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ARTICLE

Medium-term Air Quality Benchmarking for Ecosystem Monitoring and Sustainability Planning: Case Study Dallas County (U.S.A.) 2015 to 2020

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ABSTRACT

Medium-term air quality assessment, benchmarking it to recent past data can usefully complement short-term air quality index data for monitoring purposes. By using daily and monthly averaged data, medium-term air quality benchmarking provides a distinctive perspective with which to monitor air quality for sustainability planning and ecosystem perspectives. By normalizing the data for individual air pollutants to a standard scale they can be more easily integrated to generate a daily combined local area benchmark (CLAB). The objectives of the study are to demonstrate that medium-term air quality benchmarking can be tailored to reflect local conditions by selecting the most relevant pollutants to incorporate in the CLAB indicator. Such a benchmark can provide an overall air quality assessment for areas of interest. A case study is presented for Dallas County (U.S.A.) applying the proposed method by benchmarking 2020 data for air pollutants to their trends established for 2015 to 2019. Six air pollutants considered are: ozone, carbon monoxide, nitrogen dioxide, sulfur dioxide, benzene and particulate matter less than 2.5 micrometres. These pollutants are assessed individually and in terms of CLAB, and their 2020 variations for Dallas County compared to daily trends established for years 2015 to 2019. Reductions in benzene and carbon monoxide during much of 2020 are clearly discernible compared to preceding years. The CLAB indicator shows clear seasonal trends for air quality for 2015 to 2019 with high pollution in winter and spring compared to other seasons that is strongly influenced by climatic variations with some anthropogenic inputs. Conducting CLAB analysis on an ongoing basis, using a relevant near-past time interval for benchmarking that covers several years, can reveal useful monthly, seasonal and annual trends in overall air quality. This type of medium-term, benchmarked air quality data analysis is well suited for ecosystem monitoring.

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1. Introduction

Air quality and levels of harmful pollutants pose ongoing problems for many rural and urban areas, particularly from the perspective of monitoring and forecasting to provide alerts when certain threshold pollutant levels are exceeded [1,2]. It has been known for many decades that air pollutants can have substantial impacts on ecosystems as well as on human health. These impacts are related to a wide range of factors including acidification of forests, soils and water [3,4], particulate matter (PM) and ozone-related phytotoxicity. Acidification of ecosystems tends to be caused by acidic materials, particularly sulphur dioxide and oxides of nitrogen deposited from the atmosphere acidifying compounds leading to eutrophication in freshwater and marine ecosystems [5,6]. The detrimental impacts of air pollution on biodiversity loss are well documented [7,8].

Consequently, it is of ongoing importance for local areas (rural and urban) to establish and interpret medium-term (i.e., the past five years or so) and long-term (over decades) trends in air quality, both generally and for specific pollutants. Currently, understanding gained from such interpretation is being mainly used to develop strategies for city-scale traffic management, minimizing health impacts at a local scale and development planning [9], but could also be used for ecosystem monitoring. It can also help to establish casual links between certain types of human and industrial activity and locally raised and lowered levels of specific pollutants, not only for urban planning purposes [10,11] but also for ecosystem sustainability improvements.

Short-term changes in certain pollutants can cause concern in some regions that have shown steady air quality improvements over the long-term that conditions are starting to deteriorate again; for example, in parts of the U.S.A. [12] with negative implications for human health and ecosystem sustainability. Analysis of long-term trends suggests that more than half of the world is experiencing rising air pollution [13]. Careful local-area benchmarking of medium-term data has the potential to verify or refute such claims. Doing so tends to reinforce confidence in the transparency of air quality reporting. It also makes it more likely that credible actions can be formulated and implemented to better manage and mitigate air quality issues and their eco-system impacts [14].

Anthropogenic activities contributing to local and regional air pollution include the consumption of fossil fuels for power generation, transportation, and heating/cooling, agricultural activities - particularly widespread burning of crop residues [15], and atmospheric emissions from many types of industrial manufacturing plants [16]. Different human activities and land uses at different times of the year contribute to seasonal fluctuations in air pollutants in many regions [17], although their monitoring tends to focus on their impacts to urban areas. However, natural global processes associated with storms, including dust storms [18,19], complex atmospheric circulation patterns and other weather phenomena, such as seasonal mixing layer heights and inversions [20], are also responsible for the input, distribution and movement of certain pollutants in the atmosphere. Seasonal and weather-related variations in pollutant concentrations are a common feature [21,22].

Investigations, monitoring and regulations applied to air quality have been ongoing in many parts of the world for many decades [23]. These actions were stimulated initially by the great "smogs" of London of the early 1950s [24]. They have ultimately led to clean air acts and air quality standards (permissible levels) being set and closely monitored in many countries and regions, mainly focusing on human health issues [25-27]. Despite such actions, and sustained policy interventions [28], air pollution remains a cause of major health problems and premature deaths worldwide [29], as well as ecosystem damage [8]. As well as representing a major health care cost burden on society that threatens the sustainability of health care systems in some cities [30,31], it continues to reduce biodiversity at an alarming rate [32].

In the face of these challenges, urban air quality management (UAQM) has become a priority for many nations [33], with the recognition that it needs to target specific requirements at the city scale rather than national level. UAQM now, to some extent, divert attention away from rural and ecosystem air quality management. To be effective, UAQM, local air-quality programs in general, and air quality policy interventions at local and regional scales require investments in effective, well distributed and reliable ground-based monitoring networks, supplemented where possible with satellite measurements [34]. Information from such networks can provide deeper understanding of trends, interactions and seasonal variations in key pollutants. Geographical Information System (GIS-based) models that can replicate data from various sources taking account of diurnal and seasonal trends [35], combined with meaningful policies and strategies, can help to control and ultimately improve pollutant levels in the atmosphere [36].

Various gases and particulate matter, including biologically generated material such as pollen, contribute to air pollution. The Clean Air Act of the U.S.A. obliges its Environmental Protection Agency (EPA) to set national ambient air quality standards for six of the most common and problematic air pollutants (ground-level ozone (O_3); particulate matter (PM), carbon monoxide (CO), lead (Pb), sulphur dioxide (SO_2) and nitrogen dioxide (NO_2)) that it refers to as “criteria pollutants” [37]. Of these criteria pollutants, those emitted directly to the atmosphere are referred to as primary pollutants, the most common of which are CO, SO_2, NO_2 and a component of PM, with Pb becoming less problematic since the introduction of Pb-free fuels. On the other hand, secondary pollutants, formed by interactions between primary pollutants within the atmosphere, stimulated by solar radiation, are responsible for the formation of O_3 and some PM. However, focus on monitoring the criteria pollutants has meant that other important air pollutants such as benzene, methane, and ammonia, formed partially by methane’s degradation in the atmosphere, continue to be inadequately monitored and addressed in many regions [24].

Excessive concentrations of these pollutants in ambient air are well documented in the cited studies to have negative health consequences for humans, animals, crops and ecosystems. Many studies have highlighted the causal links between a wide range of human health issues and exposure to the criteria pollutants. The numbers of patients requiring hospital treatment for respiratory difficulties relating to asthma [38], chronic obstructive pulmonary disease (COPD) [39], severe bronchitis and airway inflammation show positive correlations with levels of air pollutants in many cities [40-42]. Additionally, a clear link exists between concentrations of air pollutants in the atmosphere and biodiversity loss [43].

The COVID-19 movement restrictions of 2020 provided air-quality analysts with a unique opportunity to identify certain changes in air pollution as a consequence of reduced transportation movements. However, the changes identified vary from country to country, with data analysis primarily focused on urban areas. In Vienna (Austria) O_3 level was observed to increase while NO_2 decreased [44]. In Lima (Peru), from ground-based and satellite observations, substantial reductions were observed in PM and NO_2 accompanied by increases in O_3 [45]. In Abu Dhabi (United Arab Emirates) CO, NO_2, SO_2 and benzene (C_6H_6) levels decreased whereas O_3 and PM2.5 levels increased, the latter due to sand/dust storm influences [46]. In Dongguan (China) substantial decreases in volatile organic compounds (VOCs) and nitrogen oxides (NOx) were accompanied by smaller increases in O_3, the latter occurring mostly during night-time hours [47]. The mean changes recorded at multiple measurement sites across the UK indicated substantial decreases in NO_2 and PM2.5 accompanied by smaller increases in O_3,with the greatest changes recorded at monitoring stations adjacent to the busiest urban traffic sites [48]. In all the studies mentioned, the 2020 increases in O_3 are interpreted to be a consequence of reduced NO_2 emissions, primarily related to reduced traffic movements. This outcome highlights that there are complex interactions in play amongst primary and secondary pollutants in the atmosphere. Such interactions can vary from location to location depending on meteorological conditions, natural phenomena impacting the atmosphere, and the nature and degree of anthropogenic emissions. Such interactions need to be thoroughly understood and modelled in order to enable local areas, rural and urban, to plan and successfully facilitate their transitions into low-emissions, thriving economies, with air qualities that sustain healthy populations and their local ecosystems.

