Exploring the distribution of urban building carbon emissions

A spatial approach to Westminster's decarbonisation strategy

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Abstract

To limit the catastrophic effects of climate change, cities need to be at the forefront of innovative approaches to reduce CO_2 emissions. In urban areas, CO_2 emissions are largely dominated by the heating and operation of buildings, and to reduce emissions, energy consumption in buildings must decrease significantly. However, carbon reduction initiatives are difficult to target due to insufficient information about how buildings consume energy in a spatial context. Where data is available, this is often only provided at a spatially aggregated level, or lacks spatial information. This study was carried out in collaboration with Westminster City Council to produce a novel methodology combining non-spatial data with spatially-referenced GIS polygons to produce a model which predicts energy consumption in Westminster at a building level. The model can in turn be used to produce a spatial distribution of building-by-building CO_2 emissions which can be used to inform and target emission reduction activities in line with Westminster's decarbonisation targets. The results show that the methodology can be used to successfully predict energy consumption at a granular building level, which when aggregated upwards corresponds well with measured figures. In the absence of better data, the approach presented in this study can act as a first step for cities to address their building carbon emissions, to curb their contribution to climate change.

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Finally, I would like to acknowledge the Ordnance Survey for providing me with the necessary license and data required to carry out the methodology of this work.

Declaration of Authorship

I, Signe Swarttouw, hereby declare that this dissertation is all my own original work and that all sources have been acknowledged. It is **11,106** words in length.

Signe Swarttouw, 23rd of August 2021

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1. Introduction

1.1. Background

On August 9th, 2021, the Intergovernmental Panel on Climate Change (IPCC) published a report highlighting the unequivocal scientific evidence that human activity has caused irreversible change to the earth's climate (IPCC, 2021). The report is the latest and starkest warning yet from the IPCC, which provides evidence-based information on climate change, highlighting consequences and possible response pathways. The IPCC reports provide clear evidence that to prevent further, catastrophic damage to the earth's environment, drastic action must be taken to reduce global anthropogenic carbon dioxide (CO_2) emissions, the main contributor to global atmospheric warming (IPCC, 2021).

Urban areas are some of the greatest contributors to global CO_2 emissions but are also at an increased risk of the consequences of climate change (Hobbie and Grimm, 2020). This has led to many local urban governments declaring a "climate emergency", acknowledging that they need to take action to address their city's contribution to the climate crisis. One of these local governments is Westminster City Council, the local authority of the City of Westminster within the United Kingdom's capital of London. They have set the target to become a carbon neutral city by 2040, which means that their net CO_2 emissions are zero (Jones, 2021).

Westminster's CO_2 emissions are dominated by the heating and operation of buildings within the borough. To reach Westminster's 2040 target these buildings must significantly reduce their energy consumption and resultant carbon emissions. However, information on individual building energy consumption is scarce, making it difficult to know how individual buildings contribute to total carbon emissions. Further, existing data on individual buildings is not spatially referenced, making it difficult to place information pertaining to buildings in a spatial context. This data gap contributes to significant challenges in targeting emission reduction activities in urban areas.

This paper therefore sets out to create a model using the little, non-spatial data that is available, to create a spatial distribution of accurate, granular data about individual building energy use and carbon emissions in Westminster. This information can be used for effective communication and presentation of baseline energy use in the borough, which is an important step in fostering greater engagement with climate issues among individual building and business owners in Westminster. The methodology in turn could be used to enable knowledge sharing not just for Westminster but can be scaled up to London-wide, national, as well as international efforts to reduce building carbon emissions where consumption data is unknown, and building data is scarce.

1.2. Research Question and Objectives

The aim for this report as outlined above can be defined by the following research question:

How can non-spatially referenced data be used to spatially investigate urban building CO_2 emissions?

The report aims to answer the above question by reviewing existing examples of predicting energy use in urban buildings (Objective 1), exploring the data available and using this to produce a new statistical model to predict the energy use of Westminster's buildings (Objective 2). The research will combine spatial and non-spatial data with the final objective of mapping CO_2 emissions to individual building footprints (Objective 3). The final outputs of the research are produced with the intention that they can be adapted and used by policy makers in identifying opportunities to reduce building carbon emissions in a step towards reaching Westminster's 2040 net-zero CO_2 targets.

2. Literature Review

This section introduces the background and motivation for the work carried out for this report, which has been introduced above. The section is divided in four parts, covering the scientific evidence of climate change and the urgent need to reduce global CO_2 emissions (2.1), Westminster's climate challenge (2.2), opportunities for reducing urban building carbon emissions (2.3), and the need for a spatial distribution of building emissions and previous work in predicting building energy consumption (2.4).

2.1. Climate Change and the Role of Cities

In 2018, the Intergovernmental Panel on Climate Change (IPCC) published a special report on the irreversible consequences of a global mean warming of 1.5°C above pre-industrial levels, as well as outlining actions governments and policy-makers must take to combat the global threat of climate change (Tollefson, 2018).

The IPCC special report contains mitigation pathways outlining the key changes in emissions, energy and land use required to limit global warming to 1.5°C (IPCC, 2018). A key feature of these pathways is the reduction in global anthropogenic greenhouse gas (GHG) emissions, of which increased concentrations are directly associated with rising atmospheric temperatures (IPCC, 2018). A later IPCC report, published in 2021 which focused on the scientific evidence of climate change, highlights that carbon dioxide (CO_2), methane, and nitrous oxide have all reached unprecedented concentrations (IPCC, 2021). The report concludes that carbon dioxide emissions have had the largest contribution to climate change compared to other drivers influenced by human activity. Atmospheric CO_2 concentrations have increased by 47% since the beginning of the industrial revolution, which can be attributed to the increased use of fossil fuels and a shift from rural to urban activities (IPCC, 2021).

In the 2018 IPCC Special Report of a Global Warming of 1.5, the need to reduce atmospheric CO_2 concentrations is emphasized, with a particular focus on reducing global emissions. To limit global warming to 1.5°C, the report outlines that global anthropogenic CO_2 emissions must reduce by 45% by 2030, and reach net zero by 2050 (IPCC, 2018; Tollefson, 2018). Net zero CO_2 emissions are achieved by balancing total anthropogenic CO_2 emissions with the total amount of anthropogenic CO_2 that is removed from the atmosphere over a specific period, (IPCC, 2018). Net zero CO_2 emissions can also be referred to as carbon neutral, or simply, carbon-zero.

If these targets are not reached, and mean global temperatures continue to increase, the IPCC predicts that areas across the globe will be impacted with climate events such as increased heavy rainfall and flooding in some areas, and droughts in other areas. Extreme high temperatures are predicted in most inhabited areas (IPCC, 2018). These impacts can contribute to further risks to infrastructure, resource security and human health, particularly in urban areas. By 2050, over 65% of the world's population is expected to be living in urban areas (Estrada, Botzen and Tol, 2017). Cities are likely to see amplified effects of climate impacts, due to factors such as the urban heat island effect and impervious surfaces making it difficult to manage excess rainfall (Hobbie and Grimm, 2020). These impacts are also likely to incur significant costs for cities. A study of 1,692 cities around the world by Estrada et al. (2017), found that when considering these additional climate effects specific to urban areas, the projected economic burden of climate change in cities increased by 2.6 times.

While cities are the greatest contributor to global CO_2 emissions (60%), they are also most vulnerable to the effects of climate change. However, cities are also widely known as centres of knowledge and innovation, and the density of urban areas allows for the development of efficient and low carbon infrastructure. According to C40 Cities, an international group of cities tackling climate issues through collaboration and knowledge sharing, local urban initiatives to limit global warming are the first step in large-scale global efforts to prevent climate change (C40 Cities). In tackling climate change, however, cities currently face several challenges, particularly relating to limitations to information about how the city contributes to climate change, and how and where actions to limit these contributions should be targeted. Acuto (2016) argued that cities therefore carry a big responsibility to collect, store, and share data at a local level, to provide information which is relevant for cities to successfully begin to address climate change at a global level.

2.2. Westminster's Climate Emergency

In response to the IPCC 1.5 Report, Westminster City Council (WCC), alongside other governments, organisations, and companies, have declared a *climate emergency* (Westminster City Council, 2019), recognising the urgent need to act on the causes and consequences of climate change. As part of this action, the council has made a commitment to become a carbon-neutral council by 2030, and a carbon-neutral city by 2040. This means that the council aims for all council operations to have net-zero carbon emissions by 2030, and for all emissions across the City of Westminster to be net-zero by 2040 (Westminster City Council, 2021a). The council is currently working with businesses and residents to develop a Climate Action Plan around five key themes: businesses and workplace, homes and communities, low carbon energy, travel and transport, and waste and consumption. The council aims to monitor progress towards the 2030 target annually from emissions calculated from known consumption data of Westminster-owned assets, however there is no system yet in place to monitor progress for the council's 2050 target (Westminster City Council, 2021a). Westminster's emission targets sit within London's city-wide climate goals. The London Plan (2021) outlines a target for London to become a zero-carbon city, defined locally as having net-zero carbon emissions by 2050. This is in line with the UK-wide goal outlined by the 2008 Climate Change Act, which was amended in 2019 to commit to a 100% reduction in CO_2 emissions by 2050 (Dray, 2021).

The City of Westminster has some of the highest CO_2 emissions in the UK. Based on data from the Department of Business, Energy and Industrial Strategy, Westminster's emissions per capita between 2007 and 2019 were found to be around 1.9 times greater than the national average, and 2.6 times higher than the London average (Westminster City Council, 2021a). A vast majority (86%) of Westminster-wide emissions has been found to come from the built environment, and can be attributed to the energy used to operate and heat the buildings within Westminster, primarily due to the challenges outlined in Part 2.3.3

(Jones, 2021; Westminster City Council, 2021a). This is a significantly greater portion than the UK, which attributes 40% of its carbon footprint to the built environment (UK Green Building Council, 2017). Globally this portion is 28% (World Green Building Council, 2019). The actions toward achieving Westminster's carbon emission targets are therefore likely to see a notable focus on reducing CO_2 emissions of buildings across the city.

2.3. Emission Reducing Activities

In February 2021, in collaboration with sustainability consultants Anthesis, Westminster City Council produced a report with recommendations on how to reach the council's net-zero targets (Jones, 2021; Westminster City Council and Anthesis UK, 2021). The findings of the report consolidate that Westminster's largest emissions savings potential for the borough are in the building sector and sets out a series of emission-reduction interventions for the built environment including reducing energy demand, supplying energy more efficiently and switching to low-carbon energy systems (Westminster City Council and Anthesis UK, 2021). The following sub sections will expand on relevant aspects of these interventions, including examples of how other cities have used them as part of their climate response.

2.3.1. Reducing Energy Demand

At the top of the order priority set out by the report by Westminster City Council and Anthesis (2021) is lowering energy use by reducing demand. The report argues that reducing energy demand is not reliant on changes to existing larger energy supply infrastructure, and is therefore relatively attainable in a local context (Westminster City Council and Anthesis UK, 2021). Minimising energy demand in buildings implies reducing the need for energy for heating, cooling, lighting, and running electrical appliances in buildings. This can be achieved by designing buildings to be more efficient – improving building fabric to minimise the energy needed for space heating and cooling and improving the efficiency of the lighting and electrical appliances used in buildings.

