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Original Article

Emissions Correlation Analysis of Geographic Region Selection for the Moves Model

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Abstract:
On-road vehicle emissions are one of the main sources of air pollutants and it is also one of the most difficult pollution sources to evaluate quantitatively. As a widely used mobile source emission prediction model worldwide, MOVES lacks in-depth analysis of the selection basis for localizing geographic region parameters in software simulations for non-U.S. regions. Taking Taiyuan City as an example, the emissions of different pollutants from motor vehicles are obtained by selecting eight cities with different latitudes and altitudes as geographic regions for simulation calculation under the condition that other parameters are set unchanged, and the correlations between different pollutant emissions and latitudes and altitudes of the selected geographic regions are analyzed using sensitivity and Spearman correlation coefficient, respectively. The results show that there is no significant correlation between altitude and the emissions of CO, HC, NO_x, and $PM_{2.5}$ when latitude is similar; there is no significant correlation between latitudes and the emissions of HC, NO_x, and $PM_{2.5}$ when altitude is similar, but there is a significant correlation with CO emission. Therefore, when selecting the simulated geographic region in the localization of MOVES parameters, the altitude factor can be disregarded if the latitude is similar, but in the case of similar altitudes, it is necessary to select the city with similar latitude as the simulated geographic region at the same time. This finding could help the non-U.S. regions to obtain the appropriate geographic region selection that is closer to the real emission results when using the MOVES software.

Keywords: vehicle emission, MOVES model, geographic region selection, sensitivity analysis, correlation analysis

Introduction

The significant increase in motor vehicle ownership has greatly facilitated people's daily lives, but it has also brought about unavoidable environmental problems. According to the China Mobile Source Environmental Management Annual Report (2023) released by the Ministry of Ecology and Environment, the total emissions of four pollutants (CO, HC, NO_x and PM) from motor vehicles nationwide in 2022 were 14,662 million tons, of which automobile emissions accounted for more than 90% of the CO, HC, NO_x and PM, which was the main contributor to the total air pollutant emissions[0]. Automobile emissions have become a global hazard, posing a serious threat to the human living environment. Recent global commitments like the Paris Agreement have established ambitious carbon reduction targets, and placed transportation at the forefront of national strategies to achieve them[2]. As one of the world's largest carbon emitters, China is taking more aggressive policies and measures to reduce transportation emissions. In order to assist decision-makers in formulating effective emission reduction programs, Accurate quantification of transportation-related vehicle emissions is essential.

MOtor Vehicle Emission Simulator (MOVES), developed by the U.S. Environmental Protection Agency (EPA), is the most widely used emissions calculation software in the United States, and is also widely used abroad. Compared with other major models for predicting vehicle emissions such as MOBILE, COPERT, IVE, and EMFAC, the MOVES model stands out for its ability to predict a wide range of pollutant emissions under actual driving conditions by inputting the localized parameters in an open data management system and provides a variety of application scenarios and analysis at different levels[3Error! Reference source not found.]. The latest version of MOVES released by the EPA is MOVES5, which has been greatly improved in terms of model performance enhancement and functionality improvement compared to previous versions, with more accurate and adaptable calculations, representing the latest technology in emission model development. The accuracy of emission estimation using MOVES depends on all parameter inputs, both traffic-related and non-traffic-related. When using MOVES software to estimate emissions from other areas that are not covered, it is first necessary to select the appropriate default geographic region. However, how to select a default geographic area that can get closer to the actual emissions has rarely been analyzed by researchers, and many literature choose to ignore this step or leave it unexplained, as a result, the latter researchers have fewer bases to refer to in selecting the appropriate default geographic regions when using MOVES to simulate emissions in non-software-covered areas Table 1 provides an overview of the state-of-the-art literature regarding the selection of default geographic areas when using the MOVES model for non-software covered areas.

Table 1 The simulated cities and the selection basis of the corresponding default geographic regions in MOVES software.

Research City	Vehicle Type	Corresponding Geographic Region	Basis for Selection	Reference
Xi'an	Passenger Car	Georgia County	Average annual precipitation, Altitude, Latitude, Longitude, Average Temperature, Relative Humidity	4
Xi'an	All Types	Georgia County	Latitude, Climate, Altitude	6
Beijing	Passenger Car, Taxi, Middle-Duty Vehicle, Heavy-Duty Vehicle, Light-Duty Truck, Middle-Duty Gasoline Truck, Middle-Duty Diesel Truck, Heavy-Duty Truck	Washington D.C	Longitude, Latitude	7
Beijing	Light-Duty Vehicle	Not Mentioned	Not Mentioned	8
Shenzhen	Passenger Car, Passenger Truck, Other Buses, Transit Bus,	Orange County	Temperature, Humidity, Altitude, Latitude	9

	Medium and Heavy Vehicle			
Shenzhen	All Types	Orange County	Latitude, Climate	10
Shenzhen	Truck, Passenger Car	Orange County	Climate	11
Shanghai	Truck	Not Mentioned	Slope, Temperature, Humidity	12
Shanghai	Truck	Not Mentioned	Climate, Annual Temperature, Annual Humidity	13
Shanghai	Light-Duty Vehicle	Not Mentioned	Not Mentioned	14
Yunnan	Passenger Vehicle	Not Mentioned	Not Mentioned	15
Shaanxi	Heavy-Duty Diesel Truck	State of Missouri	Latitude, Altitude, Climate, Precipitation, Humidity, Temperature	16
Shijiazhuang	All Types	New York County	Latitude, Climate	17
Hyderabad, India	Light-Duty Vehicle	Not Mentioned	Temperature and Relative Humidity	18

As can be seen from Table 1, most of the cities studied in the references are from China and a small number of Indian cities, which have not yet developed their own mature simulation software for motor vehicle pollutant emissions, so when using the MOVES model to make predictions for areas not covered by the software, the first step is to select the default geographic regions. The majority of corresponding geographic regions in the literature are selected based on the similarity of geographic and meteorological conditions such as latitude, altitude, climate, temperature, humidity, and precipitation. Since climate and average annual precipitation are mainly affected by the latitude of the region, in addition, the actual temperature and relative humidity of the simulated area can be modified and inputted in the model's open data management system as meteorological information parameters. From the above analysis, it can be concluded that the analysis of the basis for selecting the appropriate default geographic regions for non-software covered areas mainly falls on two factors: latitude and altitude.

