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Impact of the 2020 COVID-19 lockdown on NO$_2$ and PM$_{10}$ concentrations in Berlin, Germany

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**Highlights**

- Random Forest model built to quantify COVID-19 lockdown related pollutant reductions.
- Good agreement between predicted and observed NO$_2$ and PM$_{10}$ concentrations.
- Better model performance for NO$_2$ than PM$_{10}$ concentrations.
- Model found sensitive to depict intra-urban variation of pollutant reductions.
- Reductions mainly related to locally varying modifications in traffic intensity.

**Abstract**

In March 2020, the World Health Organization declared a pandemic due to the rapid and worldwide spread of the SARS-CoV-2 virus. To prevent spread of the infection social contact restrictions were enacted worldwide, which suggest a significant effect on the anthropogenic emission of gaseous and particulate pollutants in urban areas. To account for the influence of meteorological conditions on airborne pollutant concentrations, we used a Random Forest machine learning technique for predicting business as usual (BAU) pollutant concentrations of NO$_2$ and PM$_{10}$ at five observation sites in the city of Berlin, Germany, during the 2020 COVID-19 lockdown periods. The predictor variables were based on meteorological and traffic data from the period of 2017–2019. The differences between BAU and observed concentrations were used to quantify lockdown-related effects on average pollutant concentrations as well as spatial variation between individual observation sites. The comparison between predicted and observed concentrations documented good overall model performance for different evaluation periods, but better performance for NO$_2$ ($R^2 = 0.72$) than PM$_{10}$ concentrations ($R^2 = 0.35$). The average decrease of NO$_2$ was 21.9% in the spring lockdown and 22.3% in the winter lockdown in 2020. PM$_{10}$ concentrations showed a smaller decrease, with an average of 12.8% in the spring as well as the winter lockdown. The model results were found sensitive to depict local variation of pollutant reductions at the different sites that were mainly related to locally varying modifications in traffic intensity.

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1. Introduction

The global spread of the SARS-CoV-2 virus since 2019, which is mainly transmitted by aerosol and droplet dispersion, forced governments worldwide to enact mitigation measures to break the chains of virus infection. In Germany, different social contact restriction measures were applied such as the closure of retail and restaurants, the recommendation of home office, and a ban on leisure activities. This period of restrictions is usually referred to as ‘COVID-19 lockdown’. In other European countries such as Italy, Spain, and France, much stricter exit restrictions than in Germany have been enacted including legally imposed movement and travel restrictions (Barré et al., 2020). Generally, the measures strongly affected the movement patterns of urban residents (Grange et al., 2020) and resulted in a reduction in traffic and industrial activity, which in turn suggests an effect on urban air quality.

Several recent studies examined the decrease in air pollutant concentrations and fluxes during the initial COVID-19 lockdown in spring 2020 (e.g. González-Pardo et al., 2022; Venter et al., 2020; Schneider et al., 2022; Straaten et al., 2022; Nicolini et al., 2022). The studies varied by geographic settings, period of lockdown, the methodological approach as well as the magnitude of the observed pollutant reductions during lockdown. Based on satellite observations, Bauwens et al. (2020) reported decreases of NO\textsubscript{2} concentration of up to 40% over Chinese cities, whereas lower reductions of 19% and 23% were reported for the German cities of Frankfurt and Hamburg, respectively. Petetin et al. (2020) observed a 50% reduction in NO\textsubscript{2} concentrations at a number of urban background and traffic sites across 50 Spanish provinces and islands. On the intra-urban scale the reduction of NO\textsubscript{2} and PM\textsubscript{10} concentrations were studied at five sites in Graz, Austria, using a machine learning technique (Lovrić et al., 2021). The results indicated better model performance for NO\textsubscript{2} than for PM\textsubscript{10}, with lockdown reductions ranging from 37%-42% for NO\textsubscript{2} and 7%-14% for PM\textsubscript{10}, respectively. A study investigating NO\textsubscript{2}, O\textsubscript{3}, and PM\textsubscript{10} concentrations in Berlin at the height of the spring 2020 lockdown found a 40% decrease of NO\textsubscript{2} concentrations using mesoscale numerical modelling (WRF-chem), whereas no significant decrease was found for PM\textsubscript{10} (Schneidemesser et al., 2021).

