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Tracking Carbon Emissions: Mapping CO_2 in North Wales

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Abstract: In response to escalating global and national commitments to net-zero carbon targets, there is an increasing imperative to enhance awareness of carbon dioxide (CO_2) concentrations at the community level. This study investigates spatial patterns of CO_2 emissions across Wrexham County Borough, which comprises 34 administrative communities in northeastern Wales. By integrating satellite-derived CO_2 concentration datasets with official boundary data using Python-based geospatial libraries and online geographic information systems, we generated interactive spatial visualisations to identify persistent emission hotspots. The analysis reveals consistently elevated CO_2 levels in the northeastern communities, particularly Rossett and Holt. These visual outputs offer transparent, reproducible, and accessible insights to support evidence-based environmental planning, public engagement, and local policy development.

Key words: data for social good; big data analysis; human-centric computing; CO_2 emissions; geospatial analysis

1 Introduction

Carbon dioxide (CO_2) is a naturally occurring, colourless, and odourless gas that plays a fundamental role in Earth's ecological systems. While essential for biological processes such as photosynthesis and respiration, CO_2 is also the most prevalent anthropogenic greenhouse gas, contributing significantly to the intensification of the greenhouse effect and global climate change. Alongside other greenhouse gases including water vapour, methane, and nitrous oxide, CO_2 absorbs infrared radiation, thereby influencing atmospheric temperature dynamics[1].

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Since the onset of the Industrial Revolution, atmospheric CO_2 concentrations have increased markedly due to fossil fuel combustion, industrial processes, aerosol emissions, and land-use changes such as deforestation and intensive agriculture[2]. Despite its global relevance, the spatial resolution of CO_2 monitoring remains limited at the local and regional scales, impeding the development of targeted mitigation strategies.

Although elevated CO_2 levels are widely associated with adverse climate impacts, some studies suggest potential benefits, such as enhanced plant growth and vegetation expansion under higher concentrations[3–5]. Nevertheless, CO_2 remains a critical driver of climate instability, and its role in maintaining Earth's natural greenhouse effect underscores the need for balanced and context-sensitive analysis[6].

To align local interventions with broader climate objectives, community-scale CO_2 monitoring is essential. High-resolution spatial data and visualisations facilitate targeted policy responses, enable the

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evaluation of mitigation outcomes, and promote coherent climate governance. In the absence of such data, climate strategies risk being misaligned and less effective[7]. Moreover, spatial monitoring supports the assessment of geoengineering approaches, such as carbon capture and storage (CCS), while reinforcing transparency and accountability in environmental decision-making[8].

Wrexham County Borough presents a pertinent case for regional CO_2 analysis. Located in northeastern Wales and bordering England, Wrexham encompasses a diverse mix of urban, peri-urban, and rural communities[9]. The eastern corridor is densely populated, whereas the western region features elevated terrain and natural landscapes, including the Berwyn Mountains and Ceiriog Valley[10]. According to 2023 regional greenhouse gas emission estimates released by the Department for Energy Security and Net Zero, which was published on 3 July 2025, Wales's per capita emissions were estimated at 8.1 t of CO_2 equivalent (tCO_2e), significantly exceeding the UK average of 5.0 tCO_2e[11], thus, highlighting Wrexham County, a semi-urban region appropriate for emissions research.

Despite increasing commitments to net-zero targets, Wrexham currently lacks community-scale spatial data on CO_2 concentrations. Existing government monitoring frameworks rely on aggregated statistics[11], which obscure intra-regional variation and hinder targeted climate action. The absence of granular, visualised data limits the capacity of planners and stakeholders to identify emission hotspots, evaluate interventions, and align local efforts with national and global climate goals.

This study addresses this gap by applying a data-driven geospatial framework to map CO_2 concentrations across Wrexham County Borough. By incorporating insights from neighbouring Flintshire, this study aims to support scalable, locally responsive climate planning. The primary objective is to identify CO_2 hotspots, suggest possible spatial drivers of CO_2 variation, and provide replicable, community-level visualisations to inform policy development and stakeholder engagement.

2 Related Work

2.1 Drivers of atmospheric CO_2 variability

Atmospheric CO_2 levels are shaped by a complex interaction of human activities, natural processes, and geoclimatic factors[12, 13]. Natural elements like vegetation influence CO_2 through seasonal cycles of photosynthesis and respiration, acting as both sinks and sources[14–16]. Major anthropogenic sources, however, include fossil fuel combustion[17, 18] and traffic emissions[19], which dominate urban and peri-urban landscapes[20]. Meteorological parameters such as temperature, precipitation, soil moisture, wind speed, wind direction, and rainfall further affect CO_2 dispersion and mixing as seasons change, adding spatial and temporal variability to concentration patterns[21]. The combined influence of these drivers (Table 1) produces substantial spatial and temporal variability in CO_2 concentration fields, underscoring the importance of analytical approaches capable of resolving fine-scale distribution difference at the community level, rather than relying exclusively on broader regional or national averages.

Table 1 Factors influencing CO_2 emissions: a review of prior research.

Factor type	Factor	Ref. [12]	Ref. [13]	Ref. [14]	Ref. [15]	Ref. [16]	Ref. [17]	Ref. [18]	Ref. [19]	Ref. [20]	Ref. [21]	Ref. [22]
Non-anthropogenic	Meteorological parameters	√	√	√	√	—	—	—	—	—	√	—
	Biomass burning	—	—	—	—	—	—	—	—	—	—	—
	Vegetation cover	—	—	√	√	—	—	—	√	—	√	—
	Population	√	—	—	—	—	—	—	—	—	—	—
	Seasonal changes	√	—	—	√	√	—	—	—	—	—	√
	Leaf area index (LAI)	√	—	—	—	—	—	—	—	—	—	—
	Particulate aerosols	—	—	—	—	—	—	—	—	—	—	√
Anthropogenic	Fossil fuel combustion	—	√	√	—	—	√	√	√	√	—	—
	Deforestation	—	—	—	—	—	√	—	—	—	—	—
	Industrial activities	—	√	—	—	—	—	—	—	√	—	—

Note: √ indicates that the authors of the reference agree that the corresponding factor influences CO_2 emissions while — indicates the opposite.

2.2 High-resolution CO_2 mapping approaches

Advances in spatially explicit CO_2 mapping leverage diverse methodologies to capture fine-scale emission patterns and driver-response dynamics. Urban and peri-urban studies integrated satellite retrievals, ground-based networks, and ancillary datasets such as energy and land-use indicators within geographic information systems (GIS) and geostatistical frameworks. A summary of these methodologies is presented in Table 2. Techniques range from composite hotspot mapping and spatial correlation analyses[23] to kriging-based fusion of multi-satellite observations[24], grid overlays linking CO_2 data with urban morphology[25], and hybrid approaches combining remote sensing with socio-economic metrics[21, 26, 27]. Reviews underscored the value of interpretability and accessibility in GIS-enabled visualisation, while practical web-mapping tools (e.g., Folium) increasingly support neighbourhood-scale exploration and stakeholder engagement[20, 28–31].

