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What Can the COVID-19 Pandemic Tell Us About the Energy Transition? A Nitrogen Dioxide and Ground-Level Ozone Study

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Abstract: The lockdown measures imposed in Lisbon during the COVID-19 pandemic offered an unprecedented opportunity to observe abrupt changes in tropospheric NO₂ and O₃ concentrations, providing information on air quality improvements in a future dominated by electric vehicles. This study used deweathering modelling to account for meteorological influences in the data, analysing pollution changes throughout the baseline (2016–2019), COVID-19 (2020), recovery (2021), and post-COVID-19 (2022) periods. In summary, significant decreases in NO₂ concentrations were observed at both traffic and background locations, with reductions up to 30% during the COVID-19 year. This is similar to what would be expected in an aggressive energy transition scenario. Concentrations of O₃ increased by up to 20% at traffic locations; however, background O₃ concentrations remained virtually unchanged, indicating that O₃ formation is not primarily driven by NO₂ but possibly VOC. The findings in this paper suggest that future reductions in NO₂ due to vehicle electrification are unlikely to result in considerably high regional O₃ concentrations.

Keywords: air quality; traffic impact; data science; fleet electrification



Citation: Soares, A.R.; Silva, C.M. What Can the COVID-19 Pandemic Tell Us About the Energy Transition? A Nitrogen Dioxide and Ground-Level Ozone Study. *Atmosphere* **2024**, *15*, 1453. <https://doi.org/10.3390/atmos15121453>

Academic Editor: Alexandros Papayannis

Received: 17 October 2024
Revised: 13 November 2024
Accepted: 28 November 2024
Published: 4 December 2024



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1. Introduction

Ground-level ozone (O₃) has become increasingly prominent due to complexity in its prediction and its nefarious effects on both health and vegetation [1–3]. It has been shown that O₃ has implications on asthma exacerbation, acute respiratory disease, chronic obstructive pulmonary disease and several other cardiovascular and cardiopulmonary diseases [4].

It also serves as a critical trace gas in the atmosphere and is significant in the context of climate change. In the stratosphere, it is essential for absorbing ultraviolet radiation that offers protection for the environment and health [5]. In the troposphere, O₃ ranks as the third major contributor to greenhouse gas radiative forcing [6] that functions as a Short-lived Climate Forcer (SLCF) [7]. Here, it becomes a pollutant predominantly produced by human activities such as the use of internal combustion engine vehicles (ICEVs). It is a secondary pollutant formed through sunlight-initiated reactions with combustion by-products such as NO₂, but also has interplay with volatile organic compounds (VOCs) and other pollutants. The main interactions that concern us are seen in Equations (1) and (2):



These equations, as extensively explained in Soares et al. [4], are part of the main proposed mechanism of O₃ formation due to NO₂ reaction with sunlight (hν) as seen in Equation (1). Equation (2) shows the feedback loop where O₃ reverts back to NO₂ in an atmospheric cycling reaction. These reactions are intrinsically tied with the ratios between NO_x and VOCs, which can create NO_x-saturated or VOC-limited environments, as discussed in Siciliano et al.'s work [8].

The complexity of these interactions makes the prediction of O_3 a non-trivial task. Events such as the COVID-19 lockdowns offered a rare opportunity to observe changes in air quality in the presence of significant shifts in traffic activity. The COVID-19 virus was declared a pandemic on 11 March 2020 [9], and as the number of infections and deaths increased around the world, many countries took measures to curb the spread. In Portugal, the government declared a state of emergency on 19 March 2020. This was the most severe state that led to aggressive lockdowns and the closing of schools and borders, preventing the free movement of citizens. During most of 2020, a series of partial lockdowns occurred and the full extent of the dates and when they happened in Portugal can be seen in Table S1 (Supplementary Materials).

Compared to baseline data for 2010–2019, lockdowns led to substantial reductions in global total anthropogenic NO_x emissions of at least 15% in April and May 2020, with 19 to 30% reductions in the United States, Europe, the Middle East and West Asia [10]. Meanwhile, this slowdown in activity also led to an upward trend in O_3 [8,11], reinforcing the known negative correlation of NO_2 – O_3 , especially in urban centres. This has provided unprecedented insight into future scenarios of NO_2 reduction driven by the increase in battery-powered electric vehicles (BEVs) in energy transition and decarbonization efforts, since the ultimate goal is to reduce the circulation of ICEVs. [11].

To analyse the impact of COVID-19 on human activities and pollution, and to draw correlations and insights from it, several articles leverage data from satellites or ground-level air quality monitoring station (AQMS). Some studies used AQMS data in urban, suburban, or rural settings but rarely focused on comparisons, except for a few exceptions [12,13]. Correlations with traffic activity usually rely on Google mobility reports, Oxford lockdown data, and, occasionally, Waze data or other geographical positioning system (GPS) data. Few have explored the connection between the COVID-19 decrease in pollution and its similarity with decarbonized futures. Furthermore, while some studies examined changes in pollutant concentrations in the city of Lisbon during the COVID-19 pandemic [3,14–16], they had limited data at the time of publication or fell into the previously mentioned categories and their associated limitations. They also vary in their treatment of weather variability and focus, with many concentrating on the lockdown weeks without removing weather variability from the data. Weather variables, as indicated by previous research, can account for up to 65% of the variance in O_3 concentration [17]. Accounting for meteorological influences is fundamental for ensuring the integrity of our analysis. These factors play a crucial role in the formation, transport and correlation of air pollutants with prevailing atmospheric conditions. Ignoring them could introduce biases, especially when assessing exceptional events like the disruptions caused by the COVID-19 pandemic.

