Supporting Information

Four-month changes in air quality during and after the COVID-19 lockdown in six megacities in China

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Part II. Preparation of the traffic profiles for developing emission inventories (Page S7 to S12, with 1 Supplementary Table and 5 Supplementary Figures).

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Part I. Model development and training

RF1
This random forest model (RF1) was trained on datasets from January 1 to April 26 of 2015-2019 and January 1 to January 19, 2020, which were used to predict the pollutant concentrations under the scenario without lockdown (w/o lockdown) from January 20 to April 26, 2020. Hourly concentrations of NO$_2$, O$_3$, PM$_{2.5}$ and CO were the dependent variables, and the meteorological parameters (wd, ws, temp, RH, and pressure) and time predictors (year, day_julian, day_lunar, weekday, hour) served as the independent predictors (see Table S1). The training set used a random selection of 70% of the data, and the remaining 30% were used as the testing set. The random forest models were developed using the rmweather R package$^1, 2$. The number of trees was 200, and the number of variables split in each node was 4. The comparison between actual observations and predictions under the w/o lockdown scenario basically represents the overall impact from the lockdown policies in China. We note that pressure observations were not available from the meteorological datasets of Chengdu, Xi’an and Shanghai. The random forest models for the other cities (Beijing, Shenzhen and Wuhan) indicated that pressure was of very low importance (see Table S2). Therefore, it was reasonable to exclude atmospheric pressure when modeling the cities without these data. The validation for RF1 is given in Table S3.

RF2
The RF2 model was trained from January 1 to March 22, 2020 due to the availability of traffic data, and training including the actual vehicle emissions estimated based on the real-world traffic monitoring data. In addition to the independent predictors (only the datasets in 2020 were used to build RF2 because of the availability of traffic data, so day_julian was excluded), we added estimated hourly vehicle emissions to train the model (see Table S1). The mode configuration was consistent with the first random forest, i.e., 70% of the data were used for training, and the remaining 30% were used for testing. The validation for RF2 is given in Table S4.
Table S1. Potential prediction variables for the two random forest models in this study.

(a) RF1

| Codes | Prediction variables | Units |
|-------|----------------------|-------|
| Meteorological parameters | | |
| wd    | Wind direction       | deg   |
| ws    | Wind speed           | m/s   |
| temp  | Air temperature      | ºC    |
| RH    | Relative humidity    | %     |
| pressure | Atmospheric pressure | millibar |
| Time parameters | | |
| year  | Year                 | n/a   |
| day_julian | Date of the year (1-366) | n/a |
| day_lunar | The number of days after the first day of Lunar New Year | n/a |
|         | Holiday              |       |
| weekday | Day of the week (1-7) | n/a |
| hour   | Hour of the day (0-23) | n/a |

(b) RF2

| Codes | Prediction variables | Units |
|-------|----------------------|-------|
| Meteorological parameters | | |
| wd    | Wind direction       | deg   |
| ws    | Wind speed           | m/s   |
| temp  | Air temperature      | ºC    |
| RH    | Relative humidity    | %     |
| pressure | Atmospheric pressure | millibar |
| Time parameters | | |
| day_julian | Date of the year (1-366) | n/a |
| weekday | Day of the week (1-7) | n/a |
| hour   | Hour of the day (0-23) | n/a |
| Vehicle emission parameters | | |
| NOX_emission | Vehicle emissions for NOX | t/h |
| HC_emission  | Vehicle emissions for HC | t/h |
| CO_emission  | Vehicle emissions for CO | t/h |
| PM2.5_emission | Vehicle emissions for PM2.5 | t/h |
| Cities      | Pollutants | Variable Importance | Cities      | Pollutants | Variable Importance |
|------------|------------|---------------------|------------|------------|---------------------|
| Beijing    | NO\_2      | 175.3367            | Chengdu    | NO\_2      | 140.9107            |
|            | O\_3       | 61.84221            |            | O\_3       | 115.23              |
|            | PM\_2.5    | 1346.885            |            | PM\_2.5    | 1322.096            |
|            | CO         | 0.349334            |            | CO         | 0.144158            |
| Shenzhen   | NO\_2      | 90.44109            |            | NO\_2      | 90.44109            |
|            | O\_3       | 143.5465            |            | O\_3       | 143.5465            |
|            | PM\_2.5    | 152.5357            |            | PM\_2.5    | 152.5357            |
|            | CO         | 0.042347            |            | CO         | 0.042347            |
| Xi'an      | NO\_2      | 306.0133            |            | NO\_2      | 306.0133            |
|            | O\_3       | 111.4308            |            | O\_3       | 111.4308            |
|            | PM\_2.5    | 2866.504            |            | PM\_2.5    | 2866.504            |
| Shanghai   | NO\_2      | 70.34985            |            | NO\_2      | 70.34985            |
|            | O\_3       | 78.21308            |            | O\_3       | 78.21308            |
|            | PM\_2.5    | 792.2208            |            | PM\_2.5    | 792.2208            |
| Wuhan      | NO\_2      | 121.9371            |            | NO\_2      | 121.9371            |
|            | O\_3       | 65.95771            |            | O\_3       | 65.95771            |
|            | PM\_2.5    | 1349.013            |            | PM\_2.5    | 1349.013            |
|            | CO         | 0.088244            |            | CO         | 0.088244            |
Table S3. Model validation for RF1.