Generally, uncertainty about the influence of meteorological variability makes it difficult to reliably quantify and compare lockdown-related reductions of urban air pollutants between cities. Moreover, the extent to which pollutant reductions vary on the intra-urban scale, i.e. between multiple observation sites, is currently understudied. One common approach to estimate lockdown effects due to easy handling and small amount of data required, is the “before and after” comparison (Barré et al., 2020). This method compares pollutant concentrations outside the lockdown period to concentrations during restrictions. However, as airborne pollutant concentrations are strongly influenced by emission strength and meteorological conditions, comparisons with concentrations from previous years or the period outside the lockdown prove difficult (Grange et al., 2018).

The motivation of the present study is to quantify the impact of the COVID-19 lockdown conditions on intra-urban air quality at five different observation sites in Berlin, accounting for the impact of meteorological conditions. A counterfactual business as usual (BAU, e.g. Shi et al., 2021) approach was calculated using a Random Forest model, which is a powerful machine-learning technique. The model was trained with meteorological and other explanatory data from the period of 2017–2019. The BAU scenario simulates pollutant concentrations for the pandemic year 2020 that would have been observed under given meteorological conditions without accounting for the COVID-19 mitigation restrictions. The difference between the BAU and observed concentrations can be attributed to the lockdown-related reduction of pollutant concentrations. To account for local influences caused by anthropogenic emission sources, topographic features, and meteorological variation, we examine five different sites in the city of Berlin for effects on NO\textsubscript{2} and PM\textsubscript{10} concentrations. We hypothesize that (1) the lockdown period resulted in reductions for both air pollutants and (2) that the model is sensitive to resolve intra urban-differences of pollutant reductions at the individual sites.
2. Materials and method

2.1. Study area and definition of lockdown period

The study area included five sites in the German capital Berlin (Fig. 1). Berlin is the most populous German city with approximately 3.65 million inhabitants. The capital is located in the northeast of Germany and has a predominantly flat topography. The five study sites were located in the southern and eastern area of Berlin and were mainly situated next to major roads (i.e. traffic sites) with an average traffic intensity ranging from 6546 (Karl-Marx-Straße, KMS) to 23 289 (Frankfurter Allee, FRA) vehicles day\(^{-1}\).
We classified the year 2020 into two lockdown periods based on legal regulations set by the federal government, positively confirmed infection figures, and the movement patterns of Berlin’s residents based on COVID-19 community mobility reports (Fig. S1; Supplement, Google LLC, 2021). The spring lockdown period stretched from 15 March to June 1, 2020 (Period 1) whereas the winter lockdown period was from 15 December to 31 December 2020 (Period 2). Both periods were characterized by the largest decrease in the movement patterns of Berlin residents outside their own homes.

### 2.2. Data

#### 2.2.1. Air pollution data

Gaseous and particulate pollutant concentrations of nitrogen dioxide (NO₂, in μg m⁻³) and particulate matter with an aerodynamic diameter <10 μm (PM₁₀, in μg m⁻³) were gathered from the Berlin air quality monitoring network BLUME (https://luftdaten.berlin.de/lqi). NO₂ and PM₁₀ were measured at a height of 3.5–4.0 m above ground level. Both pollutants were available at 30 min temporal resolution but were aggregated to hourly resolution for data analysis. Data availability was >97% at all sites for the study period from 15 March 2017 to 30 December 2020.

#### 2.2.2. Meteorological quantities

Meteorological quantities from the German weather service (Deutscher Wetterdienst, DWD) site ‘Berlin Tempelhof’ (Lon: 13.4021; Lat: 52.4675, Altitude: 48 m above sea level) were available from the DWD Climate Data Center (Deutscher Wetterdienst, 2021). The following quantities were used as predictor variables in the Random Forest model: wind speed in m s⁻¹ (ws), wind direction in degrees (wd), temperature in °C (T), relative humidity in % (rH), and barometric pressure in hPa (P). The Tempelhof site was assumed as representative for the respective BLUME sites as the maximum distance to the BLUME site FRA was about 7 km. Furthermore, meteorological quantities were measured using the eddy covariance technique on a rooftop at the Berlin-Brandenburg airport (BER) in the southeast of Berlin (Lat: 52.3700; Lon: 13.5100; Altitude: 61 m). Data for friction velocity (u*) in m s⁻¹, Obukhov length (L) in m, and the Monin-Obukhov stability parameter ((z–d) L⁻¹) were used in the present study. Details on the measurement setup are provided in Heusinger and Weber (2017) and Konopka et al. (2021). Data availability ranged from 80% to 83%.