In the UK, the largest portion of building energy demand comes from space heating, for both domestic and non-domestic buildings (BEIS, 2018). Features such as insulation, draughtproofing, and double glazing allows less heat to escape from a building and can therefore reduce the amount of energy needed to keep a space comfortably warm. In the UK these features are commonly incorporated in new builds to meet current energy efficiency standards. As part of London's city-wide climate goals, a zero-carbon target for major residential developments has been in place for London since October 2016 and applies to major non-residential developments since 2021 (The London Plan, 2021). However, more than 80% of the UK's existing building stock is expected to still be in operation by 2050 (UK Green Building Council, 2017), over half of which was built prior to 1950 (Piddington *et al.*, 2020). Older buildings are often less able to retain heat. For this reason, retrofitting is a common practice of upgrading the fabric of existing buildings to make them more thermally insulated. Other retrofitting interventions can be used to reduce the need of artificial ventilation, as well as maximising the use of natural lighting, all contributing to a reduction in building energy use and associated carbon emissions. There are, however, also barriers to uptake of retrofitting projects. While the knowledge and tools to retrofit buildings exists, a lack of understanding of how buildings consume energy and awareness of options and benefits of retrofitting remains widespread among UK building owners, who are therefore unwilling to invest in projects (Brown *et al.*, 2018). The City of Melbourne, which has already achieved its goal of becoming a carbon-neutral city by 2020, aimed to tackle this barrier through their 1200 Buildings Programme. The programme, which is still ongoing, aims to encourage building owners to carry out emission-saving retrofitting projects by providing building emission information, tools, financial grants, and educational events. The programme aims to eliminate 383,000 tonnes of CO_2 and equivalent emissions annually (C40 Cities, 2012) from buildings in the city. The success of the project suggests that cities can benefit from sharing information and data on the benefits of retrofit.

2.3.2. Low Carbon Energy Systems

Another way to reduce energy use in cities is the use of district heating. Instead of individual properties each generating heat on-site, district heating uses a centralised heat source which is then distributed to a network of buildings. District heating can also be combined with low-carbon solutions such as the use of waste heat, or heat exchangers and pumps. For example, the city of Copenhagen, Denmark uses waste heat from local waste incineration heat-and-power plants to cover 97% of the city's heating, significantly reducing energy use and associated CO_2 emissions (C40 Cities, 2011a). In The Hague, Netherlands, as part of the city's work towards a 'climate neutral' city, a system was installed which extracts seawater and processes it via a heat exchanger or heat pump, depending on the season, which extract heat from external sources (air, water, or ground), and do not rely on the carbon-intensive combustion of fossil fuels (Marcacci, 2014). The system is able to supply a residential area of 3,000 homes with space heating and hot water, yielding a 50% reduction in CO_2 emissions (C40 Cities, 2011b; Marcacci, 2014). London has set a target of meeting 15% of the city's energy needs with district heating and renewable energy solutions (Lagoeiro *et al.*, 2019). One project already in use is the Bunhill 2 Energy Centre in the London Borough of Islington, which uses waste heat from a London Underground Network tunnel to provide low-carbon, affordable heating to nearby homes, offices, and a school (Lagoeiro *et al.*, 2019). District heating systems, however, are dependent on a spatial proximity to the heat source and would benefit from information about the spatial distribution of buildings and their energy demands.

Finally, a transition from fossil fuels to renewable energy sources will lead to a reduction in associated CO_2 emissions. At a national level, the UK electricity grid is decarbonising rapidly primarily due to investments in nuclear and wind energy. In the past decade, The UK's renewable energy supply has grown six-fold, cutting the country's carbon intensity by 58% (Staffell *et al.*, 2020), but actions can also be taken at local levels through distributed generation. Distributed generation is defined by UK Office of Gas and Electricity Markets as a source of energy which is generated at, or near the location where it is to be used. Examples include local assets used for district heating such as heat pumps and waste heat described above, but also electricity generated from small scale wind-turbines or photovoltaic (PV) panels. This form of electricity generation allows for the delivery of low-carbon energy from renewable sources, as well as reducing inefficiencies and emissions associated with transmission, due to the proximity of the source to the end user. In a collection of essays published by the Institute for Public Policy Research, Hywel Lloyd (2018, p.6) argued that a shift to a decentralised, distributed energy system in the UK will make "an energy system that is more resilient, more engaging of citizens and more appropriate to the climate challenges of the next century" (Lloyd, 2018, p.6.). In the same collection, Tingey and Webb argued that local authorities play an important role in collaborating with businesses, landlords and residents in creating a distributed system which is spatially integrated and optimised for the area's socio-spatial context (Tingey and Webb, 2018). In Santiago, Chile, the city collaborated with communities to install 18 solar

PV projects on schools, hospitals, and other public buildings. The project allowed for significant reductions in municipal utility costs and was also able to provide energy to nearby households. The project is estimated to have saved 3,419 tonnes of CO_2 emissions annually (Sustainia, 2018). Distributed energy systems, however, cannot be developed everywhere, and cities must work together with local stakeholders to form spatially-informed decisions on locations where installations are feasible (C40 Cities, 2019).

2.3.3. Westminster's Context & Challenges

The characteristics of the City of Westminster and its building stock pose several unique challenges in delivering carbon-reducing activities across the borough. Westminster is situated in Central London, and houses important buildings across government, commercial, and cultural sectors. It is home to the UK Government, the country's busiest shopping street, and other noteworthy tourist attractions, theatres, and museums (Westminster City Council, 2018)) The population of the borough is around 255,000 (London Councils, 2018), but it accommodates around 700,000 jobs and its daytime population (residents, working population, and visitors) swells to around 1,100,000 (Westminster City Council, 2018). This means that the borough's building emissions are primarily dominated by commercial operations, accounting for 71% of emissions, with domestic buildings accounting for 15% (Jones, 2021). The majority (63%) of Westminster's building stock predates 1940, and almost half (46%) was built prior to 1900 (VOA, 2020) and the borough contains around 11,000 listed buildings and 56 conservation areas which are protected due to their architectural and historic interest (Westminster City Council, 2021b). Carbon reduction solutions must therefore be identified which minimise damage to the historic environment.

A large portion of Central Westminster's buildings in both the commercial and residential sectors are occupied by tenants (Lloyd-Jones *et al.*, 2008), where the responsibility for investing in improving the thermal and energy performance of buildings falls on the landlords, while tenants are responsible for operational costs. Previous studies have found that where there is a tight housing market, landlords have no incentive and are less likely to invest in energy saving retrofits (Bird and Hernández, 2012; Fuerst and Adan, 2015). Landlords in Soho, an area in Central Westminster, were also found to be sceptical of shared sustainability solutions such as district heating (Lloyd-Jones *et al.*, 2008). Furthermore, Westminster contains many mixed-use buildings, accommodating a combination of commercial, residential and office spaces with different occupancy patterns and ownership in the same building, which add to the complexities of managing carbon-reduction activities in the area (Lloyd-Jones *et al.*, 2008).

2.4. Spatial Distribution of Emissions

2.4.1. The need for a spatial distribution of emissions

Westminster's centrality, density and cultural and historical heritage pose a significant number of challenges in delivering carbon-reduction solutions to the area. In addition to this, many people are unaware of how buildings consume energy and how they contribute to carbon emissions (Oswaldo *et al.*, 2014). A comprehensive spatial distribution of energy use and carbon emissions can act as a useful tool for prioritising locations where carbon reduction actions should be taken. By mapping carbon emissions at building level, individual buildings can be targeted for retrofitting potential, but a map can also be used to identify areas which could benefit from shared resources such as district heating and distributed generation. Integrating this data with other spatial information such as green spaces and conservation areas will support the planning and implementation of local carbon-reduction projects where resources can be allocated most efficiently to maximise both public and private investment within Westminster's dense and historical context. By making this information publicly available with effective visualisations, this information can effectively be communicated and foster a collaborative environment where businesses and building owners are also motivated to take private action (Gupta and Gregg, 2017). Beddingfield et al. (2018), argued that while some city governments provide public building energy use data for benchmarking, this is commonly in the form of large and data-heavy spreadsheets. Private building owners are unlikely to seek out and manipulate this data with the purpose of analysing performance and identifying efficiency improvement opportunities. By making this data interesting and engaging through interactive visualisations, building owners and occupiers can begin to understand and use it to improve building performance (Beddingfield, Hart and Hughes, 2018). Lin et al. (2021) argued that big data and spatial information is key in creating a smart city which addresses environmental issues while increasing resilience to climate impacts.

2.4.2. The need for top-down energy mapping

Measured energy consumption and emission data, however, is often not readily available at a building-by-building scale. In the UK, real energy consumption data is available for only 0.01% of the whole domestic building stock, and an even smaller portion is available for non-domestic buildings (Cremin and Ma, 2019). At individual building level, engineering methods such as energy use simulations from detailed information about the building fabric and climate can provide accurate predictions of energy demand (Mastrucci *et al.*, 2014; Kontokosta *et al.*, 2015). However, shifting from a single building to all buildings in an area at an urban scale, the amount of data and computational power required increases significantly, making it an impractical approach at larger urban scales (Kontokosta *et al.*, 2015; Willmann *et al.*, 2019). Previous projects have therefore used statistical methods, correlating energy use data with predictive variables relating to building characteristics. In a comparison between bottom-up engineering simulations and top-down statistical modelling, Willmann et al. (2015), found that statistical approaches were able to provide an equally accurate energy consumption prediction, while being significantly less computationally intensive compared to engineering methods. This suggests that data-driven approaches can be a viable solution for cities to gain an in-depth understanding of energy consumption at building level. The approach taken, however, is largely dependent on the data which is available.

If energy consumption data and building characteristics are both available, a statistical model can be created which estimates the relationship between the two. A study by Santin et al., (2009) used a multiple regression model to investigate the relationship of occupancy and building characteristics with energy use on residential buildings in the Netherlands. The results found that building stock characteristics such as type, occupancy and construction method all have a strong influence on the final energy use of buildings (Santin, Itard and Visscher, 2009).

This approach was taken a step further by Kontokosta et al. (2015), who used energy consumption data available for a subset of buildings in New York City to predict energy consumption data for the whole city. Their research used data from buildings which by local law are required to disclose annual energy consumption data, and a comprehensive dataset of the city's buildings, including information on use and characteristics. A multi-variable regression model was created which was accurately able to predict electricity and gas consumption data for remaining buildings in the city. The results of the model were validated against aggregate energy data available at postcode level, achieving R^2 values of 0.63 and 0.93 for gas and electricity, respectively (Kontokosta *et al.*, 2015).

In many cases, however, there is a lack of consumption data readily available at a building level. Instead, studies have explored the use of spatially aggregated consumption data available at larger geographical scales and using statistical methods to disaggregate this data to an individual building-level scale. Similarly to Kontokosta et al. (2015), Howard et al. (2012) produced a model which allowed for a detailed spatial distribution of building energy consumption in New York City. Their research, however, included no data on energy consumption at building level. Instead, the project down-scaled ZIP-code (Postcode) level consumption data to individual buildings through a robust regression model estimating energy intensities by floor area for different building function categories. From these intensities, an estimate of annual energy consumption for each building was made and visualised using maps (Howard *et al.*, 2012). The model outputs however, are not validated against known building consumption data.

