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Article

Consideration of Altered Anthropogenic Behavior during the First Lockdown and its Effects on Air Pollutants, and Land Surface Temperature in European Cities

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Abstract: Substantial reductions of the human and economic activities like road traffic for several months in 2020 were one of the consequences of the Coronavirus disease. This unprecedented change in urban metabolism also affected temperature and air pollutants. This study investigates the effects of the first COVID-19 lockdown over 43 cities in Europe. It determines the influence of anthropogenic activities on nitrogen dioxide (NO_2), ozone (O_3), and particulate matter ($PM_{2.5}$) as well as on land surface temperature (LST), and the surface urban heat island intensity (SUHII), using satellite, modelled, and mobility data. Our findings show that there are great temporal and spatial differences and distinct patterns between the cities regarding the magnitude of change of the variables under study. In general, the results indicate a significant decrease in NO_2 concentrations in most of the studied cities compared to the reference period 2015-2019. However, reductions could not be attributed to mobility changes like less traffic at transit stations, contrary to the results of previous studies. O_3 levels increased during the first lockdown mainly influenced by the decreasing NO_2 concentrations. The PM pattern was inconsistent over time and space. Similar as the NO_2 results, no relation to the altered mobility behavior was found. No clear signal could be detected for LST and the SUHII, likely due to dominating meteorological influences. Therefore, single city case studies may be misleading.

Keywords: air pollutants; COVID-19; lockdown; land surface temperature; road traffic

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1. Introduction

One of the deadliest and largest global pandemics in history, the Coronavirus disease 2019 (COVID-19), firstly appeared in November 2019 in China, Wuhan and causes respiratory illness [1,2]. The first case of COVID-19 in Europe was confirmed on February 21, 2020, in France (Spiteri et al., 2020). Until the end of April 2023 around 764.500.000 cases have been confirmed globally, with 6.915.000 deaths [3]. Europe declared 276.000.000 confirmed cases. To combat the virus and to reduce the infections and mortality, governments put in place numerous measures such as travel restrictions, school- and workplace closures, even complete lockdowns [4,5]. In consequence, unprecedented in history, the virus reduced various human and economic activities for several months [6]. This exceptional situation changed the environment in many ways. For example, changes of the anthropogenic heat release related to road traffic emissions and energy consumption for heating and cooling buildings, modified the air- and land surface temperatures (LST) of cities [7–9]. Numerous studies investigated the LST changes during the first lockdown [9–12]. They observed a general decline in LST compared to the previous year's average LST. For Andalusia a LST decline of -4.6 K (-19.3%) during the March to June 2020 compared to the same period in 2019 based on Sentinel 3 data was recorded [13]. Further, Liu et al. [9] found that during the lockdown the surface urban heat island intensity (SUHII) in China decreased by 0.25 K during the day and 0.23 K at night, and the canopy-layer UHII by 0.42 K at day and 0.39 K at night, respectively. Also, regarding the air pollutants many

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studies have already shown that the lockdown restrictions affected anthropogenic-related air pollution [4,6,13–16]. This is especially important because indoor and outdoor air pollution is one of the greatest health risks for people nowadays, claiming about seven million lives annually [17]. During the lockdown spatial differences in the intensity of changes were recorded. They are mainly explained due to different strict measures imposed by each government, the prevailing sources of the emissions and the weather [18]. Strongest air pollution drops were seen in Asia and then in Europe. Less strong drops were registered in North America and smallest changes in Africa due to less strict measures [19].

In detail, looking at nitrogen dioxide (NO_2), the European Space Agency (ESA) [20] noted a 40-50% reduction over Asia and Europe, derived from the Sentinel-5P satellite between the end of January and the beginning of February 2020 compared to the same period in 2019. The study of Tobías et al. [21] based on ground measurements showed similar signals. Here, Barcelona had reductions of -45% to -51%. Both, ground measurements and satellite-based studies concluded that the main contributors for the NO_2 reduction are the decline of road transport and industrial emissions. However, after easing the restrictions, concentrations were approximately as high as before the lockdown [18].

Observations of fine inhalable particles with diameters 2.5 µm and smaller ($PM_{2.5}$) were inconsistent. For example, in Chinese cities drops were generally greater in more industrialized cities [22].In comparison to 2017-2019 reductions of -42% were noted for Wuhan [16]. Rural areas, where agriculture is the main activity, or places where PM is more prevalent due to natural sources, PM remained at higher levels. Also, the strictness of the lockdown affected the $PM_{2.5}$ reduction. Compared to 2019, reductions of -7.1 µg/m^3 without strict measures and -21.1 µg/m^3 with strict measures were reported [22]. In South European cities there were only slight PM reductions (-8%) compared to 2017-2019 [16]. The drops were recorded especially at traffic stations and hence attributed to transport and fuel combustion reductions. However, increased domestic heating and garden activities like biomass burning compensated those declines.

A widespread increase was seen regarding ozone (O_3). For example, in Barcelona and in Andalusia higher O_3 concentrations were noted, with +33% to +57%, and +5.9% respectively, obtained from meteorological ground stations, compare to pre-covid levels [13,21]. Another study recorded an O_3 increase of +17% compared to 2017–2019 for Europe [16]. The increase is explained due to reductions in NO_x emissions resulting in lower O_3 titration leading to higher concentrations of O_3. Further, it must be considered that O_3 formation is weather dependent i.e., photochemical sensitive. The sunny weather in this period lead to a higher O_3 formation.

Thus, the emergence of COVID-19 offers a unique opportunity to comprehend and quantify the human impact on the environment. However, most studies focus only on individual cities and single variables which may not be sufficiently representative, e.g. [10,13,22–24]. Considerably fewer studies analyzed patterns within a continent or at global level, e.g. [16,18,25]. In fact, there is a lot of annual variation and thus differences between cities. Hence, cities may show significant changes in different directions. Thus, the main objectives of this article are first to perform a multiparameter analysis and to comprehensively document the spatial and temporal LST and air pollutant variations, namely NO_2, O_3, and $PM_{2.5}$, during the first lockdown period for 43 cities over Europe, compared to the reference period in 2015–2019; and secondly to determine the influence of altered anthropogenic activity on those variables.

2. Materials and Methods

2.1. Investigation period and study area

The investigation period covers the years 2015-2020. Special attention is paid to the period from March 15, 2020, to April 30, 2020, when the strict policies of the first lockdown in Europe stopped various anthropogenic activities nearly completely. The same period from 2015 to 2019 serves as reference data. A five-year baseline is chosen to minimize the impacts of inter-annual climatic variability. The study is carried out over Europe. Based on the data availability it is possible to analyze a sample of 43 cities in Europe. The cities can be seen in Figure 1.

