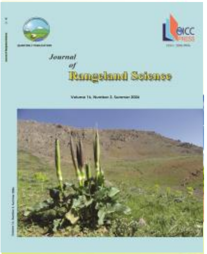

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Research Article

Spatio-Temporal Analysis of Air Pollution and Environmental Dynamics in Central Iran's Desert Rangelands Zones Using Remote Sensing and Google Earth Engine

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Abstract

Desert rangelands, despite existing within environmental regulatory frameworks, can still experience significant air pollution due to emissions from nearby urban and industrial activities. This study examines the spatio-temporal dynamics of nitrogen dioxide (NO_2), carbon monoxide (CO), sulfur dioxide (SO_2), and atmospheric UV Aerosol Index (AER_AI), also known as the Absorbing Aerosol Index (AAI), as dust concentration across of central desert rangelands in Yazd province, Iran. Utilizing Google Earth Engine and remote sensing data, pollution trends were analyzed over six years (2018–2023) in nine locations. The study also investigated the influence of environmental factors-precipitation, wind patterns, and vegetation cover-on mitigating pollution levels. The ANOVA test, mean comparisons, and time series analysis were performed using R software. Time series analyses and statistical comparisons across spatial and temporal groups revealed significant differences between years and locations in pollutant areas. Results showed significantly higher concentrations of NO_2, CO, and SO_2 in desert rangelands near urban and industrial zones compared to control sites. ANOVA tests revealed marked spatial and temporal variations, identifying urban–industrial areas as persistent hotspots. Pollutant levels of NO_2 and CO were positively correlated ($r=0.49$, $p<0.01$), while Absorbing Aerosol Index (AAI), as dust concentrations, appeared largely external, originating from sources like dry wetlands. Temperature was strongly associated with AAI ($r=0.68$, $p<0.01$), and vegetation showed no capacity to mitigate pollution. These findings underscore the critical need to incorporate environmental factors into the management of desert rangelands and the formulation of industrial development policies to ensure sustainable outcomes. Integrating such considerations can help mitigate pollution and protect fragile ecosystems in arid regions.

Keywords: Environmental factors, Atmospheric Pollution, Vegetation Cover

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1. Introduction

Industrial pollution has long been recognized as a critical environmental and public health concern globally, contributing significantly to urban air-quality degradation, climate change, and ecosystem disturbances. Despite stringent environmental regulations in numerous countries, desert rangeland zones are increasingly affected by airborne pollutants, particularly in areas with nearby industrial and urban activities, including nitrogen dioxide (NO_2), carbon monoxide (CO), sulfur dioxide (SO_2), and particulate matter. These pollutants are linked to respiratory illnesses and other health problems, especially in densely populated areas surrounding industrial hubs. As cities expand, the influence of industrial pollutants on urban microclimates has become increasingly relevant for researchers and policymakers alike, particularly with escalating global urbanization trends (Paolocci et al., 2020). The need for research on industrial air pollution remains significant due to the complex interplay between emissions, urban environmental conditions, and public health. Previous studies emphasize that, while regulatory measures have reduced emissions in some regions, persistent high levels of industrial pollutants remain a concern (Hoffmann et al., 2021). In rapidly developing nations, air quality standards and their enforcement vary, often leaving local populations exposed to hazardous pollutant levels. For instance, industrial expansion in Asia has led to pollution levels that surpass international standards, contributing to the atmospheric "brown cloud" phenomenon (Larson, 2010).

In Iran, urban and industrial growth have similarly intensified debates over the efficacy of existing pollution-control measures, while only a limited number of studies have quantified pollutant levels or assessed the environmental factors that may mediate pollution dispersion. Given the urgent need for effective policies and the variability of international standards, this study addresses a critical gap by focusing on long-term industrial air-quality monitoring in Iran—a country facing unique challenges due to its arid conditions and substantial industrial activities. Recent advances in remote sensing and statistical modeling provide robust tools for analyzing air pollution patterns and trends in desert rangeland areas. For instance, platforms like Google Earth Engine (GEE) enable large-scale, high-resolution environmental assessments using satellite data to track pollutant dispersion and seasonal trends (Gorelick et al., 2017). Studies have shown that employing time series analysis, ANOVA tests are effective methods for assessing pollutant variations across different spatial and temporal scales (Dimakopoulou et al., 2017). Additionally, environmental factors such as precipitation and wind have been examined for their roles in pollutant dispersal, with results indicating mixed success in pollutant mitigation, especially where industrial pollution is highly concentrated (Lin et al., 2024).

In Iran, research on industrial air pollution has been relatively limited compared to studies in more urbanized regions. However, existing literature highlights that desert rangeland zones in central Iran are associated with significant air quality challenges, exacerbated by the region's arid climate and limited precipitation (Mansouri & Hamidian, 2013). Research on Iran's unique meteorological and environmental conditions reveals that wind and vegetation cover may not be as effective in mitigating pollution as in regions with higher rainfall and greenery (Ebrahimi-Khusfi et al., 2020; Mirsanjari et al., 2020).

Studies were conducted on industrial emissions in some cities of Iran, like Isfahan, indicating substantial NO_2 and CO emissions, adversely affecting local air quality and public health (Yousefi et al., 2024). Despite these efforts, no study has yet been conducted on a long-term spatio-temporal assessment of multiple industrial pollutants (NO_2, CO, SO_2, and dust) in the desert rangelands of central Iran, nor has a systematic evaluation been conducted on how environmental factors such as wind, precipitation, and vegetation interact with pollutant levels. This study specifically addresses this gap by combining remote sensing and statistical approaches to deliver a comprehensive six-year analysis, offering new insights into pollution dynamics under arid climatic conditions.