This study contributes to the field in several ways: First, it provides a comprehensive macro-analysis of NO_2 and O_3 for the city of Lisbon across baseline (2016–2019, averaged), COVID-19 (2020), recovery (2021), and post-COVID-19 (2022) periods, rather than focusing on specific lockdown events. Second, it uses Waze traffic data to examine correlations between traffic levels and NO_2 emissions. Third, it compares pollution patterns between traffic and background stations throughout these periods, including examinations of weekend effects and seasonal variations. Weather variability in the data is accounted for through boosted regression trees (BRTs) to better isolate traffic-related impacts. These data are leveraged to analyse daily, monthly, seasonal and yearly trends, providing information on air quality improvements in a future dominated by electric vehicles, which is rarely discussed [11].

In summary, by analysing how the COVID-19 pandemic influenced traffic patterns and subsequently altered the concentrations of NO_2 and O_3 , this study provides information about potential air quality changes during rapid transitions in urban mobility patterns.

2. Materials and Methods

Lisbon is the capital and largest city of Portugal with a population of 545,142 inhabitants, according to the latest 2021 census, and has a land area of 100 km². It has considerable traffic flowing in and out of the city from the surrounding 18 municipalities (considered

the Lisbon Metropolitan Area), consisting of another 2901 km² and 2,325,066 inhabitants. Figure 1 shows the city and its data collection locations, which include both the AQMS and weather station (WS). The geographical coordinates are shown in Table S2 (Supplementary Materials). It should be noted that the Portuguese Environment Agency (APA)'s categorization of AQMSs as 'background' aligns more closely with 'suburban' locations as defined by EU Directive 2008/50/EC Annex VIII [18].

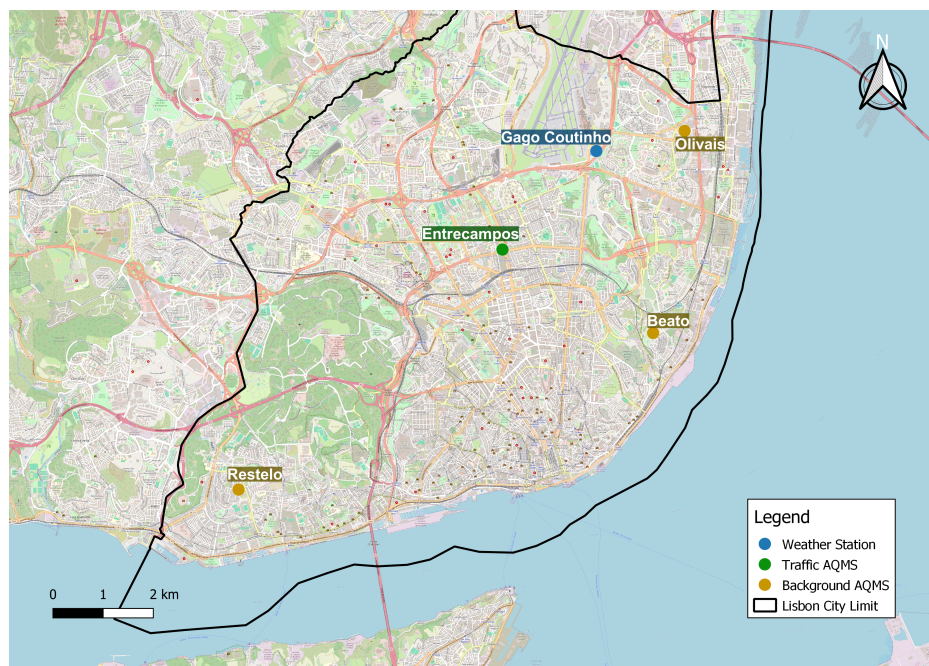


Figure 1. Lisbon AQMS and WS.

Geographically positioned in the Tagus Estuary, Lisbon is the western-most capital of Europe and the only one located along the Atlantic coast. It is often called the city of seven hills, reflecting its topography, with a predominant north wind regime that sweeps the city towards the southeast across the Tagus Estuary. However, due to the aforementioned city topography and the fact that there is new and taller construction to the north, it creates conditions that do not allow the wind to properly penetrate the city centre, creating low dispersion conditions and high concentrations of pollutants during certain meteorological events [19].

Hourly data for NO₂ and O₃ pollutants were provided by the Portuguese Regional Coordination and Development Commission (CCDR) for the period of 2016–2022 through the open-source platform QualAr created by the Portuguese Environment Agency (APA) [20]. While vehicle emissions produce various nitrogen oxides (NO_x), this study focuses on NO₂ as it is both the regulated compound in the EU air quality directives and a key precursor in O₃ formation. Although volatile organic compounds (VOCs) also play a crucial role in O₃ formation, VOC measurements during this period were too limited for analysis, with data almost completely absent during March 2020's initial lockdown, and did not meet the 75% data capture requirement specified in EU Directive 2008/50/EC. From the metropolitan area of Lisbon's 25 AQMSs, 19 measured O₃, but only 1 was classified as a traffic AQMS, as shown in Figure 1.

These AQMSs covered different time periods and all of them displayed some level of missing data throughout. This can happen, for example, due to maintenance downtime. Due to missing data (N_{miss}) constraints, we focused the study only on the city of Lisbon as there was more data availability. The AQMSs in this research were selected for being the only 4 AQMSs in the city of Lisbon. Coincidentally, they measured the same pollutants (NO₂ and O₃) simultaneously and had the least amount of missing data when compared

to other cities in Portugal. The dates on which each dataset resource was available can be found in Table 1.

