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Insignificant Changes in Particulate Matter during the COVID-19 Lockdown: A Machine Learning Study in Zagreb, Croatia

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***Abstract* -** In this paper we present an approach to investigate changes in concentration of particulate matter (PM) mass concentrations during the COVID-19 lockdown. Concentrations of PM1, PM2.5 and PM10 were measured in an urban background sampling site on the north of Zagreb from 2009 to late 2020 on a 24h basis. The concentrations were fed alongside meteorological and temporal data to Random Forest (RF) models tuned by Bayesian optimization. The models' predictions were subsequently de-weathered by meteorological normalization using repeated random resampling of all predictive variables except the trend variable. We examined three pollution periods in 2020 in detail: January and February, as pre-lockdown, the month of April as the lockdown period, as well as June and July as the "new normal". We conducted an evaluation using normalized mass concentrations of particulate matter and Analysis of variance (ANOVA). The results showed that no significant difference ($p = 0.33$) was observed for PM2.5 and PM10 in April 2020 - compared to the same period in 2018 and 2019. The noticeable change in PM1 was observed in the same period related to a higher normalized concentration in 2018, but no difference between 2019 and 2020. No significant changes were observed for the "new normal" as well. Our results thus lead to the assumption that a reduction in mobility during COVID-19 lockdown did not significantly affect particulate matter concentration in long-term.

***Keywords*:** machine learning, air quality, corona crisis, pm1, pm2.5, pm10, traffic

1. Introduction

Particulate matter (PM) is recognized as one of the major air pollutants affecting human health. Particle size plays an important role in determining pollutant respiratory deposition and thus potential health risks. Airborne particles PM10 (with aerodynamic diameter less than 10 μm) and especially its smaller fractions (e.g., PM2.5 and PM1) are known to effectively enter human body, e.g., trachea (upper throat) or bronchi, and even reach all the way down to the alveoli in the lungs, where it can penetrate from the lung alveoli into the blood (Anderson et al., 2012; Kim et al., 2015). In general, the smaller is particle size, the greater adverse health effect it has (Jakovljević et al., 2020; Li et al., 2019; Yang et al., 2020). Therefore, further reduction of PM pollution both in developed and developing countries has a potential to improve both life quality and expectancy. To better understand sources, environmental and health impacts of air pollution, long-term measurement data sets are used in source appointment, epidemiological, and air quality studies (Stojić et al., 2016). On the other hand, short-term traffic bans can be used to pinpoint pollution contributors and raise the awareness of air quality problem (Wiedensohler et al., 2018). Ironically, besides causing worldwide health and economical disturbance, the current COVID-19 pandemic has also provided means to investigate air pollution worldwide. Published evidence on the impact of the COVID-19 lockdown on concentration of ambient air pollutants highlights the importance of transport and industrial activities (Liu et al., 2021; Singh and Chauhan, 2020) [8], [9]. For example, there is clear evidence for reduced gaseous (e.g., nitrogen dioxide (NO_2)) and particulate pollutant concentrations in urban areas, which can be linked to reduced transportation due to COVID-19 [10], [11]. In a study in Zagreb, Croatia, it was found that during lockdown at the traffic measuring site concentrations decreased by 35% for NO_2 and PM1. However, at the urban background measuring site NO_2 decreased by 27% while PM1 levels remained like the year before [12]. The European Environment Agency reported that a consistent reduction of PM2.5 cannot be seen in European cities for the lockdown period [13]. The main reasons could be that local pollution sources are more various, including not only industrial activities and road traffic, but also the combustion of different fuels for the heating, as well as formation of secondary aerosols [14]. Furthermore, it is not entirely clear, how lockdown period pollutant concentrations depend on other effect/confounders, which should be accounted for, e.g., meteorology [12]. The methods used in lockdown-related air pollution studies differ, but one of the most frequently mentioned is machine learning with Random Forest regression (RF) and neural networks (NN). In our previous work [12] we used Random Forest regression to predict pollutant concentrations during the lockdown in Graz and presented the advantages of utilizing such methods over historical comparison of pollution. Similarly, RF was used to assess changes in pollutant levels during different stages of lockdown in Los Angeles by comparing predicted concentrations under different traffic emission scenarios [13]. A similar approach was used by Brancher [14] who refers to baseline models (non-lockdown periods) as "Business as usual" scenarios. The model describes hourly-averaged concentrations per pollutant per monitor to investigate air quality changes before and after lockdown and to verify the models' predictive skill to reproduce the pollutant measurements. A neural networks approach was used to investigate whether changes in air quality in Nigeria occurred primarily due to lockdown. In this case, monthly average values of ground-level fine aerosol optical depth (AODf) across Nigerian from 2001 to 2020 was used [15]. Another method for assessment of air pollution during the lockdown period is difference-in-differences (DID) model. Xu et al [16] used this method to evaluate air pollutants and air quality before and during the lockdown. The DID model calculates the effect of treatment (independent variable) on outcome (dependent variable) by comparing the average changes in each of the groups. In this case, the outcome is the level of air pollution. Control variables such as temperature, humidity, wind speed, etc. are also included. The model considers whether the lockdown was enforced or not for each date and based on this calculates relative changes in air pollution levels. The study by Gope et. al [17] used the Air Quality Index to analyse the impact of lockdown on the environment. Generally, information about air pollution is expressed through Air Quality Index (AQI) which is calculated from the concentration of the pollutants. The AQI rises with the level of pollution, so the measurement is distributed in six intervals: good, moderate, sensitive group, unhealthy, very unhealthy and maroon. The study used information about air quality from the 10 most polluted cities in the world before, during and after lockdown. Comparison of the AQI for these periods showed that most cities reduced their pollution status by one and some even two categories.