In the U.S.A., and many other countries, Air Quality Indices (AQI) are defined to quantify the prevailing levels of criteria pollutants and to provide a simple-to-interpret indicator of how good or bad those levels are. The AQI recorded by the EPA [49] provide short-term (hours to days ahead) warnings and hazard alerts to those at high risk of negative health consequences to take precautionary actions. The short-term AQI reports and variations tend to be the main means by which air pollution information is disseminated to the general public through media outlets. However, a detailed knowledge of short-term, medium-term and long-term trends in criteria emissions, and levels of other pollutants of relevance to specific regions, are essential for monitoring purposes that go beyond human health concerns. The medium- and long-term information make it possible to develop sustainable emission control strategies, to inform development decision making and to provide local environmental / ecosystem regulators to take the appropriate actions, including emergency restrictions “on-demand” in response to prevailing and/or pending hazardous air conditions.

The study compiles a daily averaged dataset for six pollutants from publicly available data records for the period 2015 to 2020 for Dallas County, one of the major urban areas of the U.S.A., situated within the regional environment of north-east Texas. It assesses that data statistically and uses monthly comparisons to define seasonal trends in those pollutants. It evaluates the data from 2015 to 2019 to benchmark the 2020 daily and monthly averages to assess the impacts of restricted transportation movements due to COVID-19 on pollutant levels. A case is made for using normalized data scales for each pollutant to facilitate unbiased benchmarking interpretations. A novel combined local area benchmark (CLAB) indicator, accumulating normalized values for all six pollutants is established and developed to assess trends in overall air quality from 2015 to 2020 in Dallas County. The CLAB approach is tailored to suit strategic planning requirements to address both environmental and urban air quality issues.

Whereas, other recent studies [44-48] have focused specifically on identifying anomalies in specific air pollutants in 2020 due to COVID-19 confinements compared to previous years, this study is focused more specifically on justifying the use of integrated medium-term air pollutant analysis to assist local air quality monitoring and planning. In doing so, its case study for Dallas County does identify and highlight 2020 air pollutant anomalies that differ somewhat from those anomalies recorded for that period in several other cities around the world. In particular, whereas C_6H_6 and CO reductions clearly occurred in 2020, definitive NO_2, O_3 and PM2.5 anomalies were not detected. Possible explanations for these distinctive air quality trends for Dallas County in 2020 are explored.

2. Materials and Methods

2.1 Compiled Dataset

Dallas County is a major urban conurbation (Figure 1) situated within the broader north-east Texas rural environment. It is located in a humid subtropical climatic zone (i.e., Cfa in the Köppen-Geiger climate classification), experiencing its driest season in winter. This climatic setting, coupled with periodic thermal inversion phenomena, influences the spatial-temporal distributions of air pollutants resulting in distinctive seasonal trends. It lies in the heart of a major shale gas producing region involving many thousands of producing gas wells in its vicinity. It has a high density of population with a strong reliance on automotive transportation and a culture and lifestyle that has not embraced mass public transit systems. It has a high incidence of childhood asthma, and many of the investments being made in air quality monitoring are targeted to address that problem. The high density of its human and road vehicle populations place substantial stresses on its air quality at certain periods of the year. This makes it an interesting urban area to assess for trends in air pollutant concentrations over the medium-term.

However, Dallas County is also interesting from an ecosystem perspective. It is located between dense pine forests (“Pineywoods”) to the east and Cross Timbers prairies to the west. The flat-lying Blackland Prairie to the east consists mainly of dark-colored shale originally supporting tallgrass prairies. To the west, the originally more undulating grasslands (Cross Timbers), now largely reclaimed as farmland, has more varied soils (sandy and loamy as well as clays and has strips of forests that cross the plains and are interspersed with scrub/ grasslands. The wetter lower-lying regions, mainly associated with river valleys and stream gulleys contain hardwood-tree species (e.g., ash, elm, hickory, juniper, mesquite, oak) and supportdiverse flora and fauna. The tallgrass prairies represent one of the most-endangered large-scale ecosystems in the United States [50].

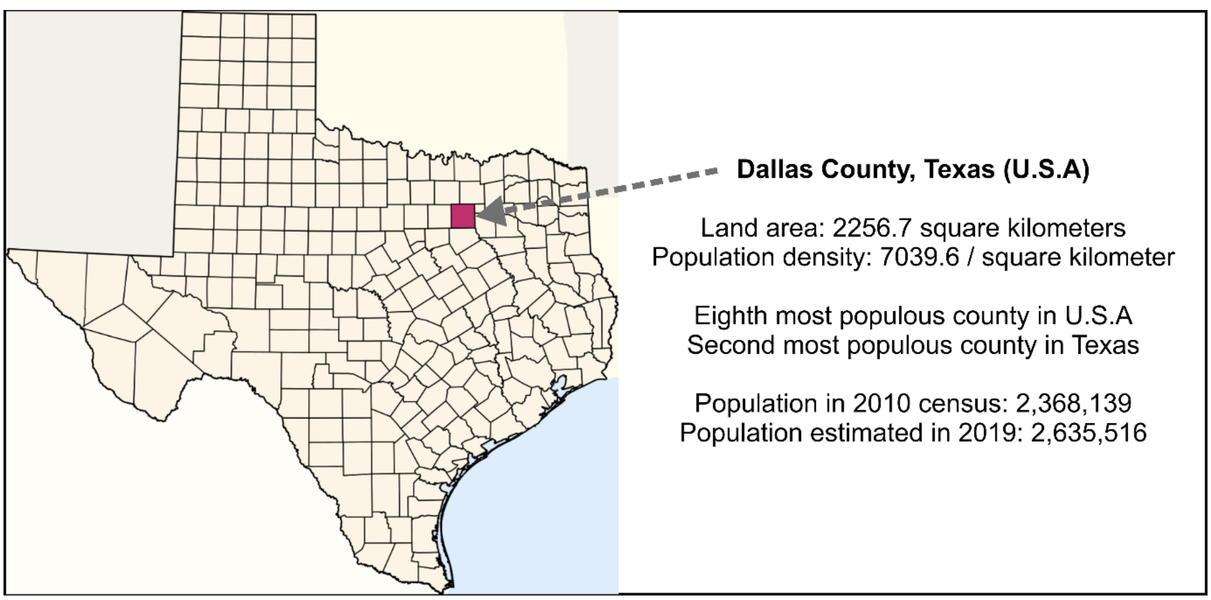

Figure 1. Dallas County location in Texas and population details qualifying it as one of the major population centers in the U.S.A. but it is surrounded by the endangered tallgrass prairie ecosystem.

Daily averaged data for six air pollutant concentrations available for Dallas County (Texas, U.S.A) were compiled for years 2015 to 2020 from the national Air Quality System (AQS) database of the Environmental Protection Agency (EPA) [49]. That database is used to assess nationwide U.S.A. compliance with air quality standards. The pollutants assessed and the specific AQS data codes identifying from where the data originate within the AQS are:

Ozone (O_3) code 44201

Carbon monoxide (CO) code 42101

Nitrogen dioxide (NO_2) code 42602

Sulfur dioxide (SO_2) code 42401

Benzene (C_6H_6) code 45201

Particulate matter less than 2.5 micrometres (PM2.5) code 88101

Unfortunately, continuous daily averaged data for other air pollutants of interest, such as methane, ammonia, lead and PM10 are not accessible via the AQS for Dallas County, as they are only being recorded on an intermittent basis. This makes them unavailable for the purposes of assessing trends in daily variations. Nevertheless, the six pollutants available provide sufficient data to illustrate the value of medium-term air quality benchmarking for this urban area.

The daily averaged data involves data recorded at variable numbers of sites within the County each day. For O_3, typically twelve readings are available for each day taken at three different locations. For CO, two readings are available each day both taken at the same site. For NO_2, typically eight readings are available for each day taken at four different locations. For SO_2, typically four readings are available for each day taken at one location. For benzene, typically one readings (and once per week two readings) are available for each day, taken at one location. For PM2.5, typically nine readings are available for each day taken mainly at one location but intermittently at a second location.

2.2 Data Pre-processing and Recording Gaps

The different numbers of data recordings available each day for the six pollutants makes pre-processing of the available data quite cumbersome to establish averaged daily data. Another issue to contend with in data pre-processing is missing data records for specific pollutants on specific days, typically caused by periodic equipment failure, maintenance or other data collection problems at specific recording sites. This is less of a problem for some pollutants than others (Table 1). For O_3 and NO_2 no days are missing, i.e., 2192 data records are available for each day of the six year period. For PM2.5 (11 missing days) there are just a few missing days occurring very intermittently across the time period of interest. For CO (58 missing days) the problem is worse as it involves a sequence of thirty-six sequential days between 9th August and 13th September 2018. However, for SO_2 (274 missing days) and C_6H_6 (102 missing days) recordings, data gaps are a more significant issue including a number of long missing sequences.