Mastrucci et al. (2014) used a similar methodology to disaggregate measured gas and electricity consumption from postcode level to residential building-level in Rotterdam, the Netherlands. However, while Howard et al. (2014) assumed that energy consumption is primarily dependent on the building function, Mastrucci et al.'s model included several other predictors, such as dwelling type, construction period, floor area, and number of occupants. The regression model was constructed using bootstrap resampling, which does not rely on measured building-specific energy consumption data to validate the results of the model. Energy savings potential for each dwelling was also calculated using national benchmarks for retrofitted buildings for different dwelling types (Mastrucci *et al.*, 2014).

2.5. Conclusion

The effects of climate change are likely to threaten the safety and well-being of the global population, with people living in urban areas likely to feel amplified impacts. To limit the impacts of climate change, the IPCC recommends that a global temperatures increase should be limited to 1.5°C, requiring that anthropogenic CO_2 emissions must reduce by 45% by 2030, and reach net zero by 2050. Cities, which are a significant contributor to CO_2 emissions, are uniquely positioned to take carbon-reducing actions. Westminster City Council, alongside other city governments, has therefore made a commitment to become net-zero by 2040. The council recognises that buildings are the largest contributor to emissions in the borough, and that this is an area where carbon reduction activities can most effectively be targeted. A comprehensive overview of the city's buildings and how they contribute to overall emissions can be a useful tool for cities in identifying potential for carbon reduction activities such as retrofits, district heating, and distributed energy generation. A key challenge is that there is a lack of real energy use data for the UK's buildings. In response to this challenge, statistical, data-driven methods can be used to model energy use at a building level, of which the approach taken is dependent on the data available. The following section of this report will outline the data which is available for Westminster, and how this and the above research has informed the chosen methodology in developing a building-level model of energy use and CO_2 emissions in the borough. This can be used by the borough to address their own 2040 target, align with the wider London plan to be carbon-zero by 2050, and the global mission to limit global atmospheric warming.

3. Methodology

The above literature review has highlighted the importance of having a comprehensive, spatial overview of how buildings consume energy in cities, and how these in turn contribute to carbon emissions. This information is beneficial in understanding where and by how much buildings need to reduce consumption to achieve ambitious zero carbon targets. Data on current building performance, however, is scarce, but can be estimated using statistical methods where there is other data available. This section will outline how a variety of data sources on building stock characteristics can be used to predict energy use of Westminster's buildings with the final objective to understand the spatial distribution of energy consumption and associated CO_2 emissions across Westminster. A spatial understanding of the borough's emissions can be used to encourage private stakeholders to take individual action, as well as identify areas which have the greatest potential for local emission reduction interventions such as district heating, maximising public investment in reducing CO_2 emissions.

Analysis was carried out using Python and R, and a reproducible analysis can be accessed through GitHub.

3.1. Ethical Considerations

The goal of this research is to provide findings which will be useful to Westminster City Council and contribute to the public benefit of understanding carbon emissions and provide insights which can be used to inform actions to reduce emissions, all in the context of a rapidly changing climate.

All data, except for data from the Ordnance Survey, is publicly accessible on the internet. The Ordnance Survey data has been accessed through an educational license, and permission has been granted for the results derived from this data to be shared with Westminster City Council, who are the main benefiters of this study.

The study uses aggregated and anonymized data to predict the performance of individual buildings in Westminster. While the study aims to provide energy consumption data at a fine level of spatial detail, it is not the purpose of the study to identify or reveal information about the private lives and habits of individuals. The study falls under UCL's ethical committee exemption 3, which states that purely observational studies of public behaviour that do not identify individuals do not need to be subject to UCL ethical approval. From these considerations, the research was not subject to approval from UCL's Ethics Committee.

3.2. Data and Methodology Workflow

The research methodology has been separated into distinct sub-processes, each relating to different objectives necessary for the final research outcome. Table 3.1 outlines all the datasets and their respective sources used in the methodology, alongside the sub-processes in which they were used. The following sub-sections will outline the methodology of each process within the methodology schematic (Figure 3.1).

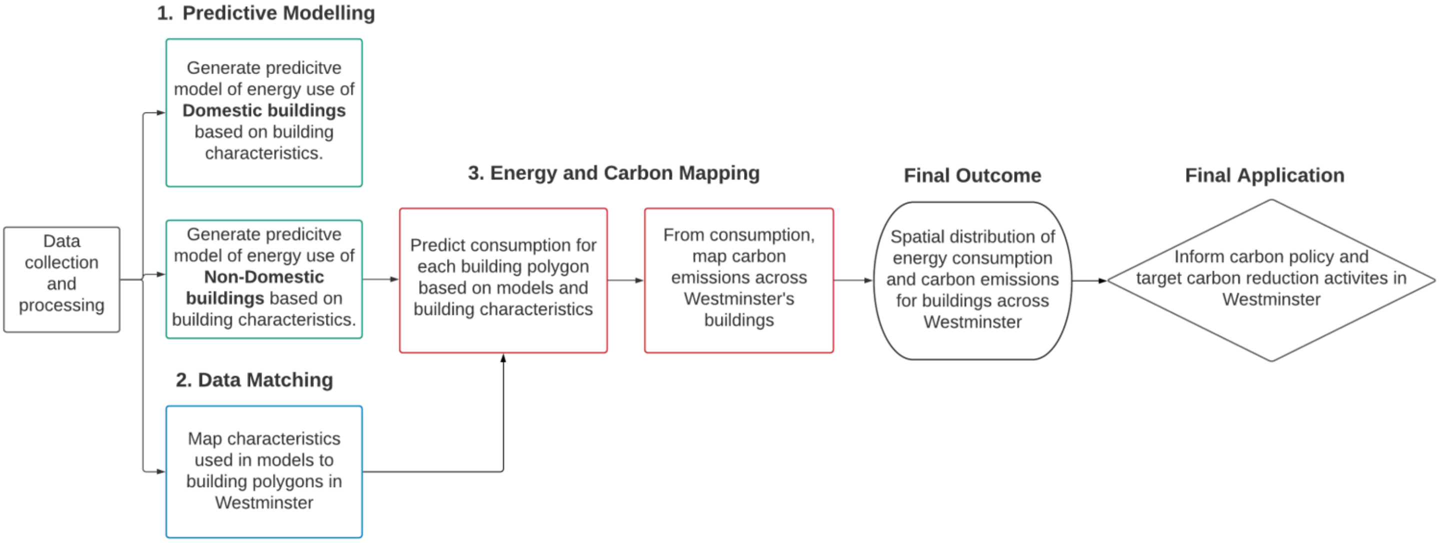

Figure 3.1. Research Methodology Outline, divided into separate parts of 1.) predictive modelling of domestic and non-domestic energy consumption, 2.) data matching of building characteristics to spatially referenced building polygons, then 3.) predicting energy consumption for each Westminster building polygon based on models and building characteristics and calculating carbon emissions based on consumption predictions, to achieve the outcome of a comprehensive spatial distribution of energy consumption and carbon emissions across Westminster, which can be used to inform carbon policy and target carbon reduction activities in the area.

Table 3.1: Sources, information extracted, and application of data used in methodology, with number referencing the methodological stage depicted in Figure 3.2

Dataset	Source	Information Extracted	Application/Process
Ordnance Survey Topography Mastermap	Ordnance Survey through Edina Digiroam (2021)	Building Polygons and TOID idenitfiers	2. Data Matching - matching building data to GIS polygons 3. Energy and Carbon Mapping - Spatial mapping of energy consumption of buildings
Ordnance Survey AddressBase	Ordnance Survey (2021)	Addresses and TOID identifiers	2. Data Matching – matching building data to GIS polygons
National Energy Efficiency Data Framework	Department of Business, Energy and Industrial Strategy (via ONS)	Anonymised building data including energy consumption statistics and property characteristics	1. Predictive Modelling – Predictive model of domestic energy consumption
EPC Records	Ministry of Housing, Communities and Local Government	All EPC Records for London	1. Predictive Modelling – Predictive model of domestic energy consumption
		All EPC Records for Westminster	3. Energy and Carbon Mapping – Predicting consumption for Westminster's domestic properties
Sub-national consumption statistics	Department of Business, Energy and Industrial Strategy (via ONS)	Postcode- level domestic gas and electricity consumption for London	1. Predictive Modelling – Predictive model of domestic energy consumption
Indices of Multiple Deprivation	Ministry of Communities, Housing and Local Government (via ONS) (2019)	2019 Indices of Multiple Deprivation Deciles at LSOA level	1. Predictive Modelling – Predictive model of domestic energy consumption
Non-Domestic ational Energy Efficiency Data Framework	Department of Business, Energy and Industrial Strategy (via ONS)	Average energy use intensities by building use category	1. Predictive Modelling – Predictive model of non-domestic energy consumption
Valuation Office Agency Ratings List	Valuation Office (2017)	Summary valuations for all commercial properties in Westminster, including information about use category and total floor area.	3. Energy and Carbon Mapping - Spatial mapping of non-domestic energy consumption of Westminster's buildings
Display Energy Certificates	Ministry of Housing, Communities and Local Government	All DEC Records for Westminster	3. Energy and Carbon Mapping - Spatial mapping of non-domestic energy consumption of Westminster's buildings

3.3. Study Area

This study focuses on the City of Westminster, a borough within the United Kingdom's capital, London. Westminster has one of the highest CO_2 emissions per capita in the country, with a majority attributed to coming from the heating and operation of buildings in the borough (Jones, 2021; Westminster City Council, 2021a). This study will therefore focus on attributing energy consumption and CO_2 emissions to individual building footprints based on building characteristics. Building footprint data for Westminster was obtained from the Ordnance Survey MasterMap Topography layer (Figure 3.2). Additional building characteristics relating to factors such as construction and occupancy were then attributed to building footprints to be used in predicting consumption and emission data at a building level.

Figure 3.2. Study Area of the City of Westminster with Ordance Survey building polygons and public green spaces (a) in relation to the London Boroughs with the City of Westminster highlighted (b). Contains OS data © Crown copyright and database rights, 2021 Ordnance Survey (100025252).

3.4. Predictive Modelling of Energy Consumption

To produce a detailed model of energy use and carbon emissions for every building in Westminster, the relationship between building stock characteristics and energy use was explored. Previous studies have found that energy consumption differs for domestic and non-domestic buildings (Kontokosta *et al.*, 2015; ND-NEED, 2021), which is expected as occupancy behaviour and energy end-uses differ significantly. Further, available energy and building stock data varies significantly between these two classifications. For this reason, energy use modelling for domestic and non-domestic buildings was carried out separately. The methodology for both classifications is outlined further in the following sections 3.4.1 and 3.4.2, respectively.

