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Performance of Kriging and EWPM for Relative Air Pollution Exposure Risk Assessment

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ABSTRACT: This study investigates the effectiveness of the Kriging interpolation model and the Emission Weighted Proximity Model (EWPM) in assessing relative exposure risk of air pollution using results from the American Meteorological Society/EPA Regulatory Model (AERMOD) as benchmarks. We used simulated exposure risk to SO_2 in the Dallas area in Texas in this evaluation. Results suggest that the relative exposure risks to SO_2 at different locations in the study area as estimated by EWMP are closer to estimated risks from AERMOD when compared with the results calculated by Kriging. In addition, study results also indicate that the relative exposure risks calculated by Kriging are similar to those from AERMOD when the density of emission sources in the area in question is high. It is therefore concluded that relative exposure risks determined by both the Kriging interpolation method and the EWPM are acceptable when it is not possible to use AERMOD. In situations when the density of emission sources is low in the study area, EWPM is a better choice than Kriging.

Key words: Exposure estimates, Environmental pollution, Environmental modeling, GIS, Spatial analysis

INTRODUCTION

Human population has been increasing at a significant rate since the beginning of the nineteenth century. As human population increases, so does its demands on various resources. Currently, human demand for potable water, food, clean air, energy, and manufactured goods as well as the requirement for habitable land are expanding. Similarly, increase in human population across the world has resulted in the need for more land for liquid and solid waste disposal. Unfortunately, with this expansion comes with increase in the amounts of pollutants that are released into the environment. Today, more and more people including children are exposed to pollutants in the environments (Bearer 1995; Ahmed *et al.*, 2009; Rehman *et al.*, 2009).

Interactions with polluted environments (e.g. air pollution) can have an adverse impact on human health. In fact, pollution has created significant health problems in some less developed countries (Krzyzanowski *et al.*, 2002; Halek *et al.*, 2010). To establish a relationship between air pollution and health effects, researchers sometimes have to rely on exposure assessment models to assess exposure risk to a pollutant (Waller *et al.*, 1999; Ryan *et al.*, 2007; Silverman *et al.*, 2007; Zou *et al.*, 2009a; Sadashiva Murthy *et al*,. 2009; Salehi *et al.*, 2010). When facing the choices of different models, researchers have to identify effective models to conduct exposure assessments that more closely reflect reality. Currently, various groups of models for assessing a location's exposure risk have been developed, including proximity models (Maheswaran and Elliot 2003; Brender *et al.*, 2008), air dispersion models (Rogers *et al.*, 2000; Bellander *et al.*, 2001), and geo-statistical models (Mulholland 1998; Jerrett *et al.*, 2005a). Previous studies indicated that among existing exposure assessment models, the American Meteorological Society/EPA Regulatory Model (AERMOD) is generally considered to be one of the most robust and reliable models with acceptable accuracy for simulating ambient exposure concentrations (Cimorelli *et al.*, 2005; Bhaskar *et al.*, 2008; Zhang *et al.*, 2008; Zou *et al.*, 2009b).

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However, few researchers in less developed countries can employ AERMOD in their studies due to two reasons. First, AERMOD is computationally very intensive and thus can only be used in small geographic areas with a few polluting sources. For environmental health research that typically involves analysis across large geographic areas over a number of years, it is simply not practical to employ the AERMOD model in less developed countries because of the computational time needed. Second, AERMOD has significant input data requirements and few researchers in those countries have the required data to run the model. Therefore, there is a need to identify a practical model that can be used by researchers who simply do not have the resources to run AERMOD.

Other models that are easily implemented and readily accessible to researchers include the Kriging interpolation model (Mulholland 1998; Jerrett *et al.,* 2005b; Leem *et al.,* 2006) and a recently proposed model called the Emission Weighted Proximity Model (EWPM) (Zou *et al.,* 2009b). The Kriging and EWPM models are significantly less computationally intensive, and they require far less data input. However, these two models have not been evaluated in terms of robustness and reliability as it has been the case for AERMOD. The purpose of this paper is to examine whether the widely used Kriging interpolation model and the recently developed EWPM are effective methods for assessing relative exposure risk of air pollution in a large geographic area. We used results from AERMOD as a benchmark to evaluate the effectiveness of a Kriging interpolation model and the EWPM. We believe that results from this study will be useful to researchers in environmental health who are interested in environmental exposure assessment of air pollution across a large geographic area. The findings will be particularly useful to researchers working on environmental exposure assessment of air pollution in less developed countries where computing resources are limited and the data required to run AERMOD are not available.

