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DOI:

[10.1016/j.scitotenv.2017.03.094](https://doi.org/10.1016/j.scitotenv.2017.03.094)

[Link to publication record in King's Research Portal](#)

Citation for published version (APA):

Lee, M., Brauer, M., Wong, P., Tang, R., Tsui, T. H., Choi, C., Cheng, W., Lai, P.-C., Tian, L., Thach, T.-Q., Allen, R., & Barratt, B. (2017). Land use regression modelling of air pollution in high density high rise cities: A case study in Hong Kong. *Science of the Total Environment*, 592, 306-315.
<https://doi.org/10.1016/j.scitotenv.2017.03.094>

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Land use regression modelling of air pollution in high density high rise cities: A case study in Hong Kong

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Keywords: Land use regression, Air pollution, GIS, Exposure assessment

Abstract

Land use regression (LUR) is a common method of predicting spatial variability of air pollution to estimate exposure. Nitrogen dioxide (NO₂), nitric oxide (NO), fine particulate matter (PM_{2.5}), and black carbon (BC) concentrations were measured during two sampling campaigns (April-May and November-January) in Hong Kong (a prototypical high-density high-rise city). Along with 365 potential geospatial predictor variables, these concentrations were used to build two-dimensional land use regression (LUR) models for the territory. Summary statistics for combined measurements over both campaigns were: a) NO₂ (*Mean* = 106 µg/m³, *SD* = 38.5, *N* = 95), b) NO (*M* = 147 µg/m³, *SD* = 88.9, *N* = 40), c) PM_{2.5} (*M* = 35 µg/m³, *SD* = 6.3, *N* = 64), and BC (*M* = 10.6 µg/m³, *SD* = 5.3, *N* = 76). Final LUR models had the following statistics: a) NO₂ (*R*² = 0.46, RMSE = 28 µg/m³) b) NO (*R*² = 0.50, RMSE = 62 µg/m³), c) PM_{2.5} (*R*² = 0.59; RMSE = 4 µg/m³), and d) BC (*R*² = 0.50, RMSE = 4 µg/m³). Traditional LUR predictors such as road length, car park density, and land use types were included in most models. The NO₂ prediction surface values were highest in Kowloon and the northern region of Hong Kong Island (downtown Hong Kong). NO showed a similar pattern in the built-up region. Both PM_{2.5} and BC predictions exhibited a northwest-southeast gradient, with higher concentrations in the north (close to mainland China). For BC, the port was also an area of elevated predicted concentrations. The results matched with existing literature on spatial variation in concentrations of air pollutants and in relation to important emission sources in Hong Kong. The success of these models suggests LUR is appropriate in high-density, high-rise cities.

1. Introduction

Land use regression (LUR) modelling is a statistical modelling method commonly used to estimate spatial variation in air pollution concentrations for population exposure assessment. The technique associates spatially heterogeneous air quality measurements with geospatial predictors. LUR models provide a relatively robust method for spatial prediction while having a lower sampling effort compared to geo-statistical models, and a lower data requirement than dispersion models (Hoek et al., 2008).

High-density high-rise cities have become a more prominent feature globally. Air quality is a significant public health risk in many of these cities (World Health Organization, 2016). Modelling concentrations and assessing exposure in these cities are important to better understand the risk and potential interventions. As high-density, high-rise cities become increasingly common in Asia, it is important to understand how modelling spatial variation and exposure may differ from European and North American cities where most LUR modelling has been focused (Hoek et al., 2008). European and North American cities likely have lower pollution and building densities, and fewer small-scale dispersed pollution sources than high-density, high-rise cities.

Hong Kong, a coastal city located in southern China, is one of the most advanced examples of a high-density, high-rise city with significant air quality issues. As one of the

most densely populated regions in the world, Hong Kong has an average population density of 6,690 people/km² with a total population of 7,240,000 as of mid-2014 (Information Services Department, 2015). Due to the clustering of developments and mountainous terrain, less than 25% of the total territory of 1,104 km² is developed, leading to extremely high population densities in some areas such as the district of Kwun Tong with density of 57,250 people/km² (GovHK, 2015; Information Services Department, 2015). The clustering effect is further enhanced by the prevalence of high-rise buildings in Hong Kong.

The objective of this study (HK2D) was to create ground level LUR models for NO₂, NO, PM_{2.5}, and BC to enhance understanding of the spatial distribution of traffic-related air pollutants and describe spatial features that are important determinants of pollutant concentration variability in Hong Kong. However, the presence of high-density high-rise developments within Hong Kong also tests the viability of LUR modelling for other cities with similar urban form. This study was conducted as part of a larger project which integrates two dimensional LUR models with vertical and population mobility components to enhance the estimation of population exposure to air pollution in Hong Kong.

