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WELL-BEING AND HEALTH OF PEOPLE AND PLACES

The impact of coronavirus-related lockdowns on air quality in England and Scotland

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Abstract: In December 2019, the first cases of the Coronavirus (COVID-19) Pandemic occurred, since then there have been several studies addressing the environmental impact of lockdowns worldwide. Some studies have indicated that air quality has improved because of the restrictions placed on travel. It was found that COVID-19 caused Particulate Matter 2.5 (PM2.5) and Daily Air Quality Index (DAQI) to decrease by about 7 µg/m3 and 5-points in China, respectively. Similarly, in the Kingdom of Saudi Arabia, a 91.12% lower concentration of Particulate Matter 10 (PM10) in the air across nine cities was noted. These studies concluded that their results were due to the reduction of industrial and travel pollution because of the lockdown. In the United Kingdom, a national lockdown was enforced on March 26, 2020, as such this study has anticipated a similar trend in air quality from this point. It was decided that this would be assessed by comparing air quality data – in particular, PM2.5 and PM10 for 2019 and 2020 across England and Scotland, the results found that air quality levels for these variables did show considerable improvements for individual sites because of lockdowns. Based on our analyses, missing data led to an overall statistically insignificant result.

Keywords: Coronavirus, Air Quality, Lockdown, England, Scotland

1 Introduction

In 2021, air pollution was the focal point of the COP26 conference, having been found as a key catalyst leading to climate change (European Commission, 2015).

Breathing clean air has been a UN-recognised human right since 1972 – the WHO defines the threshold for this as being on average PM < 10 µg/m3. Despite this, as of 2020, 74% of all European sites record reading above this threshold, causing 477,000 premature deaths (EEA, 2020). For these reasons, there has been increasing demand for innovative technologies (Redondo-Bermúdez et al., 2021) and legislation to tackle rising pollution levels (Calderon and Keirstead, 2012).

PM variables are a significant factor in air quality due to their effects on respiratory health. It consists of microscopic factors of varying shape and composition. Due to their size, these particulates can be inhaled and can pose harm to the human body (California Air Resources Board, 2021), PM2.5 in particular being more prone to risk (United States Environmental Protection Agency, 2021).

With this in mind, this study aimed to test whether the mandatory COVID-19 lockdowns reduced the PM levels in Scotland and England.

2 Data Model, Source and Explanation

The key source of the data used in this analysis comes from the DAQI and UK Air Information Resource Page, both of which can be found through the Department for Environment, Food & Rural Affairs (DEFRA, 2021b; DEFRA, 2021a, respectively) website. Since this data comes from multiple ministerial and non-ministerial departments of the UK government, as well as a significant number of public bodies, occurrences of individual biases in the formation of this resource have been counteracted and the resulting data is thus considered credible.

2.1 Daily Air Quality Index (DAQI)

DAQI data was split yearly to allow for a straightforward comparison between the two time periods. This resulted in CSV files for each year, which were downloaded and stored in a local directory.

The format of the DAQI datasets consisted of a series of daily numerical values. A set of 32 keys (date column and 31 stations measuring air quality) can be found on the first row. The first 7 entries of the 2019 DAQI dataset can be seen in Figure 1.

Figure 1: Table Showing DAQI 2019 Format Example

Date	Central Scotland	East Midlands	Eastern	Greater London	Highland	North East	North East Scotland	North Wales
01/01/2019	3	3	3	2	3	3	3	3
02/01/2019	3	3	3	2	3	3	3	3
03/01/2019	3	3	3	2	3	3	2	3
04/01/2019	3	5	3	3	3	2	2	3
05/01/2019	3	3	2	3	3	2	2	3
06/01/2019	3	2	2	2	3	2	2	3

2.2 Particulate Matter (PM10 and PM2.5)

Obtaining the PM data was more challenging than that of the DAQI. Early on it was found that datasets for the home nations had to be individually processed and collated into an overall file.

The Mathematica command *Intersection[]* was utilised to obtain the necessary columns in the PM dataset that contained viable data – the results of which can be seen in Figure 2.

Figure 2: Mathematica Query Result after Running the Intersection Command

```
intersectingScotSites = Intersection[scotSites19[[All, 3]], scotSites19[[All, 4]]]

{, Aberdeen Market Street 2, Aberdeen Union Street Roadside, East Dunbartonshire Kirkintilloch, Falkirk West Bridge Street,
 Fife Cupar, North Ayrshire Irvine High St, South Lanarkshire Lanark, South Lanarkshire Rutherglen, West Dunbartonshire Clydebank, West Lothian Linlithgow High Street 2}
```

The dataset for both 2019 and 2020 consisted of a series of numerical values with two rows per site, with the first row displaying values for PM10, and the second for PM2.5, on an hourly basis for the entire year.

Figure 3 displays an example site and the first 3 hours of readings for Scotland in 2019.

Figure 3: Example of Scotland Monitoring Site Readings for PM2.5 and PM10 in Mathematica

```
In[•]:= scot1⟦1 ;; 6, 1 ;; 5⟧ // Grid

                                                    Date           Tue 1 Jan 2019 00:00:00 GMT   Tue 1 Jan 2019 00:00:00 GMT   Tue 1 Jan 2019 00:00:00 GMT
                                                    Time           Tue 30 Nov -2 01:00:00 GMT    Tue 30 Nov -2 02:00:00 GMT    Tue 30 Nov -2 03:00:00 GMT
Out[•]= Aberdeen Market Street 2  PM10 particulate matter (Hourly measured)   4.1                 3.6                 7.7
                                                    Status         V ugm-3 (FIDAS)     V ugm-3 (FIDAS)     V ugm-3 (FIDAS)
                                  PM2.5 particulate matter (Hourly measured)  8.2                 6.2                 5.2
                                                    Status         V ugm-3 (Ref.eq)    V ugm-3 (Ref.eq)    V ugm-3 (Ref.eq)

In[•]:= (*Request all values from the second row, as these should be a time value*)
```

Performing Transposes, the resulting dimensions for Scotland in 2019 and 2020 respectively were {42,8762} and {42,8786}. With England having {122,8762} and {122,8786}.