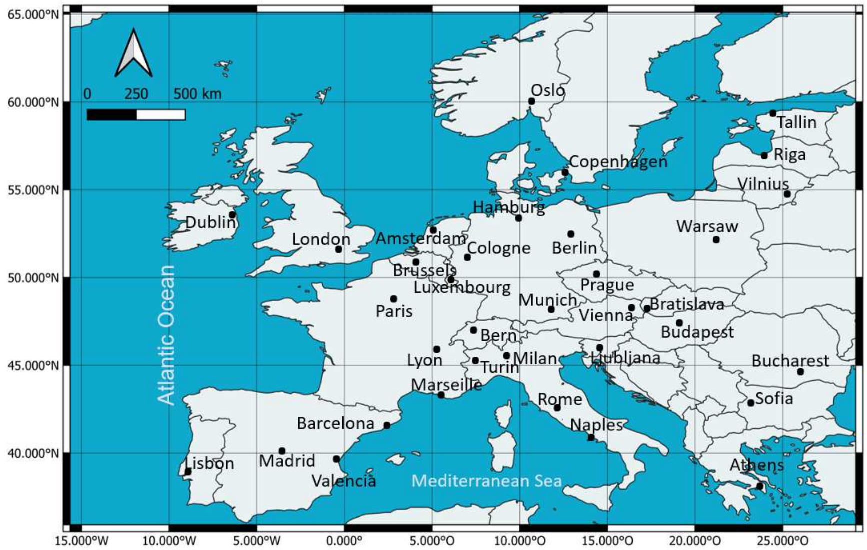

Figure 1. Cities under study.

2.2. *Air pollutants under study*

For this study, the air pollutants NO_2, O_3, and $PM_{2.5}$ are selected. Primary pollutants, i.e. directly emitted, like NO_2 are closely linked to human activity [15]. Thus, changes in air pollutant concentrations due to changes in anthropogenic behavior are expected. Main contributors to NO_2 emissions in Europe are transport (39%) and energy production (16%), commercial, residential and households (14%) and energy use in the industry (12%) [20]. Its lifetime in the atmosphere is between two to six hours at summer daytime and 12 to 24 hours during the winter and depends mainly on the meteorology [26]. Due to its short lifetime, NO_2 concentrations alter quickly when emissions change. In general, higher concentrations are found over densely populated cities, where emissions are higher than in the surrounding areas [15].

O_3 is a secondary pollutant and is thus, unlike NO_2, not emitted directly. It forms photochemically under solar radiation through chemical reactions of NO_x and volatile organic compounds (VOCs) [18]. O_3 emerges under solar radiation, thus unhealthy concentrations are predominantly yielded on sunny days [17]. In winter O_3 concentrations are lower when NO_x levels are usually high and thus titration is intense [18]. The lifetime of O_3 depends beside of the meteorology and solar radiation mainly on the chemistry of O_3 itself, its oxidant level and the NO_x and VOCs but on average its lifetime in the troposphere is about 20–24 days [27].

$PM_{2.5}$ can form through chemical reactions in the atmosphere forming secondary PM. Sources can be from gaseous pollutants like SO_2, ammonia or NO_2 especially due to power plants and combustion. On the other hand, it can be emitted directly in the form of dust, sea salt, smoke, trace elements, and crustal matter [14,17]. In Europe main anthropogenic contributors of $PM_{2.5}$ are commercial, residential and households (56%), industrial processes and product use (11%), agriculture (3%), road transport (11%), energy use in industry (6%) [28].

2.3. *Data*

This study uses the LST data product from Terra and Aqua MODIS (MxD11A1 v6.1). This data product provides the daily LST for day- and night-time for each city. The daily LST data are processed as explained in Sismanidis et al. [29] and the LST mean is calculated for each city (separately for the urban and the surrounding rural area).

From the LST the SUHII is calculated by subtracting the rural arithmetic mean from the urban. The aim of calculating the SUHII is to reduce the noise and the existing variation in the data and

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make the signal from the changed human activities more pronounced. Because the diurnal and seasonal temperature cycle is higher than the expected magnitude of temperature differences between lockdown period and non-lockdown period, we normalize these differences to enhance the signal corresponding to the changed human activities. It must be noted that the SUHII also depends on weather. However, with calculating the SUHII temperature variabilities throughout different years, the inter-annual variabilities and the magnitude of variations are reduced [30].

The air pollutant concentrations are from the Copernicus Atmosphere Monitoring Service (CAMS). The data assimilation embeds satellite and ground-based/ in-situ observations and numerical models. The used product is the CAMS daily regional analysis. Here, one daily average value for each air pollutant is given per major European city [31].

Mobility data from Google's COVID-19 Community Mobility Reports are used to examine how the numbers of visits to specific types of places changed during COVID-19 lockdown in each city. We also use these data as a proxy for anthropogenic activity. There are six types of places namely residences, transit stations, retail and recreation, grocery and pharmacy, workplaces, and parks. For residences, the percent change of average time spent at home is provided. The percentual change of one day for a specific place is related to a reference value for the respective weekday. The baseline data are the median value for each category and each weekday during the five-week period between January 3 and February 6 in 2020 before the lockdowns started. Thus, there are seven different reference values within a week [32].

2.4. Statistical Analysis

To quantify the changes between the lockdown and pre-COVID period, the data are split into two groups. The first group corresponds to the reference period 2015-2019 and the second to the lockdown period of the first COVID-19 pandemic wave (15^{th} of March to 30^{th} of April 2020). For each variable, the percentage, and the absolute difference between the two groups are computed.

To assess if the differences between the two groups are statistically significant, and to check whether the pre-COVID and COVID values come from the same theoretical distribution a two-sample one-sided, non-parametric Kolmogorov-Smirnov hypothesis test (KS-test) is carried out. It is a test procedure independent of the distribution of the data [33]. The significance level is $\alpha = 0.05$ and the test hypotheses for all variables under study but ozone are the following:

- H_0: The two distributions are identical, $F(x) \geq G(x)$ for all x, where F(x) is the lockdown- and G(x) reference period.
- H_A: They do not have the same distribution; the lockdown distributions are shifted toward lower values: $F(x) < G(x)$ for at least one x.

And for ozone:

- H_{0ozone}: The two distributions are identical, $F(x) \leq G(x)$ for all x, where F(x) is the lockdown- and G(x) reference period.
- H_{Aozone}: They do not have the same distribution; the lockdown distributions are shifted toward higher values: $F(x) > G(x)$ for at least one x.

3. Results

3.1. Multiparameter overview

Figure 2 shows the results of the individual variables of the KS-test combined with the relative changes in 2020 compared to the reference period. For the KS-test in most cases the null hypothesis can be rejected i.e., the LST, NO_2 and O_3 differences between the lockdown and reference periods are statistically significant. The statistically significant results are shown as a circle. If there is no statistically significant change in the variable, this is indicated by a rhombus as a symbol. This is the case in Eastern Europe for the O_3 values and the LST night-time values. For PM the results are variable with no clear signal regarding the spatial distribution.

