Interpretable and Transferable Models to Understand the Impact of Lockdown Measures on Local Air Quality

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ABSTRACT

The COVID-19 related lockdown measures offer a unique opportunity to understand how changes in economic activity and traffic affect ambient air quality and how much pollution reduction potential can the society offer through digitalization and mobility-limiting policies. In this work, we estimate pollution reduction over the lockdown period by using the measurements from ground air pollution monitoring stations, training a long-term prediction model and comparing its predictions to measured values over the lockdown month. We show that our models achieve state-of-the-art performance on the data from air pollution measurement stations in Switzerland and in China: evaluate up to -15.8% / +34.4% change in NO2 / PM10 in Zurich; -35.3% / -3.5% and -42.4% / -34.7% in NO2 / PM2.5 in Beijing and Wuhan respectively. Our reduction estimates are consistent with recent publications, yet in contrast to prior works, our method takes local weather into account. What can we learn from pollution emissions during lockdown? The lockdown period was too short to train meaningful models from scratch. To tackle this problem, we use transfer learning to newly fit only traffic-dependent variables. We show that the resulting models are accurate, suitable for an analysis of the post-lockdown period and capable of estimating the future air pollution reduction potential.

KEYWORDS

Air pollution, modelling, generalized additive models, GAMs, transfer learning, COVID-19, lockdown, weather-dependency

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1 INTRODUCTION

Air quality is of vital importance to human health. Medical studies have shown that PM2.5 (particulate matter of diameter less than 2.5 micron) can be easily absorbed by the lungs, and prolonged exposure may lead to respiratory impairments, blood diseases and neurodevelopmental disorders, such as autism, attention deficit disorders and cognitive delays [14]. Air pollution is also found to have a negative effect on the cognitive functions in elderly adults [48] and is associated with increased mortality rates [9, 32]. Furthermore, air pollution leads to enormous economic losses [15] and its reduction is particularly important in overpopulated urban areas.

In the context of current pandemic, recent studies show that long-term exposure to PM2.5 and NO2 increases human susceptibility to SARS-CoV-2 [24, 32] and contributes to higher fatality rates [42, 62]. There is also a worrying evidence that the virus can be found in outdoor particulate matter [56]. Although further investigations are necessary, it seems obvious that air pollution plays an important role with regard to both transmission and severity of this disease. Lockdown measures of varying duration and strictness in response to COVID-19 have shown to be effective to slow down the virus spread in winter and spring 2020 in many countries. At the same time, reduced mobility, working from home, accelerated digitalization and e-commerce made researchers wonder about the pollution reduction potential also in the context of global warming and while preserving the basic operations of cities and counties.

The 2020 lockdown provides a unique and valuable opportunity to analyze the air quality reduction patterns. Fig. 1 presents a comparison of measured air pollution in Wuhan, China over the same period of time in 2019 and 2020. Due to significantly reduced human activities, such as traffic, the concentrations of NO2 drop to low and stable levels during the lockdown compared to the same period in 2019 as shown in Fig. 1. Similar patterns are also observed for other pollutants, e.g., for PM2.5 in Wuhan, China.

Although numerous studies estimate pollution reduction during lockdown in various countries [1, 23, 24, 59], the results mostly represent aggregated differences to various baselines with no modelling of the dependency between air pollution and the local weather conditions, time-varying and land-use information. Moreover, a detailed analysis of the lockdown is difficult due to its short duration and, thus, scariness of the representative data. This paper tackles the problem by making use of the air quality and weather data measured by public stations operated by official authorities. We also propose a modelling framework that enables such analysis, and give arguments for its usefulness in broader contexts.

Today, air pollution is measured by networks of governmental stations packed with expensive analytical instruments, satellite images [5], IoT devices equipped with low-cost sensors [55], passive samplers, crowdsourcing campaigns [25], etc.. Real-time data from public and private stations can often be found online, e.g. [43].
Numerous models were developed ranging from country-scale [50] to city-scale [26, 27, 40] and aiming to predict short-term [66] and long-term pollution exposure [4]. Although there is a large body of literature investigating the relationship between industry, traffic and air pollution, it is still not well understood how changes in economic activity and traffic affect ambient air quality [60].

Challenges. The COVID-19 related lockdown measures offer a unique chance to build more knowledge in this area. However, there are numerous challenges to be solved. (1) Recent studies investigating the impact of the lockdown measures on air pollution are not correcting for the influence of weather conditions on air pollution, which can considerably distort the obtained estimates. (2) Strict lockdown measures took place only for a few weeks in countries around the world, which complicates learning a reasonable model for the lockdown period. Solving the first challenge helps to accurately compute the local pollution reductions over the lockdown period and understand their spatiotemporal variability. Solving the second challenge enables learning from the COVID-19 experience by computing different scenarios, such as estimating the air pollution reduction due to a partial back-to-normal regime or predicting pollution patterns if the lockdown would have happened during a different season or if its duration would have been extended.

