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Research article

Spatio-temporal characterization of PM10 concentration across Abu Dhabi Emirate (UAE)

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ABSTRACT

The abundance and recurrence of particulate matter in Abu Dhabi Emirate (ADE), are often derived from different emission sources such as the combustion of hydrocarbon, producing much of the PM2.5 found in outdoor air, as well as a significant proportion of PM10. Wind-blown dust from open desert areas and construction sites, landfills and agriculture, brush/waste burning, and industrial sources, has contributed markedly to the problem of the spread of haze and the long-range movement of pollutants in the country. In this study, the spatio-temporal characterization of PM10 concentration across the Emirate was analyzed utilizing geospatial interpolation, spanning the period between 2013 and 2017. The results suggest that the fluctuations of the PM10 concentration can be decomposed into three dominant types, each characterizing different spatial and temporal variations. First, the western region with PM10 showing a peak concentration during the summer season i.e., when the winds are predominantly northerlies or north-westerly, and a minimal concentration during the winter season. Second, the central region with the PM10 exhibiting a concentration surge in July–August, as a result of a mix of strong winds and high temperatures. Third, the eastern region with a low concentration of PM10. Seasonally, this component exhibits two concentration maxima during quarters 2 and 3 (summer), and two minima during quarters 1 and 4 (winter). Indeed, the seasonal variability of PM10 concentration in desertic countries like the UAE is closely linked to the seasonal variation of heat waves and dust storms, which are characteristic of the dryland climate. During the summer months, the UAE experiences high temperatures and arid conditions, creating favorable conditions for the formation of heat waves. Furthermore, it was noticed that the PM10 concentration also fluctuated markedly throughout the study period with anomalies detected in open desert areas and regions characterized by extensive industrial operations.

1. Introduction and background

The Earth's environment faces significant challenges due to air pollution, a leading driver of climate change and environmental concerns [1,2]. According to the World Health Organization (WHO), air pollution is responsible for approximately 7 million deaths annually, highlighting its severe impact on global health [3]. Primarily affecting urban areas, air pollution poses substantial risks to contemporary society, worsened by rapid urbanization, industrialization, and migration [4,5]. In 2019, it was reported by the WHO

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that 99 % of the global population resided in areas where the air quality did not meet WHO guidelines [6]. This pollution, characterized by harmful substances in the atmosphere, impacts both the environment and human health [7,8]. Areas with high population density, intense industrial activities, and arid regions are particularly susceptible to air pollution, affecting human, animal, crop, and water body health [4,9,10]. Common air pollutants like aerosols, ozone (O_3), nitrogen dioxide (NO_2), carbon monoxide (CO), and sulfur dioxide (SO_2) pose health risks, including respiratory and cardiovascular issues [8,11–13]. Particulate matter, particularly PM10, is especially hazardous. In 2016, PM10 exposure was linked to over 3 million premature deaths worldwide, with studies indicating that a 10 μg/m^3 increase in PM10 correlates with a 0.6 % rise in respiratory mortality and a 0.5 % rise in cardiovascular mortality [14].

Economic activities, especially in the Gulf Cooperation Council (GCC) countries, significantly impact air quality [15]. In Abu Dhabi Emirate, despite measures taken, specific regions still demand attention [16]. Particulate matter, including PM2.5 and PM10, has become a crucial research focus due to adverse health effects [17]. Sources influencing the variability in PM10 concentration include anthropogenic elements such as construction sites, fuel combustion, industrial processes and traffic pollution [16]. For instance, construction activities can increase PM10 levels by up to 30 % in urban areas like London [18]. Natural factors like desert dust, volcanic eruptions, meteorological elements, seasonal fluctuations, and forest fires also play a role [5,10,17]. Elevated concentrations are notably prevalent in regions characterized by intensified industrial activity, urbanization, and insufficient emission controls, significantly impacting human health, climate, and visibility. In these areas, it is crucial to precisely monitor and assess air quality, comprehend its seasonal and annual variations, and implement effective pollution control measures [7]. For example, studies have indicated that during sandstorm events in the Middle East, PM10 levels can surge to 1000 μg/m^3, greatly surpassing the WHO guideline of 50 μg/m^3 for 24-h mean concentrations [19]. This becomes essential in addressing various environmental challenges [15]. Moreover, predicting atmospheric composition is instrumental in air quality management, but it remains challenging due to complex processes and interlinked parameters affecting modeling performance [17]. Conventionally, PM concentrations are measured using ground monitoring stations equipped with specialized sensors [10]. These stations capture various meteorological parameters and air pollutant concentrations.

Air pollution data exhibit spatial variability crucial for mitigation efforts and safeguarding vulnerable populations. However, reference monitoring networks are globally scarce, prompting the use of dispersion modeling and hybrid statistical models for exposure assessment [20–22]. Wang et al. [23] utilized backward trajectory analyses and multiple linear regression models for in-situ measurements to estimate spatiotemporal variations in Air Quality Index (AQI) at a hyperlocal scale within a city.

To address the challenge of limited ground monitoring stations, interpolation of missing parameters is commonly employed using various techniques. Cheng and Lu [24] introduced the ST-2SMR method, outperforming existing approaches on hourly air quality data in Beijing. MA et al. [25] combined Inverse Distance Weighted (IDW) for spatial interpolation and bi-directional long short-term memory (BLSTM) network for temporal interpolation, enhancing PM2.5 prediction. Xu et al. [26–28] presented ST-PI-BSHADE, a superior spatiotemporal interpolation method for hourly PM2.5 data collected in 2014. Bezyk et al. [29] compared five interpolation techniques in a GIS-based study, highlighting Spline as the optimal tool for spatial and temporal pollution modeling, while Kriging improved CO_2 distribution realism in challenging areas. In urban areas with limitations, IDW was deemed more suitable than Kriging according to Ref. [30]. Rodríguez et al. [31] tackled a study marked by a significant percentage of missing data (50–70 %) and high variability in water-quality variables. IDW yielded the best imputation results, followed by RFR, HR, and SVR.

Furthermore, Seu et al. [32] conducted a literature review on handling incomplete datasets in machine learning model preprocessing. They compared imputation methods, such as K-nearest Neighbors Imputation (KNN Imputer), Bayesian Principal Component Analysis (BPCA) Imputation, Multiple Imputation by Center Equation (MICE) Imputation, and Multiple Imputation with denoising autoencoder neural network (MIDAS). Results from their experiments emphasize the effectiveness of KNN Imputer and MICE in addressing missing values, outperforming BPCA and MIDAS. Alfonso Albarracín et al. [33] employed the KNN Imputer technique from Python's sklearn.impute library to assess and complete missing data using nearest neighbor information. In air quality analysis by Dao To et al. [34], the user-friendly and effective KNN Imputer is preferred over simple imputation methods for addressing information loss. Shaadan and Rahim [35] study on time series air quality data (PM10) in Malaysia highlights the importance of handling missing values. Their exploration of imputation methods favored EM, KNN, and SKNN for different monitoring stations and varying levels of missing data.

While ground monitoring stations provide valuable data, remote sensing technologies offer a complementary approach for comprehensive monitoring with broader spatial coverage [5,10,20]. Aerosol Optical Depth (AOD) from satellite sensors serves as a valuable proxy for ground-detected PM mass concentrations, aiding in monitoring aerosol pollution [10,36,37].

Since understanding pollutant transport rates is crucial, especially within cities; remote sensing technologies, including satellites like Landsat, MODIS, SPOT, and Sentinel-5P, play a significant role in measuring various pollutants [2,7]. Hybrid models, integrating satellite-retrieved AOD and machine-learning algorithms, along with advances in deep learning, enhance predictive capacity for estimating ambient PM2.5 and PM10 concentrations, providing valuable tools for air quality studies [17,21].

In arid regions, like UAE, particulate matter concentrations are influenced by meteorology, natural dust events, and human-induced activities, with desert environments and population growth playing significant roles [16]. These dust particles, along with other sources of particulate matter such as vehicle emissions and industrial activities, contribute to elevated levels of PM10 in the air. A study conducted by Akasha et al. [38] in Dubai observed a significant increase in PM10 levels from 2013 to 2017, with an overall rate of 4.38 μg/m^3 per year. The highest monthly average concentration of PM10 was found in residential areas at 107 μg/m^3, followed by remote areas at 103 μg/m^3, traffic areas at 98 μg/m^3, and industrial areas at 92 μg/m^3.

Further research by Abuelgasim and Farahat [39] highlighted important trends in AOD in the UAE. Their study revealed higher aerosol concentrations during the summer months. From November to March, an upward trend in aerosol characteristics was noted from 2011 to 2015 compared to 2006 to 2010. Conversely, a neutral to weak decrease in AOD measurements was observed during April–September. These trends underscore the increasing influence of anthropogenic activities on aerosol levels over recent years.

