Supporting Information for

Abnormally shallow boundary layer associated with severe air pollution during the COVID-19 lockdown in China

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1. Inverse fitting

Since the PBLH and $PM_{2.5}$ are correlated but not linearly correlated under most conditions, the inverse function [$f(x) = {}^{A}/_{x} + B$] is used to fit the relationship. Following Winship and Radbill (1994), the fitting parameters (A and B) and the coefficient of determination of the PBLH–$PM_{2.5}$ relationship are derived using this inverse fitting function. The correlation coefficient of the inverse fit would be positive when PBLH and $PM_{2.5}$ are positively correlated, otherwise it would be negative. Moreover, the normalized sample density at each location in a scatter plot represents the probability distribution in two dimensions (Scott, 2015). Then setting the weighting function of the inverse fit equal to the normalized density produces the best-fitting results representing the majority of cases. The magnitude of the correlation coefficient ($R^{\dagger}$) is designed to represent the degree to which the data fit an inverse relationship.

2. Standardized multiple linear regression

We use a standardized multiple linear regression method following previous studies (Igel and van den Heever, 2015; Stolz et al., 2017). The confounding relationships between daily $PM_{2.5}$ and multiple meteorological factors are established by the standardized regression equation. The standardized regression equation with seven predictor variables x_1, x_2, x_3, x_4 (PBLH, WS, RH, and rainfall amount) and the response y ($PM_{2.5}$) can be written as:

$$y = \alpha_1 x_1 + \alpha_2 x_2 + \alpha_3 x_3 + \alpha_4 x_4 \qquad (1)$$

where y and x_i are standardized variables derived from the raw variables Y and X_i by subtracting the sample means (Y, X_i) and dividing by the sample standard deviations (δ_Y, δ_i):

$$y = \frac{Y - \bar{Y}}{\delta_Y}, \qquad x_i = \frac{Xi - \overline{Xi}}{\delta_i}, i = 1, 2, 3, 4 \qquad (2)$$

Standardized regression coefficients ignore the independent variables' scale of units, which makes the slope estimates comparable and shows the relative weights to the changes in LSP occurrence hours. A partial correlation is done to control the other predictors and to study the effect of each predictor separately.

3. Similarity check

For searching the similar meteorological condition of CLD haze event over Beijing, we use the five-day smoothed time series of each parameter during winter from 2013 to 2020. For instance, we define the PBLH condition is similar, if the difference in five-day smoothed time series is less than 20%, which means:

$$|\overline{PBLH}_A - \overline{PBLH}_{CLD}| < 20\%\overline{PBLH}_{CLD} \qquad (3)$$

where A is a five-day period, $\overline{PBLH}_A$ and $\overline{PBLH}_{CLD}$ represent the mean value of PBLH during period A and CLD, respectively. The procedure is the same for WS and RH. Moreover, we defined all three parameters are similar if the difference in five-day smoothed time series is less than 20% for both PBLH, WS, and RH.

References

Stolz, D. C., Rutledge, S. A., Pierce, J. R., and van den Heever, S. C.: A global lightning parameterization based on statistical relationships among environmental factors, aerosols, and convective clouds in the TRMM climatology, J. Geophys. Res.-Atmos., 122, 7461–7492, https://doi.org/10.1002/2016JD026220, 2017.

Igel, M. R. and van den Heever, S. C.: The relative influence of environmental characteristics on tropical deep convective morphology as observed by CloudSat, J. Geophys. Res.-Atmos., 120, 4304–4322, Winship, C. and Radbill, L.: Sampling weights and regression analysis, Sociol. Method. Res., 23, 230–257, 1994.https://doi.org/10.1002/2014JD022690, 2015.

Winship, C. and Radbill, L.: Sampling weights and regression analysis, Sociol. Method. Res., 23, 230–257, 1994

Scott, D. W.: Multivariate density estimation: theory, practice, and visualization, John Wiley & Sons, USA, 2015.