In previous literature studies, when motor vehicle pollutant emissions from non-software covered areas are estimated in the MOVES model, most are directly selecting the software default region with similar latitude and altitude to the simulated city, and then the simulated city is compared with the relevant climate and environmental conditions of the selected software default region (as shown in the basis for selection column of Table 1); however, when the similarities of the two different factors of latitude and altitude between the simulated city and the selected software default region are not consistent, should we focus on the latitude factor or the altitude factor? How do different similarities in latitude and altitude between the simulated city and the software default region affect the calculated motor vehicle emissions, respectively? And so on, these are the issues that need to be considered in the selection of default geographical regions for non-software covered areas. As a matter of fact, these issues have not been studied in depth in the previous literature. To further explore the factors that need to be considered by the MOVES model in selecting an appropriate default geographic region for non-software covered areas, Taiyuan was taken as the simulated area and parameter inputs for the model were developed based on field surveys and data collected by local agencies; with other parameter inputs remain unchanged, eight default geographic regions in the MOVES model with different degrees of similarity in latitude and altitude were chosen for motor vehicle pollutant simulations, and how latitude and altitude affect the choice of default geographic region was analyzed, so as to obtain the vehicle emission calculation results closer to the simulated area.

The remainder of this paper is organized as follows: the second section describes the parameter input process during the use of the software, including geographic region selection, motor vehicle information and meteorological information, etc., with a focus on eight different geographic regions selected for different latitudes and altitudes; the third section displays the different pollutant emissions calculated using eight different default geographic regions, the results calculated by the MOVES software for the default geographic region closest to the latitude and altitude of Taiyuan are compared with the emissions of Taiyuan calculated by the top-down method, then the correlation between latitude, altitude factors affecting the choice of default geographic region for the prediction of non-software covered areas and pollutant emissions are analyzed using sensitivity and Spearman correlation coefficients separately; the fourth section concludes the main work and discoveries of this paper.

1. Methodology

This section describes the process of developing the parameters for estimating vehicle emissions in Taiyuan using the MOVES software, including the acquisition process of various traffic-related and non-traffic-related parameters, which is characterized by considering eight different matching cities in the selection of default geographic regions.

2.1 Calculation principle of MOVES

MOVES is an emission modeling system that estimates emissions for mobile sources at the national, county, and project level for criteria air pollutants, greenhouse gases, and air toxics. The version of the model adopted in this paper is 4.0, and the vehicle emission inventory in the software is the total amount of pollutants emitted into the atmosphere from different types of vehicles in a certain time-space span, calculated according to the bottom-up approach by Equation 1:

$$EI_{b,n} = \sum_a \sum_b \sum_c \left(VEH_{a,b,c} \times VMT_{a,b,c} \times EF_{a,b,c,n}\right) \quad (1)$$

where, a is the vehicle age;

b is the vehicle type;

c is the fuel type;

n is the pollutant type;

$EI_{b,n}$ is total amount of pollutant n emitted by the vehicle type b (kg);

$VEH_{a,b,c}$ is the total number of a-year-old b-type vehicles using c-class fuel (veh);

$VMT_{a,b,c}$ is the average annual mileage of a-year-old b-type vehicles using c-class fuel (mile);

$EF_{a,b,c,n}$ is the emission factor for a-year-old b-type vehicles using c-class fuel (kg/(mile·veh)).

The paper estimates motor vehicle pollutants (CO, HC, NO_x, and PM2.5) in Taiyuan City on a city-area basis, so the county scale in MOVES is adopted for simulation.

2.2 Parameter localization process of MOVES for Taiyuan City

2.2.1 Selection of appropriate matching city

In order to make the motor vehicle pollutant simulations more accurate, it is necessary to select the U.S. cities in the model that match the geographic and climatic characteristics of Taiyuan. When selecting a geographic area, previous literature typically starts by choosing a U.S. city at a similar latitude and then comparing other geographic and climatic characteristics of that city with those of the area to be simulated, but there is no in-depth analysis of the effect of latitude or other geographical and climatic characteristics on simulation results.

As stated in the literature review section, the selection of geographic regions is mainly affected by latitude and altitude two factors. In order to explore the effects of the main geographic and climatic factors (latitude and altitude) on motor vehicle pollutant emissions in Taiyuan City, this study used Google Maps to screen cities in the United States that are similar to Taiyuan in terms of latitude but differ in altitude: Gray County, Kansas (44 meters higher than the altitude of Taiyuan), Harper County, Kansas (367 meters lower than the altitude of Taiyuan), Harvey County, Kansas (453 meters lower than the altitude of Taiyuan), Baca County, Colorado (509 meters higher than the altitude of Taiyuan), and Alamosa County, Colorado (1,499 meters higher than the altitude of Taiyuan); At the same time, cities with similar altitudes but different latitudes to Taiyuan were also selected: Gray County, Kansas (about 40 minutes difference in latitude from Taiyuan), Glasscock County, Texas (about 5 degrees difference in latitude from Taiyuan), and Daniels County, Montana (about 11 degrees difference in latitude from Taiyuan). Table 2 shows the specific geographic and climatic characteristics of Taiyuan City and the simulated regions.

