

• **Special Topic**

Ordinary kriging approach to predicting long-term particulate matter concentrations in seven major Korean cities

Sun-Young Kim¹, Seon-Ju Yi², Young Seob Eum³, Hae-Jin Choi², Hyesop Shin⁴,
Hyoung Gon Ryou¹, Ho Kim²

¹Institute of Health and Environment, Seoul National University, Seoul; ²Department of Epidemiology and Biostatistics, Graduate School of Public Health, Seoul National University, Seoul; ³Department of Geography, Seoul National University, Seoul; ⁴Geo Consulting & Information, Daegu, Korea

Objectives Cohort studies of associations between air pollution and health have used exposure prediction approaches to estimate individual-level concentrations. A common prediction method used in Korean cohort studies is ordinary kriging. In this study, performance of ordinary kriging models for long-term particulate matter less than or equal to 10 µm in diameter (PM₁₀) concentrations in seven major Korean cities was investigated with a focus on spatial prediction ability.

Methods We obtained hourly PM₁₀ data for 2010 at 226 urban-ambient monitoring sites in South Korea and computed annual average PM₁₀ concentrations at each site. Given the annual averages, we developed ordinary kriging prediction models for each of the seven major cities and for the entire country by using an exponential covariance reference model and a maximum likelihood estimation method. For model evaluation, cross-validation was performed and mean square error and R-squared (R²) statistics were computed.

Results Mean annual average PM₁₀ concentrations in the seven major cities ranged between 45.5 and 66.0 µg/m³ (standard deviation=2.40 and 9.51 µg/m³, respectively). Cross-validated R² values in Seoul and Busan were 0.31 and 0.23, respectively, whereas the other five cities had R² values of zero. The national model produced a higher cross-validated R² (0.36) than those for the city-specific models.

Conclusions In general, the ordinary kriging models performed poorly for the seven major cities and the entire country of South Korea, but the model performance was better in the national model. To improve model performance, future studies should examine different prediction approaches that incorporate PM₁₀ source characteristics.

Keywords Exposure prediction, Health effect, Kriging, Long-term exposure, Particulate matter

Introduction

There is an accumulation of cohort study results, mostly from North America and Europe, indicating an association between long-term exposure to particulate matter (PM) air pollution and human health [1-3]. Toxicological results indicate plausible bio-

logical pathways that support the association [4-6]. Cohort studies of air pollution, however, have an intrinsic limitation: the unavailability of individual-level measurements. To overcome that limitation, various exposure prediction approaches have been used to predict long-term concentrations of PM air pollution at cohort residences.

Correspondence:
Sun-Young Kim, PhD
1 Gwanak-ro, Gwanak-gu, Seoul 151-742,
Korea
Tel: +82-2-880-2759
Fax: +82-2-747-7662
E-mail: puhao@snu.ac.kr

Received: July 16, 2014
Accepted: August 12, 2014
Published online: September 22, 2014

This article is available from: <http://e-eh.t.org/>

The application of improved exposure prediction models can reduce measurement errors in individual-level air pollution concentrations and can provide more accurate and precise health effect estimates. Early cohort studies used relatively simple prediction approaches such as assigning an average measurement from monitors within an administrative area to the people residing in that area (area-averaging). Other approaches included application of a measurement at the closest monitor (nearest-monitor) and an average measurement that was weighted by distances from neighboring monitors (inverse-distance-weighting) [2,7,8]. These relatively simple methods, however, do not sufficiently represent the spatial variability of individual-level air pollution concentrations within an area. The use of such predictions may result in biased and/or imprecise effect estimates in health analyses. Recently, more sophisticated exposure models that rely on statistical approaches to incorporate spatial heterogeneity were developed. The two most common statistical modeling approaches are land use regression and kriging. Land use regression uses geographical variables as covariates in a regression framework, whereas kriging models correlation structures in addition to a specified mean structure [9-11].

In South Korea, recent cohort studies based on individual-level outcome data have investigated the association of short- or long-term exposure to air pollution with human health. Some of these studies used simple approaches such as area-averaging and inverse-distance-weighting methods [12-14]. Others adopted ordinary kriging to estimate spatially heterogeneous air pollution concentrations across individuals [15-19]. However, most of those studies limited their study areas to single cities. In addition, few studies included information on model evaluation focusing on the spatial prediction ability of the exposure models. This study aimed to construct and evaluate ordinary kriging models of long-term average concentrations of PM less than or equal to 10 μm in diameter (PM_{10}) during 2010 in seven major cities in, as well as the entire country of, South Korea.