2.3 Community-based CO_2 monitoring

While national decarbonisation policies in the UK have driven overall emission reductions through renewable energy adoption and gradual coal phase-out[32], significant sub-regional disparities remain. Community-scale monitoring addresses gaps in national inventories by capturing fine-grained variability influenced by traffic, industrial clustering[33], micro-meteorology, and street-canyon geometry[34–36]. Participatory initiatives highlight the potential of citizen-generated data but also expose challenges in standardisation, calibration, and integration with authoritative geospatial frameworks[37, 38]. In semi-urban contexts such as North Wales, dispersed settlement patterns and mixed land use further underscore the need for locally resolved evidence to support equitable, data-driven governance[9]. Addressing these gaps is vital for achieving net-zero targets. Hale et al.[39] and the IPCC[2] stressed the importance of locally tailored, accountable strategies supported by granular regional data. Without such insight, national mitigation efforts risk falling short.

2.4 Methodological implications

This study is therefore guided by three core principles: (1) focus on community-scale units to mitigate aggregation bias; (2) integrate geospatial layers with satellite-derived data to relate CO_2 concentrations to possible key drivers; and (3) ensure transparent visualisation to support public engagement and policy dialogue. Prior work demonstrates the utility of grid-based CO_2 mapping combined with socio-environmental indicators linking concentrations to population, road networks, and land cover[23, 25, 26]. Web-first GIS platforms further illustrate how interactive choropleths and hotspot layers can be operationalised for local decision-making[20, 28, 31].

2.5 Semi-urban research gap

Semi-urban areas with mixed land use and dispersed settlement patterns remain largely overlooked in high-resolution CO_2 research[20, 40]. North Wales exemplifies this gap, with transitional zoning, small-scale industry, and transport-driven emissions creating a data-poor context where neighbourhood-level evidence is critical for proportionate interventions[9, 11]. Existing studies seldom quantify how semi-urban morphology, fragmented built form, variable canopy

Table 2 Review of empirical CO_2 mapping approaches.

Study	Data source	Visualisation tool	Geographical area
Ref. [23]	Composite maps	Spatial correlation maps, composite maps	USA
Ref. [24]	Multiple satellite data	Kriging method	Global
Ref. [25]	Satellite data	Multilayer mapping	USA
Ref. [26]	Energy consumption data, calculated cross-sector emissions, satellite data	GIS	China
Ref. [27]	Satellite data from Orbiting Carbon Observatory-2 (OCO-2) (OCO-2)	Kriging method	Serbia
Ref. [28]	Interactive and web-based climate data visualizations	Climate visualization tools (CVTs)	Global
Ref. [29]	Multi-sourced datasets	GIS-based technique	Global
Ref. [30]	CO_2 sequestration monitoring	GIS-based technique	Global
Ref. [31]	CO_2 dataset from an article	Python Folium heatmap	Gulf Cooperation Council (GCC)

cover, and heterogeneous traffic regimes shape CO_2 hotspots, constraining regional climate governance and the localisation of net-zero strategies[2, 39].

2.6 Study contribution

Aligned with IPCC guidance on the value of transparent, spatially explicit data for empowering sub-national actors[41], this study operationalises a community-scale geospatial framework for Wrexham, with comparative analysis to Flintshire, to deliver interpretable visualisations that strengthen regional planning and public engagement. By integrating CO_2 fields with GIS layers to identify hotspots and link concentrations to local drivers, this work bridges technical analysis and spatial storytelling, promoting accountability and collaborative climate action. Addressing a semi-urban context largely absent from high-resolution CO_2 mapping, it contributes empirical evidence at the neighbourhood scale and demonstrates a replicable pathway for data-driven, locally accountable net-zero strategies in transitional regions.

3 Methodology

3.1 Research design

This study adopts a spatially explicit, data-driven framework to quantify and visualise community-level CO_2 concentrations across Wrexham County Borough. Demographic data collected were geocoded and validated against official administrative boundaries to ensure spatial accuracy. Historical CO_2 concentration data (1 January–30 June 2025) were retrieved via the Open-Meteo Air Quality API and pre-processed for completeness and temporal consistency. The study period was selected to capture seasonal emission peaks associated with vegetation dormancy and increased residential heating in the Northern Hemisphere. Descriptive statistical methods were employed to assess spatial and temporal variability across its 34 communities. Geospatial visualisation tools were used to map concentration distribution difference and identify emission hotspots. The framework supports reproducible sub-regional analysis and provides a foundation for future studies examining relationships between emissions, demographics, and infrastructure. Figure 1 illustrates the methodological workflow.

As defined in this study, hotspots are communities with CO_2 levels consistently above the study-wide average. They were identified by comparing each community's mean CO_2 concentration and selecting those with the highest overall values.

3.2 Data collection and pre-processing

3.2.1 Demographic and boundary data

Community-level demographic data were sourced from the Office for National Statistics (ONS), incorporating Census 2021 figures and 2022 mid-year estimates. These datasets enabled the delineation of 34 communities and were compiled into a structured dataframe using Python's libraries for subsequent geospatial mapping. Administrative boundary data were obtained via the Geoapify Boundaries API, generating multi-polygon GeoJSON representations for spatial integration.

3.2.2 Geocoding

Community names were geocoded using the GeoPy library with the Nominatim API, producing latitude and

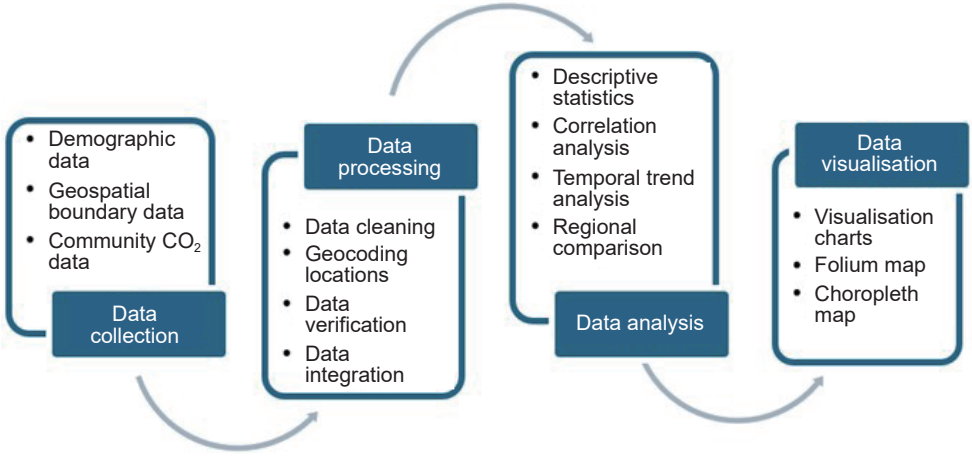


Fig. 1 Methodological workflow design of the geospatial CO_2 analysis.

longitude coordinates for each locality. A custom Python function ensured reliable querying and compliance with API constraints. The resulting geospatial dataset was merged with boundary and emissions data to enable spatial analysis.

3.2.3 Geolocation validation and mapping

Geospatial coordinates were validated and visualised using Python's Folium library[42]. Initial mapping revealed geocoding discrepancies, which were corrected through refined queries and manual verification. The final dataset ensured accurate spatial alignment within administrative boundaries and supported interactive mapping for downstream analysis.