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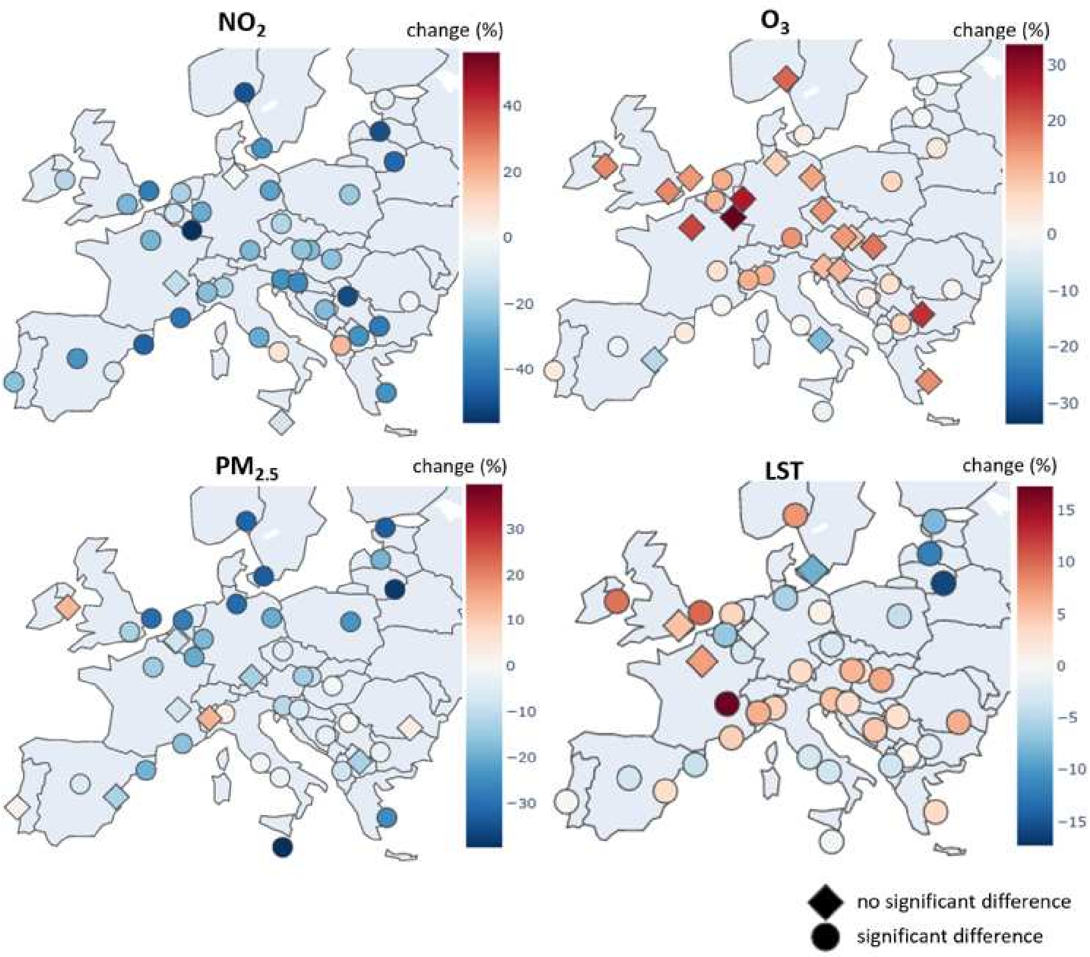

Figure 2. Relative changes in 2020 compared to the reference period 2015-2019 for NO_2, O_3, $PM_{2.5}$, and LST combined with the KS-test results. The circle means that there is a statistical significance (reject H_0), i.e., the variable altered during the lockdown period significantly compared to the reference period. The rhomb indicates there is no significant change (accept H_0) according to the KS test.

In general, a predominant decline for ground-level NO_2 was recorded. Although most of the cities showed the same signals, the magnitude of change differed city-wise. The three cities with the largest percentual NO_2 reductions are Luxembourg (-54.0% relative change, -12.3 μg/m^3 absolute change), Riga (-50.7%, -5.1 μg/m^3), and Belgrade (-50.4%, -6.8 μg/ m^3). Hamburg (+10.5%, +1.1 μg/ m^3), Tirana (+18.4%, +0.7 μg/m^3) and Naples (+11.9%, +1.7 μg/m^3) show the largest positive anomalies. For O_3 a widespread increase is evident. The largest positive anomalies are found in Luxembourg (+41.1%, +20.5 μg/m^3), Cologne (+35%, +15.7 μg/m^3) and Paris (+27.1%, +13.1 μg/m^3). In contrast to the other cities, cities in the Iberian Peninsula, Italy, and Southern France show lower O_3 concentrations in 2020. The greatest changes correspond to Naples (-12.1%, -8.9 μg/m^3), Valencia (-10.3%, -7.5 μg/m^3) and Madrid (7.2%, -5.0 μg/m^3). $PM_{2.5}$ anomalies are inconsistent over space. They decreased predominantly in Northern Europe. Strongest reductions can be observed in Tallin (-38.4%, -2.9 μg/m^3) Vilnius (-37.4%, -4.6 μg/m^3), Oslo (-28.8%, -2.8 μg/m^3). The highest increases were observed for $PM_{2.5}$ in Dublin (+43.9%, +1.5 μg/m^3), Turin (+31.4%, +5.5 μg/m^3), Milan (+19.7%, +4.1 μg/m^3).

3.2. Nitrogen Dioxide

Figure 3 shows the change in the distribution of the daily NO_2 levels averaged for all cities. Here it is apparent that the mean of the NO_2 concentration during the lockdown 2020 (dark red line) and the binned observations for the individual concentrations are left-shifted, which means that they have decreased. Furthermore, the density is reduced as well, which underlines the flatter continuous density curve for 2020. The density is calculated by dividing the frequency by the class width. Thus,

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it represents the frequency per unit for the data in each class. At this point it must be emphasized that the individual cities differ a lot. For some cities, like Barcelona the change is high, and in others, like Valetta the change is low (Figure 4).