Table 2 Geographic and climatic characteristics of Taiyuan City and the simulated regions.

City	Latitude	Longitude	Altitude	Climatic	Average Annual Temperature	Rainy Season	Average Annual Precipitation
Taiyuan	37°50′	112°30′	800m	Warm Temperate Continental Monsoon Climate	9.5°C	June-September	456 mm
Gray	37°40′	100°26′	844m	Temperate Continental Climate	14.5°C	May-September	578.8mm
Harper	37°11′	98°01′	433m	Temperate Continental Climate	11.7°C	May-September	834.7 mm
Harvey	38°04′	97°34′	347m	Temperate Continental Climate	11.7°C	May-September	834.7 mm
Baca	37°23′	102°32′	1,309m	Temperate Continental Humid Climate	15.3°C	May-September	480.6 mm
Alamosa	37°28′	105°52′	2,299m	Temperate Continental Humid Climate	15.25°C	May-September	425.9 mm
Glasscock	31°51′	101°28′	801m	Temperate Climate	15°C	May, September, October	347.5mm
Daniels	48°46′	105°43′	818m	Temperate Grassland Climate	12°C	May-July	374.6mm

This data is derived from https://www.timeanddate.com/.

2.2.2 Input of motor vehicle information in Taiyuan City

The motor vehicle information includes vehicle age, vehicle type, fuel, ownership of each type, and Vehicle Miles Traveled (VMT)[19].

(1) Localization of vehicle age, vehicle type and fuel

Motor vehicle age distribution refers to the percentage of the actual number of different age vehicles within a certain type to the total number of vehicles in that type, the sum of the age distribution for the same type vehicles is 1. The calculation of vehicle age distribution requires a large amount of basic data, but it is difficult to obtain complete statistical data in most cities in China, and Taiyuan is no exception. Therefore, based on the assumption that the age distribution of each vehicle type in Taiyuan is similar to that of Shanxi province, this paper inquires about new car registration statistics for each year through the relevant data platform of the National Bureau of Statistics and obtains the vehicle statistical data by consulting the Shanxi Province Statistical Yearbook. Combined with the above data and based on the Weibull distribution, a vehicle survival curve model was established to calculate the vehicle age distribution of each type in Shanxi Province, and the results are used as the age distribution data of actual road vehicles in Taiyuan. It is worth noting that in the MOVES model, the default maximum vehicle age is 30 years, but according to the actual situation in China, the age of vehicles is usually within 15 years, so the table lists the 15-year age distribution for Taiyuan City, as shown in Table 3.

The vehicle survival curve model based on Weibull distribution is developed with the following Equations 2-4[20]:

$$VP_{i,j,k} = S_{j,k-i} \times \varphi_{i,j}(k) \quad (2)$$

$$VP_k = \sum_j \sum_i VP_{i,j,k} \quad (3)$$

$$\varphi_{i,j}(k) = n_{i,j}(k+i)/n_{0,j}(k) \quad (4)$$

where, i is vehicle age;j is vehicle type; k is year;

$VP_{i,j,k}$ is the vehicle holdings of j-type vehicles of age i in the year k;

$S_{j,k-1}$ is the number of newly registered vehicles of type j in the $k-i$ year;

${\varphi_{i,j}}^{(k)}$ is the survival rate of j-type vehicles of age i in the k year;

VP_k is the vehicle holdings in the year k;

${n_{i,j}}^{(k+i)}$ is the number of j-type vehicles still in normal use in the year $k+i$;

${n_{0,j}}^{(k)}$ is the number of newly registered j-type vehicles in the year k, (i=0).

Table 3 Age distribution data of actual road vehicles in Taiyuan City in 2022.

Age Type	Motorcycle	Passenger Car	Passenger Truck	Light Commercial Truck	Other Buses	Transit Bus	School Bus	Refuse Truck	Heavy-Duty Truck
0	0.02	0.06	0.02	0.02	0.01	0.02	0.01	0.05	0.03
1	0.12	0.08	0.12	0.12	0.11	0.10	0.11	0.12	0.12
2	0.11	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12
3	0.09	0.11	0.13	0.13	0.11	0.14	0.13	0.08	0.11
4	0.07	0.09	0.11	0.12	0.13	0.13	0.14	0.06	0.10
5	0.06	0.10	0.08	0.13	0.09	0.12	0.09	0.05	0.08
6	0.05	0.09	0.06	0.07	0.06	0.09	0.05	0.04	0.07
7	0.05	0.07	0.04	0.05	0.05	0.1	0.07	0.03	0.03
8	0.09	0.08	0.06	0.06	0.06	0.07	0.07	0.08	0.07
9	0.06	0.06	0.06	0.05	0.05	0.03	0.05	0.09	0.07
10	0.07	0.04	0.06	0.04	0.04	0.04	0.04	0.07	0.04
11	0.06	0.03	0.04	0.02	0.04	0.02	0.04	0.06	0.04
12	0.04	0.02	0.04	0.02	0.05	0.02	0.03	0.05	0.04
13	0.02	0.02	0.01	0.02	0.02	0	0.02	0.03	0.02
14	0.02	0	0.02	0	0.02	0	0.02	0.04	0.02
15	0.07	0.03	0.03	0.03	0.04	0	0.01	0.03	0.04

Fuel type is an important factor affecting the emission of pollutants from motor vehicles, and the fuel types include gasoline and diesel, etc. The data related to fuel mainly refers to the corresponding data in the national standards for gasoline and diesel in the MOVES model.

