the health of residents residing in that area. The concentration of pollutants in the close vicinity of the highways, towns, and cities has a substantial impact on the urban population. The regenerative hot and cold regions were also predicted using the prediction model (Zhang and Batterman, 2013).

Several studies have been carried out in the past to study the impacts of air quality when in highway vicinity (Adam et al., 2015; Delfino et al., 2009; Su et al., 2009; Kim et al., 2004a, b). Highway traffic is identified as a major source of air quality degradation in nearby urban areas. Air quality data for nitrogen dioxide (NO_2) and carbon monoxide (CO) were collected in the San Francisco Bay Area. A model was used to distance-weight annual average pollution data to evaluate the traffic-related impacts. A dispersion model was used to calculate the increment of NO_2 concentration due to traffic on the highway and in the outside domain with the help of observation data. A 25 m resolution grid was used to execute the model. Structure of traffic: The air quality in the vicinity of a highway is also affected by traffic. Fluctuating NO_2 and PMx concentrations were studied on a highway in the Ruhr Area, Germany, as part of an air quality measurement effort. Main pollutant concentrations: O_3, NO_2, and PM_{10}, and the respective meteorological parameters–air temperature, relative humidity, wind speed, wind direction, rain, and solar radiation–were assessed in the surroundings of a national highway. The concentrations of the main pollutants PM_{10}, $PM_{2.5}$, NO, and NO_2 were studied at various distances and directions from selected highway sections, aiming to investigate the influence of highways in each analyzed zone (Zhang and Batterman, 2013).

Several air quality monitoring techniques have been used and are still under investigation to establish advancements. Traditional techniques of ambient monitoring rely on in situ measurements using a network of ground-based monitoring stations (Kim et al., 2004). These stations are costly to install, maintain, and repair. Real-time monitoring provides fast detections, observations, and alerts, as well as routine inspection data performance. Long-term measurements with spatial relevance, emissions, and optimal representation as a single data point have a high spatial resolution, which can help in optimizing the quality model and its approach in research. Most governmental environmental agencies around the world have their monitoring stations installed for recording pollutant concentrations (Batterman et al., 2014). In addition, remote sensing techniques have been used in environmental research, helping to observe large-scale spatial variability and provide information for short time intervals. This includes techniques consisting of satellite and ground-based remote sensing.

Significant obstacles placing limitations on ground-based monitoring, many countries, including both developed and developing nations, are increasingly supplementing and offloading the ground-based network with remote sensing instruments. It is also noted that the satellite-based model employs a moderate prediction-based approach globally that would not have been possible with the in-situ model. In a recent comparative modeling study of CO levels in urban areas, using spatial panel OLS, GWR, and machine learning algorithms to identify input parameters led to the conclusion that the machine learning algorithm is better for predictive modeling, and different statistical models have several influences on predictive modeling accuracy (Bada and Akande, 2010). Understanding such decisions demonstrates that the machine learning approach is pioneering for researchers in developing countries. However, different machine learning algorithms for the predictive model, supported by statistics and skills required in actual pollution aiming, have been problematic. Advancing several mixed models, considering multiple modeling methods can utilize the MLR effect as a model performance. Generally, a variety of statistical models with divergent profiling in features are adequate. Specific features due to the profile of optimization quality decision tools have been rolled out in very recent times (Bada and Akande, 2010).

Highways are areas with a high potential for air pollution from dust, exhaust fumes, and emissions from motor vehicles. They are widely studied in large cities and urban agglomerations. An adequate literature review reveals no comprehensive studies on highway air quality in almost all of Punjab, covering the entire state. Therefore, the reconstruction of studies in less-studied regions of Punjab could provide new insights for sustainable development, health, and highway-related policies to be pursued. Places with clean air and road design standards can also be used as EIA indicators. No study was conducted on the spatial scale prediction of air quality for highways in Pakistan using GIS-based modelling. However, this study aims to evaluate the integration of predictive modelling and spatial analysis to assess the impact of air quality on highways. The study's outcomes would help policymakers develop a governance framework for societal development and technological progress and establish air quality co-benefits, including morbidity, mortality, and agriculture.

2. Study area

The N5 Lahore-Multan Motorway, often known as the M3 Motorway, is in Pakistan's eastern region. It passes through several towns and cities, linking the cities of Lahore and Multan. Renala Khurd, Depalpur, Jahanian, Mian Channu, Sahiwal, Okara, Khanewal, Kabirwala, and Chichawatni were the nine sections of National Highway N-5 Lahore-Multan Motorway that were monitored for the priority metrics for the impact of traffic pollution on ambient air quality using the concentration monitoring of AOD, CO, HCHO, NO_2, O_3, and SO_2.