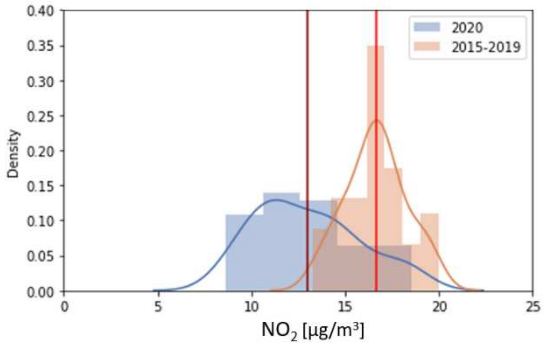
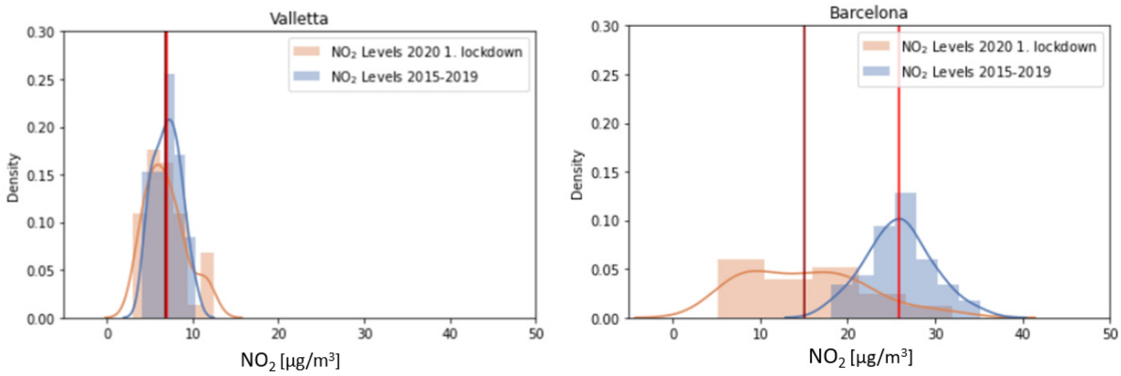


Figure 3. Distribution of the NO_2 levels[μg/m³] during lockdown and reference period averaged over all cities. The vertical line corresponds to the mean of the period, the columns to the binned observations.



(**a**) (**b**)

Figure 4 Distribution of the daily NO_2 levels [μg/m³] during lockdown and reference period for (a) Valetta and for (b) Barcelona.

The anomalies over the curfew period are shown in more detail in Figure 5. Here the differences for each day and city are shown compared to the values for each city in the reference period. In general, the changes in the Eastern European and Scandinavian cities are rather small. It is noticeable that there is almost no NO_2 concentration difference in Sarajevo. In contrast, a much lower NO_2 concentrations in 2020 (i.e., a strong negative anomaly) can be seen in Athens and Luxembourg. Some cities show an inconsistent behavior like Brussels, London, Milan, or Paris. On the other hand, Hamburg, Tirana, and Naples predominantly show a positive change in NO_2 concentrations compared to the reference period. Considering all cities, strong concentration declines in 2020 from day 81 of the year (March 22nd) approximately until day 91 (April 1st) are noticeable. Thereon, several cities show concentration increases compared to the reference period, interrupted again from negative anomalies during day 104-106 of the year (April 14th – 16th).

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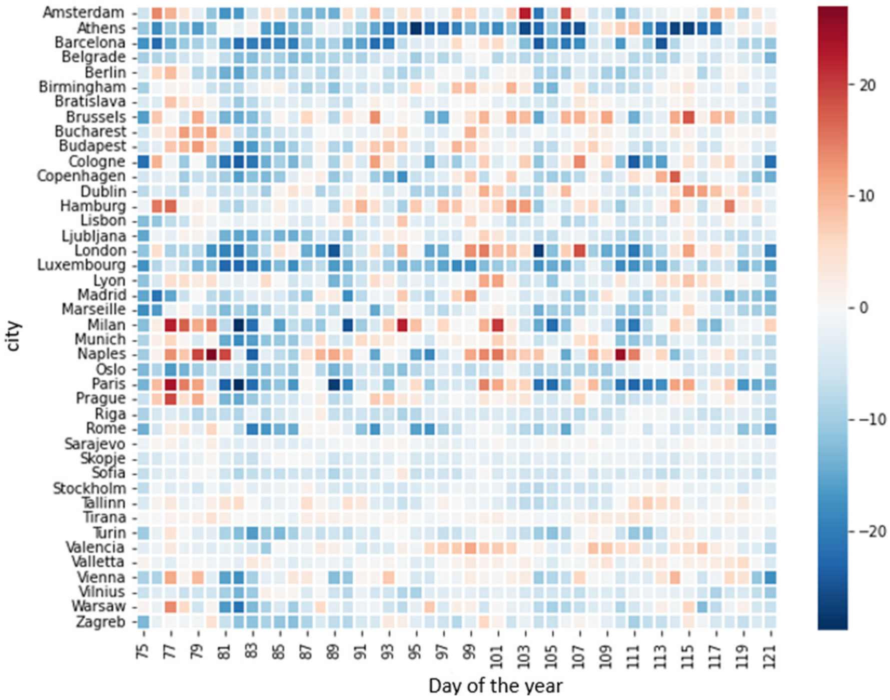


Figure 5. NO_2 anomalies [µg/m³] (15.03-30.04. 2020 vs. 15.03-30.04.2015-2019).

Looking at the average weekly pattern of all cities (Figure 6), the absolute NO_2 concentrations are not only lower but the pattern itself changed. In general, measured NO_2 concentrations increase, peaking on Fridays and decrease towards the weekend. A comparatively stronger increase in concentrations from Monday to Friday can be seen in 2020 (~3.5 µg/m³ in 2020 vs. ~2 µg/m³ in the reference period). On Sundays and Mondays, the concentrations are the same in 2020. In contrast, in the reference period, higher concentrations on Mondays compared to Sundays are observed.

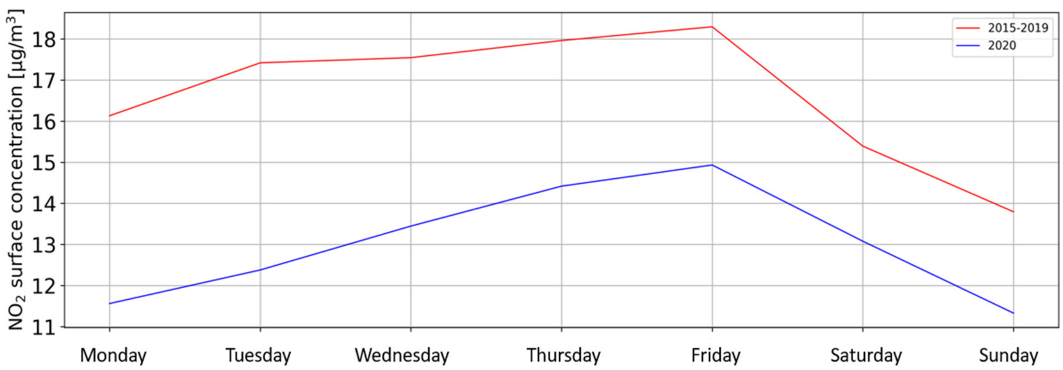


Figure 6. Weekly mean NO_2 [µg/m³] for all cities 15.03 – 30.04 in 2020 and the reference period.

