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Assessing the impact of Clean Air Action Plan on Air Quality Trends in Beijing Megacity using a machine learning technique

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ABSTRACT

A five-year Clean Air Action Plan was implemented in 2013 to reduce air pollutant emissions and improve ambient air quality in Beijing. Assessments of this Action Plan is an essential part of the decision-making process to review the efficacy of the Plan and to develop new policies. Both statistical and chemical transport modelling were applied to assess the efficacy of this Action Plan. However, inherent uncertainties in these methods mean that new and independent methods are required to support the assessment process. Here, we improved a novel machine learning-based random forest technique to quantify the effectiveness of Beijing's Acton Plan by decoupling the impact of meteorology on ambient air quality. Our results demonstrate that meteorological conditions have an important impact on the year to year variations in ambient air quality. Further analysis show that the favorable meteorological conditions in winter 2017 contributed to a lower $PM_{2.5}$ mass concentration (58 μg m^{-3}) than predicted from the random forest model (61 μg m^{-3}), which is higher than the target of the Plan (2017 annual $PM_{2.5} < 60$ μg m^{-3}). However, over the whole period (2013 to 2017), impact of meteorological conditions on the trend of ambient air quality are small. It is the primary emission control, because of the Action Plan, that has led to the significant reduction in $PM_{2.5}$, PM_{10}, NO_2, SO_2 and CO from 2013 to 2017, which are approximately 34%, 24%, 17%, 68%, and 33% after meteorological correction. The marked decrease in $PM_{2.5}$ and SO_2 is largely attributable to a reduction in coal combustion. Our results indicate that the Action Plan is highly effective in reducing the primary pollution emissions and improving air quality in Beijing. The Action Plan offers a successful example for developing air quality policies in other regions of China and other developing countries.

Keywords: Clean air action plan, Beijing, air quality, emission control, coal combustion

1. INTRODUCTION

In recent decades, China has achieved rapid economic growth and become the world's second largest economy. However, it has paid a high price in the form of serious air pollution problems caused by the rapid industrialization and urbanization associated with its fast economic growth (Lelieveld et al., 2015;Zhang et al., 2012;Guan et al., 2016). According to the World Bank, air pollution costs China's economy $159 billion (~9.9 % of GDP equivalent) in welfare losses and was associated with 1.6 million deaths in China in 2013 (Xia et al., 2016;World Bank and IHME, 2016). Accordingly, air pollution has been receiving much attention from both the public and policymakers in China, especially in Beijing - the capital of China with around 22 million inhabitants- which has suffered extremely high levels of air pollutants (Rohde and Muller, 2015;Guo et al., 2013;Zhu et al., 2012). To tackle air pollution problems, China's State Council released the action plan in 2013 which set new targets to reduce the concentration of air pollutants across China (CSC, 2013). Within the plan, a series of policies, control and action plans with a focus on Beijing-Tianjin-Heibei, the Yangtze River Delta and the Pearl River Delta regions were proposed. To implement the national Action Plan and further improve air quality, Beijing Municipal Government (BMG) formulated and released the "Beijing 2013-2017 Clean Air Action Plan" (the "Action Plan"), which set a target for the mean concentration of fine particles ($PM_{2.5}$, particulate matter with aerodynamic diameter less than 2.5 µm) to be below 60 µg m^{-3} by 2017 (BMG, 2013). Since then, the five-year period of 2013-2017 has seen the implementation of numerous regulations and policies in Beijing.

It is of great interest to the government, policymakers and the general public to know whether the Action Plan is working to meet the set targets. Research in this area is often termed as air quality accountability study (HEI, 2003;Henneman et al., 2017;Cheng et al., 2018). This is highly challenging because the actions taken to reduce the air pollutants as well as the meteorological conditions affect the air quality levels during a particular period (Henneman et al., 2017;Cheng et al., 2018;Liu et al., 2017;Grange et al., 2018). Therefore, it is essential to decouple the meteorological impact from ambient air quality data to see the real benefits in air quality by different actions.

Chemical transport models are widely used to evaluate the response of air quality to emission control policies (Wang et al., 2014;Daskalakis et al., 2016;Souri et al., 2016). However, there are major uncertainties in emission inventories and in the models themselves, which inevitably affect the outputs of chemical transport models (Li et al., 2017;Gao et al., 2018). Statistical analysis of ambient air quality data is another commonly used method to decouple the meteorological effects on air quality (Henneman et al., 2017;Liang et al., 2015), including Kolmogorov-Zurbenko (KZ) filter model and deep neural network (Wise and Comrie, 2005;Comrie, 1997;Eskridge et al., 1997;Hogrefe et al., 2003;Gardner and Dorling, 2001). But they usually gave a poor fitting, suggesting a poor performance of the KZ filter model, or did not allow us to investigate the effect of input variables in neural network models (therefore it is referred as a "black- box" model) (Gardner and Dorling, 2001;Henneman et al., 2015). More recently, new approaches based on classification trees are being developed, which are suitable for air quality weather detrending, including the boosted regression trees (BRT) and random forest (RF) algorithms (Carslaw and Taylor, 2009;Grange et al., 2018). These machine learning based techniques have a better performance compared to the traditional statistical and air quality models by reducing variance/bias and error in high dimensional data sets (Grange et al., 2018; Zhan et al., 2018a,b). However, similar to the deep learning algorithms such as neural networks, it is hard to interpret the working mechanism inside these models and as well as the results. Recent published R-packages can partly explain and visualise random forest models such as the importance of input variables and their interactions (Liaw and Wiener, 2018;Paluszynska, 2017).