Figures

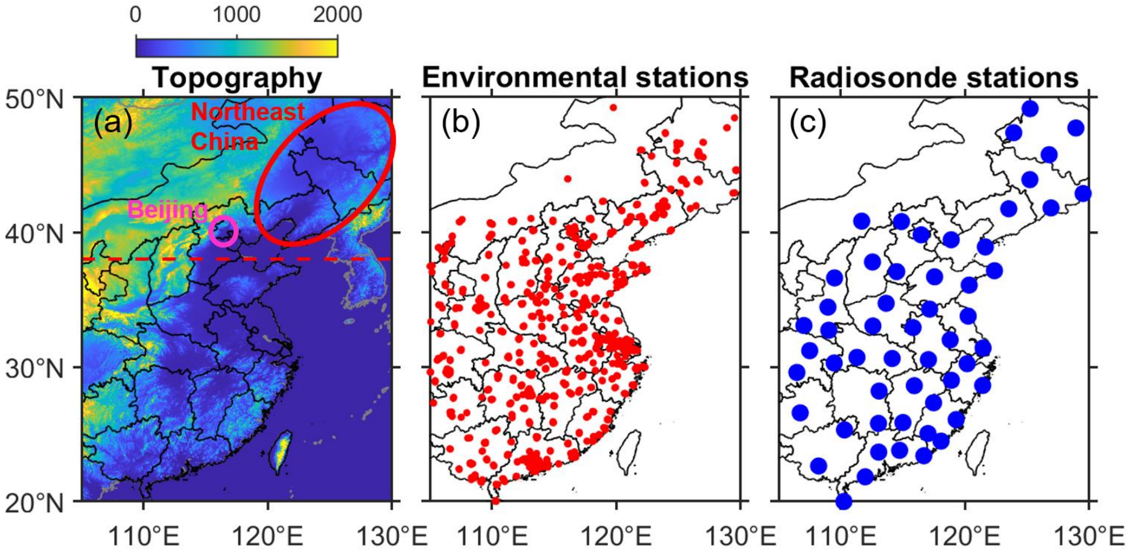

Figure S1. (a) Topography of eastern China. The red line divided northern China and southern/central China. Beijing and Northeast China are highlighted by the pink circle and red circle, respectively. (b) Locations of environmental monitoring stations. (c) Locations of radiosonde stations.

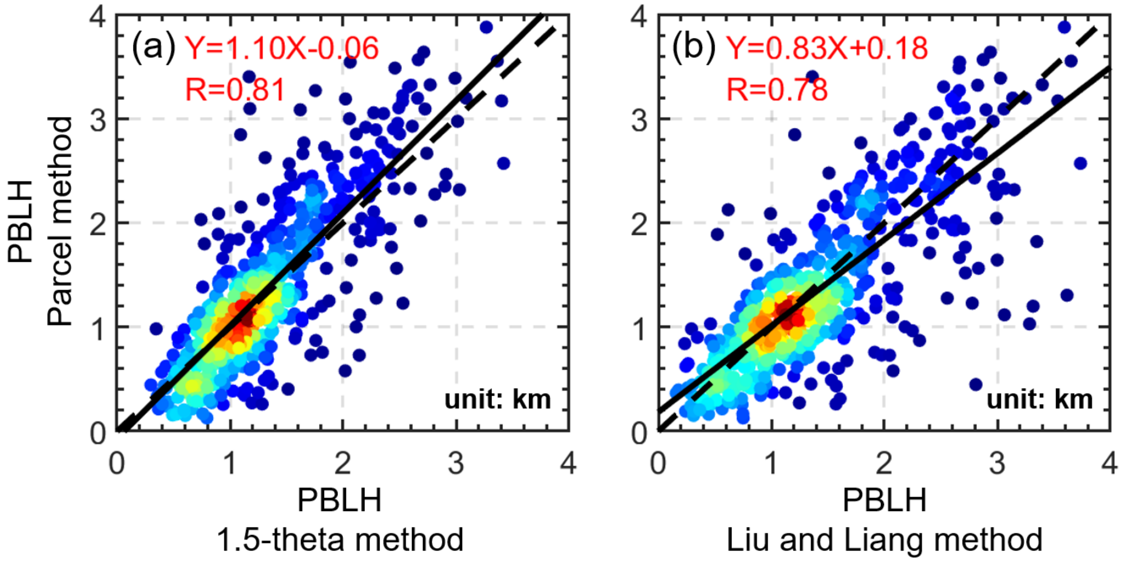

Figure S2. The comparison of PBLHs derived from parcel method and two standard methods (1.5-theta method and Liu and Liang method) at 1400 BJT during summertime. Parcel method uses morning radiosonde and surface meteorological data, and standard methods use radiosonde at 1400 BJT. The linear regression equations and correlation coefficients (R) are given in each panel.