Because of the fundamental differences between the AERMOD model and the other two models, we only compare the relative exposure risk determined by these models. By relative risk we mean the ratio between the risk values (e.g. air pollution concentrations) at a specific location (i.e. a receptor location) calculated by using each of the three models and the corresponding average of these risk values at all locations of the receptors in the area in question. In some environmental health research related analysis, it is important to use relative exposure risk assessment to distinguish different population groups exposed to different levels of risk.

MATERIALS & METHODS

AERMOD is a state-of-the-art dispersion model developed by the American Meteorological Society (AMS) and the U. S. Environmental Protection Agency (EPA) Regulatory Model Improvement Committee (AERMIC). As a near field steady-state plume model, AERMOD can simulate short-range (less than 50 km) pollutant dispersion based on planetary boundary layer turbulence structures and scaling concepts (Cimorelli et al. 2003; Holmes and Morawska 2006). The model was recommended as the regulatory model by the U.S. EPA on December 9, 2006 (Holmes *et al.,* 2006). Perry *et al.,* (1994) and Cimorelli et al. (1996, 2003, and 2005) provided detailed summaries and discussions about the principles and formulations of AERMOD.

To date, there have been many studies about the performance of AERMOD, including assessments of the accuracy and uncertainty of the model (McHugh *et al.,* 1999; Perry *et al.,* 2005; Hanna *et al.,* 2007), tests of its sensitivity (Kesarkar *et al.,* 2007; Isakov *et al.,* 2007), as well as evaluations at different temporal scales (i.e. 1-hour, 3-hour, 8-hour, monthly, and annual) (Venkatram *et al.,* 2004; Perry *et al.,* 2005; Zou *et al.,* 2010). One interesting result from these studies is that AERMOD performs much better in predicting ambient exposure concentrations at long-term (i.e. monthly and annual) temporal scales than medium-(i.e. daily) and short-term temporal scales (i.e. 1-hour; 3-hour) (Zou *et al.,* 2010). This result means that simulated ambient concentrations from AERMOD at monthly and annual scales are perhaps the best possible pollution indictors of individual exposure risk estimates at a given location. Kriging interpolation model is perhaps the most commonly used geo-statistical technique in air pollution modeling (Jerrett *et al.,* 2001). The Kriging interpolation model is known for supplying the best linear unbiased estimate of the level of air pollution (e.g. ambient air pollution concentration) at any given location in an area (Burrough and McDonnel 1998). Unlike other exposure models or interpolation techniques, Kriging predicts the level of air pollution at unmonitored locations from observational data at known locations and provides Kriging variance at unmonitored locations, which could give an accuracy assessment for the predictions. The general equations of Kriging can be expressed as shown in formula (1).

$$\hat{Z}(x_0) = \sum_{i=1}^{n} w_i(x_0) Z(x_i) \qquad (1)$$

where $\hat{Z}(x_0)$ is the best linear unbiased estimator of $Z(x_0)$ based on the value of a random field $Z(x_i)$ at unmonitored location x_0; and $w_i(x_0)$ is the weight value.

Several studies have employed Kriging to assess individual exposure risk in epidemiological studies. For example, Mulholland (1998) employed a universal Kriging technique to analyze the spatial-temporal distributions of ozone in the Atlanta metropolitan area, and found a significantly positive association between individual ozone exposure and asthma. Similarly, Jerrett et al. (2005b) produced a continuous particulate air pollution surface using the Kriging technique based upon air pollution data from 23 fixed-site monitoring observations, and found positive associations between particulate exposure and premature mortality in a small area of Hamilton, Canada. Leem et al. (2006) used an ordinary block Kriging method to predict pollutant levels for each 'dong' from the observational pollutant levels at 27 monitoring sites, and found the relationship between air pollution and preterm delivery during the third trimester of pregnancy.

The main advantage of Kriging models over AERMOD is that, Kriging requires only air pollution concentrations data at some known locations within the area under consideration to simulate pollution levels for all the unknown locations. The models can be easily implemented within the current GIS environments such as ArcGIS. However, unlike AERMOD, the performance of the Kriging model in simulating pollution levels for unknown locations with acceptable accuracy has not been conducted. Therefore, there is a need for a comparative evaluation to examine whether the Kriging interpolation model can be used as an alternative measure of exposure risk when researchers cannot use AERMOD for air pollution analysis due to the limited computation resources and/or the lack of data needed to run AERMOD.

