Environmental Health Engineering and Management Journal 2024, 11(1), 83-92
http://ehemj.com
doi 10.34172/EHEM.2024.10
Environmental Health Engineering and Management Journal

Original Article

The relationship between hot spots of air pollution and the incidence of gestational diabetes based on spatial analysis: A study on one of the most air-polluted metropolis of Iran

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Abstract

Background: Despite the serious impacts of air pollution on human health, few studies have focused on the adverse effects of air pollution on pregnancy outcomes based on the geographic information system (GIS) approach. Therefore, adopting the GIS approach, this study aimed to determine the extent to which of overlap of air pollution hotspots overlap with gestational diabetes density in Ahvaz, an air-polluted metropolis in Iran.

Methods: Data from an ongoing population-based cohort study was used for gestational diabetes mapping. Three methods were used for air pollution assessment. The inverse distance weighting (IDW) technique was used for spatial interpolation. ArcGIS10.8 was used for preparing maps.

Results: The lowest rate of gestational diabetes was estimated in District One (2.4%) while the highest rate was observed in Districts Six and Four (20.6% and 20.2%, respectively). As far as air pollution was concerned, 32.6% of mothers with gestational diabetes were residents in low-risk areas whereas 67.4% lived in high-risk areas. A higher density of gestational diabetes was estimated in high-risk air-polluted districts based on any method of air pollution assessment.

Conclusion: The density of gestational diabetes incidence increased with residence in air-polluted areas. Residence in more polluted areas is a higher risk factor for developing gestational diabetes and its complications. Providing preventive services in these areas is a priority.

Keywords: Environmental pollutants, Diabetes, Gestational, Geographic information systems

Citation: Jaafarzadeh N, Nouhjah S, Shahbazian H, Shenavar B. The relationship between hot spots of air pollution and the incidence of gestational diabetes based on spatial analysis: a study on one of the most air-polluted metropolis of Iran. Environmental Health Engineering and Management Journal 2024; 11(1): 83-92. doi: 10.34172/EHEM.2024.10.

Article History:
Received: 15 September 2023
Accepted: 5 December 2023
ePublished: 29 February 2024

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Introduction

Air pollution as a serious threat to human health is associated with many acute and long-term adverse outcomes. Increased rate of premature mortality, a significant increase in the risk of respiratory and cardiovascular disease, asthma exacerbation, increased muscle sympathetic nerve activity, and increased risk of hospital visits are among the several reported consequences of exposure to air pollutants (1-5). Based on the report of the World Health Organization (WHO), about 90% of the world's population is exposed to outdoor air pollution. Annually, over 7 million deaths and 747 million losses in healthy life years are related to exposure to ambient air pollution (6,7). According to another report, long-term exposure to air pollutants accounts for about 10 million annual deaths (8). Hypertensive systolic and diastolic blood pressure, as risk factors for cardiovascular disease, can be affected by air pollution (1).

Gestational diabetes mellitus (GDM) is defined as any degree of glucose intolerance with onset or first recognition during pregnancy (9). Gestational diabetes has been associated with an increased risk of adverse outcomes during pregnancy and later years of life in mothers and children (10-12). GDM has been associated with numerous short-term maternal complications, including increased risk of pregnancy-induced hypertension, premature rupture of membranes, antepartum and postpartum hemorrhage, and a significantly higher rate of cesarean delivery by up to 57.4% (10,13-15).

Diabetes is the most well-known long-term complication in women with a history of gestational diabetes (16). Also, an increased risk of cardiovascular disease (17), a higher risk of developing malignancies (11,18) and renal damage (19), and an increased risk of metabolic syndrome are among the long-term maternal outcomes among mothers with a history of gestational diabetes (12). Furthermore, gestational diabetes is a risk factor for short-term outcomes such as fetal macrosomia, neonatal hyperglycemia, low birth weight, stillbirth, and intrauterine growth retardation. However, these results have been inconsistent (20). Obesity, overweight, and insulin resistance are long-term metabolic outcomes associated with the offspring of these mothers (10). Also, recent studies have reported the negative effect of gestational diabetes on children's neurocognitive development (21,22).

The global prevalence of GDM is rising dramatically (1%–28%). This rate is between 3.5 and 45.3% in the EMRO region (23). A high prevalence of gestational diabetes using one-step criteria was reported in a prospective hospital-based study in Ahvaz where the present study was conducted (29.9%) (24).