Materials and Methods

From the Korean Ministry of Environment, we obtained hourly PM_{10} concentrations recorded in 2010 at 283 monitoring stations in South Korea. We selected the 2010 data as it included a larger number of monitoring sites than in other years. In South Korea, there are four types of monitoring networks: urban-ambient, near-road, regional-background, and national-background networks. Each network was established with a different purpose of air pollution sampling for pollution sources. In our analyses, we used 226 urban-ambient monitoring network sites in order to avoid influences of specific local and regional

sources, such as traffic and long-range transport from neighboring countries, on PM_{10} concentration variability. Geographic coordinates for the 226 monitoring stations were obtained from the Ministry of Environment. The coordinates were verified by comparing them with addresses in Google Maps and in the Air Korea database. Corrections were applied when site locations were mismatched. For each monitoring site, we computed daily averages from hourly PM_{10} concentrations and then averaged the daily averages to obtain an annual average. Daily averages were computed for all days in which there were more than 21 hourly measurements. To compute annual averages, we included sites for which there was at least one daily average per month for more than 9 months and less than 45 consecutive days of missing daily averages.

Kriging is a geostatistical interpolation method that predicts an estimate for an unmeasured location given the characterized mean and variance structures [20]. To characterize the mean structure, ordinary kriging assumes a constant mean over space, whereas universal kriging includes covariates in a regression framework to represent local variation. The variance feature that represents spatial dependency is assessed by using a variogram, which applies the squared differences of measurements against distances between sites for pairs of data points. The variogram is modeled, given a specified covariance function, by using three covariance parameters: range, partial sill, and nugget. The range is the distance at which a spatial correlation exists. The partial sill and nugget parameters represent spatial and non-spatial variability, respectively.

Using annual average PM_{10} concentrations across 226 sites, we derived ordinary kriging models for each of the seven major cities and for the entire country of South Korea. The seven major cities were Seoul, Busan, Incheon, Daejeon, Daegu, Gwangju, and Ulsan. We used the exponential covariance function and maximum likelihood method to estimate mean and covariance parameters. We also examined sensitivity to other covariance functions and estimation methods. Subsequently, we evaluated model performance by using leave-one-out cross-validation for city-specific models and 10-fold cross-validation for the national model. Leave-one-out cross-validation excludes the PM_{10} data for one site, constructs the model using the data for the remaining sites, predicts the PM_{10} concentration at the excluded site, and repeats the same procedure for each of the remaining sites. Ten-fold cross-validation splits all sites into 10 groups and performs the same procedure to leave-one-out cross-validation to each group of sites instead of to each site. After obtaining cross-validated predictions for all sites, mean square error (MSE) and R-squared (R^2) statistics were computed. The MSE is the average squared differences between observations and cross-validat-

ed predictions. The R^2 statistic was computed as one minus the ratio of MSE to the variance of the observations and was replaced by zero when the computed R^2 was negative.

Results

Among 226 urban-ambient monitoring sites in South Korea for 2010, 24 sites were located in Seoul (Table 1). There were less than 15 sites in Gwangju, Daejeon, Daegu, and Ulsan (6, 7, 11, and 13, respectively). Median between-monitor distances were less than 10 km in Daejeon, Ulsan, Daegu, and Gwangju (6.6, 7.5, 8.2, and 8.5 km, respectively); the distance was largest

in Busan (13.5 km). Monitoring sites were less uniformly distributed in Gwangju and Daegu than in other cities (Figure 1). The 2010 annual average PM_{10} concentration was highest in Incheon ($66.0 \mu\text{g}/\text{m}^3$) and lowest in Daejeon ($45.5 \mu\text{g}/\text{m}^3$; Table 1, Figure 2). The standard deviations of the average annual PM_{10} concentrations were larger in Busan and Daegu (9.51 and $8.48 \mu\text{g}/\text{m}^3$, respectively), and smaller in Daejeon and Seoul (2.40 and $3.33 \mu\text{g}/\text{m}^3$, respectively). Within each city, there was a tendency for similar PM_{10} concentrations to be detected at nearby monitors and less similar concentrations to be recorded at distant monitors (Figure 1).

