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LEVERAGING GEOGRAPHIC INFORMATION SYSTEM CAPABILITIES FOR URBAN AIR QUALITY EVALUATION

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ABSTRACT

Urban air pollution poses significant health risks to city dwellers worldwide. Effective air quality evaluation and monitoring are crucial for mitigating these risks. This study explores the potential of Geographic Information Systems (GIS) in urban air quality evaluation, leveraging its spatial analysis and visualization capabilities. Using GIS, we integrated air quality data from sensor networks and geographic data from urban planning and environmental agencies. Our methodology employed spatial autocorrelation, hotspot analysis, and regression analysis to identify pollution patterns and correlations with urban features.

Results show that GIS-based spatial analysis effectively identified air pollution hotspots and correlations with urban land use, transportation infrastructure, and demographic factors. The study demonstrates the value of GIS in urban air quality evaluation, enabling targeted policy interventions and improved public health outcomes.

KEYWORDS: Air Pollution, Air Quality, Geographic, Information Systems, Spatial Analysis, Public Health, Urbarn.

INTRODUCTION

In recent years, rapid economic growth has led to a significant increase in the number and concentration of atmospheric pollutants, primarily due to the large-scale emergence of chemical enterprises. This has made environmental quality a pressing issue for urban sustainable development, requiring immediate attention (Mujtaba et al., 2016).

To mitigate heavy air pollution, emergency measures such as stringent controls on motor vehicle emissions, chemical enterprise discharges, and construction dust emissions are being considered (Pope and Wu, 2014; Merbitz et al., 2012). Moreover, environmental prediction and analysis are vital in supporting ecological management decisions, ultimately enhancing atmospheric environmental quality (Chattopadiay et al., 2010).

Air quality prediction and evaluation models are crucial technical tools for detecting atmospheric environmental quality. By developing mathematical models that simulate the behavior of ecological pollutants under various topographical and meteorological conditions, researchers can gain insights into the physical and chemical mechanisms governing pollutant transport, diffusion, transformation, and removal (Superczynski and Christopher, 2011; Zhan et al., 2018). quality evaluation model, the atmospheric pollutant diffusion model is established by applying the meteorological principle to forecast the diffusion of environmental pollutants using computer technology in combination with the atmospheric dynamic principle, the atmospheric physics, and the atmospheric chemistry application foundation (Elbir et al., 2010). The air quality assessment model is classified into local scale, urban scale, and regional scale by simulation scale. In general, the urban scale is used for environmental quality prediction and evaluation (Barrile et al., 2018; Steve et al., 2008; Wang et al., 2015). Geographic information systems (GIS) can manage spatial data by spatial location and study the interrelationship among various spatial entities. The GIS technology can visualize the air quality forecast data (Righini et al., 2014; Tirmizi and Tirmizi, 2018). In this paper, GIS technology is applied to the detection and evaluation of urban air quality, and the spatial analysis ability of GIS technology is brought into full play to visually analyze the evaluation results to provide a decision-making basis for air quality prediction.

Materials and methods

Industrial sources, mobile sources, and surface sources

Establishing an urban air pollution emission list is an effective tool for assessing urban air quality, which should specifically include emission source spatial location, emission data, and emission parameters (Borrego et al., 2016; Siliello et al., 2014). There are three types of air pollution sources in urban areas: industrial, flow, and surface sources (Carbajal-Hernández et al., 2012). Table 1 shows the source identification of the pollution sources. Except for the industrial sources from which O3 comes, the common atmospheric pollutants will be generated from the three major pollution sources. Relying on GIS technology, each pollution space is located by using the longitude and latitude coordinate positioning method (Borbet et al., 2018). The industrial source estimation method includes the actual monitoring, emission factor, and material balance methods. The VOCs emission factor is generally determined regarding the Atmospheric Volatile Organic Matter Source Emission Inventory issued by the State. The flow sources are mainly motor vehicle emissions, and the main emissions are VOCs and NO_2. Surface sources include dust emission and combustion of domestic fuels, and surface sources of pollutant VOCs include vegetation, landfill sites, and hospitals.

Table 1. Source identification of pollution sources

Classification	Contaminant category

	PM2.5	PM10	SO2	NO2	CO	VOCs	O3
Industrial source	√	√	√	√	√	√	√
Flow source	√	√	√	√	√	√	
Surface source	√	√	√	√	√	√	

Uncertainty analysis of pollution source

1. Air quality is influenced by a combination of factors, including the spatial distribution and emission rates of pollution sources, as well as meteorological conditions such as wind speed and direction. Figure 1 illustrates the monthly wind speed trends in Shijiazhuang City, revealing a peak wind speed in March and a trough in October. Figure 2 presents the air pollution emission profile in downtown Shijiazhuang City, highlighting:

Surface sources as the predominant contributor to VOC emissions (63%) Industrial sources as the primary emitter of PM10, SO2, NOx, CO, and O3.