For SO_2 continuous sequences of days with missing data are:

19 October 2017 to 13 November 2017 inclusive

9 August 2018 to 30 December 2018 inclusive

1 May 2019 to 19 May 2019 inclusive

31 December 2019 to 9 March 2020 inclusive

For C_6H_6 a continuous sequence of days with missing data is:

12 August 2017 and 12 September 2017

For missing data days of up to a few days, interpolated values from adjacent available days are entered into the compiled dataset with a clear identifier marking them as interpolated. For the long missing sequences mentioned monthly averages from the six years of available data are introduced. However, those missing sequences of recorded data are identified to ensure that they do not unduly influence the medium-term trend interpretations

Table 1. Missing daily data records for Dallas County compiled dataset for six air pollutants.

Number of Missing Daily Data Records for Dallas County for 2015 to 2020						
Year	Ozone	Carbon Monoxide	Nitrogen Dioxide	Sulfur Dioxide	Benzene	PM2.5
2015	0	3	0	2	4	1
2016	0	5	0	1	22	0
2017	0	8	0	29	30	0
2018	0	36	0	146	18	2
2019	0	6	0	22	26	1
2020	0	0	0	74	3	7
Total Missing Data Days	0	58	0	274	103	11

established. Missing daily data recordings are not a problem unique to Dallas County as periodic recording equipment failures are a feature of air quality recordings made at other locations around the world that need to be contended with. For urban regions to minimize the impact of such problems it is best to not rely on individual items of recording equipment or from readings collected from just one site. Installing equipment at multiple sites across rural and urban areas can avoid data gaps, as indicated for the O_3 and NO_2 data recordings for Dallas County.

3. Results

3.1 Pollutant Medium-term Distributions and Relationships

The compiled dataset, following pre-processing is summarized in Table 2. For O_3 the similarity of the mean and 50th percentile (P50) values indicate that the data distribution is symmetrical. On the other hand, the higher values of the means versus the P50 values of the other five pollutants indicate that their data distributions are asymmetrical and positively skewed to varying degrees. SO_2 displays the highest coefficient of variations (standard deviation / mean) indicating that its distribution is more dispersed than those of the other pollutants. The NO_2 and C_6H_6 distributions are also more dispersed than the O_3, CO and PM2.5 based on coefficient of variation comparisons. It is apparent that the minimum values recorded in the compiled dataset for NO_2, PM2.5 and SO_2 are negative. Clearly, negative pollutant values are not possible. However, the EPA choses to retain them when they are recorded if they fall within the range of precision of the associated recording equipment, rather than adjust them to zero values. That approach is maintained in the compiled dataset.

Figure 2 displays the Pearson correlation coefficients (R) among the six pollutant distributions.

There are high positive R values between CO, NO_2 and C_6H_6, moderate positive R values between SO_2, CO, NO_2 and benzene, but generally poor correlations between PM2.5 and the other pollutants. There is a modest, positive R value (0.21) between PM2.5 and SO_2. On the other hand, O_3 has modest to moderate negative R values with CO, NO_2 and C_6H_6. These complex relationships suggest that when O_3 values are high CO, NO_2 and C_6H_6 values will frequently be low, and vice versa.

Although not a primary focus of this study, the relationships between these six pollutant values and

Table 2. Statistical summary of Dallas County air pollutant measurements as compiled into daily averaged dataset for the period 1st January 2015 to 31st December 2020.

2015 to 2020 (2192 data records) Daily Averages	Ozone	Carbon Monoxide	Nitrogen Dioxide	Sulfur Dioxide	Benzene	Particulate Matter <2.5 Micrometers
Identifier	O3	CO	NO2	SO2	C6H6	PM2.5
Units	ppm	ppm	ppb	ppb	ppb	micrograms / cubic meter
Minimum	0.0006	0.0172	-0.4363	-0.1000	0.0000	-0.2000
Maximum	0.0548	0.8408	28.4750	2.7677	4.1033	49.2117
Mean	0.0278	0.2004	7.5194	0.2938	0.7094	8.7784
Standard Deviation	0.0098	0.0938	4.8293	0.2573	0.4703	4.5299
Standard Error of Mean	0.0002	0.0020	0.1031	0.0055	0.0100	0.0968
Coefficient of Variation	0.3503	0.4679	0.6422	0.8758	0.6629	0.5160
10th Percentile	0.0152	0.1088	2.6031	0.0135	0.2346	3.9329
50th Percentile	0.0277	0.1850	6.2953	0.2563	0.6004	8.1075
90th Percentile	0.0409	0.3090	14.1788	0.6089	1.3000	14.2159

Pollutant Correlation Matrix Dallas Daily Averages (2015 to 2020 inclusive)

R	Ozone	Carbon Monoxide	Nitrogen Dioxide	Sulfur Dioxide	Benzene	PM2.5
Ozone	1.0000	-0.2129	-0.2816	0.0661	-0.3160	0.1284
Carbon Monoxide	-0.2129	1.0000	0.8163	0.4218	0.8070	0.0894
Nitrogen Dioxide	-0.2816	0.8163	1.0000	0.3845	0.7243	-0.0157
Sulphur Dioxide	0.0661	0.4218	0.3845	1.0000	0.3334	0.2130
Benzene	-0.3160	0.8070	0.7243	0.3334	1.0000	0.0817
PM2.5	0.1284	0.0894	-0.0157	0.2130	0.0817	1.0000

Figure 2. Pearson correlation coefficients among six pollutants.

specific meteorological variables, and potentially anthropogenic factors, have a bearing on the correlations observed between them and the seasons of the year during which their values are most likely to peak. For example, O_3 displays moderate to high positive R with outdoor temperature, and ground level solar radiation, a moderate positive R with dew point, and a modest positive correlation with wind speed. This makes it likely for O_3 to reach its peak levels in the summer months. On the other hand, CO, NO_2, and C_6H_6 show moderate negative R values with outdoor temperature, dew point, relative humidity, ground level solar radiation and wind speed. This makes it more likely for CO, NO_2, and C_6H_6 to reach peak values on the cold, dry still days of mid-winter. SO_2 and PM2.5 display poorer correlations with meteorological variables than the other pollutants considered. However, SO_2 has moderate negative correlations with relative humidity and wind speed making it more likely to peak in winter months. In contrast, PM2.5 displays modest to moderate positive R values with outdoor temperature and ground level solar radiation making it more likely to peak in the summer months.

3.2 Multi-year Trends in Air Pollutants

Figure 3 displays the daily averaged data for the six pollutants considered from 1st January 2015 to 31st December 2020. The seasonal trends are consistent with the relationships between these pollutants and meteorological variables described in Section 3.1. O_3 (Figure 3A) displays distinctive summer peaks and winter lows with an indication that annual minimum values are moving further above zero since the winter of 2016. CO, NO_2 and C_6H_6 (Figures 3B, C and E) show clear winter peaks and summer lows in all years assessed, although