2. Materials and Methods

2.1 Field Sampling

Two sampling campaigns, corresponding to warm and cool seasons, were conducted to measure roadside NO₂, NO, PM_{2.5}, and BC concentrations. Sampling of multiple pollutants over different seasons provided a more complete understanding of long-term air quality patterns. NO₂ and NO were collected together using Ogawa badges (Ogawa USA, Pompano Beach, USA) while PM_{2.5} and BC were sampled using TSI SidePak AM510 Personal Aerosol Monitors (TSI Incorporated, Shoreview, USA) and microAeth AE51 (AethLabs, San Francisco, USA) monitors, respectively, with both deployed in the same monitoring box. The HK2D sampling was coordinated with an NO₂ monitoring campaign conducted by the Environmental Protection Department (EPD) of Hong Kong using Gradko (Gradko International Limited, Winchester, England) diffusion tube samplers. HK2D and EPD sampling occurred during the same periods at many of the same locations. EPD NO₂ data was used to supplement the HK2D NO₂ data.

The first HK2D sampling campaign (SC1) ran from April 24, 2014 to May 30, 2014 (37 days) with EPD sampling also conducted within this period. The second (SC2) campaign was split into two time periods. PM_{2.5} and BC sampling ran from November 18, 2014 to January 6, 2015 (50 days). Due to civil protests in Hong Kong at the end of 2014, which affected traffic patterns, the EPD delayed their sampling from November 2014 to January 2015 (Jan. 3, 2015 to Jan. 26, 2015, 24 days) and the HK2D NO₂ and NO sampling was similarly delayed.

In total, 90 of 100 HK2D sampling sites were selected from the EPD 173 campaign sites. The remaining 73 EPD sites were excluded due to proximity to overpasses. The EPD sites were selected to capture maximum variation in concentrations within districts and were all roadside sites mainly in developed areas. Roadside sites located on a range of road types were used for sampling (final interpolated total values ranged from zero to 623,000). Developed regions of Hong Kong are generally density built up. Outdoor locations at ground-level that can be used for sample collection are therefore mainly found by roads, as in the case in many cities. For these reasons this study follows a common practice in ground-level LUR modeling of collecting samples on lampposts next to roads. While the Hong Kong territory does include large areas without urban development, these areas are not populated and therefore sampling in these locations is of little value for population human exposure assessment. In addition, such locations are often not readily accessible.

An additional 10 sites were selected for the HK2D campaigns to expand spatial coverage and capture variation in land use (Figure 1). Due to logistics limitations, pollutants were sampled at a subset of these 100 sites with NO₂ samplers deployed at 97 sites (EPD – 97 and HK2D – 43 [SC1] and 63 [SC2]), NO at 43 (SC1) and 63 (SC2), and PM_{2.5} and BC at 84 sites. Site selection was based on geographic location, annual average daily traffic (AADT), land use, and population density, aiming to capture a full range of values for these factors.

Figure 1: Map of sampling sites in Hong Kong

Samplers were preferentially deployed on lampposts approximately 2.5 m off the ground. Traffic signs, trees, and portable posts were used in a limited number of cases when a lamppost was not available. Diffusion samplers (Ogawa badges and diffusion tubes) were deployed for durations of 15 to 21 days. Ogawa badges were outfitted with two filters (one to capture NO₂ and one to capture NO_x with the difference used to calculate NO concentrations) and hung within a white shelter to protect them from sunlight and rain. The EPD deployed three diffusion tubes per site during each campaign. SidePak and microAeth sensors were deployed for 24 hours, with the exception of four two-week sampling sites, which were used for quality control and to develop temporal correction factors. These sites included the three EPD roadside air quality monitoring sites. The fourth site was one of the roadside sites during SC1 but was moved to a rooftop regulatory monitoring site in SC2. Each pair of PM_{2.5} and BC sensors was housed in a waterproof box with sampling lines run through a downward facing hole and small funnel to protect from rain ingress.

Ogawa badges and HK2D diffusion tubes (only in SC2) were co-located at 10 of the EPD rooftop air quality monitoring stations (AQMS). A SidePak and microAeth were deployed at one of these sites in SC2 for two weeks (Table 1). Ogawa badges, diffusion tubes, SidePaks, and mircoAeths were also co-located at each of the three roadside regulatory monitoring sites. Duplicate Ogawa badges (N= 8 and 11 in SC1 and SC2, respectively) were used in each campaign along with field and lab (N= 8 and 11 in SC1 and SC2, respectively) blanks.