Predisposing factors for developing GDM include obesity, advanced maternal age, family history of diabetes, and GDM in a previous pregnancy, as reported in many studies (25,26). About half of the women with gestational diabetes have no classic risk factor. Although outdoor air pollution is considered a risk factor for developing gestational diabetes, the results are controversial and inconsistent (27). A significant association of air pollutants including $PM_{2.5}$, PM_{10}, NO_2, and SO_2 with the development of gestational diabetes has been reported (28-31), but other reports did not confirm this relationship (29,32,33).

Although the underlying mechanism of the effect of air pollution on gestational diabetes is unclear, several hypotheses have been put forward to explain this association. These include peripheral and adipose tissue inflammation, elevated serum C-reactive protein and cytokines, endothelial dysfunction, and dyslipidemia (34,35).

Ahvaz is one of the most polluted cities in the world (5,36). Geographical features, urbanization, the Middle East Dust Storm, growth of polluting industries such as oil, gas, petrochemical, and steel have contributed to the alarmingly high rate of air pollution in this city (37).

Given the effect of air pollution on human health, its possible impact on gestational diabetes, and the increasing prevalence of gestational diabetes and air pollutants in Ahvaz, it is imperative that low- and high-risk areas of gestational diabetes be determined for screening programs and providing better services and care to mothers with gestational diabetes. Therefore, adopting the GIS approach, this study aimed to determine the extent to which air pollution hotspots overlap with gestational diabetes density in Ahvaz, which is an air-polluted metropolis in Iran.

Materials and Methods

In a GIS-based, cross-sectional study in 2017, data from pregnant women who participated in a cohort study of gestational diabetes were used. Life after gestational diabetes (LAGA) is an ongoing population-based cohort study that started in 2015, and two phases of this study have been completed thus far. All pregnant women covered by 25 health centers in Ahvaz were invited to participate in the study. The cohort study aimed to evaluate the risk factors of developing gestational diabetes and follow the short- and long-term adverse outcomes of GDM.

Ahvaz, the most populated and industrial metropolis in southwest of Iran, is the capital of Khuzestan province, which has an arid climate with about 1.3 million population (5,36,38). Khuzestan was introduced by the WHO as the most contaminated area globally in terms of particulate matter concentrations (37).

In this study, gestational diabetes was defined according to the International Gestational Diabetes Working Group (IADPSG) standard. Any abnormal glucose level, including fasting plasma glucose equal to or greater than 92 mg/dL, one-hour glucose equal to or greater than 180 mg/dL, and two-hour plasma glucose equal to or greater than 153 mg/dL, was diagnosed as gestational diabetes.

Air pollution data was received from eight air quality monitoring stations located in eight areas of Ahvaz city on a daily and yearly basis. The city has eight urban districts. Districts 2, 4, 5, and 6 are located in the west of the Karun River while Districts 1, 3, 7, and 8 are located in the east of this river (39,40).

Due to the limitations of using one method alone, three methods were used to assess these urban areas in terms of air pollution.

1. Establishment of industrial sources: One of the main sources of air pollution in Ahvaz is the various industrial units. Therefore, the classification of urban areas depends on the number and type of the existing and affected units in each urban area. In this method, industrial sources of air pollutants were identified, and their spatial position in each district was determined by loading in ArcGIS10.8 software.
2. Pollution load: Based on the report of the Environmental Protection Agency (EPA) on the comprehensive plan for the reduction of air pollution in Ahvaz, the main pollutants from industries, transportation, gas stations, terminals, etc., were identified and calculated in tons per year. Since aggregation of the pollution load of pollutants to achieve a single number is not possible, classification was done based on the load of each pollutant (tons) in each area. Based on the presence of each pollutant (CO, HC, SOX, NOX, PM, VOC), the areas were classified as low risk (coefficient 3), medium risk (coefficient 6), and high risk (coefficient 9). Finally, the resulting sum, which is the air pollution status of

all areas, was imported into the GIS software.

Air quality index (AQI): AQI is an indicator for daily reporting of air quality. This index is calculated for five main air pollutants, namely particulate matter, nitrogen dioxide, ground-level ozone, carbon monoxide, and sulfur dioxide. One of the pollution estimation methods to determine the spatio-temporal changes of the AQI is the integration of information from pollution measurement stations and interpolation methods in the geographic information system (GIS) environment (41). The AQI has a numerical range from 0 to more than 300, which is divided into 6 groups including good, moderate, unhealthy for sensitive groups, unhealthy, very unhealthy, and hazardous. In this study, Ahvaz was zoned based on the average AQI of the above period. Also, the average AQI was recorded by eight air monitoring stations in Ahvaz from 2015 to 2021, and a database was created. After digitization, the data were imported into ArcGIS10.8 software. AQI was statistically analyzed based on inverse distance weighting (IDW) interpolation. The IDW technique is one of the most widely used methods in spatial analysis (42). In this model, it is assumed that the characteristic value of an unknown point is the weighted average of the known values in its neighborhood. The weights are inversely related to the sampling locations and distances between predicted locations (42,43).