This study applies a similar methodological framework, integrating remote-sensing data to investigate air-quality trends and evaluate the roles of natural environmental factors in modulating pollution levels in desert rangeland settings. This study aimed to investigate the concentration of key air pollutants and address pollution dynamics and their implications for sustainable desert rangeland development across the central desert rangelands in Yazd province, Iran.

Similarly, the objective of this study was to analyze the spatial and temporal distribution of NO_2, CO, SO_2, and AAI over six years (2018–2023) in the Yazd-Ardakan desert rangelands area and evaluate environmental factors such as wind patterns, precipitation, and vegetation as potential moderators of air pollution. Specifically, the study addresses two questions: 1) how do pollutant levels differ between industrial and non-industrial zones in the Yazd-Ardakan region. 2) To what extent do wind and vegetation mitigate air pollution? By addressing these questions, this study provides data-driven insights into pollution patterns and highlights the environmental considerations necessary for future desert rangelands planning.

2. Materials and methods

2.1. Study area

Yazd-Ardakan region is located in central Iran, is a prominent desert rangelands hub characterized by its arid climate, minimal rainfall, and sparse vegetation, which

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increase the potential for pollutant accumulation in the atmosphere. With average annual precipitation of 60 mm and temperatures of 18.9°C, often exceeding 40°C during the summer months, Ardakan's climate is classified as hyper-arid (Hosseini KhezrAbad et al., 2024). This climate exacerbates the retention and dispersion of airborne pollutants; as dry conditions reduce natural pollution mitigation processes such as rainfall deposition. The area is economically significant for Iran, hosting numerous cement, tile, and metal production industries, which are documented to emit high levels of NO_2, CO, SO_2, and particulate matter (Moosavi et al., 2021). The region's flat terrain, limited vegetation cover, and persistent industrial activity make Yazd-Ardakan an important region for studying industrial pollution dynamics and their environmental impacts (Figure 1).

2.2. Database and Methodology

The primary database comprises remote sensing and meteorological data collected over the study period from 2018 to 2024. Sentinel-5P provides pollutant concentration data (NO_2, CO, SO_2), UV Aerosol Index (AER_AI), also known as the Absorbing Aerosol Index (AAI) as dust concentration. The Sentinel-5P mission includes the Tropospheric Monitoring Instrument (TROPOMI), which is a passive grating push broom imaging spectrometer. The TROPOMI was designed to support atmospheric composition and air quality monitoring services and provide measurements of aerosols, atmospheric humidity fields, cloud types and temperature, ozone, and trace gases (Reshi et al., 2024).

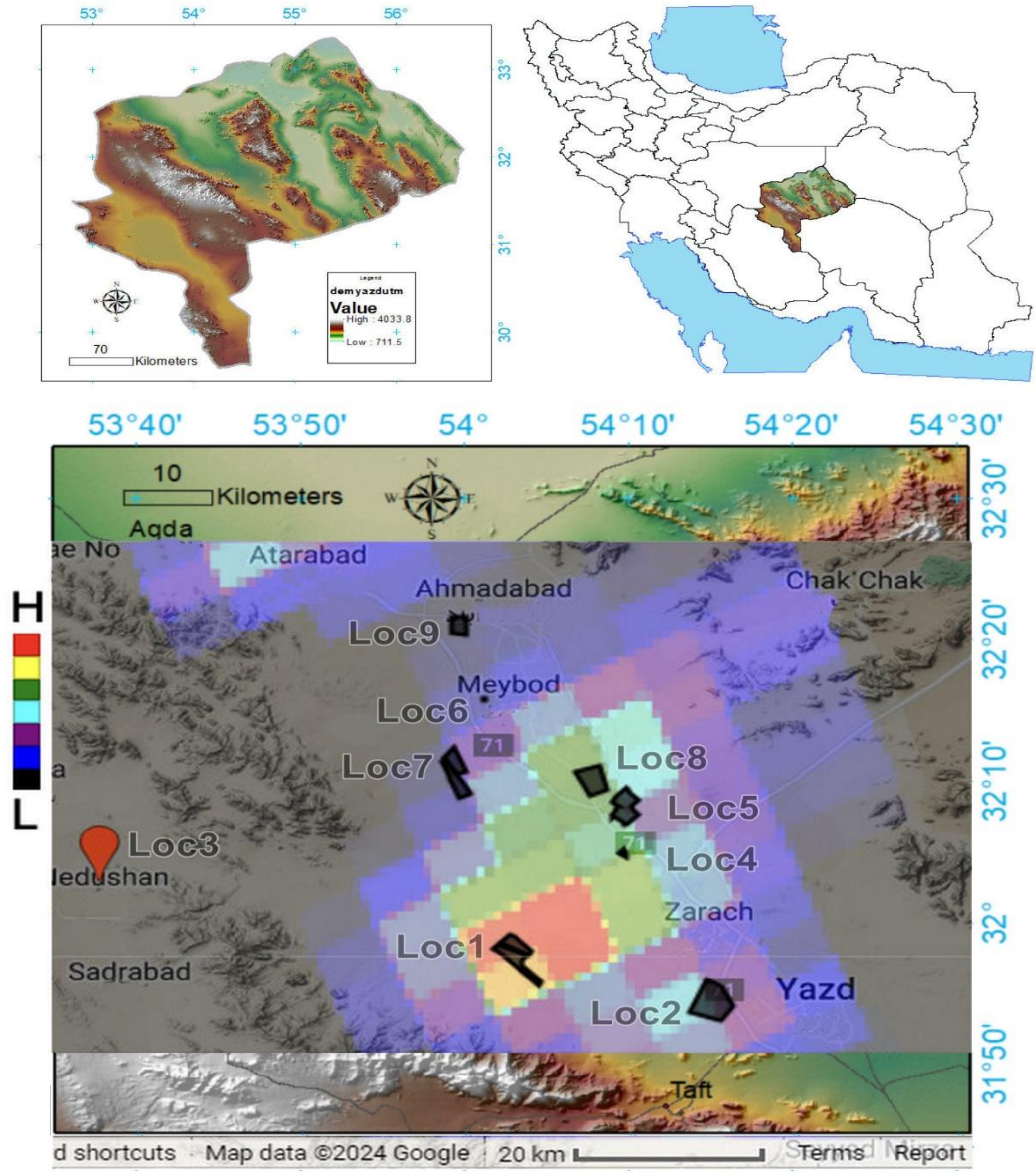

Figure 1. Map of Yazd Ardakan region in Yazd province, Iran and in nine industrial location