According to the local standard of Shanxi Province "M5-M15 Methanol Gasoline" (DB14/T 92-2008), the fuel type that is closest to the given fuel component of MOVES is selected. After data conversion and index type adjustment, the RVP of M5 and M15 methanol gasoline are 6.526 psi (for summer: March 16 - September 15) and 8.702 psi (for winter: September 16 - March 15 of the following year). The boiling range T50 and T90 are 120 °C and 190 °C, respectively, and the temperature forms required for conversion to the MOVES model are 248 °F and 374 °F. The E200 is 26.39 and the E300 is 73.19, the volume percentages of benzene, olefin and aromatic hydrocarbons are 1, 28 and 40, respectively, the volume fraction of MTBE (oxygen-containing compounds) in gasoline is 15.0139%.

(2) Localization of motor vehicle ownership

The number of motor vehicles of different types in Taiyuan in 2022 was derived from the on-site surveys and review of relevant materials, as shown in Table 4.

Table 4 Motor vehicle ownership of different types in Taiyuan in 2022.

Categorization		Instruction	Vehicle Type	Number
Passenger Vehicle	Micro	Length≤3,500mm, Engine Displacement≤1 Liter	Passenger Car	1,546,521
	Small	Length<6,000mm and Seating Capacity≤9 People		
	Medium	Length < 6,000mm and Seating Capacity for 10-19 People	Other Buses, School Bus	2,236
	Heavy	Length≥6,000mm or Seating Capacity≥20 People	Transit Bus	5,096
Truck	Micro	Length≤3,500mm, Weight≤1,800kg, excluding low-speed trucks	Passenger Truck	123,352
	Light	Maximum Designed Speed≤50 km/h, Engine Displacement≤50 ml, and Low-Speed Trucks		
	Medium	Length≥6,000mm or Weight≥4,500kg and ≤12,000kg	Light Commercial Truck, Refuse Truck	3,207
	Heavy	Weight≤12,000kg.	Heavy-duty Truck	83,708
Motorcycle	Regular	Maximum Designed Speed>50 km/h or Engine Displacement>50 ml	Motorcycle	124,467
	Light weight	Maximum Designed Speed≤50 km/h or Engine Displacement≤50 ml		

(3) Localization of VMT

Vehicle Miles Traveled (VMT) refers to the total mileage traveled by all vehicles in a given area at a given time[21]. This indicator not only reflects the traffic flow of motor vehicles, but also the burden on the entire highway system, and is directly related to energy consumption and emissions. According to the “Technical Guidelines for the Preparation of Air Pollutant Emission Inventory for Road Motor Vehicles” (hereinafter referred to as “the Guidelines”), the average annual Vehicle Kilometers Traveled (VKT)22 of each vehicle type is obtained, and then multiplied by the ownership of each vehicle type in 2022, the total VMT by each vehicle type in 2022 is obtained as shown in Table 5[22].

Table 5 VKT and VMT data for all types of vehicles in 2022.

MOVES Emission Source ID	Type of Motor Vehicle	VKT (km/vehicle)	VMT (km×10^3)
11	Motorcycle	6,000	871,269
21	Passenger Car	18,000	13,918,689

31	Passenger Truck	30,000	3,083,800
32	Light Commercial Truck	35,000	217,700
41	Other Buses	31,300	156,520
42	Transit Bus	60,000	509,600
43	School Bus	31,300	156,520
51	Refuse Truck	35,000	217,700
52,53	Heavy-duty Truck	75,000	12,556,200

2.2.3 Localization of meteorological information

The meteorological information in MOVES mainly includes temperature and relative humidity data in the study area. Temperature has a significant effect on the emission results of certain pollutants from vehicles[23], and relative humidity also significantly affects the concentration of particulate matter[24]. Monthly average temperature and relative humidity information for Taiyuan in 2022 is available on the China weather website, as shown in Figure 1.

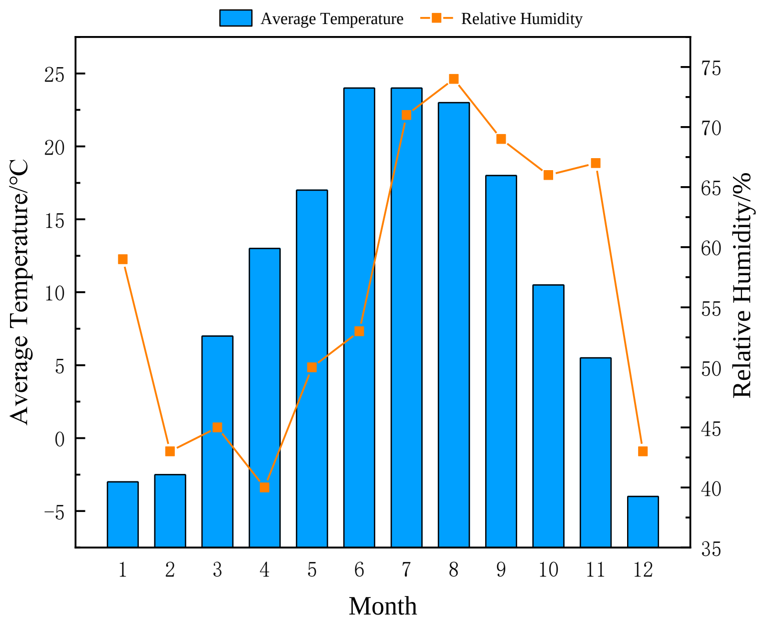

Figure 1: Average temperature and relative humidity of Taiyuan in 2022.