The latitude and longitude of patients' residences were determined using Google Earth software, and the maps were prepared using ArcGIS software.

Data were recorded and analyzed using SPSS version 22 and Excel. Also, as far as the graphic output of the data was concerned, ArcGIS software was used. Finally, IDW, hotspots, and logistic regression were used for data analysis.

Results

The associations between air pollution and developing gestational diabetes were evaluated using a geospatial approach. Based on the AQI in 2017, the estimations were done as follows: clean air (7%), healthy (29%), unhealthy for sensitive groups (48%), unhealthy (12%), very unhealthy (1%), and hazardous (3%). Also, the criteria pollutants in the same year included $PM_{2.5}$ (232 days), PM_{10} (55 days), SO_2 (4 days), and O_3 (13 days). Table 1 shows pollutant emission rates from mobile and stationary sources between 2011 and 2017 in Ahvaz. The distribution of industries in eight districts of Ahvaz is shown in Figure 1.

The location of the urban districts of Ahvaz and the location of various industrial sources of air pollution, including industrial estates, non-metallic industries, factories, and flares of exploitation units are displayed on Landsat images. The location of industries was determined based on the identification of sources, and the boundaries of the areas were extracted from existent urban maps.

Table 1. Pollutant emission rates from mobile and stationary sources in 2017 and 2011 in Ahvaz metropolis (44,45)

Pollutant emission rates from mobile and stationary sources in Ahvaz in 2017 ton/year					
Sources of pollutants	**NOx**	**CO**	**VOCs**	**SOx**	**Total PM**
Mobile sources	14602	107795	7184	111	133552
Stationary sources	18425	18613	2001	26700	67256
Pollutant emission rates from different sources in 2011 in Ahvaz Ton/year					
Industry sources	12155	25437	-	1207	113488
Transportation sources	8158	5743	-	6865	4361
Indoor sources	5016	891	-	84	693

Of the 9553 geocoded pregnancies, 749 cases (7.84%) were associated with gestational diabetes, with the lowest rate in District One (2.4%) and the highest rate in Districts Six and Four (20.6% and 20.2%, respectively). The mean age of women with gestational diabetes was 29.82 (SD, 5.20) years. According to the results of logistic regression, maternal age (OR = 1.06, CI: 1.02-1.11], FPG in the first visit of pregnancy (OR = 1.17, CI: 1.13-1.20), history of diabetes in the family (OR = 2.50, CI: 1.53-4.09), and maternal hemoglobin level (OR = 2.93, CI: 2.13-4.03) were associated with development of gestational diabetes. The highest density of gestational diabetes was found in Districts 6 and 4, while the lowest one was observed in District 5 (Figure 2). As far as air pollution was concerned, 32.6% of mothers with gestational diabetes were residents in low-risk areas whereas 67.4% lived in high-risk areas (Table 2). The frequency of gestational diabetes and details of environmental issues in eight districts using three methods of air pollution assessment are presented in Table 2.

Pollution load, air quality measurement stations, and the number of women with gestational diabetes in each district are shown in Figure 3. Classification of eight urban districts based on AQI classification based on the IDW model is presented in Figure 4. Based on all three methods of air pollution assessment, the density of gestational diabetes was higher in more polluted areas (Figures 5-7).

The overlap of Ahvaz urban districts with industrial sources and the number of patients is presented in Figure 5. Figure 6 shows a higher rate of gestational diabetes in industrial areas with a higher class of AQI. Figure 7 shows the overlap of industrial sources and the number of patients with polluted and non-polluted districts. The highly polluted areas were the residences of more women with gestational diabetes.

This map displays the pollution load, air quality measurement stations, and the number of women with gestational diabetes in each district.