Table 1: Summary of sampling campaigns

Pollutant	Equipment	Exposure Time	# Sites Sampled Sampling Period
NO	Ogawa	2-3 weeks	SC1 (N=43) 2014-04-25 to 2014-05-14
NO ₂			SC2 (N=62) 2015-01-03 to 2015-01-26
	Diffusion Tube	3 weeks	SC1 (N=89) 2014-04-21 to 2014-05-12
			SC2 (N=89) 2015-01-13 to 2015-01-24
	Combined		SC1 (N=97) SC2 (N=97)
PM _{2.5}	SidePak	24 hours	SC1 (N=80) 2014-04-24 to 2014-05-15
BC	microAeth		SC2 (N=81) 2014-11-18 to 2014-12-12
PM _{2.5}	SidePak	2 weeks	SC1 (N=4) 2014-04-24 to 2014-05-08
BC	microAeth		SC2 (N=3) 2014-11-18 to 2014-12-17

2.2 Pollutant Concentrations

Ogawa badge NO₂ and NO were analysed using ion chromatography in the Occupational and Environmental Hygiene laboratory of The University of British Columbia. Diffusion

tubes were analyzed by Gradko Environmental using U.V. spectrophotometry (Gradko, 2012).

A blank correction, the average of the appropriate diffusion samplers' field blanks deployed during the sampling campaign, was subtracted from the raw NO₂ and NO concentrations. The diffusion tubes were then adjusted towards the Ogawa badges to normalize NO₂ and NO concentrations for modeling. This correction factor was calculated by linear regression with a zero-intercept.

The first and last 5 minutes of each continuous monitoring period (PM_{2.5} and BC) were removed to account for set-up and collection of samplers. The data were also cleaned to remove periods of negative values, after filter changes, when sensors were dislodged, or during periods of significant signal noise. PM_{2.5} data were scaled to the reference Filter Dynamic Measurement System (FDMS) monitors housed in the AQMS using a correction factor derived from linear regression based on the two-week co-location runs. This bias correction factor was scaled to account for individual SidePak monitor differences using the co-location data from the 48-hour runs of all SidePaks and mircoAeths at the beginning and end of the sampling campaigns. BC was not bias adjusted as the reference monitors were not operating during the co-location period and therefore no comparison data were available. Filter loading of the microAeths, which causes under sampling of the BC level as BC mass builds up on the filter, was corrected for using the Virkkula method (Virkkula et al., 2007), where corrected BC = (1 + k * attenuation) * uncorrected BC. The k factor was derived by comparing changes in readings immediately prior to and following the microAeth's filter change. After adjustments, samples with less than 18 hours of PM_{2.5} or BC data were removed, as capture rates of less than 75% were deemed inadequate to represent the 24-hour concentration. Sites with 36 hours or more of capture (such as the two-week sites) were split evenly into subsets (18 to 35 hours) and one subset was randomly chosen to represent the site.

A temporal adjustment was then applied to all concentration data to remove the effects of temporal variation on captured concentrations, due to fluctuations in the baseline concentrations when the exposure periods varied between sampling sites. This was created by calculating the baseline concentrations for the sampling period using the average daily concentrations from all urban rooftop AQMS and then dividing by the baseline concentration for the whole sampling period:

$$CF_T = \frac{\frac{\sum_{k=1}^{11} Mean_{SP,k}}{11}}{\frac{\sum_{k=1}^{11} Mean_{R,k}}{11}} \quad (\text{Equation 1})$$

where:

k is the air quality monitoring station;

Mean_{SP,k} is the average concentration for the full sampling period for each AQMS;

$\text{Mean}_{R,k}$ is the average concentration for the sampler's exposure period for each AQMS; and

CF_T is the temporal correction factor.

NO_2 and NO corrections incorporated daily AQMS data while $\text{PM}_{2.5}$ and BC correction used hourly concentrations for average concentration calculations. As there were only two reference BC monitoring sites, both of which had incomplete temporal coverage, the BC data from the remote site were adjusted to sub-urban background site using a ratio method and then smoothed using a centered 24-hour rolling average.