3 Methodology

3.1 Data Pre-Processing: Daily Air Quality Index (DAQI)

Importing the Dataset and Removing Redundant Rows

Once the DAQI dataset was imported, the first and the last five rows were displayed to check for missing values. This was done using *//TableForm* on the selected rows.

The first and last two rows were redundant and thus had to be removed from the dataset – completed with the command *data[[2;;-3]]*.

Figure 4: Example of Imported DAQI Dataset with Removed Rows

```
data2019⟦1 ;; 5⟧ // TableForm

Form=
AQ Daily index (https://uk-air.defra.gov.uk//air-pollution/daqi?view=more-info) data from UK-AIR website
Date                                                                     Central Scotland   East Midlands   Eastern
01/01/2019                                                               3                  3               3
02/01/2019                                                               3                  3               3
03/01/2019                                                               3                  3               3

data2019⟦-5 ;; -1⟧ // TableForm

Form=
29/12/2019  2 2 2 3 3 2 1 2 2 3 2 2 2 3 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
30/12/2019  3 2 2 2 3 2 2 2 2 3 2 2 2 3 2 2 2 2 3 2 3 2 2 2 2 2 2 2 2 2
31/12/2019  2 2 3 3 3 3 2 2 2 4 3 3 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 3

End of file
```

Managing Missing Data

After inspecting input forms, a blank string was identified at the end of each row. It was decided that the best course of action was to remove any blank elements from the set: *Table[DeleteCases[data2019cleaningV1[[k]],""],{k,1,Length[data2019cleaningV1]}}*

Calibrating the Date Formats

Mathematica can misinterpret the date format as MM/DD/YYYY leading to potential errors given the time series nature of the data. To counteract this, the date was converted into the form DD/MM/YYYY matching the date format from the DEFRA website. This was done using *(DateObject[{#, {"Day", "/", "Month", "/", "Year"}}, "Day"] & /@ dateswitch2019v1)*, the result of which replaced the first column in the original dataset.

Creating the Association for the Regions

To define a series of associations, the 32 keys from the DAQI dataset were taken and threaded to each value in the list of lists to form a dataset using *Dataset@(AssociationThread[key2019, #] & /@ data2019cleaningV2[[2 ;;]])*.

Further Removal of Redundant Data

The datasets contained values for Northern Ireland and Wales – which were not the focus of this study, so this data was removed by using *KeyDrop[]*. The results can be seen in Figure 5.

Figure 5: Visualisation of DAQI Dataset after Cleaning

Date	Central Scotland	East Midlands	Eastern	Greater London	Highland	North East	North East Scotland	North West & Merseyside	Scottish Borders
Wed 1 Jan 2020	2	3	3	4	3	2	1	3	2
Thu 2 Jan 2020	3	3	2	2	3	2	1	2	3
Fri 3 Jan 2020	3	3	3	3	3	3	2	3	3
Sat 4 Jan 2020	3	3	2	2	3	3	2	3	3
Sun 5 Jan 2020	3	3	3	2	3	3	2	3	3
Mon 6 Jan 2020	3	3	3	2	3	3	2	3	3
Tue 7 Jan 2020	3	3	2	2	3	3	1	3	3
Wed 8 Jan 2020	3	3	2	3	3	3	2	3	3
Thu 9 Jan 2020	3	2	3	2	3	3	2	2	3
Fri 10 Jan 2020	3	3	3	2	3	2	2	2	3
Sat 11 Jan 2020	3	3	3	3	3	3	2	3	3
Sun 12 Jan 2020	3	3	3	3	3	3	1	3	3
Mon 13 Jan 2020	3	3	3	3	3	3	1	3	3

Exporting the Files

The clean data was then exported into file "AQ_Cleaned_2019.csv. This step was also repeated for the 2020 data and both files were stored in the local directory.

3.2 Data Pre-Processing: Particulate Matter (PM10 and PM2.5)

Importing the Dataset

The data was imported using *Import["England Sites 2019.xlsx", {"Data", 1, 4 ;; -5}]*, making the data accessible from the 4th until the 5th to the final row in the first sheet.

Removal of the "Status" Rows

The next step was to remove all the "Status" rows. This was achieved using *Position[england19trans, "PM10 particulate matter (Hourly measured)"]* and *Position[england19trans, "PM2.5 particulate matter (Hourly measured)"]* retrieving the positions of only PM2.5 and PM10. The result, which can be seen in Figure 6, was in the form of lists, and the *// Sort* command was used to combine them.

Figure 6: Example Output of PM Dataset after Sorting

```
{3, 5, 7, 9, 11, 13, 15, 17, 19, 21, 23, 25, 27, 29, 31, 33, 35, 37, 39, 41, 43, 45, 47
 49, 51, 53, 55, 57, 59, 61, 63, 65, 67, 69, 71, 73, 75, 77, 79, 81, 83, 85, 87,
 89, 91, 93, 95, 97, 99, 101, 103, 105, 107, 109, 111, 113, 115, 117, 119, 121}
```

A new table containing the date, time, site names and PM type was created using *Join[england20trans[[1 ;; 2]], england20trans[[PMAlleng20]]]*. Redundant data was removed, and the output is displayed in Figure 7.