Discussion

Air pollution as one of the environmental health risks can lead to oxidative stress and inflammatory processes

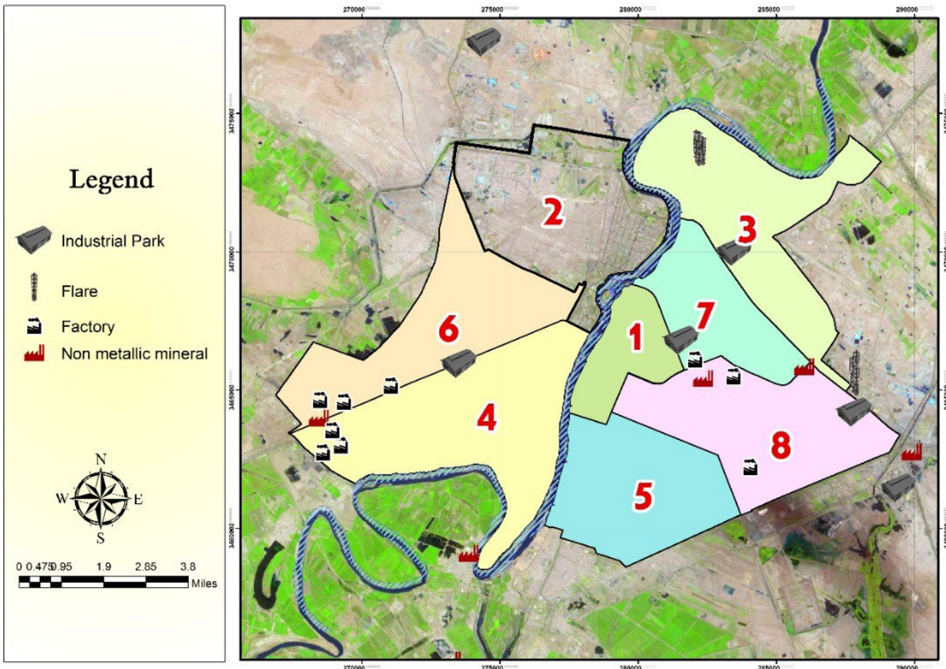

Figure 1. Distribution of industries in 8 districts of Ahvaz city

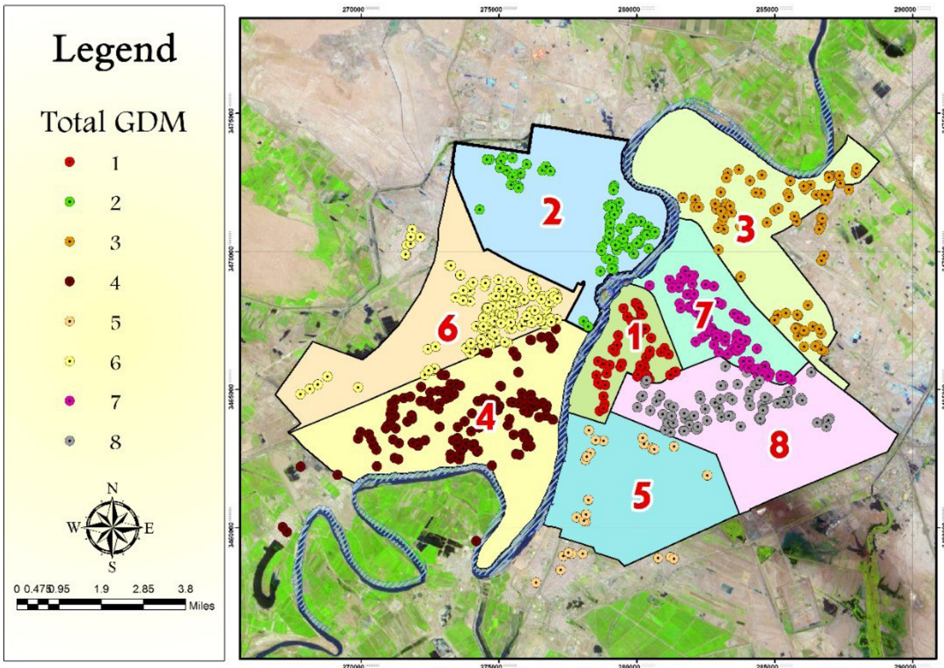

Figure 2. Distribution of the incidence of gestational diabetes in each district of Ahvaz on Landsat images

and increase the risk of insulin resistance and developing gestational diabetes in susceptible populations (35,46).

This study aimed to identify hot spots of high GDM risk and district differences. According to the results, densities of GDM incidence were higher in the most polluted districts. In other words, the highest rate of gestational diabetes was seen in Districts 6 and 4, which have the highest level of air pollution. Also, we found two different patterns of GDM rates in the eight districts studied, namely high-risk and low-risk areas. In the present study, Districts 5 and 1, which were low-risk areas of air pollution without large industrial units, had the lowest rate of gestational diabetes. Based on all three methods of air pollution assessment, the density of gestational diabetes was higher in more polluted areas.