3.4.1. Domestic Model

Previous studies into predicting energy use in domestic buildings have found that a significant amount of the variation in energy use can be explained by physical building characteristics such as age, construction type, and size (Mastrucci *et al.*, 2014). Socio-economic characteristics of the area in which the building is in have also been found to be have an influence (Bhattacharjee and Reichard, 2011). For this reason, this study explored both physical and socioeconomic property characteristics to produce a model which can accurately predict energy consumption in buildings across Westminster.

As comprehensive data on both building characteristics and energy consumption is scarce in the UK, two methodologies using different data sources were explored for this study. The first methodology used data from National Energy Efficiency Data (NEED) Framework, and the second used Postcode-level consumption data combined with Energy Performance Certificates (EPC). These both included publicly available information about domestic energy use and building characteristics and were used to build two statistical models which were compared against their ability to accurately predict energy use in domestic buildings (Figure 3.3).

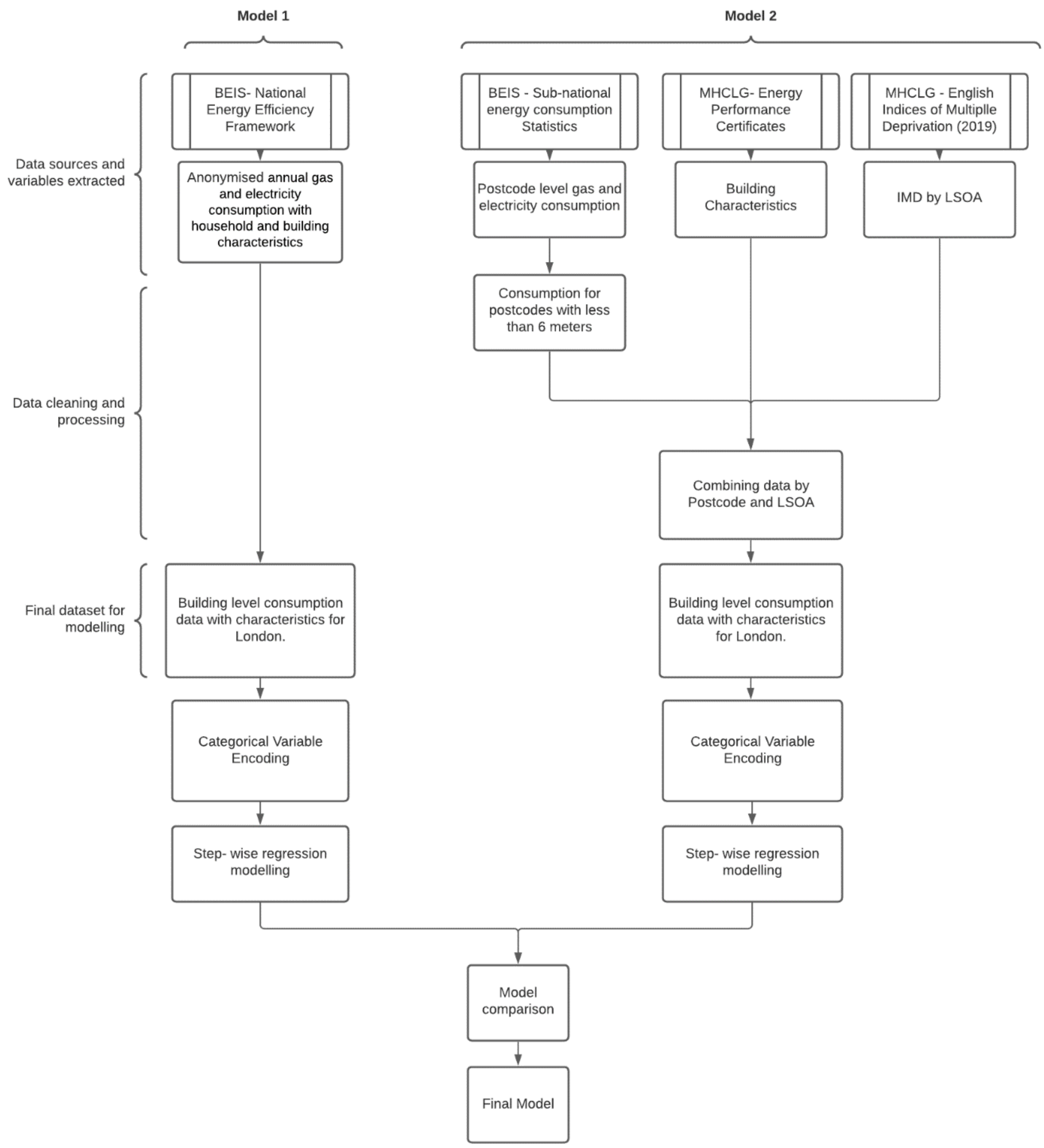

Figure 3.3. Outline of the two models explored in predicting domestic energy consumption at building level. Model 1 used individual building consumption combined with building characteristics, derived from the National Energy Efficiency Data (NEED) Framework. Model 2 used Postcode-level consumption data combined with EPC records for buildings in London and IMD data at LSOA level, to get building level consumption data with corresponding building level characteristics.

3.4.1.1. *Model 1 – National Energy Efficiency Framework*

The first model was built using the National Energy Efficiency Data (NEED) Framework, which was set up by the UK Department for Business, Energy and Industrial Strategy (BEIS) to provide a better understanding of energy consumption in UK buildings. The data framework provides publicly available data on annual gas and electricity consumption, alongside household and building characteristics for an anonymized dataset of 50,000 domestic buildings in the UK. For this study, the most recent dataset was used, which includes consumption data for each building annually from 2005 to 2017.

For the model, a mean consumption per building across the 12 years was used, to remove the influence of weather effects which may result in a higher or lower annual energy consumption. The NEED dataset includes information on what region each building is in. To make it more representative of Westminster's context, the data was initially subset to only include information on buildings located in Greater London, which are likely to have similar attributes to Westminster's buildings. The NEED dataset does not include buildings whose consumption exceed 50,000 kWh for gas and 25,000 kWh for electricity, as these exceed the maximum "plausible" values of domestic energy consumption and were therefore reclassified as non-domestic buildings (Department for Business, Energy, and Industrial Strategy, 2021b). Further, buildings consuming less than 100kWh for both energy sources were also excluded from the original data. After filtering for London and removing buildings with missing consumption data the dataset size was reduced to 6,505 domestic properties.

3.4.1.2. *Model 2 – Postcode Level Consumption Data and EPC records*

The second dataset used was domestic gas and electricity consumption data aggregated at postcode level. BEIS has data available publicly for total metered domestic gas and electricity consumption, alongside the number of meters, and mean and median consumption for postcodes across England, Wales and Scotland. This data, however, does not include any information about the buildings from which the consumption data was measured. To solve this, a methodology was adopted from the London Energy Map project (London Energy Map, 2019), which aimed to predict energy use in buildings across London. To deal with the lack of building information, the London Energy Map linked publicly available Energy Performance Certificates (EPCs) with the aggregated meter estimates by matching postcodes. This approach assumes that properties within a postcode have similar attributes, and that the median consumption in a postcode is representative of the real consumption of a building in that area (London Energy Map, 2019).

For this study, the most recent dataset was used, which includes consumption data for postcodes from 2019. Again, only data from London was selected. The consumption data was limited to postcodes with the smallest number of meters (6), as these are likely to have less variance in property characteristics. The median consumption per postcode was then assigned to each EPC property record within the postcode. The EPC data includes information relating to the energy performance of a property, as well as property characteristics such as floor area, number of rooms, and property type. For the analysis, EPC's published between 2008 and 2021 in Greater London were used. After cleaning and matching postcodes to EPC's, a dataset of 10,896 properties was left, which were used for predicting energy used based on property attributes. In line with the London Energy Map (2019) project's methodology, the categorical property type and built form variables available from the EPC data were consolidated into a single ordinal variable representative of the number of exposed sides the property has, the methodology of which is explained in Figure 3.4. Further, the Index of Multiple Deprivation (IMD) Decile was incorporated as an additional variable, based on the Lower Super Output Area (LSOA) the building is located in.

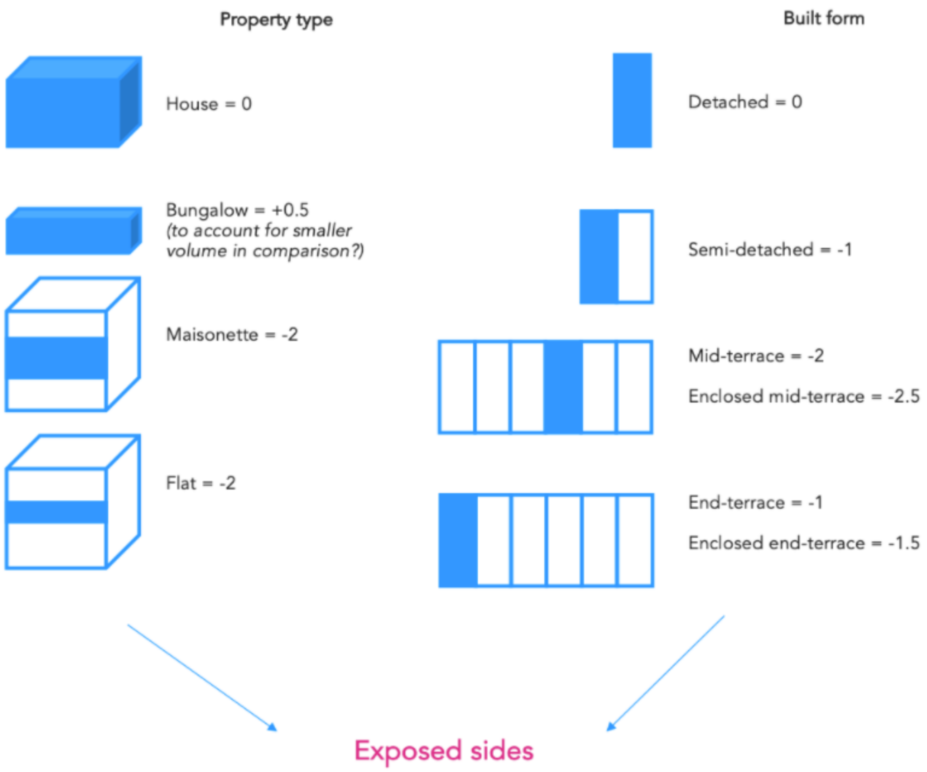

Figure 3.4: Method of determining the exposed sides of a property. Starting with 6 sides, exposed sides were removed or added according to the property type and built form as described above. Image and methodology has been taken from the London Energy Map Project (2018)

3.4.1.3. *Model construction and testing*

Tables 3.2, 3.3, and 3.4 summarise the variables selected for the two models to predict domestic gas and electricity use. The variables used have primarily been selected due to their availability in their respective datasets but aim to incorporate both physical and social characteristics which can be used to explain building energy use as seen in studies such as Mastrucci *et al*. (2014), and Bhattacharjee and Reichard (2011). It is worth noting that some variables used in both models vary in the way they are presented, due to variations in how the data has been supplied.

For example, the property age from the NEED data (Model 1), is banded into wider ranges than the EPC data (Model 2), due to a greater anonymisation of the data.