3.3. Ozone

Examining the O_3 anomalies over the whole period, lower concentrations seem to prevail at the beginning of the lockdown. Around day 80 to 90 of the year (March 22nd -March 31st), however, almost all cities show an increase in O_3 concentration (Figure 7). Very striking is the strong increase in Budapest, Berlin, Cologne, Luxembourg, and Paris. This is followed by a phase which tends to have less O_3 in 2020 that lasts until day 95 (April 5th). Until day 108 (April 18th), most cities show higher O_3 concentrations than in the reference period. The cities Lyon, Marseille, Naples, Rome, Madrid, and Valencia, show conspicuous strong negative anomalies, especially towards the end of the study period from day 109 (April 19th).

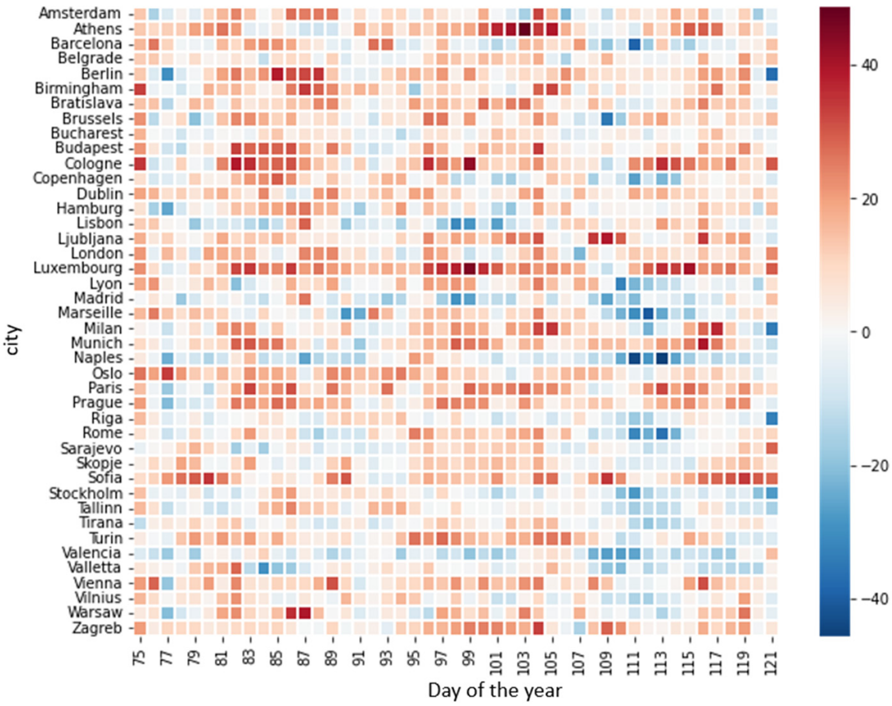


Figure 7. Ozone anomalies [μg/m³] (15.03-30.04. 2020 vs. 15.03-30.04.2015-2019).

In addition to the fact that surface O_3 concentrations are mostly higher in 2020, concentrations tend to be higher on weekends (Figure 8). The pattern itself in 2020 compared to the reference period is similar. However, there is a smaller concentration increase in 2020 (~1.9 μg/m³) towards the weekend than for 2015-2019 (~4.2 μg/m³). In addition, O_3 concentrations decrease in the reference period from Monday to Friday whereas for 2020 they do only until Wednesday. Further, the pattern is inverse in comparison to NO_2.

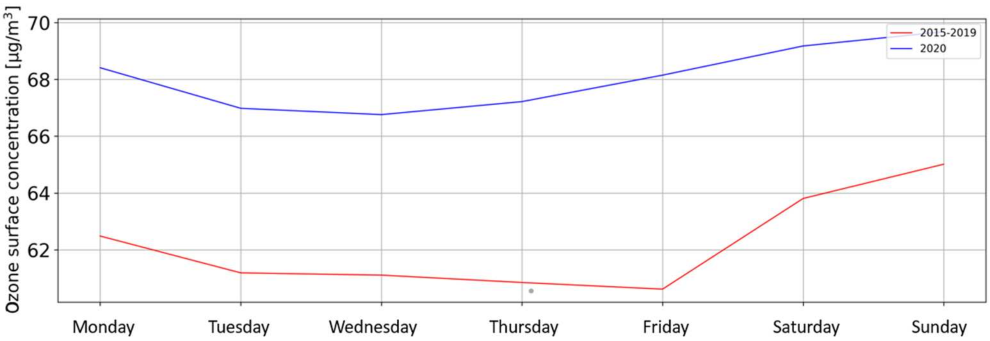


Figure 8. Weekly mean ozone levels [μg/m³] for all cities 15.03 – 30.04 in 2020 and 2015-2019.

3.4. Particulate Matter

$PM_{2.5}$ shows only a small shift of the mean concentration (Figure 9). Looking at the histograms, the bins are distributed in a greater range in 2020. Thus, both, observations with higher and also with lower daily values are recorded in 2020, even though it has a comparatively lower density curve. The anomalies are not only inconsistent over space but also over time (Figure 10). However, it is noticeable that between day 77 and 80 (March 18th - March 21st) in some cities there was a simultaneous increase of PM levels in 2020, followed by a drop until day 86 (March 27th) approximately. From day 87, with a few exceptions (e.g., Valetta, Naples), there was a positive anomaly that lasted about three days.

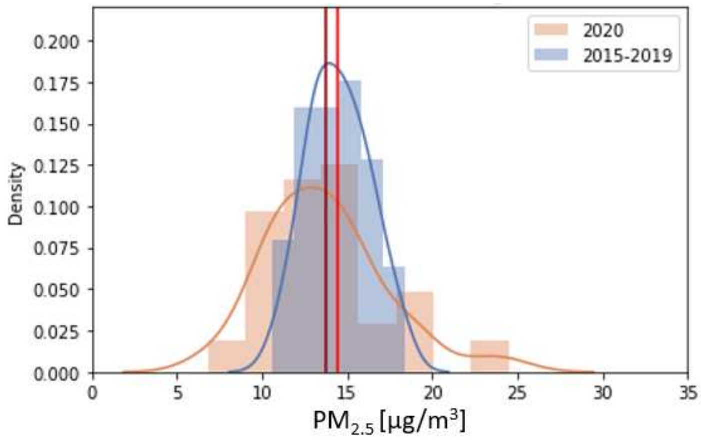


Figure 9. Distribution of the daily $PM_{2.5}$ levels [µg/m³] averaged over all cities during lockdown and reference period.