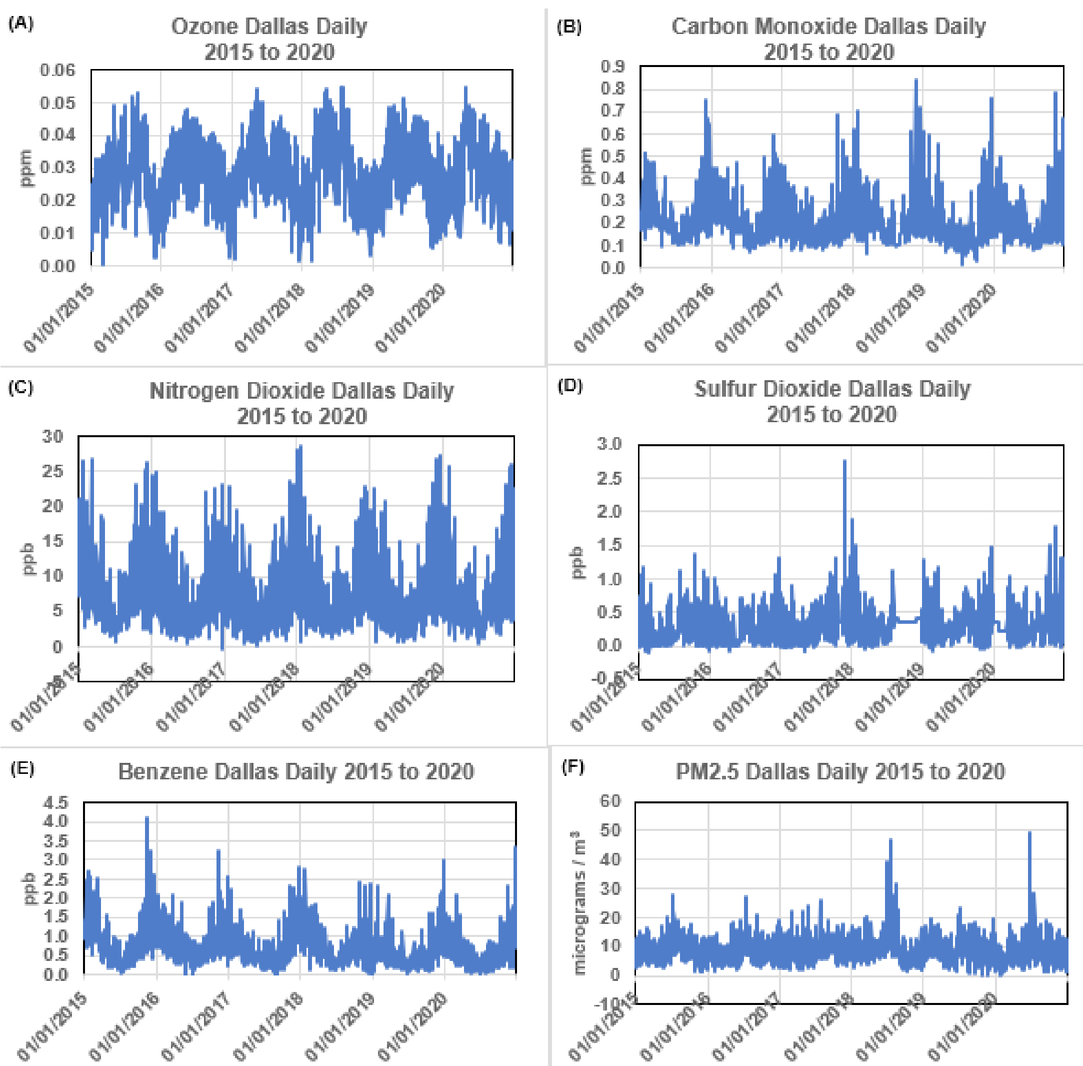

Figure 3. Multi-year trends in daily averaged data for six pollutants recorded in Dallas County for the years 2015 to 2020 inclusive. Note sequences of missing data records for SO_2 in 2018 and 2020.

the magnitudes of the winter peaks vary from year to year, most likely linked to the severity and duration of extreme winter weather that varies from year to year. SO_2 (Figure 3D) displays its highest magnitude peaks in winter with particularly high values in the winters of 2017 to 2018. Seasonal variations do exist for SO_2 but they are less pronounced than for O_3, CO, NO_2 and C_6H_6 with some sizeable peaks occurring in spring and autumn. The extensive missing data record sequence for SO_2 are also visible in Figure 3D.

Seasonality in the PM2.5 data for 2015 to 2020 is less marked than for the other five pollutants considered. However, sizeable peaks are apparent during the summers of 2018 and 2020. Clearly, it is possible to drill down into the dataset to explore specific data peaks and in many cases explain them in terms of specific meteorological conditions. As this study is focused on medium-term trends that aspect is not considered further. Overall, it is reasonable to conclude from Figure 3 that seasonal meteorological conditions and short-term weather events have a significant impact on the prevailing values of these six pollutants.

3.3 Monthly Year-on-year Air Pollutant Concentration Comparisons

Taking monthly averages of the compiled daily averaged dataset for each pollutant provides some useful additional insight to the medium-term variations in each air pollutant studied (Figure 4). Years 2015 and 2018 standout in Figure 4 as there are monthly average peaks for certain pollutants in specific months that substantially exceed values for those months from other years. For example, August 2015 and July 2018 for O_3, December 2015 for CO, October 2015 for NO_2, all winter months in

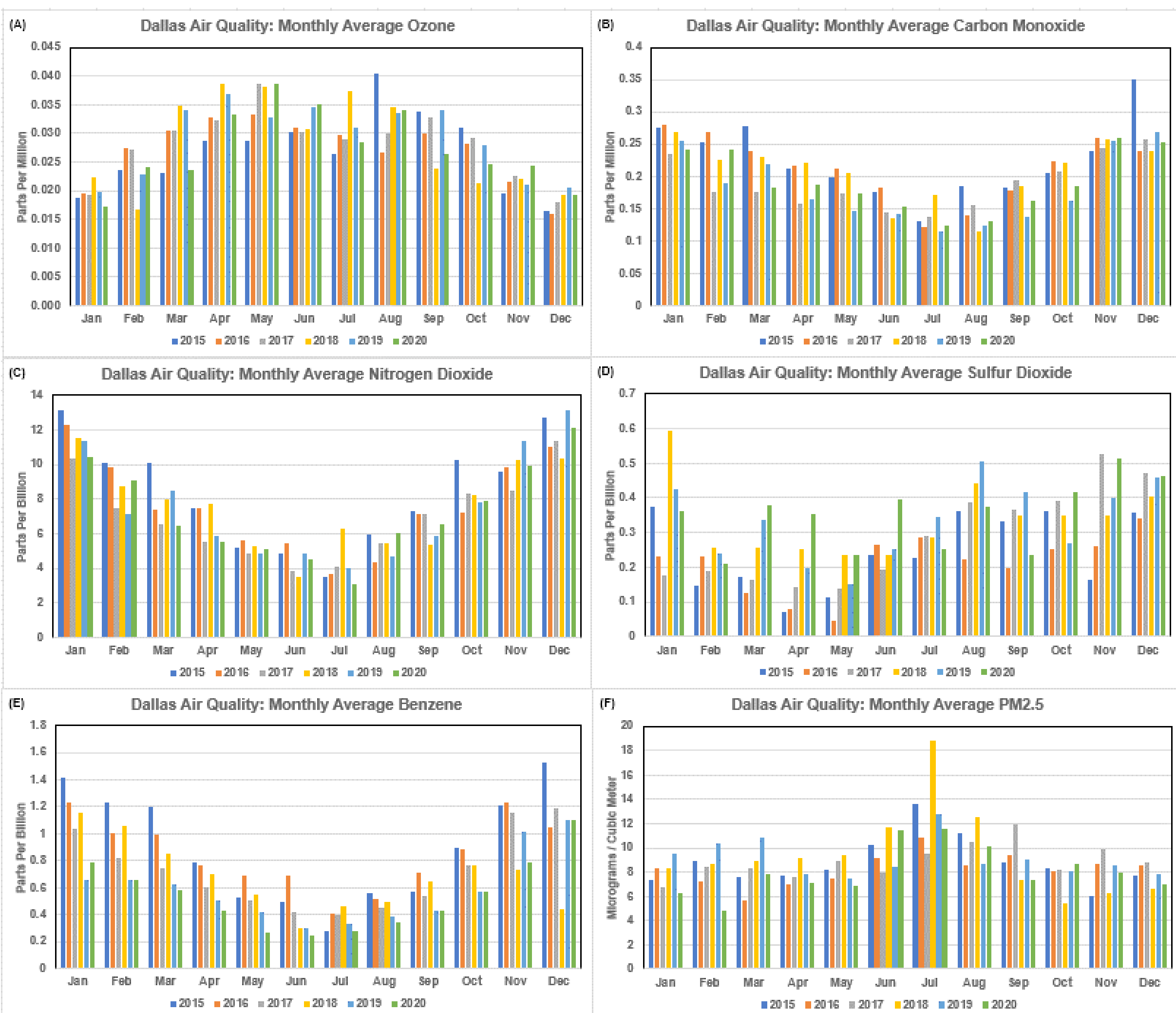

Figure 4. Monthly averages of daily averaged data for six pollutants recorded in Dallas County for the years 2015 to 2020 inclusive.

2015 for Benzene, January 2018 for SO_2 and July 2018 for PM2.5. It is generally easier to discern from Figure 4 than Figure 3 the months most likely to be associated with the lowest and highest average values for each pollutant. Clearly, it is possible to drill down using more granular daily data (and hourly data) to explore in more detail the value distributions for the anomalous months identified. For the purposes of determining medium-term trends and variability, average daily and monthly data complement each other.

The method adopted in this study is to use the characterized dataset to benchmark the pollutant values and trends recorded in 2020 by comparing them with the values recorded for the previous five years (2015 to 2019 inclusive). As well as making direct comparisons between averaged daily and monthly values for each pollutant considered, the maximum and minimum daily average values recorded for 2015 to 2019 for each pollutant are used to normalize the values for each pollutant on a scale between 0 and 1 for those years.

By expressing the pollutants in terms of the same normalized scale makes the local area benchmarking (LAB) more systematic and less prone to scale biases. Moreover, once expressed in normalized terms the pollutant values can be combined to provide a combined, unbiased, multi-pollutant local area benchmarked indicator (CLAB) against which future periods could be more meaningfully compared.

3.4 2020 Benchmarked against 2015 to 2019 Trends in Actual Value Terms

Due to the significant restrictions on population movements during 2020 as a result of the COVID-19 pandemic, vehicle transportation was substantially reduced in that year from March onwards in Dallas County, as elsewhere in the USA. Consequently, it is interesting to consider 2020 air pollutant data with a view to identifying signs in air quality changes in response to reduced vehicle emissions. An initial comparison between 2020 and 2015 to 2020 averaged monthly data values (Table 3 and Figure 5) does reveal some systematic differences. The difference is most obvious for C_6H_6 for which all months in 2020 except for December show substantial reductions compared to the monthly averages for 2015 to 2019. For CO there is also a noticeable reduction, with all months from March to October, inclusive recording values below their 2015 to 2019 averages in 2020. For NO_2 the data are not conclusive although six of the nine months between March and November have recorded values in 2020 less than the 2015 to 2019 averages for those months.