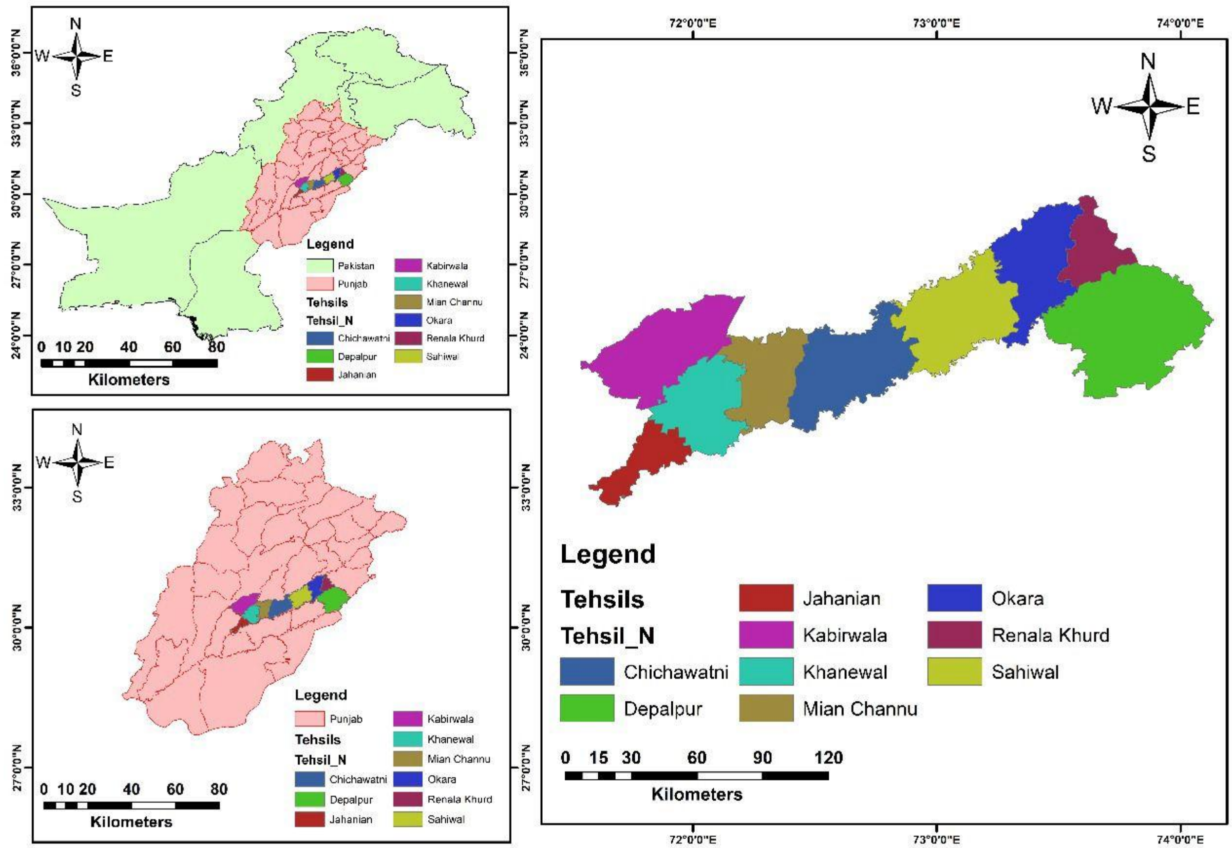

Fig. 1. Location of the sub-district administrative units (Tehsil) in Multan, Punjab, Pakistan.

These towns and cities are in Pakistan's Punjab province, in the country's northeastern corner. As a result, Pakistan's N5 Highway (Lahore-Abdul Hakeem M-3 Motorway) is situated on the country's eastern border (Fig. 1). Pakistan's geographical terrain showcases a diverse landscape comprising many natural elements such as mountains, plateaus, plains, deserts, and coastal regions. It is worth noting that Pakistan's geographical location and physiography influence the country's climate patterns, ecosystems, and socio-economic development. The precise geographical location of Pakistan delineates its borders with India to the east, Afghanistan and Iran to the west, China to the northeast, and the Arabian Sea to the south.

3. Materials and Methods

Data on concentrations (SO_2, NO_2, CO, O_3, HCHO, CH_4, and AOD) were collected from the Sentinel-5P and MODIS-based estimates to map the spatial circulation of pollutants. The remote sensing data was processed using the GEE, a cloud geospatial processing platform for analyzing planetary-scale satellite imagery and geospatial data. It combines billions of pixels of remote sensing with robust analysis capabilities, providing large-scale environmental monitoring and research (Gorelick et al., 2017). The spatial overlay analysis was performed to extract zonal statistics of the pollutants at the Tehsil level boundaries. While GEE provided the satellite data from 2018 to 2022, EPD historical ground-level readings from 2006 to 2022 were obtained. Therefore, the Inverse Distance Weighted (IDW) interpolation approach was applied to field data to produce a geographic distribution of the pollutants. The outcomes of the analysis are depicted in the maps showing the pollutants' annual average values from 2018 to 2022. The first stage in the data investigation procedure was cleaning and preprocessing the EPD data, which contained periodically observed NO_2, SO_2, CO, and PM_{10} measurements. These readings were averaged for March, June, September, and December to detect the pollutant's trends. Spatial analysis and descriptive statistics were used to investigate the pollutant's variances and trends as well as the spatial distribution of the air quality. Table 1 illustrates the data set used in this study.

Table 1: Description of the datasets used in this study

No	Parameters	Data Source	Period
1	SO_2, NO_2, CO, O_3, HCHO, CH_4,	Sentinel-5 and MODIS using the Google Earth Engine	2018-2022
2	AOD	Environmental Protection Department	2006-2022

The Sentinel-5P, part of the Copernicus mission, is designed to monitor atmospheric composition and detect various air pollutants (Veefkind et al., 2012). To ensure data quality, Sentinel-5P data includes a quality assurance band (qa_value) indicating pixel quality, ranging from 0 (poor) to 1 (good). This quality assurance is based on cloud presence, surface albedo, snow/ice pixels, signal saturation, and acquisition geometry. The Level 3 product in the GEE is produced at a resolution of 0.01 degrees from the Level 2 Sentinel-5P data (TROPMI, 2020) before being ingested into GEE. The data undergoes extensive filtering to remove poor quality pixels with a 'qa_value' less than 0.75 for the 'tropospheric_NO_2_column_number_density' band of NO_2, while other datasets (except for O_3 and SO_2) are filtered by a 'qa_value' less than 0.5. The measuring units of NO_2 , SO_2 , CO, and HCHO were converted from mol/m² to µmol/m² for consistency.

4. Results

The data from the Tehsils along the Lahore-Multan Motorway, including Renala Khurd, Depalpur, Jahanian, Mian Channu, Sahiwal, Okara, Khanewal, Kabirwala, and Chichawatni, were used to map air pollution. The spatial interpolation and temporal analysis were performed to understand the spatial and temporal patterns of the pollutants. Figure 2 shows the spatial distribution of SO_2 concentration along the Lahore-Multan Motorway. Using IDW maps, the spatial distribution of SO_2 concentration from 2018 to 2022 showed significant regional variances. The concentrations of SO_2 in 2018 varied between 0.18 and 0.26 µmol/m²; Depalpur, Okara, and Chichawatni had lower levels, while Kabirwala, Khanewal, Mian Channu, Sahiwal, and Renala Khurd had higher levels. In 2019, the values ranged from 0.08 to 0.11 µmol/m², with the highest levels observed in Renala Khurd, Okara, and Kabirwala. A progressive rise was observed in 2020, with values peaking in Kabirwala and Main Channu ranging from 0.13 to 0.18 µmol/m². This increase persisted in 2021, with concentrations in Renala Khurd being the highest, ranging from 0.09 to 0.15 µmol/m². Similar patterns were observed in 2022, with concentrations ranging from 0.11 to 0.13 µmol/m², again highest in Renala Khurd and Okara. IDW maps illustrating the spatial distribution of NO_2 concentration from 2018 to 2022 showed notable spatial patterns along the Lahore-Multan Motorway. NO_2 concentrations in 2018 varied from 81.93 to 92.46 µmol/m²; Sahiwal, Okara, and Renala Khurd had the highest amounts, while Jahanian and Khanewal had the lowest (Fig. 3).