Regarding anthropogenic sources contributing to PM10 emissions, the Abu Dhabi Air Emission Inventory 2018 [40] provides a comprehensive analysis. The primary sectors influencing PM10 levels are industrial processing, accounting for 45 % of total PM10 emissions, followed by the oil and gas sector at 28 %, and road transport at 15 %. Other sectors, including electricity production, shipping, aviation, agriculture, and livestock, collectively contribute to the remaining portion of PM10 emissions.

The combination of natural factors like dust storms and anthropogenic sources leads to the observed seasonal variability of PM10 concentration in the UAE, with higher levels during the summer months. Dust storms, also known as haboobs, are common during this time and can transport large amounts of fine dust particles over long distances. Consequently, the UAE consistently experiences high air quality index values due to sandstorms and natural dust, influenced by PM and ozone [11,16,41].

Despite hosting forty-one ground monitoring stations, the UAE's coverage is inadequate, particularly in remote areas, resulting in limited accessible data [5,37,41]. Nady and Hafez [15] observed substantial PM10 concentrations in various GCC capitals, reflected in notably high AQI scores, reaching 162 in Abu Dhabi City. This elevated value is attributed to high development rates leading to continuous construction and dust emissions, particularly in industrial areas. The highest PM10 levels were recorded during summer, and the lowest occurred in winter, aligning with the results of AQI reported by Issa and Saqer [42] in their study over Abu Dhabi Emirate between 2015 and 2017.

In recent years, significant research has been conducted to monitor and assess PM10 fluctuations in arid regions, particularly in the UAE. Notable studies include Phanikumar et al. [43] analysis of pollutants in urban and rural areas over the Emirate of Abu Dhabi using hourly averages over three years (2011–2013), and Abuelgasim and Farahat [11] study of monthly data from 2017 to 2018 across all air monitoring stations, although without reporting meteorological parameters. Another key study by Al-Jallad et al. [44] analyzed particulate matter levels and meteorological variables from 2009 to 2011 in the western desert of Abu Dhabi. More recent research by Saleous et al. [10] compared AOD with in situ PM data in the Al Ain region for 2018, and Suwaidi et al. [5] utilized Landsat 8 images and corresponding in situ measurements from 2016 to 2020 across 16 monitoring stations over the UAE. Additional contributions include Hamdan et al. [45] analysis of PM10 and PM2.5 samples in Sharjah, Katheeri et al. [46] study of 8-h PM10 averages near the Al Mirfa power plant. Furthermore, Al-Taani et al. [47] presented comprehensive PM2.5 datasets for the UAE from 1980 to 2016, highlighting the PM2.5/PM10 ratio associated with anthropogenic sources.

Despite the extensive body of research, comprehensive data encompassing all PM10 measurements across the entire Emirate of Abu Dhabi, including all operating air quality stations over three regions spanning five years, have not been published. This study addresses

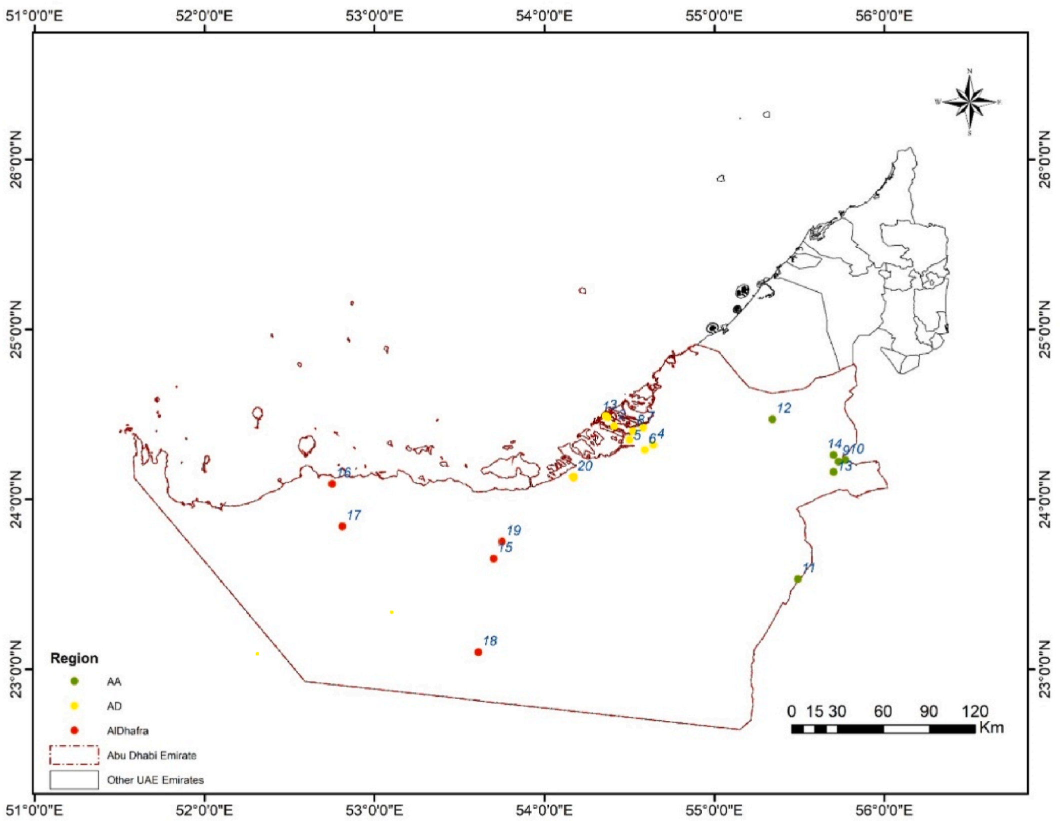

Fig. 1. Map of the study area and air quality monitoring stations.

these significant data gaps and, to the best of the researchers' knowledge, uniquely focuses on quarterly data analysis. This contrasts with other studies that primarily rely on hourly, daily, or monthly data assessments. Furthermore, the research integrates the effects of meteorological variables, offering a more holistic understanding of the factors influencing PM10 levels.

The innovative approach of this study lies in its broader temporal perspective, analyzing quarterly data over five years, and its comprehensive geographic scope, covering the entire Emirate of Abu Dhabi. By incorporating meteorological variables, the research provides deeper insights into how weather conditions impact air quality, setting this work apart from previous studies.

In response to the gaps identified in the National Agenda for Air Quality, 2031 [48] specifically related to air quality monitoring and modeling, including geo-models, this study aims to assess the effectiveness of geoinformatics in the visualization and analysis of air quality in Abu Dhabi Emirate, UAE. The study objectives include:

- Evaluating spatial interpolation methods for PM10 concentrations,
- Assessing Spatio-temporal trends from 2013 to 2017 using quarterly in-situ data and,
- Creating multi-temporal maps visualizing PM10 fluctuation across AD Emirate during the study period.

2. Materials and methods

2.1. Study area

The research focused on Abu Dhabi Emirate, the largest of the seven Emirates of the UAE. Located in the western region (24° 28′ 0.0012″ N, 54° 22′ 0.0084″E), it covers approximately 80 % of the UAE's total land area as presented in Fig. 1. The Emirate comprises three municipal regions: Abu Dhabi (Central Region), Al Ain (Eastern Region), and Al Dhafra (Western Region), serving as a prominent oil and gas hub.

While the UAE is predominantly known for its desert landscape, it does indeed have a diverse terrain and climate, characterized by varied landscapes such as: 1) Desert, most prominent feature covering a significant portion of the country and is characterized by rolling sand dunes, barren plains, and occasional oasis; 2) Mountains; 3) Coastlines, stretching along the Arabian Gulf to the west and characterized by sandy beaches, mangrove forests, and coral reefs; 4) Al Ain Oasis, located in the eastern region of the UAE, a UNESCO World Heritage Site, which showcases traditional oasis agriculture and ancient irrigation systems; 5) Sabkha, which are salt flats or coastal salt marshes. These unique landscapes are created by the evaporation of seawater, leaving behind salt crusts and various salt-tolerant plants; 6) Wetlands, including the Al Wathba Wetland Reserve, which is located southeast of Abu Dhabi. These wetlands provide habitats for a variety of bird species and are important for biodiversity conservation; and 7) Islands, such as Abu Dhabi's Yas Island and Al Saadiyat Island, are known for their luxury resorts and cultural attractions [11,49–51]. The dominance of sand and sand dunes renders the region vulnerable to significant dust outbreaks, exerting a notable impact on air quality [10].

2.2. Data

2.2.1. Air quality monitoring stations

Environmental Agency - Abu Dhabi (EAD) operates air quality monitoring stations throughout the Emirate of Abu Dhabi, each equipped with specialized sensors capturing a comprehensive array of meteorological parameters and pollutant concentrations. Monitored pollutants include PM, CO, SO_2, NO_2, and O_3, providing a holistic perspective on air quality. Also, these stations

Table 1
Air monitoring stations in AD Emirate [11].