3.2.4 CO_2 data acquisition and cleaning

Community-specific CO_2 data were retrieved from the Open-Meteo Air Quality API[43] using validated geolocation inputs. The API, based on Copernicus Atmosphere Monitoring Service (CAMS) CO_2 forecasts, provided hourly elevation-adjusted values at ~10 km resolution. Custom Python routines automated data acquisition and cleaning, including field validation, transformation, and summarisation. Non-essential fields were excluded, and key metrics were renamed for clarity. The final dataset was integrated with geospatial and demographic layers for analysis. Land use data were obtained from Wrexham LANDMAP Supplementary Planning Guidance[44].

3.3 Data analysis

3.3.1 Descriptive statistics

A unified dataset combining geolocation, demographic, and CO_2 concentration data was constructed. Descriptive statistics, including minimum (Min), maximum (Max), mean (Mean), and standard deviation (SD), were calculated to assess emission patterns across communities during the study period. Population was analysed for potential correlations with atmospheric CO_2 levels.

3.3.2 Spatial visualisation

CO_2 concentrations were visualised using line and bar charts to compare community-level values against countywide averages. Ranked plots identified high-emission zones, while stacked bar charts supported multivariate interpretation of emission patterns across top-emitting communities.

3.3.3 Correlation analysis

Preliminary correlation analysis examined associations between population and mean CO_2 concentrations. Scatter plots were used to identify trends and anomalies. Choropleth maps, integrating boundary and population data, provided visual insights into spatial distribution.

3.3.4 Identifying persistent CO_2 emission hotspots

The top ten communities with the highest mean CO_2 concentrations were identified using geospatial visualisations. Folium markers and choropleth maps highlighted spatial distribution and emission intensity. Interactive maps developed with Folium and Datawrapper enhanced interpretability and public accessibility. Mapping procedures were documented to ensure reproducibility.

3.3.5 Temporal trend analysis

Monthly trends in CO_2 concentrations were analysed to assess intra-community variability. Minimum, maximum, and mean values were computed for each community. Choropleth maps visualised temporal and spatial patterns, supporting comparative analysis.

3.3.6 Regional comparison

To evaluate regional emission dynamics, the analytical framework was replicated for Flintshire County. Community-level data were processed using consistent geospatial methods. Choropleth maps facilitated comparative interpretation, revealing similarities in CO_2 variability across both counties. Colour scale thresholds were normalised to ensure visual coherence.

All procedures prioritised transparency and reproducibility. Publicly available datasets were used exclusively for scientific, non-commercial purposes, and contained no personally identifiable information, ensuring compliance with data privacy standards.

4 Analysis and Result

Integrated datasets of communities in Wrexham County, including historical CO_2 readings, geospatial boundaries, and demographic indicators, enabled high-resolution analysis of CO_2 emission dynamics. The analytical workflow included multi-source data validation, Python-based statistical and geospatial processing, community-level ranking, choropleth mapping, monthly trend analysis, and inter-county comparison using harmonised methods. This structured approach supports granular hotspot identification and informs region-specific monitoring and mitigation strategies.

4.1 Data collection

Ambient CO_2 concentration data for 34 communities in Wrexham were retrieved from the Open-Meteo Air Quality API and pre-processed to ensure temporal consistency. Key variables, including population, geocoded coordinates, and CO_2 concentration, were compiled to support descriptive and spatial analysis. Table 3 presents the complete dataset used in this study.

4.2 Statistical analysis

Descriptive statistics (Table 4) revealed a consistent regional baseline, with mean CO_2 concentrations ranging from 4.4360×10^{-4} to 4.4610×10^{-4} (Mean = 4.4521×10^{-4}, SD = 5.90×10^{-7}). Approximately 75% of communities recorded mean values below 4.4570×10^{-4}, indicating limited spatial dispersion. Minimum concentrations showed greater variability (Mean = 4.1644×10^{-4}, SD = 5.85×10^{-6}), ranging from 4.03×10^{-4} to 4.22×10^{-4}, while peak values were more pronounced (Mean = 4.8826×10^{-4}, SD = 9.55×10^{-6}), spanning 4.72×10^{-4} to 5.11×10^{-4}—suggesting localised or episodic emission drivers.

Table 3 Wrexham communities, population, geolocation, and CO_2 concentration data.

Number	Community	Population	Latitude	Longitude	CO_2 concentration during January–June 2025 (10^{-4})		
					Mean	Min	Max
1	Abenbury	2600	53.041 589 8°N	2.944 716 9°W	4.4533	4.10	4.93
2	Acton	12 600	53.057 849 0°N	2.982 120 1°W	4.4579	4.20	4.95
3	Bangor Is-y-coed	1100	53.002 968 8°N	2.909 153 1°W	4.4533	4.10	4.93
4	Bronington	1100	52.949 685 1°N	2.765 981 9°W	4.4541	4.07	4.91
5	Broughton	7800	53.066 706 1°N	3.037 224 1°W	4.4579	4.20	4.95
6	Brymbo	5200	53.076 636 2°N	3.060 781 4°W	4.4525	4.21	4.84
7	Caia Park	12 700	53.044 685 7°N	2.973 131 8°W	4.4509	4.21	4.84
8	Cefn	6800	52.980 552 5°N	3.073 929 3°W	4.4579	4.20	4.95
9	Ceiriog Ucha	300	52.899 699 1°N	3.275 342 4°W	4.4360	4.03	4.72
10	Chirk	4400	52.932 010 9°N	3.056 386 0°W	4.4427	4.17	4.75
11	Coedpoeth	4400	53.053 982 3°N	3.063 956 0°W	4.4525	4.21	4.84
12	Erbistock	350	52.968 499 5°N	2.966 506 1°W	4.4509	4.21	4.84
13	Esclusham	3600	53.027 099 1°N	3.050 420 0°W	4.4483	4.22	4.78
14	Glyntraian	780	52.922 336 5°N	3.146 228 3°W	4.4427	4.17	4.75
15	Gresford	4.900	53.085 506 9°N	2.971 985 0°W	4.4579	4.20	4.95
16	Gwersyllt	10 700	53.073 261 6°N	3.019 467 5°W	4.4579	4.20	4.95
17	Hanmer	630	52.952 281 2°N	2.812 836 7°W	4.4523	4.05	4.96
18	Holt	1600	53.078 489 3°N	2.882 410 3°W	4.4610	4.17	511
19	Isycoed	440	53.047 829 3°N	2.891 628 4°W	4.4533	4.10	4.93
20	Llangollen Rural	2000	52.971 061 9°N	3.085 762 8°W	4.4483	4.22	4.78
21	Llansantffraid Glyn Ceiriog	980	52.931 556 6°N	3.188 845 6°W	4.4367	4.13	4.72
22	Llay	5000	53.097 079 6°N	2.999 472 5°W	4.4579	4.20	4.95
23	Maelor South	1500	52.936 647 6°N	2.834 215 7°W	4.4541	4.07	4.91
24	Marchwiel	1300	53.023 457 4°N	2.959 892 7°W	4.4509	4.21	4.84
25	Minera	1500	53.059 577 3°N	3.084 721 8°W	4.4525	4.21	4.84
26	Offa	11 400	53.039 988 4°N	3.000 935 6°W	4.4509	4.21	4.84
27	Overton	1300	52.969 840 1°N	2.934 470 4°W	4.4533	4.10	4.93
28	Penycae	3400	53.000 922 2°N	3.076 666 0°W	4.4483	4.22	4.78
29	Rhosddu	6600	53.053 379 6°N	2.996 481 7°W	4.4579	4.20	4.95
30	Rhosllanerchrugog	9300	53.012 734 6°N	3.059 416 0°W	4.4483	4.22	4.78
31	Rossett	3300	53.109 622 5°N	2.944 909 6°W	4.4610	4.17	5.11
32	Ruabon	4300	52.987 131 2°N	3.041 496 9°W	4.4509	4.21	4.84
33	Sesswick	560	53.015 931 1°N	2.912 977 9°W	4.4533	4.10	4.93
34	Willington Worthenbury	800	53.002 847 8°N	2.862 677 9°W	4.4533	4.10	4.93