As an improved traditional proximity model, EWPM computes individual exposure risk by taking into account the emission rate, the duration of emission of each emission source, and the total influences of emission sources around each receptor (Zou *et al.*, 2009b). Receptors are usually defined before an exposure risk assessment is conducted. Receptors are often the locations of individual monitoring sites or other unmonitored locations in the study area. In the EWPM, the exposure risk value at a receptor is calculated by the following formula (2):

$$R_{EWPM} = \sum_{i=1,\, j=1}^{n,m} \left(E_{i,j} \times T_{i,j} / D_{i,j} \right), \ (r <= \mathrm{k}; D_{i,j} >= \mathrm{c}) \tag{2}$$

where $E_{i,j}$ and $T_{i,j}$ are the emission rate and duration of emission of emission sources to which the i^{th} receptor is exposed; $D_{i,j}$ is the distance from the i^{th} receptor to the j^{th} influential emission source. The value of $D_{i,j}$ is set to 'c' (a constant value) when the distance from a receptor to an emission source is less than the given 'c'; '*i*' is the sequential number of receptors; *j* is the number of emission sources affecting the level of exposure; 'r' is the maximum distance of receptors to an emission source; 'k' is the potential influential distance which is determined by the physical and photochemistry characteristics of pollutants. The advantage of EWPM is that it can assess individual exposure risk with emission data only. However, unlike AERMOD, the performance of EWPM has not been examined (Zou *et al.*, 2009b). Therefore, there is also the need for a comparative evaluation to examine whether EWPM can be used as an alternative measure of exposure risk when researchers cannot use AERMOD for air pollution exposure assessment for any reason.

To conduct the comparative evaluations stated above, this study used the three models and sulfur dioxide (SO_2) emission data in 2002 in part of the Dallas-Fort Worth metropolitan area obtained from U.S. EPA. Fig. 1 shows the spatial extent of the study area. The study area encompasses six counties in the Dallas-Fort Worth metropolitan area with a total land area of about 13,818.6 square kilometers. The six counties include Collin, Dallas, Denton, Ellis, Johnson, and Tarrant with a combined total population of about 5,515,503 in the year 2000. It was estimated that a total of 52,876 tons of SO_2 were emitted in the year 2002 in the study area. Only point emission sources were used as data input for all the models. A total of 1,013 point emissions of SO_2 were recorded in 2002.

The overall evaluation consists of five steps. First, randomly distributed receptors for each county were set. Second, the concentrations for the receptors were simulated using AERMOD. Third, the exposure estimate values for all receptors were calculated with Kriging and EWPM. Fourth, the exposure estimate results from the three models were normalized to exposure intensity indices ranging from 0 to 1. Furthermore, based on the normalized exposure risk indices, statistical measures and exposure risk distribution maps were employed to examine the performances of Kriging and EWPM using results from AERMOD as benchmarks. The entire procedure is described in detail below.

AERMOD model was initialized using the ISC–AERMOD View 5.90 interface. The point emission sources extracted from the 2002 U.S. National Emission Inventory (NEI) were used as pollution source inputs of the model. The 2002 Integrated Surface Hourly (ISH)