Station ID	Station Name	Latitude	Longitude	Region	Station Location/Land Use
1	Khadejah School	24.48	54.37	Abu Dhabi	Urban - Downtown
2	Khalifa School	24.43	54.41	Abu Dhabi	Urban - Residential
3	Hamdan Street	24.49	54.36	Abu Dhabi	Urban - Traffic
4	Baniyas School	24.32	54.64	Abu Dhabi	Urban - Residential
5	Mussafah	24.35	54.5	Abu Dhabi	Industrial Center
6	Al Mafraq	24.29	54.59	Abu Dhabi	Industrial Center
7	Khalifa City	24.42	54.58	Abu Dhabi	Urban - Residential
8	Al Maqta	24.4	54.52	Abu Dhabi	Urban - Residential
9	Al Ain School	24.22	55.73	Al Ain	Urban - Residential
10	Al Ain Street	24.23	55.77	Al Ain	Urban - Traffic
11	Al Qua'a	23.53	55.49	Al Ain	Suburban - Residential
12	Suweihan	24.47	55.34	Al Ain	Suburban - Residential
13	Zakher	24.16	55.7	Al Ain	Urban - Residential
14	Al Tawia	24.26	55.7	Al Ain	Suburban - Residential
15	Bida Zayed	23.65	53.7	Al Dhafra	Suburban - Residential
16	Ruwais	24.09	52.75	Al Dhafra	Industrial Center
17	Gayathi School	23.84	52.81	Al Dhafra	Suburban - Desert
18	Liwa Oasis	23.1	53.61	Al Dhafra	Suburban - Desert
19	Habshan	23.75	53.75	Al Dhafra	Rural Industry/Hydrocarbons
20	Abu Dhabi - Tarif Road	24.13	54.17	Abu Dhabi	Suburban - Traffic

meticulously record key meteorological factors such as wind speed and direction, temperature, relative humidity, net radiation, and barometric pressure. Understanding these meteorological dynamics is crucial for interpreting pollutant concentrations [16].

The Emirate hosts a total of 20 monitoring sites, distributed as follows: 9 sites in Abu Dhabi region, 6 sites in Al Ain region, and 5 sites in Al Dhafra region. Details, locations, and the spatial distribution of these air quality monitoring stations are presented in Table 1 and Fig. 1.

2.2.2. PM10 in-situ data

The ground monitoring stations within the study area automatically record PM10 concentrations every hour in μg/m^3. Monthly PM10 data from 2013 to 2015 were acquired from the Federal Competitiveness and Statistics Center website, while quarterly data for 2016 and 2017 were obtained from the Statistics Center. In the latter, quarter 1 corresponds to January–March, quarter 2 corresponds to April–June, quarter 3 corresponds to July–September, and quarter 4 corresponds to October–December.

2.3. Methods

Utilizing ArcGIS 10.8, a Mapping and Analytics Software solution developed by Esri, GIS is employed for the spatial analysis of PM10 data over five years. However, the collected data included gaps with missing monthly values in 2013, 2014, and 2015 for some stations, complicating the aggregation process applied to quarterly data to maintain consistency with the 2016 and 2017 datasets. The missing values in the air quality monitoring data can be attributed to several factors, including instrument malfunctions (e.g., sensor failures, calibration errors), routine maintenance and calibration activities, power supply interruptions, adverse weather conditions, data transmission or archiving issues, and the migration to modern alternative methods [8,52]. Specifically, 10.417 % of monthly data in 2013, 9.167 % in 2014, and 1.25 % in 2015 were identified as missing.

To address this issue, KNN Imputation was employed, yielding a mean absolute error (MAE) of 20.11 μg/m^3 and a root mean square error (RMSE) of 29.46 μg/m^3. KNN Imputer, a class within the scikit-learn library in Python, provides a method for imputing missing values using the k-Nearest Neighbors algorithm. Imputation is a technique used to replace missing data with estimated values, a common strategy in handling real-world datasets. The code used imports the necessary libraries, including KNNImputer from sklearn. impute for KNN imputation and pandas for data manipulation. For each missing value, the KNN Imputer identifies the k-nearest neighbors using Euclidean distance among observed (non-missing) values in the dataset. The missing value is then estimated by averaging these nearest neighbors' values, preserving the data's structure and relationships. This process results in a complete dataset suitable for analysis. Importantly, the KNN imputer does not use an explicit kernel but relies on distance metrics to find and average the nearest neighbors for imputation.

Missing data can significantly affect the performance of models, making imputation crucial for creating a more complete dataset suitable for analysis and model training [53]. By filling the data gaps, this step enhances the accuracy and effectiveness of spatial map visualizations.

Following the conversion of the complete set of monthly data to a quarterly basis by determining the mean, ArcGIS tools, including Inverse Distance Weight (IDW), Kriging, and Spline, were employed for interpolation. Interpolation spatial analysis tools predict pollutant concentrations at unmonitored locations, aiding in policy formulation and decision-making. Local interpolation, focusing on short-range variation, contrasts with global interpolation, which considers both local and global spatial structures, typically resulting in smoother surfaces [54].

Kriging, a technique considering distance and variation between data points, was hindered by insufficient data points to estimate the semivariogram accurately. Spline interpolation faced challenges with sparse and unevenly distributed data, compounded by a lack of spatial autocorrelation in the dataset. As monitoring stations were not uniformly distributed, spline interpolation struggled to generate accurate surfaces. Consequently, IDW was adopted for its effectiveness in handling sparse data and lower spatial dependency [55].

IDW, as demonstrated in the study, provides the best quantitative and accurate results compared to other interpolators, this has been verified by Sajjadi et al. [56], which establishes IDW as the best interpolation method for particulate matter when contrasted with Ordinary and Universal Kriging. Consequently, offering a suitable approach for continuously changing data across a specific area [29, 55]. The IDW method is expressed by Equation (1):

$$Z(\mathrm{X0}) = \frac{\sum_{i=1}^{n} z(\mathrm{Xi}).\ d_{i0}^{-r}}{\sum_{i=1}^{n} d_{i0}^{-r}} \qquad \text{Equation 1}$$

Where Z(X0) is the value to be estimated at location X0, z(Xi) is the value measured at location Xi, r represents the weights assigned to the predicted value, and d is the distance between the known value point and the value to be estimated [57].

In this study, the KNN imputer was used to handle missing data, followed by spatial interpolation to estimate values for locations where measurements were missing. It's important to acknowledge that while these methods are effective for generating continuous datasets, the resulting values are approximations rather than direct measurements. Thus, some information might be inherently missed or approximated, introducing a degree of uncertainty into the analysis. Despite these limitations, these methods are valuable for managing missing data and allowing comprehensive analysis in the absence of complete datasets.

For enhanced analysis and interpretation of the generated quarterly PM10 maps over five years, an overlay analysis computing the mean of each quarter for the five years was conducted. This operation resulted in a consolidated layer for each quarter, facilitating trend analysis and the identification of areas with high or low pollutant concentrations. An illustration of the study workflow is presented in Fig. 2.

3. Results and discussion

Table 2 illustrates the quarterly analysis of PM10 concentrations obtained from monitoring stations throughout the study period, providing a comprehensive overview of the data's fundamental characteristics, including average, maximum, minimum, and standard deviation values. To ensure a robust analysis, additional statistical methods were employed. Trend Analysis was used to identify patterns over time, revealing seasonal variations and trends in PM10 concentrations. Correlation Analysis examined relationships with meteorological variables such as temperature, humidity, precipitation rate and wind speed, helping to understand the influence of these factors on PM10 levels. The overall average PM10 concentration across all monitoring stations was 139.5 $\mu g/m^3$, with regional averages for Abu Dhabi, Al Ain, and Al Dhafra recorded as 144.27 $\mu g/m^3$, 129 $\mu g/m^3$, and 143.48 $\mu g/m^3$, respectively. The data exhibited a range of 38.33–325 $\mu g/m^3$, indicating notable variations among monitoring stations during different seasons.

Specifically, the highest quarterly concentration occurred in the third quarter - summer season at the Habshan Station, reaching 325 $\mu g/m^3$, while the lowest concentration was observed in the fourth quarter - winter season at the Khadejah School station.

This is further demonstrated by the statistical summary covered in Table 3 that shows an observable seasonal change in PM10 concentrations throughout the study period.

The highest mean and maximum concentrations are often found in the third quarter. With the lowest maximum concentration, quarter 4 has the lowest mean concentration. Standard deviation values can be used to express the degree of variability in the data. Greater standard deviation values imply more notable variations in PM10 concentrations over the course of a given quarter.