Table 4 CO_2 concentration of 34 communities statistical summary (January to June 2025).

Statistical index	Population	CO_2 concentration during January–June 2025		
		Mean	Min	Max
Mean	3978	4.4521×10^{-4}	4.1644×10^{-4}	4.8826×10^{-4}
SD	3731	5.90×10^{-7}	5.85×10^{-6}	9.55×10^{-6}
Min	300	4.4360×10^{-4}	4.03×10^{-4}	4.72×10^{-4}
25% of communities	1100	4.4509×10^{-4}	4.10×10^{-4}	4.84×10^{-4}
50% of communities	2950	4.4529×10^{-4}	4.20×10^{-4}	4.91×10^{-4}
75% of communities	5150	4.4569×10^{-4}	4.21×10^{-4}	4.95×10^{-4}
Max	12 700	4.4610×10^{-4}	4.22×10^{-4}	5.11×10^{-4}

Population varied significantly, from 300 in Ceiriog Ucha to 12 700 in Caia Park (Mean = 3978, SD = 3731). Most communities had populations below 5150, reflecting a predominance of smaller settlements with a few densely populated areas.

4.3 Data visualisation

Spatial visualisation of CO_2 concentrations (Fig. 2) revealed marked disparities. While mean values remained below 4.50×10^{-4} in most communities, Holt and Rossett recorded the highest mean levels (4.4610×10^{-4}) and peak concentrations exceeding 5.10×10^{-4}. Ceiriog Ucha exhibited the lowest minimum value at 4.03×10^{-4}.

Benchmarking community-level maxima against the countywide mean of 4.8826×10^{-4} showed 18 communities above this threshold, with most clustering near 4.95×10^{-4}. Holt and Rossett deviated significantly, suggesting potential outlier status. However, comparing mean values of CO_2 concentration against the countywide average (4.4521×10^{-4}) confirmed only 13 communities fell below this threshold, reinforcing Holt and Rossett's classification as consistently high-emission zones. Minimum CO_2 concentrations, benchmarked against the mean-of-minima (4.1644×10^{-4}), further validated dataset consistency. Hanmer, with the lowest minimum CO_2 concentration (4.05×10^{-4}) and a peak of 4.96×10^{-4}, exhibited episodic fluctuations, while Maelor South showed a stable profile with a

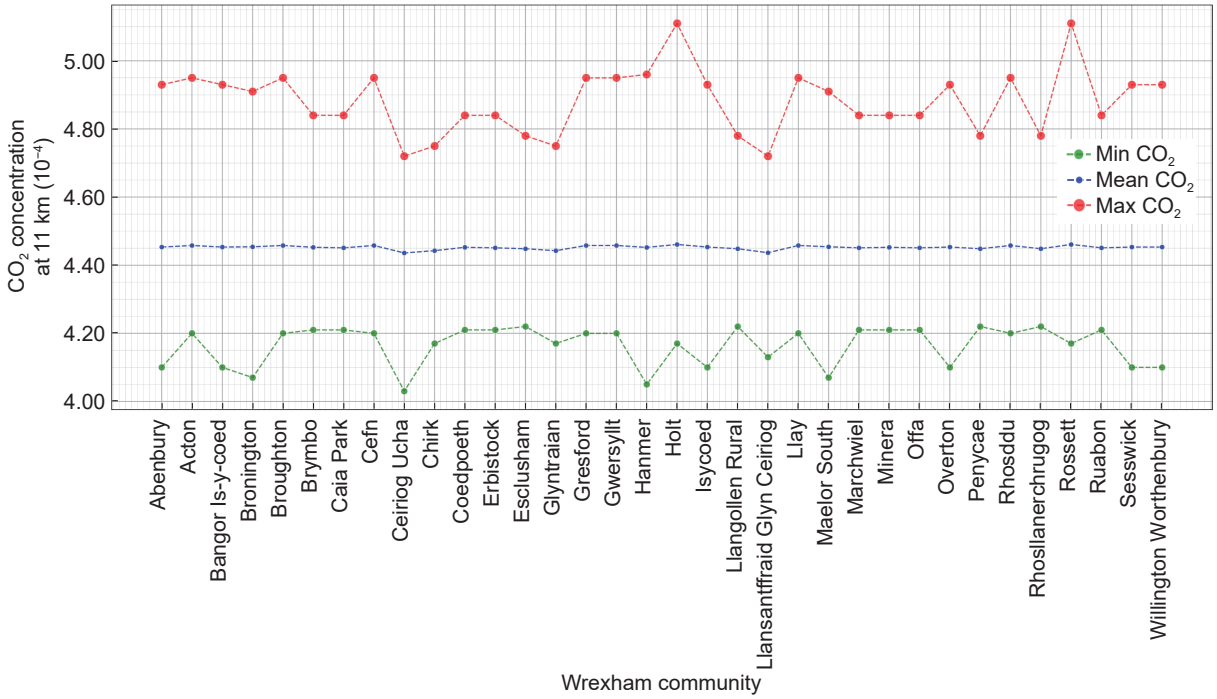


Fig. 2 Comparison of minimum, mean, and maximum CO_2 concentrations at 11 km across communities during January–June 2025.

consistently elevated mean (4.4541×10^{-4}) and minimal variation.

Ten communities with mean CO_2 concentrations exceeding 4.4540×10^{-4} were classified as high-emission zones relative to others. Ranking by maximum CO_2 values enabled assessment of episodic peaks, though interpreted cautiously due to potential outlier effects. Figure 3 presents a stacked bar chart comparing communities by mean, minimum, and maximum CO_2 concentrations. Eight communities appeared in both rankings by mean and maximum CO_2 levels, indicating persistent high emissions. Hanmer and Maelor South diverged. Hanmer ranked only by peak values, while Maelor South featured solely in the mean CO_2 concentrations list, thus highlighting the value of multi-metric approaches in spatial profiling.