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Also, Aerosol index (AI or AAI) is a measurement related to Aerosol Optical Depth (AOD) that indicates an increased concentration of tiny particles called aerosols suspended in the atmosphere. In general, a lower AI value indicates clearer skies due to a lower concentration of aerosols. Aerosol index is an ideal metric for tracking the evolution of episodic aerosol plumes from dust outbreaks, volcanic ash, significant fire events, and biomass burning. Those plumes can harm human and ecosystem health, disrupt the work of important industries, and pose significant hazards to transportation. The calculation of the aerosol index is based on wavelength-dependent changes in Rayleigh scattering in the ultraviolet (UV) spectral range, where ozone absorption is very small. The aerosol index is derived from normalized radiances using two wavelength pairs at 340 and 378.5 nanometers. UV aerosol index can be calculated even if clouds are present, enabling daily global coverage. Instruments aboard NASA's Earth-observing satellites provide worldwide aerosol index data, including near-real-time data. (https://www.earthdata.nasa.gov/topics/atmosphere/uv-aerosol-index)

Sentinel-2 and Sentinel-3 supply vegetation indices (NDVI) and land surface temperature (LST) data. Precipitation and wind data are sourced from the Global Precipitation Measurement (GPM) and ERA5 datasets, respectively (Gorelick et al., 2017). The data was processed and analyzed in Google Earth Engine (GEE), allowing for temporal and spatial analyses over the selected period. A summary of the database is presented in Table 1.

2.3. Data Preprocessing and Visualization

To begin, pollution data from Sentinel-5P was extracted, normalized, and visualized as time series in R software. Spatial mapping in GEE visualized pollutant concentrations across Yazd-Ardakan region, enabling the identification of pollution hotspots (Nodoushan et al., 2025). Vegetation indices (NDVI) from Sentinel-2 were calculated to assess the spatial distribution of green cover, while, land surface temperature from Sentinel-3 reflects temperature trends and potential heat-island effects.

2.4. Conceptual Framework

The conceptual framework is presented in Fig 2, which summarizes the methodological steps from data collection and preprocessing to statistical and spatial analyses, including time series modeling and inferential testing. This framework underpins the study's comprehensive analysis of industrial pollution and environmental interactions, providing a data-driven approach to understanding pollution dynamics in arid desert rangeland regionsThe study utilizes a combination of time series analysis, spatial mapping, and inferential statistics to assess pollution concentration trends and their relationship with environmental variables. Data processing includes calibration, atmospheric correction, and cloud masking in GEE (Figure 2).

2.5. Statistical analysis

One-way and two-way ANOVA tests, along with Tukey's test, were applied to compare pollutant concentrations across spatial and temporal categories, to detect significant differences in pollutant levels between desert rangelands and control zones over time (Al-Ateeqi et al., 2022).

2.6. Time series analysis

A time series model was applied to evaluate temporal trends and periodicity in pollutant levels, using the autoregressive integrated moving average (ARIMA) model to detect seasonal variations and forecast pollutant trends (Bhatti et al., 2021).

3. Result

In the present study, the trend of pollutant concentrations in different locations over a period of six years was investigated. The highest NO_2 concentration was recorded at LOC8 in 2020, while the lowest levels were consistently observed at LOC3. The lowest CO levels throughout the period were recorded at LOC3. For SO_2 concentrations, the highest levels were observed in LOC5 and LOC1 in 2020. LOC3 showed a noticeable increase in aerosol levels between 2021 and 2022. The pollution maps showed a general south–north trend. Localized concentrations of NO_2 and SO_2 appear in desert rangeland areas, suggesting limited dispersion of these pollutants under regional climatic conditions. CO and AAI pollution followed a south–north direction, with wider regional spread in industrial towns. This suggested that these pollutants dispersed more easily. Maps of selected air pollution were drawn for the selected time period (Fig 3).

Table 1. Overview of Data Sources, Types, Variables, and Their Temporal and Spatial Resolutions

Data Source	Data Type	Variable	Temporal Resolution	Spatial Resolution
Sentinel-5P	Atmospheric Pollution	NO_2, CO, SO_2	Daily	7x3.5 km
Sentinel-2	Vegetation Index (NDVI)	NDVI	5 days	10 m
Sentinel-3	Land Surface Temperature (LST)	Temperature	Daily	1 km
GPM	Precipitation	Rainfall	Daily	10 km
ERA5	Meteorological	Wind Speed/Pattern	Hourly	31 km