Contributions and road-map. In this paper, we solve the above challenges by building the first interpretable models for the lockdown period (LD models). We use the following pipeline to achieve the goal: Based on the historical data over the past several years before the lockdown, we train long-term interpretable pre-lockdown (pre-LD) models based on the Generalized Additive Models (GAMs) and show that they achieve comparable accuracy to the long-term and short-term models described in the literature and evaluated on the same data. The pre-LD models are used to predict air pollution for the lockdown period while taking weather conditions into account. The predictions are then compared to the actually measured values over the same period. In addition, we leverage the additive property of the GAMs and their interpretability to train weather-aware LD models using the scarce lockdown data. Towards this end, we fix environmental dependencies in the models and use transfer learning to compute a new fit for only land-use and daytime dependent parameters. We show that scarce data over only 4 weeks of lockdown are sufficient to train high-quality LD models for NO2. We use both model classes to analyze the post-lockdown data and to estimate air pollution reduction in different scenarios. Our approach is evaluated on two public data sets from China and Switzerland. The code of the models is publicly shared on GitHub\(^1\). More generally, we argue that a combination of the model interpretability and transfer learning notably simplifies result validation and increases their trustworthiness. Sec. 2 summarizes a rapidly growing body of related works on modelling air pollution exposure.

2 RELATED WORK

Big data has a huge impact on modelling environmental processes [38, 46], including air pollution. Even though the Earth generates data at a fixed pace, which doesn’t change no matter how much data is collected [51], the already collected large volumes of observational data have been successfully used for modelling environmental processes [10, 18, 57]. Long-term environmental predictions are, however, largely rooted in scientific theory, which is one of the key reasons for their predictive power [51]. Below we summarize the related works on theory-free and theory-based data-driven models when modelling air pollution and discuss the challenges we face when applying these to modelling air pollution under the COVID-19 lockdown measures.

Interpretable air pollution models. Classical dispersion models [65] are still widely used for air quality mid-term and long-term predictions and interpretable analysis. These models identify the root cause of air pollution from chemical, emission, climatological factors and combinations thereof. These models are described by a numerical function of emissions from the industry, traffic, meteorology, and other factors. A fitted model can then be used to understand the impact of each of these factors in isolation. Among the model-based predictive environmental models, GAMs have shown to be able to facilitate a high degree of accuracy while retaining explainability. Thus GAMs have been frequently used to model air pollution [6, 7, 26, 45] and run interpretability analysis. For example, estimating the impact of traffic and weather on PM and NO2 [7] and quantifying the impact of weather on NO2, PM and O3 for Melbourne [45]. Belusic et al. [6] further analyze the impact of meteorological variables numerically in a model and explain 45% of variance in CO, 14% in SO2, 25% in NO2 and 24% in PM10. We apply the model selection procedure for GAMs [4] to find the best model hyper-parameters and use log-normal pollutant values as an independent variable [34] for better prediction quality. Moreover, we leverage the additive property of GAM models to tackle data scarcity when training the LD model.

Short-term air pollution exposure prediction. Recent research results on short-term air quality prediction range from a few

\(^1\)https://github.com/johanna-einsiedler/covid-19-air-pollution
hours to a few days ahead and mainly rely on deep learning models. FFA [68] is one of the first model-free data-driven methods which forecasts air quality from meteorological and weather inputs. DeepAir [64] was proposed to learn the air pollution patterns in a deep manner, simultaneously considering individual and holistic influences. To further improve the model capacity, GeoMAN [33] used a three stage attention model learned from local features, global features and temporal geo-sensory time series. This approach shows a potential to learn the dynamic spatio-temporal correlations and to interpret the model results. Lin et al. [35] represent the spatial correlations in a graph with automatically selected important geographic features that affect PM2.5 concentrations, and use these features to compute the adjacency graph for the model. To conquer the challenge of sample scarcity, Chen et al. [12] proposed a multi-task approach to learn the representations from the relevant spatial and sequential data, as well as to build the correlation between air quality and these representations. Zhang et al. [66] found that local fine-grained weather data is helpful to predict air quality. Their method fuses heterogeneous weather, air quality and Point-of-Interest (POI) data to learn the interactions between different feature groups. Ensemble methods, such as the winning solution of the air quality prediction challenge at KDD Cup 2018 [37] are also used to further improve the accuracy of short-term air quality predictions. However, these deep learning approaches lack the ability to interpret the prediction results and usually focus on short-time horizons of a few hours to a few days.

Transferable models. Transfer learning [44] promises to light-retrain a model in order to adapt the parameters to a changed setting and requires little data. Pollution models are usually very local and not spatially transferable, e.g., across cities and countries, because the learned dependencies are location-specific and policies may vary substantially across distant areas. To transfer the knowledge from a city with sufficient multi-modal data and labels to a new city with data scarcity, Wei et al. [61] propose a method to learn semantically related dictionaries from a source domain, and simultaneously transfer these dictionaries and labelled instances to the target domain. Temporal transferability of learned dependencies is difficult due to environment and policy changes over time. For example, Cheng et al. [13] applies a learning-based approach to solve the downscaled sensor deployment problem. They try to transfer knowledge from a historical dense deployment to current sparse deployment setting by finding the most similar instances to execute the model transfer. Transferring pollution models in space or in time requires strong assumptions about the source and the target domains, such as shared similarities and other transferable structures. Without explicit assumptions or known structural similarities, a model should be trained from scratch, which is data-intensive.