City-specific variograms show little spatial dependency in all

Table 1. Summary statistics of city area, air pollution monitoring sites, and annual average concentrations for particulate matter less than or equal to $10 \mu\text{m}$ in diameter during 2010 by seven major cities in South Korea

City	Area (km^2)	Population density (n/km^2)	Monitoring sites								
			Distances (km)			PM_{10} annual averages in 2010 ($\mu\text{g}/\text{m}^3$)					
			n	Min	Median	Max	Min	Median	Max	Mean	SD
Seoul	605	16,865	24	1.82	11.23	26.93	40.76	49.16	54.44	49.13	3.33
Busan	766	4,625	17	2.96	13.52	39.18	31.29	49.71	67.78	48.84	9.51
Daegu	884	2,816	11	2.95	8.20	29.60	42.33	49.50	69.49	51.23	8.48
Incheon	1,027	2,639	15	0.98	11.10	46.23	44.92	55.32	66.00	55.34	5.95
Gwangju	501	2,860	6	2.46	8.46	12.69	37.82	43.28	55.99	44.89	6.65
Daejeon	540	2,749	7	2.17	6.55	16.17	38.64	43.90	45.54	43.34	2.40
Ulsan	1,058	1,054	13	1.52	7.47	21.46	41.29	46.39	54.81	47.61	4.92
South Korea	100,208	497	226	0.78	174.15	543.28	30.16	51.25	81.49	51.51	8.64

Min, minimum; Max, maximum; SD, standard deviation.

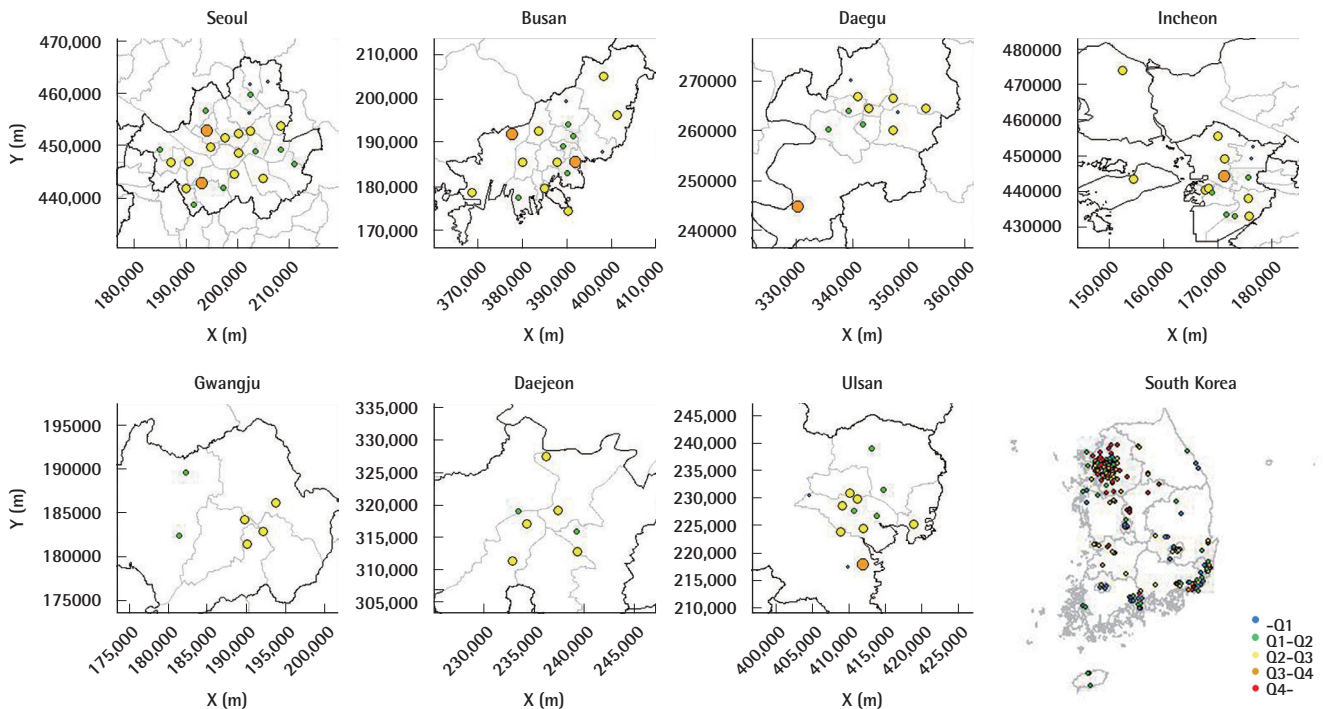


Figure 1. Maps of urban-ambient monitoring sites and annual average particulate matter less than or equal to $10 \mu\text{m}$ in diameter concentrations during 2010 in seven major cities and the entire country, South Korea.