2.3 Predictors

Candidate spatial metrics were selected based on those used in other LUR models (Abernethy et al., 2013; Allen et al., 2013; Amini et al., 2014; Brauer et al., 2006; Chen et al., 2010; Eeften et al. 2013; Hoek et al., 2008; Ryan & LeMasters, 2007; Saraswat et al., 2013; Tang et al., 2013; Wang et al., 2013), Hong Kong's public policies on growth, development and public health, and regulations on air quality (Table 2). Potential predictor variables (spatial metrics) were divided into two groups: a) variables representing a point value and b) variables representing the cumulative values of an area (buffer variables). Buffered variables were either represented as a density value (standardized by buffer area) or a total value. Whether a variable category was represented with density or total was based on usage in the literature. ArcGIS (v10.1 and 10.2) and R were used to evaluate, modify, extract, and aggregate potential predictor variables. In total 373 spatial predictor variables were calculated – 364 from spatial data layers and 9 (predicted NO_2) from the NO_2 LUR models, which were used solely for NO modelling.

Table 2: Possible prediction variables offered to variable selection procedures

Type	Potential Variables	Group Code
<i>Buffer value variables (buffer radii 50 m, 100 m, 200 m, 300 m, 500 m, 1000 m, 1500 m, 2000 m, 3000 m, 4000 m, 5000 m)</i>		
Annual Average Traffic Density (AADT) (sum in buffer)	Expressway	AADTExp
	Main roads	AADTMain
	Secondary roads	AADTSec
Road Length (sum [m] in buffer)	Expressway	ExpRL
	Main roads	MainRL
	Secondary roads	SecRL
	Elevated roads	ElvRL
Traffic Loading (AADT * road length [m] in buffer)	Expressway	ExpTrL
	Main roads	MainTrL
	Secondary roads	SecTrrL
Urban Build-up (area [m ²] or volume [m ³] /buffer area)	Building volume density	BldVolD
	Building area density	BldArD
	Population density	WPopDen

Land Use (total area [m ²] in buffer)	On street parking density	PrkArD
	Commercial	ComT
	Government	GovT
	Park	ParkT
	Mixed	MixT
	Residential	ResT
	Open area	OpArT
	Industrial	IndT
	Undeveloped lands	Lands
<i>Point value variables</i>		
Point feature (count/buffer area)	Street intersections	InterD
	Bus terminus density	BusTD
	Car park density	CarPD
	Mini bus terminus density	MiniBusD
	Temple density	TmplD
	Food stall density	FoodStD
	In aircraft flight path	Elevation
Value Extracted at Point [m above sea-level] [decimal degrees] [decimal degrees] [μg/m ³]	Aspect ratio	FlightRouteBuf
	Elevation	AspRatio
	Longitude	Long
	Latitude	Lat
Distance (Euclidean and natural log [m])	Predicted NO ₂ (NO model only)	NO2
	Ferry	(Ln)Dist_FerryTerm
	Cross boundary vehicle terminus	(Ln)Dist_CrossBrdVehTm
	Toll gates	(Ln)Dist_TollGate
	Incinerator	(Ln)Dist_Incin
	Crematorium	(Ln)Dist_Crematorium
	MTR line	(Ln)Dist_MTRLines
	MTR stations	(Ln)Dist_MTRstnts
	Coastline	(Ln)Dist_Coast
	Shipping lanes	(Ln)Dist_ShippingLanes
	High volume unrestricted shipping lanes	(Ln)DistUnRHighVol
	Airport	(Ln)Dist_Airport
	Port	(Ln)Dist_Port
	Shenzhen	(Ln)Dist_ShenzhenP
	Power stations	(Ln)Dist_PSntswoPenny

2.4 Model Building

For each pollutant, a model was built using SC1 data, SC2 data, and combined SC1 and SC2 data for sites that were sampled in both campaigns. A further three models were

built for each of the three traffic predictor types (road length, AADT, and traffic loading) for a total of 36 (4 pollutants x 3 datasets x 3 traffic predictors) models.

To be offered to models, each variable had to have at least two non-zero values. Within each of the buffered variable groups (e.g. industrial land use) buffer radii were ranked by correlation (Pearson's) with the pollutant with the top ranked buffer radius selected and any variables in that group highly correlated ($r > 0.6$) with the selected variable dropped. Next, the second and third ranked of the remaining buffer radii were also offered to models. For distance variables, either the Euclidean or natural log variable was selected based on correlation with the pollutant. All selected variables were then offered to an 'exhaustive' automated selection process (regsubset function in the **leaps** package in R (Lumley, 2009)) with maximum adjusted R^2 used for selection. The maximum number of predictors selected was set to one for every ten observations. Predictors were removed if their sign was inconsistent with a priori hypotheses, if not statistically significant ($p \geq 0.10$) and the automated selection process was then repeated until no more variables were dropped. If any model included variables with two buffer radii within 1500 m with coefficients with opposite signs the variable with the lower p-value was dropped and the variable selection process was rerun.