Table 3.2 Predictive variables used in Model 1, derived from the NEED Framework

Variable	Description	Value	Count	Percent (%)
Floor area band	Banded property floor area (m^2)	1 (under 50)	1908	29.33
		2 (51-100)	2681	41.21
		3 (101-150)	1440	22.14
		4 (152-200)	476	7.32
Age band	Banded construction age of property	1 (before 1930)	2109	32.42
		2 (1930-1972)	2747	42.23
		3 (1973-1990)	997	15.33
		4 (after 2000)	652	10.02
Main heating	Main fuel source the property uses for heating	1 (Gas heating)	5270	81.01
		0 (Other fuel source)	1235	18.99
Property type	Main property type	Bungalow	128	1.97
		Flat	2883	44.32
		Detached house	280	4.30
		Semi-detached house	1098	16.88
		Mid-terrace house	1527	23.47
		End-terrace house	589	9.05
IMD band	Index of multiple deprivation quintile (published 2015), based on LSOA the property is in	1 (most deprived)	1410	21.68
		2	1940	29.82
		3	1342	20.63
		4	1077	16.56
		5 (least deprived)	736	11.31
Council tax band	The council tax band that the property is in. Representative of the value of the property	A (lowest value)	149	2.29
		B	735	11.30
		C	1734	26.66
		D	1767	27.16
		E	1030	15.83
		F	567	8.72
		G	405	6.23
		H (greatest value)	1184	18.20

Table 3.3 Predictive numerical variables used in Model 2, based on EPC records

Variable	Description	Min	Max	Mean	Median
Total Floor area (m^2)	Measured internal floor area of property	20.43	465.50	90.30	79.00
Number of habitable rooms	Count of rooms which is not a kitchen, bathroom, or storage	1.00	9.00	4.05	4.00
Exposed sides	Number of exposed sides the property has, based on property type and built form (See Fig. 3.4)	1.50	6.50	3.82	4.00

Table 3.4 Predictive categorical variables used in Model 2, based on EPC records

Variable	Description	Value	Count	Percent (%)
Age band	Banded construction age of property	0 (before 1900)	1514	13.90
		1 (1900-1929)	1867	17.13
		2 (1930-1949)	1957	17.97
		3 (1950-1966)	1441	13.23
		4 (1967-1975)	885	8.12
		5 (1976-1982)	532	4.88
		6 (1983-1990)	586	5.38
		7 (1991-1995)	396	3.63
		8 (1996-2002)	783	7.19
		9 (2003 – 2006)	630	5.78
		10 (2007 onwards)	305	2.80
EPC rating	Energy Performance Certificate rating	B (Most Efficient)	264	2.42
		C	3703	33.98
		D	4755	43.64
		E	1786	16.39
		F	236	2.17
		G (Least Efficient)	62	0.57
IMD band	Index of multiple deprivation quintile (published 2015), based on LSOA the property is in	1 (most deprived)	1944	17.84
		2	3015	27.67
		3	2614	23.99
		4	2043	18.75
		5	1280	11.75

From the variables summarized above, the two different datasets were used to predict gas and electricity consumption based on property characteristics. Both predictive models were constructed using ordinary least squares (OLS) linear regression, with separate models being fitted for gas and electricity. The level of statistical significance was set to 5% ($p < 0.05$). This methodology is similar to the methods adopted in the studies by Kontokosta *et al.* (2015), and Mastrucci *et al.* (2014) which both used linear regression models to predict domestic energy use based on building characteristics. The categorical variables listed in Tables 3.2 and 3.4 first needed to be converted to a numerical format to be used to fit the linear model. All ordinal variables with a ranked order between values were assigned integer values ascending from 0. The categorical variables with no ordinal relationship were represented through one-hot encoding. After encoding the variables, stepwise regression, which iteratively adds and removes variables to find the combination variables which produce the strongest model, was carried out to select the statistically significant variables. The final models follow the structure of Equation 1:

$$Y = \beta + \beta_1 \cdot x_i + \beta_2 \cdot x_2 + \ldots + \beta_n \cdot x_n + \varepsilon \qquad (1)$$

Where Y is the annual energy consumption for gas or electricity for the property, β_i are the correlation coefficients and x_i the values of the predictive variables outlined in Tables 2.2, 2.3 and 2.4. OLS regression makes the assumption that Y follows a linear relationship as defined in equation 1, where the variables x are independent from each other, and that the errors ε are independent, and randomly distributed around 0.

The models were initially fit on a training dataset, comprising of 80% of the data, and validated against a test dataset. The coefficients produced by the models are summarised in Part 4, in Tables 4.1 to 4.4. The measured and predicted annual energy consumption for each building are shown in Figures 4.1 and 4.2. To consider the assumptions made in OLS, the variables were checked for multicollinearity by computing the variable inflation factor (VIF), and model residuals were checked to be independent and normally distributed. These were all found to comply with the assumptions of OLS.

3.4.1.4. *Final model selection*

From the results presented in part 4.1 of this report, the model built from the postcode level consumption and EPC data (Model 2) was chosen to be used in predicting building-level energy consumption to all of Westminster's buildings. The obtained R^2 values for the second dataset were higher, suggesting that the model was able to explain more of the variance in building energy consumption. This model used EPC data to obtain information about building characteristics. For this reason, EPC records were therefore used to attribute building characteristics to the entirety of Westminster's building stock to predict energy building level energy consumption for every domestic building in Westminster, the methodology of which is explained in Section 3.5. Several limitations to this methodology have been noted, and are discussed in Part 5.3 of this report.

3.4.2. Non-domestic buildings

In mapping non-domestic energy consumption across Westminster, a similar methodology to the domestic model was initially planned. However, following an in-depth exploration of public data, it became evident that empirical data, appropriate for statistical modelling of non-domestic buildings is even more inaccessible than for domestic buildings. Where data is available, it varies widely in scale and level of information, making applications difficult.

The only public source of real energy consumption attributed to non-domestic buildings is in the form of Display Energy Certificates (DEC), published by the Ministry of Housing, Communities and Local Government (MHCLG). DEC's provide records of real energy consumption, however only for public buildings, which are not representative of the entire non-domestic building stock. BEIS provides sub-national electricity and gas consumption data for non-domestic energy consumption, however, the smallest geographical level provided is at MSOA level. It also includes consumption from all non-domestic energy meters and does not make a clear differentiation between consumption from buildings and other non-domestic activities which require energy, i.e., street lighting or public transportation.

The BEIS has also published a Non-Domestic National Energy Efficiency Data Framework (ND-NEED). Unlike the domestic framework as discussed in section 3.4.1.1, no building-level energy data has been made available publicly. However, it does include a breakdown of median gas and electricity intensity by floorspace for different building use categories, derived from measured energy use statistics. In predicting energy consumption of buildings in New York, Howard et al. (2012) used only building use categories as predictors in their regression model, of which 86% of fitted values were within 20% of measured energy consumption (Howard *et al.*, 2012). When reviewing simple statistical models based solely on energy consumption by sector and floorspace, Bruhns (2008) argued that while these models do not contain any technical information on the determinants of energy use, they can nevertheless be a useful tool in predicting how much energy a building may use, based on its size and sector (Bruhns, 2008).

For the 212 non-domestic properties in Westminster which have published DECs, they were used to map the real energy consumption of these properties. Due to the significant challenges in obtaining sufficient and useful non-domestic building stock information, it was decided to instead make use of the energy intensities by floorspace and building use category produced from data by the ND-NEED framework to predict energy use for the remainder of non-domestic properties in Westminster. Information about floor area and non-domestic building use category for the remaining buildings was drawn from property taxation data supplied by the Valuation Office Agency (VOA). The methodology used to match this information with

Westminster's building polygons, and to calculate final consumption figures is further explained in Sections 3.5 and 3.6.

3.5. Data Matching

For this study, three different sources have been used to obtain information about building characteristics. These include EPCs for domestic buildings, and DECs and VOA ratings for non-domestic buildings. However, integrating these data sources with the spatial building data obtained from the Ordnance Survey faces practical difficulties as all these data sources use different building referencing systems. While the OS Topography data includes geo-referenced polygons which can immediately be recognised by a Geographic Information System (GIS), EPC, DEC and VOA data do not. To infer any spatial information from the results of the predictive modelling, it was therefore crucial to match this data to the spatial data supplied by the OS.

While the building characteristic data sources do not include any geo-referenced information, they all include postal addresses. These, however, are commonly manually logged and often inconsistent in how, and in which order address information is presented. This challenge has previously been addressed by Wu et al. (2018), who tried to integrate all EPC records in Southampton with a GIS, allowing for the data to be analysed spatially. They used an approximate string-matching technique to compare a property's EPC address with geo-referenced address records supplied by the Ordnance Survey, called AddressBase. The address which had the highest string similarity was then selected as a match (Wu, Blunden and Bahaj, 2018) .

In this study, a similar approach as Wu et al. (2018) was adopted, which is outlined in Figure 3.5. First, all EPC, DEC and VOA records relating to buildings in Westminster were obtained from their respective data sources. This building characteristic data was then first matched to the OS AdressBase data by postcode. For each match, the string similarity coefficient between addresses was calculated using Equation 2:

$$s = \frac{n_{match}}{N_{data}} \tag{2}$$

Where s is the similarity coefficient, n_{match} is the number of common elements in both addresses, and N_{data} is the number of elements in the EPC, DEC or VOA address. From the calculated similarity coefficient from each postcode match, the record with the highest value of s was selected as a final match. Each address in the OS AddressBase dataset includes an Topographic Identifier (TOID), which is a unique identifier assigned by the OS to identify geographical features in the UK. Each building polygon supplied in the OS Mastermap Topography dataset, also includes a TOID. By matching TOIDs, a geo-referenced dataset could be created which included property attribute information matched with GIS polygons.

It is worth noting that the OS data supplies information by building footprint, while the EPC, DEC and VOA data is supplied by property, with no matching unique identifier. After data matching, it is therefore possible that a single building polygon has multiple records associated with it (discussed in Section 3.6.2). The following section will explain how the building data was used to predict energy consumption, and in turn attributed to a every building footprint in Westminster to create a comprehensive spatial overview of energy consumption and carbon emissions across the borough.