Table 1. Timetable with all the data and resources used.

Data	Date	Reference
AQMS	01/01/2016 to 31/12/2022	[20]
Lockdowns	01/01/2020 to 31/12/2022	LxData Lisbon
Waze (Jams)	01/01/2019 to 06/09/2022	LxData Lisbon
WS	01/01/2016 to 31/12/2022	IPMA
Modelled pollutant concentration	01/01/2016 to 31/12/2022	[21]

The data gathered from all stations for the city of Lisbon consisted of 61,368 rows of hourly (1 h) measurements (N) spanning the 7 years of study.

To address the limitations posed by missing data in the traffic AQMS, we employed imputation using scikit-learn's linear regression tools using standard function parameters. This approach involved acquiring modelled data through the CAMS European Air Quality Reanalyses, accessible via the CAMS website Copernicus (2024) [21], filling the missing data in the traffic AQMS using a linear regression model. Both datasets had a good Pearson correlation (R) of 0.8 with identical right-skewed data, as seen in Figures S1 and S3 (Supplementary Materials). The robustness of this approach was demonstrated through impact analysis showing maintained mean values while reducing standard deviation (Table S6). This approach reduced the traffic missing data for O₃ from 13.6% to 0% and for NO₂ from 4% to 0%.

For the background AQMS analysis, with correlations seen in Figure S2 (Supplementary Materials), the three AQMSs were first analysed and deweathered independently and then averaged into a single composite background station to provide a comprehensive representation of background conditions. In other words, at any given hour, we averaged the three AQMSs into one. If two values were missing, the one that remained represented the background location. These approaches significantly reduced the percentage of O₃ missing values from the individual Beato, Restelo and Olivais background AQMSs (8.74%, 1.29% and 9.83%, respectively) to just 0.04% in the composite measure. The same procedure was applied for NO₂. This composite measure smooths out local anomalies and offers a complete dataset.

For the analysis of the weekend effect, Equation (3) was used. This equation is an adaptation [22] used in a previous paper by the author [23]. We determined the relative change in O₃ concentrations from weekends to weekdays, expressed as a percentage, as follows:

$$\text{weekend effect O}_3(\%) = \left(\frac{\text{Weekend peak} - \text{Weekday peak}}{\text{Weekend peak}} \right) \times 100 \quad (3)$$

To effectively apply the equation, we first identified the O₃ 8-h maximum daily average (8 h MDA) concentrations for each day. These values were then averaged on a yearly basis. The weekend effect percentage, which may be either positive or negative, indicated an increase or decrease in O₃ concentrations during weekends compared to weekdays.

Hourly weather data were obtained from the Portuguese Institute for Sea and Atmosphere (IPMA). These data span the 7 years with 61,368 rows of data containing maximum temperature (T_{max}), maximum global radiation (GR_{max}), average relative humidity (RH_{med}), wind intensity (W_{int}), wind direction (W_{dir}), total precipitation (pp) and atmospheric air pressure (Ap). These data were used for the deweathering (DW) process only.

Modelling involved the analysis of 61,368 hourly observations for each of the pollutants and weather data. In our effort to account for these variables, we employed RStudio (Version 2024.04.1+748) using the deweather package from the OpenAir suite, created by Carslaw [24]. The boosted regression tree (BRT) methodology combines the strengths of regression trees with gradient boosting, making it particularly effective for handling

non-linear relationships and interactions between meteorological variables and pollutant concentrations. This method systematically builds a sequence of decision trees, where each tree learns from the errors of previous trees, ultimately creating a robust model for weather-pollution relationships. The model performance was validated using multiple metrics, including R-squared, RMSE and MGE (see Table S5 in Supplementary Materials), with correlation coefficients ranging from 0.81 to 0.86 across all pollutants and stations.

Regarding data imputation, we employed scikit-learn's linear regression tools, which showed strong correlation ($R = 0.8$) between measured and modelled data (Figure S1). The impact of imputation on data statistics was carefully evaluated, with the results showing maintained mean values while reducing the standard deviation (Table S6), indicating the successful preservation of data integrity while accounting for missing values. While this package is user-friendly and incorporates the robust BRT methodology within the gradient boosting models framework, we still encountered over- and under-fitting constraints when applying the testMod and buildMod standard functions, seen in the examples of the package, to our dataset.

Thus, we invested significant effort in visually scrutinizing the initial results. Visual inspection helps to ensure that the model is capturing underlying trends and not just noise. It provided a qualitative check on the model's predictions and complements quantitative metrics. We proceeded to create a new testMod function that allowed us to fine tune the hyperparameters. We ran independent models for each pollutant and each AQMS, with the aim to achieve an optimal balance between data accuracy and the integrity of the signal. The code can be found in the Supplementary Materials.

For clarity, our hyperparameter tuning was designed to optimize the performance of our model by maximizing the coefficient of determination (R-squared) for our test data, while also minimizing the Root-Mean-Squared Error (RMSE) and Mean Gross Error (MGE) across both the training and test datasets. Full details can be found in Supplementary Materials. Using these optimized settings, the predictive BRT model created a new time series data for each pollutant, adjusting the original concentrations to exclude estimated weather effects. This enabled a more accurate analysis of air pollution trends, independent of meteorological variability.

Afterwards, arbitrarily high numbers were run (100 times) to find the average variable importance (in %) in these same models for O_3 and NO_2 , for both traffic and background. The code can be found in Supplementary Materials.