Here, we developed a novel machine learning technique based upon the random forest algorithm and the latest R-packages to quantify the role of meteorological conditions in air quality thus evaluate the effectiveness of the Action Plan in reducing air pollution levels in Beijing. The results were compared with the latest emission inventory as well as results from previous study which used a chemical transport model - the Weather Research and Forecasting (WRF)-Community Multiscale Air Quality (CMAQ) model (Wong et al., 2012;Xiu and Pleim, 2001).

2. MATERIALS AND METHODS

2.1 Data Sources

Hourly air quality data for six key air pollutants ($PM_{2.5}$, PM_{10}, NO_2, SO_2, O_3, and CO) was collected across 12 national air quality monitoring stations in Beijing. Hourly meteorological data including wind speed (ws), wind direction (wd), temperature (temp), relative humidity (RH) and pressure (press.) recorded at

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Beijing International Airport were downloaded using the "worldMet"- R package (Carslaw, 2017b). Data was analyzed in R Studio with a series of packages, including the "openair", "normalweatherr", and "randomForestExplainer" (Liaw and Wiener, 2018;Carslaw and Ropkins, 2012;Carslaw, 2017a;Paluszynska, 2017).

2.2 Modelling

Figure 1 shows a conceptual diagram of the data modelling and analysis which consists of three steps:

1) Random forest (RF) model development:

A decision tree-based random forest regression model describes the relationship between hourly concentrations of an air pollutant and it predictor variables (including time variation such as month 1 to 12, day of the year from 1 to 365 and hour of a day from 0 to 23, and meteorological parameters such as temperature, pressure, and relative humidity). The RF regression model is an ensemble-model which consists of hundreds of individual decision tree models.

As shown in Figure 1, we firstly construct the RF model from a training data set (e.g., 70% of the all data available) of observed concentrations of a pollutant and its predictor variables and then validate the model by unseen data sets (testing data sets).

The original data sets contain hourly concentration of a particular air pollutant and its predictor variables that include time variables (t_{trend}, the day of the year (from day 1 to 365), week/weekend (Monday to Sunday), hour (0 to 23)) and meteorological parameters (wind speed, wind direction, pressure, temperature, and relative humidity). These time variables represent effects upon concentrations of air pollution by diurnal, weekday/weekend day and seasonal cycles and t_{trend} represents the trend in time which captures the long-term change of air pollutant due to changes in policies/regulations, which was calculated as:

$$t_{trend} = year_i + \frac{t_{JD-1}}{N_i} + \frac{t_H}{24N_i}$$

where, N_i is the number of days in a year i, t_H: diurnal hour time (0-23); t_{JD}: day of the year (1-365) (Carslaw and Taylor, 2009).

The data sets were randomly divided into two data sets with a fraction of 0.7: 1) a training data set to construct the random forest model and 2) a testing data set to test the model performance for unseen data sets. The model is defined as a good performance if the correlations between observed and predicted values for both training and testing data sets are high (r^2 >0.8).

In the construction of a RF model, the bagging algorithm (which uses bootstrap aggregating) randomly sample observations and their predictor variables with replacement from a training data set. A single regression decision tree is grown in different decision rules based on the best fitting between the observed concentrations of a pollutant and their predictor variables. The predictor variables are selected randomly to gives the best split for each tree node. The hourly predicted concentrations of a pollutant are given by the final decision as the outcome of the weighted average of all individual decision tree. By averaging all predictions from bootstrap samples, bagging process decreases variance, thus helping the model to avoid over-fitting. To validate the model for unseen data sets, a test data set which represents 30% of entire data sets is input into the random forest model which has been constructed from training data sets. The performance, validation and explanation of the models are supplied in details in the section S3, Figure S1-S5.

2) Weather normalisation:

A weather normalization technique predicts the concentration of an air pollutant at a specific measured time point but with various meteorological conditions (termed as "weather normalised concentration"). Meteorological normalization technique was firstly introduced by Grange et al. (2018). Both time variable (month, hour) and meteorological parameters, except the trend variable were re-sampled randomly and was added into the random forest model as input variables to predict the concentration of a pollutant (Grange et

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al., 2018;Grange and Carslaw, 2019). The final concentration of that pollutant, referred hereafter as meteorological normalised concentration, is by aggregating 1000 predictions produced from the RF model. By this way, the model results in a predicted concentration of pollutant by normalization of the impact of seasonal and weather variations. However, it is unable to investigate the seasonal variation of trends for a comparison with the trend of primary emissions. Therefore, we enhanced the meteorological normalization procedure.

