LancasterAQ: A High Resolution Street Level Dataset of Ultrafine Particles

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Abstract

We present a mobile dataset of ultrafine particles (UFPs) in Lancaster, UK, with measurements taken by car and bike over 5 days in May 2022. UFPs are a constituent of air pollution and comprise of particulate matter (PM) less than 0.1μm in diameter. UFPs are unregulated and less measured than larger constituents of PM, despite being harmful to health and an important part of the atmospheric and meteorological system. By making mobile UFP measurements, we have produced a street level dataset that captures the high spatial variability of UFPs at the scale an individual experiences it. The dataset is accessible through the LancasterAQ Python package and lends itself to modelling spatially or on a network. This dataset's potential use cases include route planning under constraints of air pollutant exposure, identifying processes that affect air pollution at street level, and investigating the causal relationship between human activity and UFPs.

1 Introduction

We present an air quality dataset collected in Lancaster, United Kingdom (UK) that comprises of ultrafine particles (UFPs) measurements, collected by a combination of vehicle-borne and bicycle-borne instrumentation. The high-resolution at which UFPs have been measured makes this a novel dataset that will enable further research into the impacts of UFPs on human health and enable more informed public policy. The aim of this paper is to provide the required knowledge to use and understand the data.

Exposure to poor air quality is a major hazard to human health with an estimated 4.2 million premature deaths globally each year resulting from outdoor air pollution [2], including particulate matter (PM). UFPs are PM less than 0.1 μm in diameter and are linked to a range of negative health effects, including cardiovascular and pulmonary diseases [12]. However, UFPs are not included in current premature death estimates and are currently unregulated in air quality standards worldwide, in part, due to the lack of systematic measurement. UFPs are directly emitted from combustion sources, although they are also created by atmospheric reactions. In urban environments, the primary source of UFPs is traffic, including tailpipe, road abrasion, and non-exhaust emissions (e.g., brake and tyre wear) [8].

UFPs concentrations vary across space and time and are influenced by physical (e.g., meteorology and atmospheric chemistry) and social (e.g., rush hour traffic and public transport use) processes.

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Therefore, datasets measured at a high spatiotemporal resolution are essential to understand the behaviour and impacts of UFPs. Existing air quality products range from coarse global-scale reanalysis [e.g., 5, 7] to small and localised low-cost static sensor networks (e.g., Purple Air). However, these datasets seldom contain measurements of UFPs, let alone provide information at scales appropriate for their high spatiotemproal variability.

Better measurements of UFPs will improve our understanding of meteorological, climate, and social systems. Through atmospheric reactions they form important seeds for cloud creation, currently a major source of uncertainty in modelling climate change and a possible method for geoengineering climate solutions. Socially, it will be possible to quantify the effects of pollution intervention and design impactful policies, such as active traffic management, low-traffic neighbourhoods and low-emission zones.

Our new dataset of mobile UFP measurements is an important addition to existing air quality products. It provides highly resolved UFP concentrations at the street level of an under measured, but important pollutant. Our data is available through a Python package[1] that facilitates statistical modelling from either a spatial or network perspective. Finally, as our dataset is collected in the small city of Lancaster, UK, it contrasts with existing mobile datasets, which focus on larger cities (e.g., Breathe London and Chen et al. [1]).

Our mobile dataset can be used in a number of impactful ways, including the following:

- Route planning to factor in UFP exposure levels [e.g., 16, 15].
- Decision making and experimental design for sensor placement [e.g., 3].
- Investigating causal relationships from UFPs to human behaviour and urban design [e.g., 14].

2 Data description

Table 1: Summary of data collected from this measurement campaign including average meteorological variables temperature, humidity and surface pressure. Driving measurements are shown in blue and cycling in red.