In 2017, the total VOC emissions in Shijiazhuang's central urban area reached 31,101.36 tons, according to available data. Figure 3 breaks down the urban atmospheric pollutant VOCs emission sources:

Vegetation (36.57%) Industrial activities (33.25%) Architectural ornaments (14.05%)

The quantitative assessment of VOC pollutant emission sources involves selecting representative emission factors and activity level data. However, this process is subject to uncertainties stemming from Instrument calibration error Limited source test representativeness Random variability

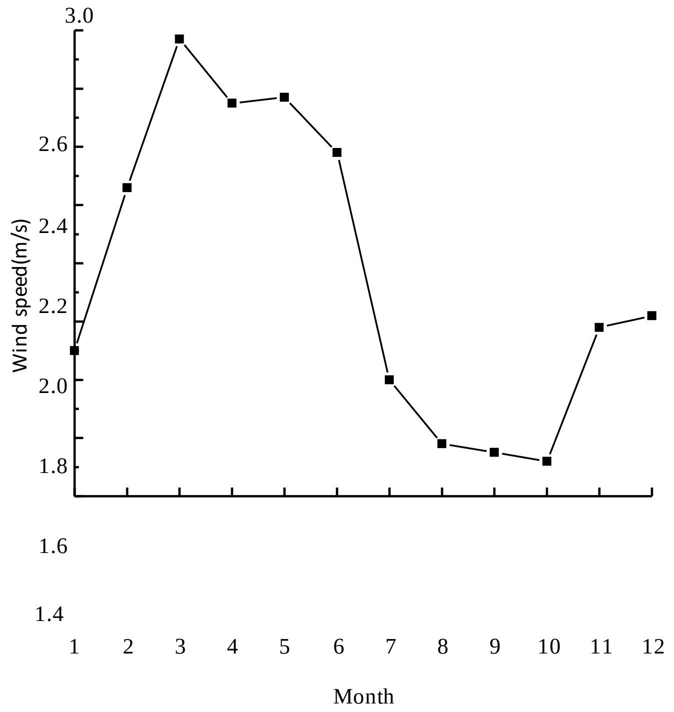
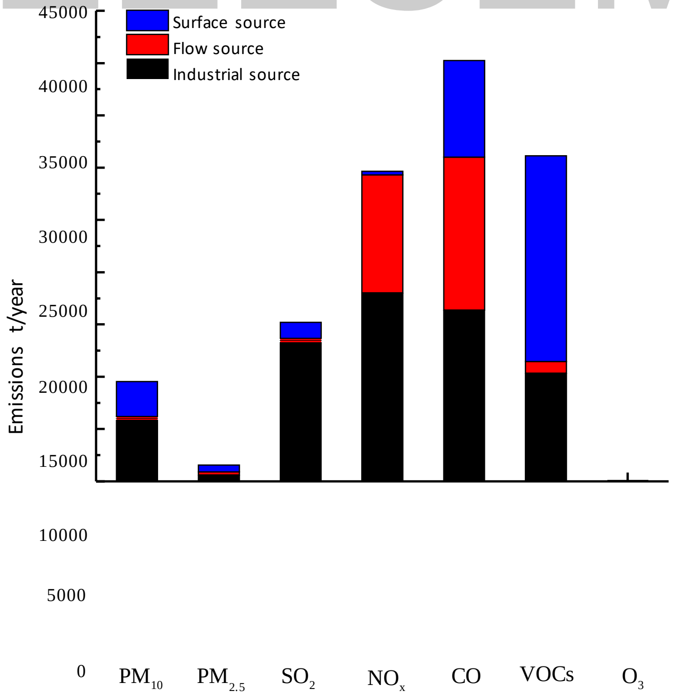


Figure 1. Shijiazhuang City monitors monthly average wind speed



Basic data required for the model operation

AERMOD model is used to calculate the atmospheric pollutant concentration. When simulating the horizontal diffusion of industrial source plume pollutants, the mass concentration of grid coordinate point (x, y, z) is assumed to be c (x, y, z) without considering the influence of topography. Considering the influence of the topography conditions, the total mass concentration of the grid point c (x, y, z) is shown in Equation

$$C_r(x,y,z) = \lambda c(x,y,z) + (1 - \theta)c(x,y,z) \quad \text{(Eq.1)}$$

where, θ represents the decomposition streamline height; λ and θ represent the weight functions for horizontal and vertical point source diffusion states, respectively, as shown in Equations 2 and 3:

$$\lambda = 0.5(1 + \xi) \quad \text{(Eq.2)}$$

$$\xi = \frac{\int_0^H C(x,y,z)d_Z}{\int_0^\infty c(x,y,z)d_Z} \quad \text{(Eq.3)}$$

The basic data required for the model operation include pollution source parameters, meteorological data parameters, predicted point source coordinates, and ground and high-altitude meteorological data. For industrial chimneys, the point source parameters include the height of the chimney, outlet inner diameter, discharge velocity, and emission rate, while the surface source parameters include height, direction angle, length, and emission rate.