Spatial distribution of CO_2 concentrations was visualised using Folium and Datawrapper. Figure 4 displays a Folium-generated Marker map[42] of high mean CO_2 concentrations, with Holt and Rossett identified as the highest hotspots (mean = 4.46096×10^{-4}). The interactive choropleth map in Fig. 5 illustrates regional distribution difference, with Ceiriog Ucha recording the lowest mean (4.43598×10^{-4}) and a corresponding maximum of 4.72×10^{-4}. These patterns

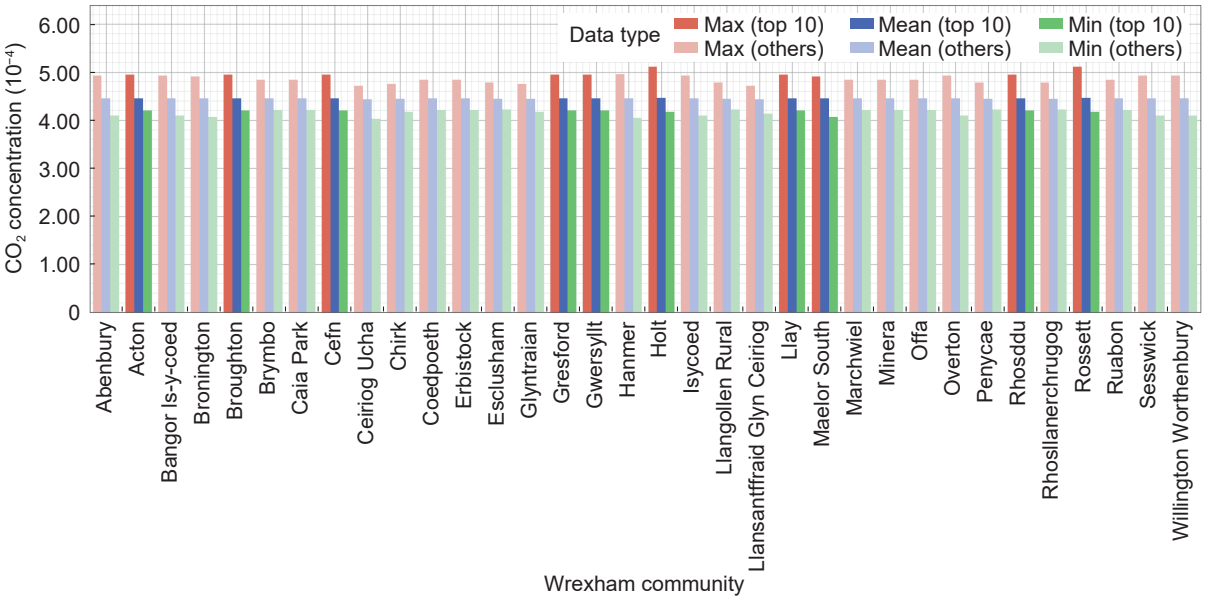


Fig. 3 Stacked bar chart highlighting top ten communities' maximum, mean, and minimum CO_2 concentrations.

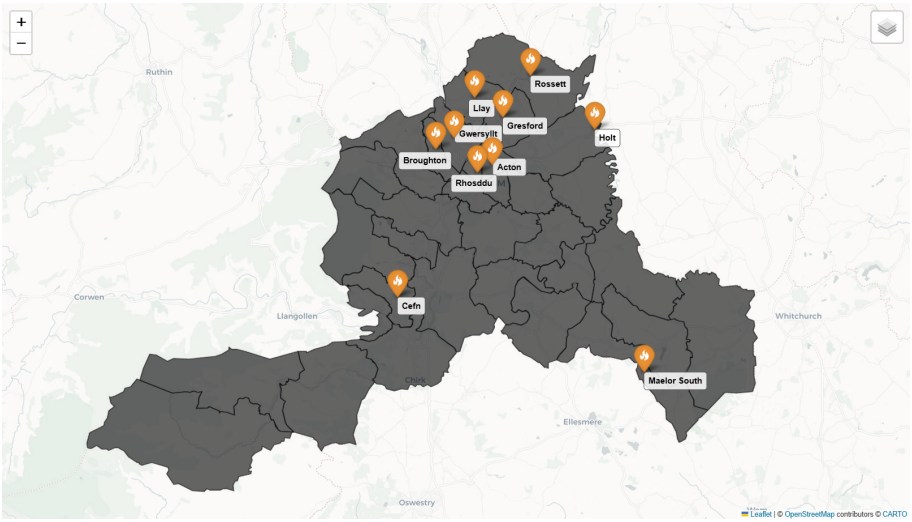


Fig. 4 Folium-generated marker map of the top ten mean CO_2 communities.

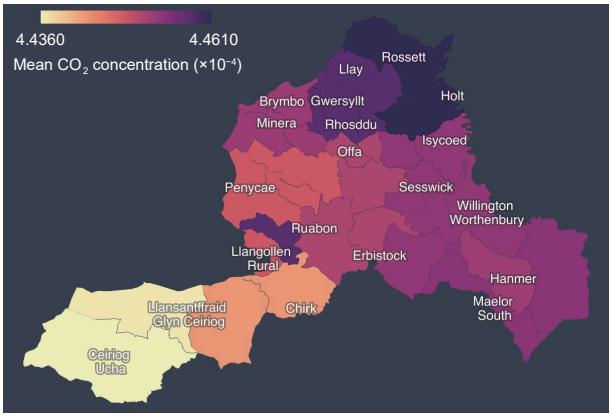


Fig. 5 Wrexham county communities choropleth map showing mean CO_2 concentration values during January–June 2025. The figure is created with Datawrapper.

align with statistical findings and reinforce the identification of persistent high-emission zones.

Comparative analysis of Figs. 5 and 6 generated using the Datawrapper tool[45], integrated with Geoapify[46] communities' boundary data, shows elevated CO_2 levels in both urban and semi-rural areas, with hotspots predominantly clustered in the northeast. This spatial bias suggests influence from localised environmental or anthropogenic factors beyond population.

4.4 Population-CO_2 correlation

Population (Fig. 6) analysis provided further context. Five communities, Acton, Caia Park, Gwersyllt, Offa, and Rhosllanerchrugog, each exceeded 8000 residents. Additional above-average populations were observed in Broughton, Cefn, and Rhosddu, while Brymbo, Gresford, and Llay surpassed the county mean by approximately 1000 residents. Most communities fell below this threshold, indicating substantial demographic variation. These patterns support preliminary assessment of potential correlations between population and ambient CO_2 concentrations.

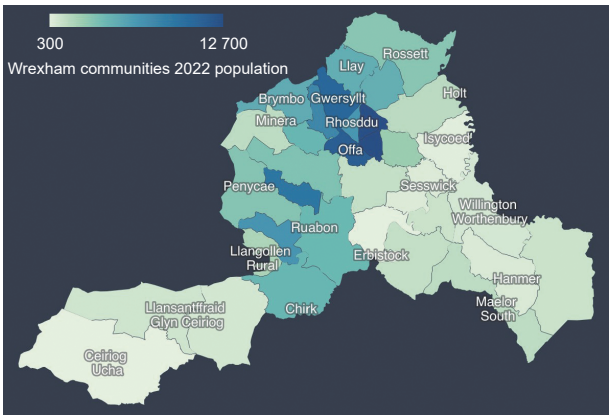


Fig. 6 Wrexham county communities choropleth map showing ONS 2022-mid year population based on the Census 2021. Creat with Datawrapper.