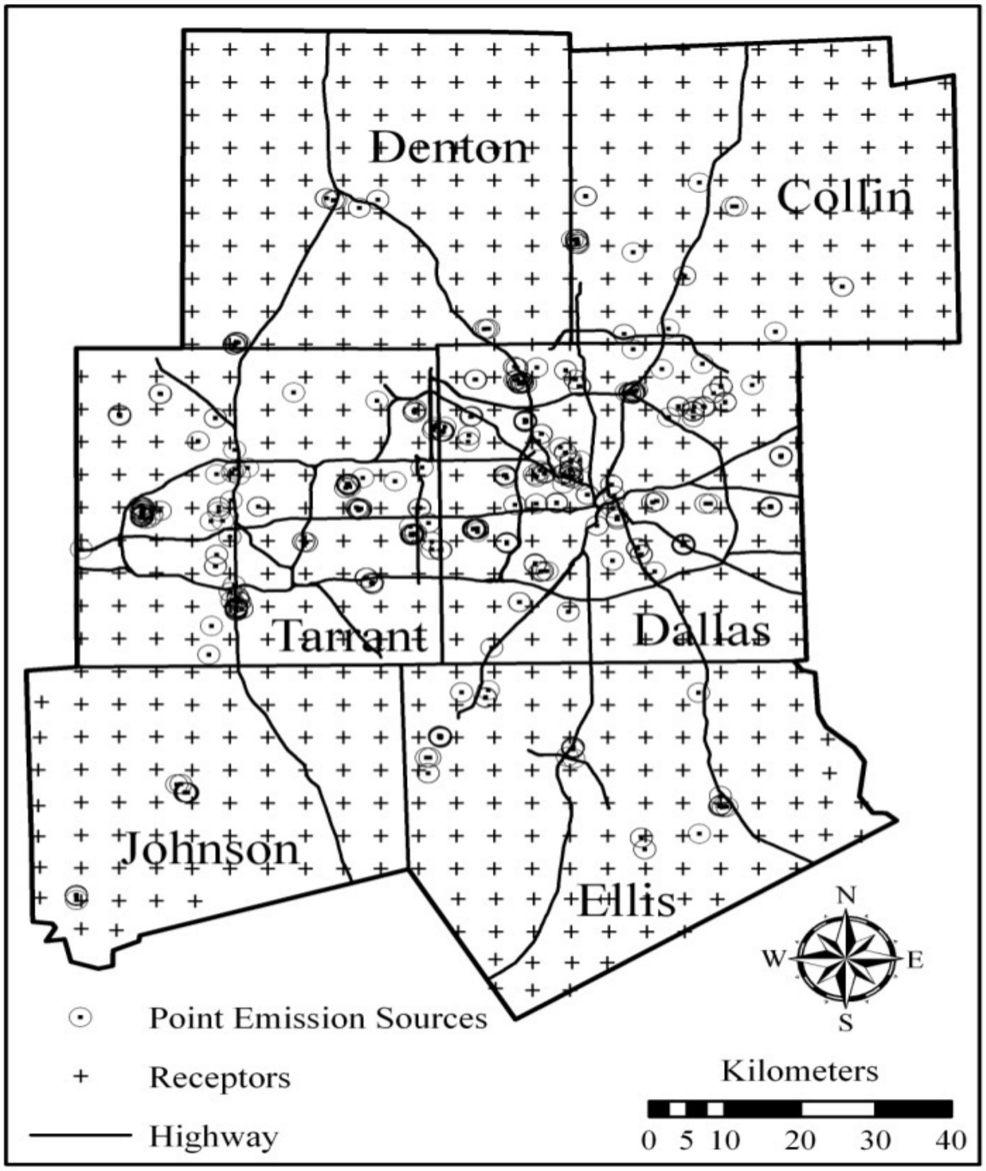

Fig.1. Point emission sources in Dallas-Fort Worth metropolitan area in 2002

database and Radiosonde database (RAOB), which were obtained from the U.S. National Climatic Data Center (NCDC) and the U.S. National Oceanic and Atmospheric Administration (NOAA), respectively, were used as input for the AERMOD Meteorological Processor (AERMET) to calculate the hourly meteorological parameters (e.g. Monin-Obukhov length and convective velocity scale) for AERMOD. During the AERMET run, the Abedo, Bowen Ratio, and Surface roughness were set to 0.15, 0.60, and 0.50 for Johnson and Ellis counties, and 0.15, 0.60, and 1.0 for Collin, Denton, Tarrant, and Dallas counties. These values are recommended by the guideline of Texas Commission on Environmental Quality (TCEQ)'s published AERMOD modeling parameters. The 1º U.S. Geological Survey (USGS) Digital Elevation Models (DEMs) at the scale of 1: 250,000 were used as input for AERMOD Terrain Processor (AERMAP) to assign the terrain heights of emission sources and receptors. For the access to all the data stated above, please refer to our previous work in detail (Zou et al. 2010). The exposure concentrations for receptors were separately simulated for each county due to the modeling extent limitation (less than 50 km from a pollution source) of AERMOD (Cimorelli *et al.*, 2003).

For the Kriging model, we used a two-step process. First, we used the ordinary Kriging module in ArcGIS Software 9.2 to generate a continuous surface of emission covering the entire study area. Second, we extracted the emission values at the locations of the receptors from the continuous surface and used the values to represent the emission quantity at the locations of the receptors.

We followed the following three steps to estimate exposure risk of each receptor using the EWPM. First, the distances of each receptor to all the emission sources within 50 km were calculated. Second, the value of 'c' was set to 0.4 km and all the distances of receptors to the emission sources that are less than 0.4 km were replaced with this threshold value. Third, the exposure risk value of each receptor was computed using formula (2).