Model verification method

For the convenience of simulation, the simulation results of the atmospheric diffusion model are verified by using the developed AERMOD system, and necessary corrections are made to the model. The AERMOD model has been used by some scholars to verify the simulation results of SO_2. The results show that the correlation coefficient between the monitored value and the simulated value of SO_2 is 0.67, which indicates that the AERMOD model has good applicability to the simulation of SO_2 emissions. In addition, some researchers have applied the AERMOD model to the industrial point source pollutant emission area, which proved that the AERMOD model has good practicability in simulating pollution diffusion in the small and medium scale research area, and provides effective prediction data for air quality evaluation.

Discussion

Model validation

Table 2 is the emission list of pollution sources in downtown Shijiazhuang City. In selecting data of AERMOD model, it is necessary to add pollutants according to the factors of pollutants, and predict and simulate the residential areas, cultural areas and industrial areas in downtown Shijiazhuang City, with the secondary ambient air quality standard. The topographical parameters input in the AERMOD model include longitude and latitude coordinates and elevation, and the ground meteorological data include wind speed, wind direction, total cloud volume and dry-bulb temperature, where the wind direction, wind speed, and dry-bulb temperature are the average value of observation data 24 times a day, and the total cloud volume is the average of 5 observations per day. Table 3 shows the location of project concerns for prediction. According to the requirements of environmental air quality monitoring and monitoring location, five representative concerns are set up in this study and the model is simulated for a total of 20 days.

Table 2. List of pollution sources in downtown Shijiazhuang

Classification	Contaminant category						
	$PM_{2.5}$	**PM_{10}**	**SO_2**	**NO_2**	**CO**	**VOCs**	**O_3**
Industrial source	5853.37	608.2	13309	18014.2	16372.20	10334.1	75.8
Flow source	323.88	292.0	377.86	11268.01	14612.88	1089.8	
Surface source	3330.04	630.15	1507.73	320.15	9204.15	19665.36	
Total	9507.29	1530.35	15194.59	29602.36	43189.23	31089.26	75.8

Table 3. Forecast project focus location

Concern point	Position (m)		
	X	**Y**	**Altitude**
Mine monitoring station	6918.81	-9254.65	65.91
City No. 1 Middle School	11038.22	4099.08	64.83
Monitoring station	11428.7	3151.55	67.03
Daying Street monitoring station	6773.08	1044.0	62.02
Stylistic center monitoring station	10975.48	754.73	67.45

Forecast results and analysis

Figure 4 is a comparison between the predicted results and monitoring results of VOCs of five concerns It can be seen that the predicted concentration values of VOCs in Shijiazhuang No. 1 High School are relatively high, while the predicted concentration values of the monitoring station are relatively low, which is mainly because the selected monitoring station is located in the suburb of Shijiazhuang, and related to the coal or biomass fuel of the surrounding residents, the predicted values and monitoring values ofthe other three stations have the same trend. Table 4 is the predicted results of VOCs of five concerns, and Table 5 is the daily average predicted results of VOCs. The annual concentration of VOCs in Shijiazhuang City is predicted with the concern where the daily average concentration of VOCs is the highest among the five concerns as the monitoring point. The concentration of VOCs predicted by the AERMOD model is 0.1668 mg/m^3, accounting for more than 110% of the standard rate, and appears in October in Shijiazhuang City, which is the month with the lowest wind speed.

Conclusions

In this paper, GIS technology is applied to the detection and evaluation of urban air quality, and the spatial analysis ability of GIS technology is brought into full play to visually analyze the evaluation results. The concrete conclusions are as follows:

(1) The surface source is the largest source of VOCs, with a sharing rate of over63%, and vegetation, industrial, and architectural ornaments are the three major sources of VOCs, accounting for 36.57%, 33.25%, and 14.05% respectively.

(2) The basic data required for the AERMOD model operation include pollution source parameters, meteorological data parameters, predicted point source coordinates, and ground and high-altitude meteorological data. The research indicates that the AERMODmodel has good applicability to the simulation of SO2 emissions.

(3) The comparison between predicted results and monitoring results of VOCs of five concerns in Shijiazhuang City shows that the predicted concentration values of VOCs in Shijiazhuang No. 1 High School are relatively high, while the predicted concentration values of the monitoring station are relatively low, and the predicted values and monitoring values of the other three stations have the same trend.

Here only considers the impact of multiple point sources on the concentration of VOCs in Shijiazhuang City. The follow-up study can be made with additional pollution sources such as linear and surface sources to more roundly evaluate urban air quality.

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