| Cities    | Pollutants | Validation parameters |   |
|-----------|------------|-----------------------|---|
|           |            | R²        | FAC2    | MB      | NMB     | RMSE    |
| Beijing   | NO₂        | 0.8186   | 0.9468  | 0.1210  | 0.0026  | 12.5972 |
|           | O₃         | 0.8680   | 0.8975  | 0.3271  | 0.0070  | 11.9000 |
|           | PM₂₅       | 0.8372   | 0.8313  | 0.4906  | 0.0075  | 29.0782 |
|           | CO         | 0.8679   | 0.9600  | 0.0017  | 0.0016  | 0.3593  |
| Chengdu   | NO₂        | 0.7623   | 0.9871  | -0.1158 | -0.0023 | 10.8854 |
|           | O₃         | 0.9077   | 0.9691  | -0.0439 | -0.0009 | 10.9027 |
|           | PM₂₅       | 0.9198   | 0.9776  | 0.0746  | 0.0011  | 12.9654 |
|           | CO         | 0.8717   | 0.9995  | -0.0025 | -0.0023 | 0.1513  |
| Shenzhen  | NO₂        | 0.6875   | 0.9868  | 0.1642  | 0.0051  | 8.8645  |
|           | O₃         | 0.8129   | 0.9829  | -0.0437 | -0.0007 | 13.2779 |
|           | PM₂₅       | 0.8333   | 0.9878  | -0.0057 | -0.0002 | 6.8650  |
|           | CO         | 0.9065   | 1.0000  | -0.0001 | -0.0001 | 0.0675  |
| Xi'an     | NO₂        | 0.8067   | 0.9841  | -0.3792 | -0.0067 | 11.9245 |
|           | O₃         | 0.8938   | 0.9253  | 0.3168  | 0.0086  | 10.8321 |
|           | PM₂₅       | 0.9265   | 0.9680  | 0.1188  | 0.0013  | 19.3292 |
|           | CO         | 0.9343   | 0.9998  | -0.0093 | -0.0052 | 0.2214  |
| Shanghai  | NO₂        | 0.7748   | 0.9883  | 0.1107  | 0.0023  | 11.9725 |
|           | O₃         | 0.8537   | 0.9459  | 0.1555  | 0.0024  | 13.2539 |
|           | PM₂₅       | 0.8198   | 0.9418  | 0.0943  | 0.0018  | 16.8955 |
|           | CO         | 0.7869   | 0.9978  | 0.0041  | 0.0051  | 0.1572  |
| Wuhan     | NO₂        | 0.7632   | 0.9800  | -0.3061 | -0.0061 | 13.2176 |
|           | O₃         | 0.8511   | 0.8698  | 0.9280  | 0.0222  | 13.0690 |
|           | PM₂₅       | 0.8819   | 0.9812  | -0.2967 | -0.0041 | 16.2995 |
|           | CO         | 0.7594   | 0.9985  | -0.0034 | -0.0030 | 0.2108  |
Table S4. Model validation for RF2.