Impact of COVID-19 on air quality. Lockdown measures in response to COVID-19 pandemic offer a unique opportunity to improve prediction of policy impacts reinforcing work-from-home and changing to low-emission mobility vehicles such as bicycles. The study in [39] assessed NO2 reduction based on satellite imagery by NASA and ESA in multiple COVID-19 epicenters. A similar assessment of the impact of SARS-CoV-2 in other areas is provided in [5]. The relationship between air pollution and lockdown measured was studied in [59] using satellite data and ground level sensor data. The weather adjustment is taken into account but modelled as a simple linear dependency. A recent report [58] estimates NO2 reduction for major European cities during the lockdown when compared to previous years. The results suggest a reduction from 16-18% in Budapest and Berlin to over 60% in Paris and Bucharest.

Building a good predictive model for the lockdown period is challenging due to a short lockdown duration of only several weeks in most countries. In contrast to all previous efforts, we are one of a few to provide a weather and season-compensated estimate of pollution reduction over the lockdown period2, and we are the first to use transfer learning to train an interpretable model for the COVID-19 lockdown period valuable, for the analysis of the future air pollution reductions due to policy change and technological progress.

3 OVERALL FRAMEWORK

We first describe the data sets used in the paper and then present the overall modelling framework.

3.1 Data Sets

This section describes the data sets we use to train and test the pre-LD and LD models for China and Switzerland. We also shortly describe the progress and the duration of the lockdown measures. Note that both countries implemented very different air pollution reduction policies over the years. Also the severity of the lockdown measures varied considerably. Both facts highlight robustness of the modelling approach presented in the paper.

Beijing and Wuhan. We collect air quality data3, including PM2.5, PM10, O3, NO2, CO and SO2, from 35 stations in Beijing and 10 stations in Wuhan from Jan 1, 2016 to June 30, 2020. Our scripts also fetch meteorological data4 for the same station locations every hour during the same period of time. Each record comprises the following parameters: weather situation (sunny, cloudy, overcast, foggy, snow, small rain, moderate rain, and heavy rain), relative humidity, temperature, pressure, wind speed, and wind direction data. The lockdown periods in Beijing and in Wuhan was between Jan 23 and Apr 8, 2020. According to the local environmental situation for each air quality station, the stations in Beijing are categorized

| Country   | Class          | Local situation               | # stations |
|-----------|----------------|-------------------------------|------------|
| Switzerland | No Traffic   | Located offside the road      | 1          |
|           | Low Traffic   | ≤30,000 VPD                   | 3          |
|           | High Traffic  | >30,000 VPD                   | 1          |
| China     | Urban         | Urban Beijing, parks          | 12         |
|           | Rural         | Countryside, parks            | 11         |
|           | Suburban      | Polluted transfer zones       | 7          |
|           | Road          | Urban, high traffic           | 5          |

Table 1: Classification of stations in Switzerland (by # vehicles per day (VPD)) and in China (by location type).

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2The only similar study conducted in parallel to this work, using Random Forests modelling and reporting similar results for Switzerland can be found here: https://empa-interim.github.io/empa.interim/swiss_air_quality_and_covid_19.html visited 2020-10-26
3https://quotsoft.net/air/ visited 2020-10-12
4https://darksky.net/ visited 2020-10-12
The set of modalities may vary from one station to another, although NO2, PM10 and O3 are measured by all stations. Stations are spread across the area, although bigger cities including Zurich and St. Gallen have more than one station at representative locations. We use the data from 5 stations measuring NO2, PM10, O3, CO, relative humidity, temperature, pressure, wind speed, and wind direction on the hourly basis from Aug 1, 2015 to July 31, 2020. The lockdown in Switzerland took place between Mar 16 and Apr 27, 2020 [8, 53]. According to the traffic conditions, the stations are classified into three classes: No Traffic, Low Traffic and High Traffic. The details are summarized in Table 1.

In all considered areas the available data has hourly time resolution. However, we use daily aggregates to build and validate our models. We also note that the lockdown severity in Wuhan was the highest and in Switzerland the lowest.

### 3.2 Framework

Fig. 2 shows the overall framework of the proposed approach. We rely on Generalized Additive Models (GAMs) due to their popularity, accurate prediction ability and model interpretability. These are described in Sec. 4.1. We first use pre-lockdown (pre-LD) data comprising weather parameters and date/time features (see Sec. 4.2) to train pre-LD GAM models. As part of the training, we rely on the model selection algorithm described in Sec. 4.3 and validate the obtained models in Sec. 4.4. The pre-LD GAM models are then used to analyze the pollution reductions over the lockdown (LD) period. As next, due to data scarcity and the inherent inability to train GAM models from scratch for the LD period, we apply transfer learning mechanism to adapt the trained pre-LD GAM models to the LD period (in Sec. 6). We refer to the resulted models as LD models. We leverage domain knowledge to justify the validity of the applied knowledge transfer: the impact of weather factors on air quality remains largely the same despite the lockdown. We therefore, fix the pre-LD model parameters describing the weather dependency during the transfer procedure, and only retrain the date/time parameters that represent human mobility to obtain the LD models. We show that the sparse data collected over the lockdown is sufficient to generate meaningful LD models for NO2 using this approach.