Also, in District 3, despite the presence of industrial units (flares of oil units), the rate of GDM was low, which may be due to the distance of this district from the 25 health

Table 2. The frequency of gestational diabetes and details of environmental issues in eight districts based on the three methods of air pollution assessment

Source of air pollution definition	District 1	District 2	District 3	District 4	District 5	District 6	District 7	District 8	Total GDM in low-risk area	Total GDM in high-risk area
Industrial establishment method	Low risk	Low risk	Low risk	High risk	Low risk	High risk	High risk	High risk	244	505
Number of patients	59	86	81	152	18	155	108	90	244	505
AQI	Low risk	Low risk	High risk	High risk	Low risk	High risk	High risk	High risk	163	586
Pollution load (tons per year)	Low risk	High risk	High risk	High risk	Low risk	Low risk	Low risk	High risk	340	409
District environmental issues	Lack of large industrial units – most residential use	Lack of large industrial units – pollution from transportation	The largest number of flares – Largest population – The largest area	The highest level of pollution	Lack of large industrial units – minimal residential use	The largest population – Presence of industrial units	Presence of the Karun industrial zone - Affected by Karun Oil Unit No. 2	The highest level of pollution – the highest level of industrial use – 12% of residential land - 32% of industrial use - 30% of barren use	-	-

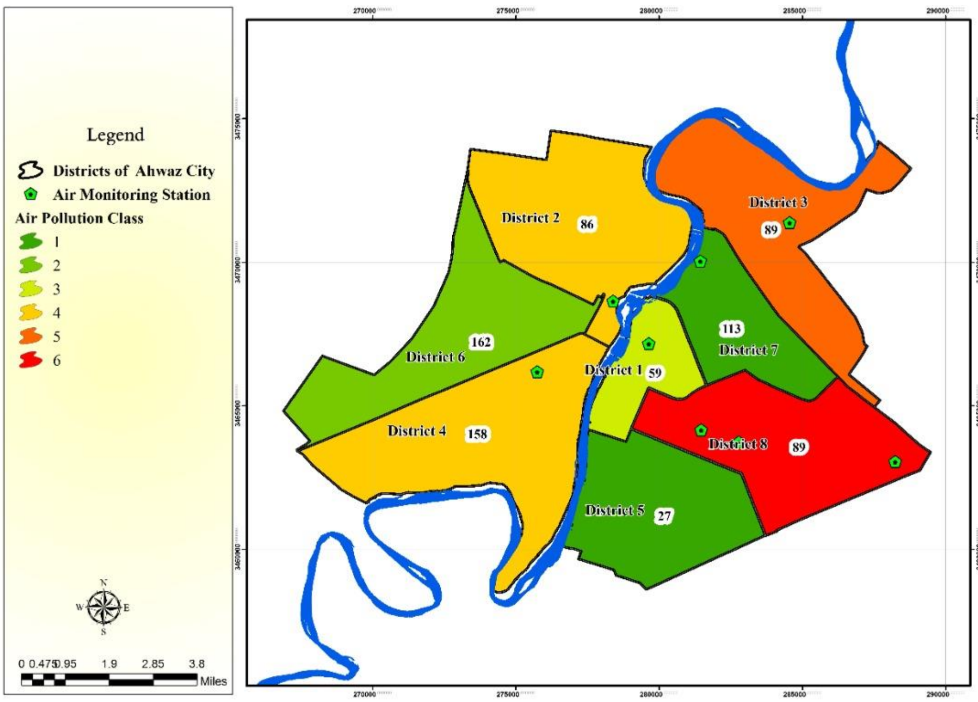

Figure 3. Distribution of gestational diabetes in eight districts based on air pollution load

centers of our sampling site. The effect of long distance on the adherence to postpartum follow-up in women with gestational diabetes has been shown in our previous report (47). Furthermore, since Khuzestan province is a flat land and comprises a southeastern extension of the Mesopotamian plain, the spread of pollution from one district to another is not unlikely.

GIS technique and disease mapping technology as effective tools in disease surveillance have been applied in different studies to better understand the discrepancies between different regions and health care planning (48-50).

Spatial epidemiology has been used to control not only many infectious diseases such as diarrhea, pneumonia, malaria, and immunodeficiency virus epidemics, but also several non-communicable diseases like cancer, cardiovascular disease, diabetes, hypertension, and obesity (51,52). In the recent COVID-19 crisis, the use of spatial analysis also had a major contribution to overcoming the pandemic (53).