For O_3, the 2020 data oscillates around the 2015 to 2019 month averages imply that there is no significant difference in O_3 values for 2020. On the other hand, the SO_2 data for 2020 do show some seasonal variations in relation to the 2015 to 2019 averages. For months March to June SO_2 was substantially higher than the 2015 to 2019 average. For months July to September 2020 SO_2 was lower, and for months October to December it was substantially higher than the 2015 to 2019 average. The 2020 trend in SO_2 is not so easily explained as being a direct consequence of restrictions in transport movements due to the COVID-19 pandemic. It may be related to intermittent usage of coal-fired power plants in north-east Texas, but further analysis is necessary to verify that possibility. For the first nine months of 2020, all months, excluding June, recorded lower PM2.5 values than the 2015 to 2019 monthly averages. However, the most significant reductions were for the months of January and February and are clearly unrelated to COVID-19 transportation restrictions. The unusually mild weather conditions in those months during 2020 may be responsible for the lower than average PM2.5 values recorded. Despite substantially lower PM2.5 values from March to May 2020 than for those months in 2015 to 2019, it remains unclear whether these reductions were in some way related to COVID-19 restrictions.

Table 3. Comparison of monthly averaged daily data for Dallas County for six air pollutants for periods 2015 to 2019 and 2020.

Month	Ozone	Carbon Monoxide	Nitrogen Dioxide	Sulfur Dioxide	Benzene	PM2.5
Units	ppm	ppm	ppb	ppb	ppb	μg/m^3
Averages for the period 2015 to 2019						
Jan	0.0199	0.2622	11.7195	0.3601	1.1021	8.0470
Feb	0.0236	0.2228	8.6621	0.2141	0.9561	8.7172
Mar	0.0306	0.2287	8.1041	0.2105	0.8805	8.3019
Apr	0.0335	0.2065	7.3927	0.1789	0.6974	8.5575
May	0.0343	0.1868	5.1505	0.1370	0.5386	8.2860
Jun	0.0313	0.1556	4.4824	0.2364	0.4417	9.5100
Jul	0.0306	0.1347	4.3226	0.2875	0.3764	13.1335
Aug	0.0331	0.1443	5.1763	0.3853	0.4821	10.3529
Sep	0.0309	0.1753	6.5638	0.3337	0.5802	9.3143
Oct	0.0275	0.2037	8.3633	0.3244	0.7753	7.6119
Nov	0.0213	0.2507	9.9170	0.3400	1.0711	7.8944
Dec	0.0159	0.2225	9.8689	0.3536	0.8528	6.8537
Averages for 2020						
Jan	0.0173	0.2406	10.4405	N/A	0.7891	6.2223
Feb	0.0241	0.2416	9.0358	N/A	0.6588	4.8745
Mar	0.0236	0.1834	6.4240	0.3780	0.5852	7.7744
Apr	0.0332	0.1879	5.5393	0.3535	0.4298	7.0975
May	0.0387	0.1730	5.1023	0.2344	0.2680	6.8957
Jun	0.0350	0.1524	4.5585	0.3973	0.2423	11.3922
Jul	0.0284	0.1235	3.0464	0.2513	0.2789	11.6150
Aug	0.0341	0.1296	6.0267	0.3749	0.3376	10.0814
Sep	0.0264	0.1612	6.5875	0.2367	0.4292	7.3907
Oct	0.0247	0.1849	7.8551	0.4149	0.5660	8.7108
Nov	0.0243	0.2584	9.8938	0.5157	0.7864	7.9963
Dec	0.0193	0.2537	12.1182	0.4632	1.0970	7.0128

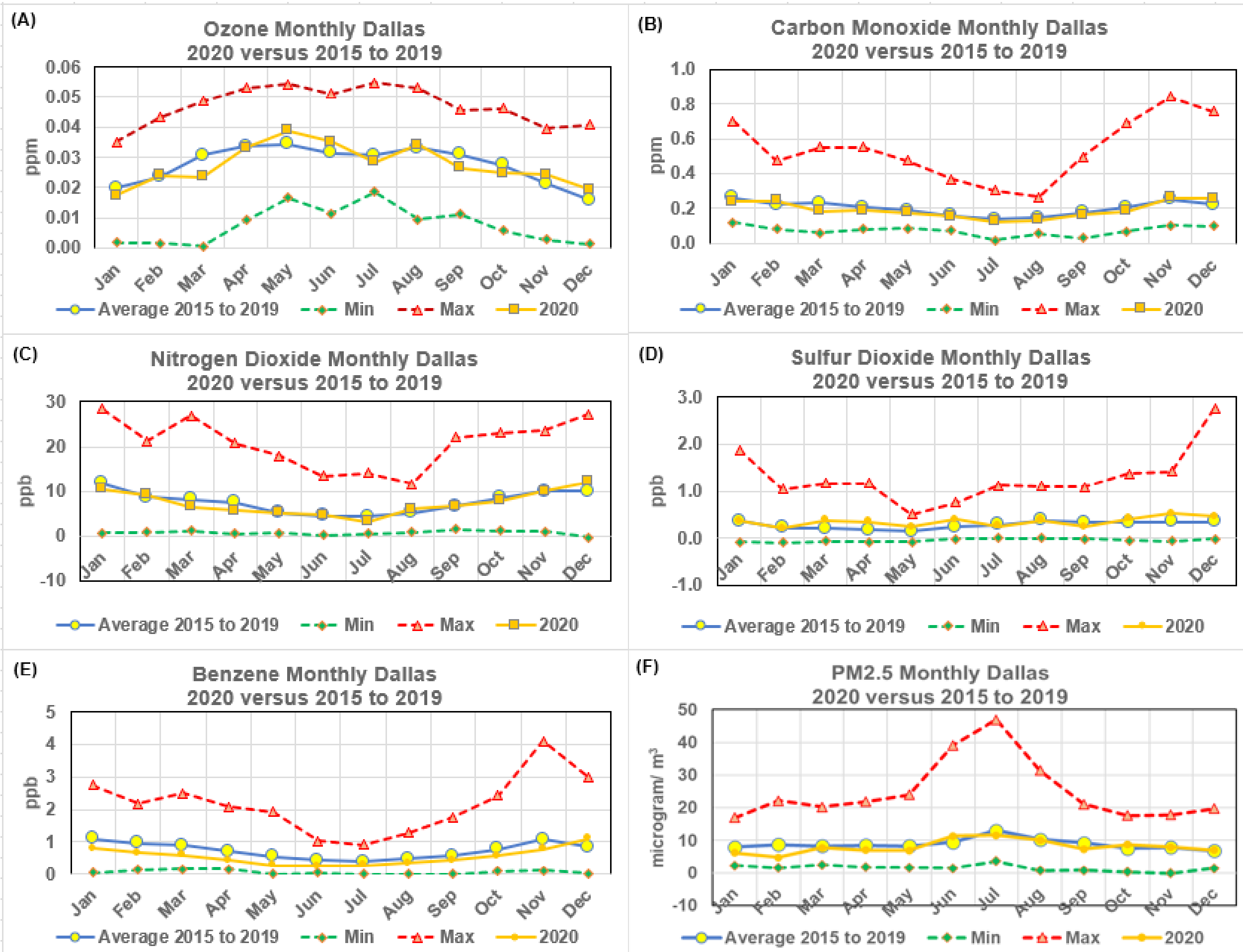

Figure 5. Monthly averages of daily averaged data for six pollutants recorded in Dallas County benchmarking year 2020 against the average, maximum and minimum values for 2015 to 2019.

In summary, the comparison between the 2020 monthly averaged data and 2015 to 2019 monthly averages for Dallas County reveals systematic reductions in C_6H_6, CO and possibly NO_2 that are most likely a consequence of reduced local transportation movements due to COVID-19 restrictions. On the other hand, 2020 data for O_3, SO_2 and PM2.5 do not appear to have been impacted in a systematically obvious direction by the COVID-19 restrictions.

3.5 Benchmarking 2020 Pollutants Using Normalized Values

To remove scale biases between the pollutants and make them more conducive to deriving a meaningful multi-pollutant indicator, the daily data are normalized so each pollutant average daily value for the period 2015 to 2019 is scaled between 0 and 1. This is achieved by adjusting the average daily values with equation 1.

$$nV_p=(aV_p-Min_p)/(Max_p-Min_p) \tag{1}$$

where:

nV_p is the normalised daily averaged value for pollutant p;

aV_p is the actual daily averaged value for pollutant p;

Min_p is the minimum daily averaged value between 1 January 2015 and 31st December 2019 for pollutant p;

Max_p is the normalised daily averaged value between 1 January 2015 and 31st December 2019 for pollutant p.

There are other normalization methods that could be used (e.g. to a scale of -1 to +1, or with reference to standard deviation or specific percentiles). These were trialled but did not lead to significant differences in the dispersions of the normalized distributions. One issue that needs to be considered in the case of certain pollutant distributions is that they can be highly skewed by just a few extreme data points. The normalization method selected, involving maximum and minimum values for each pollutant is sensitive to potentially extreme erroneous recordings. For instance, pollutants exhibiting very few data points recording a very large maximum value (e.g. SO_2 in late 2017, Figure 3D) will be scaled in a way that is substantially influenced by those points. This will make most of the normalized pollutant values will be much smaller than one than they would be if those few points were ignored. Implicitly, this imposes a small indirect weight of such pollutant distributions. In this example of the method, these few extreme values have not been filtered out. However, in applying the method more generally it may in some instances be justified to apply some data filtering prior to normalization.