Figure 7: PM Dataset after Removal of Redundant Rows

	Date	Tue 1 Jan 2019 00:00:00 GMT	Tue 1 Jan 2019 00:00:00 GMT	Tue 1 Jan 2019 00:00:00 GMT
	Time	Tue 30 Nov −2 01:00:00 GMT	Tue 30 Nov −2 02:00:00 GMT	Tue 30 Nov −2 03:00:00 GMT
Bexley - Belvedere	PM10 particulate matter (Hourly measured)	28.2	18.4	14.4
	PM2.5 particulate matter (Hourly measured)	16.	12.7	6.1
Bexley - Belvedere West	PM10 particulate matter (Hourly measured)	31.6	20.8	15.8
	PM2.5 particulate matter (Hourly measured)	19.5	13.7	7.2

Turning Hourly Measurements into Daily Values by Averaging Results

After re-selection, the data needed to be partitioned in sets of 24, converting hourly data to daily. The average value was then calculated using *N@(Mean /@ (Partition[eng19dat, 24]))*.

After using a "ReplaceAll" command to remove "No Data" string values, the dimensions of the concentrated dataset were {60,365} with one value for each day of the year.

The same method of finding average daily values was used for both PM10 and PM2.5 – partitioning individually, then mapping the mean across the list of lists by using *N@Mean/@*.

Visualizing the Daily Mean

A table was created by forming headings (Site, Particulate Matter, Dates) and joining these with the average daily values of the respective sites by PM type.

This required first joining all the datasets together, which was done using *Partition[Flatten@Table[{england19CleanTEMP[[row, 1;;2]], eng19DailyMean[[row]]}, {row, 1, Length[eng19DailyMean]}], 367]*. These were joined to the headings using *Prepend[eng19joinedTab, eng19heading]*. Figure 8 displays an example site after this process.

Figure 8: PM Dataset after Converting to Daily Mean Values

```
eng19dailyMeanTable[[1 ;; 2, 1 ;; 10]] // Grid
```

Site	Particulate Matter	Tue 1 Jan 2019 00:00:00 GMT	Wed 2 Jan 2019 00:00:00 GMT	Thu 3 Jan 2019 00:00:00 GMT	Fri 4 Jan 2019 00:00:00 GMT	Sat 5 Jan 2019 00:00:00 GMT	Sun 6 Jan 2019 00:00:00 GMT	Mon 7 Jan 2019 00:00:00 GMT	Tue 8 Jan 2019 00:00:00 GMT
Bexley – Belvedere	PM10 particulate matter (Hourly measured)	13.4833	17.8833	21.975	31.3125	24.4083	25.1708	19.2708	20.2958

Exporting the File

The file was exported and stored in a local directory alongside the other data files.

Visualizing the Co-ordinates, Sites, Zone and Environment Types

Finding Co-ordinates of the Monitoring Sites

FindGeoLocation[] was mapped across all sites. During this process, some elements contained missing values. To progress, these values had their respective co-ordinates re-mapped with the alternatively sourced correct co-ordinates. Then, the command *LatitudeLongitude* was used to create a set of coordinates.

Finding Zones and Environment Types of the Monitoring Sites

To find where the monitoring sites fell in the England region, the DAQI dataset was re-imported. This dataset contained all the regions of the respective monitoring sites for both countries. Only the rows with England regions were initially selected from it. The same steps were repeated to find the environment type.

Once obtained, the data was tabulated (Figure 9).

Figure 9: Tabulated PM Station Data

Latitude	Longitude	Site	Zone	Environment Type
51.4895°	0.147359°	Bexley - Belvedere	Greater London Urban Area	Urban
51.4964°	0.133155°	Bexley - Belvedere West	Greater London Urban Area	Urban
52.1999°	0.128022°	Cambridge Gonville Place	Eastern	Urban
51.524°	-0.143934°	Camden - Euston Road	Greater London Urban Area	Urban
51.7632°	-0.573073°	Dacorum Northchurch High Street	Eastern	Urban
54.968°	-1.60607°	Gateshead Tyne Bridge	Tyneside	Urban
52.5798°	1.73482°	Great Yarmouth South Denes	Eastern	Urban
51.4949°	0.0121162°	Greenwich - John Harrison Way	Greater London Urban Area	Urban

Similar methods were carried out on the remaining datasets to bring them to a pre-processed form.

3.3 Data Pre-Processing: Zones and Environment Types

In order to determine the closest zone to sites based on their coordinates, this study utilized a Microsoft Excel file which contained all sites from the AirQuality regions and used an advanced VLOOKUP. This formula was used to assign the closest zone and then use a regular VLOOKUP to pull the environment type.

The advanced VLOOKUP listed below compares the latitude and longitude of the sites being used in the PM datasets with the ones listed from the AirQuality sites. Once this comparison was made, the information required was extracted and assigned to the individual sites.

=LOOKUP(1,1/FREQUENCY(0,SIN((RADIANS(I$2:I$153-$D3))/2)^2+SIN((RADIANS(J$2:J$153-$E3))/2)^2COS(RADIANS(I$2:I$153))COS(RADIANS($D3))),$H$2:$H$153)

3.4 Techniques

The direction of this analysis was not pre-defined. Consequently, multiple methods were trialled throughout the study. It was predicted that average PM would be reduced by COVID-19 because of restricted vehicular travel and work from home mandates. The daily data was analysed to see to what extent the predicted reduction in PM was visible. Outcomes were then visualized in tables for values, as well as several different graphics including Ridgeline graphs and List plots.