The mixing layer height (MLH) in km was derived from ceilometer measurements on the rooftop of the main building of Technische Universität, which belongs to the Urban Climate Observatory (UCO) Berlin for long-term observations of atmospheric processes in cities (Scherer et al., 2019). The COBOLT algorithm was used to determine the MLH at 15 s resolution and aggregated to hourly values (Wiegner et al., 2020). The data were available from January 2018 until the end of August 2020, therefore not covering the entire year 2017 and the remainder of 2020. Hence, data availability was lower than for the other variables (69%).

#### 2.2.3. Traffic data

Traffic data, i.e. the number of cars (VEH) and heavy-duty vehicles (HDV) at hourly resolution, were provided by the Traffic Information Center Berlin. To quantify the influence of the traffic rate on air pollutants, five locations in close proximity to the observation sites of the BLUME network were selected. The maximum distance between a BLUME site and the respective traffic counting site was 125 m at site SSS. Data availability of traffic counts were >98%.

#### 2.2.4. Collinearity

Collinearity in the predictor variables was taken into account by analyzing the correlation between predictors (Fig. S2 – Fig. S6; Supplement). Collinearity defines a lack of independence of the predictor variables and can lead to misidentification and misinterpretation of the
relevant predictors. A Spearman correlation coefficient of \( r = 0.7 \) is reported as a threshold value for identification of collinearity (Dormann et al., 2013). We found no signal for collinearity, except for variables like the friction velocity and the wind speed (\( r = 0.71 \)), which are in fact closely related.

2.3. Random forest model

To quantify the effects of the COVID-19 lockdown on air pollutants concentrations of \( \text{NO}_2 \) and \( \text{PM}_{10} \), we established a random forest (RF) model (Grange et al., 2018). A RF model is composed of several individual decision tree models and quantifies the relationship between the air pollutant concentration (response variable) and its predictor variables (Fig. 2a). The following predictor variables were used to build the RF model: meteorological variables (cf. section 2.2), traffic intensity of vehicles and heavy-duty vehicles, Julian day as seasonal trend term, day of the week, hour of the day and a Unix time stamp as a temporal trend term for the whole period (15 March 2017 to 30 December 2020). This is a cumulative numerical value based on the number of seconds that have elapsed since 00:00:00 UTC on January 1, 1970, which can be better handled by the calculation model than ‘human’ time formats. The model was trained using these input variables from the time prior to Period 1, i.e., 15 March 2017 to 31 December 2019 at hourly resolution. Subsequently, the model was applied in ‘prediction mode’ for the year 2020 to calculate pollutant concentrations based on the temporal variation of the predictor variables (Fig. 2c). In total, the algorithm generated 500 decision trees. The number of variables to be split was 4, whereas the minimum node size was set to 5 (Grange et al., 2020). The RF algorithm randomly selects the training data (70%) from the input data and withhold the ‘test data’ (30%) when training the model (Fig. 2b). The RF model was built using the R packages “rmweather” (Grange et al., 2018, 2020), and “Ranger” (Wright and Ziegler, 2017).

2.4. Model evaluation

The RF model was validated using a random out-of-bag sample (‘test data’) that were withheld during model building. For this ‘test data’ we predicted concentrations and compared them to observed values (evaluation step A; Fig. 2b). In the next step (evaluation step B; Fig. 2d), concentrations were predicted for the entire year 2020 (Fig. 2c). The evaluation period was defined for the time span from 15 January to 15 March 2020. A potential impact due to New Year’s Eve events was avoided by not using the first 15 days of the year, i.e., 01 January to 14 January 2020. In the final evaluation step C, the model was applied in ‘prediction mode’ for the same spring/winter period as the lockdown-period in 2017, 2018, and 2019, i.e., 15 March to 01 June 2017/2018/2019 and 15 December to 31 December 2017/2018/2019 (Fig. 2e). The model performance was evaluated using the coefficient of determination.
(R²), the RMSE divided by the average concentration (normalized root mean square error; nRMSE), and the Spearman rank correlation coefficient (SCC).

The importance of a predictor variable in the RF model can be determined by the increase in the prediction error, which results from a random permutation of the values of an explanatory variable (Lu et al., 2021). Hence, variables with a high importance had major impact on predicted BAU concentrations.