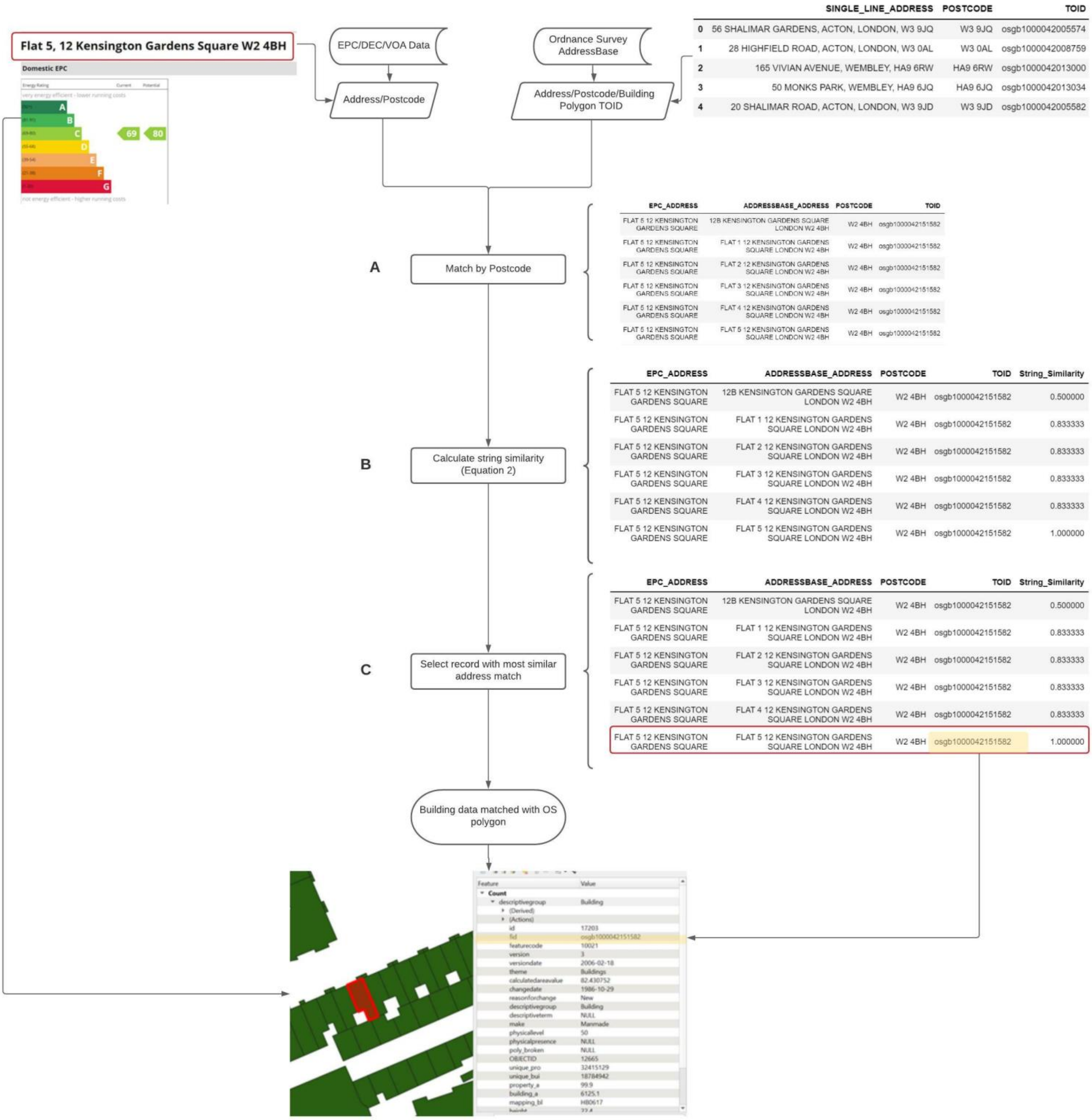

Figure 3.5: A worked example of the data matching workflow showing matching between building characteristic data derived from EPC, DEC and VOA data, and building polygons from the Ordnance Survey. First, the address from the EPC/DEC/VOA record is matched with OS AddressBase data by postcode (A). For each match, the string similarity (Equation 2) between addresses is calculated (B). The match with the highest similarity is selected, and the EPC/DEC/VOA record is linked to the corresponding OS GIS Polygon by matching TOIDs (C).

3.6. Energy and Carbon Mapping

After selecting a method to predict energy consumption for both domestic and non-domestic buildings, these were applied three different public datasets relating to building characteristics to estimate the energy consumption of Westminster's entire building stock.

3.6.1. Predicting consumption:

The OLS regression models from Section 3.4.1. were applied to all public EPC records published for Westminster, to predict annual gas and electricity consumption for a total of 91,146 domestic properties in the borough. According to Westminster City Council, Westminster has approximately 105,772 residential properties (Westminster City Council, 2018), meaning an energy estimate has been made for around 86% of its building stock .

The building categories supplied by the VOA for all non-domestic building properties in Westminster were first simplified to match the building categories used in the ND-NEED Framework. From these, a gas and electricity intensity calculated from the ND-NEED was assigned to each property based on its simplified building use category. To predict total energy use for each property, the energy intensity was then multiplied by the floor area value supplied by the VOA data. The VOA categories, simplified categories and energy use intensities are summarised in Table 3.5. Using this methodology, energy use for a total of 27,219 properties was calculated.

Finally, there are published DEC records for 414 properties in the borough. These have measured values for annual gas and electricity consumption and were therefore used in place of predicted values.

Table 3.5 Building use categories used by ND-NEED, with the corresponding building categories used by the VOA, with assigned energy intensities from ND- NEED data.

ND – NEED Category	VOA Building Categories	Gas intensity (kWh/m2)	Electricity intensity (kWh/m2)
Arts, Community and Leisure	Cinemas, Community centres, Libraries/Museums, Sports centres, Sports grounds	127	31
Education	Nurseries, State schools, Private schools, Universities	172	59
Emergency Services	Ambulance/Fire stations, Police stations	189	54
Factories	Factories	82	33
Health	Health Centres, Hospitals	184	188
Hospitality	Restaurants, Hostels, Hotels, Holiday homes/Guesthouses, Pubs	284	187
Offices	Offices	164	75
Shops	Shops	204	125
Warehouses	Warehouses	61	30
Other	Bus stations/moorings, Cemeteries, Docks, Electricity hereditaments, Garages, Markets, Military premises44, Sewage treatments	204	49

3.6.2. Combining data

As mentioned previously, many of the building polygons supplied by the OS include more than one property. From the OS AddressBase data, it was possible to infer how many unique properties existed within a single building polygon. Missing properties were allocated to be either domestic or non-domestic, depending on the classification of the known properties in the building polygon. After calculating the number of domestic and non-domestic properties in a building, the energy estimates produced from the known property (EPC, VOA and DEC) records was used to generate an estimate of energy consumption for the entire building. Where the number of records matched the number of properties in a building, consumption was summed to get a building total. Where there was only data for a portion of properties in a building, the median consumption was calculated and multiplied by the number of remaining properties, assuming that all properties within a building have similar characteristics and consumption patterns.

The calculated energy consumption was finally summed for each building to get a single gas and electricity consumption value for each building polygon. Energy use intensities were also calculated for each building by dividing the total consumption by the total building footprint. This was carried out for domestic and non-domestic estimates separately, but a combined total consumption was also calculated – considering that many of Westminster's buildings contain a combination of domestic and non-domestic premises.

3.6.3. Estimating CO_2 emissions

From the total gas and electricity consumption estimated for each building (both domestic and non-domestic), an estimate was made for the CO_2 emission intensity of each building using the 2021 emission conversion factors for gas and electricity (Department for Business, Energy, and Industrial Strategy, 2021a). In the UK, emission conversion factors are published annually by the government to facilitate the reporting and monitoring of organisation's greenhouse gas emissions. Table 3.6 summarises the conversion factors used for this study, representing the amount of CO_2 equivalent (CO_2e) in kilograms that is emitted for each kWh of energy consumed. CO_2e is a way of consolidating all greenhouse gas emissions into a common unit, and converts amounts of other gases to the equivalent amount of carbon dioxide with the same global warming effect (Jones, 2021).

Table 3.6 CO2 equivalent emission factors for gas and electricity, used to estimate building carbon emissions from energy use.

Energy Source	CO_2 equivalent emission factor (kg/kWh)
Gas	0.18316
Electricity	0.21233

4. Results

The following section of the report presents the results of the methodology described in Part 3, used to produce a granular estimate of building level energy use and carbon emissions of Westminster's building stock.

4.1. Domestic Energy Modelling

The regression modelling workflow outlined in Section 3.4.1 was carried out for the two different sets of data, the results of which are outlined in Tables 4.1 to 4.4. Figures 4.1 and 4.2 show the predicted vs. actual consumption values for gas and electricity, respectively. From the tables, both datasets produced statistically significant coefficients for the selected variables, however the R-squared values produced using EPC records and postcode - level consumption (Model 2) were greater, suggesting that the variables used in those models are more suited to explain the variation in gas and electricity consumption. These models were subsequently chosen to predict energy consumption of Westminster's domestic properties. The results confirm findings from previous studies that building characteristics influence domestic energy use (Mastrucci *et al.*, 2014; Kontokosta *et al.*, 2015), however the coefficients of determination (R^2) produced from these are not as high, suggesting that there may be other factors influencing variation in energy use which have not been incorporated in the models.

Table 4.1 Ordinary Least Squares (OLS) regression results for predicting annual gas consumption (kWh) from Model 1, derived from the NEED framework: coefficients (β) with standard errors in parentheses

Variable	
Intercept	5788 (890)*
Floor area band	2923 (168)*
Main heating fuel	3829 (700)*
Age band	-2063 (115)*
Council tax band	1432 (88)*
Property type - Detached	3158 (459)*
Property type - Mid-terrace	-3385 (261)*
Property type - End-terrace	-1212 (341)*
Property type - Flat	-2801 (314)*
p-value	2.2e-16
RMSE	5937
R-squared	0.499

Notes: *$p < 0.05$, N= 5345

Table 4.2 Ordinary Least Squares (OLS) regression results for predicting annual gas consumption (kWh) from Model 1, derived from the NEED framework: coefficients (β) with standard errors in parentheses

Variable	
Intercept	3352.31 (214)*
Floor area band	523 (63)*
Main heating fuel	-1591 (100)*
Age band	-245 (40)*
IMD band	-76 (31)*
Council tax band	446 (33)*
Property type - Detached	886 (179)*
p-value	2.2e-16
RMSE	2392
R-squared	0.175

Notes: *$p < 0.05$, N= 6505

Table 4.3 Ordinary Least Squares (OLS) regression results for predicting annual gas consumption (kWh) from Model 2, based on EPC and postcode level consumption data: coefficients (β) with standard errors in parentheses

Variable	
Intercept	-2006 (326)*
Floor area	59 (168)*
Age band	-312 (21)*
Exposed sides	1249 (53)*
EPC rating	601 (72)*
IMD	355 (21)*
p-value	2.2e-16
RMSE	4715
R-squared	0.538

Notes: *$p < 0.05$, N= 5345

Table 4.4 Ordinary Least Squares (OLS) regression results for predicting annual electricity consumption (kWh) from Model 2, based on EPC and postcode level consumption data: coefficients (β) with standard errors in parentheses

Variable	
Intercept	824 (140)*
Floor area	29 (1)*
Number of rooms	165 (28)*
Exposed sides	259 (26)*
EPC rating	132 (32)*
IMD	72 (11)*
p-value	2.2e-16
RMSE	2465
R-squared	0.350