3. Results

3.1 Results of MOVES software simulation

In this paper, based on the MOVES model, five cities with similar latitude but different altitude to Taiyuan and three cities with similar altitude but different latitude to Taiyuan were selected as the simulated geographic regions of the software to estimate the pollutant emissions, the calculation results are shown in Figures 2 and 3.

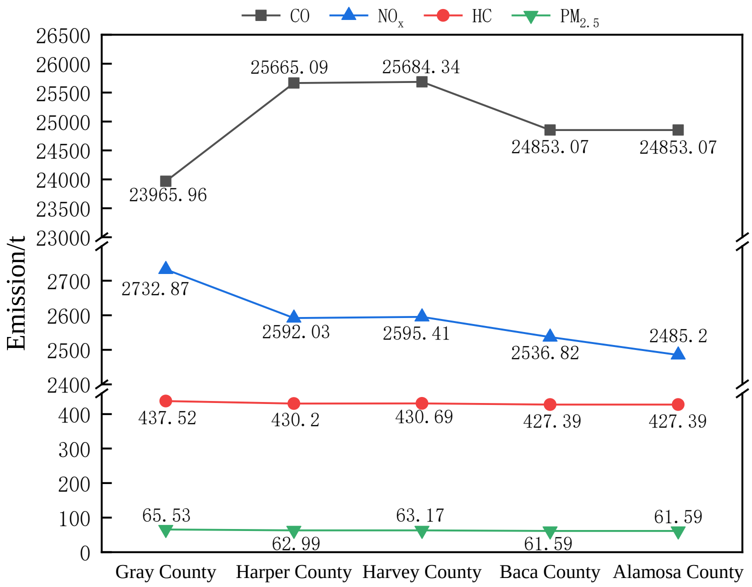

Figure 2: Comparison of the MOVES model simulation results under altitude change.

The calculated emissions of different pollutants from motor vehicles are not the same for the simulated cities at the similar latitudes but at different altitudes, as shown in Figure 2. According to the statistical graph, as the altitude difference between the simulated area and Taiyuan City changes from small to large (the cities on the horizontal coordinate are arranged in this order), the CO emissions show a trend of increasing first and then decreasing, and finally tended to be stable, with a change range of 1,718 t; the NO_x emissions show a continuous downward trend with a slight upward fluctuation in the middle of the process, with a change range of 248 t; the emissions of HC and $PM_{2.5}$ show minimal variation, with fluctuation ranges not exceeding 3% and 7%, respectively. The results show that the emissions of CO and NO_x have obvious change trend, while the emissions of HC and $PM_{2.5}$ are not significantly affected by altitude. The emissions of CO are the largest, serving as the primary pollutant, which is 9.66 times more than that of NO_x, 58.06 times more than that of HC, and 397.06 times more than that of $PM_{2.5}$ on average.

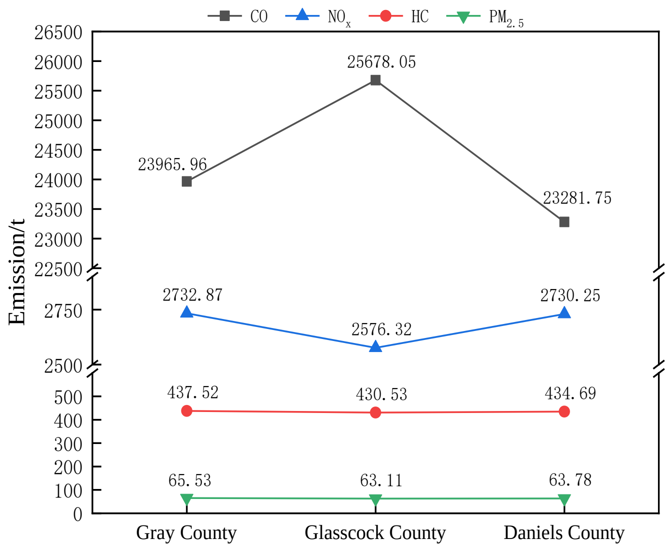

Figure 3: Comparison of the MOVES model simulation results under latitude change.

The calculated emissions of different pollutants from motor vehicles are different for the simulated cities at the similar altitudes but at different latitudes, as shown in Figure 3. According to the statistical graph, as the latitude difference between the simulated area and Taiyuan City changes from small to large, the CO emissions show a trend of increasing initially and then decreasing, with a change range of 2,396 t; the NO_x emissions show a trend of decreasing first and then increasing; the emissions of HC and $PM_{2.5}$ show minimal variation, with fluctuation ranges not exceeding 2% and 4%, respectively. The results show that the emissions of CO and NO_x have obvious change trend, and the emissions of HC and $PM_{2.5}$ are not significantly affected by latitude. The emissions of CO are the largest, serving as the primary pollutant, which is 9.07 times more than that of NO_x, 55.98 times more than that of HC, and 378.99 times more than that of $PM_{2.5}$ on average.

3.2 *Comparison with the top-down approach calculation results*

The top-down approach in the application of motor vehicle emissions quantification is a method of calculating emissions based on VMT and vehicle emission factors[25]. This approach is based on the aggregation of emissions from individual vehicles or small groups of vehicles to estimate the total emissions for a larger area or fleet. It is commonly used in air quality management and transportation planning to understand the impact of vehicle emissions on air quality at the macro level. Its calculation equation is as follows:

$$Q_j = \Sigma P_j \times E_j \times V_j \times 10^{-6} \quad (5)$$

where, Q_j is the annual emissions of CO, CO_2, NO_x, and $PM_{2.5}$ for j-type vehicles, t;

P_j is the ownership of j-type vehicles in the area, vehicle;

E_j is the emission factor for j-type vehicles (data from the "Guidelines"), g/km;

V_j is the annual average vehicle kilometers traveled (VKT) for j-type vehicles, km/vehicle.