There are mixed results published regarding the lockdown and "new normal" effects on particulate matter. With many methods being used there is a lack of a standardized approach for understanding these phenomena. In this work, we present the assessment of particulate matter in three mass fractions (PM1, PM2.5 and PM10) based on daily measurements over a long period of 12 years and the use of machine learning combined with meteorological normalization to compare pre-, during and post-lockdown timeframes. Our initial hypotheses were that the lockdown and the "new normal" both caused reductions in particulate matter concentration which are evaluated by using ANOVA on the normalized data. A reduction during the "new normal" is hypothesized due to a restriction on travels which affect Croatia's tourism and more working from home.

2. Materials and Methods

2.1. Particulate matter and meteorological measurements

Aerosol PM concentrations were measured in Zagreb, Croatia, in sampling site located in the northern, residential part of city (45°50'7'' N, 15°58'42'' E, 116 m a.s.l.,). The area is characterized by modest traffic and population density. The household heating (gas and/or wood) season usually starts in October and lasts until April. The PM samplers (Sven Leckel, engineering office, Berlin, Germany) were positioned at about 20 m from the nearest street. 24-hour samples of PM1, PM2.5 and PM10 fractions of particulate matter have been collected continuously every day on quartz filters (Whatman, QM-A

Quartz Microfibre Filters, 47 mm in diameter). PM mass concentrations were determined gravimetrically (Mettler TOLEDO MX5 balance) according to the EN 12341:2014 standard. Before and after the sampling, filters were conditioned at a constant temperature (20 ± 1°C) and relative air humidity (45 – 50 % RH) for 48 h. Meteorological parameters (temperature, RH, wind speed and direction, pressure, and precipitation) were obtained from the Croatian Meteorological and Hydrological Service. The lockdown period information for the city of Zagreb was from 13th of March to 11th of May 2020 (ref. https://www.koronavirus.hr/en).