In our algorithm, only weather data (MET data) sets were re-sampled. We also enhanced the code to re-sample the MET data for a long term period rather than MET data during the conducted study. In particular, thirty-year MET in Beijing (1988-2017) was used to enable a better representation of average meteorological conditions. MET data variables at a specific selected hour of a particular day in the input data sets was replaced randomly by the MET data at that hour for a period of 2 weeks before and after that selected data in the 30 year MET data set (1988-2017). For example, the MET data at 8:00 15/01/2015 could be randomly replaced by the MET data at 8:00 am in any date from 1st to 30th January of any year in 1988-2017.

3) Theil-Sen regression:

Theil-Sen regression technique estimates the concentration of an air pollutant after meteorological normalization to calculate their long-term trends. The Theil-Sen approach, which computes the slopes of all possible pairs of pollutant concentrations and takes the median value, has been commonly used for long-term trend analysis over recent years. By selecting the median of the slopes, the Theil-Sen estimator gives us more accurate confidence intervals even with non-normally distributed data and non-constant error variance (Sen, 1968). The Theil-Sen function is provided via the "openair" package in R.

3. RESULTS AND DISCUSSIONS

3.1 Observed Levels of Air Pollution in Beijing During 2013-2017

Annual concentration of $PM_{2.5}$ and PM_{10} in Beijing measured from the 12 national air quality monitoring stations declined by 34 and 19 % from 88 and 110 μg m^{-3} in 2013 to 58 and 89 μg m^{-3} in 2017, respectively. Similarly, the annual mean levels of NO_2 and CO decreased by 16 and 33 % from 54 μg m^{-3} and 1.4 mg m^{-3} to 45 μg m^{-3} and 0.9 mg m^{-3} while the annual concentration of SO_2 showed a dramatic drop by 68 % from 23 μg m^{-3} in 2013 to 8.0 μg m^{-3} in 2017. Along with the decrease of annual mean concentration, the number of haze days (defined as $PM_{2.5}$ > 75 μg m^{-3} here) also decreased (Figure S6). These results confirm a significant improvement of air quality and that Beijing officially achieved its $PM_{2.5}$ target under the Action Plan (annual average $PM_{2.5}$ target for Beijing is 60 μg m^{-3} in 2017). On the other hand, the annual mean concentration of $PM_{2.5}$ is still substantially higher than the China's national ambient air quality standard (NAAQS-II) of 35 μg m^{-3} (Table S1) and the WHO Guideline of 10 μg m^{-3}. While PM_{10}, $PM_{2.5}$, SO_2, NO_2 and CO showed a decreasing trend, the annual average concentration of O_3 increased slightly by 4.9 % from 58 μg m^{-3} in 2013 to 61 μg m^{-3} in 2017. The number of days exceeding NAAQS-II standards for O_3-8h averages (160 μg m^{-3}) during the period 2013-2017 was 329, accounting for 18 % of total days.

3.2 Air Quality Trends After Weather Normalization

A key aspect in evaluating the effectiveness of air quality policies is to quantify the impact of emission reduction and meteorological conditions on air quality (Carslaw and Taylor, 2009; Henneman et al., 2017), the key factors regulating air quality. By applying a random forest algorithm, we decoupled the effect of meteorological condition to show the normalized air quality parameters – under the condition of the 30-year average (1988-2017) meteorological conditions (Figure 2). The temporal variations of ambient concentrations of monthly average $PM_{2.5}$, PM_{10}, CO, and NO_2 do not offer a clear trend from 2013 to 2017 because of the spikes in the winters. However, after the weather normalization, we can clearly see the decreasing true trend (Figure 2). The trends of the normalized air quality parameters represent the effects of emission control and, in some cases, associated chemical processes (for example, for ozone, $PM_{2.5}$, PM_{10}).

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SO_2 showed a dramatic decrease while ozone increased year by year (Figure 2). The normalized annual average levels of $PM_{2.5}$, PM_{10}, SO_2, NO_2, and CO decreased by 7.4, 7.6, 3.1, 2.5, and 94 µg m^{-3} year^{-1}, respectively, whereas the level of O_3 increased by 1.0 µg m^{-3} year^{-1}.

Table 1 compares the trends of air pollutants before and after normalization (the meteorological conditions were randomly selected in the model for the past 30 years (1988-2017)). The annual average concentration of fine particles ($PM_{2.5}$) after weather normalization was 61 µg m^{-3} in 2017, which was higher than their observed level of 58 µg m^{-3} by about 5.2%. This suggests that Beijing would have missed its $PM_{2.5}$ target of 60 µg m^{-3} if not for the favorable meteorological conditions in winter 2017 and the emission reduction contributed to 10 out of the 13 µg m^{-3} (77%) $PM_{2.5}$ reduction (71 to 58 µg m^{-3}) from 2016 to 2017. Overall, the emission control led to a 34%, 24%, 17%, 68%, and 33% reduction in normalized mass concentration of $PM_{2.5}$, PM_{10}, NO_2, SO_2 and CO from 2013 to 2017 (Table 1).

When meteorological conditions were randomly selected from 2013-2017 (instead of 1998-2017) in the RF model, the normalised level of $PM_{2.5}$ in 2017 was 60 µg m^{-3}. This indicates that our modelling results are robust. Additional uncertainty in the meteorological normalised levels of $PM_{2.5}$ obtained from a random forest model is discussed later in Section 3.3.