Figure 7 displays a scatter plot comparing communities' mean CO_2 concentrations with their 2022 population (the most recent official figures available at the time of analysis, derived from the Census 2021). A weak positive correlation (r = 0.284) was observed, suggesting that population is not a strong predictor of ambient CO_2 levels. This implies that spatial variability in CO_2 concentrations is likely driven by non-demographic factors such as transport activity, land use, topography, and industrial emissions.

Further comparison of population and mean CO_2 concentrations among the top ten hotspot communities supports this conclusion. Several high-emission areas, including Holt, Maelor South, and Rossett, recorded below-average populations. Notably, Rossett ranked second in mean CO_2 concentration (Fig. 6) despite its modest demographic size, reinforcing the need for a multi-factorial analytical approach.

4.5 Intra-community CO_2 concentration variability

Monthly analysis from January to June 2025 identified Rossett and Holt as consistently high-emission communities, with an overall mean of 4.4610×10^{-4} and a peak of 4.4956×10^{-4} in March 2025 (Fig. 8).

Both ranked among the top ten communities in all months except May, which marked a deviation in

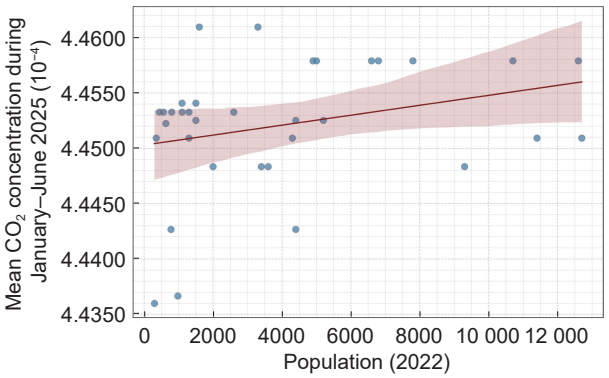
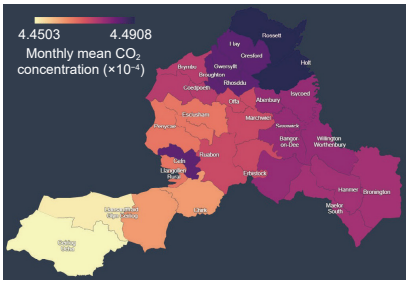
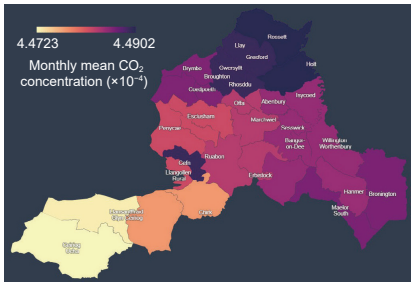


Fig. 7 Relationship the population in 2022 and the mean CO_2 concentration during January–June 2025. A fitted regression line illustrates the overall trend.



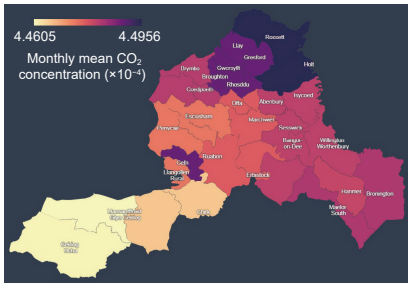
Community	Monthly mean CO_2 concentration (10^{-4})
Holt	4.4908
Rossett	4.4908
Gresford	4.4849
Broughton	4.4849
Rhoosddu	4.4849
Cefn	4.4849
Llay	4.4849
Acton	4.4849
Gwersyllt	4.4849
Sesswick	4.4788

(a) January 2025



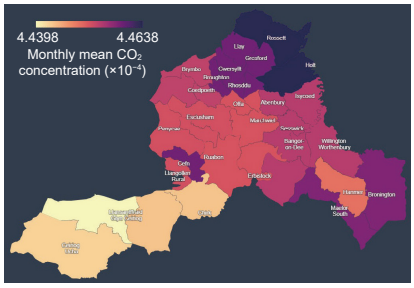
Community	Monthly mean CO_2 concentration (10^{-4})
Holt	4.4902
Rossett	4.4902
Cefn	4.4891
Gwersyllt	4.4891
Gresford	4.4891
Llay	4.4891
Acton	4.4891
Rhosddu	4.4891
Broughton	4.4891
Maelor South	4.4862

(b) February 2025



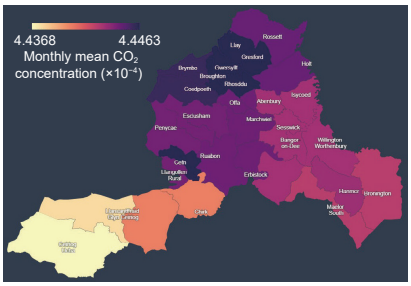
Community	Monthly mean CO_2 concentration (10^{-4})
Holt	4.4956
Rossett	4.4956
Cefn	4.4896
Gwersyllt	4.4896
Gresford	4.4896
Llay	4.4896
Acton	4.4896
Rhosddu	4.4896
Broughton	4.4896
Maelor South	4.4825

(c) March 2025



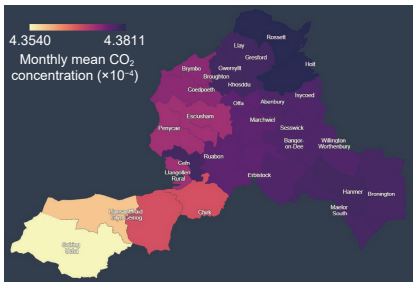
Community	Monthly mean CO_2 concentration (10^{-4})
Holt	4.4638
Rossett	4.4638
Gresford	4.4591
Broughton	4.4591
Rhosddu	4.4591
Cefn	4.4591
Llay	4.4591
Acton	4.4591
Gwersyllt	4.4591
Bronington	4.4582

(d) April 2025



Community	Monthly mean CO_2 concentration (10^{-4})
Rhosddu	4.4463
Llay	4.4463
Broughton	4.4463
Acton	4.4463
Cefn	4.4463
Gwersyllt	4.4463
Gresford	4.4463
Brymbo	4.4457
Coedpoeth	4.4457
Minera	4.4457

(e) May 2025



Community	Monthly mean CO_2 concentration (10^{-4})
Holt	4.3811
Rossett	4.3811
Hanmer	4.3790
Gwersyllt	4.3789
Broughton	4.3789
Rhosddu	4.3789
Cefn	4.3789
Llay	4.3789
Acton	4.3789
Gresford	4.3789

(f) June 2025

Fig. 8 Monthly mean CO_2 concentration differences across Wrexham (during January–June 2025) with embedded monthly top ten community tables.

spatial patterns. During May, communities such as Rhosddu, Llay, Broughton, Acton, Cefn, Gwersyllt, and Gresford recorded the highest mean CO_2 concentrations, averaging 4.4463×10^{-4}.

Figure 8 also illustrates a progressive decline in mean CO_2 concentrations following the March peak, confirming seasonal variability. Choropleth maps constructed from monthly data reinforce these trends, highlighting persistent hotspots alongside temporal shifts in emission dynamics. The anomaly in May suggests potential changes in local emission sources or atmospheric dispersion, warranting further investigation.