### 4 INTERPRETABLE LONG-TERM AIR POLLUTION PREDICTIVE MODELS

This section describes the process of training a pre-LD model to be later used to estimate the air pollution level if no lockdown would have happened. We require a high degree of model interpretability for the following two reasons: (1) the prediction time horizon should cover the whole lockdown period of several weeks and thus the models should have sufficient predictive power for long-term predictions, and (2) model interpretability is essential to understand the impact of mobility drop on the reduction of air pollution and to learn from these conclusions. For these reasons, we adopt GAMs that have been successfully used to model air pollution in the past research [26], yet leverage additional optimizations [4, 11] and statistical tests to ensure their robustness and optimize performance as described below. Since pollutant concentrations vary greatly depending on location and the surroundings of the monitoring station, a separate model was fitted for each station.

#### 4.1 Generalized Additive Models (GAMs)

GAMs have been proposed in 1986 by Hastie and Tibshirani [28] and blend properties of generalized linear models with additive models. The impact of the predictive variables is captured through non-parametric smooth functions. These are then summed up and related to the response variable via a link function:

\[
g(E(Y)) = s_1(x_1) + s_2(x_2) + \ldots + s_p(x_p),
\]

where \( E(Y) \) is the expected value of the dependent variable \( Y \). \( g(\cdot) \) is a link function between its argument and the expected value to the predictor variables \( x_1, \ldots, x_p \), and \( s_1(\cdot), \ldots, s_p(\cdot) \) denote non-parametric smooth functions. The statistical distribution of the concentration of air pollutants, similarly to many other environmental parameters, closely follows a log-normal distribution [34]. Thus, a logarithmic link function \( g(\cdot) \) has been chosen similarly to [26]. The instance of our GAM model is therefore

\[
\ln(Y) = a + s_1(x_1) + s_2(x_2) + \ldots + s_p(x_p) + b_1 \cdot Z_1 + b_2 \cdot Z_2 + \ldots + b_q \cdot Z_q + \epsilon,
\]

where \( a \) is the intercept, \( Z_1, \ldots, Z_q \) denote categorical variables along with their respective weights \( b_1, \ldots, b_q \) and \( \epsilon \) is an error term.

#### 4.2 Explanatory Variables

The explanatory variables we use comprise meteorological variables: wind speed (WS), wind direction (WD), precipitation (P), temperature (T), dew point (DP) and relative humidity (RH). To ensure an accurate feature representation of the wind direction, the polar coordinates are transformed into cartesian coordinates:

\[
WD_x = \sin\left(\frac{WD}{360} \cdot 2\pi\right), \quad WD_y = \cos\left(\frac{WD}{360} \cdot 2\pi\right).
\]
Furthermore, an additional variable, referred to as PCA, is created by performing the Principal Component Analysis on the precipitation, humidity, dew point and temperature variables. PCA is a dimensionality reduction method to reduce the mutual correlations between the included variables. We augment the set of explanatory variables above with their lagged versions for one, two and three days. Wind speed (WS) and PCA are augmented with their respective rolling averages over the previous weeks. In addition, a categorical variable for month (M) is introduced to account for seasonal changes. Julian Day (JD) is included to capture long-term trends. For Beijing and Wuhan, a variable for the Chinese New Year (NY) is added to the pool of variables to reflect a significant deviation of the human activity over this period from the rest of the year. These categorical variables are often included when modelling air pollution [4, 20].

4.3 Model Selection Algorithm

For the selection of the model covariates we use a forward elimination procedure. The algorithm closely follows the framework used in similar research designs in the environmental sciences [4, 11]. Two key indicators are used for the model selection: the Akaike Information Criterion (AIC) [2] and the Variance Inflation Factor (VIF) [19]. The AIC is an estimate of the in-sample prediction error that is commonly used to compare the quality of different statistical models for a given data set [29]. The aim of the indicator is to regularize the model by balancing the goodness-of-fit against model complexity and thereby avoiding both underfitting and overfitting. The AIC is calculated as follows:

\[
AIC = 2k - \ln(l), \tag{4}
\]

where \(k\) is the number of model parameters, and \(l\) denotes the maximum value of the model likelihood.

The VIF measures the degree of collinearity between independent variables, i.e., if they have a close to linear relationship and are thus not independent from each other. Collinearity may cause problems in regression-like techniques as it inflates the variance of regression parameters and thus may lead to wrong identification of the relevant predictors [16]. The VIF is calculated as follows:

\[
VIF = \frac{1}{1 - R^2_i}, \tag{5}
\]

where \(R^2_i\) is the coefficient of determination of the regression of the \(i\)-th variable with all other explanatory variables.