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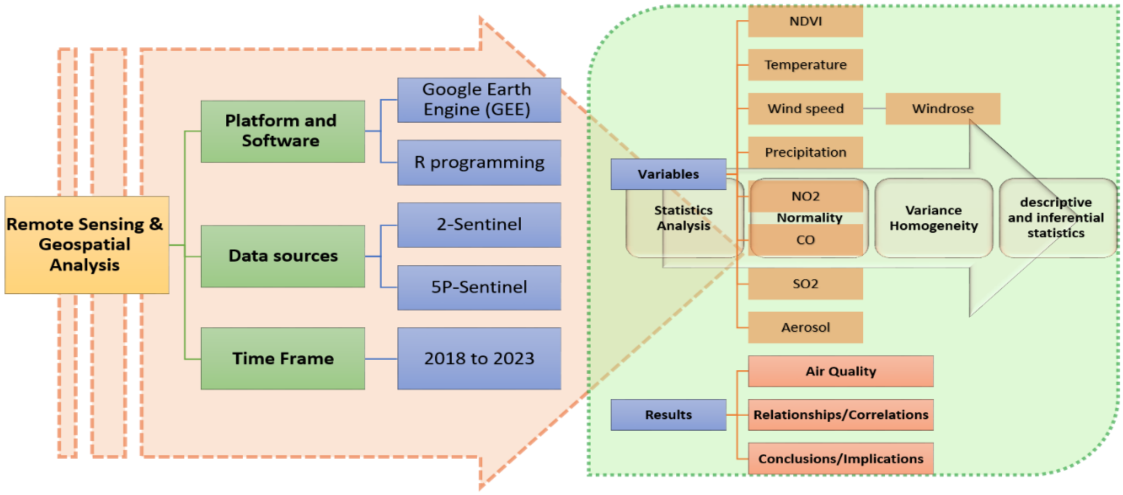

Figure 2. Flowchart of remote sensing and geospatial analysis for air quality assessment (2018–2023)

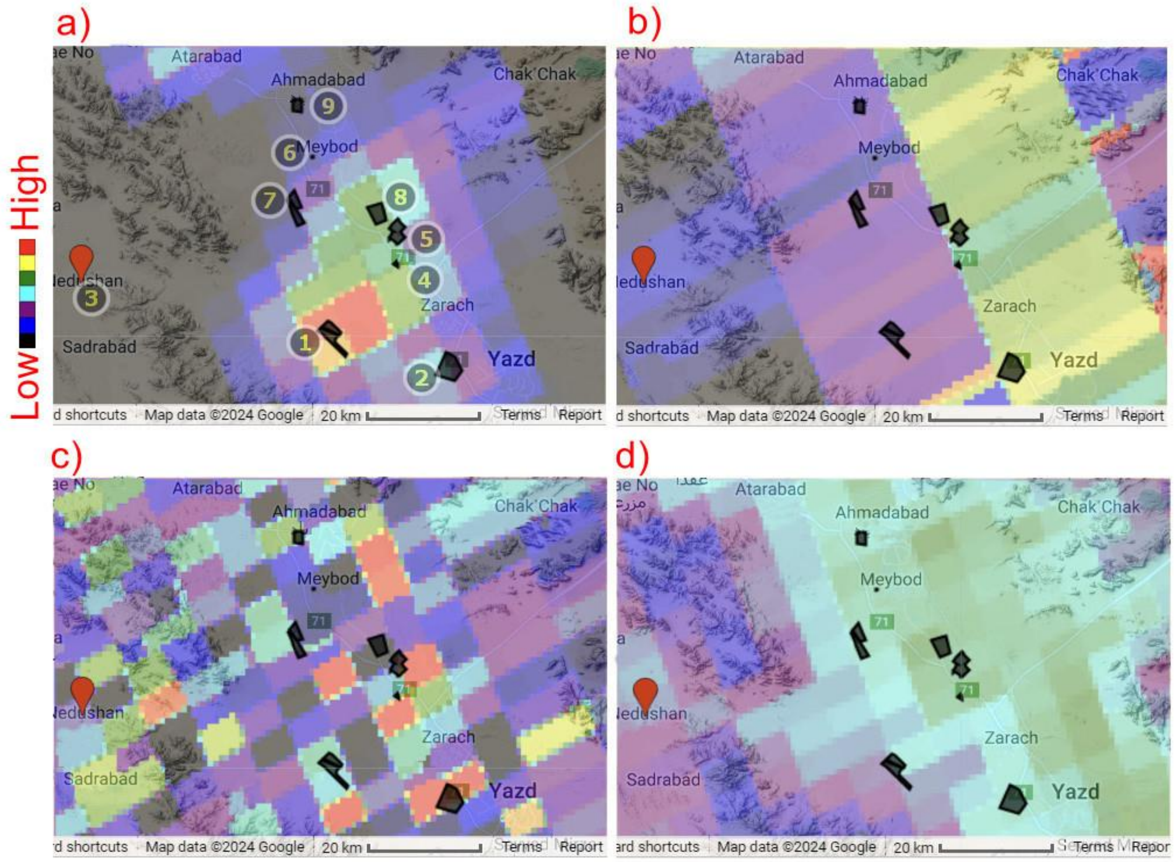

Figure 3. Maps of air pollution in the area, a) NO2 and Location numbers, b) CO, c) SO2, and d) dust

Table 2. Results of one-way ANOVA and mean comparison between locations for environmental factors and ambient air pollutants

Environmental factors and ambient air pollutants	Loc1	Loc2	Loc3	Loc4	Loc5	Loc6	Loc7	Loc8	Loc9
Wind speed (m/s)	0.598c	0.324ab	0.205a	0.392ab	0.379ab	0.501bc	0.612c	0.525bc	0.452bc
Total precipitation (mm)	0.522a	0.427a	0.516a	0.360a	0.348a	0.308a	0.389a	0.354a	0.368a
Temperature 2m (C°)	9.74b	10.12c	7.02	10.34c	9.73b	8.41a	8.23a	8.62a	9.19b
Soil Temperature (C°)	10.13bc	9.91b	8.26a	9.83b	9.87b	10.29bc	10.59c	10.53c	10.87c
Surface Runoff (mm)	1.80a	3.79b	1.77a	3.86b	4.02c	3.48c	1.93ab	3.74b	3.27b
NDVI (dimensionless)	0.032a	0.037 b	0.051bcd	0.064d	0.035ab	0.040abc	0.031a	0.053cd	0.031a
UV Aerosol Index	-0.66c	-0.41b	-0.47b	-0.44b	-0.39b	-0.39b	-0.50a	-0.53a	-0.56a
NO_2 (mole^4/m^2)	2.79c	2.27bc	0.34a	1.71b	1.65b	2.20bc	2.08bc	2.15bc	2.04bc
CO (mol/m^2)	0.029bc	0.029bc	0.023a	0.028b	0.028b	0.029bc	0.029bc	0.030c	0.029bc
SO_2 (mol/m^2)	13.54 c	7.30 b	1.17 a	8.42 abc	9.91abc	13.80c	2.91ab	3.48ab	11.03bc