Ultimately, for the AQMS comparison, hourly data were converted into O_3 8 h MDA, and NO_2 to 24 h averages for subsequent analysis. This format is commonly used in health risk assessment studies [4] and aligns with government regulations and European directives on pollution limits [23].

As part of a project initiated by the Lisbon municipality titled "Understanding the Impact of the COVID-19 Pandemic on Mobility and the Environment" [25], students from various universities were granted access to traffic data from the Waze app and lockdown data from the Portuguese government, as noted in Table 1.

The Waze dataset does not provide direct vehicle counts but it offers proxy metrics such as the number of reported traffic jams and associated statistics like their GPS location, speed, delay, length and jam intensity. Previous research indicates that jam length is the most reliable metric for assessing urban mobility patterns [26].

To examine both NO_2 and O_3 concentrations, we adopted a macro-analytical approach by aggregating the total distance, in km, of traffic jams across the city for each hour and day, allowing us to make direct comparisons with pollutant data.

The goal of this study is not to examine specific weeks immediately before and after lockdown periods, but rather to adopt a comprehensive perspective on broader trends concerning NO_2 and O_3 concentrations. Although incorporating data from the entire year may dilute the percentage changes, the overall impacts on air quality are expected to remain significant and noticeable. Nevertheless, since many studies in this field focus specifically on the lockdown period, we adapted Equation (3), substituting the typical weekend and

weekday categories with 24 h daily averages of NO₂. This adjustment allowed us to analyse NO₂ concentrations during the two weeks leading up to the lockdown on 19 March 2020, and compare them with the second week following the lockdown. This approach aligns with the methodology used in other studies [27].

3. Results and Discussion

The results in this section cover a 7-year period from 2016 to 2022. We have organized the statistical analysis into four distinct periods: the pre-COVID baseline (2016–2019, average), the COVID-19 period (2020), the recovery period (2021) and the post-COVID period (2022). The only exception to this timeline is the initial traffic impact analysis, which uses Waze data from 2019 to 2022 only.

3.1. How Did Traffic Impact NO₂ Pollutant Concentrations in Lisbon?

The implications of COVID-19 on both traffic activity and air pollution are shown in Figure 2, which overlays the time series of both Waze and pollutant data with the median km of length in jams plotted together with boxplots of NO₂ concentrations from 2019 until 2022.

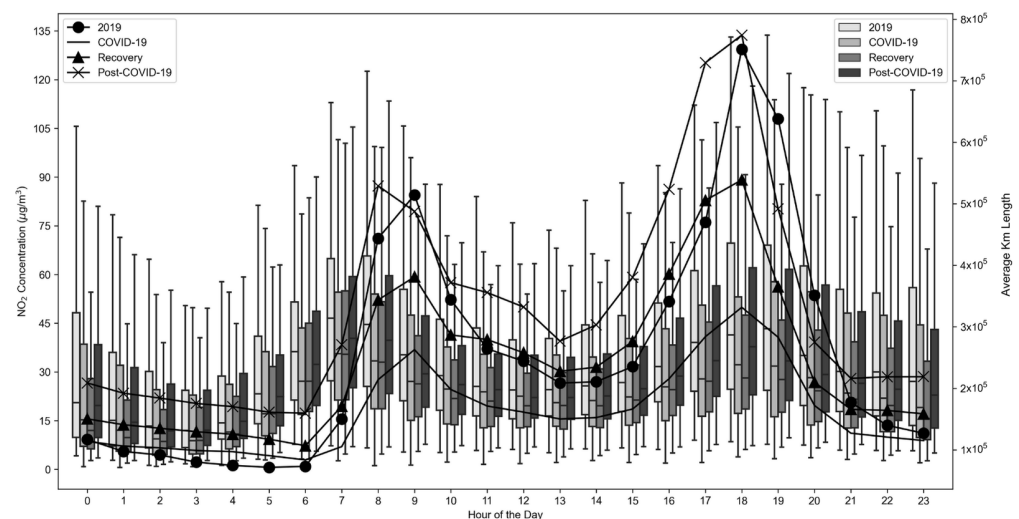


Figure 2. Line plot showing the median length of traffic jams in Lisbon (in km) from Waze data overlapping NO₂ concentration boxplots (2019–2022).

From a macro perspective, the abrupt halting of movement provoked a decrease of 37% in km of traffic jams from 2019 to the COVID-19 year. This caused the reduction in NO₂ concentrations. The magnitude of differences in NO₂ concentrations is most pronounced during Lisbon's peak traffic hours, typically from 6 to 10 h and 16 to 20 h. Observations show that, from 2019 to 2020, the most significant median NO₂ reductions occurred during these hours, dropping from 46.7 to 33.4 $\mu\text{g}\cdot\text{m}^{-3}$ between 6 and 8 h and from 43.3 to 31.8 $\mu\text{g}\cdot\text{m}^{-3}$ between 17 and 19 h.

Notably, in the post-COVID-19 period, despite traffic congestion returning to baseline levels, NO₂ concentrations have remained lower. This sustained reduction can likely be attributed to several factors, including changes in the composition of the vehicle fleet, delayed atmospheric reactions and noticeable shifts in peak traffic times, which now tend to occur an hour later in the morning and have a more extended post-peak period in the afternoon. These shifts likely reflect enduring behavioral changes in work schedules, influenced by the widespread adoption of remote work policies after the COVID-19 pandemic. However, further research is needed to make definitive conclusions.