**Model selection algorithm.** Our implementation of the model selection algorithm closely follows [4]. The algorithm executes as follows: (1) For each explanatory variable we fit a GAM model comprising just this single variable. The model with the lowest AIC is selected. (2) We iteratively search for the next best variable to be added to the existing model. Variables with \(VIF > 2.5\) are filtered out. Among the constructed candidate models, the one with the lowest AIC is chosen. The threshold of 2.5 corresponds to the coefficient of determination \(R^2 = 0.6\). This conservative threshold setting was deemed appropriate taking into account the frequent interactions, and thus collinearity, between weather variables. Scientific papers dealing with weather data often adopt the threshold of 2.5 [4], whereas higher cut-off values, e.g., 4, 5 and 10 are found in the literature [11, 31, 41]. Step (2) is repeated until the addition of any other explanatory variable leads to an increase of AIC.

### Table 2: \# stations where the corresponding explanatory variable was chosen by the model selection algorithm.

| Variable name | Abbr. | Switzerland | Beijing | Wuhan |
|---------------|------|-------------|---------|-------|
| Wind speed    | WS   | 3 5 24 8   | -       | -     |
| Wind dir. X   | WDx  | 7 3 16 18  | 7 10    | -     |
| Wind dir. Y   | Wdy  | 1 2 12 7   | 1 10    | -     |
| Precipitat.   | P    | 2 3 -      | 1 -     | -     |
| Temperat.     | T    | 1 4 -      | - -     | -     |
| Rel. hum.     | RH   | - 27 66 11 | 9 9     | -     |
| Day           | M    | 1 - -      | 1 -     | 9     |
| Julian Day    | JD   | 3 1 10     | 8 4     | -     |
| New Year      | NY   | - 34 20 6  | 5 5     |       |
| Dew Point     | DP   | 2 1 -      | - -     | -     |
| PCA           | PCA  | 7 3 14 18  | - 9     |       |
| Weekday       | D    | 2 - -      | 1 -     | 8     |

The results of the model selection algorithm for all stations in China and Switzerland are displayed in Table 2. The value of each cell represents the frequency of the corresponding explanatory variable being selected into the GAM models. Only occurrences chosen by the model selection algorithm are listed in the table. Ultimately, the Weekday variable (D) was explicitly added to all models where it hasn’t been automatically selected. This decision was made to specifically take into account weekly pollution periodicity patterns to reflect the traffic changes during the lockdown period. This technique has been used in a similar research design to analyse the long-term air pollution trends [4].

4.4 Model Validation

We assess the quality of the trained pre-LD models using cross-validation. The results for NO2 and PM for Switzerland, Beijing and Wuhan are shown in Fig. 3. Taking into account the temporal dependencies in the air pollution data, the models for different stations are fitted on 3, 6, 9, 12, 18 and 24 months of train data prior to a chosen date and tested on the data from the subsequent month. The chosen cut-off date is the start of each month in the year 2019. We observe that two years of data is necessary to train the pre-LD GAM models of good quality. Considering more historical data does not substantially improve the model accuracy. For this reason, all further evaluations are based on the pre-LD models trained on two years of data preceding the lockdown in each region.

**Eastern Switzerland.** For the Swiss stations the model has an average RMSE in cross validation of 7.7 for NO2 and 4.7 for PM10. Barmypadimos et al. [4] use GAM models fitted on detailed weather data to analyse PM10 trends in Switzerland. Their models fitted on 16 years of data reach a RMSE between 2.2 and 3.2 for PM10 for large test data sets, see Table 3. We thus conclude that the quality of the obtained GAM models is comparable to published results.

**Beijing.** For the stations in Beijing the average RMSE for PM2.5 in cross validation is 32.9. Zhang et. al. [67] compare different models for short-term (between 6h and 24h) PM2.5 predictions in Beijing over 2016-2018. The RMSE of these short-term models ranges between 26.9 and 44.1. Thus, our model matches well the performance of the current state-of-the-art predictive short-term models, while predicting a much longer time period and allowing
for an immediate analysis of the fitted dependencies. In contrast to these short-term predictive models, however, our GAM models need much more (two years compared to a few days) training data to achieve acceptable accuracy. We note that historical weather data is often publicly available, which makes model training on large historical data sets possible.

In the next section, we use the trained pre-LD models to estimate pollution reduction due to the COVID-19 lockdown measures.

5 IMPACT OF COVID19 ON AIR POLLUTION

Conceptually, estimating the impact of intervention measures on air pollution shares similarities with evaluating the impact of medical treatment on the disease progression [36]. Following the standard evaluation procedure, one would have to first randomly assign days to either the pre-lockdown or the lockdown condition and then estimate the impact of policies by calculating the mean difference. Obviously, random assignment of days to the condition is not feasible due to the inverse causality. Therefore, different approaches are implemented in the literature.