3.5 Descriptive Statistics

Several variables were assigned to the data for the Site name, location, environment type and region, making the data easily identifiable upon extraction.

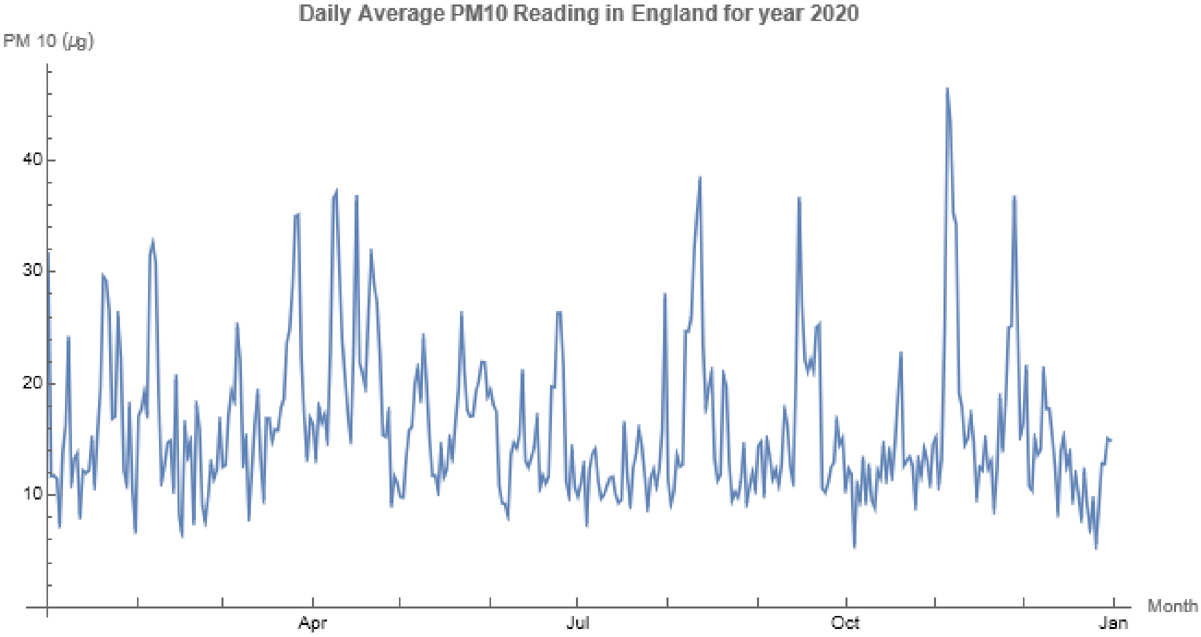
Descriptive statistics including Minimum, Maximum, Mean, and Standard deviation were obtained. This was useful in visualizing and checking for normality. A significant proportion of the data was in a temporal format to determine whether the hypothesis – mandated COVID-19 lockdowns caused a measurable reduction in air pollution – could be accepted or rejected.

3.6 Modelling Approaches

To visualize the pattern for the average daily PM10 readings across the entirety of England, a series of codes were needed to address tasks such as taking the daily average across all sites and creating a visual of a Temporal object. In calculating the averages, the daily mean for PM10 readings for each site was inspected. Transposing the data allowed the mean command to be mapped across the dataset. This was achieved using *Mean /@ (Transpose@eng20PM10DailyMean)* and gave the daily average over the whole of England.

It was then possible to create pairs of values in the form {Date, Average Reading} by transposing the data, the command *TemporalData[]* could then be utilized to create a temporal object from the pairs. This was then used to visualize the PM10 average readings which can be seen in Figure 10.

Figure 10: Daily Average PM10 Reading in England for the year 2020



3.7 Correlation Between Average Particulate Matters and Air Quality Score

One aim was to test correlation between average PM and average Air Quality scoring. Using the Central Scotland Region as a direct test of the feasibility of this method, the outcome suggested a weak positive correlation (r=0.3). Accordingly, this method was deemed infeasible. Focus shifted to making use of different graphical methods to investigate average change.

4 Results

According to World Health Organisation (WHO, 2021), there are 4 levels of PM10 and PM2.5 that can affect our health, categorised as:

1. Good (air pollution is PM < 10 μg/m^3)
2. Moderate (air pollution is between 10 and 15 μg/m^3)
3. Poor (air pollution is between 15 and 25 μg/m^3)
4. Very poor (air pollution is more than 25 μg/m^3)

Tables comprised of the Minimum, Maximum, Mean and Standard Deviation for PM values for the 2019 - 2020 dataset for both countries were created. For each table, the best and worst averages were highlighted. In England, the monitoring site in Slough had the best average of 8.26 µg/m³ and Maidstone had the worst with 26.33 µg/m³. England had a moderate level of Air Pollution with only one site categorized as "Very Poor."