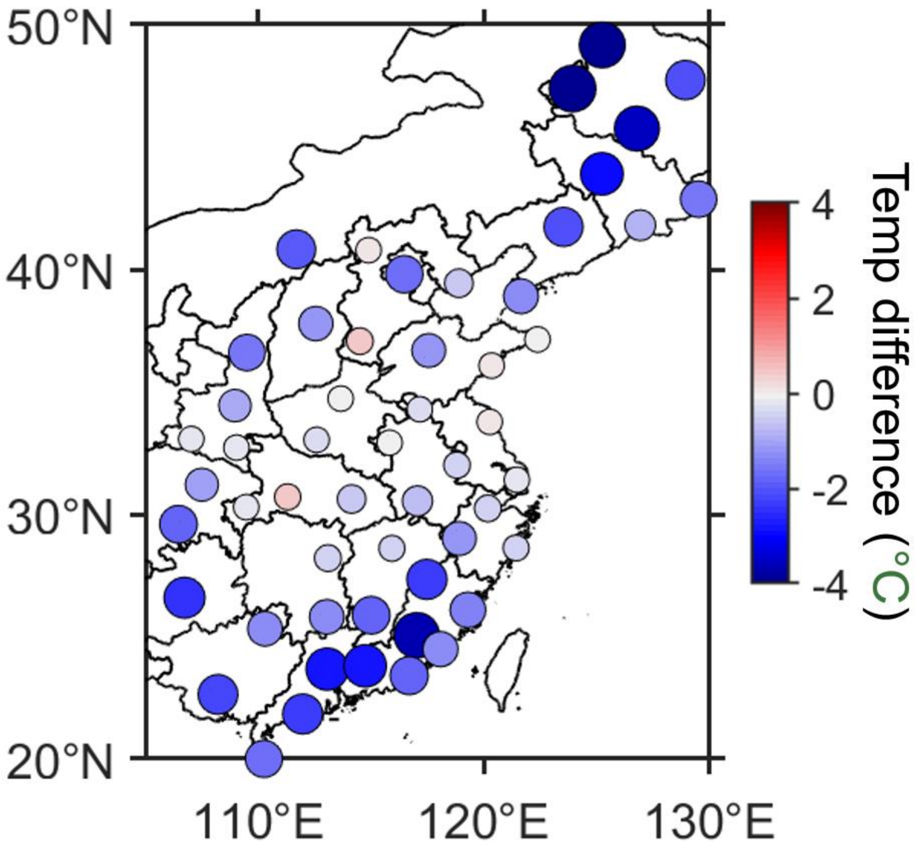

Figure S3. The differences in daytime temperature between mean values during the COVID-19 lockdown and the climatological mean during the same period of the years 2016 to 2019.

