A place-based carbon calculator for England

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February 15, 2021

Summary
We report on progress towards creating an interactive place-based carbon calculator for England. The purpose of the calculator is to enable policymakers and the public to understand the spatial variation in per capita carbon footprint and monitor progress towards decarbonisation. The calculator will be launched in the summer of 2021 as a free web tool. The paper highlights the challenges and methods used to calculate carbon footprints for small areas and how new developments in web mapping can enable the presentation of large complex spatial datasets with minimal cost.

KEYWORDS: Carbon, Footprint, Place-based, Web mapping, Vector Tiles

1. Introduction

Climate change is a global issue, which stems from the cumulative actions of many individuals. As understanding where your carbon footprint comes from is an important step to reducing it, carbon calculators have been created for people to estimate their carbon footprint based on their behaviours. Yet calculating individual footprints and placing the burden on individuals to change fails to recognise that peoples' choices are constrained by a host of contextual factors, many of which vary from place to place. In contrast, place-based approaches successfully engage communities and policymakers (Evans & Karvonen, 2014). Therefore, there is a knowledge gap in terms of the spatial variation in carbon footprints and the extent to which choices or circumstances determine carbon emissions.

The CREDS Place-Based Carbon Calculator aims to fill this gap by calculating a per capita carbon footprint for each Lower Super Output Area (LSOA) in England and providing this data in an accessible policy-relevant format with supporting statistics and explanations. LSOAs are statistical regions with an average population of 1,500. LSOAs were chosen for their small size, allowing the identification of local patterns while also having sufficient datasets to estimate the carbon footprint accurately. LSOAs are also well understood by the primary audience for the tool, Local Authority planners. This paper outlines how the carbon footprints were calculated and demonstrates how web mapping's latest developments can be used to create compelling interactive data visualisations for small area spatial datasets.

2. Calculating the carbon footprint of each LSOA in England

Previous attempts at localising carbon footprints have focused on downscaling national footprints (CSE, 2021; Jones & Kammen, 2014; Moran et al., 2018) or extrapolation from surveys and economic modelling (Yang et al., 2020). Such approaches often rely on the strong correlations between income, consumption, and carbon footprints (Minx et al., 2013; Wiedenhofer et al., 2018) so they may miss spatial patterns not based on income. In contrast, our approach focuses on bottom-up data as much as possible, which requires an almost complete understanding of everything the residents have done over an entire year. Unfortunately for researchers, such Orwellian surveillance does not exist in England.

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Nevertheless, there is enough data about the most common high carbon activities to make a reasonable approximation of the majority of a local area's carbon footprint. Some datasets are already published for LSOAs annually, such as gas and electricity consumption. Other datasets require interpretation or modelling to connect the available data to the appropriate location, such as using administrative data from annual car safety inspections (MOT tests) to calculate miles driven per LSOA (Cairns et al., 2017).

Where spatially disaggregated data does not exist, e.g. food consumption, it is possible to use survey-based research (Owen & Barrett, 2020). As spatially disaggregated data on household income is available, it is possible to join that data with surveys' findings to produce representative local footprints for the parts of the footprint that cannot be calculated directly. These surveys usually disaggregate into income bands of 5-10%; thus, a small amount of spatial variation is provided by different areas' varying household income.

Table 1 Summary of the main components of the LSOA carbon footprint, with their relative proportions to the UK's overall carbon footprint and the spatial and temporal resolution of the data used in calculations.

Consumption category	% of carbon footprint	Spatial resolution	Temporal resolution
Electricity, gas and other fuels	25.3%	LSOA	Annual for gas and electric
Operation of personal transport equipment	16.7%	LSOA	2011 snapshot, modelled to annual
Transport services	13.1%	LSOA for land transport, Survey for air transport	2011 snapshot, modelled to annual
Food	12.7%	Survey, modelled to LSOA	One-off estimate for 2017
Other	32.2%	Survey, modelled to LSOA	One-off estimate for 2017

Table 1 shows that the most significant components of the carbon footprint also have the most detailed spatiotemporal data. While the *other* category covers a third of the UK's total footprint, it contains a long tail of 29 minor sources ranging from restaurants and hotels (4.88%) to postal services (0.04%) (DEFRA, 2020, 2021). For many of these categories, it is less clear that the spatial perspective is the best way to understand the variation in consumption. So, while they are included in the carbon calculator for context, they are not the primary focus of a place-based tool.