2.2. Data processing and model training

The concentrations of PM1, PM2.5 and PM10 were prepared in a flat table together with temporal information (day of week, Julian date (days counted from 1st of January 1970), month, year, holiday tag, etc.), and meteorological variables (maximum daily temperature (T), minimal daily T, difference of max and min T, average T, maximum daily pressure (p), minimum daily p, difference of max and min p, average p, maximum daily relative humidity (RH), minimum daily RH, average RH, difference of max and min RH, wind speed, precipitation), which are given here as independent or predictive variables. The data has been collected over a long period (years 2009 – 2020) in a daily frequency. Several missing data points were imputed with backfilling (missing values filled with the ones from day after). This way one retains a higher amount of data for model training. One longer missing period for PM1 was linearly imputed. Data processing and model training was conducted with Python (www.python.org, v3.7.10). The machine learning method and pipeline used in this work is presented previously in [2] and [8] and published in our repository. The assumption is that the concentrations of particulate matter (PM1, PM2.5, PM10; dependent variables) can be modelled based on temporal and meteorological variables as independent ones, listed in Section 2.2. Air pollution modeling was done using Random Forests (RF) [19]. This method has been found to be suitable for air quality data analysis and modeling air pollution in several studies [18], [20]. The models were trained for every individual pollutant (PM1, PM2.5, PM10), with their concentrations being our predicted (target) variables. The hyperparameters of each model were optimized with a 10-fold cross-validation with Bayesian optimization which showed useful in our previous regression models [21]. Individual predictive models were trained using data between 1st of January 2009 and 31st of December 2019 (training data set, TDS). Several other datasets were created from the data of 2020 indicating different validation and interest periods. These are: the model validation set, MVS (1st of January 2020 – 15th of March 2020), lockdown set, LDS (1st of April 2020 – 30th of April 2020) and new normal set, NNS (1st of June 2020 – 31st of July 2020). Prior to modelling, we analysed the 2020 data on "out-of-ordinary" events in the year, which might have affected pollutant concentration in Zagreb and therefore model results. Such events included Zagreb-earthquake (22nd of March 2020), resuspended dust events on 26th – 30th of March [2], [13], and construction works near the measurement site in August 2020. The events are shown visually in Figure 1. Since these events might introduce some bias, we excluded the respective timeframes from our analyses. Therefore, even though the lockdown timeframe lasted longer than the one given as LDS, several dust events needed to be excluded. We have also split a subset from MVS for comparison to LDS (comparison set or CS) which is set between the 1st of January and 29th of February 2020. The subset is shorter than MVS for reason of several construction activities at the site in March. LDS and NNS present the time frame in focus of our investigation of the of lockdown pollution. MVS was used to better understand the model generalization. The time frames (datasets for 2020) are visually presented in Figure 2.

2.4. Meteorological normalization (de-weathering)

We followed the methodology from Grange et al [23], [24] for meteorological normalisation of the daily particulate matter time series. Meteorological normalization was achieved by firstly creating a ML model per pollutant which generalizes well on unseen data. In the next step the models are repeatedly randomly sampling all predictive variables (except Julian day) without replacement and predicting pollutant concentration using individual RF models using the sampled data. This procedure removes the short-term variation in the time series as shown. The predictive models for each pollutant did 100 predictions each which then were averaged into the normalized time series (normalized PM1, PM2.5, PM10).