According to the principles of the three models for calculating individual exposure risk, the results from AERMOD are exposure concentrations with unit 'μg/m^3', while the results from Kriging and EWPM are relative exposure intensities with units 'g' and 'g/km', respectively. To make the exposure risk values from these three different models comparable, the simulated values from the models were normalized using formula (3).

$$Y_i = (x_i - x_{\min})/(x_{\max} - x_{\min}) \tag{3}$$

where Y_i is the normalized exposure risk index at the location of the i^{th} receptor; x_i is the exposure estimate values or concentrations calculated or predicted by the respective model; $x_{\min}$ is the minimum value of the exposure estimates for receptors from the respective model; and $x_{\max}$ is the corresponding maximum. After the normalization, a relative exposure risk ranging in values from 0 to 1 is obtained for each location of a receptor for all three models.

A statistical evaluation of the normalized exposure risk indices from Kriging, EWPM, and AERMOD could provide an illustration of the models' performances. Similar to the statistic evaluations of model performance in previous studies (Olesen 1995; McHugh *et al.*, 1999; Luhar and Hurley 2003; Perry *et al.*, 2005), this study used a set of standard statistical measures (including bias estimate, spearman correlation coefficients, fractional bias (F_b), index of agreement (*IOA*) and robust highest concentration *(*RHC_R*)*) to evaluate the performances of Kriging and EWPM relative to the performance of AERMOD.

Bias estimate is used for measuring the difference between an estimated value and the true value of a parameter. In this study the mean of the normalized exposure risk index from AERMOD is the true value while the index from Kriging or EWPM is considered to be the estimated value. The lower the value of the *bias* estimate the lower the difference between the true value and the estimated value. *Bias* estimate is often defined as $\bar{S} - \bar{O}$, where $\bar{S}$ is the estimated value (in this study, the mean of the normalized exposure risk indices from either Kriging or EWPM) and $\bar{O}$ is the true value (in this study, the mean of the normalized exposure risk indices from AERMOD.

Spearman Correlation is used to establish the relationship between two variables. In this study, the relationship is established between the normalized exposure risk indices from Kriging and AERMOD or between the normalized exposure risk indices from EWMP and AERMOD. It is usually defined as $\sum_1^n (S-\bar{S})(O-\bar{O})/[(n-1)\delta_S \delta_O]$, where S is the normalized exposure risk indices from either Kriging or EWPM ; O is the normalized exposure risk indices from AERMOD; δ_S and δ_O are the standard deviations of exposure risk indices from Kriging or EWPM and AERMOD, respectively. The values of correlation vary from -1.0 to 1.0. A negative value indicates inverse linear relationship between the two variables. A positive value suggests there is a direct linear relationship between the two variables. A value of zero (0) indicates no relationship between the two variables.

Fractional bias is used for measuring the residual error between an estimated value and the true value of a parameter. In this study, the true value represents the normalized exposure risk indices from AERMOD while the estimated value represents the normalized exposure risk indices from EWMP or Kriging. It is often expressed as $2(S-\bar{O})(S+\bar{O})$, where $\bar{S}$ is the estimated value (in this study, the mean of the normalized exposure risk indices from either Kriging or EWPM) and $\bar{O}$ is the true value (in this study, the mean of the normalized exposure risk indices from AERMOD). The fractional bias value for an ideal model is zero.

IOA is used to determine the degree to which signs and magnitudes of two variables are related. The two variables under consideration in this study are the exposure risk indices from Kriging or EWPM and the exposure risk indices from AERMOD. *IOA* is defined as $1 - [\overline{(S-O)^2}/\overline{(|S-\bar{O}|+|O-\bar{O}|)^2}]$], where S is the normalized exposure risk indices from either Kriging or EWPM ; O is the normalized exposure risk indices from AERMOD; $\bar{S}$ is the mean of the normalized exposure risk indices from either Kriging or EWPM; and $\bar{O}$ is the mean of the normalized exposure risk indices from AERMOD. The value of *IOA* for an ideal model is 1.0 while the theoretical minimum value is 0.0 (which represents no agreement between the two variables).

RHC_R is used for examining whether the ranked estimated exposure values for a given area simulated by an exposure assessment model has the same distribution as the ranked exposure values observed in the area. RHC_R is usually defined as $C_n + (C - C_n)\ln[(3n-1)/2]$ (Cox and Tikvart 1990), where $C_{(n)}$ is the n^{th} largest estimated or truth value, C is the mean of the n-1 largest estimated or truth values, *n* is the number of estimated or truth values employed to characterize the upper end of the exposure risk distribution. In this study the estimated values are the exposure risk indices from Kriging or EWPM while the true values are the exposure risk indices from AERMOD, and *n* is the number of a quarter of receptors in each county.