While the method outlined above is not definitive, especially as the underlying datasets have limitations or omissions. For example, the MOT data lacks information on motorbikes. Furthermore, there is no definitive way to calculate a carbon footprint (Gao et al., 2014), nor is the carbon footprint a perfect measure of environmental sustainability (Laurent et al., 2012). Nevertheless, the method is sufficiently robust to provide an informative local footprint that can aid in policymaking and communicating complex ideas to the public. Especially when linked to other datasets that can explain why areas have different footprints. For example, high emissions from private cars may be explained by poor access to public transport. Thus, a web map is an appropriate way to disseminate the data produced by this research.

3. Harnessing web mapping as a data visualisation tool

Web mapping has become a ubiquitous technology for presenting spatial data, particularly to non-expert audiences who do not use traditional GIS software. A recent innovation in web mapping is replacing raster tiles, maps made of many small static images, with vector tiles. While vector tiles were initially designed for serving base maps, they provide several advantages to the spatial data visualiser. Firstly, vector tiles are often smaller than their raster equivalents, meaning less server space is required and faster downloads to the user. Secondly, vector tiles can hold many different attributes for the same geometry, allowing multiple choropleth maps to be produced from the same tileset. Thirdly, compression of both geometries and attributes allows for the visualisation of many complex geometries, such as the 32,844 LSOAs in England. Finally, vector tile attributes are accessible to the browser allowing client-side interactivity and analysis in addition to any features offered by the mapping library. These capabilities are demonstrated in Figure 1.