The most common is based on the comparison of the measured air pollution over the lockdown period in 2020 to the same time interval in 2019. However, air pollution is known to depend on weather conditions, their recent history, season as well as policy updates that prohibit an accurate estimation of pollution reductions due to COVID-19 lockdown interventions. In this section we provide pollution reduction estimates that take weather-related parameters into account. In the next section, we introduce a way to refine these estimates using the measurements during the lockdown.

Local weather highly impacts the daily change of air pollution. In Fig. 4, we compare the weather conditions during the lockdown period in 2020 and during the same period in 2019. We observe that in Switzerland, the lockdown weather was warmer, dryer, and less windy than in 2019. Similar observations apply to Beijing and Wuhan. In addition, we notice a change in the wind direction, which is a significant pollution predictor in these regions due to a strong pollution transfer phenomenon [66]. The significant role of wind in the Beijing and Wuhan models is also reflected in Table 2 by a high number of the pre-LD GAM models where WS and WD were chosen as important explanatory variables by the model selection algorithm.

To estimate pollution reduction during the lockdown, we leverage the pre-LD models trained on the pre-LD data as outlined in Sec. 4, and use these to predict air pollution concentrations over

Table 3: pre-LD and LD model performance in cross-validation, comparison to related works.
the lockdown period. We then compute the difference between the predicted and actually measured values to estimate the impact of the lockdown measures in each region. Overall, the estimated pollution change over the LD period compared to the same time period in 2019 in Switzerland evaluates to -15.8 % / +34.4 % for NO2 / PM10. For Beijing and Wuhan we estimate changes of -35.3 % / -3.5 % and -42.4 % / -34.7 % in NO2 / PM2.5 respectively.

**Eastern Switzerland.** Since NO2 is highly impacted by traffic, we put the obtained NO2 reduction estimates in the context of traffic reduction reported by Apple and Google based on the observed change in usage of their services.

The Apple Mobility Trends Report [3] publishes aggregated estimates of the changed driving behavior of their users based on the navigation requests. The data suggests an average reduction of driving activity in Switzerland of 40.4 % compared to the baseline of Jan 13, 2020. As shown in Table 4, this traffic drop translated into a reduction of NO2 between 10.4 % and 16.2 % for Low Traffic and High Traffic stations respectively as predicted with our models, when using the same baseline. Fig. 5 compares the output of the pre-LD models to the observed values in 2019 and 2020 for these classes. For the station located off the road, we find an increase of 18.9 %. In this case, the average NO2 is very low and its positive change can be regarded as marginal and likely attributed to weather phenomena not captured by our explanatory variables. A similar increase of 27.4 % was reported by [23] for another rural station in Switzerland.

Counter-intuitively, we found an increased PM10 concentrations over the lockdown period despite reduced traffic intensity. However, an intense Sahara dust event occurred in Switzerland during the lockdown month starting on Mar 26, 2020 [52, 54]. Sahara dust events are known to significantly increase PM concentrations in southern and middle Europe. Studies in Greece found Sahara dust contribution to PM2.5 of up to 82 % for severe events [49]. A similar investigation in Turkey [36] indicates that Sahara dust is responsible for the increase of PM10 concentrations of up to 96 %. As can be seen in Fig. 5 the Sahara dust event in Switzerland resulted in a major increase in PM10 values which is not captured by our explanatory variables and explains the overall increase in PM10 despite reduced traffic.

The Google Community Mobility Report [22] offers statistics on the estimated times spent in certain areas such as workplaces, groceries and parks. The statistic is derived from the user behavior using the Google Maps service. The median value of the period between Jan 3, 2020 and Feb 5, 2020 is used as a baseline for this calculation. The resulting estimates are listed in Table 5 and indicate e.g., a reduction of time spent in grocery stores of 13.1 % and a reduction of transit of 48.8 %. Using the same baseline, our model indicates a reduction of NO2 of 15.9 % for Low Traffic stations and of 15.5 % for High Traffic. For the No Traffic station as well as for all classes for PM10, we again observe an increase due to the reasons explained above.

We show example predictions for Low Traffic and High Traffic stations in Switzerland in Fig. 5. We observe that the measured NO2 and PM10 values differ significantly from the values in 2019 for the same time period. For the majority of days, measured NO2 concentrations lie below the pre-LD model predictions. This is, however, not the case for PM10 for the reasons given above.

**Beijing and Wuhan.** We estimate an average NO2 reduction of 38.6 % and 55.9 % for Beijing and Wuhan, respectively. The detailed comparison for the traffic-based area breakdown is shown in Table 6. We compare our weather-aware predictions to the published results [5] obtained based on the analysis of the satellite images over the lockdown period (see TROPOMI [5] and OMI [5] in Table 6). Our results for NO2 reductions are more conservative for urban areas, although fall within the confidence intervals of the satellite imagery based predictions. In low-traffic areas we give slightly higher reduction estimates, yet within the confidence bounds.