The range of values in 2019 was between 82.72 to 93.56 µmol/m², with considerable increases observed in Depalpur and Chichawatni. NO_2 levels by 2020 ranged from 78.65 to 86.57 µmol/m², with peaks in Sahiwal, Okara, and Depalpur, indicating a continuous rise from Jahanian to Renala Khurd. With concentrations ranging from 85.23 to 97.54 µmol/m² in 2021, the trend persisted, and Sahiwal and Renala Khurd were shown to be significantly polluted. The 2022 data indicated concentrations ranging from 84.24 to 94.25 µmol/m², with the highest levels again in Okara and Renala Khurd (Fig. 3).

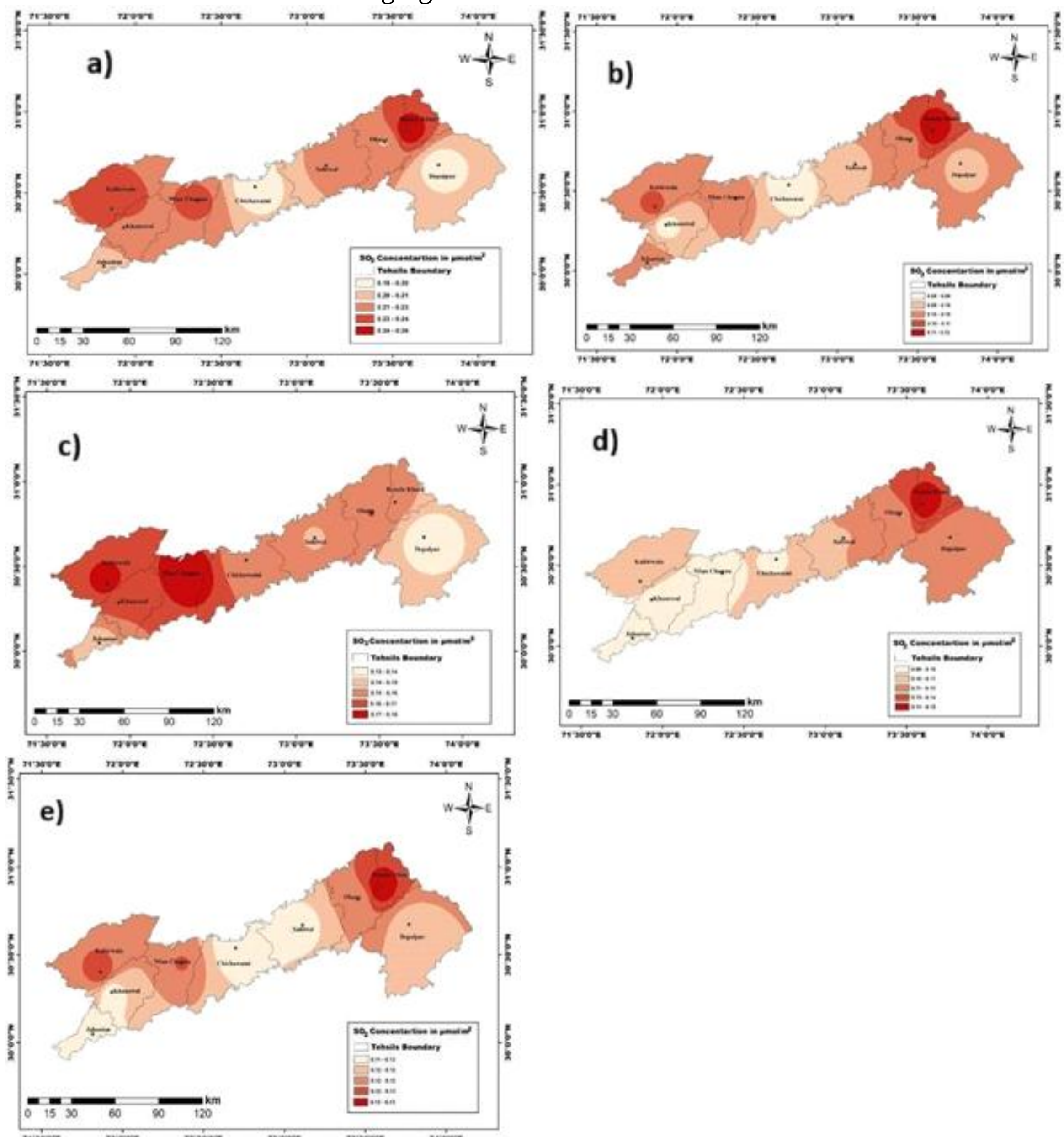

Fig. 2. Spatial distribution of SO_2 concentration along Lahore-Multan Motorway a) 2018, b) 2019, c) 2020, d) 2021, e) 2022.