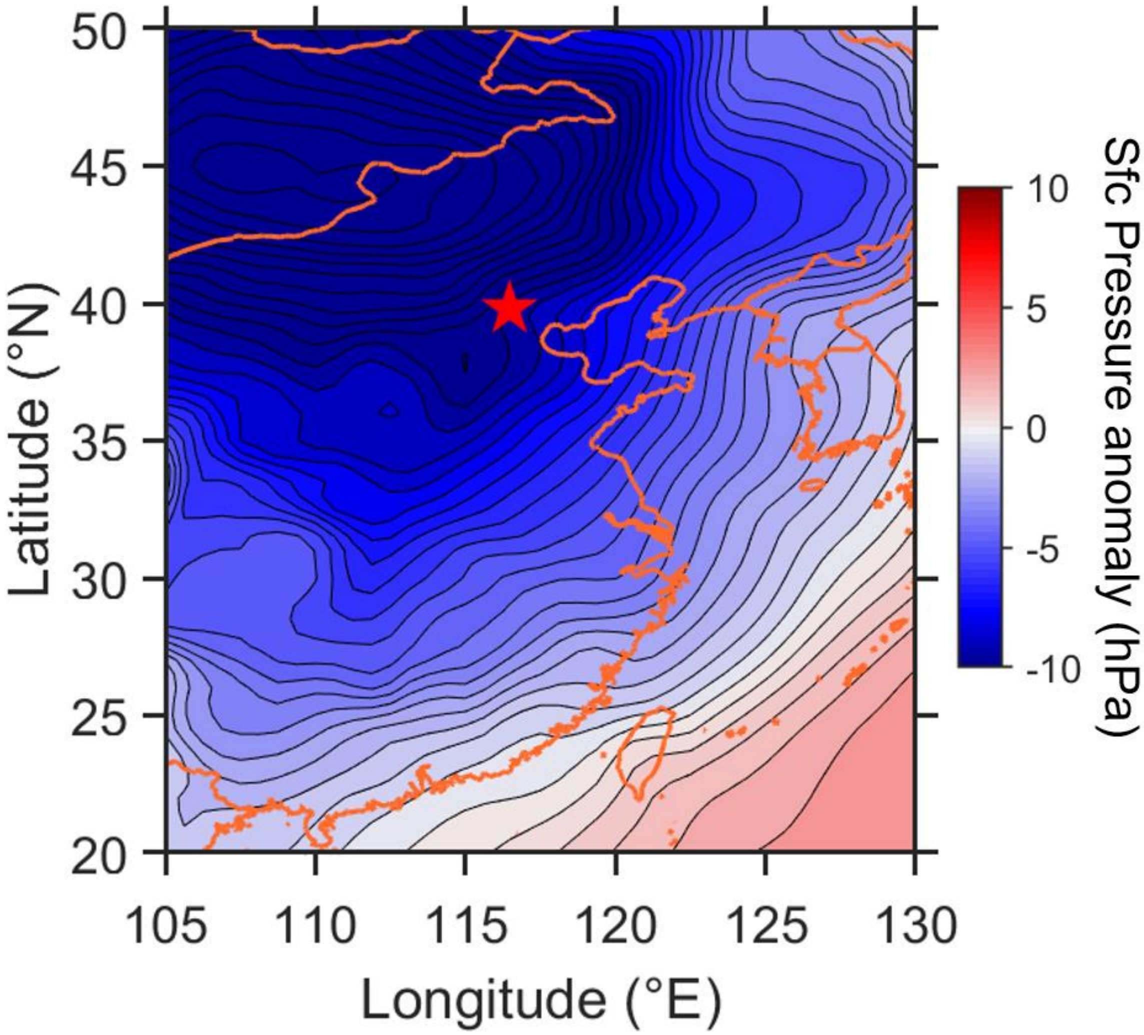

Figure S4. The surface pressure anomalies (relative to the monthly mean) during the CLD haze event. The location of Beijing is marked as the red star. The orange line indicates the coastline/border. The data are obtained from MERRA-2 reanalysis data.