The observed $PM_{2.5}$ mass concentration reduced by 30 µg m^{-3} from 2013 to 2017, whereas the normalized values by 32 µg m^{-3}. Similarly, the observed PM_{10} and SO_2 mass concentration reduced by 30 and 15.5 µg m^{-3} from 2013 to 2017, whereas the normalized values by 33 and 17.9 µg m^{-3}. These results suggest that the effect of emission reduction would have contributed to an even better improvement in air quality from 2013 to 2017 (except ozone) if not for meteorological variations year by year.

Figure 3 shows that the Action Plan has been highly effective in improving air quality of Beijing at both the urban, suburban and rural sites, particularly for SO_2 (16-18 % year^{-1}), CO (8-9 % year^{-1}), and $PM_{2.5}$ (6-8 % year^{--}). The Action Plan also led to a decrease in PM_{10} and NO_2 but to a lesser extent than that of CO, SO_2 and $PM_{2.5}$, indicating that PM_{10} and NO_2 were significantly affected by other less well controlled sources. For example, Figure 2 suggested that the high levels of PM_{10} in spring were mostly affected by the frequent Asian dust events. Urban sites showed a bigger decrease in $PM_{2.5}$, PM_{10}, and SO_2 concentrations in comparison to the rural and suburban sites.

3.3 Impact of Meteorological Conditions on $PM_{2.5}$ levels: A Comparison with Results from CMAQ-WRF Model

We compared our RF modelling results with those from an independent method by Cheng et al. (2018) who evaluated the de-weathered trend by simulating the monthly average $PM_{2.5}$ mass concentrations in 2017 by the CMAQ model with meteorological conditions of 2013, 2016 and 2017 from the WRF model. The WRF-CMAQ results show that the annual average $PM_{2.5}$ concentration of Beijing in 2017 is 61.8 and 62.4 µg m^{-3} if under the 2013 and 2016 meteorological conditions, both of which higher than the measured value – 58 µg m^{-3}. Thus, the modelled results are similar to those from the machine learning techniques, which gave a weather-normalized $PM_{2.5}$ mass concentration of 61 µg m^{-3} in 2017.

Figure 4 also shows that the $PM_{2.5}$ concentrations would have been significantly higher in November and December in 2017 if under the meteorological conditions of 2016. In contrast, the $PM_{2.5}$ concentrations would have been lower in spring 2017 of under the MET data of 2016 or 30-year normalised MET data. Since severe $PM_{2.5}$ pollution and haze events almost always occur in winter in Northern China (Cai et al., 2017), the more favourable meteorological conditions in the two months contributed appreciably to the lower measured annual average $PM_{2.5}$ level in 2017. It also suggests the monthly levels of $PM_{2.5}$ strongly depend upon the monthly variation of weather.

Comparison of model uncertainties from the two methods

Figure 5 compares observation and prediction of monthly concentrations of $PM_{2.5}$ by the WRF-CMAQ model and the RF model. The correlation coefficient r^2 between monthly value was 0.82, whereas that from the random forest method is >0.99 for both the training and test data sets. The difference between monthly observed $PM_{2.5}$ value and those simulated by the WRF-CMAQ model ranged from 3 to 33.6%, resulting in 7.8% difference in yearly value. By contrast, the deviation between observed and predicted $PM_{2.5}$ value ranges from 0.4-7.9% with an average of 1.5%. In the modelled concentration of $PM_{2.5}$ from the random forest technique, the standard variation of those 1000 predictions by a random forest is 0.35, accounted 0.6% of $PM_{2.5}$ concentrations in 2017.

3.4 Evaluating the Effectiveness of the Mitigations Measures in the Clean Air Action Plan

The weather normalised air quality trend (Figure 2) allows us to assess the effectiveness of various policy measures to improve air quality to some extent. In particular, the SO_2 normalized trend clearly shows that the peak concentrations in the winter months decreased from 60 µg m^{-3} in Jan 2013 to less than 10 µg m^{-3} in Dec 2017 (Figure 2). This indicates that the control of emissions from winter-specific sources was highly successful in reducing SO_2 concentrations. The Multi-resolution Emission Inventory for China (MEIC) shows a major decrease in SO_2 emissions from heating (both industrial and centralized heating) and residential (mainly coal combustion) (Figure S7), which is consistent with the trend analyses. On the other hand, the “based line” SO_2 concentration – the lowest ones in the summer (Figure 2) – also reduced somewhat during the same period. The “based line” SO_2 mainly came from non-seasonal (winter) sources including power plants, industry, and transportation (Figure S7). Overall, the MEIC estimated that SO_2 emissions decreased by 71 % from 2013 to 2017 (Figure S7), which is close to the 67% decrease in normalized SO_2 (Table 1). According to the Beijing Statistical Year Books (2012-2017), coal consumption in Beijing declined remarkably by 56 % in 6 years as shown in Figure 6 (Karplus et al., 2018;BMBS, 2013-2017). The slightly faster decrease in SO_2 concentrations relative to coal consumption (Figure S8) was likely due to the adoption of clean coal technologies that were enforced by the “Action Plan for Transformation and Upgrading of Coal Energy Conservation and Emission Reduction (2014-2020)” (Karplus et al., 2018;Chang et al., 2016). In summary, energy re-structure, e.g., replacement of coal with natural gas (Figure 6; Section S2), is the most effective measure in reducing ambient SO_2 pollution in Beijing.