Figure 11: Tables Highlighting the Best and Worst Averages for Sites in England

	Minimum	Mean	Maximum	Standard Deviation
{Bexley - Belvedere}	4.47083	18.6522	70.8167	11.3193
{Bexley - Belvedere West}	4.775	17.4711	69.6625	9.97769
{Cambridge Gonville Place}	0.975	18.5222	63.0875	8.7078
{Camden - Euston Road}	8.2375	21.4346	68.9	9.82563
{Dacorum Northchurch High Street}	3.1375	18.1582	399.079	29.7801
{Gateshead Tyne Bridge}	2.7375	14.1382	71.9083	9.32891
{Great Yarmouth South Denes}	4.29167	19.1321	74.4583	13.2854
{Greenwich - John Harrison Way}	2.54583	14.0537	62.8292	10.1093
{Greenwich - Woolwich Flyover}	8.42917	22.6247	81.3417	10.654
{Hackney - Old Street}	5.25833	19.6312	67.0167	10.5411
{Havering - Rainham}	2.52083	16.7153	64.7625	9.75557
{Heathrow Green Gates}	2.5125	12.7818	55.5417	8.58185
{Heathrow LHR2}	2.79583	13.3706	57.2	9.21743
{Hitchin Stevenage Road Particulates}	1.29583	16.9524	64.3208	10.3073
{Hounslow Brentford}	5.59167	18.7169	71.2208	10.6819
{Hounslow Chiswick}	3.60417	18.3859	57.3458	9.18535
{King's Lynn Stoke Ferry Buckenham Drive}	0.0416667	9.30137	32.5	5.46158
{King's Lynn Stoke Ferry Wretton Road}	3.	10.5638	29.2083	4.71339
{Luton Dunstable Road East}	1.35833	15.676	63.0375	10.5869
{Maidstone Upper Stone Street}	7.11779	26.3292	71.4555	10.769
{North Tyneside Coast Road}	3.49583	17.2554	68.275	10.2015
{Norwich Castle Meadow}	1.95833	18.4315	71.9167	9.71114
{Salford M60}	2.90417	20.7436	72.8292	11.3033
{Scunthorpe East Common Lane Osiris}	0.833333	15.4037	106.	11.5756
{Slough Lakeside 2 Osiris}	2.4375	8.25992	50.1667	9.01064
{South Cambs Girton Rd}	1.63333	16.1904	56.9125	7.49114
{Tower Hamlets - Blackwall}	3.9125	14.6081	74.6083	12.7505
{Tower Hamlets - Victoria Park}	4.70417	17.4519	65.3417	10.0796
{Waltham Forest Dawlish Rd}	2.8625	16.0745	57.0417	8.60731
{Watford Town Hall}	3.70833	14.3986	53.6458	8.99925

	Minimum	Mean	Maximum	Standard Deviation
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{South Cambs Girton Rd}	1.63333	16.1904	56.9125	7.49114
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{Waltham Forest Dawlish Rd}	2.8625	16.0745	57.0417	8.60731
{Watford Town Hall}	3.70833	14.3986	53.6458	8.99925

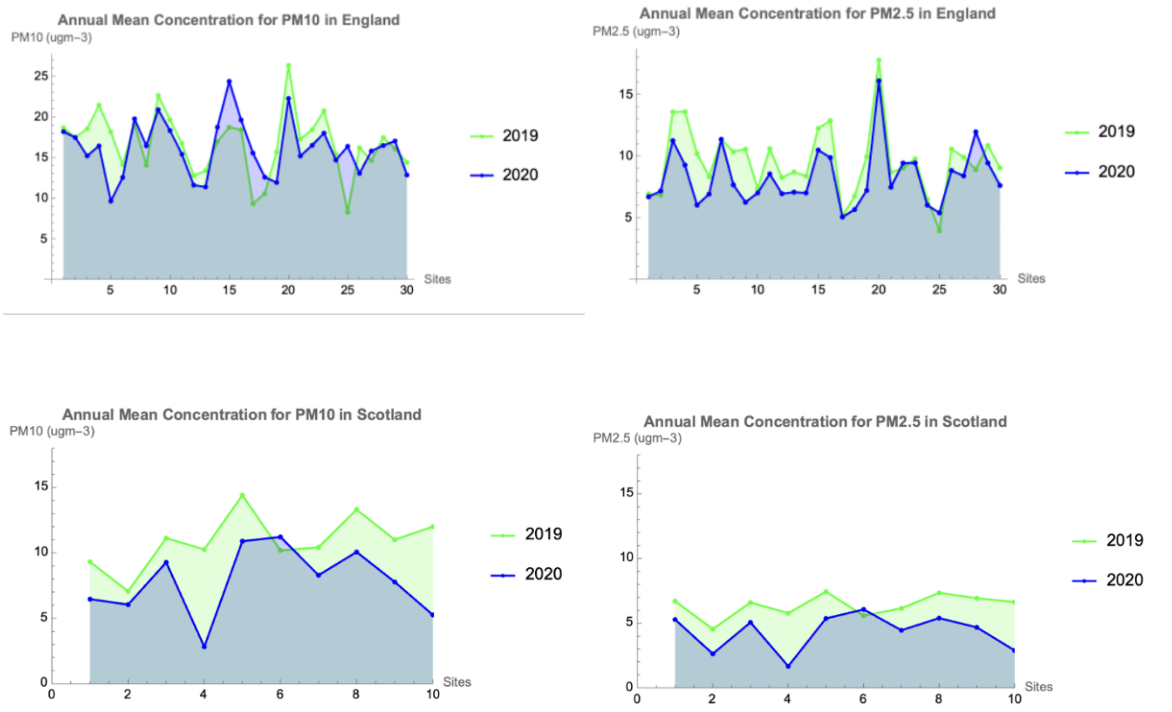
Table 1: Number of Sites in England that fall within the 4 Levels of Air Pollution

	µg/m³ <10	10< µg/m³ <15	15< µg/m³ <25	µg/m³ >25
Number of Sites	2	7	20	1
Percentage Represented	6.7%	23.3%	66.7%	3.3%

4.1 Annual Mean Concentration Comparison with Both Years

The figure and table above suggest a moderate decrease in PM levels from 2019 - 2020, which is better visualised using Line Graphs. Upon overlaying graphs of 2019 and 2020 for all pollutant types (Figure 12), a large majority of sites can be seen to have experienced a reduction in pollutants, with PM10 consisting of 9 sites in Scotland and 20 in England, while PM2.5 consisting of 9 sites in Scotland and 25 in England.