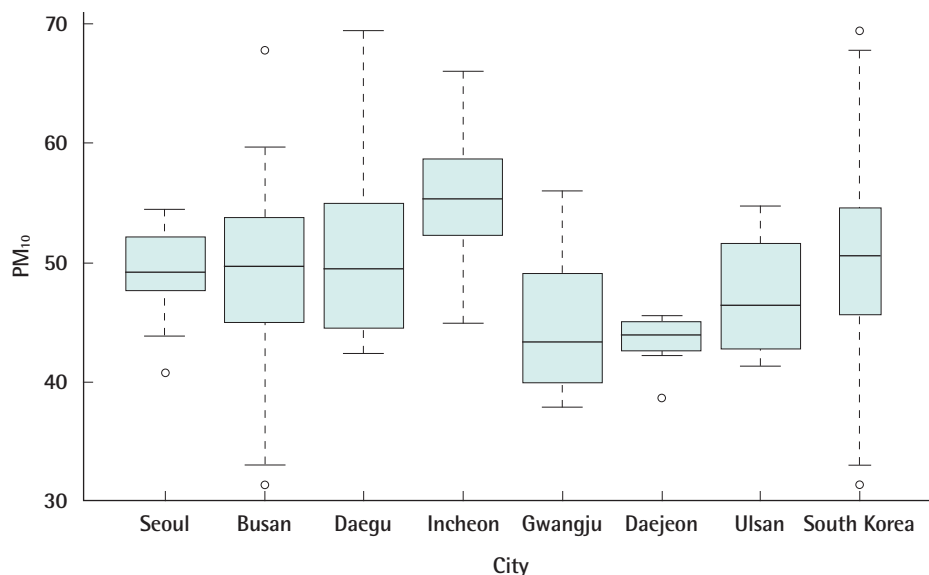


Figure 2. Box plots of particulate matter less than or equal to 10 µm in diameter (PM₁₀) annual average concentrations during 2010 across urban-ambient monitoring sites for seven major cities and the entire country, South Korea.

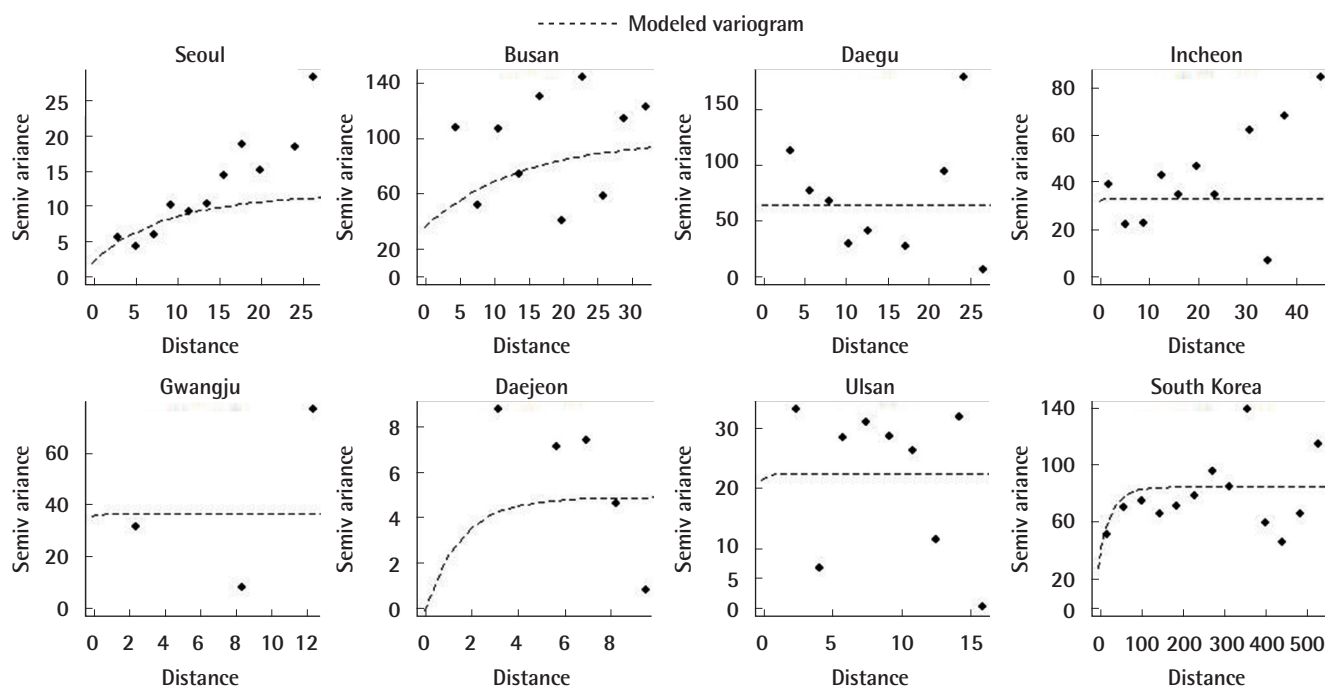


Figure 3. Empirical and modeled city-specific and national variograms for particulate matter less than or equal to 10 µm in diameter annual averages during 2010 in South Korea.