4.6 Regional CO_2 distribution

Figure 9 presents harmonised choropleth maps of Wrexham and Flintshire, enabling direct comparison of CO_2 concentration distribution difference. Flintshire's south-eastern corridor, including Saltney (4.4777×10^{-4}), Broughton, Bretton, Hawarden, Sealand, Queensferry, and Shotton, exhibited consistently elevated mean values (averaging 4.4724×10^{-4}). Adjacent Wrexham communities such as Rossett, Holt, Llay, and Gwersyllt recorded slightly lower concentrations, averaging below 4.4610×10^{-4}.

Flintshire displayed a broader CO_2 concentration range (4.4424×10^{-4}–4.4777×10^{-4}) compared with Wrexham (4.4360×10^{-4}–4.4610×10^{-4}), yet cross-boundary analysis revealed continuity in emission patterns. Rossett's mean CO_2 concentration of 4.4609×10^{-4} closely aligned with those of neighbouring Flintshire communities, suggesting regional homogeneity. Spatial clustering of elevated CO_2 concentration in south-eastern Flintshire and north-eastern Wrexham indicates influence from localised environmental or anthropogenic drivers. These findings underscore the need for targeted regional analysis and responsive mitigation strategies across North Wales.

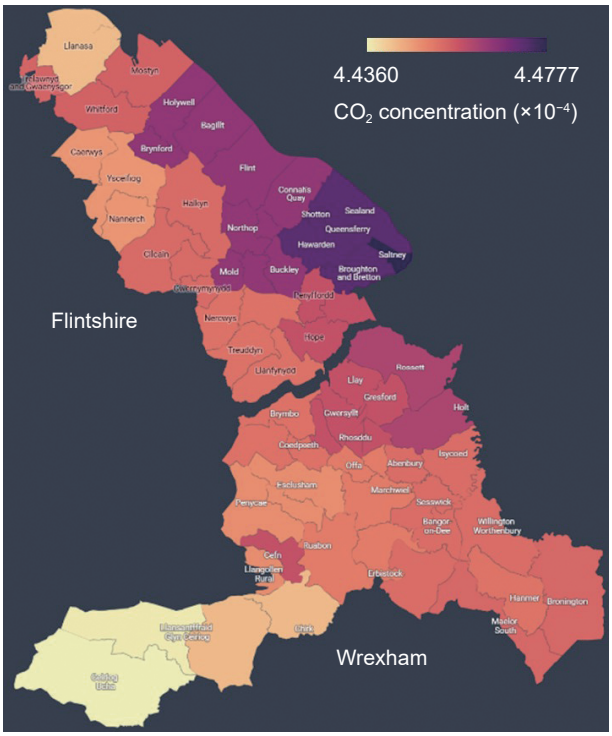


Fig. 9 Regional CO_2 concentration distribution map of Wrexham and Flintshire during January to June 2025.

4.7 Summary of key findings

Analysis across Wrexham's 34 communities revealed complex interactions among spatial, temporal, and demographic variables influencing ambient CO_2 concentrations. Holt and Rossett consistently recorded the highest mean and maximum values, reaffirmed through monthly analysis (January–June 2025), except for May, when both fell marginally below the top ten, both averaging 4.4447×10^{-4}.

A spatial cluster comprising Llay, Gresford, Gwersyllt, Broughton, Rhosddu, Acton, and Cefn (mean approximately 4.4580×10^{-4}) further highlighted elevated CO_2 concentrations, predominantly in the north-east. Cefn, located in the south-west, was the exception.

Correlation analysis (Fig. 7) showed a weak relationship between population and CO_2 concentration (r = 0.284), suggesting greater influence from non-demographic factors such as transport, land use, and topography. Comparative mapping (Figs. 5 and 9) revealed continuity in elevated CO_2 concentrations across the Wrexham–Flintshire border, with north-eastern Wrexham and south-eastern Flintshire forming a coherent high-emission zone.

These findings support a dual-scale analytical approach, capturing intra-county anomalies, and inter-county distribution difference and offer actionable insights for targeted monitoring, policy development, and public engagement aligned with regional climate objectives.

5 Discussion

5.1 Interpretation of key findings

Spatial analysis revealed consistently elevated ambient CO_2 concentrations in Wrexham's north-eastern communities, particularly Rossett and Holt. Their high monthly averages suggest influence from localised sources such as traffic, residential heating, or nearby emission points. A temporary decline in May 2025, when both fell outside the top-emitter rankings, indicates possible meteorological or seasonal effects on dispersion.

Cefn's inclusion among the top ten communities, despite its geographic separation from the north-east cluster, suggests a distinct localised driver. Such anomalies warrant further investigation into spatially linked anthropogenic and environmental factors.

Comparative analysis with Flintshire showed similarly elevated concentrations in south-eastern communities, Broughton, Bretton, Hawarden, Sealand, Queensferry, Shotton, and Saltney; mirroring high-emission zones in Wrexham (Holt, Rossett, Llay, Gresford, Gwersyllt, Broughton, Rhosddu, and Acton). Choropleth maps (Fig. 9) confirmed spatial continuity across the Wrexham–Flintshire boundary, indicating a regional hotspot potentially driven by industrial activity, transport corridors, or heating demand.

Wrexham's land use data were employed to understand and further explain possible drivers of high CO_2 emissions. Integration of boundary maps with land use and geospatial CO_2 data revealed that both Holt and Rossett communities lie within this low-lying fertile region in the plains of River Dee known as Dee Terraces. Agricultural land in this area is rated Grade 1 agricultural grounds and is therefore characterised by intensive agricultural farming[42, 43, 47]. Additionally, the area has constantly been under developmental pressure due to its natural beauty, causing it to lose its rural charm and some vegetation cover. These factors could explain their recorded high CO_2 concentrations.

To contextualise these findings, UK Local and

Regional Greenhouse Gas Emissions Statistics (2005–2023), published by the Department for Energy Security and Net Zero (3 July 2025), were reviewed. Wales reported higher per capita emissions than most UK regions, primarily from industrial (2.7 t CO_2 equivalent per capita) and agricultural (1.6 t CO_2 equivalent per capita) sectors[48], supporting the proposition that elevated CO_2 concentrations in the Wrexham–Flintshire corridor may stem from localised sources such as industrial activities or agriculture.

These spatial patterns underscore the need to refine community-level inventories and prioritise monitoring in persistently high-emission zones. The findings support community level targeted mitigation and cross-boundary policy coordination in North Wales.

5.2 Comparison with existing literature

The observed CO_2 distribution across Wrexham and Flintshire includes both expected and unexpected patterns. While urban density is often associated with elevated emissions, several semi-rural communities recorded high mean concentrations, challenging the assumption that population is the primary driver of high CO_2 emissions.

This aligns with the results of Zhu et al.[12], who found that near-surface CO_2 concentrations in China were influenced more by spatial location and the interactions between natural factors, and human activities, than population alone. Yang et al.[16] similarly highlighted seasonal dynamics as independent drivers. The roles of vegetation, fossil fuel combustion, domestic heating, industrial activity, and agriculture are likely relevant to Wrexham's peripheral communities.