3. Results and discussion

3.1. Traffic variation

Mobility patterns suggest that contact restrictions had a considerable effect on urban road traffic (Fig. 3). Especially during the spring lockdown Period 1 the passenger car rate declined significantly, by up to a weekly mean of 320 vehicles h⁻¹ at FRA and 120 vehicles h⁻¹ at KMS during the morning rush hour, respectively. A smaller decline was observed for the HDV rate. The VEH rate remains lower than in 2017–2019 over the remainder of the years at all locations except KMS. Conversely, the HDV rate increased at MRD, SHS and for a short period at SSS in 2020. We assume that a higher share of delivery traffic and package deliveries is responsible for the increase in heavy traffic, especially at the MRD site.

3.2. Model evaluation

The model performance for the Evaluation-step B was better for NO₂ than PM₁₀ as indicated by an average R² = 0.72 for comparison of modelled and observed NO₂ concentrations and R² = 0.35 for PM₁₀, respectively. The nRMSE for NO₂ = 0.26 was distinctly lower than that for PM₁₀ (0.41). The model evaluation showed different results for the retained PM₁₀ ‘test data’ (Fig. 4a) than for the evaluation period B (Fig. 4b). The mean coefficient of determination for PM₁₀ was R² = 0.73, which was similar to the R² of the NO₂ ‘test data’ (R² = 0.74). Since the results in the step A were significantly better, local events may have had an impact on the concentrations in the evaluation period B that the model could not reproduce.
The time series of measured and modelled NO\textsubscript{2} indicate high agreement of NO\textsubscript{2} before the lockdown periods at each site with only little systematic deviations (Fig. 5). From early to mid-January, observed concentrations were slightly higher on average than modelled values. Towards the end of evaluation period B differences between observed and modelled BAU concentrations became evident at all sites except SSS.

In accordance with the larger nRMSE for PM\textsubscript{10}, the deviations between the modelled BAU PM\textsubscript{10} concentrations and the measured values were higher than for NO\textsubscript{2} (Fig. 6). Although the temporal pattern of simulated values matched the observations, the modelled concentrations were systematically higher than the observations. Three local maxima that were observed at each site in January 2020 could not be reproduced by the model and were probably influenced by factors not depicted by the set of predictor variables. Recent studies document that PM\textsubscript{10} usually has a higher contribution from long-range transport whereas NO\textsubscript{2} is more affected by local, urban contributions (e.g. Lovrić et al., 2021). The predictor variables to specifically address the influence of long-range transport (e.g. output from back-trajectory models) were not subject to the RF model. Hence, the contribution from long-range transport is likely underestimated in the current model for PM\textsubscript{10}. However, this does not influence the quantification of intra-urban (site) differences, as long-range transport should affect those sites similarly.

The comparison between the BAU and observed PM\textsubscript{10} concentrations for the retained data (evaluation step A, Fig. 2) was similar to the results for NO\textsubscript{2} concentrations. That the ‘test data’ results were better than in evaluation period B is likely due to local events, e.g. a mild winter of 2019/20 with high wind speeds in February favored dilution and lower pollutant concentrations (Umweltbundesamt, 2021). The RF model did not accurately reproduce these situations. Several studies in which pollutant concentrations were predicted using the RF method support our finding that PM\textsubscript{10} concentrations were predicted with lower accuracy in comparison to gaseous pollutants (e.g. Lovrić et al., 2021). This may be due to different reasons exerting an effect on PM\textsubscript{10} concentrations such as long-range transport of particulate pollution or secondary formation of particles. Both processes might have a strong effect on particle concentrations, but are less relevant for gaseous pollutants.