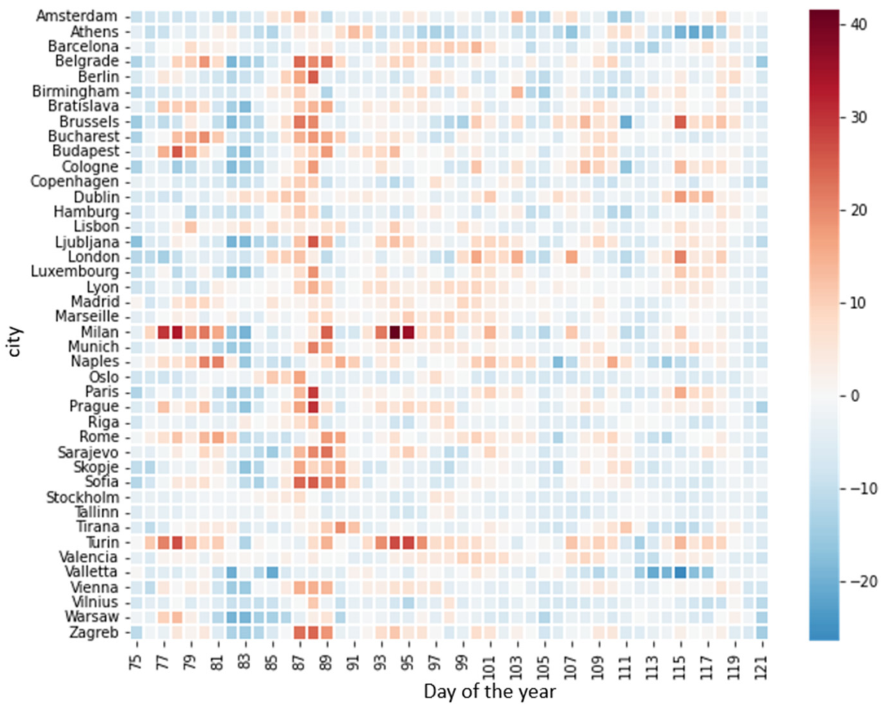
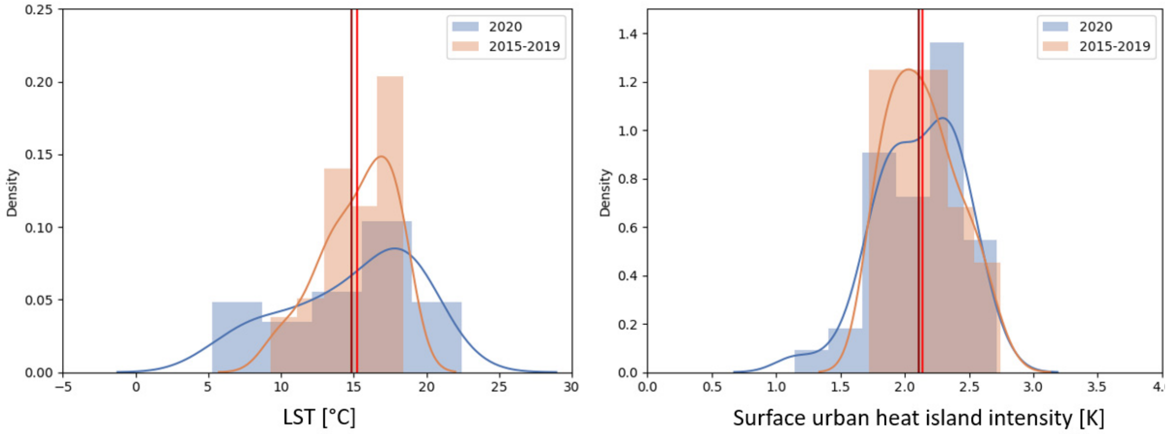


Figure 10. $PM_{2.5}$ anomalies [µg/m³] (15.03-30.04. 2020 vs. 15.03-30.04.2015-2019).

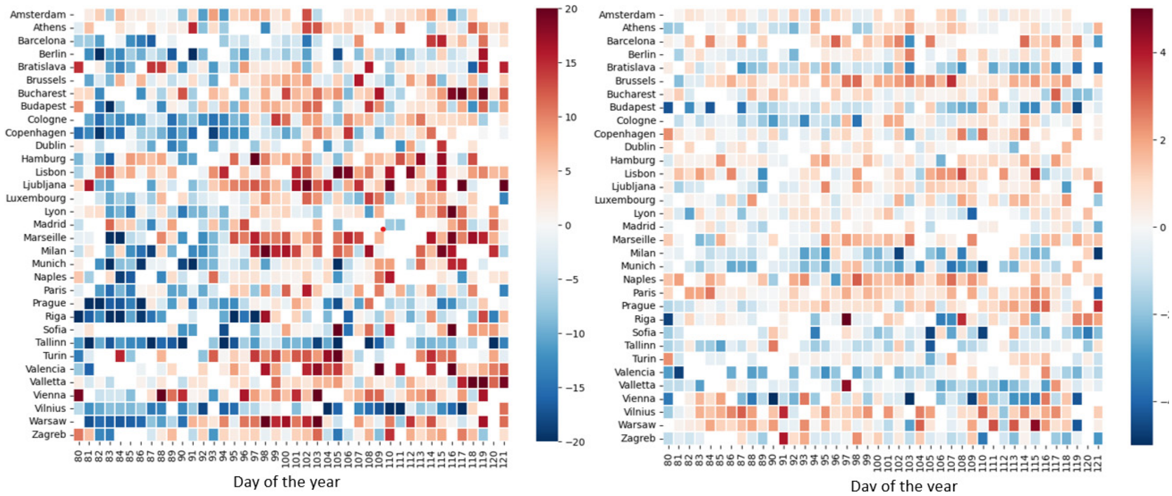
3.5. Land Surface Temperature

For both, LST and SUHII there is no clear signal of change (Figure 11). In total there was only a very slight LST and SUHII reduction. Weather uncorrected data show both, higher and lower LST in 2020 compared to the reference period and diverge strongly temporally and spatially (Figure 12).



(**a**) (**b**)

Figure 11. Distribution of the (a) LST [°C] and (b) SUHII [K] averaged over all cities during lockdown and reference period.



(**a**) (**b**)

Figure 12. (a) LST [°C] and (b) SUHII [K] anomalies (15.03-30.04. 2020 vs. 15.03-30.04.2015-2019).

3.6. Mobility Data

Figure 13 shows the percentual change of anthropogenic mobility during the study period (red box: March 15th to April 30th, 2020) and the time after the first lockdown in Madrid and Stockholm. The cities of Madrid and Stockholm were selected as examples of a strict lockdown and a lockdown with very few ordinances, respectively. Spain and Italy in general had the most stringent measures, while the government of Sweden imposed almost no restrictions [34]. Scandinavian and Baltic cities had less strict measures, which was also the case in Germany, where schools have been closed, but the industrial sector remained largely open [35].

