



Supplement of

Development and application of a multi-scale modeling framework for urban high-resolution NO₂ pollution mapping

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Section S1. Urban heat island scheme

The Urban Heat Island effect refers to a phenomenon that the temperature of urban atmosphere and surface is higher than that of nearby rural areas, of which intensity can be quantified by using the temperature difference. UHI is caused by the thermodynamic effect of the special underlying surface structure induced by urbanization and the influence of human activities. In past decades, the intensity of UHI in Beijing has been increasing at a rate of 1.35 °C every decade, and has gradually expanded from within the 2nd Ring Road to the 6th Ring Road and its surrounding areas (Ge et al., 2016). When the UHI intensity is high, the circulation between urban and suburban areas will enhance the boundary layer height and turbulence intensity in urban areas, and reduce the concentration of primary pollutants such as NO_x which are easily affected by the local climate. After adding the UHI scheme to the model, the overestimation of the simulation can be reduced, and the simulation is more consistent with the observed concentration (Sarrat et al., 2006).

Here, based on the algorithm used in AERMOD (Cimorelli et al., 2005), we estimated the influence of UHI on turbulence in urban areas, especially in the afternoon (16:00-23:00), to reduce the overpredicted pollutant concentrations caused by the overestimation of atmospheric stability in this period. During this period, due to the large amount of anthropogenic heat generated by transportation, cooking and other human activities, as well as the gradual release of solar radiation stored by buildings in daytime, the UHI intensity in Beijing increase to the peak (Wang et al., 2017). In the calculation, we still regarded each road as a basic unit for the calculation, and first estimated the sensible heat flux $H_{u,UHI}$ (W/m²) caused by UHI and the height of the mixing layer $Z_{mix,c}$ (m) formed by thermal turbulence. And then the mixing height Z_{mix} , convective velocity scale w^* , surface friction velocity u^* , and Monin-Obhukov length L_{MO} were recalculated based on AERMOD method (Cimorelli et al., 2005; EPA, 2019), as follows,

$$\begin{cases} H_{u,UHI} = \alpha \rho c_p \Delta T_{u-r} u^* \\ Z_{mix,c} = Z_{mix,ref} (P/P_{ref})^{0.25} \end{cases}$$

where, α is the empirical coefficient, with a value of 0.03. ρ is air density (kg/m³) and calculated by air pressure and temperature. c_p is the specific heat capacity of air at constant pressure, with a value of 1004 J/kg·K. ΔT_{u-r} is the temperature difference between urban and suburban areas, which is set with the value of 3°C according to the observation of several meteorological ground observation stations and satellite remote sensing data (Wang et al., 2017). $Z_{mix,ref}$ and P_{ref} are the reference boundary layer height and urban population, with values of 400 m and 2 million, respectively (Cimorelli et al., 2005). P is the total population of urban areas in the research region, with the value of 9.2 million in our study domain for 2020 based on the WorldPop dataset (Bondarenko et al., 2020).

Section S2. Vertical mixing scheme

Since the settings of vertical pressure layers in the CMAQ and the WRF model are same, the concentrations induced by non-vehicle sources provided by the CMAQ-ISAM model can be regarded as the background concentration at the top of the urban canopy layer (UCL). If the influence of

turbulence changes on the mixing of background concentration is not taken into account, the pollutant concentration at night stable boundary layer is easy to be significantly overestimated (Benavides et al., 2019). Therefore, we assumed that the concentration relationship between the top of UCL and the near surface is affected by atmospheric stability, local street canyons and building morphology.