Gray County, Kansas, as the closest city to Taiyuan in altitude and latitude among the seven cities, was selected as the simulated geographic region for MOVES to estimate motor vehicle pollutant emissions, and the results are compared with the pollutant emission calculations of Taiyuan based on the top-down approach, as shown in Table 6.

Table 6 Comparison of the results of different calculation methods.

Methods Pollutants	$CO(10^4 \times t)$	$HC(10^4 \times t)$	$NO_x(10^4 \times t)$	$PM_{2.5}(10^4 \times t)$
The top-down approach	31,395.41	962.54	9,428.40	303.40
The MOVES model	23,965.96	437.52	2,732.87	65.53

As can be seen from Table 6, the annual emissions of motor vehicle pollutants CO, HC, NO_x and $PM_{2.5}$ in Taiyuan in 2022, calculated by the top-down approach, are approximately 1.31, 2.2, 3.45 and 4.63 times the emissions calculated by the MOVES model for CO, HC, NO_x, and $PM_{2.5}$, respectively. In similar studies, Yao et al[26] estimated vehicle emissions using the MOVES model and the top-down approach, respectively, and also pointed out that the results of the MOVES model were relatively small, with a difference of 1.26 times for CO, 3.4 times for NO_x, and 4.37 times for $PM_{2.5}$, which is in accordance with the results in this paper. The main reason for the discrepancy between the results from the MOVES model and the top-down approach may be that most vehicles in Taiyuan have already met the National VI emission standard by the test year 2022, while the emission factors of different vehicle types used in the top-down approach are derived from the "Guidelines", which only counts the emission factors of vehicles that are National V emission standard and below, as a result, the pollutant emission data obtained by using the top-down approach are larger than the actual emission data. On the other hand, the MOVES model can more accurately reflect the actual motor vehicle pollutant emissions in Taiyuan in 2022 because it incorporates more local data on vehicle activity levels and other emission-related parameters.

4. Discussion

4.1 *Impacts of altitude and latitude on emissions*

When using the MOVES software to simulate pollutant emissions in non-U.S. regions, it is common practice to input local meteorological data (such as temperature, humidity, etc.) to model the emission process. Many researchers adopt this approach for emission simulations but often overlook the influence of geographic factors like latitude and altitude on emissions. In reality, meteorological conditions directly determine the results of emission calculations, and altitude and latitude are important factors in determining these meteorological conditions. Therefore, ignoring these factors may lead to biases in the simulation results, especially in the case of complex geographic conditions or inaccurate meteorological data.

The impact of altitude on emissions are mainly reflected in air density and temperature variations: As altitude increases, air density gradually decreases. Changes in air density affect engine combustion efficiency, thereby influencing vehicle emissions; Higher-altitude regions typically have lower temperatures, especially at night or during winter. Low-temperature environments affect cold-start engine emissions and increase the amount of pollutant emissions during engine startup.

The influence of latitude on emissions mainly manifests in the following ways: (1) Solar radiation: Latitude determines the intensity and seasonal variation of solar radiation. High-latitude regions receive weaker solar radiation, particularly in winter, leading to lower temperatures that affect vehicle emission characteristics. For example, colder environments prolong the time required for engines to reach optimal operating temperatures, increasing cold-start emissions. (2) Seasonal variations: Higher-latitude regions exhibit more pronounced seasonal changes, with long, harsh winters and short, mild summers. These variations influence vehicle operation patterns and emission characteristics. For instance, vehicles may undergo more frequent cold starts in winter, while high temperatures in summer may result in increased evaporative emissions. (3) Weather patterns: Latitude also affects regional weather patterns, such as precipitation, wind speed, and humidity. These meteorological conditions not only directly impact emissions, but also influence the dispersion and deposition of pollutants.

In conclusion, while directly inputting meteorological data may suffice for general emission simulations, accounting for altitude and latitude becomes crucial in cases requiring higher precision or where meteorological data is unreliable. By integrating geographic factors with meteorological data, a more comprehensive understanding of real-world emissions can be achieved, providing a more scientific basis for the formulation of pollutant control policies.

4.2 *Parameter sensitivity analysis*

Sensitivity analysis is a method for in-depth study and quantification of the sensitivity of a model or system's output data to the changes in input parameters, through which it is possible to understand the degree of influence of different variable parameters on the results[27]. Particularly in the environmental science and engineering fields, sensitivity analysis can help researchers to identify and analyze which factors have the greatest impact on the emission of environmental pollutants. In previous literature, some scholars have used sensitivity analysis to investigate the effect of each input parameter on different pollutant emission factors at the micro level of MOVES; However, no one has analyzed the effect of geographic region selection parameters on different pollutant emission factors when using MOVES to simulate pollutant emissions in non-U.S. regions, since the selection of geographic regions is mainly influenced by altitude and latitude (the reasons for which have been analyzed in the introduction section). Therefore, this paper quantifies the influence of the two indirect parameters, altitude and latitude, which determine geographic region selection, on pollutant emission factors by sensitivity analysis. By calculating and comparing the sensitivity coefficients of these parameters, it is possible to evaluate more accurately their role in influencing the pollutant emission process. The method of calculating the sensitivity coefficient used in this paper is shown in Equation 6:

$$SAF = \frac{\Delta A/A}{\Delta F/F} \quad (6)$$

where, SAF is the sensitivity coefficient;

A is the pollutant emission factor;

ΔA is the change of pollutant emission factor;

F is the input parameter;

ΔF is the change of the input parameter.