Date	Time	Data count	Temp. (°C)	Humid. (%)	Press. (mb)
Tuesday 03/05/2022	0827-1045	9650	9.2	84.6	1010
	1353-1655	10924	12.5	77.9	1009
	0757-0953	6637	8.7	85.5	1010
Wednesday 04/05/2022	0855-1219	12256	10.5	100.0	1005
	1454-1800	11155	11.6	77.9	1006
	0854-1051	6539	10.4	100.0	1005
Thursday 05/05/2022	1013-1315	10907	12.3	83.7	1012
	1553-1858	11132	12.5	81.8	1012
	1001-1143	5391	11.5	85.7	1012
	1550-1709	4494	13.3	77.2	1013
Friday 06/05/2022	1057-1414	11823	12.3	88.8	1011
	1053-1210	4521	12.3	88.7	1011
Sunday 08/05/2022	0910-1124	8020	12.4	69.2	1017

2.1 Collection

UFP measurements were made by car and bicycle over 5 days during one week in May 2022 in Lancaster, UK. Measurements were made between 8am and 7pm, and were designed to maximise

[1] https://pypi.org/project/LancasterAQ/

temporal coverage and sample the city's road and cycle networks. Measurements were made over $\sim$ 3 hours for driving and $\sim$ 90 minutes for cycling. One driving measurement campaign was also carried out on a Sunday morning to give an indicative background UFP concentration. In total, we completed 8 measurements by car and 5 by bicycle. Routes were driven with the aim of driving past 6 key waypoints: 1) the A6, which is the main road from the city centre out to the university and the M6 motorway; 2) the one-way system that goes around the city centre and is the main thoroughfare between Lancaster and the adjoining urban centre of Morecambe; 3/4) Bowerham and Hala, which are both residential areas with some schools and a frequent bus route; 5) the Greyhound Bridge, which is a major bottleneck in Lancaster; and 6) the Lune Industrial Estate. The cycling routes sampled key cycling infrastructure including the canal towpath and popular cycle paths through the city centre. Where cycle paths were unavailable, cycling was done on the road.

All UFPs measurements were made using the NAQTS V2000[2]. Two devices were co-located prior to deployment for calibration. Flow and zero checks were done daily before monitoring. For the vehicle-based monitoring, a V2000 was put in the rear passenger seat with a tube out of the window facing towards the front of the vehicle, following the testing methodology outlined by Lim et al. [9] that also used a V2000. For the bicycle-based measurements, we modified a bicycle trailer to carry the V2000. UFP loss corrections for the sample tubes were calculated before measurements. Measurements were made at 1 second time intervals and were geo-located using an onboard global positioning system (GPS).

2.2 Metadata

Lancaster is a city in North West England, with a population of 52234 as of the last census. All routes started and finished at Lancaster University, located approximately 5km south of the city centre. In total, we covered 397km and collected 31.5 hours (113449 data points) of on-road UFP data (113449 data points), which is summarised in Table 1 alongside complementary meteorological metadata collected by Lancaster University's weather station, Hazelrigg.

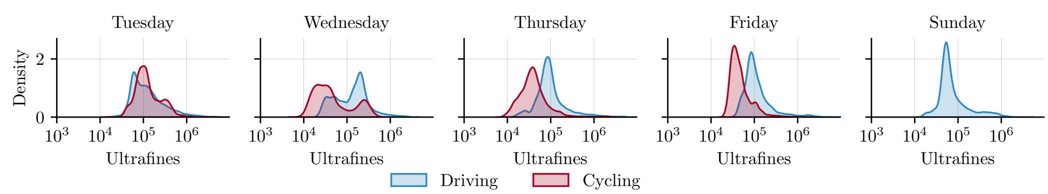

Figure 1: Kernel density estimate of log UFP levels stratified by the day of the week and the vehicle used to collect the readings.