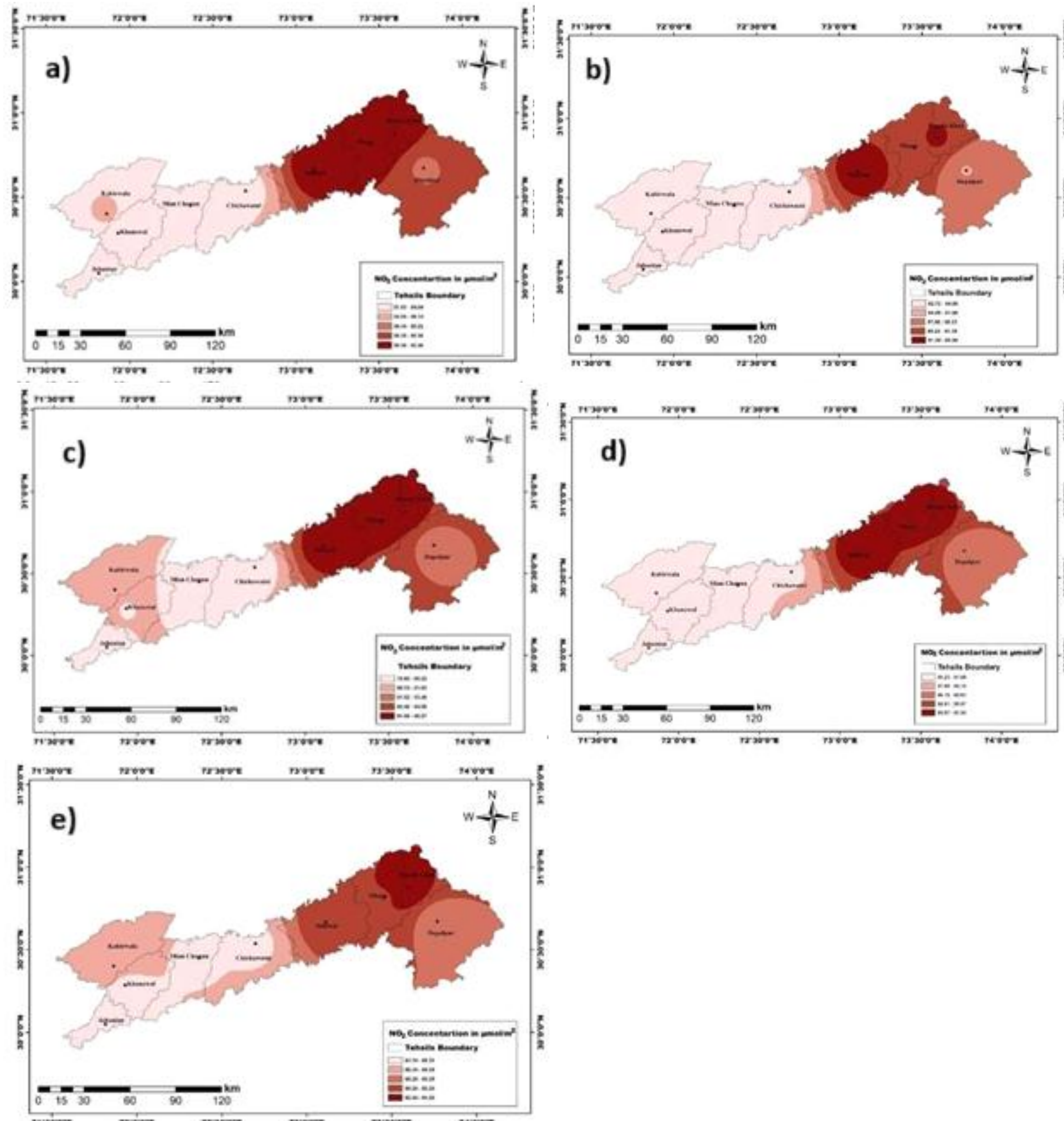

Fig. 3. Spatial distribution of NO_2 concentration along Lahore-Multan Motorway a) 2018, b) 2019, c) 2020, d) 2021, e) 2022.

The increase persisted in 2021, with concentrations in Renala Khurd being the highest, ranging from 0.09 to 0.15 µmol/m². The 2022 data showed a similar pattern, with concentrations ranging from 0.11 to 0.13 µmol/m², again highest in Renala Khurd and Okara. During 2018 and 2022, there were notable regional differences in the carbon monoxide (CO) concentration spatial distribution, as depicted by IDW maps, in Jahanian, Khanewal, Kabirwala, Mian Channu, Chichawatni, Sahiwal, Okara, Depalpur, and Renala Khurd. CO levels in 2018 varied from 38.85 to 39.44 µmol/m², with Sahiwal, Okara, and Jahanian having the highest amounts. The CO levels increased from Jahanian towards Renala Khurd in 2019, with an overall lower range of 36.57 to 37.77 µmol/m². The CO concentrations in 2020 varied from 37.29 to 38.51 µmol/m², exhibiting a rising trend toward Depalpur and Okara (Fig. 4).

The pattern persisted with concentrations ranging from 38.79 to 40.30 µmol/m² in 2021, with Renala Khurd and portions of Okara and Depalpur having the highest CO levels. By 2022, the CO concentration ranged from 36.30 to 37.56 µmol/m², again showing higher levels in Renala Khurd, Okara, and Depalpur.

The concentration of CH_4 in different places varied in 2018, ranging from 188058 to 1900007.12 micromoles per square meter (Fig. 5). The concentrations in 2019 showed a rising slope from Kabirwala to Sahiwal, ranging from 188452 to 1896122.50 micromoles per square meter. This trend persisted. Similar fluctuations in concentrations were observed in 2020, with Sahiwal continuously showing greater values than other places (1904133.75 to 1914230.5 micromoles per square meter). In 2021, there were variations in CH_4 concentrations throughout different regions, potentially due to industrial and agricultural practices. The range of readings was 1918699.75 to 1920961.12 micromoles per square meter. Finally, in 2022, concentrations ranged from 1913865.37 to 1919840.37 micromole per square meter, showcasing variations in methane emissions or concentrations across the studied regions, likely influenced by factors such as regional industrial activities, agriculture methods, and topographical characteristics.

The spatial distribution of Aerosol Optical Depth (AOD) concentration from 2018 to 2022 in the study area (Fig. 6). In 2018, low AOD values in areas like Depalpur and Sahiwal showed cleaner air, while high values in regions like Kabirwal, Jahanian, and Khanewal suggested an increase in aerosol concentration. From Sahiwal and Chichawatni to Khanewal and Jahanian, AOD values steadily increased in 2019, upholding this pattern. Regional differences intensified by 2020, with Renala Khurd and Okara revealing lower AOD levels in distinction to Jahanian, Khanewal, and the localities. In 2021, a prominent increase was seen in particulate matter, particularly in areas like Kabirwala, Jahanian, and Depalpur, as evidenced by the rising AOD levels. In 2022, this continued, with high AOD values demonstrating greater airborne particulate matter concentrations, specifically in Kabirwala in the Punjab region. There are noticeable patterns of variation in the spatial distribution of formaldehyde (HCHO) concentration between 2018 and 2022 (Fig. 7).

Between 0.19 and 0.22 micromoles per square meter, HCHO concentrations progressively rose in 2018 from Depalpur to Jahanian. Comparably, concentrations of 0.18 micromoles per square meter were consistently seen in most regions in 2019; nevertheless, there were minor rises in places like Khanewal and Chichawatni. The highest levels of HCHO were found in industrialized areas like Kabirwala and Sahiwal by 2020, when concentrations ranged from 0.181 to 0.187 micromoles per square meter. Potential environmental or industrial influences on HCHO emissions are indicated by the fact that this pattern continued in 2021, with steady concentrations in some places and minor increases in others. Lastly, concentrations continued to be comparatively constant throughout the region, highlighting formaldehyde's continued presence in the atmosphere. The values in 2021 varied between 127838.10 and 129012.94 micromoles per square meter, with the areas from Renala Khurd to Kabirwala showing relatively higher concentrations. In 2022, O_3 concentrations showed changing ozone levels along the road, ranging from 127273.97 to 127974.34 micromoles per square meter (Fig. 8).