In this study, based on the method proposed by Benavides et al. (2019), the ratio of wind speed between the near surface of the road and the top of surrounding buildings was used as a proxy parameter in the model to characterize the turbulence intensity which affects the vertical concentration mixing between the top of UCL and near surface. However, Benavides et al. assumed that the average wind speed in the street canyon was proportional to the angel between the top wind direction and the central axis of the road, and the logarithmic wind profile to was still used to represent the change of wind speed within UCL, resulting in the influence of the street canyon effect on vertical mixing of background concentration was not considered. In this study, when the grid receptor was located in the street canyon, the MLSCF scheme was used to describe the wind profile within UCL. Otherwise, the logarithmic wind profile was used to calculate the wind speed at the specified height. This parameter scheme mainly calculated the background concentration mixing ratio (fac_{bg}), which was multiplied by the background concentration provided by the CMAQ-ISAM model to estimate the background concentration at the specified height near the ground. Based on the estimated sensible heat flux (H_u , W/m^2) from the WRF model, convective boundary layer (H_u >0) and stable boundary layer (H_u <0) were distinguished, and the effect of building density around the receptor site on fac_{bg} was also considered, as follows:

$$fac_{bg} = \begin{cases} 1 - F + F \times \frac{WS_{sfc}}{WS_{bh}}, & bd > 0.1\&H_{u} > 0\\ \frac{WS_{sfc}}{WS_{bh}}, & bd > 0.1\&H_{u} \le 0\\ 1 - 5bd + 5bd \times \frac{WS_{sfc}}{WS_{bh}}, & bd \le 0.1\&H_{u} > 0\\ 1 - 10bd + 10bd \times \frac{WS_{sfc}}{WS_{bh}}, & bd \le 0.1\&H_{u} \le 0 \end{cases}$$

where, F=m+abs(0.25-bd), where *m* is an empirical parameter with value of 0.1. The transition value of H_u changed from 0.3 to 0 in this research compared with the Benavides's study in order to avoid the double-counting of impacts from the UHI effect.

Section S3. NO_x photochemical parameter scheme

The NO_x photochemical parameter scheme applied in this study includes two reactions:

$$\begin{cases} NO_2 + hv \rightarrow NO + O_3 \\ NO + O_3 \rightarrow NO_2 \end{cases}$$

Kim et al. compared two-reaction scheme with CB05 gas phase chemical mechanism by incorporated them into SinG model to estimate roadside NO₂ concentration, and found a similar results, while the computing time cost of two-reaction scheme was significantly less than that of the CB05 mechanism (Kim et al., 2018). Therefore, the simplified two-reaction scheme was incorporated into the model in

this study to characterize the NO_x photochemical process. During simulation, the NOx (NO+NO₂) emitted from vehicles is first regarded as an inert gas and only the primary concentration after diffusion is simulated. Then, assuming a photo-stationary equilibrium condition, the concentrations of NO, NO₂ and O₃ are calculated using the two-reaction scheme, as follows:

$$\begin{cases} [NO_2] = (b - \sqrt{b^2 - 4c})/2 \\ [NO] = [NO]_b + [NO_2]_b + [NO_x]_d - [NO_2] \\ [O_3] = [O_3]_b + [NO_2]_b + \zeta [NO_x]_d - [NO_2] \\ b = k1/k2 + [O_3]_b + [NO]_b + 2[NO_2]_b + (1 + \zeta)[NO_x]_d \\ c = ([O_3]_b + [NO_2]_b + \zeta [NO_x]_d)([NO]_b + [NO_2]_b + [NO_x]_d) \end{cases}$$

where, $[NO_x]_d$ is the primary concentration of NO_x directly simulated by RLINE model when taken as an inert gas. $[NO]_b$, $[NO_2]$, and $[O_3]_b$ are the background concentrations of NO, NO₂ and O₃ from nonvehicle sources, respectively, which are provided by CMAQ-ISAM model. If the vertical mixing scheme is used in the hybrid model, $[NO]_b$, $[NO_2]$, and $[O_3]_b$ are derived by multiplying background concentrations from CMAQ-ISAM model with fac_{bg}. The unit of concentrations in these formulas is mol/m³. ζ is the ratio of NO₂ to NO_x in vehicle emissions, with a value of 0.2 (Valencia et al., 2018; Benavides et al., 2019). The reaction rates of the photolysis of NO₂ and the oxidation of NO were set to be *k1* and *k2* respectively, and calculated as follows (Hurley, 2005):