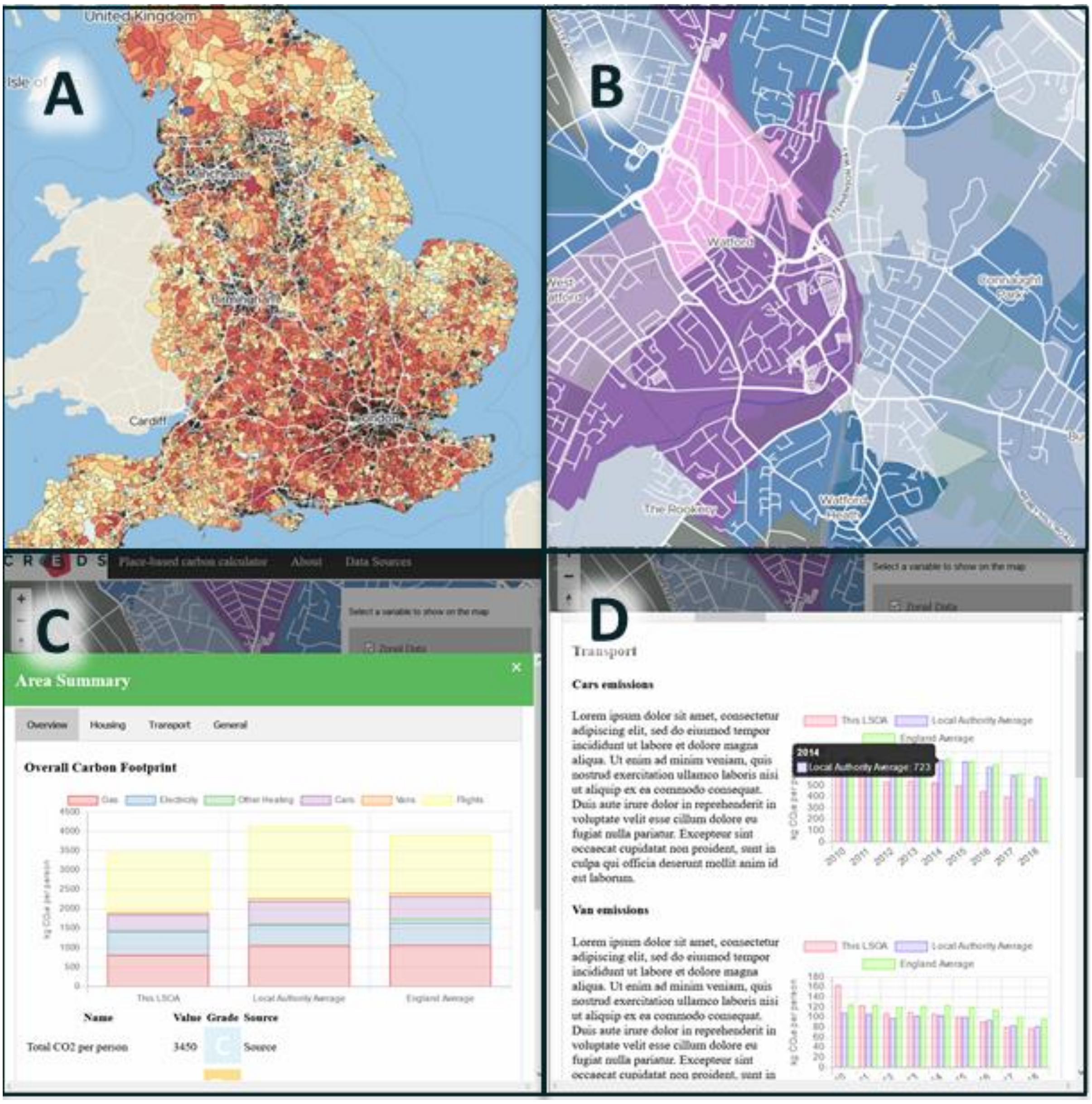

Figure 1 Screenshots from the Carbon Calculator website. A) Zoomed out view demonstrating the ability to render a choropleth map of all 32,844 LSOAs in England. B) Zoomed in view of the same tileset, showing the high spatial resolution, visualising different attributes with unique colour palettes, and seamlessly combining the data layers and base map to allow roads and place names to appear on top of the data. C) A popup report triggered by clicking on any LSOA showing graphs produced dynamically from the vector tiles' attributes. D) Another part of the popup report showing time-series data from the vector tiles dynamically joined to other datasets (local and national averages).

The tilesets can be produced using open-source software in a simple workflow. Firstly, data analysis was performed using the programming language R (R Core Team, 2014), with the results exported as a GeoJSON file containing LSOA boundaries and attributes. The command-line utility *tippecanoe* (Mapbox, 2021b) converted the GeoJSON file into a folder of vector tiles, which were uploaded to a file server. The visualisation of the tiles was done using the Mapbox GL JS library (Mapbox, 2021a).

Additional data visualisation is possible by passing attribute data to a graphing library (e.g. Chart.js (Chart.js, 2021), see Figure 1c). Several techniques have been developed to maximise the capabilities of the carbon calculator. It was found that producing multiple GeoJSON files with geometry optimised for different zoom levels produced better results than simply relying on the inbuilt capabilities of Tippecanoe to simplify geometry data. It was also found that the maximum number of attributes that could reasonably be attached to a vector tile was between 150 and 200. However, the file size could be substantially reduced by rounding numeric data to three significant figures. This is due to the key-value lookup system vector tiles employ for storing attribute data. Thus, the key performance metric is the number of unique values in the attribute data.

4. Conclusions

This paper has set out the case for using a place-based approach to calculating carbon footprints, highlighting the methods used to calculate an area's footprint, and presenting that data in a policy-relevant and accessible format. The Carbon Calculator will be publicly available in the summer of 2021. Simultaneously, the entire dataset, the R code used for analysis, and the HTML/JavaScript code used to build the website will be made available for download as open data and open-source software. The project is intended to increase understanding of climate change and advance the field of interactive data visualisation.

5. Acknowledgements

The authors gratefully acknowledge support from UK Research and Innovation through the Centre for Research into Energy Demand Solutions, grant reference number EP/R 035288/1

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