Similar to the studies cited in this paper, it is evident from the data that lockdown restrictions and subsequent halting of traffic activity had an impact on local air pollutant concentrations [28].

3.2. Did COVID-19 Have Any Impact on the Weekend Effect or Seasonality of O₃?

Using Equation 3, we calculated the weekend effect, presented in Table 2. A significant reduction was observed in the weekend effect during both the COVID-19 and recovery periods for both traffic and background AQMSs.

Table 2. Percentage changes in AQMS O₃ concentrations during weekends.

AQMS	Baseline	COVID-19	Recovery	Post-COVID-19
Traffic	10.5%	8.5%	5.5%	8.5%
Background	7.3%	5.3%	1.3%	6.9%

In a recent study conducted in Toronto, significant reductions in pollutant concentrations were observed during weekends, even leading to negative weekend effect values [29]. Although the analysis for Lisbon did not reach negative weekend effect values, the substantial drop to as low as 1.3% during the recovery period suggests a possible NO_x-saturated environment, similar to the conditions observed in Toronto [29].

Regarding seasonality and O₃ concentrations, the most significant changes occurred during the COVID-19 pandemic, particularly in the spring, as shown in Figures S8–S15 (Supplementary Materials). This season experienced a noticeably higher frequency of elevated O₃ concentrations, reaching approximately 75 µg·m^{−3}, compared to baseline levels. Although the highest individual concentrations were recorded in summer, spring consistently exhibited high levels throughout the pandemic. During the recovery period, summer saw an increased frequency of elevated concentrations. However, in the post-COVID-19 period, there has been a gradual decline in these frequencies, indicating a return to baseline levels.

For NO₂, changes in seasonality were less pronounced. However, an increase in data variability was observed across all periods during and after COVID-19, along with a rise in the frequency of lower concentration levels. These shifts are most likely driven by the traffic variability introduced during the lockdown periods.

3.3. Data Correlations Prior to Modelling

The Pearson correlation (R) coefficients depicted in Table S3 (Supplementary Materials) show a strong correlation between traffic and background AQMSs for both NO₂ and O₃ for the period from 2016 to 2022. The moderate negative correlation between NO₂ and O₃ of −0.54 and −0.49 for traffic and background, respectively, was expected due to their known complex chemistry [8,23]. Meteorological variables such as GR_{max}, T_{max}, Ap, W_{int} and W_{dir} can display weak to moderate correlations with NO₂ and O₃ concentrations. Despite these relatively weak correlations, their impact on modelling cannot be understated as they often play a crucial role in the formation of O₃ and the dispersion of both NO₂ and O₃.

3.4. Deweathering Model Performance

To properly analyse the progression of pollutant concentrations over the periods, the NO₂ and O₃ data for traffic and background AQMSs seen in Figure 1 underwent a DW process. The hyperparameters obtained are found in Table S4 (Supplementary Materials). Good predictive models were achieved for both NO₂ and O₃ concentrations in background locations and areas affected by traffic emissions. Model metrics and performance are depicted in Table S5 and Figure S4 (Supplementary Materials). The metrics obtained are acceptable and in line with other studies [27].

The weather variables with relevant predictive importance are shown in Figure S5 (Supplementary Materials). It is expected that variables such as GR_{max}, W_{dir} and W_{int} significantly impact the variability of NO₂ and O₃ concentrations by influencing the dispersion and chemical transformation processes of these pollutants. The displayed scores then indicate the relative contribution of each variable to the model's predictive accuracy.

We consider the DW model's performance good, primarily for reducing noise from weather variables. As shown in Table S6 (Supplementary Materials), the means are identical, but the standard deviation values are significantly smaller. We then use the newly created time series for NO₂ and O₃, transforming them into O₃ 8 h MDA and NO₂ 24 h averages for further analysis.

3.5. How Did COVID-19 Impact NO₂ and O₃ Pollution in Lisbon?

To illustrate the progression of NO₂ and O₃ levels, the percentage change was calculated from baseline to the COVID-19 period, baseline to the recovery period and baseline to the post-COVID-19 period.

The contribution of NO₂ (in %) for each period was also calculated, as shown in Figure S6 (Supplementary Materials). This analysis highlights that taking a broader, macro approach can dilute the visible effects of lockdowns. It is important to note that many COVID-19 environmental impact studies, such as those by Shi et al. [27] and Siciliano et al. [8], primarily analysed data from the two to three weeks before COVID-19 lockdowns and the subsequent periods following the restrictions. A similar analysis was conducted following the methodology explained by Shi et al. [27]. The results in Figure S7 (Supplementary Materials) show significant NO₂ reductions during both pre- and post-lockdown weeks, with Lisbon experiencing traffic-related NO₂ drops of −40.3%. This aligns with findings from other cities, such as Berlin and London, which reported decreases of −29.3% and −53.5%, respectively. Additionally, it is consistent with other studies examining COVID-19-related air pollution changes in Lisbon, which recorded NO₂ reductions of approximately −40% during April 2020 [14,15].

Expanding the analysis to encompass the entire year of the period's data as proposed, the daily data DW concentrations of NO₂ 24 h averaged and O₃ 8 h MDA are shown in the boxplots of Figure 3.