cities except Seoul and Busan (Figure 3). Estimated range and partial sill parameters were zero or close to zero in five of the cities (Table 2). The cross-validated R²s were zero and the MSEs were generally large in five of the cities (Table 2). Daejeon, with the lowest PM₁₀ variability, had a relatively small MSE despite having a low R². In Seoul and Busan, cross-validated R²s were 0.31 and 0.23, respectively. The national model produced slightly higher R² (0.36) than those in the city-specific models. The re-

sults were not sensitive to the application of different covariance functions or the use of different parameter estimation methods. Figure 4 indicates that there was good agreement between observed and cross-validation predicted PM₁₀ concentrations across the monitoring sites in Seoul, Busan, and the entire country of South Korea. However, variability in the predicted values was smaller than that in the observations, resulting in low R²s.

Discussion

We fitted city-specific and national ordinary kriging models to predict individual-level long-term concentrations of PM₁₀ in South Korea. For the seven major cities in this study, the performance of the city-specific models was generally poor. The national model performed better than the city-specific models. These findings were consistent with those obtained from sensitivity analyses that used different covariance models and parameter estimation methods.

Many cohort studies into air pollution in South Korea have used ordinary kriging to estimate individual-level or fine-scale

Table 2. Estimated covariance parameters and cross-validation statistics of ordinary kriging prediction models for particulate matter less than or equal to 10 µm in diameter annual averages during 2010 in seven major cities and the entire country, South Korea

City	Covariance parameters			Cross-validation statistics	
	Range (km)	Partial sill	Nugget	MSE	R ²
Seoul	8.80	9.47	2.19	7.67	0.31
Busan	13.79	62.62	36.27	69.36	0.23
Daegu	0.00	0.00	65.33	79.76	0.00
Incheon	0.00	0.00	33.02	37.91	0.00
Gwangju	0.00	0.00	36.84	58.23	0.00
Daejeon	1.47	4.89	0.00	5.86	0.00
Ulsan	0.00	0.00	22.38	26.26	0.00
South Korea	29.46	55.84	28.97	47.72	0.36

MSE, mean square error.

area-level concentrations of air pollution including PM₁₀ [15-19]. Some of these studies have reported evaluation of ordinary kriging models based on the leave-one-out cross-validation approach [17-19]. Leem et al. [17] and Seo et al. [18] reported good agreement between observed and cross-validation predicted PM₁₀ concentrations in Incheon and the seven major cities included in our study. Because these studies used temporally- and spatially-resolved health outcomes such as preterm birth and low birth weight, their ordinary kriging was performed on a monthly scale. Large temporal variability relative to spatial variability in predicted monthly concentrations over space might have contributed to good agreements in those studies. The level of agreement may decline when the analysis focuses on spatial prediction ability after excluding temporal variability. Kim et al. [21] in a study of six US metropolitan cities showed that temporal variability in two-week average predictions of PM <2.5 microm in diameter (PM_{2.5}) components obtained from spatio-temporal prediction models was larger than spatial variability [21]. When temporal variability was adjusted, cross-validated R²s dramatically decreased depending on the city and the PM_{2.5} component. In an assessment of annual average PM₁₀ concentrations in Ulsan, Son et al. [19] compared MSEs from ordinary kriging with those obtained from area-averaging, nearest-monitor, and inverse-distance-weighting methods by using cross-validation. Although the MSE of the ordinary kriging model was smaller than the MSE of the other three approaches, all four methods produced large MSEs that were greater than the vari-