Tahmasebi et al conducted a cross-sectional study in Isfahan, Iran, using data from 1467 patients with diabetes based on the GIS technique. They found a higher density

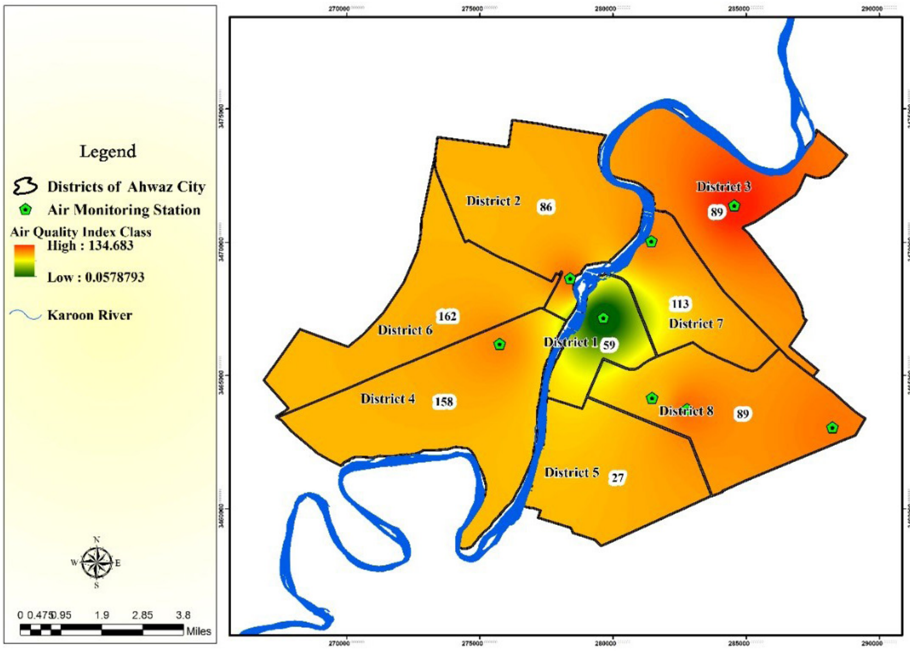

Figure 4. Classification of eight urban districts based on air quality index classification using the inverse distance weighting (IDW) model

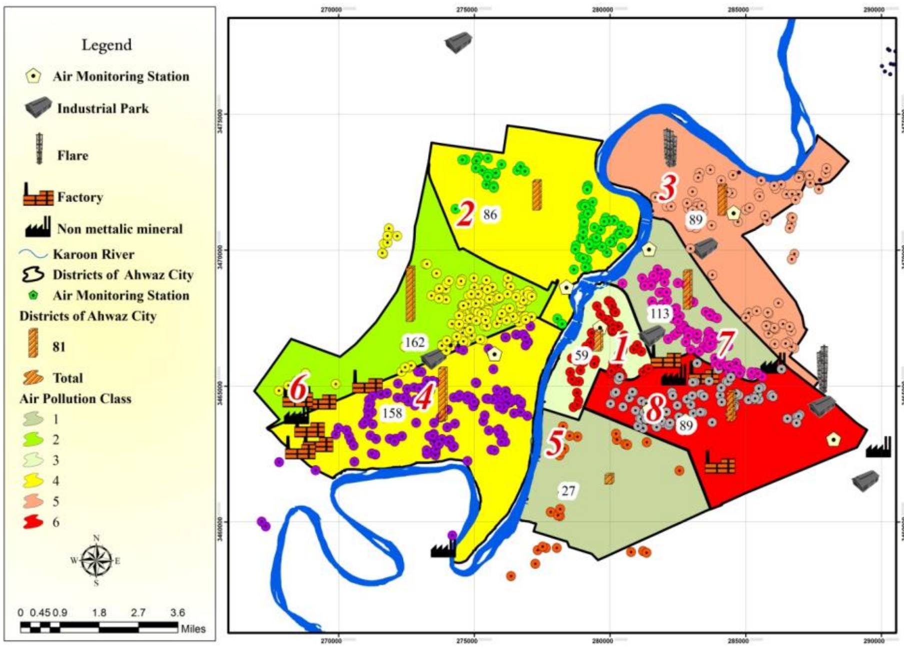

Figure 5. The overlap of Ahvaz urban districts with industrial sources, air pollution class, and the number of patients

of diabetic population in highly polluted areas (54).

Of course, limited studies have applied the GIS technique in diabetes-related research. However, consistent with the results of the present study, a variation in GDM rate by location of maternal residence was reported by MacQuillan in Michigan. They identified areas with high rates of GDM in Michigan using geospatial analysis (55). Also, Cullinan et al. found geographic inequalities in accessibility to GDM screening in Ireland using GIS (56).