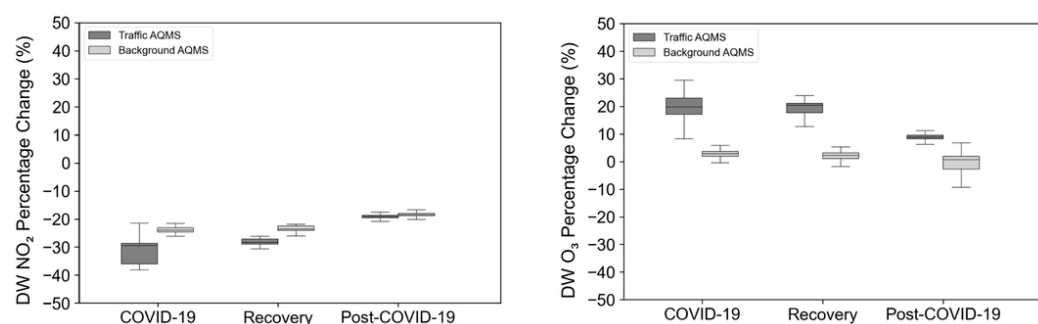


Figure 3. Percentage changes in DW NO₂ and O₃ concentrations comparing baseline with COVID-19, recovery and post-COVID-19 periods.

A lower magnitude decrease in NO₂ was expected. Indeed, when considering the whole year as baseline, NO₂ concentrations show a decrease of −30 and −24% during the COVID-19 period in both traffic and background AQMSs, respectively. The recovery period did not significantly alter this trajectory, with concentrations remaining lower than the baseline concentrations, though they exhibited a slight increase during the post-COVID-19 period.

In what concerns O₃ concentrations, traffic AQMS registered an increase of 20% during the COVID-19 period compared to the baseline, similar to several cities in the world [8,27,30].

However, in contrast to most cities in the world, the background AQMS shows a marginal increase of 2 to 3% during lockdown times, indicating stable O₃ concentrations through all studied periods. Similar occurrences were observed in London, Los Angeles and Paris, also showing minimal changes of around 1.8–2.4% in urban background O₃ concentrations [27].

3.6. How Did Traffic and Background AQMSs Compare with Each Other?

During the baseline period, background AQMS recorded higher O_3 concentrations at $54.8 \mu\text{g}\cdot\text{m}^{-3}$ compared to traffic AQMS $46.5 \mu\text{g}\cdot\text{m}^{-3}$, as shown in Figure 4. In contrast, NO_2 concentrations were lower at background AQMS with $23.9 \mu\text{g}\cdot\text{m}^{-3}$ than at traffic AQMS with $39 \mu\text{g}\cdot\text{m}^{-3}$. Lower minimum values of NO_2 and higher maximum values of O_3 concentrations, when comparing background to traffic locations, are expected due to lower traffic emissions. This is because O_3 is primarily formed through photochemical reactions between NO_x and VOCs under sunlight, and in areas with lower NO_x emissions, there is reduced O_3 titration, allowing for higher O_3 concentrations.

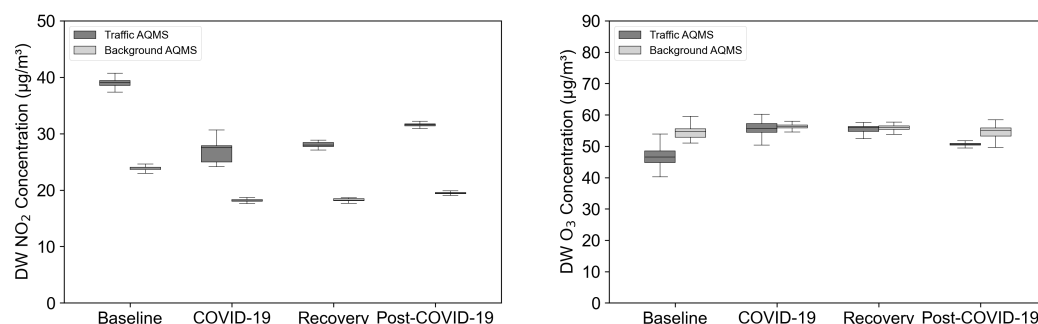


Figure 4. DW concentration changes in NO_2 and O_3 , comparing baseline with COVID-19, recovery and post-COVID-19 periods.

During the COVID-19 period, Lisbon's O_3 concentrations at traffic AQMS increased significantly to $55.7 \mu\text{g}\cdot\text{m}^{-3}$, nearly matching those at background locations, which remained relatively stable across all periods, fluctuating between 54.6 and $56.3 \mu\text{g}\cdot\text{m}^{-3}$. At the same time, NO_2 concentrations dropped to $27.5 \mu\text{g}\cdot\text{m}^{-3}$ at traffic AQMS and $18.1 \mu\text{g}\cdot\text{m}^{-3}$ at background AQMS. This substantial reduction in traffic activity, and thus traffic emissions, is the most plausible explanation, as illustrated in Figure 2.

In the recovery period of 2021, while there was some return to normalcy, there were still some periods of lockdown as seen in Table S1, although for a shorter period and not as stringent. This is reflected in Figure 2 as well. Through the figures, it is clear that traffic activity, especially those related to the use of ICEVs, have a substantial impact in air pollutant concentrations and dynamics.

In the post-COVID-19 period of 2022, NO_2 concentrations showed a slight increase but remained below baseline levels, even though traffic congestion appeared to return to pre-pandemic levels. At the same time, O_3 concentrations experienced a slight decrease. These variations highlight the complex interplay between traffic activity and weather conditions in influencing air quality. It is worth noting that NO_2 concentrations may not return to original baseline levels, as Lisbon appears to follow a similar long-term trend of approximately 1% reduction per year, according to the data. This is consistent with trends observed across Europe, where annual reductions in NO_2 concentrations of 1% to over 2% have been reported [31].