Different letters (a, b, c) within rows indicate significant differences between locations
The map of locations in the Yazd Ardakan region is presented in Figure 1

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Results showed significant differences in wind speed among the studied locations. The highest mean wind speeds were recorded mainly in the southern and northern parts of the study area (LOCs 8 and 1). In contrast, central locations such as LOC4 and LOC5 showed lower wind speeds. Further analysis indicated that areas with higher wind speed generally exhibited lower pollutant concentrations. This pattern suggested that stronger winds might have contributed to pollutant dispersion in these regions. Precipitation showed no significant variation between locations or years, indicating limited influence of rainfall on the removal of pollutants during the study period. NDVI values were lowest in the extensive desert rangelands, where vegetation density was sparse and pollution levels were relatively high. These findings imply that limited vegetation cover and reduced surface roughness may have facilitated pollutant accumulation in those areas.

Climatic factors such as wind, precipitation, and vegetation cover, which are considered to influence pollution in the region, exhibit a similar distribution across the desert rangelands. However, at location 3, the control point, wind speed was lower due to its position at the foot of the mountain and away from the plain. Precipitation levels, on the other hand, were comparable across all locations. The amount of vegetation density also shows lower values in the south of the region (location 1) and in the middle of the region (locations 5, 6 and 7) and in the north of the region, i.e., location 9. This is also due to the filling of the region with factories and industrial facilities in these areas.

Results of mean comparison between locations for environmental factors and ambient air pollutants is presented in Table 2. The distribution of air pollution showed low levels of pollution at location 3 (the control point) compared to other locations. Air pollution showed higher values in areas where large industrial, steel, and coal facilities are located. These areas, LOCs 1, 6, and 9, which are located in the south, middle, and north of the region, showed higher industrial pollution. On the other hand, dust pollution showed the same situation in these places. The result showed less pollution in the control location. Pollution levels were consistently higher in the southern (LOC1), central (LOC5–6), and northern (LOC9) regions, primarily due to the concentration of steel, glass, and coal industries (Table 2).

The Result of two-way ANOVA to examine the effects of location and year for NO_2 and CO, SO_2, and UV aerosol index pollutants are presented in the Fig 4 to7. For nitrogen dioxide (NO_2) concentrations across different locations during the period from 2018 to 2023, results showed noticeable spatial and temporal variability. The lowest NO_2 level was recorded at LOC3. In contrast, the highest concentrations were observed at LOC2 in 2020 and at LOC8 in 2021, respectively, indicating potential localized emission sources or environmental factors contributing to elevated NO_2 levels in those specific years (Figure 4).

For carbon monoxide (CO) concentrations between 2018 and 2023, results demonstrated similar spatial patterns to those observed for NO_2. The lowest CO levels throughout the period were recorded at LOC3. The highest concentration was found at LOC8 in 2021, suggesting a significant emission event or increased local sources during that year (Figure 5).

For sulfur dioxide, (SO_2) concentrations showed that LOC5 and LOC1 had the highest levels in 2020. Both locations exhibited a marked upward trend in SO_2 levels leading up to that year. In contrast, the lowest concentrations over the entire study period were consistently observed at LOC3 and LOC7 (Figure 6).

For aerosol concentrations, the result showed that all locations exhibited relatively similar trends over time, with no major spatial disparities. However, LOC3 showed a noticeable increase in aerosol levels between 2021 and 2022, suggesting a temporary rise in local emissions or environmental conditions influencing particle concentrations during that period (Figure 7).

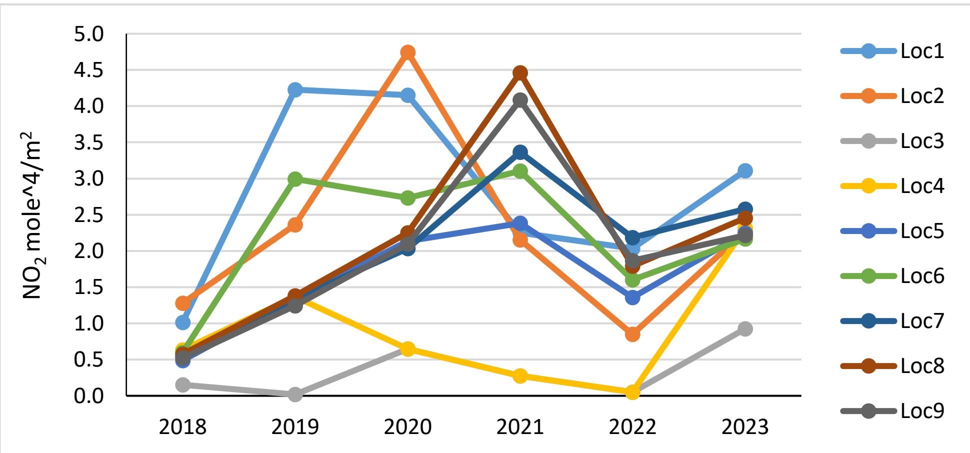

Figure 4. Temporal and spatial variations of nitrogen dioxide (NO_2) concentrations from 2018 to 2023 across nine Locations