Fig. 3 shows the average quarterly PM10 concentrations for the three regions - Abu Dhabi (central), Al Ain (eastern), and Al Dhafra (western), respectively. A consistent trend is evident across regions, wherein PM10 concentrations increase from the first to the second quarter, peak in the third quarter, and experience a significant decrease in the final quarter. Notably, the variation in concentration between the second and third quarters is less pronounced in the Al Dhafra region and highly active areas such as Baniyas School, Mussafah, and Al Mafraq in Abu Dhabi region. This phenomenon is attributed to the unique environmental conditions of the UAE, characterized by high temperatures, strong winds facilitating dust movement, and the occurrence of dust storms. Furthermore, PM10

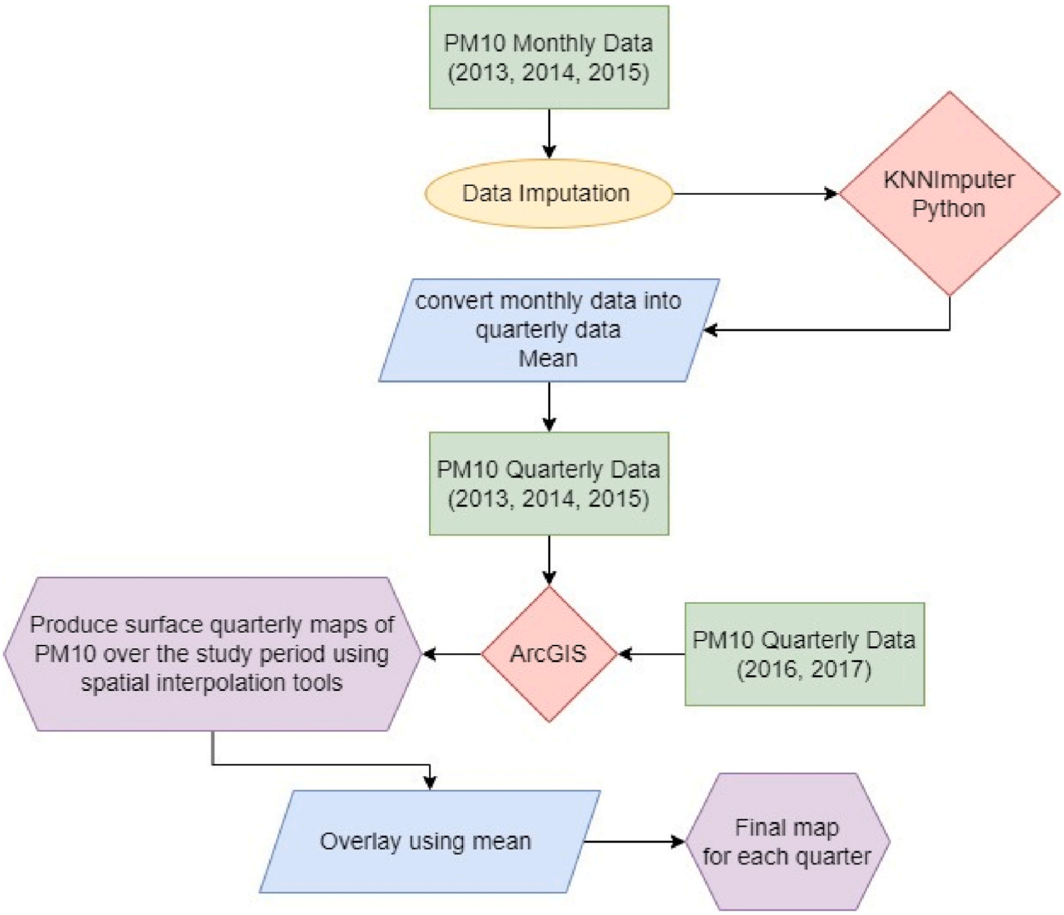

Fig. 2. Methodological flowchart.

Table 2
Descriptive statistics of the in-situ PM10 concentrations in µg/m^3 (2013–2017).

Air Quality Monitoring Stations			Mean				Maximum				Minimum				Standard Deviation			
Station ID	Region	Station Name	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
1	Abu Dhabi	Khadejah School	100.86	143.55	170.81	67.16	129.33	176.00	204.67	89.50	64.60	118.90	120.67	38.33	20.89	26.60	33.73	18.37
2	Abu Dhabi	Khalifa School	93.22	141.85	176.13	72.67	108.67	175.00	239.60	92.90	55.40	123.00	95.33	48.67	19.24	20.78	54.79	19.91
3	Abu Dhabi	Hamdan Street	108.98	137.75	179.66	81.57	176.33	220.33	225.33	89.33	50.90	104.40	154.00	76.20	45.16	47.16	27.82	4.86
4	Abu Dhabi	Baniyas School	116.25	160.43	163.15	83.21	141.00	203.33	207.00	100.20	78.40	125.50	65.00	55.67	20.82	36.92	57.16	18.37
5	Abu Dhabi	Mussafah	137.97	189.21	189.21	110.66	167.00	231.33	227.60	118.00	118.40	163.40	142.33	97.00	17.13	27.02	30.62	8.42
6	Abu Dhabi	Al Mafraq	161.73	217.71	231.07	131.48	196.33	251.33	290.40	168.10	133.67	192.80	208.00	115.30	27.02	22.45	33.76	21.25
7	Abu Dhabi	Khalifa City	104.64	150.85	183.44	81.62	119.00	175.00	264.30	111.90	89.00	123.90	122.50	68.67	11.06	19.52	51.48	17.48
8	Abu Dhabi	Al Maqta	97.50	149.31	180.48	77.33	122.67	189.00	230.50	97.20	65.10	130.67	156.00	65.67	19.55	23.55	32.26	12.19
9	Al Ain	Al Ain School	89.39	142.53	148.28	76.01	112.90	175.33	161.00	96.30	59.40	123.40	137.67	66.00	19.30	23.63	8.59	12.66
10	Al Ain	Al Ain Street	101.59	128.52	140.72	75.80	118.67	196.33	194.33	98.67	68.60	85.00	105.00	55.33	18.14	41.22	33.08	16.14
11	Al Ain	Al Qua'a	91.35	156.49	175.25	72.68	111.20	204.00	212.33	80.80	68.67	122.30	144.33	63.33	14.19	38.70	28.09	8.20
12	Al Ain	Suweihan	93.43	139.15	153.53	75.51	122.40	178.33	180.67	91.10	63.40	99.40	121.20	59.33	20.00	38.79	26.76	11.95
13	Al Ain	Zakher	78.57	119.01	144.53	67.12	111.00	143.00	164.33	88.40	57.33	96.67	128.00	52.33	18.28	20.53	15.64	15.42
14	Al Ain	Al Tawia	94.86	142.99	149.96	76.27	116.40	188.33	166.67	88.67	70.90	101.20	119.50	71.70	18.51	38.72	18.74	7.09
15	AlDhafra	Bida Zayed	106.97	163.10	165.55	76.35	139.30	210.67	192.33	91.20	68.33	135.33	130.00	66.67	25.60	29.32	23.27	9.15
16	AlDhafra	Ruwais	104.21	158.17	175.31	78.51	125.67	220.17	209.30	94.90	74.10	112.90	135.10	68.33	20.09	46.10	26.84	10.62
17	AlDhafra	Gayathi School	101.89	146.84	138.13	69.05	132.00	223.33	158.50	93.80	68.60	118.33	117.67	53.67	27.26	43.81	17.74	15.71
18	AlDhafra	Liwa Oasis	124.24	170.09	152.97	65.30	191.00	267.00	168.00	78.90	75.70	123.10	135.20	57.33	38.22	60.90	14.93	8.32
19	AlDhafra	Habshan	106.57	182.89	212.02	82.27	129.33	248.67	324.00	133.33	72.00	127.50	156.80	63.33	24.41	57.81	69.66	28.80
20	Abu Dhabi	Abu Dhabi - Tarif Road	97.50	167.92	185.33	65.09	118.00	220.17	209.33	77.17	77.00	115.67	161.33	53.00	20.50	73.89	33.94	17.09

Table 3
Statistical summary of quarterly variations in PM10 concentrations in μg/m^3 (2013–2017).

	Mean	Max	Min	STD
Quarter 1	105.84	191.7	50.9	29.97
Quarter 2	155.03	267	85	40.48
Quarter 3	170.33	324	65	39.38
Quarter 4	79.72	168.1	38.33	20.52

constituents include sea salts originating from the nearby Arabian Gulf. Additionally, the presence of industrial hubs, including cement and ceramic factories, in proximity to desert and sand dunes areas contributes to elevated PM10 concentrations [11,58–61].