The calculated normalized values are referred to as local area benchmark (LAB) values. Summing the LAB values of the daily averages for all six pollutants and dividing that sum by six yields an essentially unweighted combined local area benchmark (CLAB). Calculated in this way the CLAB is essentially an average of the LAB values, but it does not have to be so. A case to be made in certain local areas to differentially weight the individual LAB values, according to their relative significance locally or to compensate for certain highly skewed LAB distributions. To illustrate the method and the general value of the CLAB indicator the simple unweighted average approach is presented here.

Table 4 displays a statistical summary of the LAB and CLAB values for 2015 to 2019 (the period used to provide the benchmark) and for 2020 (the period being benchmarked). Comparison of the 2020 LAB values with those for the period 2015 to 2019 reveal that the mean LAB values are lower for 2020 for five out of the six pollutants considered (SO_2 is higher in 2020). However, it is also apparent with maximum LAB values above 1.0 that O_3 and PM2.5 experienced peaks in 2020 that exceeded the maximum values experienced from 2015 to 2019. On the other hand, the minimum LAB values for 2020 for all individual pollutants were greater than zero, indicating that none of the 2020 pollutant values fell below the minimum experienced between 2015 and 2019.

Figure 6 cross plots the daily average LAB values to highlight some of the key influencing factors on the lower LAB values for 2020 versus 2015 to 2019. LAB_{C6H6} versus LAB_{O3} (Figure 6A) superimposes the normalised distribution for these two distributions. The concentration of averaged daily LAB_{C6H6} values for 2020 below 0.3 is clearly apparent, with only six daily averaged LAB_{C6H6} values above 0.5 in 2020. Although the LAB_{O3} values for 2020 extend across most of the range covered by the 2015 to 2019 data, it is notable that there are no 2020 LAB_{O3} values less than 0.1.

LAB_{C6H6} versus LAB_{CO} (Figure 6B) superimposes the normalised distribution for these two distributions. The concentration of averaged daily LAB_{C6H6} and LAB_{CO} values are clearly both concentrated below 0.3 in 2020, with only four daily averaged LAB_{C6H6} and LAB_{CO} values both exceeding 0.5 in 2020. Figure 6A and B highlight that meaningful differences do exist between the daily averaged LAB values for C_6H_6 and CO between 2020 and those recorded in the previous five years. This reinforces the inferences drawn from the monthly averaged actual value data (Figure 5).

Table 4. Statistical summary of local area benchmarks (LAB) for individual pollutants and combined LAB for six pollutants combined. Daily average values for 2015 to 2020 are benchmarked against the maximum and minimum values for 2015 to 2019.

Local Area Benchmarks (LAB) for Dallas County for 2020 versus 2015 to 2019							
Normalized to 0 to 1 for 2015 to 2019	LAB_{O3} Ozone	LAB_{CO} Carbon Monoxide	LAB_{NO2} Nitrogen Dioxide	$LABS_{SO2}$ Sulfur Dioxide	LAB_{C6H6} Benzene	$LAB_{PM2.5}$ PM2.5	$CLAB_{Dallas}$ Combined LAB /6
2015 to 2019	Normalised to 0 to 1 scale using minimum and maximum values recorded between 2015 and 2019						(∑LAB)/6
Minimum	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0976
Maximum	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.6215
Mean	0.5051	0.2248	0.2773	0.1334	0.1812	0.1930	0.2525
Standard Deviation	0.1805	0.1140	0.1684	0.0888	0.1154	0.0940	0.0721
Coefficient of Variation	0.3574	0.5069	0.6072	0.6655	0.6370	0.4869	0.2855
2020							
Minimum	0.1128	0.0678	0.0252	0.0236	0.0024	0.0019	0.1002
Maximum	1.0014	0.9279	0.9101	0.6509	0.8127	1.0465	0.5886
Mean	0.4958	0.2105	0.2647	0.1568	0.1314	0.1758	0.2392
Standard Deviation	0.1796	0.1126	0.1598	0.0918	0.1007	0.1040	0.0690
Coefficient of Variation	0.3623	0.5348	0.6037	0.5855	0.7661	0.5913	0.2885

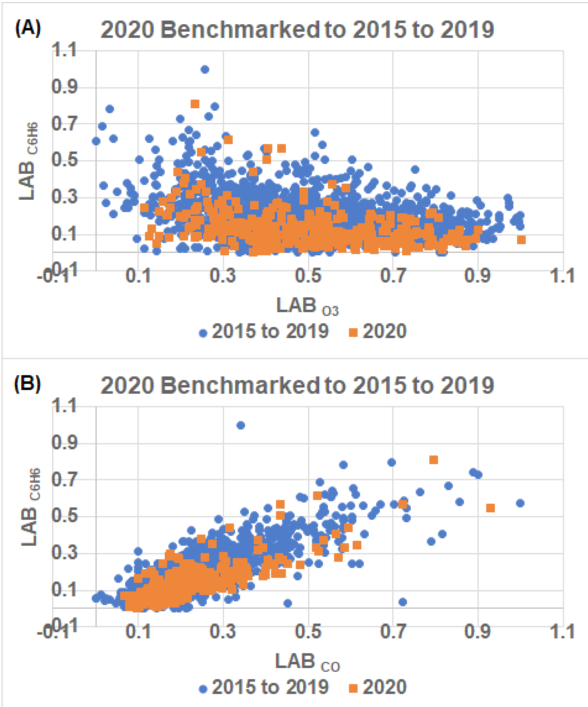

Figure 6. Daily average LAB data cross plots for those pollutant distributions showing the greatest differences between 2020 and 2015 to 2019.

3.6 Configuring a Useful Multi-pollutant Multi-year Local Benchmark

Once the individual pollutant values are all normalised to similar LAB scales it becomes more meaningful to combine them to generate an indicator that assesses their collective impact on air quality on a daily basis. The CLAB indicator calculated for analysis here simply sums the six dividual LAB values on a daily basis and divides that sum by six to provide an unweighted indicator.

The minimum, maximum, mean and standard deviation CLAB values (Table 4) are all lower for 2020 compared with CLAB for 2015 to 2019, whereas the coefficients of variation are quite close for those two periods (slightly higher for 2020). The lower mean CLAB value for 2020 compared with that for 2015 to 2019 is what should be expected taking into account the lower C_6H_6 and CO values that occurred in most months of 2020 (Figure 5).

Figure 7 displays the daily CLAB values from 1st January 2015 to 31st December 2020. This benchmarked indicator, combining the normalised inputs from all six pollutants considered, shows distinct seasonality with peaks occurring each year in the first and fourth quarters. This is due to the combined influence of the winter peaks of CO, NO_2, C_6H_6, and to a lesser extent SO_2, countering the summer peaks associated with O_3 and PM2.5. Considering 2020 relative to the previous five years, Figure 7 shows a greater number of low CLAB values close to 0.1 (i.e., best overall air quality conditions) spread across 2020 compared to those previous years. On the other hand, the number of fourth quarter CLAB peaks above 0.5 are higher for 2020 than for any fourth quarter of the five previous years. The absence of CLAB peaks above 0.4 in the first quarter of 2020 is more difficult to interpret. This is likely to be influenced in part by the lack of recorded SO_2 data for January and February 2020 (monthly averages from 2015 to 2019 are used for each daily SO_2 values in January and February 2020 CLAB calculations). However, the substantially lower CLAB monthly average values for January and February 2020 than the CLAB averages for those months from 2015 to 2019 (Table 5) suggests that other factors have also influenced this; most likely the milder first quarter weather conditions experienced in Dallas in the first quarter of 2021.

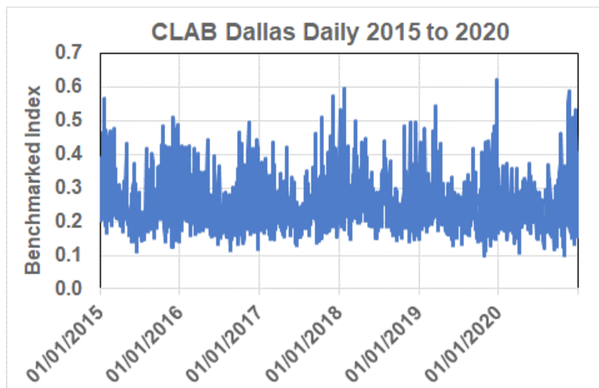

Figure 7. Multi-year CLAB trends combining the normalized daily averaged data for six pollutants recorded in Dallas County for the years 2015 to 2020 inclusive.

The monthly average CLAB values for Dallas County are also informative (Table 5; Figure 8).