Figure 12: Comparing the Annual Mean Concentrations from 2019 - 2020 for PM2.5 and PM10 in England and Scotland



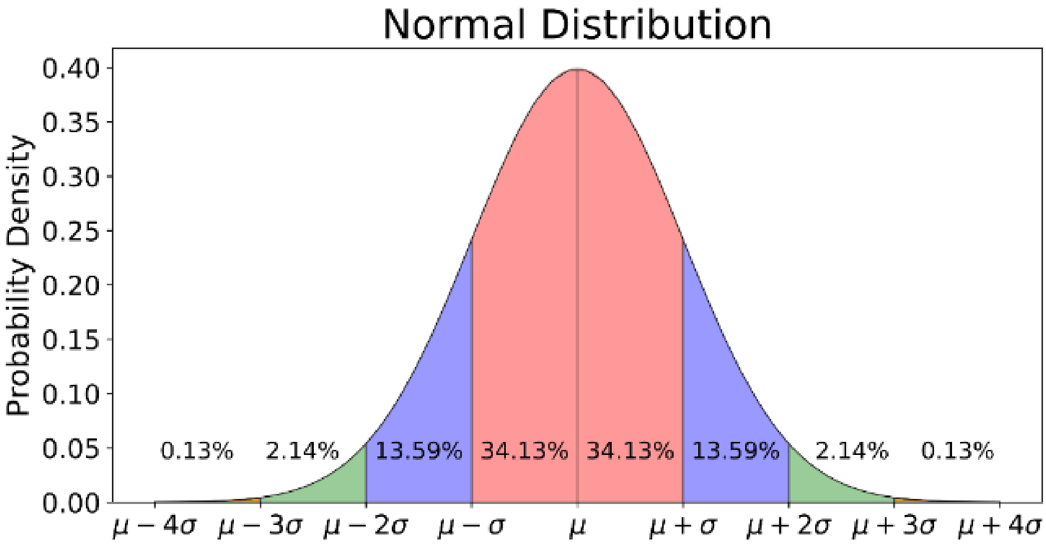
4.2 Probability Distribution

The calculated values of the mean (μ) and Standard Deviation (σ) were then used as parameters for a Normal Distribution, with the PDF being:

$$\frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(x-\mu)^2}{2\sigma^2}}$$

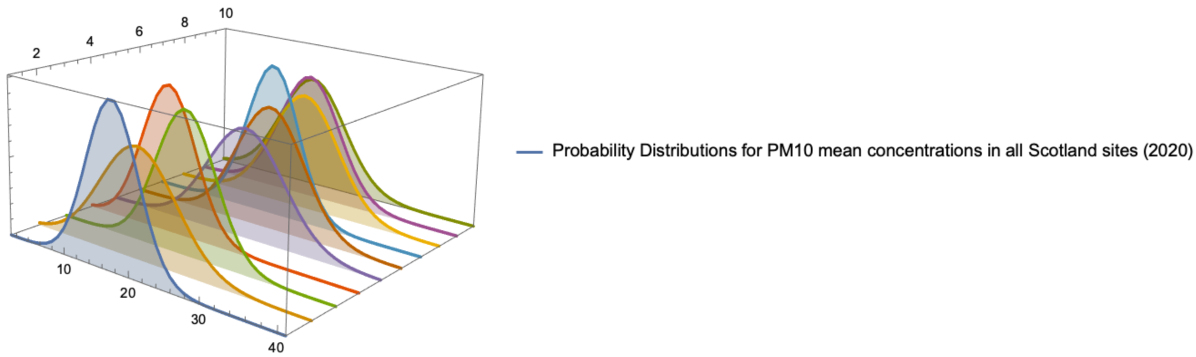
A Normal Distribution PDF has a symmetrical bell-shaped curve with μ being central and represents the average PM value of a site on a particular day, whilst σ constitutes the dispersion of these values in a particular site.

Figure 13: Normal Distribution PDF



Considering the ridgeline graphs for Scotland shown in Figure 14, it is possible to identify sites with a higher PM by looking at the position of the highest peak along the x-axis, with the lower PM levels being the bell curves with peaks closer to zero. Dispersion can be observed by how wide each of the figures are.

Figure 14: Probability Distribution for PM10 Mean Concentration of All Scotland Sites in 2020



4.3 Quantifying the difference in PM10 levels in the sites of Slough and Maidstone in 2019 and 2020

To better understand the changes in PM10 values over the years, English monitoring sites with the highest and lowest average were selected. The Normal Distributions of the PM10 values for 2019 and 2020 have different shapes; moreover, the intersection between these areas is minimal, which indicates the 2020 values were affected by other external factors.

The probability distribution was constructed to compare with another similar distribution. A two-sample z-test for means was used to check if both normal models created for the sites Slough and Maidstone were the same.