2.5 Evaluation

Models were evaluated using leave-one-out cross validation (LOOCV) and, for NO₂ models, where more sampling sites were available, hold-out validation (HOV) with 20 sites held for evaluation. A sensitivity test was also conducted where the modelling domain was limited to Hong Kong Island and Kowloon.

Evaluation of model assumptions were tested using diagnostic plots, Variance Inflation Factor (VIF), and Moran's I. While there is no consensus in LUR modeling on VIF cutoff, based on the available literature the cutoff was set at 3 (Aguilera et al, 2008; Amini et al., 2014; Clougherty et al., 2013; Eeftens et al., 2012; Gulliver et al., 2013; O'Brien, 2007).

3. Results

3.1 Measurements

The combined measured concentrations from both campaigns were: a) NO₂ (*Mean* = 106 $\mu\text{g}/\text{m}^3$, *Median* = 98 $\mu\text{g}/\text{m}^3$, *SD* = 38.5, *N* = 95), b) NO (*Mean* = 147 $\mu\text{g}/\text{m}^3$, *Median* = 131 $\mu\text{g}/\text{m}^3$, *SD* = 88.9, *N* = 40), c) PM_{2.5} (*Mean* = 35 $\mu\text{g}/\text{m}^3$, *Median* = 35 $\mu\text{g}/\text{m}^3$, *SD* = 6.3, *N* = 64), and BC (*Mean* = 10.6 $\mu\text{g}/\text{m}^3$, *Median* = 10 $\mu\text{g}/\text{m}^3$, *SD* = 5.3, *N* = 76). Concentration distributions for all the pollutants were skewed slightly right. Substantial spatial variation in concentration was seen across the territory for all pollutants. NO₂, NO, and BC concentrations differed by one order of magnitude across the territory. The

highest concentrations of gaseous pollutants were found in Kowloon and Hong Kong Island, the central and the traditional developed regions of Hong Kong. This pattern was not reflected for PM_{2.5} and BC concentrations where higher concentrations were measured in the northern regions of the New Territories, closer to the border with Mainland China. Statistically significant differences in concentrations between sampling campaigns were only noted for PM_{2.5} concentrations ($t(63) = -17.80$, $p < 0.001$) where SC2 mean, medium, minimum, and maximum were approximately 20 $\mu\text{g}/\text{m}^3$ greater than in SC1.

3.2 Model Results and Evaluation

From the total 36 models (9 for each pollutant), preferred models were selected: the combined SC1 and SC2 road length models, herein referred to as the preferred models (Table 3). Road length models overall performed slightly better than those with the other traffic variables, and road length was the most reliable traffic variable, as continuous road type data were available as inputs whereas traffic counts had to be interpolated between measurement locations to provide complete spatial coverage. Since the goal of the modeling was to predict long-term exposure, the combined SC1 and SC2 models were preferred. For preferred models R^2 values ranged from 0.46 (NO₂) to 0.59 (PM_{2.5}). The number of predictor variables in these models ranged from four to eight (depending on sample size) and all models included at least one traffic variable. Landuse was also present in all preferred models.

Table 3: Preferred LUR model results

Model	Variables	β	Partitioned R^2 - Dominance	Parameters
NO₂ ($\mu\text{g}/\text{m}^3$)	Intercept	7.84e+01		R^2 : 0.46
	ExpRL.1000[m]	1.61e-03	0.060	Adj. R^2 : 0.43
	MainRL.50[m]	9.67e-02	0.134	LOOCV R^2 : 0.39
	ElvRL.5000[m]	3.02e-04	0.221	HOV R^2 : 0.56
	OpArT.300[m]	-1.27e-04	0.047	RMSE: 27.7 $\mu\text{g}/\text{m}^3$ LOOCV RMSE: 29.5 $\mu\text{g}/\text{m}^3$ HOV RMSE: 28.3 $\mu\text{g}/\text{m}^3$ N: 75 Moran's I: -0.256 Measured ($\mu\text{g}/\text{m}^3$): Mean = 107 [43, 213]
NO ($\mu\text{g}/\text{m}^3$)	Intercept	7.07e+01		R^2 : 0.50
	ElvRL.500[m]	1.06e-02	0.192	Adj. R^2 : 0.48
	BldVolD.25[m]	3.73e+00	0.148	LOOCV R^2 : 0.28
	IndT.25[m]	1.98e-01	0.078	RMSE: 62.1 $\mu\text{g}/\text{m}^3$
	WPopDen.100[m]	5.29e+02	0.082	LOOCV RMSE: 761 $\mu\text{g}/\text{m}^3$ N: 40 Moran's I: -0.0068 Measured ($\mu\text{g}/\text{m}^3$): Mean = 147 [21, 376]
PM_{2.5} ($\mu\text{g}/\text{m}^3$)	Intercept	3.67e+01		R^2 : 0.59
	ExpRL.25[m]	8.91e-02	0.056	Adj. R^2 : 0.54
	Dist_ShenzhenP[m]	-3.09e-04	0.168	LOOCV R^2 : 0.43
	CarPD.1000[m]	4.17e+05	0.151	RMSE: 4.0 $\mu\text{g}/\text{m}^3$
	CarPD.25[m]	1.68e+04	0.057	LOOCV RMSE: 4.7 $\mu\text{g}/\text{m}^3$
	GovT.100[m]	-3.81e-04	0.066	N: 64