The most noteworthy aspect of the data presented here is the similar behavior of traffic and background AQMSs in terms of O_3 concentrations. While NO_2 still shows a clear difference between traffic and background AQMSs, the narrowing gap in O_3 concentrations between these locations is particularly evident during the COVID-19 and recovery periods. This contrasts with trends observed in certain areas of Spain, Italy, and the United Kingdom, where O_3 levels increased in both urban and rural environments, as reported by Putaud et al., Martorell et al. and Wyche et al. [13,30,32]. In our case, Lisbon has presented a stable background O_3 , which could be explained by transitions in O_3 formation regimes [33]. It appears that when NO_2 is around $25 \mu\text{g}\cdot\text{m}^{-3}$, the effect on the O_3 formation is marginal. Thus, higher NO_2 concentrations are associated with lower O_3 levels.

Overall, despite the lower NO_2 and the increase in O_3 for the traffic AQMS, the values presented are well within standard O_3 regulations of $120 \mu\text{g}\cdot\text{m}^{-3}$ 8 h limits as

recommended per APA, and even within more stringent limits such as the ones from the WHO at $100 \mu\text{g}\cdot\text{m}^{-3}$.

3.7. What Can We Hypothesize about the Energy Transition Given What We Learned from COVID-19?

The parallels between the COVID-19 lockdown measures and a potential shift towards an energy transition are evident in the way the sudden halt in traffic activity resulted in reduced NO_2 emissions. This mirrors the potential environmental benefits of transitioning from ICEVs to electric vehicles (EVs) in a decarbonization scenario.

In Figure 2, the impact that COVID-19 lockdowns had on traffic and consequently on NO_2 concentrations is evident. If a transition towards a fully EV fleet were to take place, resulting in a significant reduction in NO_2 emissions from ICEVs, it is plausible that DW O_3 concentrations in background locations across Lisbon could plateau at around $70 \mu\text{g}\cdot\text{m}^{-3}$, while NO_2 levels might decrease by approximately 30%. This inference, however, does not account for the intricate balance between NO_2 reductions, O_3 concentrations and atmospheric chemistry, underscoring the need for continued research into the complexities of urban air chemistry.

Despite traffic activity rebounding to, and in some cases surpassing, baseline levels, NO_2 concentrations have not reverted to their baseline levels. This trend aligns with the continuous 1% to >2% annual decrease in NO_2 levels observed across Europe. This observation is particularly contradictory given that the Portuguese vehicle fleet is relatively old, with an average age of 13.5 years in 2021. Additionally, vehicles manufactured before 2014 adhere to less stringent NO_x EURO regulations [34].

However, as shown in Figure 5, the number of circulating gasoline vehicles has decreased, while the number of diesel vehicles has increased, along with a rise in alternative fuel types, such as BEVs and Plug-in Hybrid Electric Vehicles (PHEVs) [35]. Therefore, the adoption of less-polluting technologies in 2021 and 2022, or a delayed response in atmospheric chemistry to previous pollution levels, might explain this apparent contradiction.

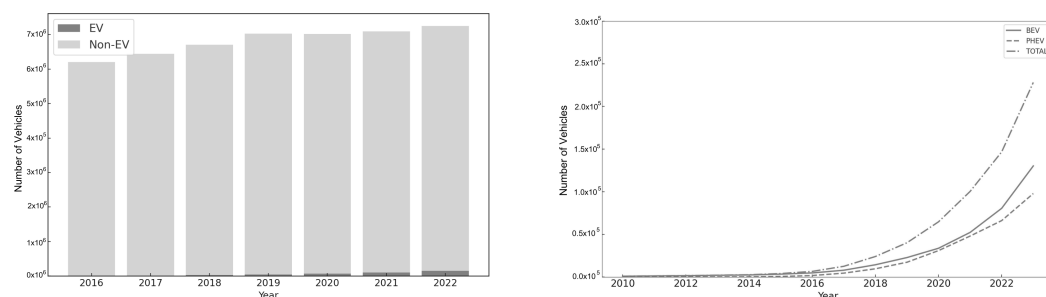


Figure 5. On the left: Data from Instituto Nacional de Estatística of the Portuguese circulating Vehicle fleet. On the right: Data from the Association of Electric Vehicle Users (UVE) taken from The Portuguese Automobile Association (ACAP) of circulating EVs. The Total relates to BEV + PHEV.

4. Conclusions

This study aimed to characterize the influence of traffic on the progression of NO_2 and O_3 concentrations, analysing these pollutants in relation to the weekend effect, seasonality and the response of traffic and background AQMSs to sudden changes in emissions. Furthermore, it explored insights related to the energy transition, taking advantage of the unique conditions created by the COVID-19 pandemic lockdowns, which drastically reduced traffic emissions. The analysis spanned the baseline period (2016–2019, averaged), the COVID-19 period (2020), the recovery period (2021) and the post-COVID-19 period (2022).

The COVID-19 lockdowns resulted in a significant decrease in traffic and consequently in NO_2 concentrations. While traffic levels rebounded post-COVID-19, this did not lead to a proportional increase in NO_2 concentrations. This decoupling indicates that factors beyond traffic volume influence NO_2 concentrations. Possible explanations include changes in the

fleet composition, with more EVs and diesel vehicles being adopted, or a delayed response in atmospheric chemistry that may become clearer in future analyses.

This study observed a diminished “weekend effect” during the COVID-19 and recovery periods, suggesting an overall reduction in weekly variability. However, in the post-COVID-19 period, this effect has nearly returned to baseline levels.