5. Discussion

Substantial alterations in air quality among different regions can be seen in the spatial dispersal of numerous atmospheric contaminants along the Lahore-Multan Motorway from 2018 to 2022. These pollutants contain nitrogen dioxide (NO_2), sulfur dioxide (SO_2), carbon monoxide (CO), formaldehyde (HCHO), ozone (O_3), methane (CH_4), and aerosol optical depth (AOD). Over the use of Inverse Distance

Weighting (IDW) maps, the data's investigation shows how pollutant concentrations have altered over time, representing a variety of causes and local impacts. Over the five-year sequence, SO_2 concentrations varied noticeably, ranging from 0.08 to 0.26 µmol/m² (Table 2). Higher quantities were frequently noted in Kabirwala and Renala Khurd, two industrial regions. Likewise, NO_2 values ranged from 78.65 to 97.54 µmol/m², with Sahiwal and Renala Khurd being prominent hot spots for pollution. CO amounts range between 36.30 and 40.30 µmol/m², with higher values in urban and industrial areas. CH_4 concentrations varied from 188058 to 1920961.12 micromoles per square meter, replicating the effects of agriculture and industry pollutants.

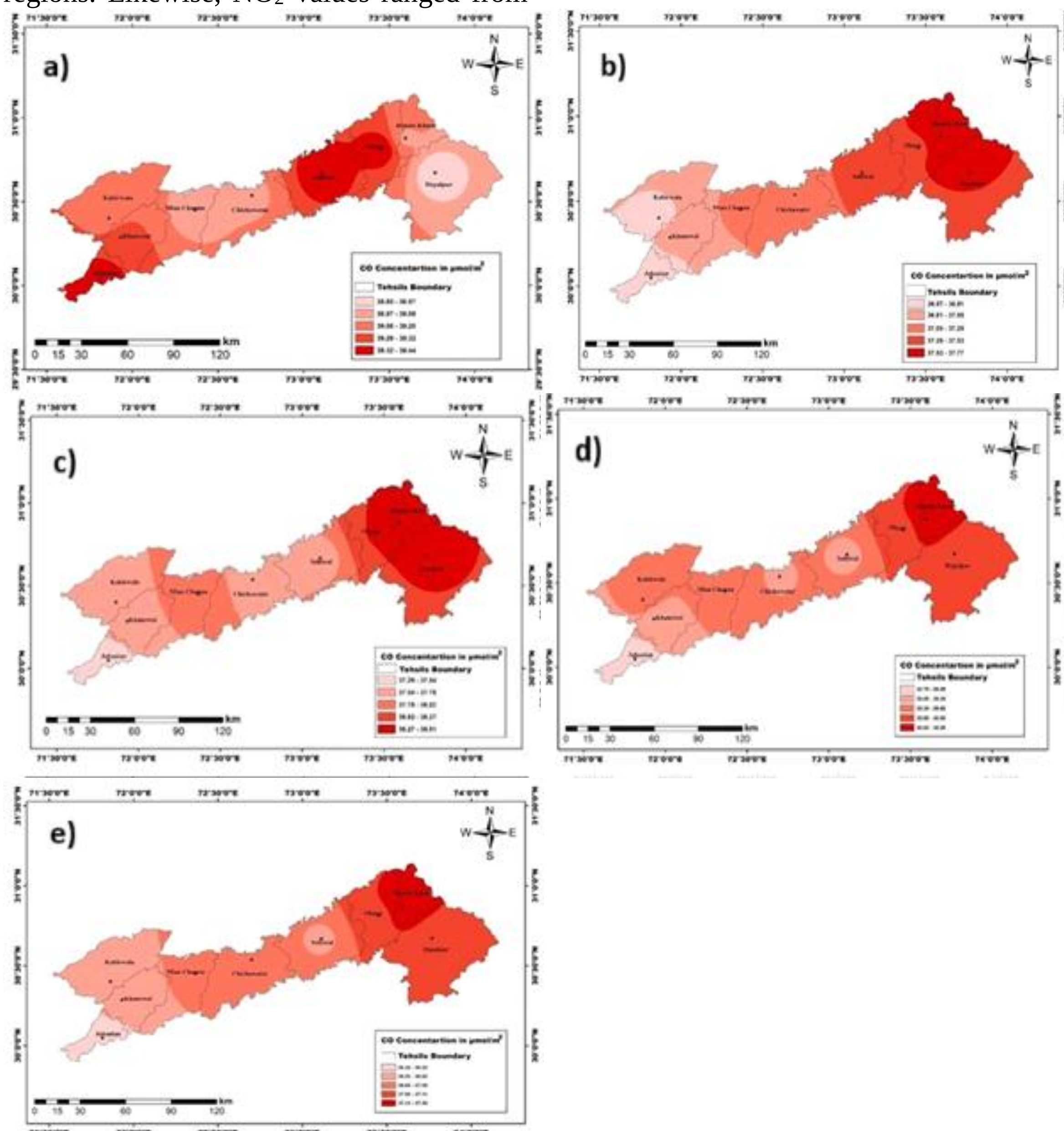

Fig. 4. Spatial distribution of CO concentration along Lahore-Multan Motorway a) 2018, b) 2019, c) 2020, d) 2021, e) 2022.

The spatial distribution of AOD showed increasing levels of particulate matter, specifically in areas like Jahanian and Kabirwala. Temporarily, HCHO concentrations steadily displayed an industrial effect, with greater levels found in locations where high industrial activities take place. Local variations were seen in the concentrations of O_3, with Okara and Renala Khurd showing higher values. These results highlight the complicated interactions among emissions sources, atmospheric processes, and local issues that shape the air quality along the Lahore-Multan Motorway.

The study shows that integrating geospatial data and the travel demand model can be utilized to assess the air quality levels on highways. Construction activities and biomass emissions are the Punjab region's main sources of dust and carbon monoxide. The proposed methodology uses data collar models developed at the University of Engineering and Technology (UET) in Lahore, Pakistan. A predictive model for PM_{10} was developed utilizing the building construction data and applied to Lahore-Sheikhupura Road (LSR). It is validated against the observed Environmental Protection Department (EPD) data. The more important aspect is designating the number of small and large sites for installing a Met station and observation for the correct data collection of BPR curves. The BPR curves developed in the present research will be useful for future traffic assignments.