| Cities                  | Pollutants | R²       | FAC2    | MB      | NMB     | RMSE   |
|-------------------------|------------|----------|---------|---------|---------|--------|
| Beijing                 | NO₂        | 0.9062   | 0.9642  | -0.3966 | 0.0132  | 5.7751 |
|                         | O₃         | 0.8994   | 0.9642  | -0.2922 | -0.0066 | 8.0216 |
|                         | PM₂.₅      | 0.9276   | 0.8857  | 0.8819  | 0.0170  | 14.1507|
|                         | CO         | 0.9175   | 0.9846  | 0.0155  | 0.0196  | 0.1648 |
| Chengdu (urban area)   | NO₂        | 0.9145   | 0.9896  | 0.3942  | 0.0116  | 6.5847 |
|                         | O₃         | 0.9108   | 0.8893  | -0.5114 | -0.0124 | 9.2632 |
|                         | PM₂.₅      | 0.9375   | 0.9965  | 0.7432  | 0.0137  | 6.9370 |
|                         | CO         | 0.9072   | 1.0000  | 0.0080  | 0.0108  | 0.0799 |
Part II. Preparation of the traffic profiles for developing emission inventories

Case 1: Beijing

The original method of constructing link-level traffic profiles was reported by Yang et al.\(^3\), who basically used link-level traffic congestion index in the urban area (i.e., within the Fifth Ring Road) and traffic monitoring of intercity highways. The traffic congestion index could be applied to accurately estimate the actual speed and to further estimate the change in traffic volume compared with the baseline conditions. Following this framework, we collected network-level traffic congestion index (see Fig. S1[a]) for the duration of the study to adjust the traffic activity and speed for a passenger vehicle fleet (e.g., light-duty passenger vehicles and medium- and heavy-duty buses) in the urban area and the entire city. In addition, we obtained hourly, link-level speed profiles from March 13 to 31 using open-accessed map software (www.amap.com) to validate the method (see Fig. S1[b])\(^4\). We also used the intercity highway monitoring data to estimate the traffic activity of freight trucks and passenger vehicles traveling outside the Fifth Ring Road (see Fig. S1[c]). Compared with the pre-Spring Festival levels, the average speeds in Beijing increased overall by 43% from January 24 to February 9, and traffic volumes decreased by 58% (see Fig. S2).

![Fig. S1](a) Daily variation of traffic congestion index (TCI) in the urban area (i.e., within the Fifth Ring Road) and the whole city of Beijing; (b) Comparison of daily average speed predicted by the network-level TCI and the real-world speed obtained from Amap during Mar 13 to 31; (c) Relative volume comparing with the average level during Jan 1 to 14 for light duty vehicles (LDV), heavy duty vehicles (HDV), light duty trucks (LDT), medium duty trucks (MDT), and heavy duty trucks (HDT) traveling outside the Fifth Ring Road.

**Notes:**
The daily average speeds for urban area and the whole city were predicted based on network-level TCI data during Mar 13\(^{th}\)
to 31st in corresponding areas using the relationship between TCI and road speed proposed by Yang et al3. Quadratic functions were proposed to express the relationship between TCI and road speed according to the official guideline of Beijing Municipal Administration of Quality and Technology Supervision and BTI, 20115.

The hourly-based, link-level speed profiles of 1520 roads obtained from Amap navigation app during Mar 13th to 31st served as the validation set. The observed speeds in urban area and the whole city were averaged by day to validate the predicted daily average speed.

(a)

(b)

Fig. S2 Daily variations in (a) relative traffic speed and (b) relative total volume comparing with the basic level (the average level during 1.4-1.18) for observed road segments in the urban (within Fifth Ring Road) and non-urban (outside Fifth Ring Road) areas of Beijing.
Case 2: Chengdu

We selected the urban area within the Third Ring Road of Chengdu (~210 km²) as the research domain for RF2 because most of the available traffic observations were located within this region. Hourly traffic profiles including the volume and the fleet mix were obtained from 1454 traffic sensors operated from January 1 to March 22, 2020, which transmitted real-time traffic volumes including the vehicle category, fuel type and emission standards. Link-level speed data were synchronously collected from a floating car system supported by the Amap application covering 1541 road links. Fig. S3 shows the distribution of the traffic monitoring system. Compared with the pre-Spring Festival levels, the average speeds in urban area (within the Third Ring Road) of Chengdu increased by 14% from January 24 to February 9, and traffic volumes decreased by 62% (see Fig. S4).