Suburban areas such as Gayathi School and Liwa Oasis (located in desert rural areas) within the Al Dhafra region demonstrated comparatively elevated PM10 levels during the summer seasons (quarters 2 and 3) and lower levels during the winter season (quarter 4). This phenomenon can be primarily attributed to the inherent desert terrain of the sites, leading to the transport of dust particles from the surrounding desert and more distant locales, such as the Empty Quarter desert, associated with westerly and northwesterly winds at relatively low to medium wind speed (Fig. 4). Additionally, the analysis of the data revealed lower levels of PM10 in the western region during weekends, attributed to reduced activities during that time [43–45].

In contrast, distinctions observed between the Abu Dhabi region and the Al Dhafra region can be explained by the presence of local sources, prevailing meteorological conditions unique to each region, and the influence of wind patterns, including the potential transport of desert dust from external sources. The Abu Dhabi region, specifically its city and the coastal areas [37], is predominantly affected during the summer season by the northerlies or northwesterly Shamal wind, which moves towards the UAE through the Arabian Gulf, originating from Iran [39,58,59]. Generally, lower PM10 values were observed in the Abu Dhabi region, particularly in urban centers like Hamdan Street and Khadejah School. This could be attributed to a reduced impact from desert dust to urban air pollution or the prevalence of a highly variable sea breeze as the dominant transport mechanism [43,45].

Al Ain region emerged with the lowest concentrations of PM10 when compared to the Abu Dhabi and Al Dhafra regions. This can be attributed to the comparatively limited industrial dust-related activities in Al Ain region, coupled with its greener environment, which may reduce susceptibility to sandstorms and transportation of emissions.

A detailed examination of the data indicates that variability among monitoring stations with distinct activities is negligible when compared to the influence of the land use land cover specific to each location. This observation suggests that natural processes such as dust storms and industrial emissions play a predominant role in airborne pollutant generation specifically PM10 compared to anthropogenic activities in arid and semi-arid regions like UAE. Additionally, adverse meteorological conditions can contribute to heightened dust activity [11,45,60,63].

Annual average concentrations of PM10 were represented for each region and compared with the findings reported by EAD [16] spanning the years 2007–2020. The effectiveness of the quarterly data, combined with the utilization of KNNImputer for addressing missing data, is underscored in Fig. 5, where the aggregated quarterly data for the same period demonstrates its power and reliability.

In Fig. 5, fluctuations in annual average PM10 concentrations are evident, attributable to various factors, both natural and anthropogenic. In arid regions, temporal variations in PM10 concentrations are intricately linked to seasonal weather patterns. Dry seasons with increased wind speeds lead to the resuspension of dust, contributing to higher PM10 levels [39,44], while precipitation during wet seasons aids in dust settlement. Alterations in land use and vegetation, notably due to agricultural practices and urban development, significantly influence PM10 emissions. Activities such as land preparation, plowing, and vegetation modifications contribute to variations in PM10 concentrations. It has been reported that the agricultural sector's emissions of PM10 in Abu Dhabi Emirate in 2015 were minimal, contributing only 1 % of the total 9888 tons [40]. Human-induced factors, including construction and industrial processes, significantly heighten PM10 concentrations. According to the Abu Dhabi Air Emissions Inventory published in 2018 [40], the primary sources of PM10 emissions were industrial areas, locations with high road traffic, and offshore oil and gas activities. Table 4 presents other sectoral PM10 emissions, and Fig. 6 shows the locations of these emission sources by sector within the Emirate of Abu Dhabi.

Industrial processing activities, such as cement production, metal industries, and other manufacturing processes, are major contributors to PM10 emissions. These emissions are particularly concentrated in industrial hubs like Mussafah, ICAD, KIZAD, and Al Ain Industrial City. The oil and gas sector are other significant sources of PM10 emissions, primarily due to offshore and onshore oil extraction and processing activities, with substantial contributions from oil refineries and gas processing facilities. Road transport also plays a critical role in PM10 emissions, mainly through exhaust emissions and non-exhaust sources such as tire and brake wear. High-traffic areas, especially on Abu Dhabi Island and major highways, are identified as hotspots for these emissions. Additionally, other sectors contribute to PM10 levels, including electricity production, where emissions result from fuel combustion in power plants, and shipping and aviation, where emissions stem from fuel combustion in ships and aircraft.

Temperature inversions, where warm air traps pollutants near the ground, can influence the yearly pattern of PM10 concentrations [64]. This phenomenon can be explained by considering how temperature fluctuations contribute to the creation of new particles through the gas-to-particle conversion process, as well as the scattering of aerosols and their absorption characteristics [39,44,47]. Natural sources, such as desert dust, contribute to particulate matter, with wind erosion transporting particles over long distances. Changes in meteorological conditions, including wind speed and direction, are the main parameters controlling air mass flow and significantly influence the transport and dispersion of PM10, leading to seasonal variations in concentrations that affect the average yearly reported values [5,10,11,43,45,61].

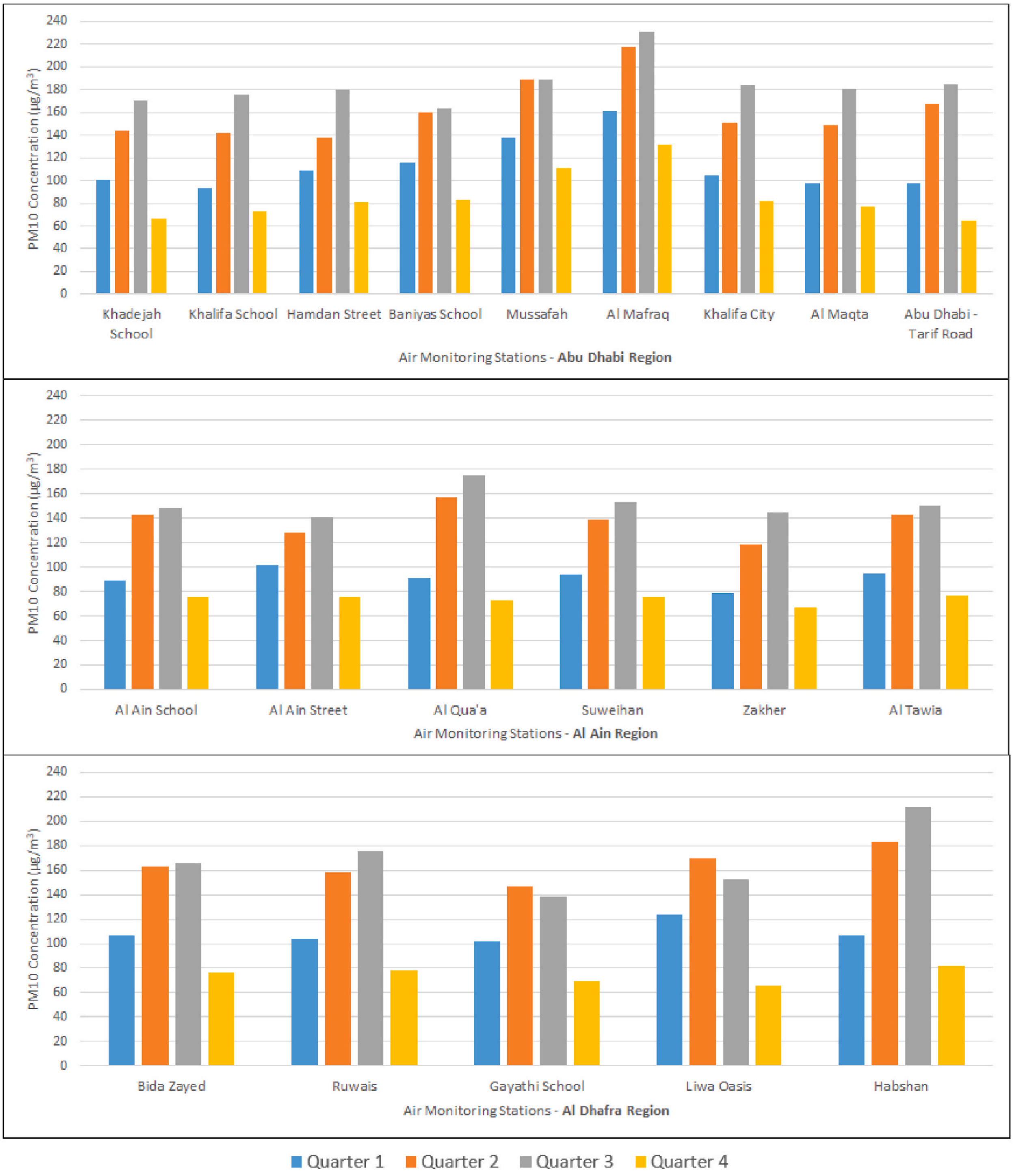

Fig. 3. Average quarterly concentration of PM10 in μg/m^3 per region (2013–2017).

Understanding the interplay of meteorological parameters is crucial for accurately assessing and analyzing PM10 levels in arid regions. To accurately interpret these trends, information regarding the aforementioned factors in the three regions is illustrated in Fig. 7 where the reported data is acquired from the Statistical Yearbook of Abu Dhabi 2014, 2015, 2016, 2017, and 2018 published by the Statistics Centre - Abu Dhabi [65–69].