When $|SAF|>1$, the change of the parameter has a great impact on the pollutant emission factor, so it is called a sensitivity coefficient; when $0.1<|SAF|\leq 1$, the change of the parameter has a certain impact on the pollutant emission factor, so it is called a general sensitivity coefficient; when $|SAF|\leq 0.1$, the change of the parameter has a small impact on the pollutant emission factor, so it is called a non-sensitivity coefficient. When $SAF > 0$, the emission factor is positively correlated with the change of parameter, while when $SAF < 0$, the emission factor is negatively correlated with the change of parameter.

In this paper, the average values of sensitivity coefficients of altitude and latitude to different pollutant emission factors are calculated for different simulated region selections, respectively, and the results are shown in Table 7.

Table 7 Sensitivity coefficients of altitude and latitude to different pollutant emission factors for different simulated region selections.

	Simulated Regions	Latitude	Altitude(m)	Sensitivity Coefficient (SAF)			
				CO	HC	NO_x	$PM_{2.5}$
Different Altitude	Gray County	37°40′	844	-0.795	-0.001	-0.030	-0.001
	Harper County	37°11′	433				
	Harvey County	38°04′	347				
	Baca County	37°23′	1,309				
	Alamosa County	37°28′	2,299				
Different Latitude	Gray County	37°40′	844	-141.569	0.330	10.073	0.080
	Glasscock County	31°51′	801				
	Daniels County	48°46′	818				

As can be seen from Table 7, the changes in altitude have a great impact on the emission factors of CO, but relatively small impact on the emission factors of HC, NO_x, and $PM_{2.5}$. $0.1<|-0.7950|\leq 1$, therefore, the altitude is a generally sensitivity parameter relative to the CO emission factor, and the emission factors of CO are negatively correlated with changes in altitude, which means that with the increase of altitude, the emission factors of CO show a decreasing trend.

The changes in latitude have a great influence on the emission factors of CO and NO_x, while it has a certain influence on the emission factors of HC, and in comparison, the influence on the emission factors of $PM_{2.5}$ is negligible. Therefore, latitude is a sensitivity parameter for CO and NO_x, and more specifically, the changes in latitude have a much greater impact on the emission factors of CO than that of NO_x, and there is a negative correlation between the emission factor of CO and the change in latitude, which indicates that the emission factor of CO has a decreasing trend with the increase of latitude, this finding has important implications for the environmental management of transportation emissions in high-latitude regions. On the contrary, the emission factor of NO_x has a positive correlation with the change of latitude, which reveals that the emission factor of NO_x has an upward trend with the increase of latitude, this may be related to the unique climatic conditions and vehicle emission sources in high-latitude regions. For the emission factor of HC, the change in latitude cannot be ignored as a general sensitivity parameter, and its positive correlation indicates that the emission factor of HC increases with the increase of latitude, although its sensitivity is not as significant as that of CO and NO_x emission factors.

4.2 Correlation analysis by SPSS

After the sensitivity analysis, in order to further analyze and verify the accuracy of the effect of changes in altitude and latitude on the pollutants, these data are further examined at a deeper level.

The SPSS software has a powerful data processing capability that greatly simplifies the data processing process, and it is widely used in statistical analysis across various disciplines. Many scholars and researchers have used the SPSS software for data analysis and have made numerous achievements[28]. Therefore, it is feasible to analyze the trends of pollutant emissions at different altitudes and latitudes using the correlation analysis method in the SPSS software.

Common correlation analysis methods include: Pearson, which is used to measure the linear correlation between two continuous variables; Spearman, which is used to measure the hierarchical (non-linear) correlation between two variables; Kendall, another non-parametric method for measuring correlation, is suitable for evaluating the monotonic relationship between two ordered variables by comparing the consistency of data pairs to determine whether they increase or decrease simultaneously[29]. In the correlation analysis, the normality test function of the SPSS software is first used to examine the pollutant emission data under the change of altitude and latitude. If the data do not fit the normal distribution, it indicates that the assumptions of the parametric test such as Pearson's correlation are not met. In this case, it is more appropriate to use a non-parametric test such as Spearman's hierarchical correlation analysis, which does not assume normality of the data.

The Spearman correlation coefficient, usually denoted by the Greek letter ρ, is a parameter indicator used to measure the correlation of two variables, and its calculation equation is as follows:

$$\rho = 1 - \frac{6\Sigma\, d_i^2}{n(n^2-1)} \qquad (7)$$

where, ρ is the Spearman correlation coefficient;

d_i is the ranking difference between the order of altitude or latitude and the corresponding order of each pollutant emission from small to large for the ith geographic region;

n is the number of input parameters.

When performing the calculation of the Spearman correlation coefficient, the value of ρ is between -1 and 1. If $0.7<|\rho|\le 1$, it indicates that the emission is very closely related to the parameter change; if $0.4<|\rho|\le 0.7$, it indicates that the emission is closely related to the parameter change; if $0<|\rho|\le 0.4$, it indicates that the emission is not closely related to the parameter change; if $0<\rho<1$, it indicates that the emission is positively correlated with the parameter change; if $-1<\rho<0$, it indicates that the emission is negatively correlated with the parameter change. The closer the value of ρ is to 0, the weaker the correlation between emissions and parameter changes, and the closer the value of ρ is to ±1, the stronger the correlation between emissions and parameter changes.