$$\begin{cases} k1 = 10^{-4} \times \delta \times \text{TSR} \\ k2 = 9.24 \times 10^5 \times \exp(-1450/T) / T \\ \delta = \begin{cases} 4.23 + 1.09 / \cos Z, & 0 \le Z \le 47 \\ 5.82, & 47 < Z \le 64 \\ -0.997 + 12(1 - \cos Z), & 64 < Z \le 90 \end{cases}$$

where, all parameters were from the WRF model. TSR is the total solar radiation (W/m²). *Z* is the solar zenith angle (°). *T* is the ambient temperature (K).

Supplementary Figures



Figure S1. Spatial distribution of street canyon geometry in Beijing (© Microsoft). (a) Length of actual street canyon to the total street length, (b) Height to width ratio, (c) Length to height ratio and (d) Height symmetrical ratio.



Figure S2. Computational domain and grid arrangement in CFD validation cases with the background wind being perpendicular (a-b) or parallel (c-d) to the axis of street canyons. In the first validation case (a-b), the vertical profiles of time-averaged velocity components (stream-wise velocity U and vertical velocity W) are measured at point V₁. In another validation case (c-d), the vertical (point V₂) and horizontal (z=0.11H) profiles of time-averaged stream-wise velocity U are measured.



Figure S3. Model performances of CFD validation cases in street canyons perpendicular (a-b) or parallel (c-d) to the wind direction at the roof level. (a) Vertical profiles of U at point V_1 ; (b) Vertical profiles of W at point V_1 ; (c) Horizontal profiles of U at z=0.11H; (d) Vertical profiles of U at point V_2 . In each validation case, three grid arrangement are tested, where the minimum sizes of hexahedral cells near wall surfaces are 0.1 m (fine grid), 0.2 m (medium grid) and 0.5 m (coarse grid) respectively. Moreover, the standard and RNG k- ε turbulence models are tested respectively.



Figure S4. Comparison between the predicted wind speed in street canyons with different background wind direction and aspect ratio and other research results.



Figure S5. Model performance statistics of machine learning for V_x and V_y in street canyon. (a) MAE; (b) RMSE; (c) RE; (d) R.



Figure S6. The partial dependence plots of each predictor variable in RF model for V_x (a-f) and V_y (g-l). The blue line stands for the smooth fitting curves. The labels above the x-axis shows deciles, minimum and maximum of the predictor variable.



Figure S7. Diurnal variation of background concentration mixing ratio at roadside monitoring sites in Beijing in summer 2019. The vertical mixing ratio=concentrations near surface/at the top of UCL



Figure S8. Observed and predicted hourly (a-c) or 8-h maximum averaged (d-f) O_3 concentrations from different models at near-road sites: (a, d) CMAQ model; (b, e) CMAQ-RLINE model; (c, f) CMAQ-RLINE_URBAN model.



Figure S9. Diurnal variations of observed and predicted hourly averaged O_3 concentrations from different models at near-road monitoring sites: (a) DSH; (b) NSH; (c) QM; (d) XZM; (e) YDM.



Figure S10. Spatial distribution of hourly averaged NO₂ concentrations from (a, b) CMAQ model and (c, d) CMAQ-RLINE_URBAN model at (a, c)12:00-13:00 and (b, d) 18:00-19:00.



Figure S11. Frequency distribution of predicted monthly averaged NO2 concentrations from (a) all source and (b) only vehicles. Two-mode Gaussian models, which are shown by purple and blue curves, are used to fit for the distribution.