Despite the estimated overall traffic reduction of 70 % for Beijing [5], the estimated PM2.5 concentrations over the lockdown decrease only slightly, stay unchanged or even slightly increase (see Table 6). Similar results were also obtained for Beijing when using the Chemical Transport Model [65]. The explanation provided in the research literature attributes this phenomenon to the impact of high ozone along with the considerably reduced NO2 that led to the increased oxidation capacity in the ambient air [21, 47]. This resulted into more intense particle formation from the agricultural emissions, e.g., ammonia (NH3), brought into the city with the wind. Our statistical model does not model pollutant interactions and thus does not capture these effects. Interestingly, in Wuhan there is no evidence that a similar increase of oxidation capacity occurred during the lockdown. This observation is aligned with our predictions for Wuhan that show an estimated reduction of PM2.5 of up to 65.7 % over the lockdown period.

**Figure 4:** Weather comparison for the lockdown periods in 2020 to the same period in 2019 in Switzerland, Beijing and Wuhan.

**Table 4:** Estimated pollution reduction in Eastern Switzerland compared to the traffic reduction reported by Apple [3].

|                | No Traffic | Low Traffic | High Traffic |
|----------------|------------|-------------|--------------|
| NO2            | +18.9      | +122        | -10.0        |
| PM10           | +38.6      | -16.2       | +16.3        |
| PM2.5          | -40.38     |             |              |

**Table 5:** Estimated NO2 reduction estimates.
which caused unexpectedly high values in the measurements during the lockdown period in the beginning of 2020.

Figure 5: Sample predictions for NO2 and PM10 for Eastern Switzerland. Green zones show the Sahara Dust Storm period [54].

Figure 6: Sample predictions for NO2 and PM2.5 for Beijing, China. Green zones show the pollution transfer phenomenon, which caused unexpectedly high values in the measurements during the lockdown period in the beginning of 2020.

Figure 7: Spatial distribution of pollution reduction for (a) NO2 and (b) PM10 in Switzerland, (c) NO2 and (d) PM2.5 in Beijing and (e) NO2 and (f) PM2.5 in Wuhan. Red means increasing and blue means reduction in the plot.
The average predictions for urban and rural stations in Beijing are exemplified in Fig. 6. Measured NO2 values are significantly below pre-LD predictions, whereas measured PM2.5 concentrations almost coincide with the predictions by the pre-LD model. For the PM2.5 predictions, both the LD and pre-LD models fail to accurately predict two spikes in the beginning of the considered period, as shown in the green zones of Fig. 6. The reason for this is the pollution transfer phenomenon: Air pollution is brought by the wind from the surrounding non-lockdown cities to Beijing [17], and results in unexpectedly high measured air pollution concentrations in the city [68]. Our proposed method could be easily adapted to acquire better prediction results by including prior knowledge about the pollution propagation patterns that are specific to Beijing [69]. This is, however, out of scope of this paper, yet would be interesting to model as part of future work. Apart from these two spikes highlighted in the plot, our proposed LD model achieves reasonable prediction accuracy compared to the observed ground truth values in 2020.

We also provide the spatial distribution of the pollution reductions over the lockdown period across all stations in our data sets in Fig. 7. When comparing major cities under analysis (Wuhan and Beijing in China; St. Gallen and Zurich in Eastern Switzerland), we conclude that NO2 and PM reductions were higher in cities with stricter enforced intervention measures. Given the major events and unexpected developments with regard to PM2.5 and PM10 in Switzerland and Beijing during the lockdown period, we consider only NO2 in further modelling. We note however that PM2.5 reduction in Wuhan was not affected by these events and confirms our expectations. We observe an average 65.7% reduction of PM2.5 in Wuhan when comparing our pre-LD model predictions to measured values (see Table 6).

6 LEARNING LOCKDOWN MODELS

In the previous section we showed how to accurately estimate pollution reduction with a pre-LD model by comparing the model predictions to the actually measured values. The lockdown period gives us the bottom-line by how much humans in different regions, given their cultural and political differences, can reduce their activities in a fear of getting infected by a virus. Having a bottom-line is useful when evaluating future policy changes, sector restructuring due to technological advances, process optimizations, etc.. In this section we describe the construction of the LD models by transfer learning and show the value of both models in the analysis of the developments in the post-lockdown period.

Transfer learning is a popular technique to apply the knowledge gained by solving a particular task to a related task [61]. Since the lockdown period was too short to fit GAM models for this time period, we apply transfer learning to pre-LD models to derive models for the lockdown period. In this step we re-train the models on the scarce lockdown data to only fit the variables where we suspect the dependencies may have changed due to lockdown, i.e., the day of the week. These variables serve as proxy for the traffic intensity. All weather dependencies in the LD model are considered to be the same as in the pre-LD model, which is confirmed by the domain experts. Therefore, the knowledge gained with regards to the influence of the weather and seasonality on air pollution can be transferred to the lockdown period. Thus, there is no need to train the entire model from scratch.