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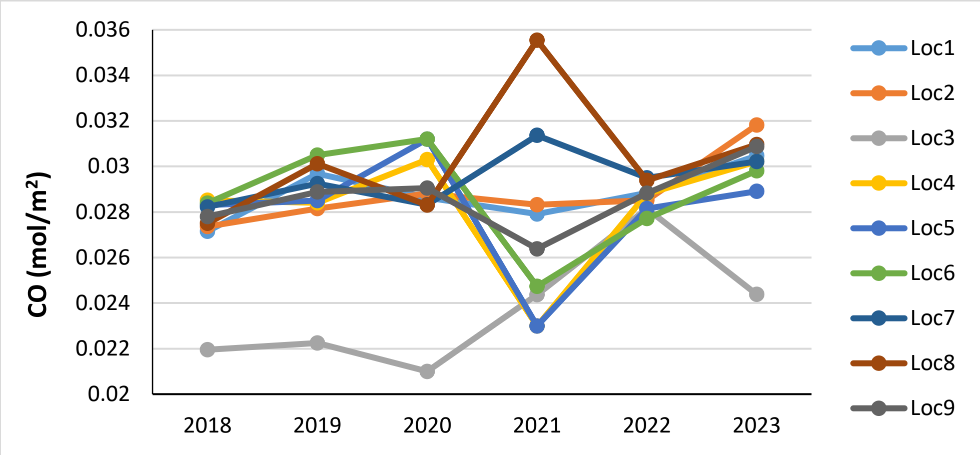

Figure 5. Temporal and spatial variations of carbon monoxide CO concentrations from 2018 to 2023 across nine Locations

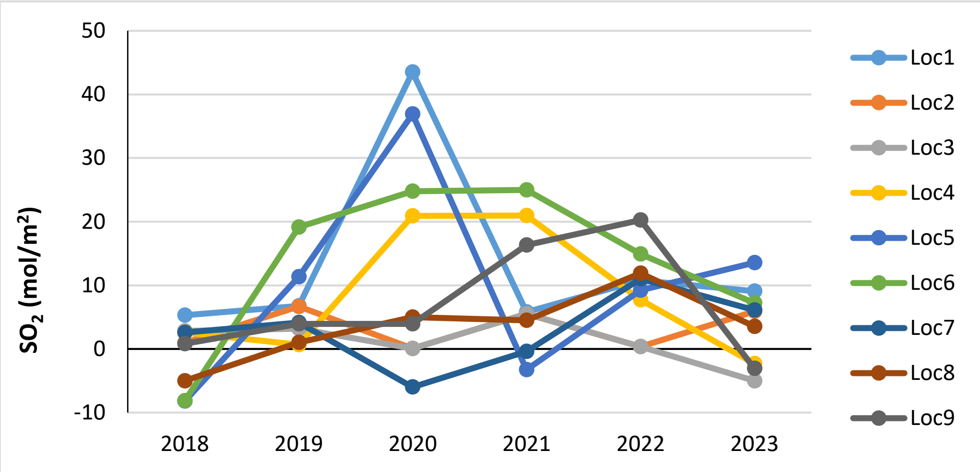

Figure 6. Temporal and spatial variations of sulfur dioxide (SO_2) concentrations from 2018 to 2023 across nine locations

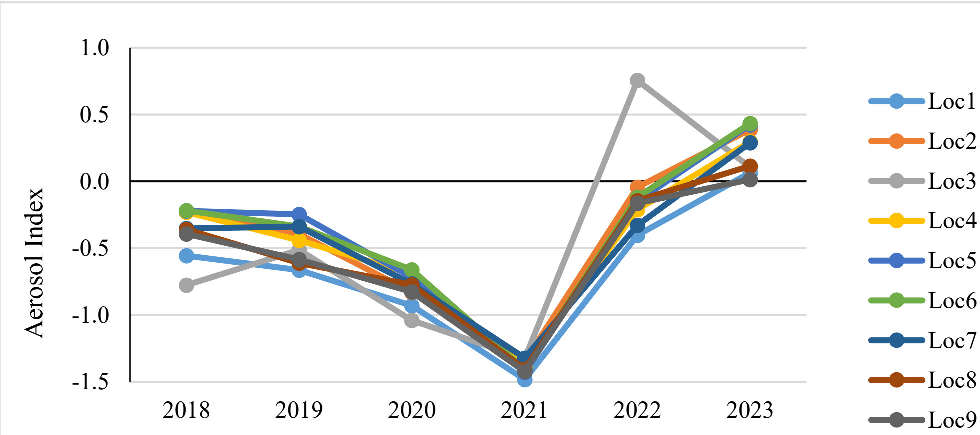

Figure 7. temporal and spatial variations of aerosol index (AAI) or dust concentrations from 2018 to 2023 across nine locations

3 The relationship between pollution and environmental data and their significance level is presented in Table 3.

There were strong positive correlations between NO2 with CO, SO2, and Ozone (O3). Indicating a strong relationship between four pollutants. Similarly, SO2 had positive correlations with both O3 and annual precipitation, indicating that in areas with high rainfall, the amount of SO2 and O3 has increased. Aerosol Index had positively correlated with both air temperature and Soil temperature. The precipitation was negatively correlated with both soil temperature and surface runoff. In contrast, vegetation density negatively correlated with soil temperature. While three was a strong positive correlation between aerosol index and temperature ($r = 0.68$, $P<0.01$), indicating higher AAI levels on hot and dry days. Air and soil temperatures also showed a strong positive relationship ($r = 0.81$, $P<0.01$). Among pollutants, NO_2 and CO, there was positive correlation ($r = 0.49$, $P<0.01$), and SO_2 showed a similar positive association (Table 3).