The average monthly temperature presented in Fig. 7 (a) exhibited consistent trends throughout the study period, with a peak average temperature of around 45 °C in July followed by August. Generally, the summer season is hotter in Al Ain and Al Dhafra

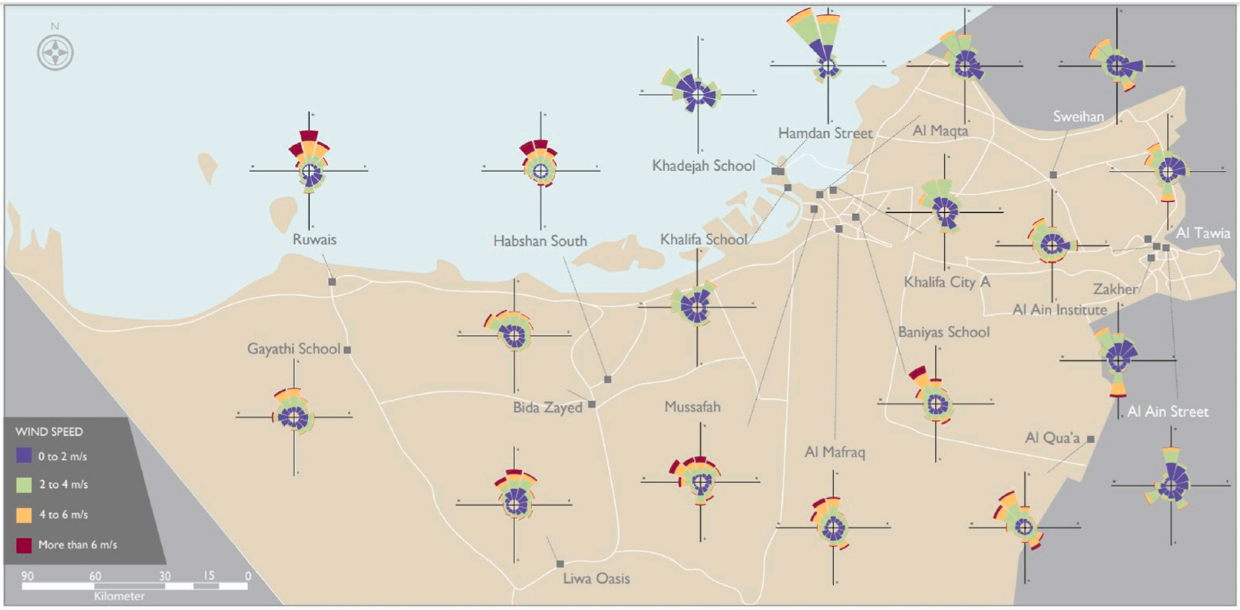

Fig. 4. Wind speed and direction data in Abu Dhabi Emirate stations from 2007 to 2019 [62].

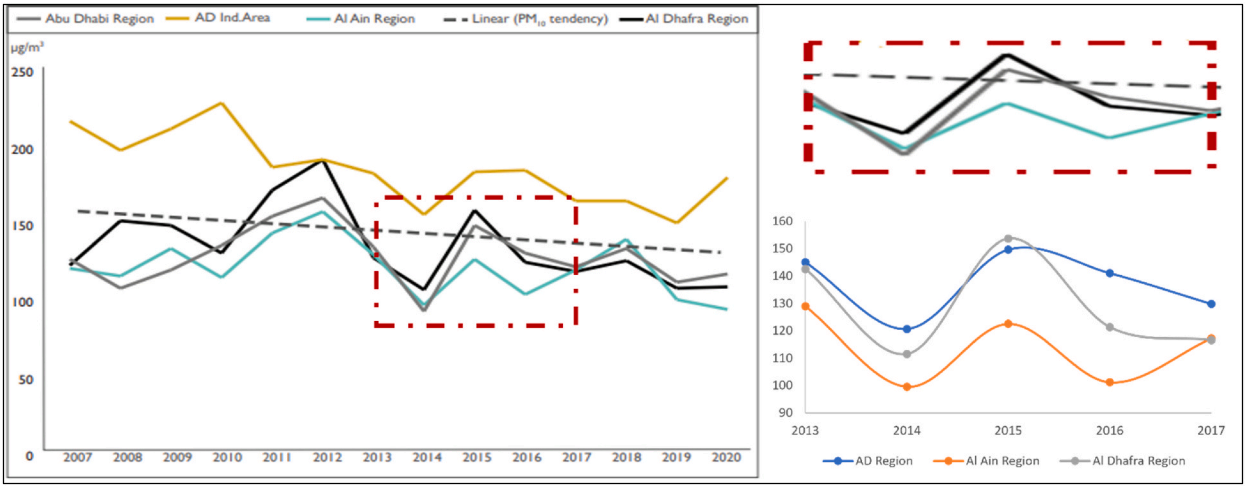

Fig. 5. Annual average PM10 concentrations, modified from Ref. [16].

Table 4
Sectoral emissions of PM10 (t/yr) in Abu Dhabi Emirate, 2015 [40].

Sector	PM10 Emissions (t/yr)	Contribution (%)
Industry	4429	45
Oil and Gas	2793	28
Road Transport	1464	15
Electricity	173	2
Shipping	192	2
Aviation	15	<1
Agriculture	96	1
Livestock	727	7

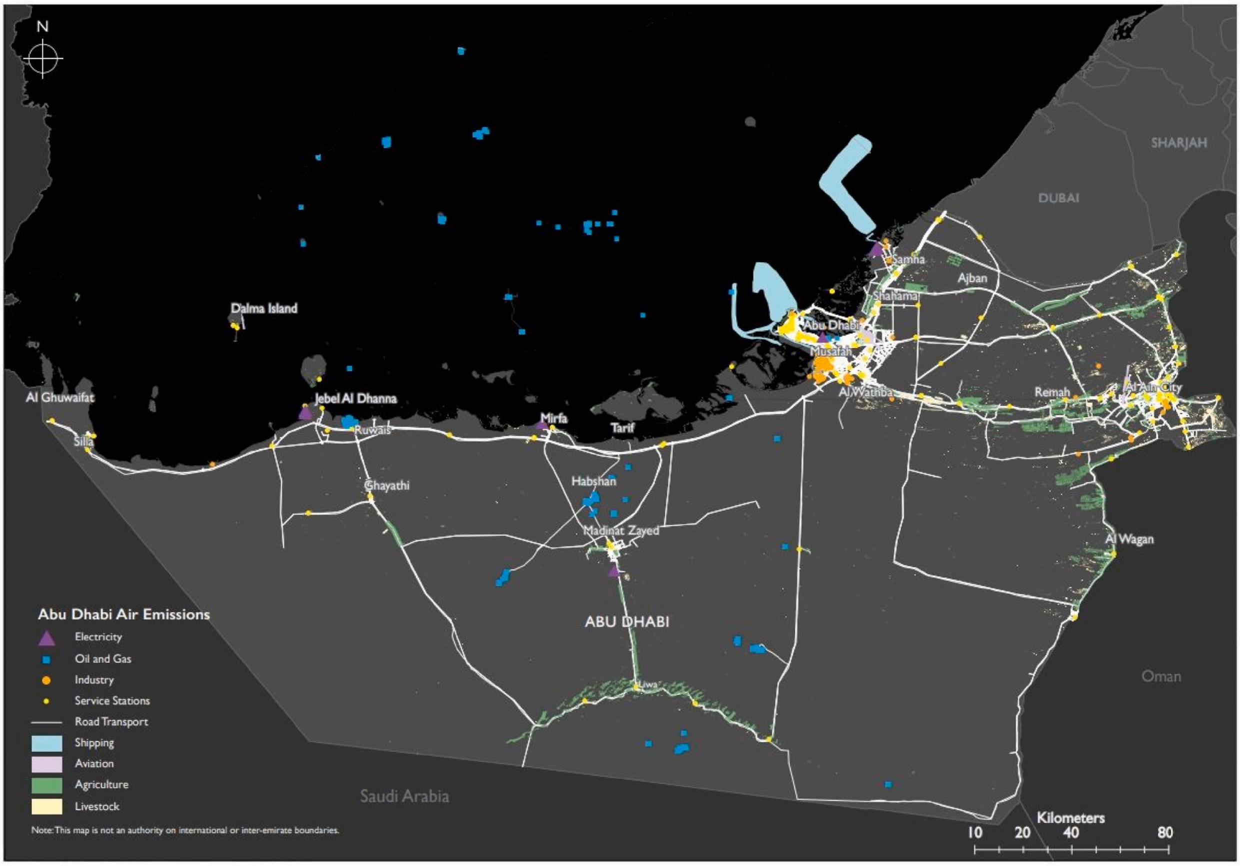

Fig. 6. Location of the emission sources by sector in Abu Dhabi Emirate [40].

regions compared to the Abu Dhabi region.