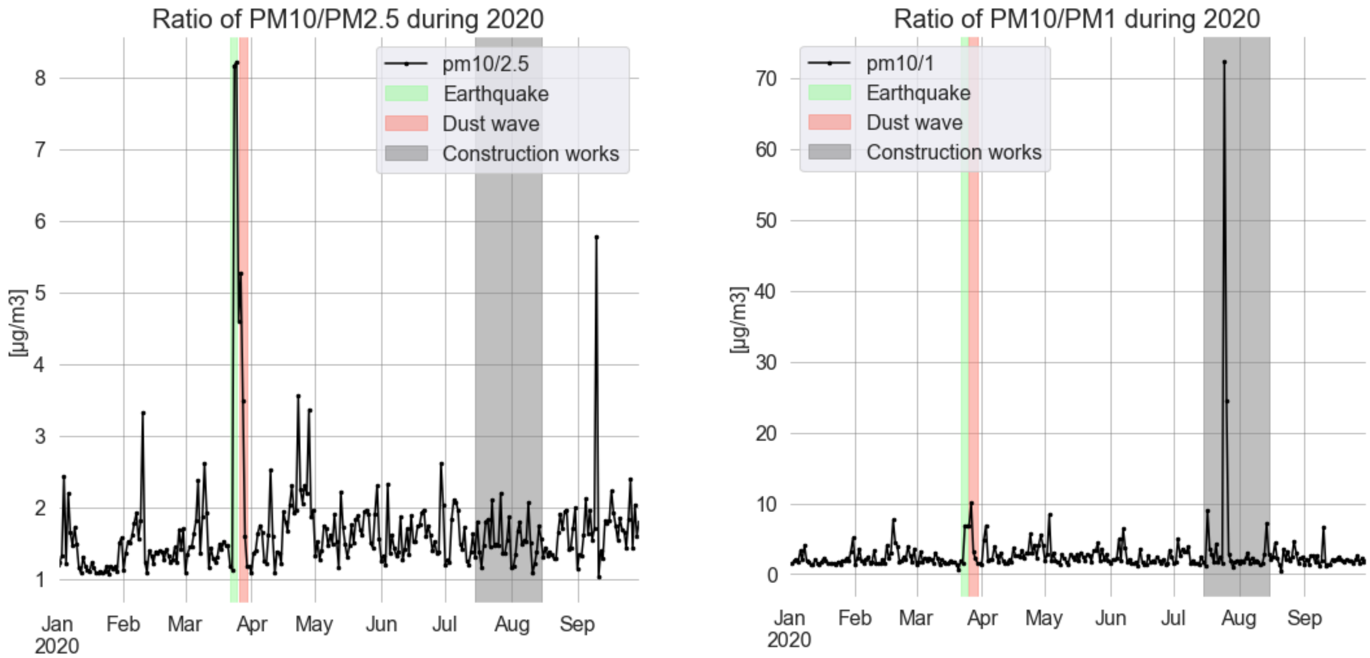

Figure 1. Out-of-ordinary events during 2020 shown as ratio between PM10/PM2.5 and PM10/PM1. The events in March 2020 are assigned to either the Zagreb-earthquake on 22nd of March, the sand dust event between 24th and 30th of March, or construction works at the site in early March, August and September. These events were excluded from the analysed timeframes.

3. Results and Discussion

The models scores by means of root-mean-square-error and R2 are given in Table 1. Based on R2 results, all three models show good predictive values (good generalization). The root-mean-square-error (RMSE; the standard deviation of the residuals) is also shown in Table 1. The prediction quality is similar for PM10 and PM2.5, while it increases for PM1. When comparing the R2 scores to our previous work [14], the observed values in this study suggest a reasonably good generalization with R2 scores above 0.7.

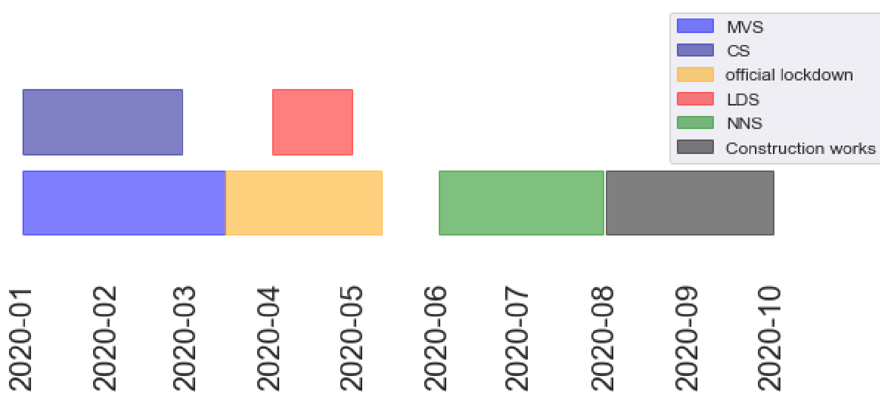

Figure 2. Datasets for 2020: model validation set-MVS (1st January-15th March); comparison set-CS (January and February); official lockdown (13th March-11th May); lockdown set- LDS (1st- 30th April); new normal set-NNS (1st June-31st July); construction works (March).