	IndT.25[m]	1.38e-02	0.089	Moran's I: -0.228 Measured ($\mu\text{g}/\text{m}^3$): Mean = 35 [25, 51]
BC ($\mu\text{g}/\text{m}^3$)	Intercept	2.51e+03		R ² : 0.50
	ExpRL.3000[m]	9.48e-05	0.091	Adj. R ² : 0.44
	ExpRL.50[m]	1.76e-02	0.075	LOOCV R ² : 0.31
	Long[decimal degree]	-2.19e+01	0.089	RMSE: 3.7 $\mu\text{g}/\text{m}^3$
	CarPD.50[m]	3.23e+04	0.044	LOOCV RMSE: 4.6 $\mu\text{g}/\text{m}^3$
	ComT.500[m]	-2.74e-05	0.037	N: 76
	ResT.50[m]	-8.74e-04	0.050	Moran's I: -0.129
	MixT.500[m]	-2.32e-05	0.053	Measured ($\mu\text{g}/\text{m}^3$): Mean = 11 [6, 28]
	Lands.500[m]	-1.50e-04	0.065	

The LOOCV R^2 values for the preferred models were between 15% to 44% lower than the models' R^2 values (Table 3). The NO_2 HOV R^2 values for all the NO_2 models were greater than most of the LOOCV R^2 with the exception of two of the traffic loading models. This was unexpected as it is generally assumed that HOV values should be lower than the LOOCV R^2 (Wang et al., 2012). In the preferred NO_2 model, the HOV R^2 was higher than the model R^2 , which was also unexpected.

Diagnostic plots showed that the models met the conditions of linearity, homoscedasticity, and normality. Moran's I values of the residuals for the preferred models ranged from -0.26 to -0.0068, meaning spatial correlation ranged from slightly dispersive to slightly clustered, and that spatial autocorrelation was not a concern. This absence of spatial autocorrelation also meant that interpolated residuals could not be used as an additional predictor variable. Multicollinearity was a concern during the modelling process and a few of the initial 36 models were rerun due to high VIF values. A major source of multicollinearity was large buffered predictor variables, particularly 4000 m and 5000 m, as correlation was high for variables of this buffer size between most spatial metrics. Final models had VIF values under 3.

Prediction surfaces were created for the preferred models (Figure 2). Predictions were truncated to $\pm 20\%$ of the range of the corrected combined SC1 and SC2 measured concentrations entered into the models, with exception of the NO_2 model since the predicted values were within this range (Amini et al., 2014; Henderson et al, 2007).

Figure 2: Prediction surfaces for the preferred (combined SC1 and SC2 road length) models described in Table 3.

4. Discussion

4.1 Performance of HK2D LUR models

Modelling captured important spatial parameters and represented spatial patterns of air quality in Hong Kong that were consistent with the literature (Chiu & Lok, 2011; Environment Bureau, 2013; Kok et al., 1997; Shi et al., 2016; Tian et al., 2011; Yu et al., 2004). Higher concentrations of gaseous pollutants were centered in Kowloon and the northern region of Hong Kong Island. The higher NO₂ values in downtown Hong Kong were due to influence of road length variables in the model and consistent with the importance of motor vehicle traffic as an important source of local NO₂ (Environment Bureau, 2013; Tian et al., 2011). The areas of lowest concentrations in the New Territories appear to be due to the open area land use class. Concentrations may have lower accuracy in these areas given the lack of sampling locations in these areas due to their inaccessibility and the emphasis of the campaign and modeling on characterizing populated areas.

Though NO is mainly a primary pollutant and NO₂ is mainly secondary they are chemically linked and have similar emission sources (e.g. traffic). Therefore on a

regional scale similar spatial distributions were expected. At a 10 m resolution, the prediction surface was dominated by the building volume density variable in the 25 m buffer and therefore resulted in a more heterogeneous spatial distribution than the other prediction surfaces, which is consistent with the more transient temporal state of NO. The smoothed, using the mean value in a 500 m circle from the original NO prediction surface raster cells, surface (Appendix A) depicts the expected regional distribution with higher concentrations in Kowloon and northern Hong Kong Island, similar to NO₂.