Table 3. Correlation of pollution gases and environmental Data

Variables	NO_2	CO	SO_2	AAI	O_3	Wind speed	Total precipitation	2 m Temp.	Soil Temp.	Surface runoff
Nitrogen dioxide NO_2	1.00									
Carbon monoxide CO	0.49^{**}									
Sulfur dioxide SO_2	0.48^{**}	0.15								
Aerosol index (AAI)	-0.32^{*}	0.23	-0.23							
Ozone (O_3)	0.53^{**}	0.23	0.40^{**}	-0.17						
Wind speed	0.19	0.37^{*}	0.29^{*}	-0.01	0.27^{*}					
Total precipitation	0.30^{*}	-0.03	0.51^{**}	-0.36^{*}	0.49^{**}	0.36^{*}				
Temperature 2 m	-0.15	0.21	-0.25	0.68^{**}	-0.12	-0.09	-0.38^{*}			
Soil temperature	0.16	0.30^{*}	-0.21	0.53^{**}	0.07	-0.20	-0.45^{**}	0.81^{**}		
Surface runoff	0.05	0.00	-0.03	0.08	-0.03	-0.15	-0.46^{**}	0.01	0.22^{**}	
NDVI	-0.07	-0.17	-0.07	-0.16	0.10	-0.16	0.11	-0.19	-0.27^{*}	-0.20

* $p < 0.05$, ** $p < 0.01$,

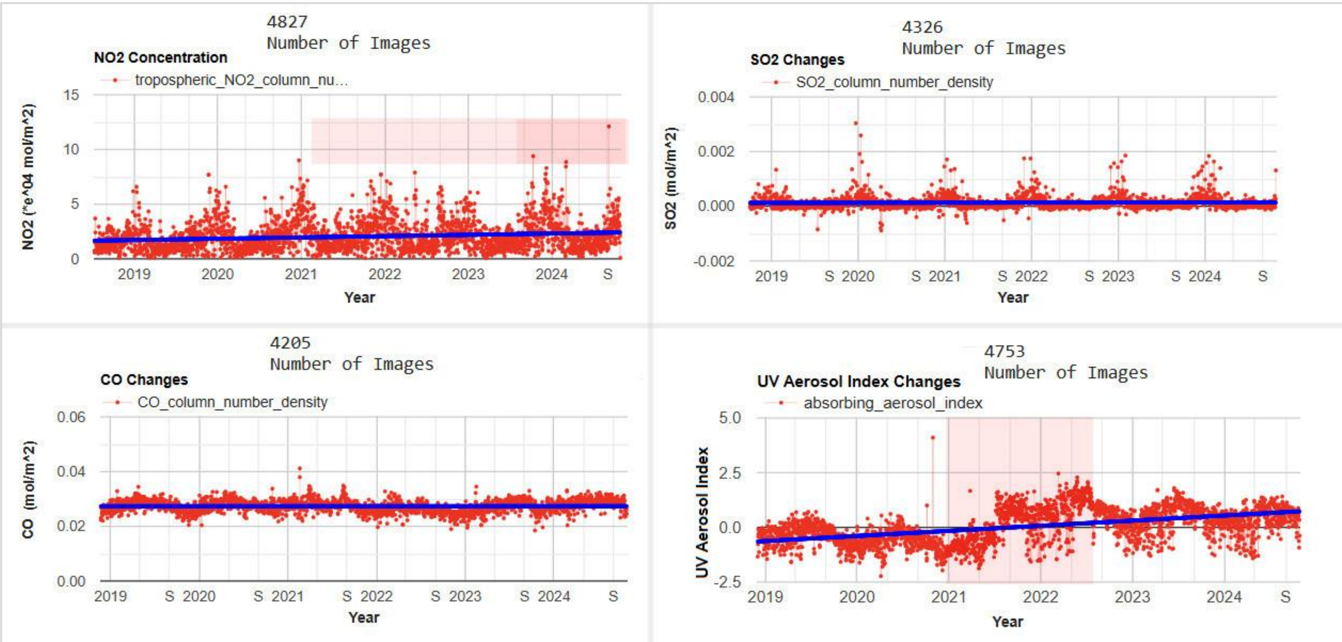

Figure 8. Pollution daily time series for NO_2 and CO, SO_2, and UV aerosol index pollutants in all locations

The time series charts using Sentinel 5P daily images over this period show the use of over 4,000 images per chart. These charts also show seasonal fluctuations in pollution, but their overall trend shows some control in the region. Dust shows a more increasing situation for the reasons explained in the statistical controls. Time series of air pollution trends were performed using a huge database of satellite images in GEE (Figure 8).

4. Discussion

The findings in this study reveal critical insights into the complexities of industrial pollution dynamics in semi-arid regions, particularly highlighting the specific roles of climatic and environmental factors in influencing pollutant dispersion and accumulation. As we consider these results in the context of broader research, a clear narrative emerges on the compounded impacts of industrialization in ecologically fragile areas. This discussion will evaluate how these observations relate to the international literature, examining both the broader implications of pollution in industrialized semi-arid regions and the efficacy of environmental interventions.

One of the prominent patterns observed in this study is the south-north distribution of air pollution, with areas proximate to heavy industries such as steel, glass, and coal plants recording the highest pollution levels. This observation is consistent with patterns commonly reported in other semi-arid industrial regions worldwide, where proximity to heavy industries is often associated with elevated pollution levels. For example, in industrialized parts of South Asia, similar spatial patterns are observed, where pollution dispersion correlates with both the density and type of industry as well as regional climatic variables (Shi et al., 2018). In our study area, the control point (location 3) showed lower pollution levels, an outcome consistent with international observations in

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areas less impacted by industrial activity (Guo et al., 2021). The seasonal variation noted, with higher aerial index levels during dry, hot periods, echoes patterns found in other arid and semi-arid regions. For instance, studies in the southwestern United States reveal similar correlations between dust levels and seasonal dryness, largely due to the region's susceptibility to windborne particles and reduced vegetation cover (Flagg et al., 2014). Additionally, our finding of a significant correlation between air temperature and dust levels speaks to the vulnerability of arid zones to temperature-driven increases in particulate matter. This relationship has been documented in North Africa's Sahel region, where a rise in air temperatures amplifies dust transport from desert surfaces (Knippertz & Todd, 2012).