The significance test of the SPSS software is used to evaluate the likelihood of random variation in the correlations revealed by Spearman correlation coefficient, thus providing a scientific method to distinguish whether the relationship is real or accidental. P-value is usually used for significance test, if $P<0.05$, the correlation is usually considered significant, indicating that the correlation is highly likely to have a real effect; if $P>0.05$, the correlation is considered not significant, indicating that the correlation is likely to occur by chance.

Spearman correlation analysis can assess the relationship between two variables, especially if the data does not satisfy a normal distribution or the relationship is not linear, which is important for understanding the relationship between the variables. The significance test provided by the SPSS software can help to determine whether the results are statistically significant. Therefore, the significance test and Spearman correlation analysis by the SPSS software after sensitivity analysis not only deepen the understanding of the calculation results, but also enhance the credibility and persuasion of the findings. This analysis process helps us to better understand the patterns and trends behind the data and provides reliable statistical support for subsequent research and decision-making. The results of the correlation analysis by SPSS are shown in Table 8.

Table 8 Correlation analysis of altitude and latitude with different pollutants emissions under different geographic region selection

	Simulated Regions	Latitude	Altitude(m)	Spearman correlation coefficient ρ/ P-value			
				CO	HC	NO_x	$PM_{2.5}$
Different Altitude	Gray County	37°40′	844	-0.667/0.219	-0.667/0.219	-0.7/0.18	-0.667/0.219
	Harper	37°11′	433				

	County					8	
	Harvey County	38°04′	347				
	Baca County	37°23′	1,309				
	Alamosa County	37°28′	2,299				
Different Latitude	Gray County	37°40′	844	-1/0.01	0.5/0.667	0.5/0.667	0.5/0.667
	Glasscock County	31°51′	801				
	Daniels County	48°46′	818				

As can be seen from Table 8, the significance P-values of the correlation analysis between motor vehicle pollutant emissions and altitude for the simulated geographic regions with different altitudes are all greater than 0.05, indicating that there is no statistically significant correlation between the pollutant emissions and altitude in the five simulated geographic regions with different altitudes based on the MOVES model. Moreover, the correlation calculated by Spearman correlation coefficient is likely to be the result of random fluctuations in the sample rather than by the substantial effect of altitude as a geographical factor.

By studying the relationship between latitude and motor vehicle pollutant emissions, it is found that for the pollutant CO, the Spearman coefficient is -1, it is shown that the CO emission is closely related to the change of latitude, and the correlation is negative, which indicates that the CO emission decreases significantly with the increase of latitude. This is further confirmed by the significance test of the SPSS software with a P-value (0.01) of less than 0.05, indicating that there is a significant correlation between CO emissions and latitude, while the significance of HC, NO_x and $PM_{2.5}$ are greater than 0.05 indicating that these three pollutants do not have a significant correlation with latitude. The combined analysis shows that the effect of latitude on motor vehicle pollutant emissions is more significant.

5. Conclusion

This paper focuses on how non-U.S. cities make decisions in the selection of geographic region parameters when using the MOVES software to predict motor vehicle emission in order to obtain more accurate prediction results. Firstly, the influencing factors determining the selection of geographic region were analyzed through literature review, which identified latitude and altitude as the main factors affecting geographic region selection. Then, Taiyuan City was chosen as a non-U.S. city to be simulated, by selecting the geographic region parameters with different latitudes at similar altitudes and different altitudes at similar latitudes in the software, the emissions of different pollutants were calculated. Finally, the effects of altitude and latitude on pollutant emission factors were analyzed by SAF sensitivity analysis, and the correlation between altitude and latitude and pollutant emissions was analyzed by Spearman's hierarchical correlation analysis in the SPSS software.

The results of motor vehicle pollutant simulations show that the CO emissions are the largest in Taiyuan's on-road motor vehicle emissions, followed by NOx emissions, and finally HC and PM2.5 emissions, so CO is the main pollutant in the results of motor vehicle pollutant simulations in Taiyuan City. Overall, the changes of CO and NO_x emission factors are more obvious in the four pollutant calculation results of the MOVES model with HC and $PM_{2.5}$ are less affected by the changes of altitude and latitude.

By calculating the sensitivity coefficients and the correlation analysis results of the SPSS software, it is found that the calculated sensitivity coefficient of altitude to CO is less than 1, which is a general sensitivity parameter when the latitude is determined in MOVES software, indicating that the effect of altitude on the emission factor of CO is not significant, and the correlation significance calculated by the SPSS software is greater than 0.05, which further proves that there is no significant correlation between altitude and the emission factors of CO. The sensitivity coefficients of the other three pollutants (NO_x, HC, and $PM_{2.5}$) are smaller than CO and are also not significantly correlated with altitude. As a result, the effect of altitude on the emission factors of the four pollutants is small, and the geographical factor of altitude can be disregarded when localizing the geographic region selection for the MOVES model.

The sensitivity coefficient of CO is greater than 1 when the altitude is determined in the MOVES software, indicating that latitude is an important sensitivity parameter and has a great influence on the emission factor of CO, and the correlation significance calculated by the SPSS software is 0.01, which further confirms that latitude has a significant influence on the emission factor of CO; while for the emission factor of NO_x, although the calculated sensitivity coefficient is also greater than 1, indicating that latitude also affects the emission factor of NO_x, the correlation significance calculated by the SPSS software is greater than 0.05, which may imply that the selection of the reference sites is not sufficiently representative of the wide geographic distribution because the number of the current simulated regions is limited, leading to a lack of generalizability of the results. Therefore, when using MOVES software to localize the simulation for geographic region selection, cities with similar latitude should be selected as the simulated geographic regions if the altitude is already determined to ensure the accuracy and reliability of the simulation results.

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