Both PM_{2.5} and BC predictions exhibited a north-south/west-east gradient, with higher concentrations in the north/west. This appears to be due to regional transport from mainland China. A similar northeast/southwest gradient in PM₁₀ concentrations had been noted previously in an analysis of the rooftop AQMS was attributed to transport from mainland China (Chiu and Lok, 2011). Further, Kok et al. (1997) reported elevated BC concentrations in the western regions of the territory and similarly attributed these higher levels to regional sources. A recent LUR model of PM_{2.5} restricted to downtown Hong Kong indicated similar spatial patterns as the HK2D model (Shi et al., 2016). For BC, the port as well as coastal areas along major shipping routes were also areas of elevated predicted values. Yu et al. (2004) had noted the port as an important emission source affecting spatial distribution of BC levels with increases in background BC concentrations around the port depending on the seasonal direction of the prevailing wind. Shipping lane variables were not, however, present in any of the final models.

In addition to describing the expected spatial distribution of pollutant concentrations and providing estimates for all populated regions of the territory, the degree of explained variance of the models, while modest, were within the range seen with other LUR modelling efforts (e.g. Hoek et al., 2008). Given the complex urban morphology of Hong Kong compared to most of the European and North American cities with previously developed LUR models, somewhat reduced explained variance was expected. Modeling in Asian locations such as Hong Kong is likely to be more challenging than in North America and Europe given the high regional levels of air pollution and overall higher range of concentrations. Compared to LUR models developed in other Asian cities where ambient concentrations, urban morphology, vehicle use, and building design may be similar, LUR models developed with dedicated sampling campaigns reported similar R² values (Table 4). This was even the case for many of the Asian location models developed using only regulatory monitoring network sites, which tend to have higher R² but are more likely to be subject to overfitting, given the limited numbers of sampling sites, and may also not include the full range of concentrations and land use or traffic characteristics. Compared to the one other published Hong Kong LUR model, the explained variance is similar; Shi et al. (2016) using a 300 m resolution PM_{2.5} model for only the core of Hong Kong reported a higher adjusted R² (0.63) compared to the HK2D PM_{2.5} (0.54), but this difference appeared to be due to the spatial aggregation of data. At smaller aggregation scales (200 m, 100 m, and 50 m), models from the Shi et al. study all had adjusted R²'s of 0.51 or lower.

Table 4: LUR modelling for other Asian cities

Location	Reference	Sampling Sites (n)	Predictors (R ² ; no. of predictors)
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Changsha, China	Li et al., 2015	Field campaign (n = 80) NO ₂ (n = 40 PM ₁₀)	NO ₂ (0.41-0.51) PM ₁₀ (0.32-0.39) ¹
Jinan, China	Li et al., 2010	Regulatory air quality monitoring sites (n = 14)	SO ₂ (0.62; 3) NO ₂ (0.64; 3) PM ₁₀ (0.60; 3)
Shanghai, China	Meng et al., 2015	Ambient air quality monitoring sites (n = 38)	NO ₂ (0.82; 4)
Shanghai, China	Meng et al., 2016	Ground level air pollution monitoring sites (n = 28)	PM ₁₀ (0.80; 4)
Tianjin, China	Chen et al., 2010	Ambient air quality monitoring sites (n = 20; another 10 used to validate)	NO ₂ (0.74; 5, heating season) (0.61; 4, non-heating season) PM ₁₀ (0.72; 4, heating season) (0.49; 3, non-heating season) NO ₂ (0.59; 5)
Metropolitan area of Seoul, Kyunggi, and Incheon, Korea	Lee et al., 2012 [Conference paper]	Regulatory air quality monitoring sites (n = 102)	
New Delhi, India	Saraswat et al., 2013	Field campaign (n = 18, morning; n = 37, afternoon)	Ultrafine particle number concentrations (0.28; 1 morning) (0.23; 2, afternoon) ²
Shizuoka prefecture, Japan	Kashima et al., 2009	Regulatory air quality monitoring sites (n = 83)	NO ₂ (0.54; 5) SPM (0.11; 1)
Ulaanbaatar, Mongolia	Allen et al., 2013	Field campaign deployment (n = 37)	Wintertime NO ₂ (0.74; 5) SO ₂ (0.78; 2)

The HK2D modelling followed many of the best practices outlined for LUR modelling. Multiple pollutants were sampled to characterize air quality and two extensive roadside sampling campaigns were undertaken to account to seasonality in pollution levels. All models in this study had at least 40 training sites as has been recommended (Hoek et al., 2008; Wang et al., 2012). Sampling sites were selected that maximized the range of values in pollution concentrations and spatial variables. During model building a substantial number of plausible spatial predictors were offered, to ensure no relevant spatial metric was overlooked, and predictor selection was limited to one for every ten observations to avoid potential for overfitting (Harrell, 2015; Harrell et al, 1996), although this may have led to more conservative results

Although we offered a very large number of potential predictors to models and used a comprehensive modeling framework, the results are modest compared to other LUR

¹ For Li et al. (2015) only the circular buffer models were included as they are directly comparable.