### 3.3. Variable importance

For predicted NO\textsubscript{2}, the predictor variables vehicle traffic intensity, time of day, wind direction and heavy-duty vehicle intensity (except HDV and SSS) had the strongest influence at the five study sites (Fig. 7). This is in agreement to other studies which reported direct NO\textsubscript{2} emissions from internal combustion engines of road vehicles as a major source of measured NO\textsubscript{2} concentrations in European cities (Carslaw et al., 2016; Kamińska, 2019; Sayegh et al., 2016). The strong influence of the time of day may be attributed to the temporally varying influence of primary NO\textsubscript{2} emissions, i.e. rush hours vs. non-rush hours. The correlation analysis indicates a positive correlation of the vehicle traffic rate with the time of day (Fig. 2; Supplement). In contrast to NO\textsubscript{2}, the influence of vehicle traffic on predicted PM\textsubscript{10} was much smaller (Fig. 7). An analysis of particulate matter sources based on data from the BLUME monitoring network indicated that local traffic contributed a share of
34% to PM$_{10}$ mass concentrations whereas long-range transport contributed with 46% (Hainsch, 2004). Additionally, particulate matter originates from a variety of urban sources such as residential heating and industry (Querol et al., 2004). The Julian day exhibited major influence on PM$_{10}$ at all sites, indicating a strong seasonal effect on pollutant concentrations such as increased concentrations during stagnant atmospheric conditions as introduced by wintertime temperature inversions. This is supported by the high importance of air temperature on modelled PM$_{10}$ concentrations. Grange et al. (2020) reported similar findings of strong seasonal effects in the variation of pollutants. The major effect of wind direction may point to local sources other than traffic that contribute to local particulate pollution such as residential or industrial combustion (e.g., Querol et al., 2004).

The mixing layer height (MLH) and atmospheric stratification ($z$–d $L^{-1}$) generally had only minor influence on the model predictions of both NO$_2$ and PM$_{10}$ at the different sites. However, it must be noted that data availability was lower for mixing layer height, as it was not available for 2017 and the last four months of 2020.

3.4. Quantification of pollutant reductions during lockdown periods

3.4.1. NO$_2$

During the spring lockdown in 2020 (Period 1), significantly lower NO$_2$ concentrations in comparison to the reference period were observed (Fig. 8). The BAU concentrations, however, showed a much smaller decrease than observed values. About two months after relaxation of the lockdown restrictions, the observed concentrations were close to the BAU scenario. Hence, the COVID-19 restriction measures resulted in a significant decrease of NO$_2$ concentrations, which increased again after the relaxations of restrictions in June. From September to October, short-term exceedances of measured values relative to model values were observed at all sites. Similar to Period 1, the model results in Period 2 point to a distinct decrease of NO$_2$ concentrations due to restriction measures. Previously published studies document that primary NO$_2$ emissions from vehicle exhaust account for the largest share of measured NO$_2$ concentrations in many European cities (Carslaw et al., 2016; Casquero-Vera et al., 2019). The short lifetime of the secondary pollutant NO$_2$, however, does not support downwind transport far from the emission source (Bassani et al., 2021). Hence, NO$_2$ concentrations are likely to decrease as anthropogenic emissions are reduced (Petetin et al., 2020).
BAU concentrations were determined not only for lockdown periods in 2020, but also for the same time spans in the previous years 2017, 2018 and 2019 (evaluation step C). The model over-predicted the concentrations by about 2.5% for the spring period in 2017, 2018, and 2019 and by about 2.2% in the winter period (Fig. 9). Given the slight systematic overestimation at all sites, a similar model uncertainty should be assumed for the 2020 pandemic year.

Higher differences between the BAU and observed NO$_2$ concentrations were evident during the two lockdown periods in 2020 (Fig. 9). Largest reductions emerged at the sites SHS and FRA with an average decrease of $-27.9\%$ and $-27.4\%$ during Period 1. The smallest reduction occurred at MRD with $-15.1\%$. During Period 1 with more severe restrictions than the second (winter) lockdown (Period 2) the average difference between measured values and model predictions at all sites was $-21.9\%$.

In Period 2, the MRD site showed the largest average difference with $-33.6\%$. Measured NO$_2$ concentrations during the second lockdown were $-22.3\%$ on average in comparison to the BAU scenario. A similar relative reduction during both lockdown periods may be attributed to a larger reduction at MRD in Period 2. At the other study sites, the NO$_2$ decrease in Period 2 was smaller than in Period 1. Overall, the sites FRA, MRD, SHS and SSS were characterized by similar relative reductions. Traffic data suggests that the increase in the number of heavy-duty vehicles in the vicinity of MRD during Period 1 may be a reason for the smaller decrease of NO$_2$ concentrations. However, the variation in the reduction estimates between the sites indicate that the model is sensitive to local influence.

### 3.4.2. PM$_{10}$

Lower PM$_{10}$ concentrations during evaluation period B were observed in early 2020 in comparison to the previous years 2017, 2018 and 2019 (Fig. 10). In addition to the measured concentrations, also the BAU concentrations were lower than the observed concentrations in previous years. At the start of June, these concentrations again approached BAU concentrations, similar to 2020. However, a concentration reduction in the two periods only occurred in the pandemic year 2020.