The arid conditions of the UAE, characterized by insufficient rainfall (as shown in Fig. 7 (b)) and the presence of dry soil, stimulate dust loading and its longevity in the atmosphere [39,44].

During the study period, relative humidity peaked in the Abu Dhabi region, with average levels ranging between 40 % and 80 %. Thus, other regions exhibited lower average relative humidity levels due to their open desertic areas, which are characterized by dryness compared to coastal areas (Fig. 7 (c)). Notably, humidity did not show a significant intercorrelation with temperature, as evident from their respective trends. Additionally, months experiencing a reduction in PM10 levels were characterized by relatively high relative humidity. Al-Jallad et al., Al- Taani et al., Filonchyk et al., and Abuelgasim et al. [44,47,61,70] supported this phenomenon which can be attributed to the impact of air moisture on the settling of suspended particles.

Fig. 7 (d), illustrates that the predominant wind speeds are mainly observed during the second and third quarters, exhibiting a positive correlation with PM10 concentrations [39,44,58,59,70]. The wind direction presented in Fig. 4 is also crucial in governing air mass flow. Northwesterly and westerly winds passing over polluted areas and deserts are directed toward the UAE [39], contributing to increased aerosol concentrations primarily during the summer season, though southerly winds are frequently observed as well [47].

To portray the results, the spatial distribution of PM10 concentrations across the Abu Dhabi Emirate is illustrated in Fig. 8, displaying seasonal averages over a five-year period. The graphical representation includes twenty spatial maps, delineating the four quarters per year and the corresponding average maps for each quarter. The observed seasonal pattern of PM10 concentration consistently revealed higher levels between April to September compared to the period from October to March, affirming a significant correlation between the time of year and PM10 concentration [5].

Notably, peak values were consistently observed during the summer season [10,11,13,71], attributed to the extensive use of domestic cooling systems in the UAE during the summer months [11].

The seasonal variability in PM10 concentrations is elucidated by the frequency of dust events in the region, coupled with atmospheric conditions. Summer PM10 levels peak due to increased dust activity, influenced by dust transport from the Sahara, the border of Iran with Afghanistan, and the Karakum desert. The primary driver of seasonal variation is the Shamal wind [72]. This prevailing wind direction persisting throughout the year, originating from the northwestern sector and spanning the range of 270°–360° [43], with varying intensity and duration in summer and winter. The summer Shamaly is particularly frequent and closely linked to dust events across the Gulf region. The presence of suspended dust and dust storms is further governed by high wind speeds impacting

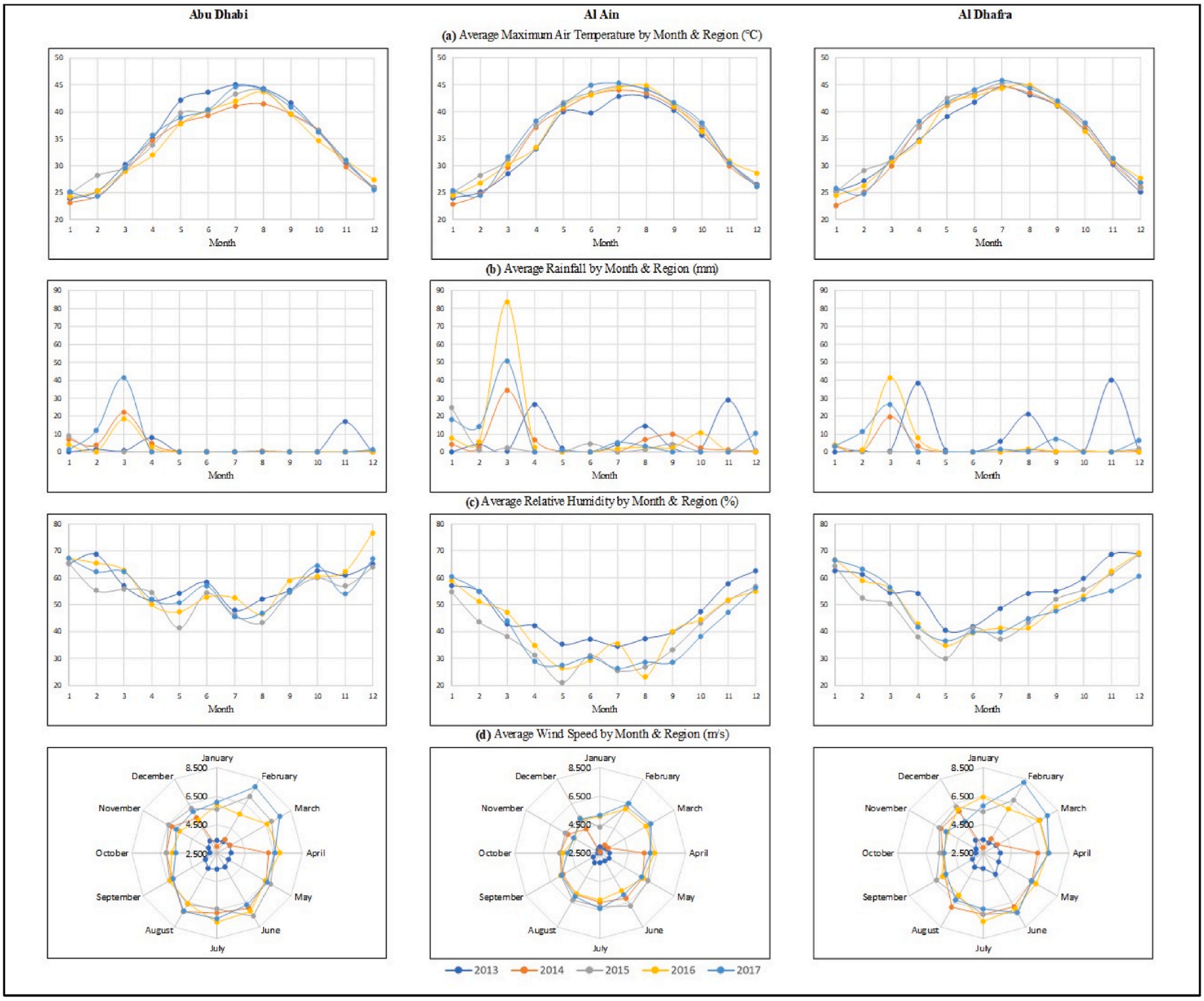

Fig. 7. Meteorological data over the study period (2013–2017) for the Abu Dhabi Emirate:**(a)** Average maximum air temperature (°C), **(b)** Average rainfall (mm), **(c)** Average relative humidity (%), **(d)** Average wind speed (m/s).

visibility [43,72]. According to the data reported by the National Center of Meteorology (NCM), over the study period, the number of sandstorm days with visibility less than 1000 m was zero in 2013, three in 2014, one in 2015, three in 2016, and one in 2017. These sandstorms mainly occurred in the third quarter, in July, August, and September, which are coupled with high temperatures, relatively high wind speeds, and negligible rainfall precipitation observed in Fig. 7 during the third quarter. Additionally, they were more frequently observed in the Al Ain region than in Abu Dhabi region, where urbanization and high multi-story buildings obstruct their advancement. Analyzing the trend from 2013 to 2017, a remarkable increase in urbanization and air pollution is observed.

The highest PM10 concentrations were recorded in 2015, ranging between 65 and 325 μg/m^3, with anomalies identified in quarters two and three. Hotspots, such as Mussafah industrial zone, Liwa desert, and Habshan (an oil and gas industrial hub), exhibited elevated concentrations, with Habshan reaching values exceeding 300 μg/m^3. Additional hotspots include Al Mafraq, Ruwais, and Gayathi School, characterized by desert areas or regions with intensive industrial activities. This trend in 2015 in the Abu Dhabi, Al Ain, and Al Dhafra regions is associated with minimal rainfall of 40.1, 357.1, and 34.8 mm. Conversely, the year 2016 experienced a total rainfall of 100.5, 1060.3, and 840.8 mm in Abu Dhabi, Al Ain, and Al Dhafra regions respectively, as reported by The National Center of Meteorology and Seismology, Statistics Centre - Abu Dhabi and evident in Fig. 7 (b). The rainfall was primarily occurring during the first quarter, particularly in March as shown in Fig. 9. This is reflected in lower PM10 concentrations observed during the same period compared to other years, making 2016 an exceptional year due to the washout effect of rainfall on airborne particulate matter. It is important to acknowledge the complexity of the relationship between rainfall and PM10 concentrations, influenced by factors such as rainfall intensity, duration, local sources of particulate matter, and atmospheric conditions. Rainfall may lead to a temporary improvement in air quality or, in certain scenarios, contribute to increased particle levels.