Eight of the twelve months of 2020 (and six of the 8 months from March to October of that year) have lower CLAB monthly average values than those for 2015 to 2019 (Figure 8B). On the other hand, the November and December 2020 CLAB values are higher than for 2015 to 2019, markedly so for December 2020. The November and December 2020 substantial increases in CLAB relative to previous year monthly averages may be, at least in part, explained by increased transport vehicle movements associated with the Thanksgiving and Christmas holidays and eased COVID-19 restrictions. The maximum monthly CLAB values for 2020 are substantially lower in all months except November for 2020 compared to months from 2015 to 2019. On the other hand, only five months of 2020 have lower minimum monthly CLAB values versus

Table 5. Monthly averaged CLAB comparisons benchmarking 2020 versus 2015 to 2019 data for Dallas County.

Combined Local Area Benchmark (CLAB) Monthly Average Values for Dallas County						
	2015:2019	2020	2015:2019	2020	2015:2019	2020
	Monthly Average		Monthly Minima		Monthly Maxima	
Month	$CLAB_{Dallas}$	$CLAB_{Dallas}$	$CLAB_{Dallas}$	$CLAB_{Dallas}$	$CLAB_{Dallas}$	$CLAB_{Dallas}$
Jan	0.2798	0.2407	0.1508	0.1733	0.5946	0.3661
Feb	0.2534	0.2351	0.1511	0.1449	0.4676	0.3709
Mar	0.2682	0.2238	0.1455	0.1365	0.5423	0.3576
Apr	0.2603	0.2389	0.1568	0.1108	0.5423	0.3293
May	0.2361	0.2363	0.1445	0.1638	0.4439	0.3722
Jun	0.2227	0.2418	0.1128	0.1491	0.3938	0.3171
Jul	0.2286	0.2007	0.1370	0.1191	0.4396	0.2864
Aug	0.2434	0.2409	0.1161	0.1659	0.4021	0.3676
Sep	0.2480	0.2129	0.1359	0.1185	0.4637	0.3229
Oct	0.2551	0.2403	0.0976	0.1002	0.5097	0.4626
Nov	0.2684	0.2780	0.1250	0.1560	0.4936	0.5886
Dec	0.2763	0.2807	0.1214	0.1344	0.6215	0.5325

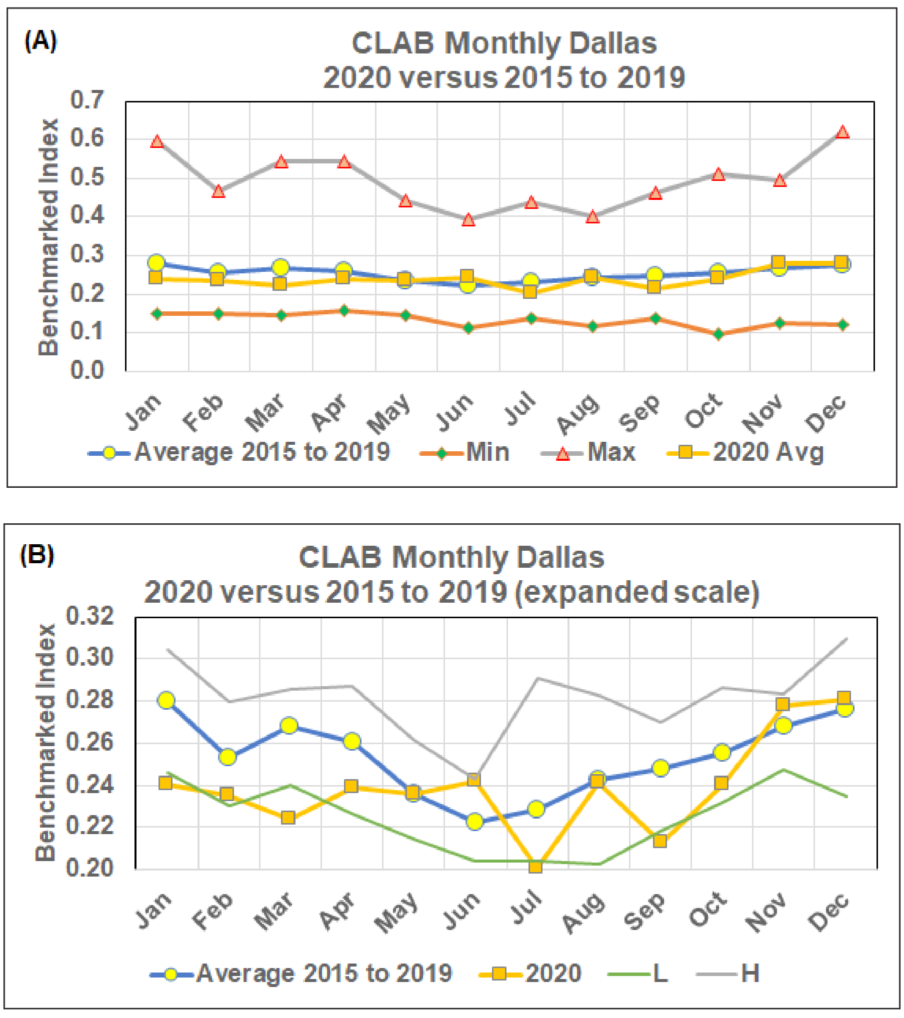

Figure 8. Monthly CLAB values for 2020 versus 2015 to 2019 for Dallas County. The maximum and minimum monthly values shown in (A) are for 2015 to 2019. Lines L and H in (B) represent minimum and maximum monthly averages for 2015 to 2019, respectively.

months from 2015 to 2019, and the fourth quarter 2020 has higher minimum CLAB values versus 2015 to 2019.

In summary, the daily and monthly CLAB values suggest that in 2020 the air quality conditions were anomalous versus those for 2015 to 2019. Most 2020 months through to October recorded substantial air quality improvements versus 2015 to 2019, whereas November and December 2020 air quality was poorer. The monthly averaged CLAB values for Dallas County for 2015 to 2019 reveal much less of a contrast in overall air quality between January and December than that shown for 2020 (Table 5; Figure 8). An explanation for that difference requires detailed analysis of meteorological and anthropogenic factors.

4. Discussion

4.1 Benefits of Monitoring Medium-term Air Pollution Trends

The Dallas County case study highlights the benefits of considering a medium-term perspective of air quality for a specific environment combining the trends of multiple pollutants. Today's focus on air quality is overwhelmingly directed towards short-term air quality monitoring and/or forecasting of individual pollutants on an hourly and daily basis for the benefit of human health considerations. That short-term focus is essential to provide timely health warnings to vulnerable individuals when poor air quality conditions occur. The air quality indices (AQI) used in the U.S.A. [49], with similar approaches applied in many other countries, are well established. As well as being easy to report and interpret, AQI provide the means for the EPA (and equivalent bodies in other countries) to rapidly communicate prevailing air quality conditions on a local and national level.

Once recorded, the local short-term air quality data are routinely archived and made available for analysis. However, relatively few areas conduct and learn from regular, ongoing medium-term (i.e., the past five years or so) look-backs and benchmarking analysis focusing on daily or monthly time intervals. The historical data archive tends to be used more frequently by regulatory bodies for displaying trends over periods of decades, to confirm that air quality has substantially improved on that time scale or in comparison with other regions (e.g. EPA [26]). Also, the Texas Commission on Environmental Quality [51] publishes long term air quality pollutant trends, dating back to the 1990s, highlighting the substantial reductions achieved in reducing key air pollutants as population has risen over that period. There is a wealth of data available for the medium-term, the analysis of which is less well assessed, reported or focused on ecosystem sustainability issues.

4.2 Accounting for Climatic and Anthropogenic Influences on Air Quality

Each local area has a set of unique factors influencing its air quality. Typically, these local influences are dominated by seasonal atmospheric, climate and meteorological factors, but with industrial activity, transportation movements, road network layouts, power generation mix (coal and gas versus renewables) and availability of mass transit systems also having discernible anthropogenic influences. These unique influences on a local environment's air quality mean that nationally determined and regulated AQI may not be providing the necessary depth of insight with which to monitor local air quality evolution. Moreover, some air pollutants may be having a much greater influence than others in specific local areas, and on specific ecosystems. In order to best plan for the future, to achieve sustainable development without damaging air quality or ecosystems, it is considered essential for each local area to understand its air quality trends over the medium-term, as well as the more commonly reported short-term and long-term perspectives. This is best conducted using daily and monthly averaged data, accompanied by the ability to drill down into hourly data to better understand the characteristics of specific spikes in poor air quality.