(a) Coverage of on-road speed probes

(b) Coverage of traffic volume sensors

Fig. S3 Distribution of traffic monitoring system in Chengdu. The right panels majorly indicate the area within the Third Ring Road of Chengdu (i.e., the research domain of RF2)
Land-use random forest (LURF) models were developed to estimate the spatial distributions of link-level traffic speed and volume for the research domain. A total of 272 land use indicators that potentially affected traffic characteristics were selected to train the LURF models, including road features, population density, land cover, points of interest (POI), and distance to important sites (see Table S5 for a full list of predictors). To model traffic volumes, one additional indicator for vehicle category recognition (vehID) (vehID 1 to 3 represent light-duty vehicles [LDVs], medium-duty vehicles [MDVs], and heavy-duty vehicles [HDVs], respectively) was included according to the resolution of the traffic sensors. The split between passenger and freight vehicles for each vehicle category was developed based on previous camera records with a finer resolution, which was used to refine the fleet mix to match the EMBEV model. The speed and volume LURF models were trained separately for 24-h of each day in R using the ranger package\textsuperscript{6}. The model performance was validated using a 10-fold cross-validation scheme (see Fig. S5). The link-level speed and volume for the three vehicle categories covering the entire road network of the research domain during the research period were then predicted based on the LURF models.
## Table S5. Potential prediction variables considered in traffic modeling.

| Codes         | Prediction variables                                      | Units        |
|---------------|-----------------------------------------------------------|--------------|
| Road features |                                                           |              |
| mid_x / mid_y | Longitude/latitude of midpoint of roads                   | n/a          |
| Rank          | Road type                                                 | n/a          |
| LaneNum       | Lane number of the road segment                           | count        |
| SpdLmt        | Speed limit of the road segment                           | km/h         |
| rd1_*m        | Total expressway length in buffer                         | meters       |
| rd2_*m        | Total arterial road length in buffer                      | meters       |
| rd3_*m        | Total sub-arterial road length in buffer                  | meters       |
| rd4_*m        | Total minor road length in buffer                         | meters       |
| rd1_CN*m      | Total expressway lane number in buffer                    | count        |
| rd1_CL*m      | Highway length * lane number in buffer                    | meters       |
| rd2_CN*m      | Total arterial road lane number in buffer                 | count        |
| rd2_CL*m      | Arterial road length * lane number in buffer              | meters       |
| rd3_CN*m      | Total sub-arterial road lane number in buffer             | count        |
| rd3_CL*m      | Sub-arterial road length * lane number in buffer          | meters       |
| rd4_CN*m      | Total minor road lane number in buffer                    | count        |
| rd4_CL*m      | Minor road length * lane number in buffer                 | meters       |
| Population and land cover |                          |              |
| pop_*m        | Population density                                        | count/meters²|
| city_county*  | Urban area                                                 | meters²      |
| cropland*     | Cropland area                                              | meters²      |
| bareland*     | Undeveloped land area                                      | meters²      |
| grassland*    | Grassland area                                             | meters²      |
| POI counts    |                                                           |              |
| transit*      | Traffic poi                                                | count        |
| restaurant*   | Restaurant poi                                             | count        |
| office*       | Business poi                                               | count        |
| mall*         | Mall poi                                                   | count        |
| hotel*        | Hotel poi                                                  | count        |
| education*    | Educational poi                                            | count        |
| bank*         | Bank poi                                                   | count        |
| recreation*   | Recreation poi                                             | count        |
| touristic*    | Tourist spot poi                                           | count        |
| Distance to importance sites |                                |              |
| D_airport     | Distance to the nearest airport                            | meters       |
| D_port        | Distance to the nearest port                              | meters       |
| D_logistic    | Distance to the nearest freight transfer station          | meters       |
| D_CBD         | Distance to the nearest CBD                                | Meters       |
| Temporal indicators |                                |              |
| hour          | Hour in a day (0 - 23)                                     | n/a          |
| is_daytime    | is_daytime = 1, during 7:00 to 18:00                      | n/a          |
| is_holiday    | is_holiday= 1 for weekends and national holidays          | n/a          |

Note: * Buffer value variables (buffer radii 50 m, 100 m, 200 m, 300 m, 500 m, 1000 m, 2000 m, 3000 m, 4000 m, 5000 m)
Fig. S5 The spatial generalization performance of (a) speed and (b) volume random forest model validated by a 10-fold cross-validation scheme.
### Part III. Supplementary Tables

**Table S6.** Implementation time of lockdown policies in the six megacities.

| Cities  | Beginning of the lockdown | End of the lockdown a |
|---------|---------------------------|-----------------------|
| Beijing | Jan 24th                  | Apr 30th              |
| Chengdu | Jan 24th                  | Feb 26th              |
| Shenzhen| Jan 23rd                  | Feb 24th              |
| Xi’an   | Jan 25th                  | Feb 28th              |
| Shanghai| Jan 24th                  | Mar 24th              |
| Wuhan   | Jan 23rd                  | May 2nd               |

Note: a The beginning and end of the lockdown indicates the implementation and lift of control actions required by the Level-1 public health emergency response.