Given that the Al Ain region consistently maintains PM10 levels below 215 μg/m^3 and less, it emerges as a favorable residential option for individuals with respiratory vulnerabilities when compared to the Abu Dhabi and Al Dhafra regions. On the other hand,

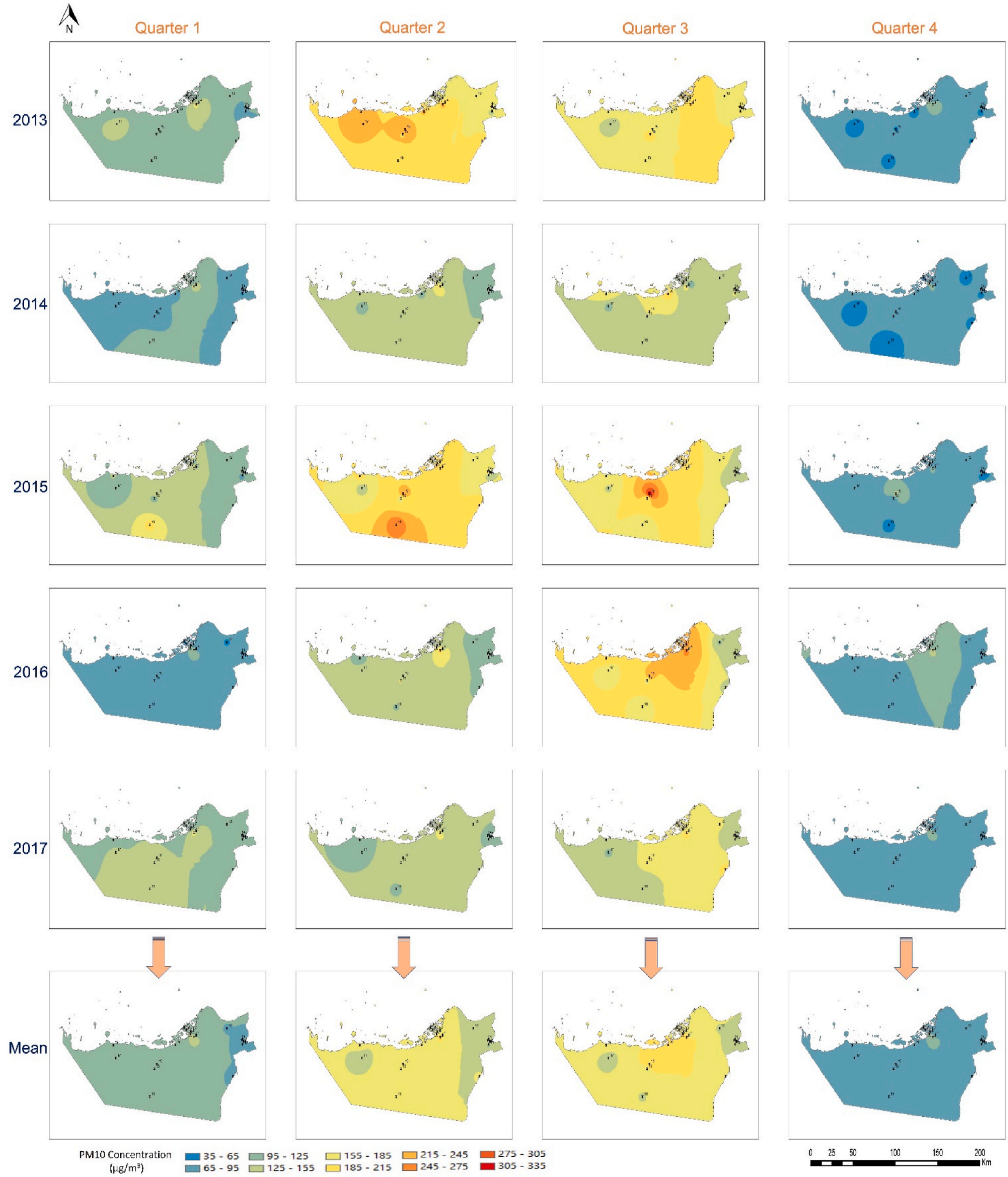

Fig. 8. Seasonal spatial maps of PM10 in Abu Dhabi Emirate over the study period (2013–2017).

there is significant growth in these areas. According to Ref. [39], Abu Dhabi city, in particular, is experiencing an annual urbanization rate of 5 %. This growth is coupled with increased energy consumption, intense traffic, the operation of water desalination plants, and industrial facilities. Collectively, these factors contribute to a substantial increase in anthropogenic aerosol emissions [15]. In response, the UAE has undertaken comprehensive efforts to prioritize its air quality agenda.

The identified patterns offer valuable insights for effectively managing pollutant concentrations [73] and devising appropriate

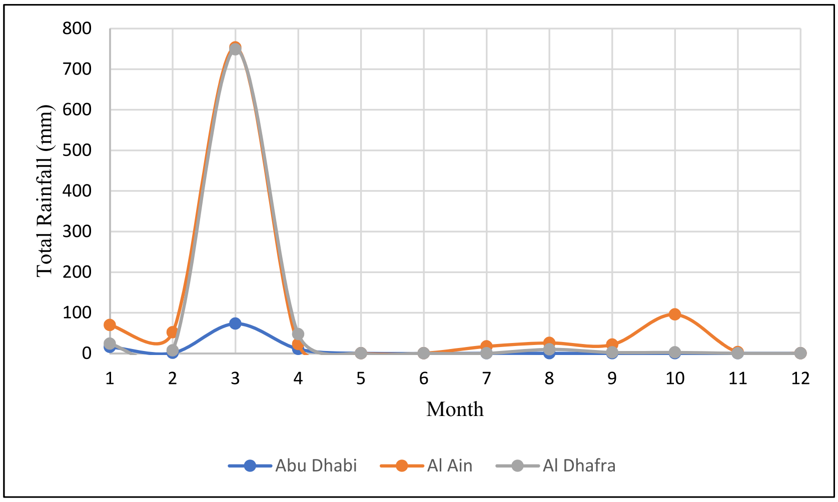

Fig. 9. Total monthly rainfall in Abu Dhabi Emirate in 2016.

mitigation strategies aligned with climate projections, urban planning considerations, and the industrial progression of the emirate.

4. Conclusion and recommendations

Geoinformatics plays a pivotal role in advancing the monitoring and assessment of air pollution, particularly in rapidly growing urban environments. This study endeavors to delineate the spatiotemporal variations of PM10, the predominant air pollutant, in one of the world's fastest-growing dryland cities.

Utilizing KNNImputer in Python and ArcGIS, monthly in situ data were employed to interpolate missing values observed in 2013 and 2014. Subsequently, these interpolated values were aggregated to quarterly values, enhancing the portrayal of spatial maps across the study period. Results revealed elevated PM10 concentrations during the second and third quarters, linked to the extended summer season in this arid land region. These elevated levels were predominantly observed in rural desert areas and industrial zones, thereby demonstrating clear spatiotemporal variability of PM10 throughout the study area regardless of rural or urban-suburban areas. This variability is primarily attributed to factors such as dust storms, heat waves, and other seasonal weather conditions, particularly during heat waves.

While providing valuable insights into PM10 variability within the Abu Dhabi Emirate and its regions, augmenting the number of air monitoring stations to encompass diverse air pollutants and meteorological parameters is advocated to enhance air quality studies and modeling. As this study represents an initial phase in the monitoring and modeling of PM10 and other air pollutants within the Abu Dhabi Emirate, an expanded network of monitoring stations will support the research and assist fellow researchers.

Remote sensing detection capabilities and GIS techniques have indeed opened new avenues for studying and addressing air quality issues. By integrating these technologies with in situ data, researchers and decision-makers can gain a comprehensive understanding of air pollution and develop effective strategies for mitigation through; 1) Data acquisition of different types, extents and dates; 2) Spatial Analysis with GIS; 3) Modeling and Prediction, which can simulate and predict pollutant concentrations and dispersion patterns in different scenarios, helping in assessing the effectiveness of mitigation measures, predicting future air quality conditions, and evaluating the potential impact of urban planning decisions on air pollution levels; 4) Development of Decision Support Systems (DSS) allowing for the identification of optimal locations for monitoring stations, planning emission control strategies, and implementing targeted interventions to improve air quality and; 5) Public Awareness and Communication through visualization and communication of air quality information to the public using interactive maps, online platforms, and mobile applications.

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Data availability

Data will be made available on request.

CRediT authorship contribution statement

Rana Saqer: Writing – original draft, Visualization, Methodology, Investigation, Formal analysis. **Salem Issa:** Writing – review & editing, Supervision, Project administration, Methodology, Conceptualization. **Nazmi Saleous:** Writing – review & editing, Conceptualization.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT v3.5 in order to improve the English language in some parts of the manuscript. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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