RESULTS & DISCUSSION

Fig. 2 is a map illustrating the spatial distribution of the top 25 percent most risky areas within the study area generated by the three models. The first map (Fig. 2a) was generated from the normalized risk indices simulated by the AERMOD. The second map (Fig. 2b) was generated from the normalized risk indices based on simulation results from Kriging. The third map (Fig. 2c) was produced from the normalized risk indices from the EWMP. As can be seen from the three maps, in all six counties in the study area, the spatial distribution of the top 25 percent most risky areas within the study area generated by EWPM (Fig. 2c) is similar to the one generated by AERMOD (Fig. 2a). On the other hand, the spatial distribution of the top 25 percent most risky areas generated by the Kriging model (Fig. 2b) is different from that of the one generated by AERMOD (Fig. 2a), both in terms of the locations of these areas as well as the overall spatial patterns of these most risky areas.

While these maps give us a general idea about the relative correctness of the simulated exposure risk from

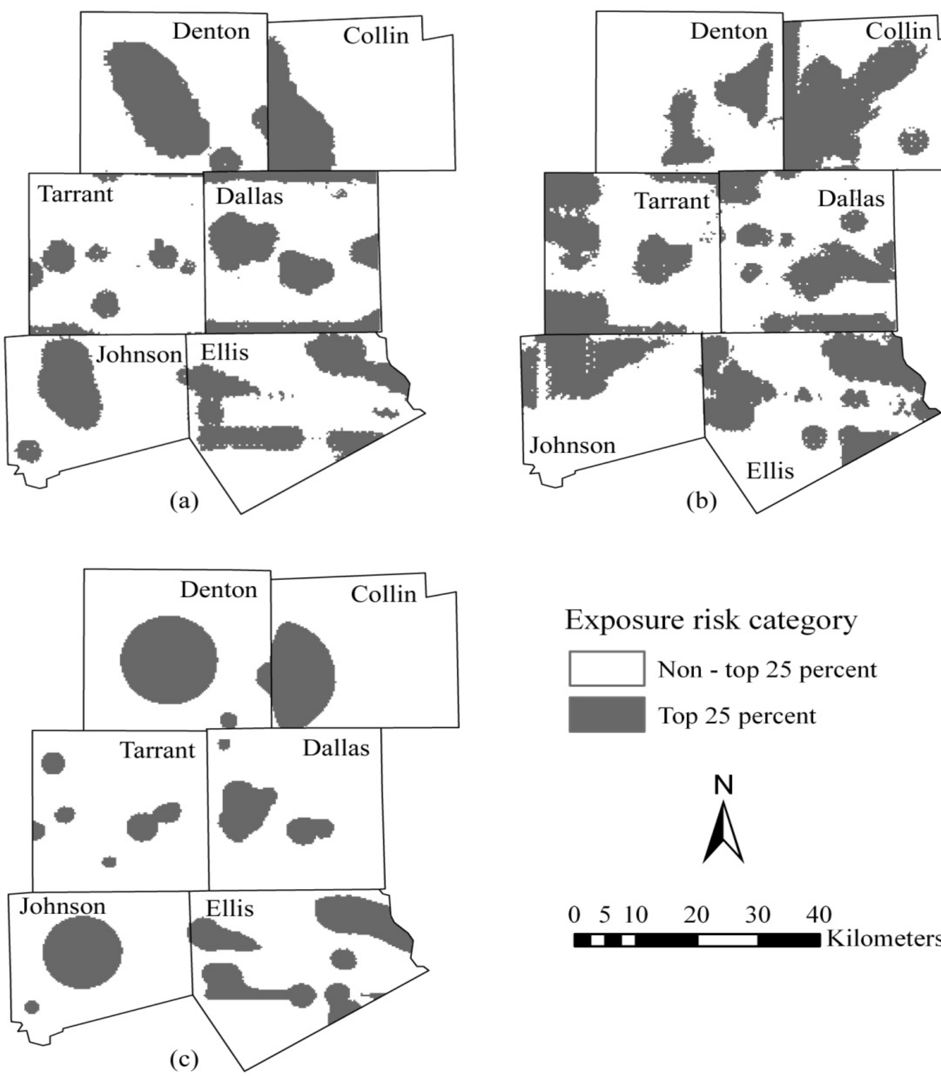

Fig. 2. Distributions of the top 25 percent of risk areas in Dallas-Fort Worth metropolitan area in 2002 simulated by different models. (a): AERMOD, (b): Kriging, and (c): EWPM

the three models, they do not provide quantifiable results measuring the effectiveness of the models. We follow the tradition of the atmospheric research community and use the set of statistical measures described in the 'MATERIALS and METHODS' section of this article to measure the performance of the three models (Olesen 1995; McHugh *et al.*, 1999; Luhar and Hurley 2003; Perry *et al.*, 2005). The results for the statistical analyses in each of the six counties are presented in Table 1.