Fine and inhalable mixture of solid and liquid particles with diameters smaller than 2.5 micrometers are known as particulate matter ($PM_{2.5}$). Atmospheric chemical processes and fuel combustion lead to the formation of these particles. Particulate matter poses major health risks (57). Using satellite-based spatiotemporal models, Fleisch et al evaluated the association of exposure to $PM_{2.5}$ and neighborhood traffic density with gestational diabetes. They used data from the Massachusetts Registry of Vital Records, and women younger than 20 years with greater exposure to $PM_{2.5}$ were found to have a higher risk of developing GDM (OR = 1.36, 95% CI: 1.08, 1.70) for each interquartile range increment during the second trimester (58).

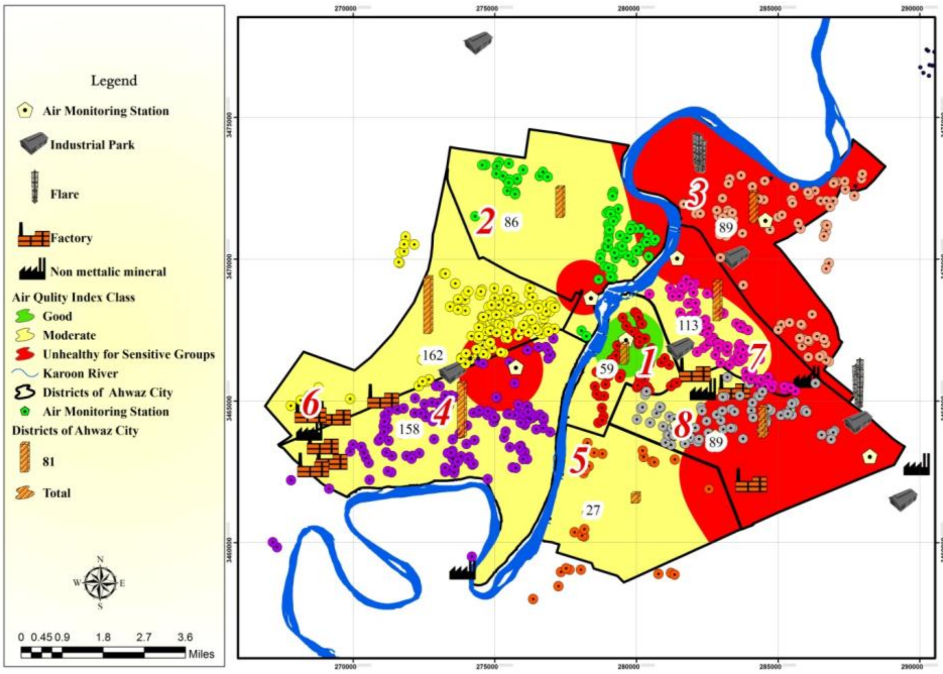

Figure 6. The overlap of Ahvaz's average AQI with industrial sources and the number of patients

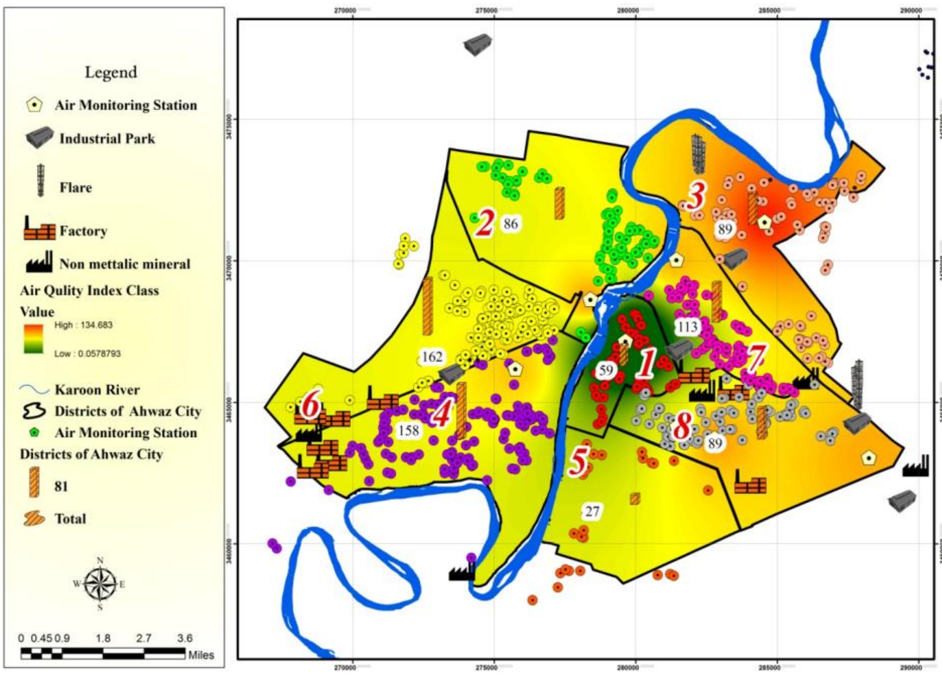

Figure 7. The overlap of industrial sources and the number of patients with polluted and non-polluted districts