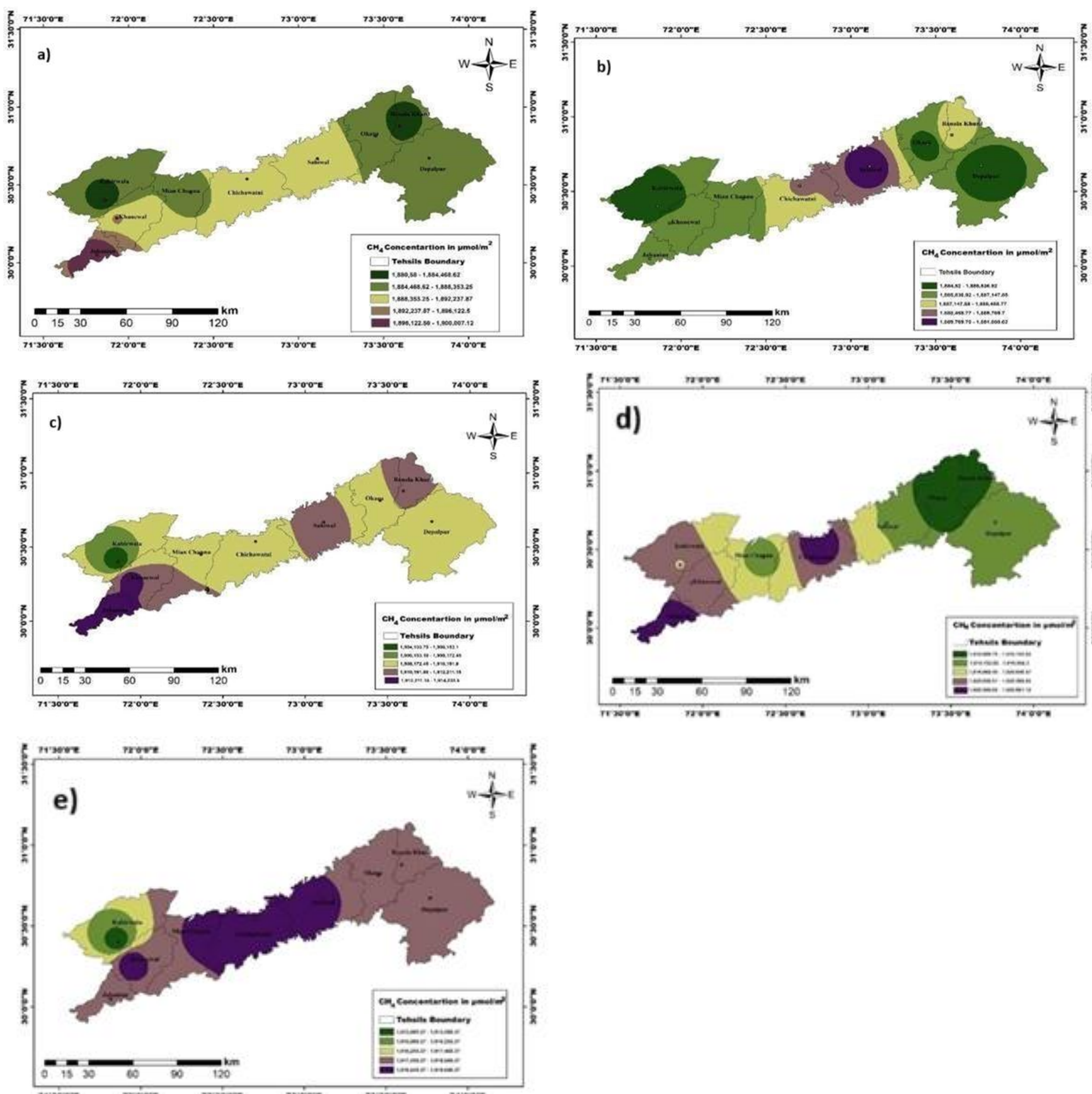

Fig. 5. Spatial distribution of CH_4 concentration along Lahore-Multan Motorway a) 2018, b) 2019, c) 2020, d) 2021, e) 2022.

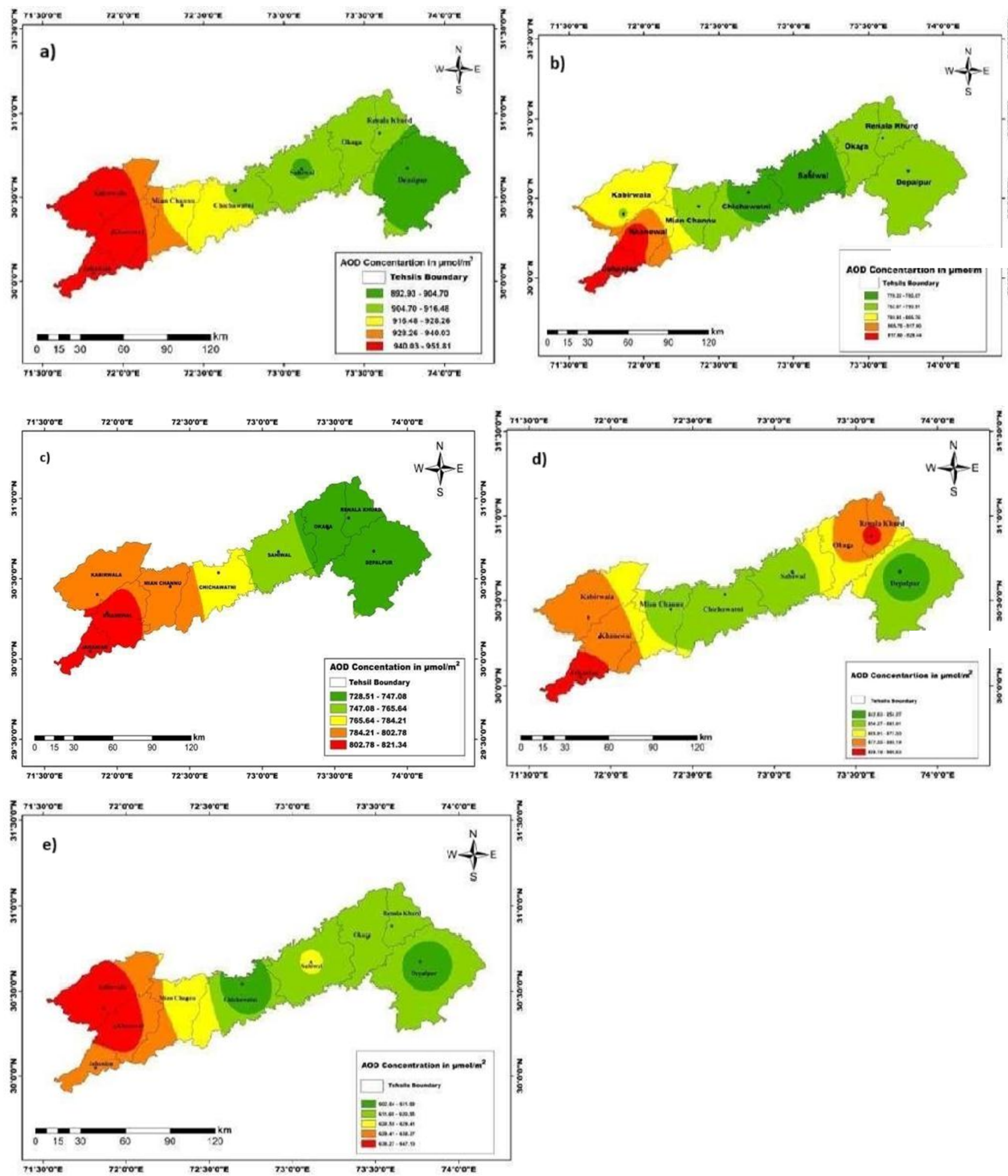

Fig. 6. Spatial distribution of AOD along the Lahore-Multan Motorway a) 2018, b) 2019, c) 2020, d) 2021, e) 2022.