Table 1. Results of the machine learning models for PM-concentrations shown on the validation set (MVS).

	RMSE	**R2 score**	**Mean**
PM10	11.630	0.714	18.849
PM2.5	11.001	0.709	13.600
PM1	8.219	0.713	9.102

Once models were trained, the data was normalized (de-weathered) as described in Section 2.3. To evaluate change in airborne pollution concentrations due to the lockdown, we assessed yearly trends by means of median and first quartiles of the normalized time series. Three timeframes were compared (Figure 3), namely the months of January and February together (CS) and June together with July (NNS) which we consider to be the new normal (post-lockdown changes). Normalized time series during the months of April (LDS) every year is given in Figure 4. In Figure 3a, for CS (January and February, pre-lockdown reference) there is a continuous reduction from 2009 to 2018 for all size fractions of PM. However, starting with 2019 an unexpected increase for the normalized vectors can be observed.

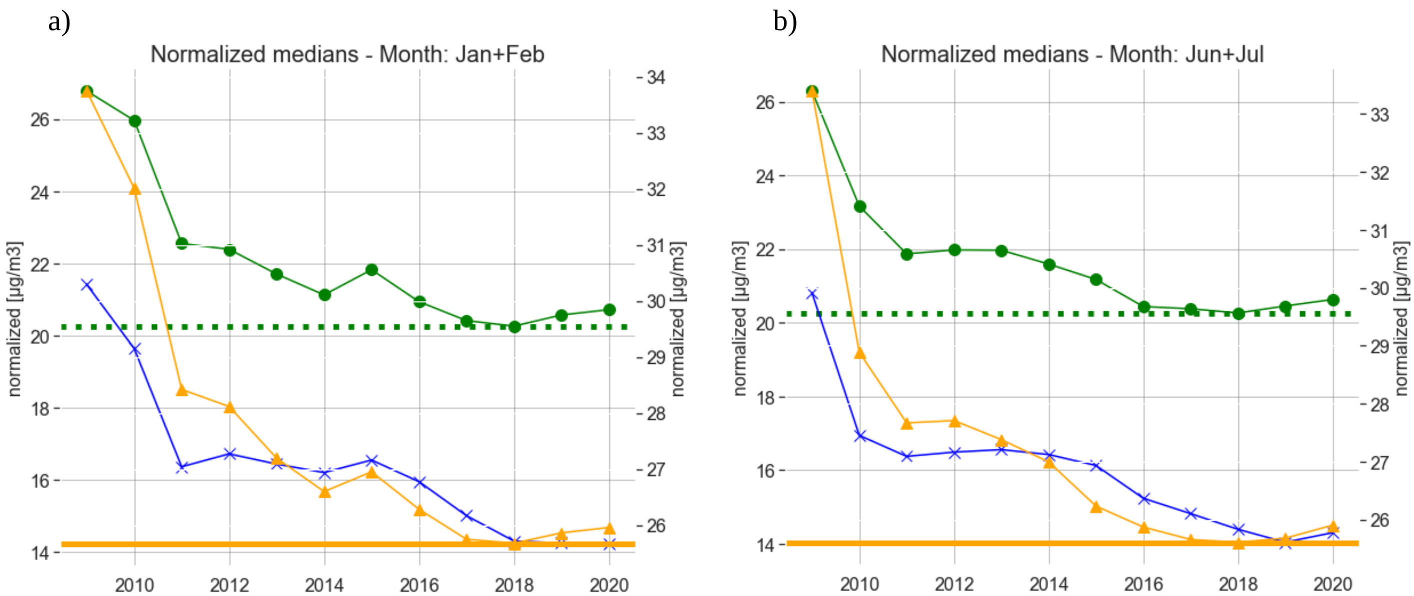

Figure 3. a) Normalized medians for January and February (CS) during 2009 -2020, b) Normalized medians for June and July (NNS) during 2009 -2020. The green line is PM10 related to the respective right axis, while blue and orange are PM1 and PM2.5 concentrations respectively referred to the left axis.