As could be seen from Table 1, for Collin County, Kriging overestimated the exposure risk values with a mean bias estimate of 0.031 when the AERMOD normalized mean exposure risk index is used as a benchmark, whereas EWPM overestimated the benchmark value by only 0.005. In other words, overestimation from Kriging is larger than that of the EWPM. These results indicate that EWPM is a better surrogate of AERMOD than Kriging. Similar results are also observed in Denton, Johnson, Ellis, and Dallas counties. The biases of the means of the normalized exposure risk indices from Kriging are all higher than the biases from EWPM when AERMOD values are used as benchmarks with the exception of Tarrant County where the bias of the mean of the normalized exposure risk indices from EWPM is greater than the corresponding bias from Kriging.

The results from spearman correlation coefficients (*Cor.*) of the normalized risk indices are consistent with the results from the bias estimates. For all six counties, the normalized risk indices from EWPM show a stronger correlation with the normalized risk indices from AERMOD when the correlation value is compared with that between the normalized risk indices from Kriging and AERMOD. The correlation values from the six counties between Kriging and AERMOD range from -0.191 to 0.378. On the other hand, the correlation values from the six counties between EWPM and

Table 1. Performance evaluation of Kriging and EWPM in indicating exposure risk estimates in six counties with AERMOD as benchmark

Study site	Model type	*N*	*Mean*	*Bias*	*Cor.*	F_b	*IOA*	RHC_R
	AERMOD		**0.040**	**0.000**	**1.000**	**0.000**	**0.000**	**1.000**
Collin	Kriging	**446**	0.009	0.031	0.230	1.270	0.071	0.218
	EWPM		0.045	0.005	0.889	0.115	0.897	0.968
	AERMOD		**0.029**	**0.000**	**1.000**	**0.000**	**0.000**	**1.000**
Denton	Kriging	**399**	0.116	0.087	-0.191	1.200	0.463	1.248
	EWPM		0.029	0.000	0.735	0.000	0.684	1.059
	AERMOD		**0.047**	**0.000**	**1.000**	**0.000**	**0.000**	**1.000**
Johnson	Kriging	**397**	0.070	0.023	0.279	0.393	0.427	0.497
	EWPM		0.069	0.022	0.823	0.378	0.890	1.421
	AERMOD		**0.036**	**0.000**	**1.000**	**0.000**	**0.000**	**1.000**
Ellis	Kriging	**660**	0.062	0.024	0.378	0.499	0.425	2.733
	EWPM		0.045	0.011	0.688	0.295	0.571	1.471
	AERMOD		**0.011**	**0.000**	**1.000**	**0.000**	**0.000**	**1.000**
Tarrant	Kriging	**674**	0.088	0.076	0.219	1.540	0.121	1.213
	EWPM		0.127	0.116	0.754	1.671	0.413	1.565
	AERMOD		**0.015**	**0.000**	**1.000**	**0.000**	**0.000**	**1.000**
Dallas	Kriging	**971**	0.103	0.089	0.112	1.508	0.560	1.165
	EWPM		0.098	0.083	0.787	1.482	0.612	1.495

N is the number of receptors in each county

RHC_R was used to indicate the top 25 percent of the exposure risk spectrum.

Bias: $\overline{S} - \overline{O}$

Cor.: $\sum_{1}^{n}(S-\overline{S})(O-\overline{O})/[(n-1)\delta_S\delta_O]$

F_b : $2(S-\overline{O})(S+\overline{O})$

IOA: $1-[\overline{(S-O)^2}/\overline{(|S-\overline{O}|+|O-\overline{O}|)^2}]$

RHC_R: $C_n + (C - C_n)\ln[(3n-1)/2]$

AERMOD range from 0.688 to 0.889. These results further suggest that, when compared to Kriging, results from EWPM are closer to results from AERMOD.

The results from Fractional Bias (F_b) in Table 1 also show that the mean errors of the normalized risk indices from Kriging (ranging from 0.393 to 1.508) are greater than the corresponding ones from EWPM (ranging from 0.115 to 1.482) in Collin, Denton, Johnson, Ellis, and Dallas counties when the AERMOD normalized risk indices are used as benchmarks. However, in Tarrant County, the value of F_b from Kriging is 1.540, which is slightly smaller than the value of F_b (1.671) from EWPM when the AERMOD normalized risk indices are used as benchmarks. Overall, these results once again confirm that EWPM produces results closer to those from AERMOD than Kriging.