Notes: *p < 0.05, N= 5345

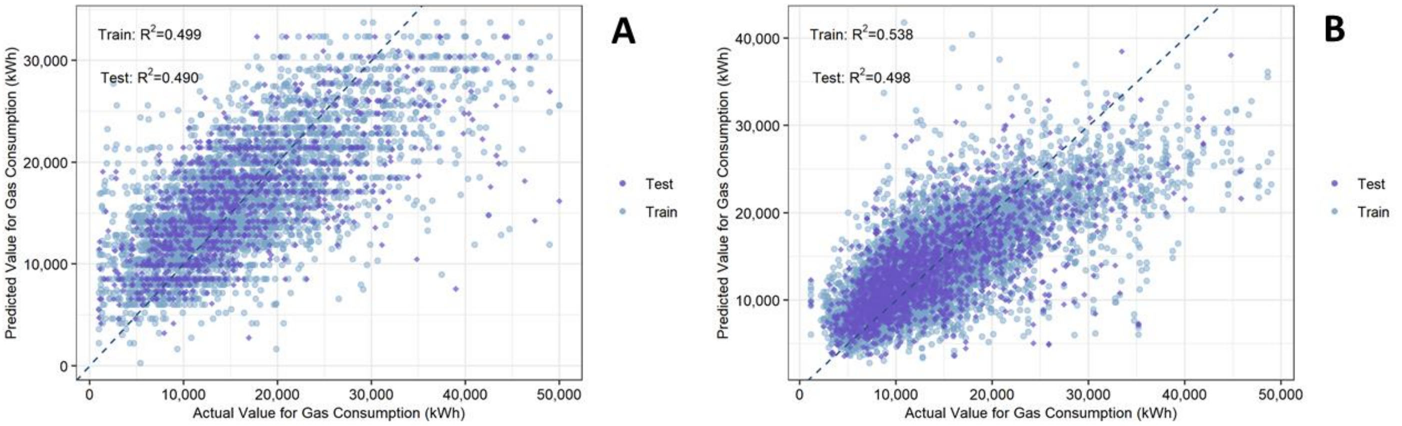

Figure 4.1 Predicted value of annual building gas consumption vs actual gas consumption for (a) Model 1: NEED dataset and (b) Model 2: Postcode consumption and EPC data. The results derived from the testing (20%) and training (80%) datasets are shown in different colours. The dotted line indicates a perfect prediction

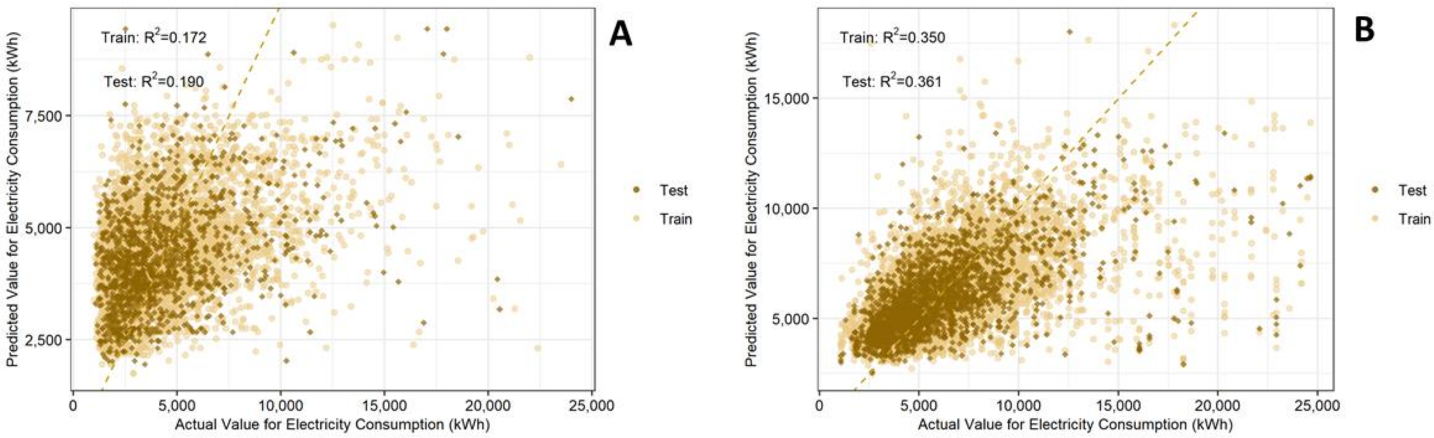

Figure 4.2 Predicted value of annual building electricity consumption vs actual electricity consumption for (a) Model 1: NEED dataset and (b) Model 2: Postcode consumption and EPC data. The results derived from the testing and training datasets are shown in different colours. The dotted line indicates a perfect prediction

Figures 4.3 and 4.4 shows the domestic gas and electricity use intensity mapped to Westminster's buildings, calculated by dividing the consumption predicted for the building with its total floor area, according to the workflow outlined in Section 3.6. Following the prediction at a building level, consumption results were aggregated at LSOA level. The total predicted consumption was compared to the total measured consumption at LSOA level, data collected from private energy suppliers and aggregated and published by the Department of Business, Energy and Industrial Strategy. The results are shown in Figures 4.5 and 4.6.

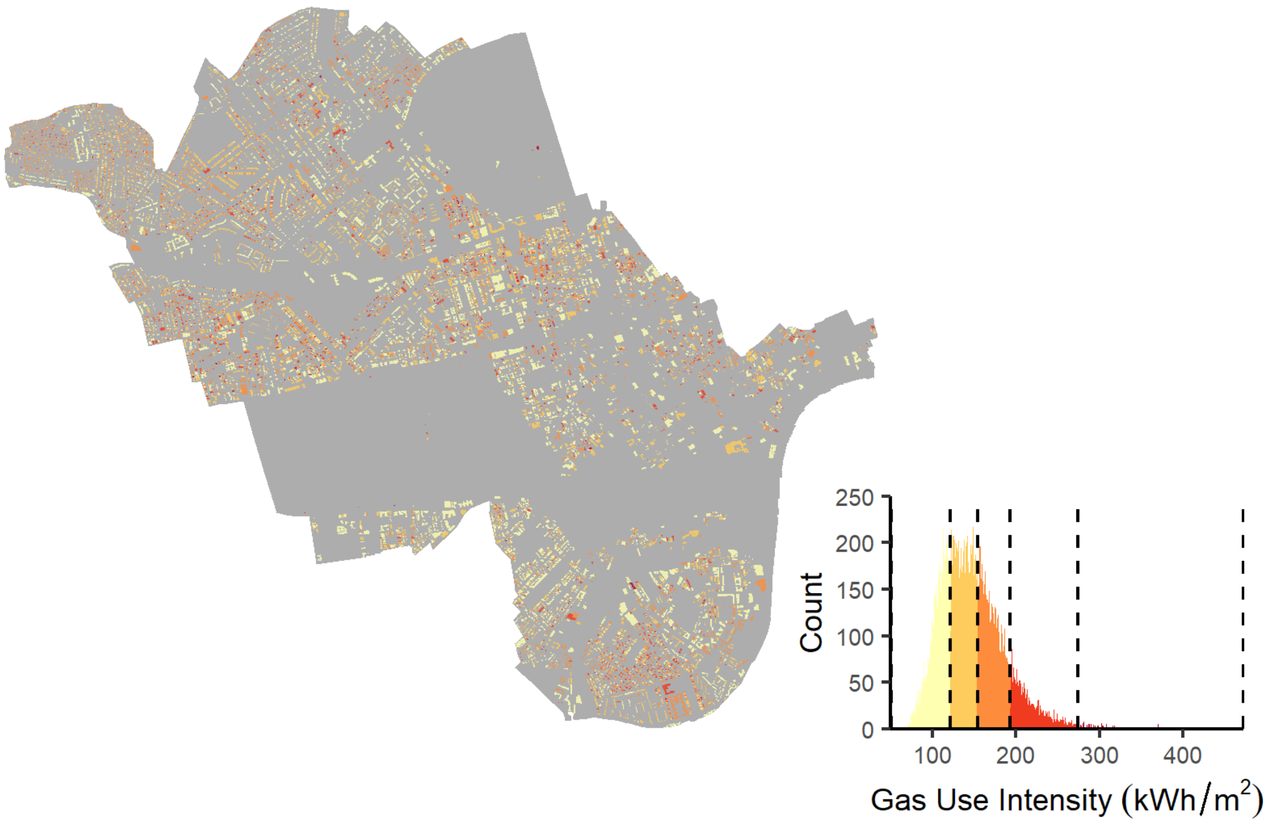

Figure 4.3: Westminster's building polygons with colour indicating the banded domestic gas use intensity of the building. The histogram indicates the distribution of gas use intensity of Westminster's domestic buildings and the ranges of the mapped colour classes. Contains OS data © Crown copyright and database rights, 2021 Ordnance Survey (100025252).

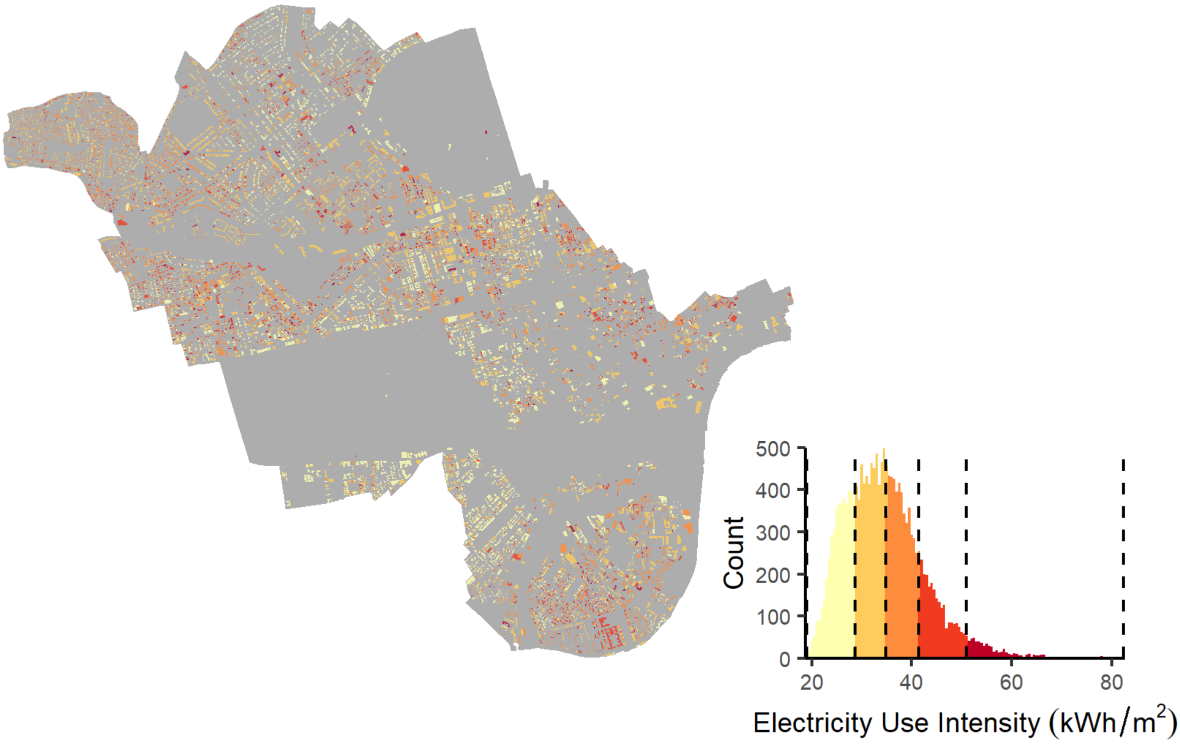

Figure 4.4: Westminster's building polygons with colour indicating the banded domestic gas use intensity of the building. The histogram indicates the distribution of gas use intensity of Westminster's domestic buildings and the ranges of the mapped colour classes. Contains OS data © Crown copyright and database rights, 2021 Ordnance Survey (100025252).