A noteworthy observation from this study is the limited role of vegetation in reducing air pollution, specifically in semi-arid regions heavily industrialized with large-scale facilities. This reflects a broader consensus in environmental research that, while vegetation serves as a significant sink for pollutants in humid and temperate climates, its effectiveness diminishes in semi-arid zones where water scarcity restricts plant growth and density (Naorem et al., 2023). Vegetation's limited effectiveness in semi-arid zones may be attributed to ecological mechanisms such as low leaf area index (LAI), reduced stomatal conductance, and limited transpiration capacity due to water scarcity. Sparse vegetation struggles to mitigate pollution effectively due to limited biomass and the reduced functionality of ecosystems (Wang et al., 2022). In the Yazd-Ardakan desert rangelands, these limitations are even more pronounced due to the region's hyper-arid climate and extreme summer temperatures, which severely restrict both natural vegetation growth and artificial afforestation efforts. Unlike some semi-arid regions where seasonal precipitation still supports moderate vegetation density, Yazd-Ardakan's persistent water scarcity and poor soil fertility further reduce vegetation's potential to act as a pollution buffer. This suggests that the general assumption of vegetation as a viable mitigation strategy in arid zones may need to be refined when applied to hyper-arid, industrially dense environments such as central Iran.

The negative correlation between vegetation density and climatic factors like surface runoff and soil temperature in this study highlights additional complexities. Arid-zone studies have noted that plant cover, though beneficial, can also exacerbate issues under extreme temperatures by creating heat-island effects in some instances (Abedrabboh et al., 2025). These findings emphasize that while vegetation offers some benefits, it is not a panacea for pollution control in such challenging climates and should be considered as part of a multifaceted strategy rather than a standalone solution.

Wind and precipitation have been traditionally regarded as natural dispersion agents for pollutants; however, our findings showed that their impact varies significantly depending on location. Higher wind speeds in certain polluted zones indicate a potential dispersive effect, yet, paradoxically, pollution concentrations remain high in these areas. This phenomenon is echoed in studies from Asia, where high winds are observed to carry pollutants across vast distances but do not necessarily dilute concentrations within desert rangelands zones (Li et al., 2020). The low wind speeds at the control point (location 3), due to its mountainous position, further underscore the role of topography in moderating wind effects and potentially aiding pollution entrapment in low-lying desert rangeland areas.

The distinct pollution signatures tied to specific industries, such as steel, coal, and ceramics, reflect known patterns of industrial emissions documented in various regions worldwide. Steel production, in particular, is associated with high SO_2 and NO_2 emissions, as observed northeast of China (Sun et al., 2019). Our findings of high pollution levels in locations 1, 6, and 9, dominated by heavy industries, underline a universal trend in industrial pollution, where pollutant concentration is directly proportional to industrial activity density. The observed increase in pollution levels during 2020–2021 coincides with reports of a rapid rebound in industrial production following the easing of COVID-19 restrictions. Although direct production data for our study area are limited, similar rebound patterns have been widely documented internationally (Niu et al., 2022). Our study highlighted that despite environmental policies, the persistent issue of dust, primarily sourced from beyond the desert rangelands region, complicates efforts. This underscores the necessity of collaborative, cross-border environmental policies and dust control programs, particularly in areas where dust transport crosses national boundaries (Zhang, 2021).

While the implementation of technological filters and waste recycling in our study area suggests some level of pollution control, the results showed that these measures might not suffice in environments heavily impacted by external dust sources and industrial density. The literature points to more comprehensive approaches in addressing industrial pollution, particularly in the use of advanced scrubbers, stricter emission standards, and continuous environmental monitoring (Mukherjee et al., 2024).

The data suggested that local policies must account for both localized industrial impacts and external dust influx, possibly through international cooperation and investment in green technologies. Our results align with global

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recommendations that underscore the importance of multi-faceted strategies that include stringent emission controls, enhanced vegetative cover where feasible, and advanced monitoring technologies (Chen et al., 2024). Notably, areas of study in Europe, such as Italy's Po Valley, have demonstrated that integrated policies encompassing industrial emission controls, urban vegetation planning, and international environmental agreements are crucial for long-term sustainability (Raffaelli et al., 2020).

5. Conclusion

This study analyzed six years of air pollution dynamics across the Yazd–Ardakan desert rangelands in central Iran using Sentinel satellite data and spatial–statistical modeling. Significant spatial and temporal variations were observed for major pollutants (NO_2, SO_2, CO, and dust) and environmental parameters. The highest concentrations of NO_2 and SO_2 were recorded near industrial zones, particularly in steel and ceramic production areas, whereas CO and dust exhibited broader regional dispersion along a south–north gradient. Areas with stronger wind speeds generally showed lower pollutant accumulation, highlighting the role of atmospheric circulation in pollutant dispersion. Conversely, low vegetation density and sparse surface cover in the desert rangelands were associated with higher pollution levels, reflecting the limited buffering capacity of ecosystems under arid conditions. The findings highlighted that effective air quality management in semi-arid industrial regions requires integrated, region-specific strategies. Localized emission controls alone are insufficient; coordinated regional actions addressing dust transport and industrial emissions are essential. Strengthening emission monitoring networks, promoting cleaner industrial technologies, and integrating satellite-based monitoring with ground observations could substantially enhance environmental management. Future research should focus on combining remote sensing with predictive modeling to better forecast pollution patterns and support evidence-based policymaking aimed at protecting both the environment and public health in fragile desert ecosystems.

Authors Contribution
Authors have contributed equally in preparing and writing the manuscript.

Availability of data and materials
The data that support the findings of this study are available on request from the corresponding author.

Conflict of interests
I certify that there is no actual or potential conflict of interest concerning this article.

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