During NNS (the months of June and July, Figure 3b) a reduction in pollution comparing to previous years was expected due to lower tourism rate and the travel ban as well as working from home and many isolations. In case of April when the lockdown took place (LDS; boxplots in Figure 4), PM2.5 and PM10 mass concentration increases were observed from 2017 to 2018, which dropped in 2019 and further in 2020 comparing to 2018. The results are slightly different form PM1 which is steadily dropping. To assess whether the changed observed in normalized PM-time series are significant, we utilized ANOVA. For each of PM1, PM2.5 and PM10 a test was created with the year (2018, 2019, 2020) as the independent variable and the normalized concentrations as the dependent variable. ANOVA showed that yearly changes for April do not show statistical significance for PM2.5 ($p = 0.33$) and PM10 ($p = 0.33$). while PM1 shows significant changes with a $p = 0.003$, the difference coming from 2018 having higher normalized concentrations (median PM1= 14.8 µg/m3) comparing to 2019 (median PM1= 14.2 µg/m3) and 2020 (median PM1= 14.1 µg/m3). Similar results were obtained for the NNS (new normal) with PM2.5 ($p = 0.15$) and PM10 ($p = 0.23$) showing no significant difference as well as PM1 ($p=0.06$).

These results are aligned with some of the published work, as there is mixed proof on whether PM was truly affected, at least for sites not heavily affected by traffic. In our previous work [12], it was found that a drop in PM10 mass concentration during the lockdown in Graz, Austria is rather inconsistent when comparing it to gaseous pollutants (e.g., NO2). A drop in NO2 gas concentrations was found to be around 40%, while PM10 mass concentration decrease was in the range of 6-14%. This was however analysed without normalizing the values. Given the comparison to the observed reduction in traffic, one could conclude that the reduced traffic was not a dominant contributor to the changes in PM10 atmospheric load. Xu et al. using difference-in-differences method to compare air pollution before and during lockdown in China, found no change in PM10 and PM2.5 concentrations.