**Table S7.** Information of air quality and airport meteorological stations among the six cities.

| Cities  | Number of national air quality stations | Meteorological stations | Longitude | Latitude |
|---------|-----------------------------------------|-------------------------|-----------|----------|
| Beijing | 12                                      | PEK*                    | 116.585   | 40.08    |
| Chengdu | 8                                       | CTU                     | 103.947   | 30.579   |
| Shenzhen| 11                                      | SZX                     | 113.811   | 22.639   |
| Xi’an   | 13                                      | XIY                     | 108.752   | 34.447   |
| Shanghai| 10                                      | SHA                     | 121.336   | 31.198   |
| Wuhan   | 11                                      | WUH                     | 114.208   | 30.784   |

Note: *The codes in parentheses indicate the International Air Transport Association (IATA) abbreviation of airports.

**Table S8.** Importance of each independent variables in the modified RF1 for PM$_{2.5}$ concentrations in Beijing.

| year     | n    | r    | weekday | hour | wd   | ws   | temp | RH   | pressure | OX        |
|----------|------|------|---------|------|------|------|------|------|----------|-----------|
| 519.066  | 8    | 1455.396 | 1338.105 | 196.358 | 310.347 | 333.259 | 426.320 | 850.223 | 3048.239 | 182.555 | 5224.01 |

Note: The codes in parentheses indicate the International Air Transport Association (IATA) abbreviation of airports.
Part IV. Supplementary Figures

(a) Beijing

(b) Chengdu

(c) Shenzhen

(d) Xi’an

(e) Shanghai

(f) Wuhan

**Fig. S6** Observations (actual) and predictions (w/o lockdown) for daily NO$_2$ concentrations in the six cities.
Fig. S7 Observations (actual) and predictions (w/o lockdown) for MDA8 O\textsubscript{3} concentrations in the six cities.
Fig. S8 Observations (actual) and predictions (w/o lockdown) for daily PM$_{2.5}$ concentrations in the six cities.
Fig. S9 Observations (actual) and predictions (w/o lockdown) for daily CO concentrations in the six cities.
Fig. S10 Difference between observed and predicted ambient NO₂ concentrations among different types of air quality stations in Beijing.

Note: There are 34 official air quality sites (12 national level (used in RF1) and 22 municipal level) in Beijing totally. These sites consist of 11 urban sites, 11 suburban sites, 1 background site and 5 traffic site, and 6 sites used to monitor cross-boundary pollution transport. The air quality observations from municipal-level sites were accessed from Beijing Municipal Environmental Monitoring Center (http://www.bjmemc.com.cn/).
Fig. S11 History_met_predictions (predictions when meteorological parameters in 2019 were employed as the input) and predictions (w/o lockdown) for NO$_2$ concentrations in the six cities.
Fig. S12 Difference between observed and predicted MDA8 O₃ concentrations in the six cities.
Fig. S13 Difference between observed and predicted ambient PM$_{2.5}$ concentrations in the six cities.
Fig. S14 Difference between observed and predicted ambient CO concentrations in the six cities.
Fig. S15 Observations (actual) and predictions (w/o lockdown) for daily OX (OX=NO$_2$+O$_3$) concentrations in Beijing.
Fig. S16 (a) Observations (actual), and predictions (w/o lockdown) from the modified RF1 model using OX observations and predictions (i.e., OX_observation_predicted and OX_prediction_predicted, respectively) for daily PM$_{2.5}$ concentrations in Beijing. (b) Predictions from the original RF1 model which excluded OX concentrations and from the modified RF1 using OX predictions. The differences between these two curves are not significant.
Fig. S17 Trends in traffic NO$_X$ emissions in (a) entire municipality of Beijing and (b) urban area of Chengdu in different periods. We averaged daily emissions every 10 days to indicate the overall trend.
Fig. S18 Weekly differences between observations (actual) and predictions (w/o traffic emission changes) for MDA8 O₃ and daily PM₂.₅ concentrations in entire Beijing and urban Chengdu.
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