The use of Folium and Datawrapper reflects a broader shift toward open-source geospatial platforms for environmental monitoring. This approach is consistent with the findings of Refs. [14, 20, 31], which demonstrated that browser-based visualisation tools enhance public engagement and interpretability. By presenting spatial data in accessible formats, this study contributes to participatory governance and best practices in climate communication.

5.3 Methodological insights and technical contributions

This study introduces a reproducible framework for assessing regional CO_2 dynamics, integrating statistical analysis, geospatial modelling, and interactive visualisation. The January–June 2025 period was selected to capture seasonal maximum CO_2 concentrations, enhancing sensitivity to emission anomalies.

High-resolution data from the Open-Meteo Air Quality API provided robust coverage. Geocoded community coordinates were combined with verified administrative boundaries to produce accurate base maps. Folium supported spatial validation, while Datawrapper choropleths visualised maximum and mean CO_2 concentrations, enabling hotspot identification and trend analysis.

Python libraries such as Pandas and NumPy facilitated scalable data processing, statistical summarisation, and emission ranking. Consistent pipelines across both counties ensured reproducibility, and modular code structures enabled efficient temporal analysis. This approach revealed multi-dimensional emission patterns that would otherwise remain obscured.

By linking structured atmospheric datasets with interactive geospatial tools, the study advances regional environmental analytics. The approach is flexible enough for similar semi-urban regions and scalable for UK-wide policy assessment.

5.4 Limitations

Several limitations should be noted. The analysis was restricted to January–June 2025, capturing seasonal CO_2 concentration peaks but excluding drawdown patterns typically observed later in the year. This limits long-term generalisability and predictive modelling.

CO_2 concentration data for Wrexham communities were collected from the Open-Meteo API using communities, centre point coordinates, from location name geocoding. The CO_2 emissions data retrieved represent archived forecasts derived from air-quality model output (based on CAMS) sampled hourly. While this reduces ground-level precision, it limits the mismatch in the scale grid size between the coarse-level grid of satellite data (10 km^2) and a community-level area (approximately 3 km^2). Hence, it should not be treated as precise community-level CO_2 measurement but an estimate. This, however, does not diminish the proportionate representation of CO_2 concentration in those local areas. This thereby justifies the robustness of our spatial conclusions. Moreover, the data do not account for multi-source emissions within each community as this would

require out-of-scope multiple visits to collect ground level CO_2 measurements at various locations to obtain exact reliability. Such modalities could improve spatial accuracy.

Causal inference was constrained by the absence of complementary datasets, including meteorological conditions, traffic volumes, vegetation cover, and industrial activity. As a result, observed relationships remain correlative.

Geospatial resolution was limited to administrative boundaries, which do not account for intra-community land use or microclimatic variation, potentially obscuring finer-scale emission heterogeneity.

While Datawrapper enhanced spatial interpretability, limitations in colour scale customisation may affect distribution difference perception and accessibility, particularly for visually impaired users. This highlights the need for inclusive visualisation practices.

Finally, time constraints limited broader data acquisition and cross-regional validation. The findings therefore represent a foundational layer for understanding regional atmospheric behaviour upon which further research may build.

5.5 Implications for policy and public engagement

This study offers actionable insights for environmental governance and public engagement in North Wales. The identification of CO_2 hotspots in north-eastern Wrexham and south-eastern Flintshire provides a data-driven foundation for targeted interventions, including sensor deployment, land-use audits, and seasonally adjusted mitigation strategies.

Interactive maps developed using Datawrapper serve both analytical and communicative functions. Their web-accessible format enables transparent dissemination of CO_2 data to residents, researchers, and policymakers, supporting participatory decision-making and informed planning for emission control and green infrastructure.

The mapping framework also facilitates cross-sectoral collaboration. The UK's carbon capture, usage, and storage (CCUS) initiative, beginning with Hynet in north-west England[49, 50], could benefit from the spatial modelling approaches demonstrated in this study. Overlaying emission trends on geographic basemaps allows rapid identification of priority zones for investment and infrastructure deployment.

Beyond policy, the platform is adaptable for educational and citizen science applications. Choropleth maps can be repurposed to monitor variables such as temperature, biodiversity, or population. Community involvement in such efforts fosters environmental stewardship, enhances public understanding, and improves data quality, particularly in under-monitored areas.

Commercially, the framework supports private-sector innovation in CO_2 monitoring technologies. Companies developing ground-level sensors may align with government priorities on emissions tracking and compliance, enabling public-private partnerships in climate adaptation.

Overall, the methodological and visual tools developed in this paper advance scientific understanding while supporting integrated strategies for policy development, public engagement, and regional investment in emission mitigation.

5.6 Recommendations for future research

Extend temporal coverage: Incorporate full-year or multi-year datasets to capture seasonal drawdown effects, interannual variability, and cyclical anomalies, improving trend analysis and climate modelling.

Integrate multi-modal monitoring: Combine satellite data with surface sensors, drone surveys, and aircraft-based observations to enhance spatial resolution and enable dynamic source attribution.

Enrich spatial modelling: Include auxiliary variables such as traffic density, industrial activity, topography, land use, vegetation indices, and green space coverage to strengthen causal inference and support targeted mitigation.

Apply machine learning: Use supervised learning, anomaly detection, and time-series forecasting to scale monitoring efforts and enable early identification of emission hotspots.

Evaluate policy impact: Employ longitudinal designs to assess CO_2 patterns before and after interventions (e.g., green infrastructure rollouts or heating retrofits), generating evidence for policy refinement.

Strengthen citizen science: Develop community-based sensor networks and participatory mapping initiatives to supplement formal monitoring, enhance data richness, and foster public engagement. Open-data platforms can support collaborative problem-solving.

Broaden geographic scope: Expand analysis to additional Welsh counties and bordering English jurisdictions to identify transregional emission corridors and inform harmonised mitigation strategies.

6 Conclusion

This study offers a detailed assessment of community-level CO_2 concentration patterns across Wrexham and Flintshire, revealing persistent emission hotspots in north-eastern Wrexham (Rossett and Holt) and south-eastern Flintshire (Saltney and adjacent communities). These findings highlight the influence of localised environmental and anthropogenic drivers within semi-urban landscapes.

For the January–June 2025 study period, which alignes with seasonal CO_2 peaks in the Northern Hemisphere, our analysis enhanced analytical sensitivity and captured elevated pre-photosynthetic concentrations. The combined use of satellite-derived data, statistical modelling, and interactive visualisation via choropleth mapping and monthly trend profiling enabled intuitive interpretation and informed targeted mitigation strategies.

Despite limitations in ground-level validation and contextual variables, the integration of geospatial analytics with open-access data demonstrates strong potential for supporting environmental governance. The visual tools developed promote policy formulation, public engagement, and citizen-led stewardship.

The analytical framework established here is scalable and transferable. Future research should extend temporal and spatial scopes, incorporate auxiliary datasets, and apply advanced predictive techniques to improve source attribution and forecasting. Strengthening cross-boundary collaboration and community participation will be critical to developing responsive, data-informed strategies for managing CO_2 concentrations and advancing regional climate objectives across North Wales and beyond.

Conflict of Interest

The authors declare no conflict of interest.

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