Coal combustion is not only a major source of SO_2, but also an important source of NO_x and primary particulate matter (PM) in Beijing (Streets and Waldhoff, 2000;Zíková et al., 2016;Lu et al., 2013;Huang et al., 2014). Precursor gases such as SO_2 and NO_x from coal combustion also contribute to secondary aerosol formation (Lang et al., 2017). MEIC emission inventory showed that 8.8-29 % of NO_x was emitted from heating, power and residential activities, primarily associated with coal combustion. As shown in Figure S8, the normalized NO_2 concentration is also decreasing, but much slower than that of SO_2. Most notably, the level of SO_2 dropped rapidly in 2014 but the level of NO_2 decrease by a small proportion. The different trends between SO_2 and NO_2 indicate that other sources (e.g. traffic emissions, Figure S8) have a greater influence on ambient concentration of NO_2 than coal combustion, although the chemistry of the $NO/NO_2/O_3$ system will tend to “buffer” changes in NO_2 causing non-linearity in NO_x-NO_2 relationships (Marr and Harley, 2002). NO_2 decreased more rapidly from January 2015, particularly by 17%, 18%, 10%, 15% (Figure 2) in the first six months of 2015, which suggests that emission control measures implemented in 2015 were effective, including regulations on spark ignition light vehicles to meet the national fifth phase standard, and expanded traffic restrictions to certain vehicles, including banning entry of high polluting and non-local vehicles to the city within the sixth ring road during daytime, and phasing out of 1 million old vehicles (Yang Z, 2015) (Section S2).

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Normalized $PM_{2.5}$ decreased faster than NO_2, but slower than SO_2 (Figure S8). Yearly peak normalized $PM_{2.5}$ concentrations decreased from 2013-14 to 2015-2016 but slighted rebounded in 2016-2017. The monthly normalized peak $PM_{2.5}$ concentration reduced from 115 µg m^{-3} in Jan 2013 to 60 µg m^{-3} in Dec 2017. The biggest drop is seen in winter 2017, which decreased by more than half from the peak value in winter 2016, suggesting that "no coal zone" policy (Section S2) to reduce pollutant emission from winter specific sources (i.e., heating and residential sectors) were highly effective in reducing $PM_{2.5}$. The normalized "based line" concentration – lowest values in each year – also decreased from 71 µg m^{-3} in summer 2013 to 42 µg m^{-3} in summer 2017. This suggests that non-heating emission sources, such as industry, industrial heating and power plants also contributed to the decrease in $PM_{2.5}$ from 2013 to 2017. These are broadly consistent with the $PM_{2.5}$ and SO_2 emission trends in MEIC (Figure S7). A small peak in both $PM_{2.5}$ and CO in June/July seen in Figure 2 from 2013 to 2016 attributed to agricultural burning almost disappeared over the period of the measurements and simulations in 2017, suggesting the ban on open burning is effective.

The normalized trend of PM_{10} is similar to that of $PM_{2.5}$, except that the rate of decrease is slower. The trend agrees well with PM_{10} primary emission for the summer (Figure S7). The biggest drop in peak monthly PM_{10} concentration is seen in winter 2017, which decreased by more than half from the peak value in winter 2016, suggesting that "no coal zone" policy (Section S2) to reduce pollutant emission from winter specific sources (i.e., heating and residential sectors) were highly effective in reducing PM_{10}, similar to that of $PM_{2.5}$. The rate of decrease of peak PM_{10} emission is slower than that of PM_{10}, which may suggest an underestimation of the decrease in MEIC. The normalized "based line" concentration – lowest values in each year (Figure 2) – also decreased from substantially from 2013 to 2017. This indicates that non-heating emission sources, such as industry, industrial heating and power plants also contributed to the decrease in PM_{10}. This is consistent with those trend in MEIC (Figure S7). The peaks in the spring are attributed to Asian dust events.

The normalized CO trend shows that the peak CO concentration reduced by approximately 50% from 2013 to 2017 with the largest drop from 2016 to 2017 (Figure 2). The decreasing trend in total emission of CO in MEIC is slower from 2015 to 2017, suggesting that the emission may be overestimated in these two years. During 2013-2016, the CO level decreased by 26 % and 34 % for both winter and summer ("baseline"). Similar to the normalized $PM_{2.5}$ trend, a small peak of CO concentration occurred in Jun-July during 2013-2016, which is likely associated with open biomass burning around the Beijing region. This peak disappeared in 2017. A major decrease in normalized CO levels in winter 2017 is attributed to the "no-coal zone" policy (see below Section S2; Figure S7).