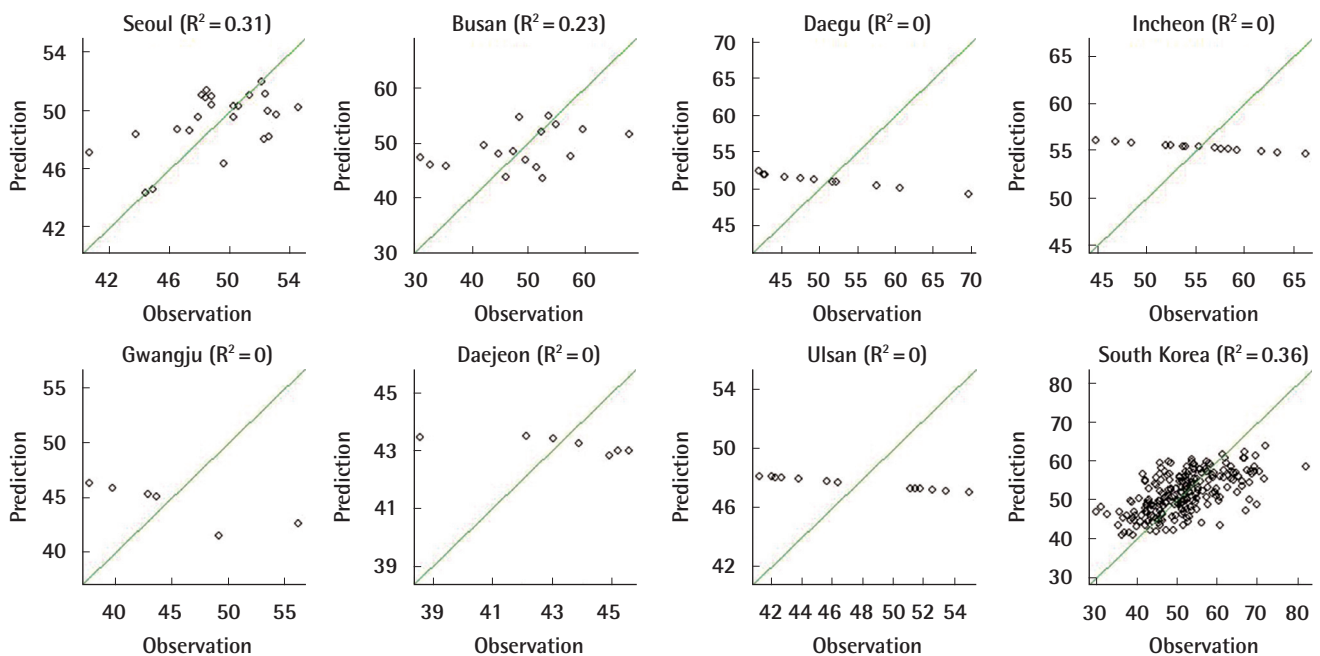


Figure 4. Scatter plots of observed and cross-validation predicted annual averages of particulate matter less than or equal to 10 µm in diameter during 2010 in seven major cities and the entire country, South Korea.

ance of the data, indicative of poor model performance. In order to assess model performance, we computed R^2 values (in addition to MSE) which show the proximity to unity of the relationship between observed and cross-validation predicted values relative to the variability in the data. Evaluation of spatial prediction ability in exposure prediction models is crucial for providing spatially-predictable individual air pollution estimates to future cohort studies that will examine the association of air pollution with critical health endpoints such as event occurrence and progression of chronic diseases.

Performance of the ordinary kriging models developed in the present study was generally poor, possibly because of our use of a simple mean structure. Ordinary kriging assumes a mean that is constant over space. However, PM air pollution concentrations are affected by local and/or regional sources, which can result in fine- and/or regional-scale spatial heterogeneity [6,22]. For example, PM_{10} concentrations at a monitor located next to a busy road or a power plant could be markedly high and may be clearly different from those at nearby monitors. Previous studies of source apportionment for PM air pollution in Daejeon, South Korea showed that motor vehicle and combustion/industry sources contributed substantially to PM_{10} concentrations [23, 24]. Exposure prediction models may not accurately represent actual PM_{10} concentrations over space if the contributing local and/or regional sources are not considered in the models. We suggest that future studies investigate exposure prediction models that incorporate geographical variables in land use regression, either alone or combined with a spatial correlation structure within a universal kriging framework.

In addition to our use of a simple mean structure, the small number of monitoring sites and/or the presence of insufficient spatial variability could have resulted in the poor model performance in this study. In the five cities with R^2 's equal to zero, the numbers of monitoring sites were less than 15 and/or spatial variability of PM_{10} concentrations was relatively small. A simulation study showed that ordinary kriging models produced an increase in MSE when the number of monitoring sites decreased from 22 to 12 [25]. We excluded approximately 60 monitoring sites from near-road and regional- and national-background networks that were established to monitor local or regional sources, because ordinary kriging captures spatial variability based only on large-scale spatial correlation. Land use regression or universal kriging approaches would allow inclusion of these monitors, as they would incorporate variables related to the PM sources. In addition, variability in PM_{10} concentrations in the seven major cities was small with coefficients of variation of 8-19% in the cities and 17% in the entire country. Variability could increase if monitoring sites from other networks are included.

We found better model performance in the national kriging model than in the city-specific models. The better performance of the national model further indicates the importance of increasing the number of monitoring sites and the spatial variability in air pollution data. For the cities in our study with low numbers of monitoring sites, it may be preferable to use predictions from the national model rather than those from the city-specific models when the association between long-term PM concentrations and health outcomes is to be assessed in epidemiological studies.