Observed values were lower than modelled values in Period 1 at the FRA and KMS sites, except for two short-term peaks. At the MRD, SHS and SSS sites, the measured values did not decrease until the beginning of May and only showed a small difference from the BAU values. At the beginning of August, variation of observed values was not accurately captured in the model output. During winter months, the number and intensity of concentration peaks increased. With the onset of the lockdown in mid-December, measured concentrations declined sharply with values below BAU concentrations. By the end of 2020, the measured values increased again and approached the BAU values.

Similar to the NO$_2$ results, the model generally over-predicted the BAU concentrations. Consequently, deviations ranging from 0% to $-8\%$ were observed in 2017, 2018 and 2019 (evaluation step C; Fig. 11). The five study sites were characterized by an average deviation of $-2.0\%$ during the first (spring) period. In the second (winter) period larger differences between measured and model values occurred, with the largest deviation of $-6.2\%$ occurring in 2019. The average deviation of the winter period resulted in $-4.3\%$.

The measured concentrations were lower than the BAU scenario in both lockdown periods of 2020. On average, the concentrations in Period 1 were reduced by $-12.8\%$. The PM$_{10}$ values decreased most strongly at KMS ($-17.8\%$) and least at MRD ($-7.0\%$). In Period 2, the average deviation was similar to Period 1 with a reduction of $-12.8\%$. The highest reduction was estimated for KMS ($-20.0\%$), the lowest at the SHS site with $-7.7\%$.

### 4. Conclusion

The COVID-19 lockdowns in 2020 were unprecedented events, which strongly influenced the mobility of people worldwide and resulted in a decrease of anthropogenic emissions of air pollutants. However, uncertainties in the influence of meteorological variability on airborne concentrations of gaseous and particulate pollutants makes...
quantification of pollutant reductions due to the COVID-19 lockdown very challenging. In the present study, a machine learning technique trained with meteorological and traffic predictors covering the period from 2017 to 2019 was used to quantify spatial variation of pollutant reductions for NO$_2$ and PM$_{10}$ at five observation sites in urban Berlin.

The RF model evaluation documented better model performance for NO$_2$ than PM$_{10}$ concentrations. The comparison between the BAU and measured values indicated that NO$_2$ concentrations during the COVID-19 lockdowns decreased by $-21.9\%$ (Period 1) and $-22.3\%$ (Period 2) on average across the five study sites. The decrease in PM$_{10}$ concentrations was about half as large, with an average of $-12.8\%$ during the two periods. Hence, the higher influence of traffic on NO$_2$ concentrations is consistent with the stronger decrease of NO$_2$ during the lockdowns. The reduction of both gaseous and particulate pollutants, however, differed depending on the respective location of the observation site. The KMS, SSS, SHS and FRA sites show a higher degree of similarity in NO$_2$ reduction. At MRD the concentration reduction during Period 1 was much smaller than at the other sites, whereas it was almost twice as large in Period 2. Reduction differences between individual sites indicate that the model is sensitive to local influence on pollutant concentrations. Traffic data suggests that an increase in the share of heavy-duty vehicles at MRD in Period 1 was responsible for the smaller reduction of NO$_2$ in contrast to Period 2.

An urban-scale study with a larger number of observation sites might be useful to further study the sensitivity of the random forest approach in quantifying the local variation of pollutant reduction. The implementation of an air mass trajectory model accounting for the influence of long-range transport might improve model predictions of PM$_{10}$. The present study, however, demonstrates a major impact of road activity on local urban air quality for both gaseous and particulate pollutants. The improvement of air quality during the COVID-19 lockdowns was a short-term effect that can be used as an example for future approaches to mitigate air pollutants. To estimate the impacts of mitigation measures on airborne pollutants adequate models are needed that account for the influence of weather variation on pollutant concentrations. The weather-normalization approach as applied in the present random forest model is a promising approach for future applications.

CRediT authorship contribution statement

Mona Schatke: Conceptualization, Methodology, Formal analysis, Writing – original draft. Fred Meier: Writing – review & editing. Boris...
Fig. 11. Percent difference (%) between hourly measured and BAU PM$_{2.5}$ concentrations at the five study sites for periods 1 (spring) and 2 (winter) in the years 2017–2020. Values are based on arithmetic means. Bars depict the interquartile range, i.e. median, 25 and 75 percentile.

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