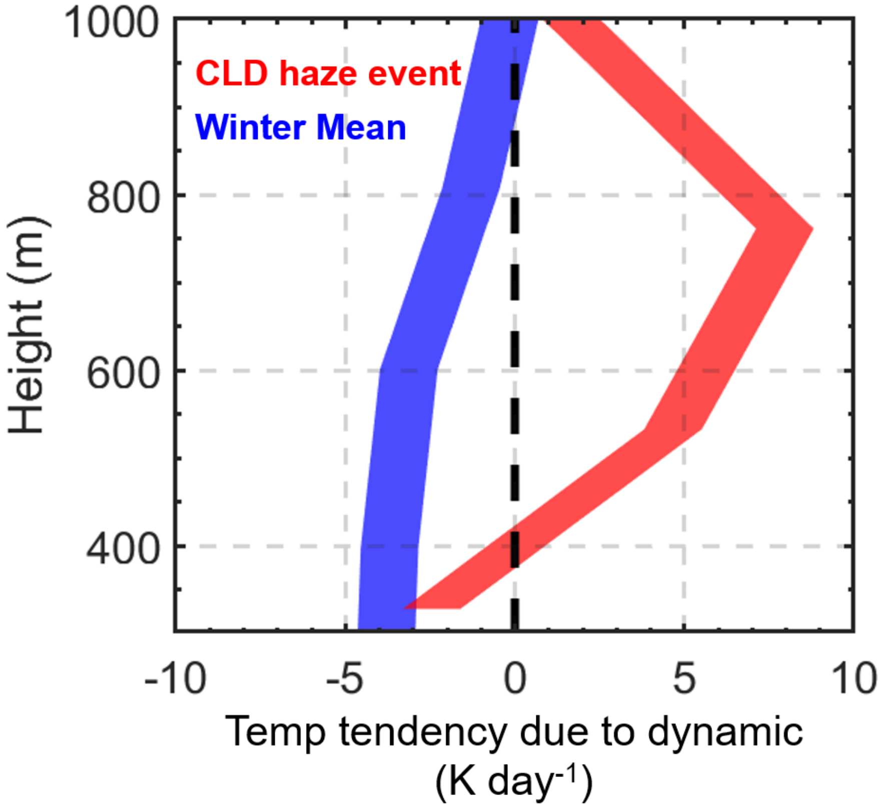

Figure S5. Profiles of temperature tendency due to the dynamic processes from MERRA-2 reanalysis data. Red line represents the value at 1230 BJT during the CLD haze event, and blue line represents the corresponding mean value during winter. The structure of temperature tendency during the CLD haze event facilitate the temperature inversion, and thus increase the lower-atmosphere stability and reduce the PBLH.

Tables

Table S1. List of radiosonde stations over Beijing and northeast China. (http://data.cma.cn/en/)

Regions of interest	Station code	City	Elevation (m)
Beijing	54511	Beijing	30
Northeast China	54662	Dalian	90
	50953	Harbin	143
	54161	Changchun	239
	50745	Qiqihar	148
	54292	Yanji	256

Table S2. Statistics of the partial correlation coefficients of the relationships between $PM_{2.5}$ and multiple meteorological parameters (PBLH, WS, RH, and rainfall amount) during CLD. Also shown are standardized multiple regression equations of $PM_{2.5}$ onto the meteorological parameters. Asterisks (*) denote the correlations that are statistically significant at the 95% confidence level. PBLH shows significant partial correlations with $PM_{2.5}$ over both Beijing and Northeast China.

ROIs	**Partial Correlation Coefficients with $PM_{2.5}$ (y)**			
	PBLH (x_1)	**WS (x_2)**	**RH (x_3)**	**Rainfall (x_4)**
Beijing	-0.50*	-0.05	0.18	-0.42*
	Standardized multiple regression: $y = -0.59x_1 - 0.05x_2 + 0.18x_3 - 0.45x_4$			
Northeast China	-0.44*	-0.41*	0.14	-0.19
	Standardized multiple regression: $y = -0.40x_1 - 0.41x_2 + 0.09x_3 - 0.13x_4$			

Table S3. $PM_{2.5}$ and meteorology during CLD haze event and other three shallow PBL periods during 2013–2019.

	Date	$PM_{2.5}$ ($\mu g\ m^{-3}$)	PBLH (m)	WS (m/s)	RH (%)
CLD haze event	20200213	212	425	2.3	84
	20200212	195	648	1.2	60
	20200211	232	437	1.6	60
	20200210	116	429	1.2	47
	20200209	127	507	1.6	58
Period I	20170104	287	237	1.3	78
	20170103	287	332	1.7	72
	20170102	231	133	2.3	67
	20170101	497	301	1.5	88
	20161231	312	545	1.4	70
	20161230	166	647	1.3	67
Period II	20161221	407	378	1.1	78
	20161220	362	241	1.3	89
	20161219	205	558	1.2	56
	20161218	213	512	1.1	61
	20161217	206	320	1.7	58
	20161216	108	522	1.2	47
Period III	20151226	239	245	1.9	79
	20151225	553	238	1.5	97
	20151224	58	296	1.5	74
	20151223	211	539	1.3	73
	20151222	306	168	1.9	86
	20151221	215	420	1.3	68