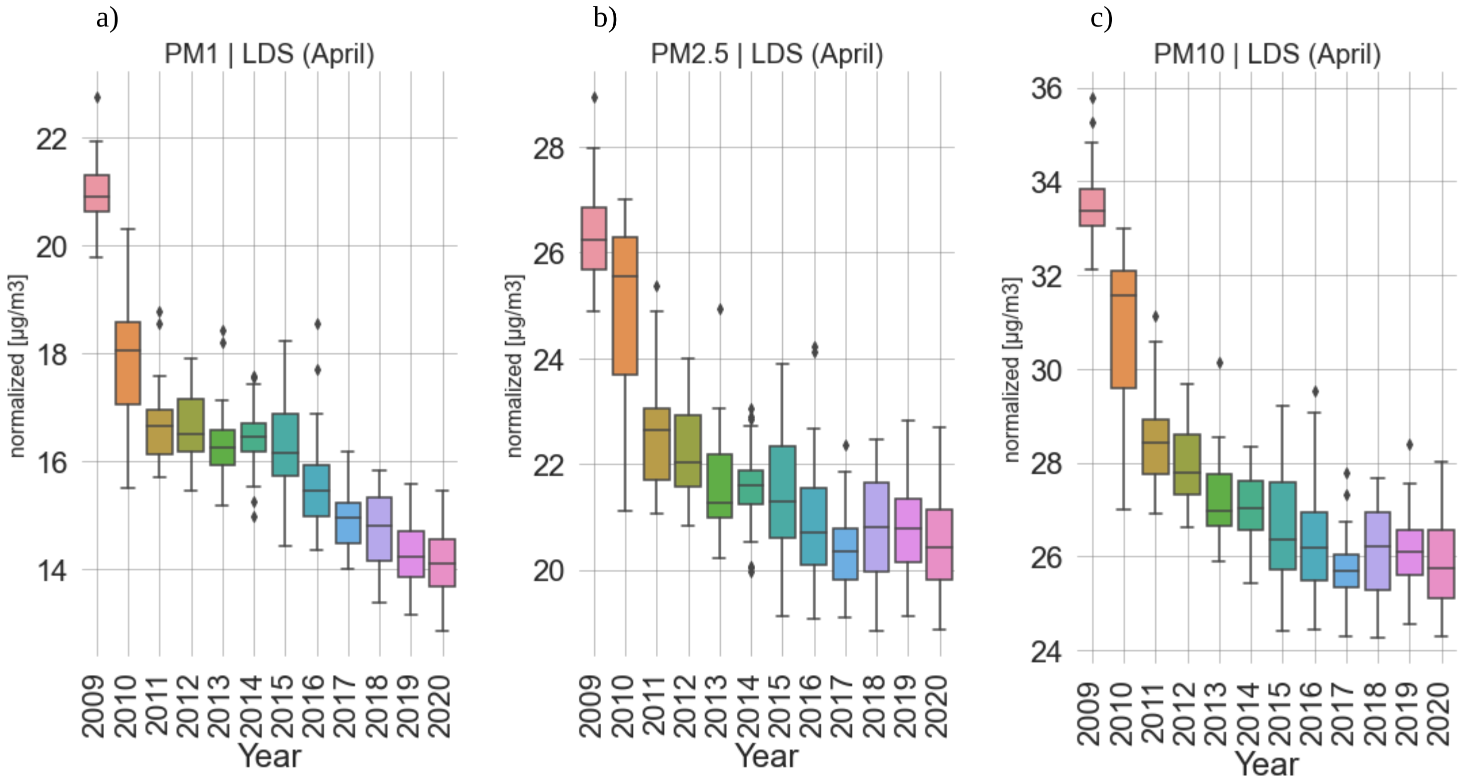

Figure 4. Boxplots of April normalized concentrations through the years for a) PM1, b) PM2.5, c) PM10.

This finding implies that the main PM source can be other than traffic. Although concentrations displayed short-term declines within three days after the lockdown policy was implemented, when compared to measurements from different monitoring sight that acted as control group, the differences decreased [1]. A large study which, however used weather-corrected analysis from 21 European countries showed no lockdown changes in PM10 levels in Romania and Croatia. Meanwhile, PM10 levels decreased in 17 countries with Portugal leading with 55% lower PM10 concentrations due to lockdown measures. An increase in PM10 was noted for Switzerland and Hungary with 4% and 3%, respectively [3]. Our results are in accordance with a study by Etchie et al who confirms no effect on PM by the lockdown [15]. A study which also used RF and meteorological normalization shows only moderate decrease for PM10 [15].

4. Conclusion

In this work we evaluated the effects of the lockdown on PM mass concentration in Zagreb, Croatia. Our study hypothesis was; the COVID-19 lockdown (April 2020) and the “new normal” (June, July 2020) would both cause a decrease in PM1, PM2.5, and PM10 mass concentrations due to changed human behaviour and mobility. To investigate the observed decrease in PM concentrations, we employed Random Forests (RF) combined with meteorological normalization. The RF models utilized in this study exhibited a reasonably good generalization on the test set (R2 scores ~ 0.7). We extracted the trend component of the PM mass concentration and compared it to pre-, during and post-lockdown timeframes. The results by means of normalized concentrations showed that over the course of 2009 – 2017/2018 PM concentrations dropped, however no significant changes were observed in PM mass concentrations due to the lockdown or post-lockdown events. Besides that, given that NO_2 reductions was earlier observed at the same site, one can speculate that a reduction in mobility did not affect particulate matter to a significant extent. This will be further investigated by introducing traffic observation in future work.

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