Similar to the results related to the correlation coefficients discussed above, the results from the index of agreement (*IOA*) in Table 1 show that the values of *IOA* of the normalized risk indices between EWPM and AERMOD in all six counties are much higher than the corresponding ones between Kriging and AERMOD. The values of *IOA* between EWPM and AERMOD in the six counties range from 0.413 to 0.897, while the corresponding ones between Kriging and AERMOD vary from 0.121 to 0.560. These results also indicate that, compared to Kriging, the normalized risk indices calculated by EWPM are much closer to the ones generated by AERMOD.

The results from the RHC_R analysis of top 25% exposure risk locations also show that even though EWPM overestimated or underestimated the RHC_R values for individual counties when using $\mathrm{RHC_R}$ values from AERMOD as benchmarks, the RHC_R values from EWPM are closer to the RHC_R values from AERMOD than the corresponding RHC_R values from the Kriging interpolation method. The exceptions are the RHC_R values from Tarrant and Dallas Counties where the $\mathrm{RHC_R}$ values for Kriging are closer to the benchmark $\mathrm{RHC_R}$ values than the corresponding values of RHC_R for EWPM. Overall, these results once again confirm that EWPM is a better surrogate for AERMOD than Kriging.

To summarize, this study evaluated the performance of Kriging and EWPM in estimating the exposure risk to SO_2 in part of the Dallas-Fort Worth metropolitan area using results from AERMOD as benchmarks. Overall, the results indicated that EWPM is a better surrogate for AERMOD than the Kriging interpolation method. Bias estimates of the means of the normalized exposure risk indices from EWPM and Kriging using the AERMOD normalized exposure risk index as benchmark values indicated that EWPM performs better in estimating the average exposure risk in the study area than Kriging. For the six counties in the study area, the bias estimates from EWPM in five of these six counties were lower than the corresponding bias estimates from Kriging. The only exception was Tarrant County. In Tarrant County, the bias estimate of the means of the normalized exposure risk index from EWPM is higher than the corresponding bias estimate from Kriging. However, these results could be attributed to the high density of emission sources in Tarrant County. Additional research is needed to further investigate how density of emission sources would affect the relative performance of the EWPM and Kriging.

Like many studies, this study also has some limitations. First, environmental exposure risk is induced by both point, areal, and linear emission sources. However, since Kriging and EWPM accept only point emission sources as input, the study was conducted using only point emission sources as input for all the three models (Kriging, EWPM, and AERMOD) to make the results from the three models comparable. Second, due to the modeling extent limitation (less than 50 km from emission source) of AERMOD (Cimorelli et al. 2003), the exposure risks for receptors were simulated county by county using AERMOD, Kriging, and EWPM. However, this could result in an under estimation of exposure levels for receptors located in areas close to the boundaries of each county. This is because the exposure risks of receptors near the borders of one county can be influenced by emission sources located in a neighboring county.

CONCLUSION

Accurate air pollution exposure risk assessment is critical for studying the relationships between air pollution and health outcomes. Due to insufficient air quality monitoring sites and the high cost of sampling exposure risks in non-monitored areas, researchers often rely on exposure models (e.g. air dispersion models, proximity models, and human intake models) to assess individual exposure risk at unmonitored sites. Although several exposure assessment models have been developed, few of them have been validated in terms of robustness and reliability. One of the most robust and reliable models with acceptable accuracy for simulating ambient exposure concentrations is AERMOD. However, researchers in less developed countries do not have the resources to use AERMOD for their studies covering large geographic areas due to the computational resource requirements and high data input demands of the model. This study investigated the effectiveness of Kriging interpolation method and the EWPM for calculating relative exposure risk of SO_2 in the Dallas area in Texas and compared the results of these two models from those of AERMOD. The results indicated that EWPM performed better than the Kriging interpolation method. However, it was observed that it is possible that the Kriging interpolation method may perform better than EWPM when the density of emission sources in the area in question is high. But additional studies are needed to verify this possibility. It can therefore be concluded that, both the EWPM and the Kriging interpolation methods are acceptable methods for assessing relative exposure risks of air pollution when it is not possible to use AERMOD in the area of interest. When the density of mission sources in the area in question is low, the EWPM is a preferred model than the Kriging interpolation method.

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