2.3 Limitations

While the data are available at a high time resolution (1 second), we recognise that the data are temporally limited as the measurements were only taken for portions of 5 days in May 2022. This was partially mitigated by using a sliding start time each day, which varied the time windows captured. Some covariate information is available for the meteorological conditions, which are important for UFPs levels, but there are no associated traffic data available, which represents a key source for UFPs. Finally, the data are right-skewed and exhibit discontinuities which makes modelling a challenging task that we address in Section 3. Nevertheless, the data are amenable to modelling approaches on a range of supports, including spatial grids [10] or networks [13, 11].

3 Preliminary analysis

In this section, we will present a brief summary of the dataset. We do not aim to explore any patterns in the data, but rather highlight some of the information they contain, to enable and motivate wider community engagement. The World Health Organisation define UFP counts of less than 1000 particles/cm^3 as low and counts greater than 20000 particles/cm^3 are considered high [17].

[2]https://www.naqts.com/our-technology/v2000/

Within the data presented here, the smallest measurement is 748 particles/cm^3 and 0.1% of all measurements are less than 1000 particles/cm^3. Conversely, the largest collected measurement is 874034 particles/cm^3 and 18.8% of all measurements surpass the 20000 particles/cm^3 threshold.

For regression modelling, one could either use UFP or $\log$UFP as our response variable. In Figure 1 we explore its shape through a set of kernel density estimates: one per day of the week and vehicle type. The modelling challenge here is immediately apparent through the measurements' right-skew.

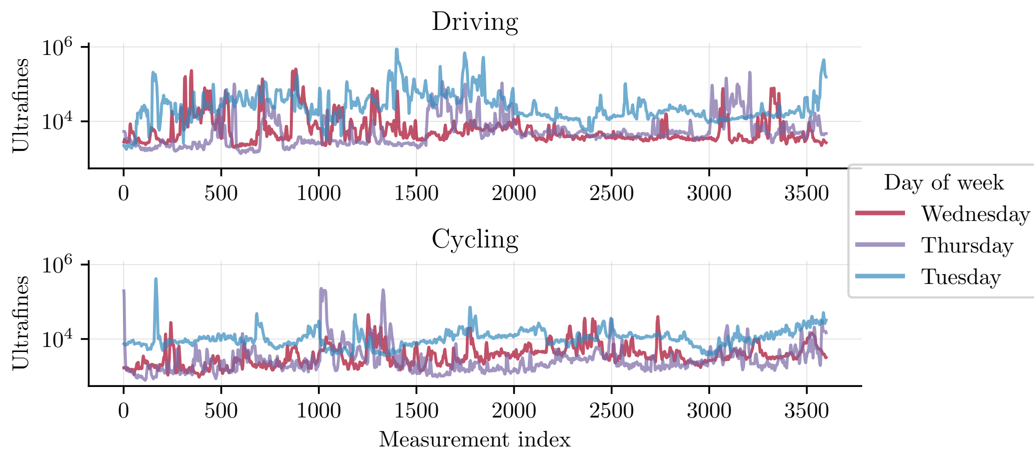

Figure 2: 1 hour of log-scaled UFP measurements with a 2-second moving average applied. Each line represents an individual journey.

As data collection process here is sequential, a natural task one may wish to carry out is time series modelling. In Figure 2 we plot the time series associated with four trips: the cycling and driving journeys that were carried out on both the Tuesday and Wednesday mornings. For easier visualisation, the data have been log-scaled and a 2-second moving average has been applied. However, even with these transformations applied, the roughness of the data is apparent.

4 Conclusion

To allow members of the climate science and atmospheric communities to more easily access the data, we have created and published a Python package titled `LancasterAQ` on PyPi. Through this package, the UFPs data can be loaded into a Python module as either a tabular GeoPandas DataFrame [6], or a networkx graph object [4].

With this data, we will initially model UFP concentrations on a graph structure [13] to produce local exposure maps and a route planner which accounts for exposure to poor air quality. This is only possible due to the dataset's high resolution. Our motivation for publishing this data is to encourage the applied machine learning community to investigate and model questions including the influence of humans on UFPs, the links between climate, clouds and UFPs, and how public policy can mitigate impacts on our changing social and physical world.

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