The Hypotheses tested were: H0: µ1= µ2H0: $\mu1 = \mu2$, with H1: µ1≠ µ2H1: $\mu1 \neq \mu2$.

Table 2: Results of the two-sample z-test

	2019		2020		2019-2020	2019-2020
Sites	Mean µg/m^3	St Dev	Mean µg/m^3	ST Dev	Z-value	P-value
Slough Lakeside 2 Osiris	8.26	9.01	16.37	11.94	0.246	>0.10
Maidstone Upper Stone Street	26.33	10.77	22.27	8.12	-0.301	>0.10

The paired z-test between two normal variables is dependent on the Mean and Standard Deviation:

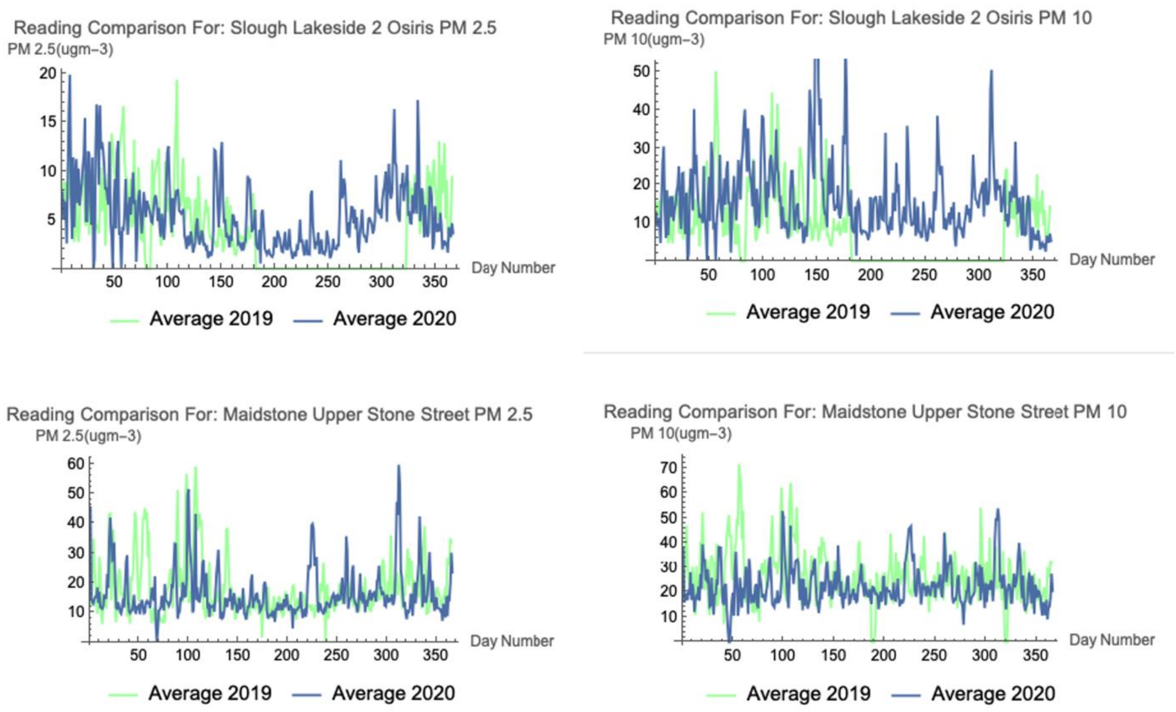
$$Z = \frac{\overline{X_1} - \overline{X_2}}{\sqrt{\sigma_{X_1}^2 + \sigma_{X_2}^2}}$$

The resultant z-values were 0.246 and –0.301 respectively, with p-values above 0.10, implying these datasets do not present a significant difference between the 2019 and 2020 datasets.

4.4 Understanding the seasonality of two English sites

Despite the outcome of the test, it is still possible to understand the air pollution change throughout the years (See Figure 15).

Figure 15: Daily Mean Comparison of PM10 and PM2.5 for Slough and Maidstone Sites from 2019 and 2020



5 Discussion

5.1 Air Quality of England and Scotland

England and Scotland had moderate to poor levels of air quality in 2019, according to the WHO. However, both countries recorded air quality levels for PM2.5 and PM10 better than most countries in Europe (European Environment Agency, 2021):

Table 3: Recorded Air Quality Levels for England, Scotland and Most Countries in Europe for 2019 and 2020

	2019	2019	2020	2020
Pollutant	PM10 mg/m3	PM2.5 mg/m3	PM10 mg/m3	PM2.5 mg/m3
England	16.71	9.55	16.14	8.23
Scotland	10.91	6.37	7.81	4.35
Europe, mode of means (2018)	≈18.5	≈13.5	/	/

In 2020, average PM levels improved. Scotland was able to stay within the “good” threshold of 10mg/m3 set up by the WHO. In 2019, the worst air pollution means recorded were Fife, Cupar (7.43 μg/m^3 PM2.5, 14.40 μg/m^3 PM10) and Maidstone Upper

Stone Street (17.78 μg/m^3 PM2.5, 26.33 μg/m^3 PM10). These sites improved in 2020 with both pollutants (Fife 5.37 μg/m^3 PM2.5, 10.89 μg/m^3 PM10 and Maidstone with 16.10 μg/m^3 PM2.5, 22.28 μg/m^3 PM10) representing an overall improvement.

5.2 Air Quality in Towns versus Countryside

In the initial stages of analysis, a comparison between rural and urban sites was considered. However, there was an inadequate number of qualified rural sites. Despite our hypothesis, the only two rural sites (King's Lynn Stoke Ferry Buckenham Drive and King's Lynn Stoke Ferry Wretton Road) recorded higher pollution in 2020 than 2019, but this sample is too small to be representative.