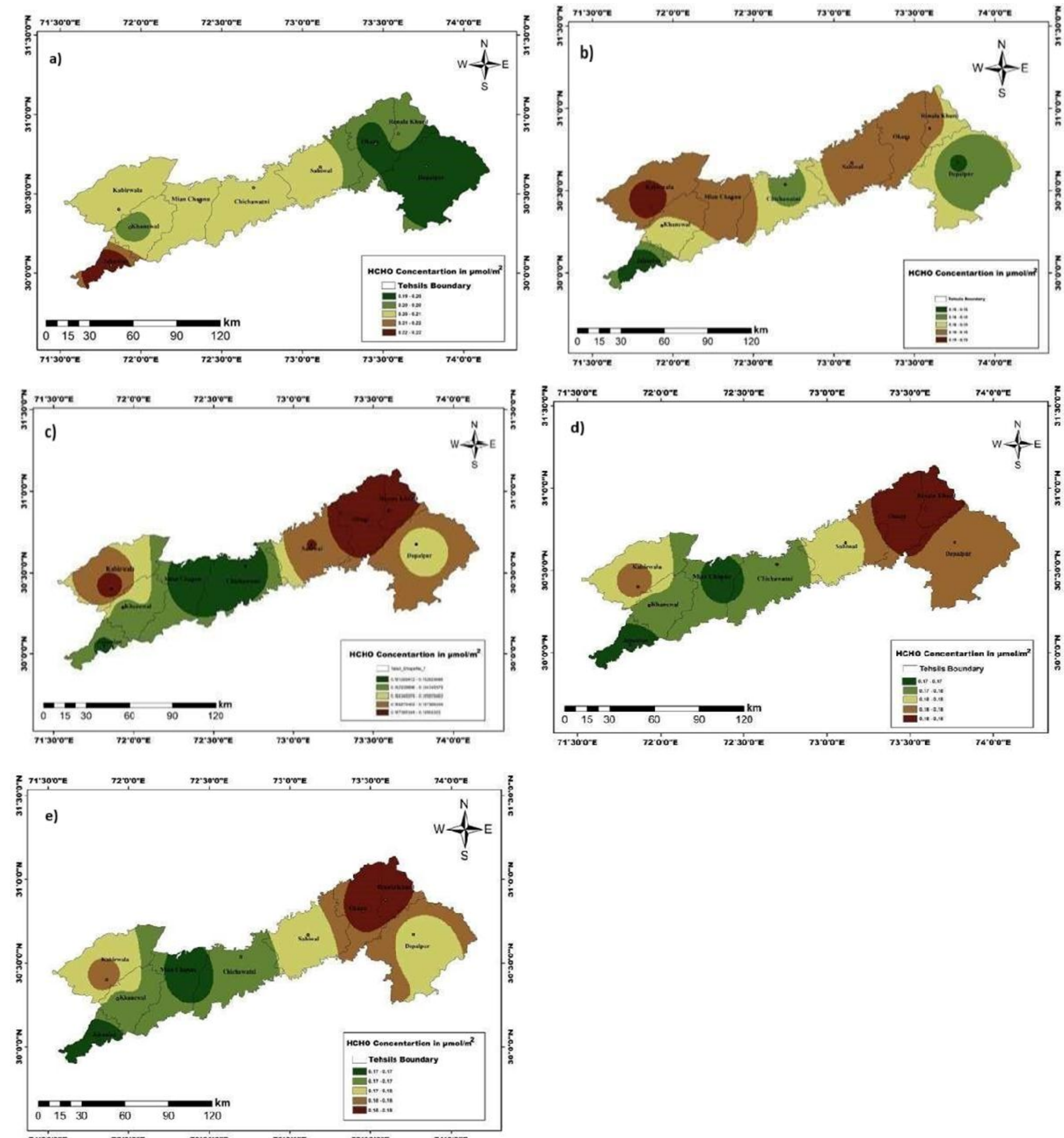

Fig. 7. Spatial distribution of HCHO concentration along Lahore-Multan Motorway a) 2018, b) 2019, c) 2020, d) 2021, e) 2022.

6. Conclusion

Overall, the level of air pollution along the Lahore-Multan Motorway from 2018 to 2022 shows dynamic dissimilarities driven by numerous emission sources and local environments. Variations in the concentrations of NO_2, SO_2, O_3, CO, HCHO, CH_4, and AOD highlight how complicated the changing aspects of air quality in the research region are. To improve air quality and ensure sustainable growth along traffic corridors, the pragmatic trends highlight the need for targeted actions to minimize vehicular, industrial, and agricultural emissions, specifically in hot spot locations like Renala Khurd and Kabirwala. Policymakers may address the numerous causes of pollution and strive toward developing improved and more functional communities while diminishing the effects of climate change by focusing on detailed monitoring and mitigation practices.

Table 2: Annual variation of atmospheric pollutants along Lahore Multan motorway (2018-2022).