The DW analysis indicates that while weather conditions impact pollutant concentrations, they do not alter the fundamental trends observed between traffic and background AQMS locations. This highlights the consistent influence of local sources over meteorological conditions.

There was a convergence in behavior between traffic and background AQMSs during COVID-19, with traffic locations showing increased O₃ concentrations, but background AQMS remained nearly stagnant. This implies broader regional influences on O₃ concentrations. The apparent plateau of background O₃ concentrations could indicate that we are reaching a limit determined by these broader factors. It suggests a complex balance in O₃ formation, where reductions in traffic NO₂ emissions do not necessarily lead to proportional increases in O₃ concentrations at a regional scale. It also suggests that O₃ formation is not primarily driven by NO₂ in both the traffic and the background locations, but possibly, VOC. The stable background O₃ concentrations could be attributed to transitions in O₃ formation regimes during these emission changes. Thus, lockdown measures provided an unprecedented opportunity, revealing that short-term reductions in traffic emissions could significantly lower NO₂ concentrations without causing a corresponding spike in O₃ concentrations at background locations.

The COVID-19 pandemic underscores the potential air quality benefits of reducing traffic emissions. While the findings highlight the positive impact of transitioning from ICEVs to EVs, especially in reducing NO₂ concentrations, it is crucial to recognize that O₃ formation is influenced by more than just NO₂ reductions. Since VOCs play a significant role in O₃ production, simply reducing NO_x emissions from vehicles may not automatically lead to lower O₃ levels. Effective air quality improvement will require addressing VOC emissions from other urban sources as well. Additionally, careful consideration of the energy sources powering EVs is needed to prevent the displacement of emissions to power generation sites. Managing both NO₂ and VOCs is essential to ensure that urban air quality improves holistically without unintended side effects.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/atmos15121453/s1>, Figure S1: Pearson correlation for modelled O₂ data versus Traffic AQMS; Figure S2: Pearson correlation for modelled O₂ data versus background AQMS. Top left: Restelo vs. Beato. Top right: Restelo vs. Olivais. Bottom: Beato vs. Olivais; Figure S3: Distribution and residuals comparison between the traffic AQMS and modelled CAMS O₂ data; Figure S4: Model prediction versus measured concentrations; Figure S5: Average weather impact on NO₂ and O₂ for traffic and background AQMS; Figure S6: Percentage of yearly contribution of NO₂ concentrations for the months of January to March for all periods for the traffic AQMS; Figure S7: Two weeks prior to and after COVID-19 lockdown on the 19 march of 2020 comparison; Figure S8: Histogram of baseline O₂ concentrations; Figure S9: Histogram of COVID-19 O₂ concentrations; Figure S10: Histogram of recovery O₂ concentrations; Figure S11: Histogram of post-COVID-19 O₂ concentrations; Figure S12: Histogram of baseline NO₂ concentrations; Figure S13: Histogram of COVID-19 NO₂ concentrations; Figure S14: Histogram of recovery NO₂ concentrations; Figure S15: Histogram of post-COVID-19 NO₂ concentrations; Table S1: Lockdown phases and their dates in Portugal; Table S2: Locations of the data collection systems used; Table S3: Correlation table. Traffic is T and background is BG; Table S4: Hyperparameters of the models used with number of Trees, Learning Rate (LR), bag fraction, and in-teraction depth; Table S5: Comparison of model statistics for different pollutants and station types; Table S6: Summary Statistics for Raw and Deweathered (DW) O₃ and NO₂ concentrations in µg·m⁻³.

Author Contributions: C.M.S.: Study conception, design, and revision. A.R.S.: Data collection, analysis, interpretation of results, and draft manuscript preparation. All authors have read and agreed to the published version of the manuscript.

Funding: This work was funded by the Portuguese Fundação para a Ciência e a Tecnologia (FCT) I.P./MCTES through national funds (PIDDAC)—UIDB/50019/2020 UIDB/50019/2020 (<https://doi.org/10.54499/UIDB/50019/2020>), UIDP/50019/2020 (<https://doi.org/10.54499/UIDP/50019/2020>) and LA/P/0068/2020 (<https://doi.org/10.54499/LA/P/0068/2020>).

Data Availability Statement: The datasets generated and/or analysed during the current study are available in the Supplementary Materials provided.

Acknowledgments: We acknowledge and appreciate Ricardo Deus from Instituto Português do Mar e da Atmosfera (IPMA) for providing extensive weather stations data. We would also like to thank Lisbon Town Hall for the proposal and the acceptance of our participation in the COVID-19 challenge and making available to us a data package containing Waze traffic, lockdown dates, pollutants and meteorological data. The use of LSA SAF products in publications is also kindly acknowledged.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

AQMS	Air Quality Monitoring Station
APA	Portuguese Environment Agency
BEV	Battery-powered Electric Vehicle
BRT	Boosted Regression Tree
CCDR	Portuguese Regional Coordination and Development Commission
DW	Deweathering
EV	Electric Vehicle
GPS	Geographical Positioning System
ICEV	Internal Combustion Engine Vehicle
IPMA	Portuguese Institute for Sea and Atmosphere
MDA	Maximum Daily Average
NO ₂	Nitrogen Dioxide
NO _x	Nitrogen Oxides
O ₃	Ozone
PHEV	Plug-in Hybrid Electric Vehicle
SLCF	Short-lived Climate Forcer
VOC	Volatile Organic Compound
WS	Weather Station

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