It is important to develop exposure prediction models that accurately represent spatial variability in air pollution concentrations for the goal of health effect analyses. Recent cohort studies developed more sophisticated prediction approaches that incorporate geographical and meteorological variables in order to reduce measurement errors in exposure estimation and to provide valid and precise effect estimates in health analyses [9,26,27]. A simulation study reported larger bias in health effect estimates of predictions obtained from the nearest-monitor method than from ordinary kriging, when there was an underlying spatial structure in air pollution concentrations [25]. In a simulation study that compared health effect estimates of predicted long-term $PM_{2.5}$ concentrations obtained from ordinary kriging to those from land use regression, the kriging-derived predictions produced an unacceptable level of bias in the health effect estimates [28]. Recent papers described various features of measurement errors in exposure estimates from exposure prediction models that can result in bias and uncertainty of health effect estimates and development of measurement error-correction methodology [29,30]. Given the increase in the number of cohort studies focusing on assessing causal associations with air pollution in South Korea, it is necessary to develop exposure prediction models that will produce scientifically meaningful results from epidemiological analyses.

This study suggests that an ordinary kriging model alone would be insufficient for predicting PM_{10} concentrations that represent spatial variation across individuals and for assessing long-term associations of PM_{10} with health endpoints in seven major cities, South Korea. Future studies should investigate alternative prediction approaches to better represent individual-level PM_{10} concentrations. Such alternative approaches should incorporate geographical characteristics related to specific sources of PM_{10} .

Acknowledgements

This research was supported by the Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education (900-20130078).

Conflict of Interest

The authors have no conflicts of interest with material presented in this paper.