4.3 Value of Local Air Quality Benchmarks Integrating Multiple Pollutants

Whereas it is important to monitor and assess the trends in individual pollutants, particular from a local area human-health risk perspective, it is also important to take a more holistic approach combining data from multiple air pollutants. This provides a better understanding of the periods and conditions when overall air quality is at its best and worst, and when anthropogenic influence are likely to be more substantial. Such information can then be usefully considered in relation to impacts on specific species or the biodiversity of entire ecosystems To do this effectively, it is appropriate to normalize the values of each pollutant to the same scale range thereby making it possible to combine data from multiple air pollutants into combined local area benchmarks (CLABs) as demonstrated by the Dallas County case study.The question for many areas to address, as a first step, is what air pollutants measurements should be included in an overall air-quality/CLAB indicator. Initially, this is likely to be determined by the data that is available in the archive from a limited number of measuring stations. For the Dallas County case study six pollutants were assessed because daily average data for them were available in the EPA AQI database. For Dallas County, it would be useful to also consider ammonia, methane, volatile organic compounds (VOC) and lead as possible components of a CLAB indicator, as these pollutants all contribute to overall air quality. As developed for this study the CLAB indicator is unweighted with respect to specific pollutants as the normalized values for each pollutant are simply summed and divided by six to generate the CLAB value. In some areas, where pollution caused by a specific pollutant(s) is of more concern than others, or pose more of a threat to specific ecosystems, a case could be made to justify generating a weighted CLAB; applying higher weights to pollutants of most concern than to others. However, as mentioned in Section 3.5, that possibility is not explored in this study.

A case can be made to broaden the daily averaged data maintained in many areas to include a wider range of pollutants. Of course, to do so requires additional investment to increase the quantity of recording equipment, locations sampled and data handling. Comprehensive medium-term benchmatrking requires continuous recording and archiving of relevant data at multiple local sites on an hourly basis to ensure appropriate data is collected. The Dallas County case study highlights that where only one recording site is used for certain pollutants the risk of data gaps increases.

4.4 COVID-19-related Air Quality Influences of 2020

The COVID-19 movement restrictions of 2020 have certainly justified taking a close look at their impacts on air quality in many areas, particularly in densely populated urban areas with high traffic movements in normal times. As the medium-term air quality case study for Dallas County has shown, discernible reductions in certain pollutants most commonly associated with transportation movements (i.e., benzene and carbon monoxide) did occur for many months of 2020. However, 2020 air quality changes observed in Dallas County relative to the 2015 to 2019 period are quite complex and not all are easily explained solely in terms of anthropogenic influences. For instance, the better overall air quality conditions observed for January and February 2020 versus 2015 to 2019 cannot be attributed to COVID restrictions, which did not begin until March 2020. They are most likely due to milder than normal meteorological conditions. On the other hand, the poorer overall air conditions of November and December 2020 may be a combination of increased transportation movements during the holiday periods of those months and/or meteorological factors. More analysis is required for 2020 air quality data, drilling down into hourly data for some additional insight. Also, a medium-term benchmarking air quality assessment for 2021 air quality data, when it becomes available should provide useful ongoing annual comparisons.

It is of interest to compare the anomalous air quality trends observed in Dallas County with those reported for other cities around the world. Specifically, the 2020 monthly averages compared to those of 2015 to 2019 for Dallas County display clear reductions in C_6H_6, CO and, for July only, NO_2, but not clear persistent anomalies O_3, SO_2 and PM2.5 in 2020. This contrasts with the findings reported from other cities. In Vienna [44], Lima [45], Abu dhabi [46], Dongguan [47] and across the United Kingdom [48] substantial decreases in NO_2 and smaller increases in O_3 were reported in 2020, in addition to reductions in CO, C_6H_6. Vienna, Lima and United Kingdom also recorded PM2.5 reductions [44,45,48], although Abu Dhabi recorded increased PM2.5 attributed to the influence of increased dust storms [46]. The lack of substantial NO_2, O_3 and PM2.5 anomalies in the air quality of Dallas County is therefore somewhat surprizing. In the United Kingdom it was noted that the greatest changes in NO_2 and O_3 levels were associated with recording made adjacent to the busiest urban traffic routes [48].

There are several local factors that need to be taken into account when attempting to explain the 2020 air quality anomalies in Dallas County compared with those recorded in the mentioned cities around the world. There are a number of oil refineries located within Dallas County, reduced output from which in 2020 could have contributed to the more substantial reductions in C_6H_6 than the changes observed in other pollutants. Most of the air pollutant recording stations are not located next to the busiest highways which may contribute to the absence of anomalies in NO_2 and O_3 being recorded in Dallas County during 2020. Gasoline dominates the road transport fuel consumed in Dallas (as is the case for other cities in the United States), diesel is used to a much lesser extent, even for heavy good vehicles than elsewhere in the world. As diesel generates more NOx and PM2.5 than gasoline when combusted in vehicle engines, this may account in part for the lack of substantial NO_2 reductions observed in Dallas County in 2020. The lack of a substantial 2020 NO_2 anomaly in Dallas also explains the lack of a positive O_3 anomaly during that period. Other local climatic factors, such as periodic dust storms of varing intensity and the occurrence of thermal inversions during winter and spring, have the potential to obscure some of the anthropogenic influences on Dallas County air quality in 2020, particularly those relating to PM2.5. With the limited information available it is not possible to specifically attribute the lack of NO_2, O_3 and PM2.5 anomalies observed in Dallas County in 2020 to one or other of these possible contributing factors.

In more normal times a case could be made for using a rolling averages of the past five years of data to repeat an in depth medium-term air quality benchmarking assessment for local area conditions. However, the anomalous nature of air quality in 2020, and most likely in 2021 in many areas, suggests that, for most purposes, it would not be appropriate to incorporate data from those two years to assess other years. 2015 to 2019 data may therefore remain relevant as an air quality benchmark in many areas for several years to come.

5. Conclusions

A case is made to complement short-term air quality index reporting of individual pollutants, on an hourly and daily basis, with medium-term, local-scale benchmarking of annual data using daily and monthly averaged assessments for multiple pollutants. This is of value for both human-health risk identification purposes and for ecosystem sustainability monitoring. Due to meteorological and seasonal drivers having strong but unique influences on local air quality conditions, benchmarking has to include data from multiple past years to capture fluctuating weather impacts. Five years of recent past, daily averaged historical air quality data can provide a useful medium-term perspective that adequately captures seasonal meteorological and anthropogenic fluctuations. It is effective to normalise the data to a consistent scale (e.g. 0 to 1) for each pollutant to provide local area benchmarks (LAB) for each pollutant. Normalized data can then be combined for multiple relevant pollutants to provide an integrated indicator of local air quality in the form of a combined local area benchmark (CLAB). CLAB assessments can then provide a daily, monthly and seasonal assessment of relative local air quality for a period of interest benchmarked to a medium-term reference period.

The adverse consequences of the COVID 19 pandemic, in 2020 and beyond, has made it possible to comparatively analyse the operation and evolution of various air pollutants in specific cities and local urban areas around the world. This is the case because for many months on many human activities, specifically related to transport movements, came to a near standstill, substantially reducing consumption of fossil fuels (gasoline, diesel and aviation fuels) and their associated atmospheric emissions.

The proposed CLAB approach using public data from six air pollutants (ozone, carbon monoxide, nitrogen dioxide, sulfur dioxide, benzene, and particulate matter <2.5) is applied to a case study for Dallas County, one of the largest urban areas of the U.S.A. That city is situated in an environmentally sensitive region as it is surrounded by the highly endangered tallgrass prairie ecosystem. This case study provides a detailed assessment of air quality for 2020 compared to 2015 to 2019, providing unique insights to the impacts of the COVID-19 human confinements of 2020 on medium-term air quality trends. The monthly averaged data reveal improvements in benzene and carbon monoxide levels, and to a lesser extent nitrogen dioxide, for many months in 2020. Those improvements can be largely attributed to reduced traffic movements. On the other hand, changes in the other monitored pollutants show more complex variations without obvious improvements relative to the 2015 to 2019 period. The CLAB analysis does show better overall air quality conditions in Dallas County throughout most of 2020 but poorer conditions in November and December 2020 versus 2015 to 2019.

Medium-term air quality benchmarking, using LAB and CLAB analysis, has the potential to provide local areas with useful information on overall air quality based on the integrated trends of multiple air pollutants. Such information can be beneficial for both urban and ecosystem sustainability planning, by assisting local areas in designing sustainable developments taking into account overall air quality trends and the specific complexities of local ecosystems. Such an approach should help to facilitate long-term improvements in air quality in cities/ large urban areas by focusing attention on specific local factors and trends rather than concentrating mainly on national objectives and trends or regional influences.

In order to improve air quality conditions in the future associated with large urban areas and their surrounding environments that are sensitive to air quality, the results of this study justify taking the following steps.

1) Substantially improve the density of local-area air quality recording sites to facilitate effective medium-term air quality benchmarking on an ongoing basis, striving to minimize data gaps. Too few recording sites makes it difficult to interpret, distinguish and understand all the local level influences on air quality, and runs the risk of periodic data gaps.

2) Expand recording to include a wider range of pollutants that are of relevance locally (e.g., ammonia, methane) in addition to those considered nationally as critical pollutants.

3) Take medium-term, local air quality measurements, including integrated benchmarks such as CLAB, into

account when formulating plans for new developments, in order to avoid local adverse consequences.

To achieve this requires more investment in recording stations with an emphasis on establishing reliable short-, medium- and long-term air quality databases at the local level.

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The author has no conflicts or competing interests related to any of the content of this study.

Author Contributions

David A. Wood is the sole author and responsible for all the content.

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