3.5 Implications and Future Perspectives

We have applied a machine learning based model to successfully identify the key mitigation measures contributing to the reduction of air pollutant concentrations in Beijing. However, three challenges remain. Firstly, it is not always straightforward to link a specific mitigation measure to improvement in air quality quantitatively. This is because often more than two measures were implemented at a similar timescale, making it difficult to disentangle the impacts. Secondly, we were not able to compare the calculated benefit for each mitigation measure with the intended one designed by the government due to a lack of official data. If data on the intended benefits are known, this will further enhance the value of this type of study. Thirdly, the ozone level increased slightly during 2013-2017, especially for the summer periods (Table 1). Because ozone is a secondary pollutant, it is not possible to directly compare the trend with emission of precursor pollutants. The mechanisms of this increase are complex and out of the scope of this study.

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Our results confirmed that the "Action Plan" has been highly effective in improving real (normalized) air quality of Beijing (Figure 3). However, it would have failed to meet the target for annual average $PM_{2.5}$ concentrations if not for better than average air pollutant dispersion (meteorological) conditions in 2017. This suggests that future target setting should consider meteorological conditions. Major challenges remain in reducing the $PM_{2.5}$ levels to below Beijing's own targets, as well as China's national air quality standard and WHO guidelines. Another challenge is to reduce the NO_2 and O_3 levels, which show little decrease or even an increase from 2013 to 2017. The lessons learned in Beijing thus far may prove beneficial to other cities as they develop their own clean air strategies.

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TABLE LEGENDS:

Table 1: A comparison of the annual average concentrations of air pollutants before and after weather normalization

FIGURE LEGENDS:

Figure 1: A diagram of long-term trend analysis model
Figure 2: Air quality and primary emissions trends
Figure 3: Yearly change of air quality in different area of Beijing
Figure 4: Relative change in monthly $PM_{2.5}$ levels in 2017 under different weather conditions
Figure 5: Comparison of MRF-CMAQ and RF models' performance
Figure 6: Primary energy consumption in Beijing

Table 1. A comparison of the annual average concentrations of air pollutants before and after weather normalization.

Pollutants	**$PM_{2.5}$**		**PM_{10}**		**NO_2**		**SO_2**		**CO**		**O_3**	
year	Obs.	Nor.	Obs.	Nor.	Obs.	Nor.	Obs.	Nor.	Obs.	Nor.	Obs.	Nor.
2013	88	93	110	123	54	58	23	26.3	1.4	1.5	58	59
2014	84	85	119	121	57	56	20	20	1.2	1.3	55	56
2015	80	75	107	106	50	50	13	13	1.3	1.2	58	59
2016	71	71	98	101	47	48	10	10	1.1	1.1	63	60
2017	58	61	90	93	45	48	7.5	8.4	0.9	1.0	60	61

Note: Obs: observed concentration. Nor.: Concentration after weather normalization. Unit: $\mu g\ m^{-3}$ for all pollutants, except CO ($mg\ m^{-3}$)

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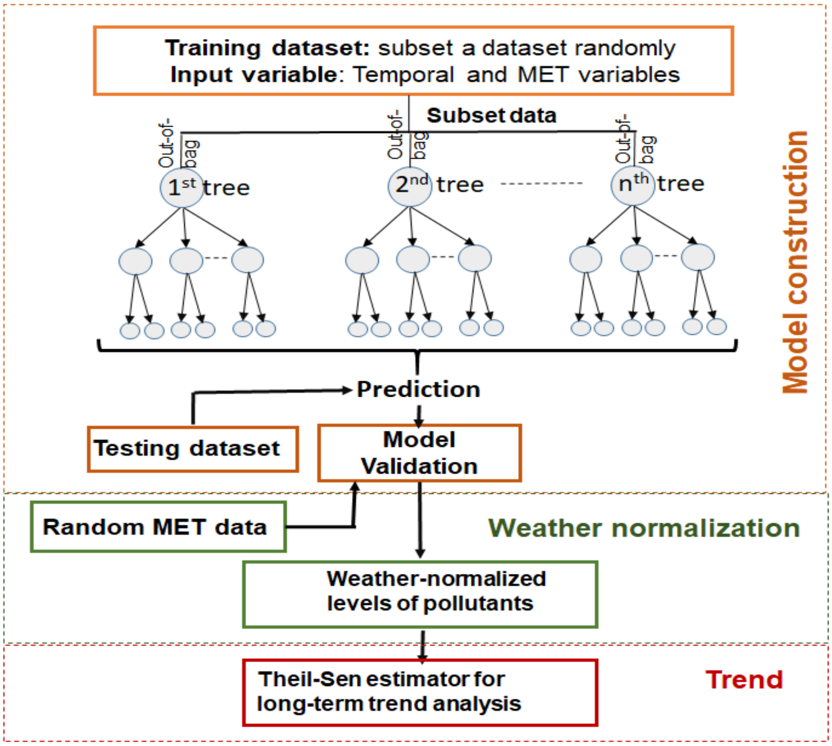