Supplementary Tables

Species	Mean Observation (m/s)	Mean Simulation (m/s)	FAC2	MFB (%)	NMSE (%)	R		
Validation case with the perpendicular background wind								
и	-0.48	-0.50	1.00	-5	2	0.98		
W	-0.37	-0.39	1.00	-4	5	0.58		
Validation case	with the parallel backgr	ound wind						
u(L=21.7H)	0.68	0.73	1.00	-7	3	0.97		
u(L=43.5H)	0.58	0.59	1.00	-1	0	0.99		

Table S1. Model performance statistics for the velocity components in CFD validation cases.

Note: The coarse grid arrangement and standard k-ε turbulence model are used. *MFB: Mean fractional

Terms	Expression	Coefficients
1	Intercept	0.532
2	$\max(0.5 - Vbg_x, 0)$	-0.623
3	$\max(Vbg_{x}-0.5, 0)$	0.111
4	$\max(2.5 - Vbg_y, 0)$	-0.131
5	$\max(Vbg_y-2.5, 0)$	-0.010
6	$\max(0.5 - H/W, 0)$	2.315
7	$\max(H/W-0.5, 0)$	-0.259
8	$\max(0.774 - z/H, 0)$	-0.812
9	$\max(z/H-0.774, 0)$	2.774
10	$\max(2.5-Vbg_x, 0) \times \max(0.5-H/W, 0)$	-1.103
11	$\max(Vbg_x-2.5, 0) \times \max(0.5-H/W, 0)$	0.249
12	$\max(0.87-Vbg_x, 0) \times \max(0.774-z/H, 0)$	0.481
13	$\max(Vbg_x-0.87, 0) \times \max(0.774-z/H, 0)$	-0.444
14	$\max(2.5-Vbg_x, 0) \times \max(z/H-0.774, 0)$	-1.151
15	$\max(Vbg_x-2.5, 0) \times \max(z/H-0.774, 0)$	-1.139
16	$\max(0.5-Vbg_y, 0) \times \max(0.5-H/W, 0)$	-3.536
17	$\max(Vbg_y-0.5, 0) \times \max(0.5-H/W, 0)$	0.028
18	$\max(0.5-H/W, 0) \times \max(0.774-z/H, 0)$	0.897
19	$\max(H/W-0.5, 0) \times \max(0.774-z/H, 0)$	0.664
20	$\max(Vbg_x-2.5, 0) \times \max(H_1/H_r-1.33, 0) \times \max(z/H-0.774, 0)$	-2.054
21	$\max(Vbg_x-2.5, 0) \times \max(1.33-H_1/H_r, 0) \times \max(z/H-0.774, 0)$	6.242

Table S2. Coefficients in $V_{\boldsymbol{x}}$ fitting of Multivariate Adaptive Regression Splines

Terms	Expression	Coefficients
1	Intercept	2.117
2	$\max(2.5-Vbg_y, 0)$	-0.812
3	$\max(Vbg_y-2.5, 0)$	0.624
4	$\max(1-H/W,0)$	0.455
5	$\max(H/W-1, 0)$	-0.335
6	$\max(0.75 - H_l/H_r, 0)$	-0.081
7	$\max(H_l/H_r-0.75, 0)$	-0.690
8	max(0.079- <i>z</i> / <i>H</i> , 0)	-14.220
9	$\max(z/H-0.079, 0)$	0.200
10	$\max(0.5-Vbg_x, 0) \times \max(H_1/H_r-0.75, 0)$	0.428
11	$\max(Vbg_{x}-0.5, 0) \times \max(H_{1}/H_{r}-0.75, 0)$	-0.036
12	$\max(2.5-Vbg_y, 0) \times \max(H/W-1, 0)$	0.152
13	$\max(2.5-Vbg_y, 0) \times \max(1-H/W, 0)$	-0.265
14	$\max(2.5-Vbg_y, 0) \times \max(H_1/H_r-0.75, 0)$	0.230
15	$\max(Vbg_y-2.5, 0) \times \max(H_1/H_r-0.75, 0)$	0.109
16	$\max(2.5-Vbg_y, 0) \times \max(z/H-0.079, 0)$	-0.090
17	$\max(2.5-Vbg_y, 0) \times \max(0.079-z/H, 0)$	5.602
18	$\max(Vbg_y-2.5, 0) \times \max(z/H-0.226, 0)$	0.536
19	$\max(Vbg_y-2.5, 0) \times \max(0.226-z/H, 0)$	-2.361
20	$\max(1-H/W, 0) \times \max(H_1/H_r-0.75, 0)$	0.480
21	$\max(H/W, 0) \times \max(H_1/H_r-0.75, 0)$	-0.052