References

1. Beelen R, Raaschou-Nielsen O, Stafoggia M, Andersen ZJ, Weinmayr G, Hoffmann B, et al. Effects of long-term exposure to air pollution on natural-cause mortality: an analysis of 22 European cohorts within the multicentre ESCAPE project. *Lancet* 2014; 383(9919):785-795.
2. Laden F, Schwartz J, Speizer FE, Dockery DW. Reduction in fine particulate air pollution and mortality: extended follow-up of the Harvard Six Cities study. *Am J Respir Crit Care Med* 2006;173(6): 667-672.
3. Pope CA 3rd, Burnett RT, Thun MJ, Calle EE, Krewski D, Ito K, et al. Lung cancer, cardiopulmonary mortality, and long-term exposure to fine particulate air pollution. *JAMA* 2002;287(9):1132-1141.
4. Brook RD, Rajagopalan S, Pope CA 3rd, Brook JR, Bhatnagar A, Diez-Roux AV, et al. Particulate matter air pollution and cardiovascular disease: an update to the scientific statement from the American Heart Association. *Circulation* 2010;121(21):2331-2378.
5. Sun Q, Hong X, Wold LE. Cardiovascular effects of ambient particulate air pollution exposure. *Circulation* 2010;121(25):2755-2765.
6. US Environmental Protection Agency. Integrated science assessment for particulate matter (final report); 2009 [cited 2014 Sep 12]. Available from: <http://cfpub.epa.gov/ncea/cfm/recordisplay.cfm?deid=216546>.
7. Lipsett MJ, Ostro BD, Reynolds P, Goldberg D, Hertz A, Jerrett M, et al. Long-term exposure to air pollution and cardiorespiratory disease in the California teachers study cohort. *Am J Respir Crit Care Med* 2011;184(7):828-835.
8. Miller KA, Siscovick DS, Sheppard L, Shepherd K, Sullivan JH, Anderson GL, et al. Long-term exposure to air pollution and incidence of cardiovascular events in women. *N Engl J Med* 2007;356(5): 447-458.
9. Eeftens M, Beelen R, de Hoogh K, Bellander T, Cesaroni G, Cirach M, et al. Development of Land Use Regression models for PM(2.5), PM(2.5) absorbance, PM(10) and PM(coarse) in 20 European study areas; results of the ESCAPE project. *Environ Sci Technol* 2012;46(20):11195-11205.
10. Hoek G, Beelen R, de Hoogh K, Vienneau D, Gulliver J, Fischer P, et al. A review of land-use regression models to assess spatial variation of outdoor air pollution. *Atmos Environ* 2008;42(33):7561-7578.
11. Jerrett M, Burnett RT, Ma R, Pope CA 3rd, Krewski D, Newbold KB, et al. Spatial analysis of air pollution and mortality in Los Angeles. *Epidemiology* 2005;16(6):727-736.
12. Kim E, Park H, Hong YC, Ha M, Kim Y, Kim BN, et al. Prenatal exposure to PM₁₀ and NO₂ and children's neurodevelopment from birth to 24 months of age: mothers and Children's Environmental Health (MOCEH) study. *Sci Total Environ* 2014;481:439-445.
13. Lim YH, Kim H, Kim JH, Bae S, Park HY, Hong YC. Air pollution and symptoms of depression in elderly adults. *Environ Health Perspect* 2012;120(7):1023-1028.
14. Son JY, Bell ML, Lee JT. Survival analysis of long-term exposure to different sizes of airborne particulate matter and risk of infant mortality using a birth cohort in Seoul, Korea. *Environ Health Perspect* 2011;119(5):725-730.
15. Hwang SS, Kang S, Lee JY, Lee JS, Kim HJ, Han SK, et al. Impact of outdoor air pollution on the incidence of tuberculosis in the Seoul metropolitan area, South Korea. *Korean J Intern Med* 2014;29(2): 183-190.
16. Kim BJ, Kwon JW, Seo JH, Kim HB, Lee SY, Park KS, et al. Association of ozone exposure with asthma, allergic rhinitis, and allergic sensitization. *Ann Allergy Asthma Immunol* 2011;107(3):214-219.
17. Leem JH, Kaplan BM, Shim YK, Pohl HR, Gotway CA, Bullard SM, et al. Exposures to air pollutants during pregnancy and preterm delivery. *Environ Health Perspect* 2006;114(6):905-910.
18. Seo JH, Leem JH, Ha EH, Kim OJ, Kim BM, Lee JY, et al. Population-attributable risk of low birthweight related to PM10 pollution in seven Korean cities. *Paediatr Perinat Epidemiol* 2010;24(2): 140-148.
19. Son JY, Bell ML, Lee JT. Individual exposure to air pollution and lung function in Korea: spatial analysis using multiple exposure approaches. *Environ Res* 2010;110(8):739-749.
20. Banerjee S, Carlin BP, Gelfand AE. Hierarchical modeling and analysis for spatial data. Boca Raton: CRC Press; 2004, p. 21-68.
21. Kim SY, Sheppard L, Bergen S, Szapiro AA, Sample PD, Kaufman JD, et al. Prediction of fine particulate matter chemical components for the Multi-Ethnic Study of Atherosclerosis cohort: a comparison of two modeling approaches [cited 2014 Aug 28]. Available from: <http://biostats.bepress.com/uwbiostat/paper398>.
22. Health Effects Institute (HEI). Traffic-related air pollution: a critical review of the literature on emissions, exposure, and health effects [cited 2014 Sep 12]. Available from: <http://pubs.healtheffects.org/view.php?id=334>.
23. Chung YS, Kim SH, Moon JH, Kim YJ, Lim JM, Lee JH. Source identification and long-term monitoring of airborne particulate matter (PM_{2.5}/PM₁₀) in an urban region of Korea. *J Radioanal Nucl Chem* 2005;267(1):35-48.
24. Lim JM, Lee JH, Moon JH, Chung YS, Kim KH. Source apportionment of PM₁₀ at a small industrial area using Positive Matrix Factorization. *Atmos Res* 2010;95(1):85-100.
25. Kim SY, Sheppard L, Kim H. Health effects of long-term air pollution: influence of exposure prediction methods. *Epidemiology* 2009;20(3):442-450.
26. Sampsona PD, Szpiro AA, Sheppard L, Lindström J, Kaufman JD. Pragmatic estimation of a spatio-temporal air quality model with irregular monitoring data. *Atmos Environ* 2011;45(36):6593-6606.
27. Yanosky JD, Paciorek CJ, Suh HH. Predicting chronic fine and coarse particulate exposures using spatiotemporal models for the Northeastern and Midwestern United States. *Environ Health Perspect* 2009;117(4):522-529.
28. Alexeeff SE, Schwartz J, Kloog I, Chudnovsky A, Koutrakis P, Coull BA. Consequences of kriging and land use regression for PM_{2.5} predictions in epidemiologic analyses: insights into spatial variability using high-resolution satellite data. *J Expo Sci Environ Epidemiol*

- ol 2014. Doi: <http://dx.doi.org/10.1038/jes.2014.40>.
29. Szpiro AA, Sheppard L, Lumley T. Efficient measurement error correction with spatially misaligned data. *Biostatistics* 2011;12(4): 610-623.
30. Szpiro AA, Paciorek CJ. Measurement error in two-stage analyses, with application to air pollution epidemiology. *Environmetrics* 2013;24(8):501-517.