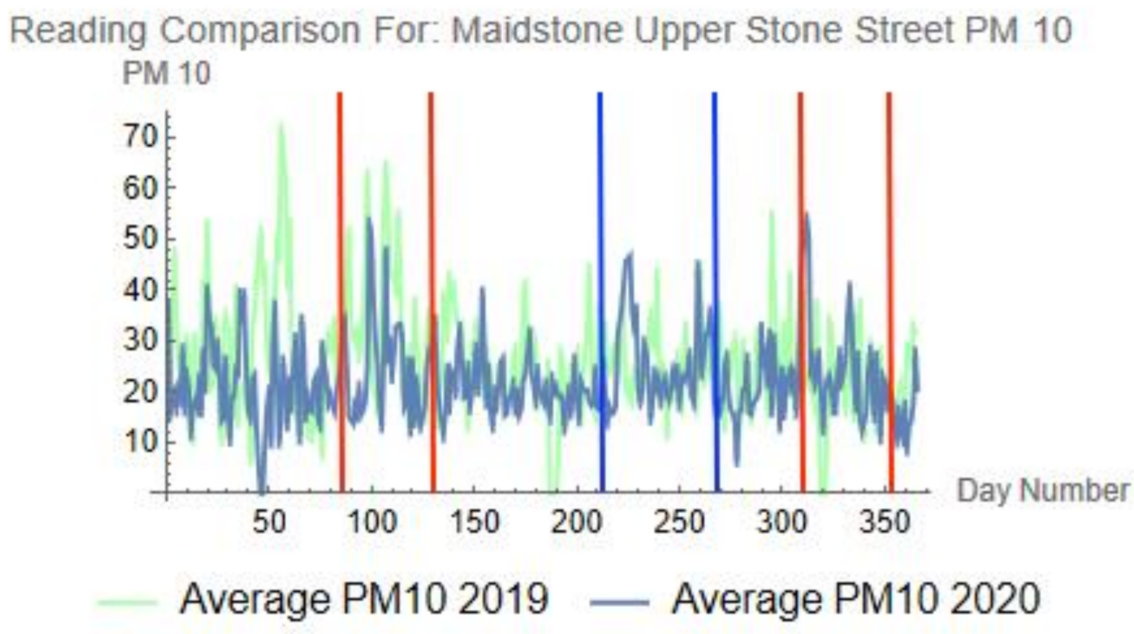
5.3 COVID-19 Pandemic Effect on the Air Quality Level

The most significant result of the research is represented by the overlay graphs of England and Scotland for PM2.5 and PM10. 90% of sites recorded lower PM10 values between 2019 and 2020, including extreme decreases in sites including Falkirk (PM10 from 10.27 μg/m^3 to 5.77 μg/m^3; 44% decrease) and Camden (PM2.5 from 13.60 μg/m^3 to 9.25 μg/m^3; 32% decrease). This significant change in air pollution level in 2020 suggests the mandated lockdowns could be linked to air quality.

Due to the limited time and computational power to develop the research, a Paired Z-Test was only evaluated between the data samples for PM10 in 2019 and 2020 for the sites of Slough Lakeside 2 Osiris and Maidstone Upper Stone Street. The results of z-value 0.246 ($p>0.10$) and z-value –0.301 ($p>0.10$), having no real statistically significant difference.

Figure 16 uses the UK lockdown timeline (Institute for Government, 2021), highlighting two lockdowns (between red lines) and one “return to normality” phase (purple) (Institute for Government, 2021). The lockdown phases can be seen to correlate with the reduction of the PM10 levels (days 85 to 132), while during the ease of restrictions (days 217 to 260) the level of pollution rose to a similar level to 2019.

Figure 16: Comparison of PM10 Values from 2019 to 2020 for Maidstone Site with COVID-19 Lockdown Indicators



Although statistically non-significant, a decreasing trend in the level of PM10 and PM2.5 can be observed.

6 Conclusion

This study analysed changes in air pollution levels between 2019 and 2020 in England and Scotland, and its linkage to Covid Lockdowns. The main result shows a visible reduction of air pollution, with 32 sites recording improvements in PM, but the difference in PM levels between years was not statistically significant, rejecting the initial hypothesis.

Covid Lockdowns have affected the production of emissions produced by means of transport and heavy industries, improving air quality levels across the world (Ming *et al.*, 2020). Studies like this one conducted in the US, UK, China, Brazil and Saudi Arabia (Zangari *et al.*,2020; Jephcote, 2021; Nakada and Urban, 2020; Aljahdali *et al.*, 2021, respectively), found no significant impact on air quality in the short-term, but it is thought that an extended lockdown would result in cleaner air.

The decision was made not to make use of MongoDB or MySQL due to the resultant dataset not being vast. If this study were to be scaled up in size and duration, MySQL would be useful for specific search term querying. Future analyses have the potential to include plotting predictors which make use of splines in a nonlinear model style fit so that we can predict future values based upon many things such as how the values are clustered.

Moreover, Particulate Matter is only one of the many air pollutants that impact human health and climate change. A broad range of poisonous gases contribute to air pollution including carbon monoxide, nitrogen dioxide, ozone, and sulphur dioxide. Extending this study would enable the collection of these datasets and evaluation of the impact of Covid Lockdowns on them. Finally, it would be possible to extend the research to create an air quality forecasting tool with heat maps like the ones in weather apps.

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