Table S3. Coefficients in $V_{\rm y}$ fitting of Multivariate Adaptive Regression Splines

Stations	H/W	bd	bh (m)	bhsd (m)	z_0 (m)
DSH	0	0.01	4.97	1.68	1
NSH	0	0.13	19.61	31.96	1.06
QM	0.22	0.2	9.98	3.56	1.37
XZM	0.35	0.18	14.11	16.22	2.11
YDM	0	0.22	10.13	4.55	1.02

Table S4. Geometric characters for each monitoring site

**H/W*, bd, bh, bhsd, and z_0 represent street canyon aspect ratio, average building height (m), height standard deviation (m) and plane density, respectively (Benavides et al., 2019).

Sites	Scenario	MB	RMSE	NMB	NMGE	FAC2	IOA	R
DSH	CMAQ	-15.6	33.4	-28	48	0.53	0.45	0.52
	CMAQ-RLINE	28.2	63.1	51	69	0.73	0.20	0.50
	CMAQ-RLINE_URBAN	-6.2	28.5	-11	36	0.84	0.58	0.60
NSH	CMAQ	-20.5	37.9	-33	50	0.53	0.12	0.30
	CMAQ-RLINE	30.2	65.1	49	65	0.76	-0.12	0.33
	CMAQ-RLINE_URBAN	17.2	39.8	28	48	0.81	0.15	0.28
QM	CMAQ	-6.0	23.9	-14	42	0.64	0.45	0.59
	CMAQ-RLINE	20.4	55.2	47	68	0.8	0.11	0.47
	CMAQ-RLINE_URBAN	3.5	23.7	8	38	0.86	0.50	0.47
XZM	CMAQ	-8.5	25.3	-18	44	0.61	0.36	0.54
	CMAQ-RLINE	26.0	59.7	56	72	0.76	-0.06	0.41
	CMAQ-RLINE_URBAN	11.3	28.0	24	44	0.86	0.36	0.42
YDM	CMAQ	0.6	25.5	1	44	0.66	0.43	0.58
	CMAQ-RLINE	23.0	56.2	53	73	0.72	0.05	0.45
	CMAQ-RLINE_URBAN	5.4	25.0	12	39	0.86	0.50	0.50

Table S5. Model performances under different scenarios for each station

*MB: Mean bias; RSME: Root mean squared error; NMB: Normalized mean bias; NMGE: Normalized mean gross error; FAC2: Fraction of predictions within a factor of two; IOA: Index of agreement; R: correlation coefficient.

Table 50. The performance of workf model compared with observations.								
Variables	Sample size	Observed Average	Simulated Average	MB	NMB	RMSE	R	
WS10 (m/s)	732	2.5	3.7	1.2	46	1.9	0.6	_
WD10 (°)	456	190.4	169.0	-8.0	-4	49.5	0.4	
T2 (°C)	742	25.8	29.0	3.2	12	3.5	0.9	
RH (%)	741	64.3	50.4	-13.9	-22	17.4	0.9	

Table S6. The performance of WRF model compared with observations.

*WS10: wind speed at the height of 10 m; WD10: wind direction at the height of 10 m; T2: Temperature at the height of 2 m; RH: Relative humidity; MB: Mean bias; RSME: Root mean squared error; NMB: Normalized mean bias; R: correlation coefficient.

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