After the restrictions have been imposed in mid-March, the mobility was clearly reduced. All categories were visited less, except of "residential" because more time was spent at home. In general, the greatest changes can be observed in the categories retail & recreation and transit stations; and the least in parks & grocery, and pharmacy. After easing the restrictions, mobility gradually increased again, with parks being visited more than usual. It must be stated that the baseline is in February and that fewer parks are visited in winter than in summer anyway. However, the mobility behavior has still not returned to the levels seen in summer 2020. Furthermore, the data show a weekly pattern. People were more outside and less at home on weekends, but in total less than usual. Regarding the workplaces and transit stations more people worked from home and did not use the public transport. In contrast on weekends most of the employees do not work and changes are rather marginal.

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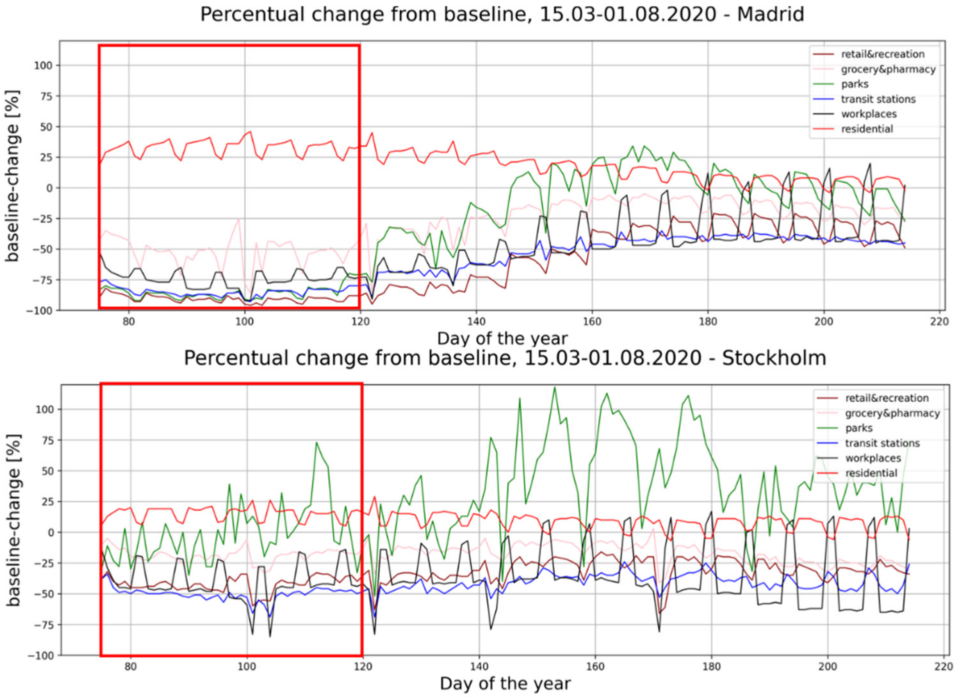

Figure 13. Percentual mobility change from the baseline, Madrid and Stockholm during 15.03-01.08.2020.

Comparing the two cities, in Madrid, mobility was much more restricted, public life almost came to a halt and thus the mobility data show a greater decline. Transit stations, park visits, and retail & recreation had a change of almost -90%. Furthermore, significantly more time was spent at home. Buying groceries was the only allowed opportunity to leave the house [34]. In contrast, in Stockholm the surplus of time spent at home was significantly lower (~+20%) than for Madrid (~+35%). Also, changes at transit stations and workplaces were only about 50%. From the end of March and ongoing, parks were visited more than during the baseline period, reaching a maximum of +75%. At the beginning of June, the visit to parks increased considerably compared to the baseline in Stockholm (the large daily variations are because park visits are influenced by the weather conditions). Thus, the two exemplary selected cities clearly illustrate how different strictness levels are reflected in changes in mobility behavior.

In Figure 14 we examine how the daily mobility is related to the variables under study, where each point corresponds to the value of one city on one day. As an example, the change of the number of visitors at transit stations is selected. The other categories follow the same pattern except of "residential" which shows an inversed pattern (not shown). The data distribution of the change of visitors at transit stations and the absolute NO_2 values is clearly not linearly correlated (Figure 14 a). Furthermore, it is useful to look not only at the absolute NO_2 values, but also at the change in NO_2 concentrations compared to the change at the transit stations. The representation of two rates of change allows inferences about how the NO_2 values change related to the change of the number of visitors at the transit stations. In Figure 14 (b) it can be seen that there were less people at the transit stations and that the NO_2 concentration has predominantly decreased during COVID-19. More importantly it becomes evident that the change of visitors at the transit stations has no visible influence on the NO_2 change. Overall, we could not establish a clear relationship between the mobility and the variables under study.

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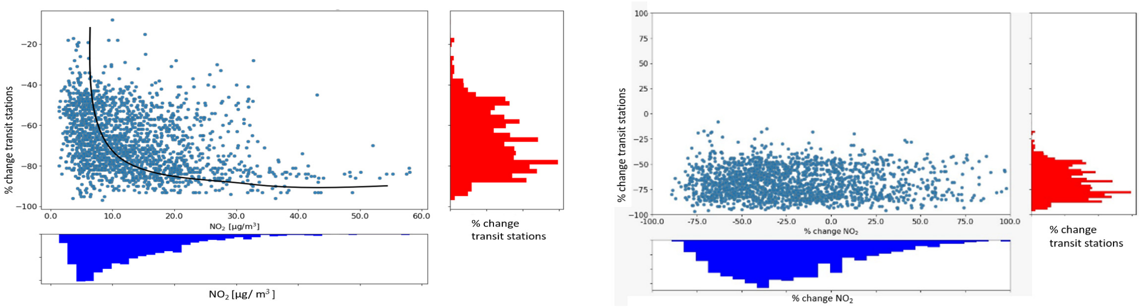

(a) (b)

Figure 14. (a) Absolute NO_2 concentrations vs. percentual change at the transit station during the 1. lockdown 2020; (b)Percentual change of NO_2 vs. percentual change at the transit station for the lockdown period.

4. Discussion

Nitrogen dioxide

In agreement with many other studies [15,19,21,36,37] strong reductions of NO_2 levels over most European urban areas are observed. Regarding the weekly pattern of the air pollutants several studies depicted the same results as stated here. Masiol et al. [38] explain the pattern by arguing that less NO_2 is emitted on weekends due to the fact that less people drive to work, and that heavy-duty vehicles are not allowed to drive on Sundays in most European cities. The pollutants accumulate within the week and reach their maximum on Friday since commuter traffic is reduced in weekends. The fact that NO_2 concentrations are very similar on Mondays and Sundays in 2020 suggests that fewer people drove to work during the lockdown. Contrary, under normal conditions, more emissions are emitted on Mondays than on weekends.