6.1 Model Validation

Due to the scarcity of measured data over the lockdown period, we validate the model by cross-validation using only 3 successive days as test data. The remaining data from the lockdown period is then used for training. This way, we get 14 estimates for the out of sample prediction RMSE. The summary of the average RMSE values for the lockdown model can be found in Table 3 and shows similar or better model performance for NO2 compared to the quality of the pre-LD models. For NO2 in Eastern Switzerland, we can clearly see that the LD model closer matches the observed values. On average, the LD models have a RMSE of 7.41 whereas the pre-LD models have a RMSE of 7.66. This shows that the fine-tuned LD model reflects well the dependency between air pollution and explanatory variables for the short lockdown time period. For Beijing and Wuhan the model performance improvement is more pronounced. We obtain a RMSE for the LD models of 13.08 and 12.26 for both cities respectively.
We now use both models \(pre-LD\) and \(LD\) to investigate the optimal mixture thereof capable of explaining the observed pollution values after the lockdown period. By doing so we aim to estimate to what extent have human mobility and the inherent traffic gone back to normal. To run this analysis, we minimize the absolute sum of differences between the true observations and the mixture of the \(pre-LD\) and \(LD\) model predictions.

\[
\arg \min_{\alpha} \frac{1}{|T|} \sum_{t \in T} |\alpha \cdot m_{t}^{LD} + (1 - \alpha) \cdot m_{t}^{pre-LD} - m_{t}|, \tag{6}
\]

where \(m_{t}\) is the measured value at time \(t \in T\), \(T\) is a post-lockdown period of length \(|T|\) under consideration, \(m_{t}^{LD}\) and \(m_{t}^{pre-LD}\) are the predictions obtained with \(LD\) and \(pre-LD\) models respectively. The dependent variable \(\alpha\) shows the contribution of the \(LD\) model when explaining the post-lockdown pollution measurements. The results of this analysis for all areas are summarized below.

**Eastern Switzerland.** For Eastern Switzerland we look at NO2 concentrations over 2 months after the lockdown, the period between May 1 and June 30, 2020. As depicted in the third column in Table 7, for the No Traffic class we observe mostly the same situation as before the lockdown with only 1% \(LD\) model being able to explain the measurements. This is no surprise, since the station in this class is barely affected by traffic conditions and the predictions of both \(LD\) and \(pre-LD\) models yield very similar results. For the Low Traffic class, NO2 values match the pollution levels one would expect in a lockdown situation with 77% significance. For the High Traffic class, the \(pre-LD\) model dominates with 58% significance as can be seen in Fig. 9. The High Traffic station is located on the outskirts of the city whereas all Low Traffic stations are in the city center. We thus conclude that during the three months after the lockdown, the mobility in Zurich and St. Gallen largely resembled the lockdown situation, whereas transport in and out of the city was already closer to the pre-lockdown levels. This is potentially related to a rebound of economic activity and associated transportation after the ease of the lockdown measures end of April, 2020.

**Beijing and Wuhan.** For Beijing and Wuhan we investigate the post-lockdown period between Apr 9 and June 1, 2020. For this time period we observe that NO2 values in Beijing remain largely to lockdown levels and the \(LD\) model dominates with significance of 94% to 100%. We attribute this to the high number of emergency response levels in Beijing that were in place until end of April and have been gradually relaxed throughout May [63]. For Wuhan the \(LD\) model shows only 35% significance. These findings should be seen in the context of a more strict lockdown in Wuhan than in Beijing. For this reason, our \(LD\) model is trained on the data which correspond to the lowest mobility levels in the country in contrast to other cities and regions.

| Region          | Class  | LD model contribution \([\alpha \cdot 100\%]\) | Hypothetical reduction 2019 |
|-----------------|-------|---------------------------------|-----------------------------|
| Eastern Switzerland | No Traffic | 1 | -2.8 |
|                 | Low Traffic  | 77 | -26.6 |
|                 | High Traffic | 42 | -27.2 |
| Beijing         | Urban      | 94 | -47.2 |
|                 | Rural      | 92 | -73.6 |
|                 | Suburban   | 100 | -66.6 |
|                 | Road       | 100 | -30.6 |
| Wuhan           | Average    | 35 | -54.6 |

Table 7: Optimized mixture of \(pre-LD\) and \(LD\) model to explain observed NO2 values in the post-lockdown period.

These minor performance differences can be attributed to a shorter extent have human mobility and the inherent traffic gone back to normal. To run this analysis, we minimize the absolute sum of differences between the true observations and the mixture of the \(pre-LD\) and \(LD\) model predictions.
6.3 Hypothetical Year-Long Reductions

We can use the LD model to predict the impact of the hypothetical traffic reduction policies on air quality. We demonstrate this using the year 2019 as an example and base the LD model predictions using weather traces from the whole year. The estimated impact of a hypothetical year-long lockdown on NO2 reduction between Jan 1, 2019 and Dec 31, 2019 is compared to the measured values in 2019. The results are summarized in the last column of Table 7. In this paper, we show how transfer learning can be used to update air pollution models should the weather relationships, policies or human activity change. Due to a known model structure and interpretability, it is easier to ensure validity and trustworthiness of such updates and support automated decision making and control. In the future, we plan to extend the LD and pre-LD models to spatial predictions by incorporating land-use data similar to [26], and provide a visualization tool to show the effects of various policy measures and compare these to the lockdown baselines.

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