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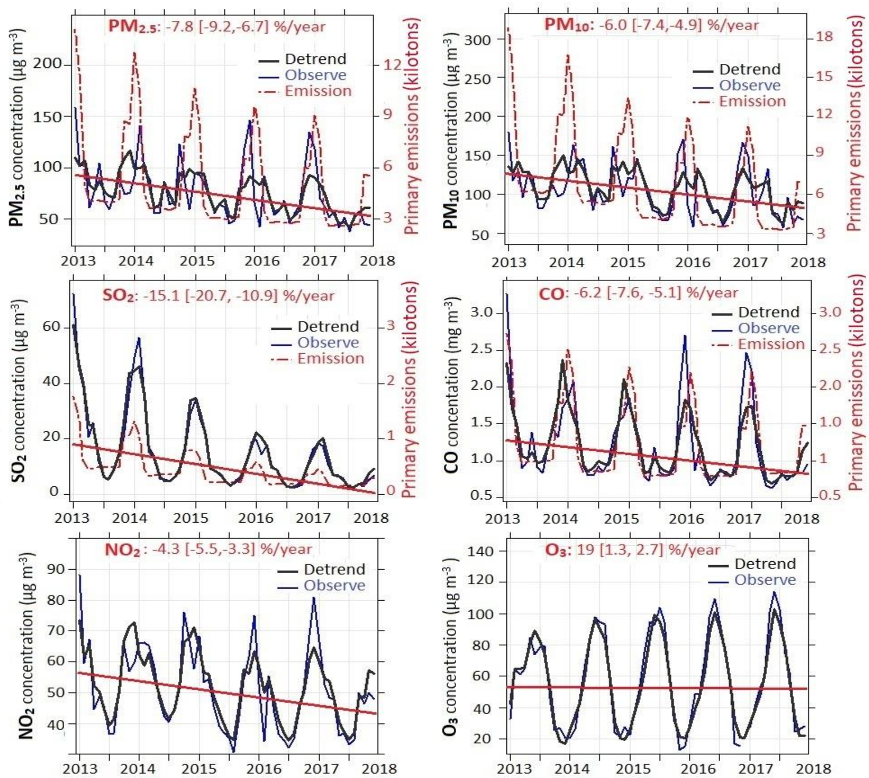

Figure 2. Air quality and primary emissions trends. Trends of monthly average air quality parameters before and after normalization of weather conditions (first vertical axis), and the primary emissions from the MEIC inventory (secondary vertical axis). De-trend means weather normalized. The red line shows the Theil-Sen trend after weather normalization. The black and blue dot lines represent weather normalized and ambient (observed) concentration of air pollutants. The red dot line represents total primary emissions. The levels of air pollutants after removing the weather's effects decreased significantly with median slopes of 7.2, 5.0, 3.5, 2.4, and 120 μg m^{-3} $year^{-1}$ for $PM_{2.5}$, PM_{10}, SO_2, NO_2, and CO, respectively, while the level of O_3 slightly increased by 1.5 μg m^{-3} $year^{-1}$.

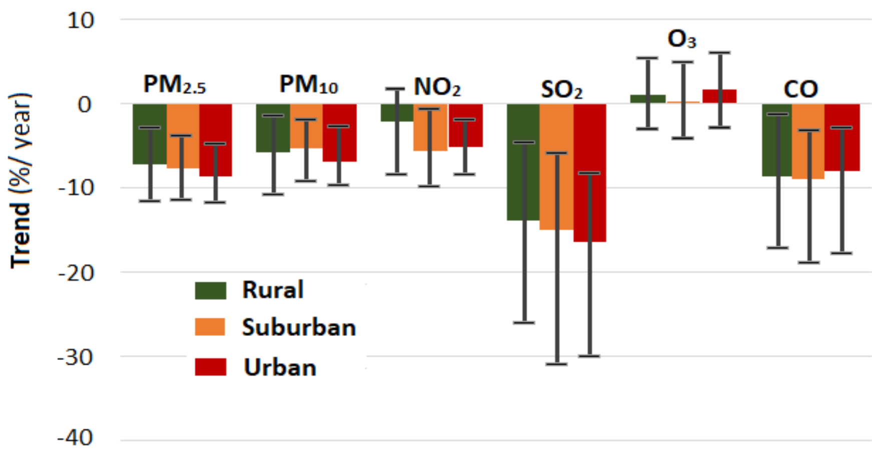

Figure 3. Yearly change of air quality in different area of Beijing. This figure presents yearly average changes of weather normalized air pollutant concentrations at rural, suburban and urban sites of Beijing from 2013 to 2017. Specifically, average yearly changes are for SO_2 (-14%, -15%, -16 % year^{-1}- for rural, suburban, and urban areas, respectively), CO (-9%, -9%, -8% year^{-1}), $PM_{2.5}$ (-7%, -8%, -9% year^{-1}), PM_{10} (-6%, -5%, -7% year^{-1}), NO_2 (-2%, -6%, -5% year^{-1}) and O_3 (1%, 0.3%, 2% year^{-1}). The error on the bar shows the minimum and maximum yearly change.