² Only models without rooftop concentrations as a predictor are shown.

studies, particularly European and North American. Despite this, results suggest that LUR is still a useful and efficient approach to assess spatial variation in air pollutant concentrations even in a complex environment such as Hong Kong with high regional levels of air pollution, complex terrain, marine influences and numerous sources. Both the range of concentrations and the spatial patterns reflect the previous literature. As an exposure assessment tool for Hong Kong, the final models are expected to provide estimates that are accurate in magnitude and provide more detailed information than previously available on spatial variation.

4.2 Application of LUR Modelling in Other High-Density High-Rise Cities

The demonstration of reasonable LUR models to describe spatial variability in pollutant concentrations in Hong Kong suggests this to be a viable modelling method for high-density, high-rise cities, which are especially common in Asia. Further, these results suggested the utility of model development using traditional sampling methods and traditional, less labour/data-intensive predictors. More complex urban development predictors, such as aspect ratio, that one might expect to be important in modelling a high-density, high-rise city did not have a large impact on the final modelling. The preferred NO₂, PM_{2.5}, and BC models contained conventional LUR predictors (traffic, land use, coordinates, and distance to large regional emission sources), along with car park density. Road length, the least labour-intensive traffic variable to calculate, was the best performing traffic related variable.

Despite the large number of spatial predictor variables offered to the HK2D models, the unexplained variance was not reduced. This suggested a complex relationship between spatial metrics and pollution concentrations and not that potential spatial predictors were missed. This complex relationship may also limit performance of other air quality modelling methods.

This study suggested the added complexity in the spatial distribution of air pollutants in high-density high-rise cities was reflected in the models' performance rather than the selection of predictors. The modeling of the whole of Hong Kong, rather than just the downtown core as in Shi et al. (2016) where urban/building morphology predictors were important in the models, may also be a factor in the selection of more traditional, less labour/data intensive predictors. However, results from sensitivity analyses where the modeling domain was restricted to only Kowloon and Hong Kong Island did not select any more of the urban/building morphology predictors than the preferred models.

4.3 Limitations

Limitations of this study include error in the direct comparability to reference monitors and the focus of the model on developed areas. The lack of bias correction for NO₂, NO, and black carbon measurements indicates that these concentrations may not be directly comparable to measurements from the reference monitoring network. Many LUR models, for example the ESCAPE studies, do not correct measured concentrations to

reference monitors in regulatory networks (Beelen et al., 2013; Cyrys et al., 2012). Further, as in other LUR models since sampling was not conducted throughout the full year, the predicted values do not fully characterize annual averages. The sampling focused on developed lands and used only roadside sites, indicating that the models are more suited to predicting concentrations in developed (populated) areas and may be biased towards selecting traffic variables. This makes it difficult to validate predictions made in undeveloped park areas with the current dataset. However, as the modelling was focused on human exposure it is reasonable to only consider developed areas.

5. Conclusion

LUR modelling was found to be a suitable method to describe spatial variability in air pollution concentrations within a high-density, high-rise city. This provided a viable option for long-term exposure estimates in these cities where air quality is a public health threat due to large populations, high concentration of air pollutants, and morphologies limiting dispersion. Understanding air pollution exposure allows for policies and public information on area or activities associated with high exposure. LUR models can also be used for exposure estimates in epidemiologic studies. LUR models described here are used as base models for more complex population exposure estimates incorporating vertical measurements and population mobility components to more accurately assess population exposure.

Acknowledgements

We are grateful to the Environmental Protection Department of HKSAR for their assistance during the field campaigns and granting access to air quality monitoring stations and pollution data.

Funding: This study was supported by the Health Effects Institute, Boston, USA under Research Agreement 4941-RFA13-1. M. Lee was supported in part by funding from a Natural Sciences and Engineering Research Council (Canada) CREATE-Atmospheric Aerosol Program fellowship at The University of British Columbia.

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Appendix A: NO surface smoothed over 500 m