The association between air pollutants and gestational diabetes has been reported with controversies. In a retrospective cohort study in Houston, Texas, Rammah et al studied maternal exposures to total and speciated $PM_{2.5}$, nitrogen dioxide (NO_2), and ozone (O_3) in the preconception period, and in the first and second trimesters of pregnancy. They found higher odds of developing GDM in women who were exposed to total and speciated $PM_{2.5}$ (59).

The relationship between exposure to ambient $PM_{2.5}$, PM_{10}, NO_2, and $PM_{2.5}$ chemical constituents and GDM was evaluated using electronic health record data of 395,927 pregnant women in a cohort study in Southern California by Sun et al. They reported that a mixture of ambient pollutants increases the risk of GDM. Black carbon $PM_{2.5}$ and NO_2 were associated with the highest risk of developing GDM (60).

In a systematic review and meta-analysis, Elshahidi reviewed the evidence of the association between ambient air pollution and the incidence of GDM. The effect estimates of the relationship between GDM and air pollutants ranged from 0.97 (95% CI: 0.94–0.99) for PM_{10} to 1.47 (95% CI: 0.88–2.06) for CO. However, only NO and SO_2 showed statistically significant effect estimates. In most studies, the second trimester was the most vulnerable period (61).

Although GIS has already been used in the literature to investigate the association between air pollution and diabetes, this is the first study to investigate non-classical and environmental risk factors for developing gestational diabetes using GIS. Another strength of this study was the employment of three methods to determine air-polluted areas. These data can help policymakers and public health practitioners decide which areas to target for gestational diabetes prevention services. Our findings have important implications for the provision of GDM screening services.

Limitations

One of the most important limitations of this study was the removal of missing data, which may lead to bias in the results. Missing data as one of the main problems in environmental data always is possible due to the large volume of information (62). Another limitation is the small number of monitoring stations in Ahvaz. Interpolation for the classification of urban areas from the perspective of the AQI was done based on the existing stations, which can cause errors in the analysis and estimation. Therefore, in this study, the pollution load model was used to classify urban areas.

Future studies are recommended based on satellite images such as MODIS satellite data and products for monitoring of air quality.

Conclusion

According to the results of the present study, residence in air-polluted areas was associated with a higher density of gestational diabetes incidence. Providing gestational diabetes screening services, prenatal care, and prevention of long-term complications of GDM should be a priority for mothers living in more polluted areas.

Acknowledgments

The authors wish to thank the research chancellor of the Ahvaz Jundishapur University of Medical Sciences for approval of the study protocol (D-01020).

Authors' contribution

Conceptualization: Neamatollah Jaafarzadeh, Sedigheh Nouhjah, Hajieh Shahbazian.
Data curation: Sedigheh Nouhjah, Hajieh Shahbazian.
Formal analysis: Sedigheh Nouhjah, Bamshad Shenavar.
Investigation: Neamatollah Jaafarzadeh.
Methodology: Neamatollah Jaafarzadeh, Bamshad Shenavar.
Project administration: Sedigheh Nouhjah.
Resources: Neamatollah Jaafarzadeh, Sedigheh Nouhjah, Hajieh Shahbazian, Bamshad Shenavar
Software: Bamshad Shenavar.
Supervision: Sedigheh Nouhjah, Neamatollah Jaafarzadeh.
Validation: Sedigheh Nouhjah, Neamatollah Jaafarzadeh, Hajieh Shahbazian, Bamshad Shenavar.
Visualization: Hajieh Shahbazian, Sedigheh Nouhjah, Neamatollah Jaafarzadeh, Bamshad Shenavar
Writing–original draft: Sedigheh Nouhjah.
Writing–review & editing: Hajieh Shahbazian, Neamatollah Jaafarzadeh, Sedigheh Nouhjah, Bamshad Shenavar.

Competing interests

The authors declare that they have no competing interests.

Ethical issues

Ethical consideration approved by the Ethics Committee of Ahvaz Jundishapur University of Medical Sciences (Ethical code: IR.AJUMS.REC.1401.074). All patients signed a written informed consent form.

Funding

No fund.

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