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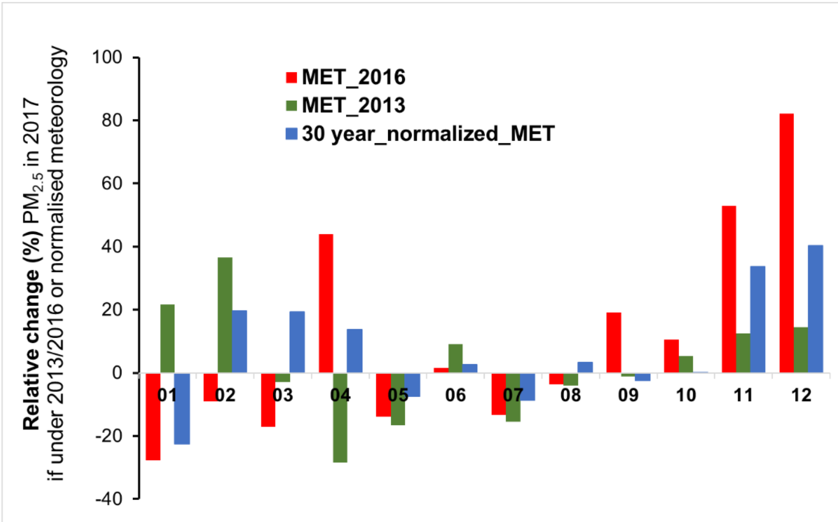

Figure 4. Relative change in monthly $PM_{2.5}$ levels in 2017 under different weather conditions. This figures presents relative changes (%) in monthly average modelled $PM_{2.5}$ concentrations in 2017 if under the 2016 (red) and 2013 (green) meteorological condition using CMAQ model and under averaged 30 years of meteorological condition using the machine learning technique**.** A positive value indicates $PM_{2.5}$ concentration would have been higher in 2017 if under the 2013 or 2016 meteorological conditions. Under the meteorological condition of 2016, monthly $PM_{2.5}$concentration in 2017 would have been approximately 28% lower in January but 53% to 82% higher in November and December. This suggests that 2017 meteorological conditions were very favourable for better air quality comparing to those in 2016. If under the meteorological condition of 2013, monthly $PM_{2.5}$ concentration in 2017 would have been higher in January (22%) and February (36%) but only slightly higher in November (12%) and December (14%).

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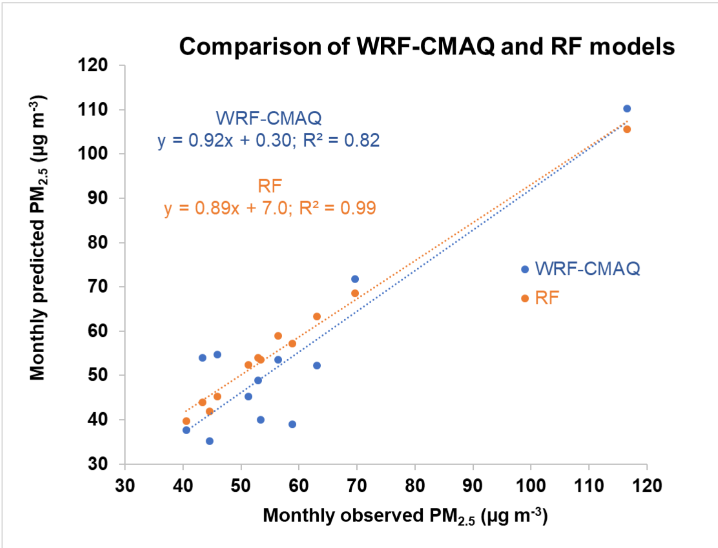

Figure 5. Comparison of MRF-CMAQ and RF models' performance

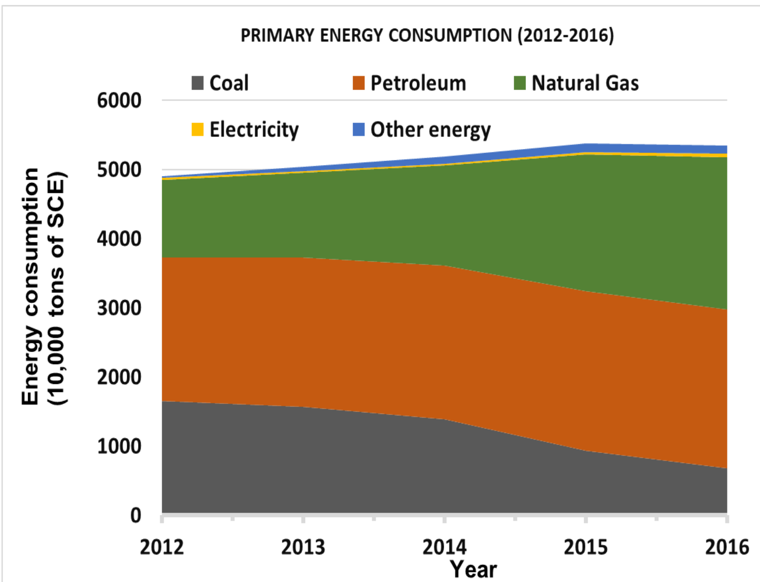

Figure 6. Primary energy consumption in Beijing**.** Petroleum consumption remained stable (21-23 million tonnes coal equivalent (Mtce)) over the years while natural gas and primary electric power increased significantly by 1.8 times and reached 23 Mtce in 2016. Coal consumption declined remarkably by 56.4% from 15.7 Mtce in 2013 to 6.8 Mtce in 2016. The proportion of coal in primary energy consumption in 2016 was 9.8 %, within its target of 10 % set by the Beijing government.