Ozone

The predominant increase of O_3 is related to the strong declines of NO_2, a precursor of O_3. Beside meteorological conditions, the ratio of NO_2 and VOCs determines the ozone production. If NO_2 levels decrease, the VOC/NO_x ratio is high, chemical titration with NO is reduced and O_3 levels increase. However, the response of O_3 formation to changes in the VOC/NOx ratio is nonlinear [14,23,36,39]. The study of Shi et al. [39] state that reductions in traffic-related NO emissions lead to increases in O_3 concentrations during daytime. Further, they emphasize that sunny weather during the lockdown enhances the oxidizing process and leads to higher photochemical production of O_3. However, possible divergences can be explained by the fact that O_3 is regionally well-mixed and can be transported downwind which can dominate local signals [36]. Thus, there is a high probability that the observed reductions of O_3 in some cities like Madrid, Valencia or Naples can be attributed to meteorological processes.

With respect to the weekly pattern, it can be attributed indirectly to the human metabolism because of its chemical relationship to NO_2. O_3 shows the inverse pattern of NO_2 i.e., an increase on weekends. This increase is observed in large parts of the world [16,40,41] and can be associated to a reduction in traffic i.e., NO_2 emissions, followed by a reduced titration of O_3 [13,21]. However, in 2020 the changed human metabolism influences slightly the "business as usual" pattern and causes changes in the weekly course.

Particulate Matter

PM surface concentration changes are weak and inconsistent with no clear increase or decrease signals even within one city over the study period. Several studies corroborate partly these results [36,39]. They also do not show a geographical homogenous signal. Strong variations can be expected since PM has various emission sources [42], hence, no clear relationship between PM and traffic is found. On the one hand, reductions in primary emissions of PM and its precursors like NO_2 and

VOCs, emitted for example from cars, lead to declines. At the same time the emissions from sectors such as agriculture, e.g., fertilizing, biomass combustion, waste burning, construction works, industry, etc., were not strongly affected by those measures. Especially in western Europe, PM levels were high in early spring due to fertilizer spreading [36,43]. Furthermore, it must be considered that the lockdown took place in early spring, when air temperatures were still cool, and residential heating was necessary. With the surplus of time spent at home simultaneously heating in the houses increased. In particular, wood burner stoves contribute to high PM levels [42,43]. Another reason for inconsistent signals in PM levels are local and regional meteorological conditions. PM levels can be influenced by temperature, humidity, precipitation, vertical mixing, and advection [25]. Moreover, regional, and long-range air mass transport can significantly affect local PM concentrations positively or negatively [43]. For example, reductions in PM levels from road traffic can be overwhelmed by PM air mass transportation from more polluted regions [39]. All these factors counteracted the reductions in traffic and contributed to inconsistent signals. Finally, traffic related measures to reduce harmful PM in cities have already been implemented within the EU before the lockdown started [42]. The fact that no strong changes in the PM levels were recorded can therefore also be due to previously taken measures, which aimed to improve the air quality over the years.

Relationship of the air quality variables and LST with the mobility data

In contrast to other studies [44], we were not able to observe a clear relationship between the air pollutants, the LST, and the mobility variables even though, other works clearly attribute the NO_2 declines to traffic depletion due to the stay-at-home order [14,15,45]. The transport sector is the largest contributor to NO_2 emissions in Europe [28]. Thus, changes of surface NO_2 levels serve as an indicator of altered human activities and local mobility. However, the results of this study indicate that the change of visitors at the transit stations have no or only low influence on the NO_2 emissions. Even though the results show that the number of visitors to transit stations has fallen significantly, this does not necessarily imply that less buses or trains operated, since timetables were likely maintained. This is also supported by Ropkins and Tate [46], which suggests that public transport in the UK, especially buses, did not stop during the lockdown. Therefore, the air pollutants from this source remained close to the pre-covid levels. Nevertheless, the fact that a general decline in NO_2 values was recorded may be due to great reductions of traffic with privately-owned cars and is not related to public transport. However, the mobility data only consider for the transit stations, the public transport and not individual car driving.

PM also shows a weak relationship with the mobility data. This is in line with the findings of Efe [47]. The weak correlations with "transit" and "workplaces" imply that PM is not strongly associated with human mobility. Although some studies showed positive correlations between mobility and PM, attributing the drop in PM to traffic restrictions, e.g., [48], several studies obtained similar pattern like the ones observed here. For example, the study of Munir et al. [43] shows the same negative, weak correlation with $PM_{2.5}$, whereas they considered only Northern England. They assume that PM concentrations are primarily regulated by weather and regional PM transportation than by traffic. Furthermore, in a dispersion modelling experiment in Sheffield, it gets clear that PM emissions are mainly controlled by point sources and not by traffic [49]. The lockdown took place in spring when most households still used heating. Household heating is a substantial contributor to PM levels. This is especially relevant considering that people were ordered to stay at home as much as possible to combat the virus [36]. Shi et al. [39] illustrate in their study that $PM_{2.5}$ shows a complex response to the lockdown measures. Road traffic has rather a small contribution to PM. In contrast, secondary sources like residential solid fuel use and industrial activity have a larger impact on PM levels. Also, non-lockdown-affected sectors such as agriculture and livestock contribute to PM emissions [21,36]. Thus, changes in people's mobility behavior do not always lead to reduced PM levels, because traffic is not the sole origin of PM.

Finally, it must be emphasized that there is not simple monocausality between the air pollutants, the temperature, and the human mobility. There are several factors that have not been highlighted in this work like meteorological conditions and chemical-physical reactions that influence the air pollutant levels. In fact, it would be too trivial to get a linear relationship between temperatures and air pollutants and the change in human activities, which depend very much on atmospheric conditions. Since the cities under study have very different microclimates a simple derivation and inference to a single component is not possible.

Thus, it is crucial to include meteorological data into similar analyses. Especially for temperature changes but also for air pollutant changes -in particular O_3- there remain open questions due to a dominating weather effect and the complexity of other meteorological and chemical factors which must be revised in future work.

5. Conclusions

We investigated the changes and the relationships of air pollutants and LST with data describing the human activity in 43 European cities. Our findings show that there are considerable spatial and temporal differences between cities and spatial patterns regarding the magnitude and even the direction of change. Coinciding with previous studies the results depict reductions in anthropogenic activities like visiting parks, transit stations, workplaces or retail and recreation during the lockdown. Simultaneously, NO_2 concentrations declined as much as -54% (in Luxemburg) compared to the reference period. In contrast, ozone levels increased, with greatest relative changes also in Luxembourg (+41.1%). The O_3 increase is attributed to a lower titration of O_3 by NO due to the substantial decline in local NO_x emissions. LST and PM varied spatially and temporally. Within our analysis we depicted that some variables are more closely linked to human activity than others. Most pronounced is NO_2. Here, especially the human activity can be seen in the weekly cycle. However, we were not able to attribute the changes to specific changes in the mobility behavior. Many previous studies suggested that restrictions have a significant impact on anthropogenic activities and correspondingly on urban temperatures and air pollutants. Owing to the complexity of meteorological factors, open questions remain especially regarding the change in SUHII and LST. Future work should aim to accurately capture the influence of prevailing weather pattern on temperature changes.

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