Gases	Range	2018	2019	2020	2021	2022
SO_2	Low	0.18-0.20	0.08-0.09	0.13-0.14	0.09-0.10	0.11-0.12
umol/m²	High	0.24-0.26	0.11-0.12	0.17-0.18	0.14-0.15	0.12-0.13
NO_2	Low	81.93-84.84	81.72-84.39	78.66-80.23	80.23-83.49	84.24-86.24
µmol/m²	High	90.34-92.48	91.29-93.34	91.99-96.87	95.67-97.84	92.25-94.25
CO	Low	38.85-38.97	36.57-36.81	37.29-37.54	38.79-39.09	34.20-34.56
µmol/m²	High	39.32-39.44	37.53-37.77	38.27-38.51	40.00-40.30	37.21-37.68
O_3	Low	122115.26-122467.28	126322.37-126617.94	128042.00-128341.82	127838.10-128073.07	127373.07-127448.06
µmol/m²	High	123480.97-123822.22	127504.54-127900.21	129157.12-129457.14	128777.97-129912.94	127974.34-129149.43
HCHO	Low	0.19-0.20	0.15-0.16	0.10-0.12	0.17-0.18	0.17-0.18
µmol/m²	High	0.22-0.23	0.18-0.19	0.14-0.16	0.18-0.19	0.18-0.19
AOD	Low	892.93-904.70	776.82-782.07	728.51-747.08	847.63-854.57	602.84-611.89
	High	940.03-951.81	817.26-829.44	802.78-821.34	899.10-900.03	638.27-647.19

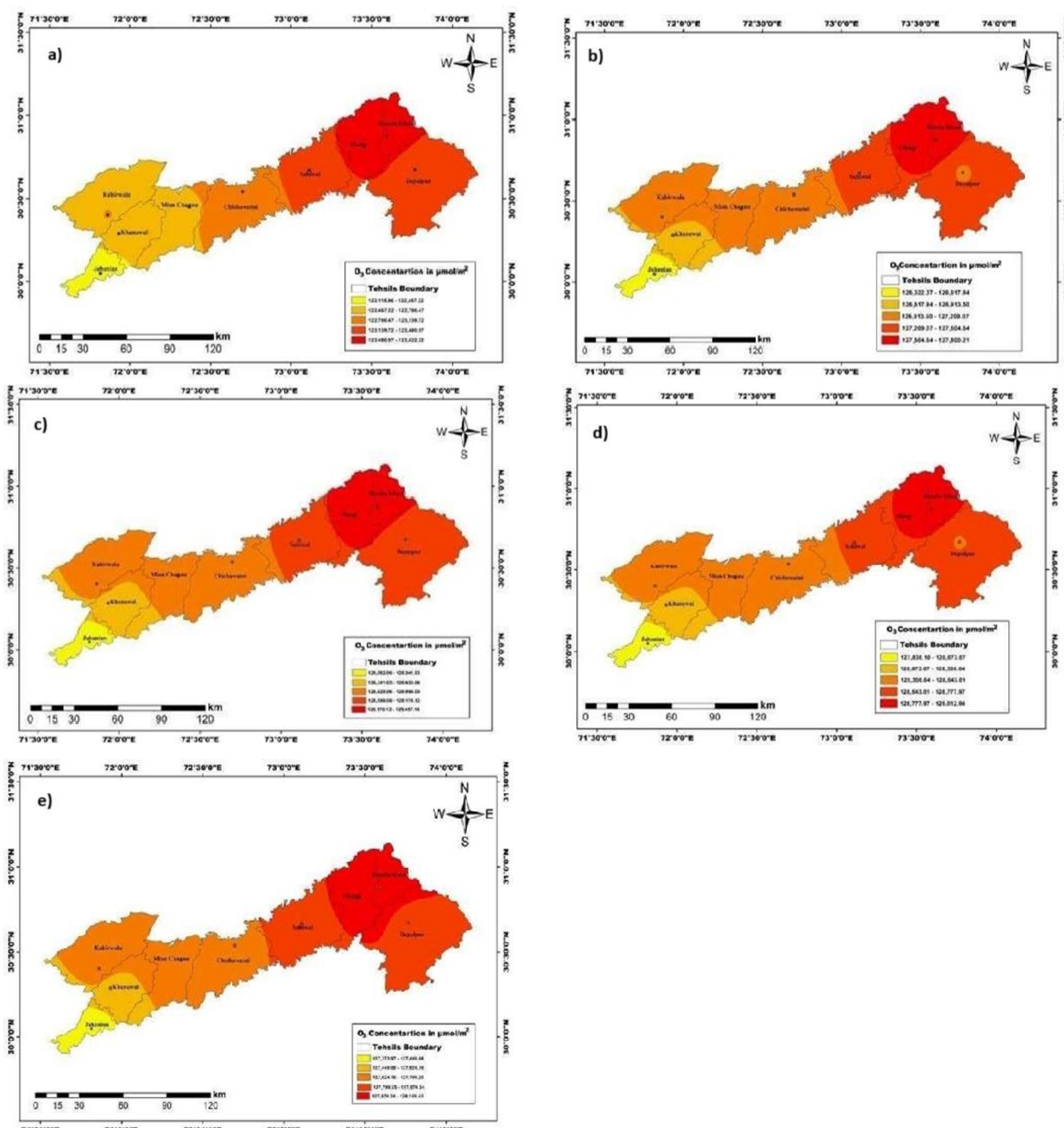

Fig. 8. Spatial distribution of O_3 concentration along Lahore-Multan Motorway, a) 2018, b) 2019, c) 2020, d) 2021, e) 2022.

The changes in air quality levels contribute to increased carbon dioxide emissions and intensify the impact of climate change. This study will help reduce the environmental impact of infrastructure development on highway projects, which includes deforestation, land degradation, and biodiversity loss in the specified region. This study also provides valuable, insightful information to help understand the impact of climate change and develop adaptation plans to deal with these land use changes. Thus, studying changes in air quality levels is essential for local community development across highways. This study investigated the impact of air quality on highways in the most urbanized province of Punjab. Various data types were collected, integrated, and modelled to predict air quality.

The empirical study involved samples of three primary pollutants: CO, AOD, and NO_2. Stack-convolutional prediction models assessed the relationship between air quality variations and traffic conditions. In future studies, it is suggested that the day of the week, vehicular speed, vehicular count, and special days' emissions may be studied as they significantly impact various pollutants, showing different patterns. The results of the study provided useful insights and can be used by transportation agencies for policy formulation. For those provincial governments fostering urbanization processes, these studies provide insights into conducting new approaches for dealing with environmental health conditions. In this context, it is recommended for future research in this domain, can be more efficient by combining data-driven models.

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Author contributions

Nausheen Mazhar, Amina Abrar, and Aqsa Zulfiqar led the conceptualization, methodology, and data analysis conducted the overall analysis. Sawaid Abbas supervised the study and provided resources and technical inputs for the research. Sohail Abbas reviewed and edited the manuscript of the paper. Eisha Jabbar and Humna Akmal reviewed and edited the manuscript.

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Data availability

The datasets used and/or analyzed during the study are available on request from the corresponding author.

DECLARATIONS

Conflict of interest: The authors declare no competing interests.

Ethics approval and consent to participate.

The authors declare that they followed the ethics in scientific research.

Consent for publication.

Not applicable

Competing interests

The authors declare no competing interests.

Conflict of interests: The authors reported no potential conflict of interest.

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