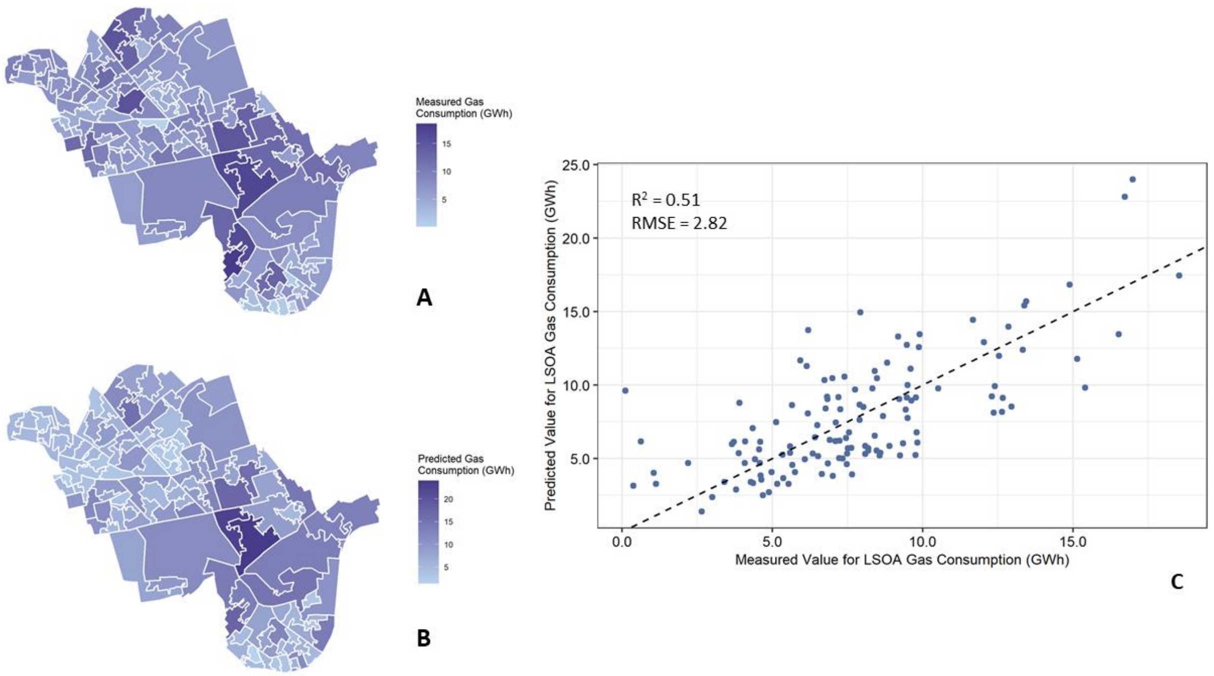

Figure 4.5: Choropleth of Westminster's LSOAs A) measured, and B.) predicted building gas consumption, and C.) a scatter plot showing the relationship between the measured and predicted building gas consumption at LSOA level. The predicted values have an R^2 of 0.51 and a root mean squared error (RMSE) of 2.82.

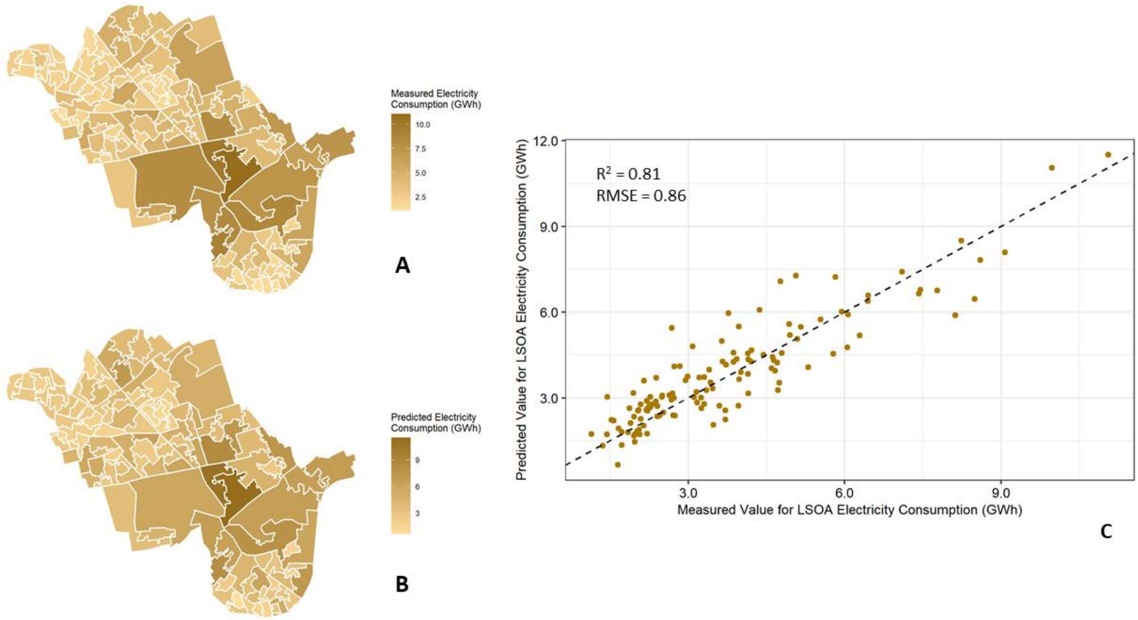

Figure 4.6: Choropleth of Westminster's LSOAs A.) measured, and B.) predicted building electricity consumption, and C.) a scatter plot showing the relationship between the measured and predicted building electricity consumption at LSOA level. The predicted values have an R^2 of 0.81 and a root mean squared error (RMSE) of 0.86

4.2. Non-Domestic Energy Modelling

Westminster's non-domestic gas and electricity use intensities derived from the Non-Domestic National Energy Efficiency Framework (ND-NEED) were mapped to Westminster's buildings, following the methodology outlined in Part 3.4.2, and are shown in Figures 4.7 and 4.8. However, as there is no comprehensive data published relating to non-domestic building consumption, these results could not be validated against aggregated consumption statistics in the same way as the domestic estimates.

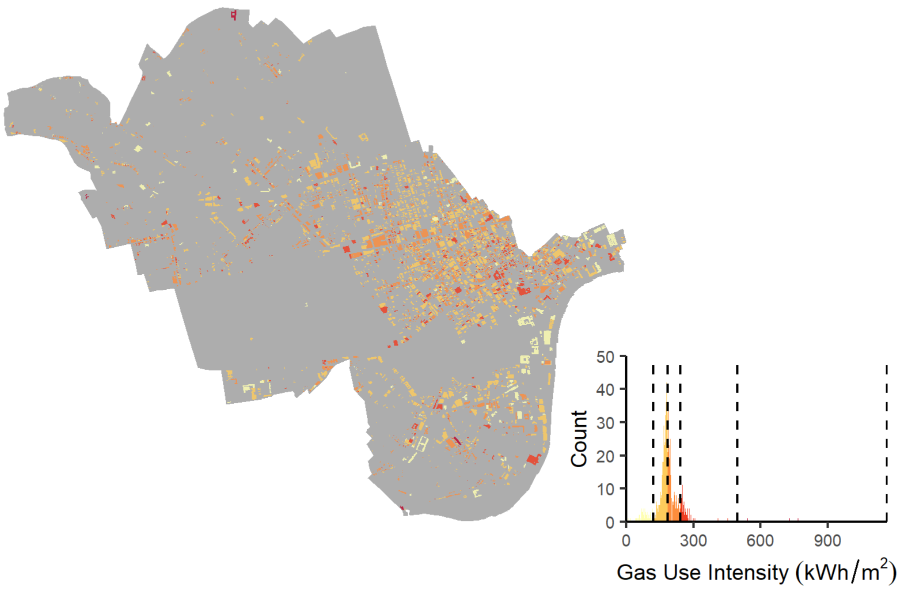

Figure 4.7. Westminster's building polygons with colour indicating the banded non-domestic gas use intensity of the building. The histogram indicates the distribution of gas use intensity of Westminster's non-domestic buildings and the ranges of the mapped colour classes. Contains OS data © Crown copyright and database rights, 2021 Ordnance Survey (100025252).

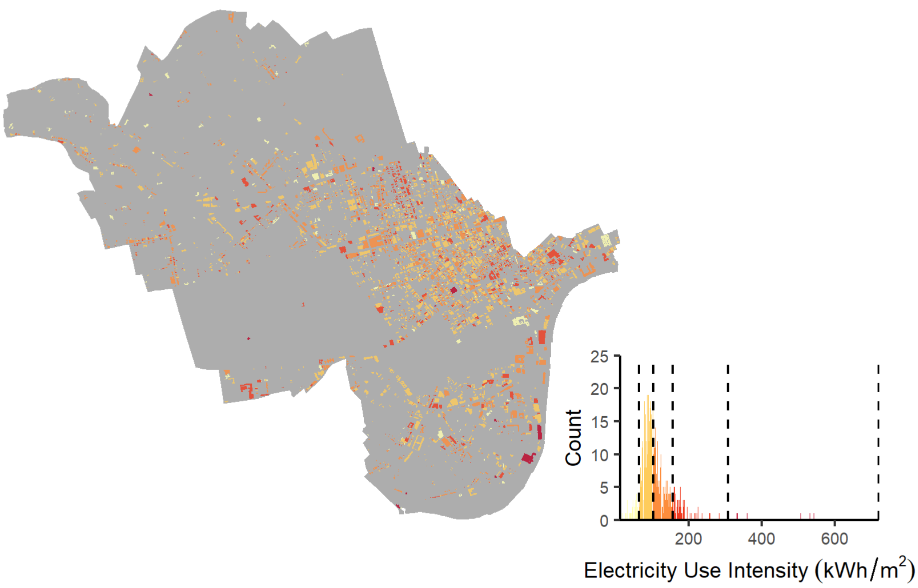

Figure 4.8. Westminster's building polygons with colour indicating the banded non-domestic electricity use intensity of the building. The histogram indicates the distribution of electricity use intensity of Westminster's non-domestic buildings and the ranges of the mapped colour classes. Contains OS data © Crown copyright and database rights, 2021 Ordnance Survey (100025252).

4.3. Carbon Intensity

Figure 4.9 shows the estimated annual carbon dioxide equivalent (CO_2e) emissions per square meter for every building footprint in Westminster, based on the total gas and electricity consumption estimated for each building. Emissions intensities were also plotted on a hexbin map (Figure 4.10.) where Westminster is divided into equally sized hexagons, to allow for the identification of areas of the borough where high carbon emissions are concentrated.

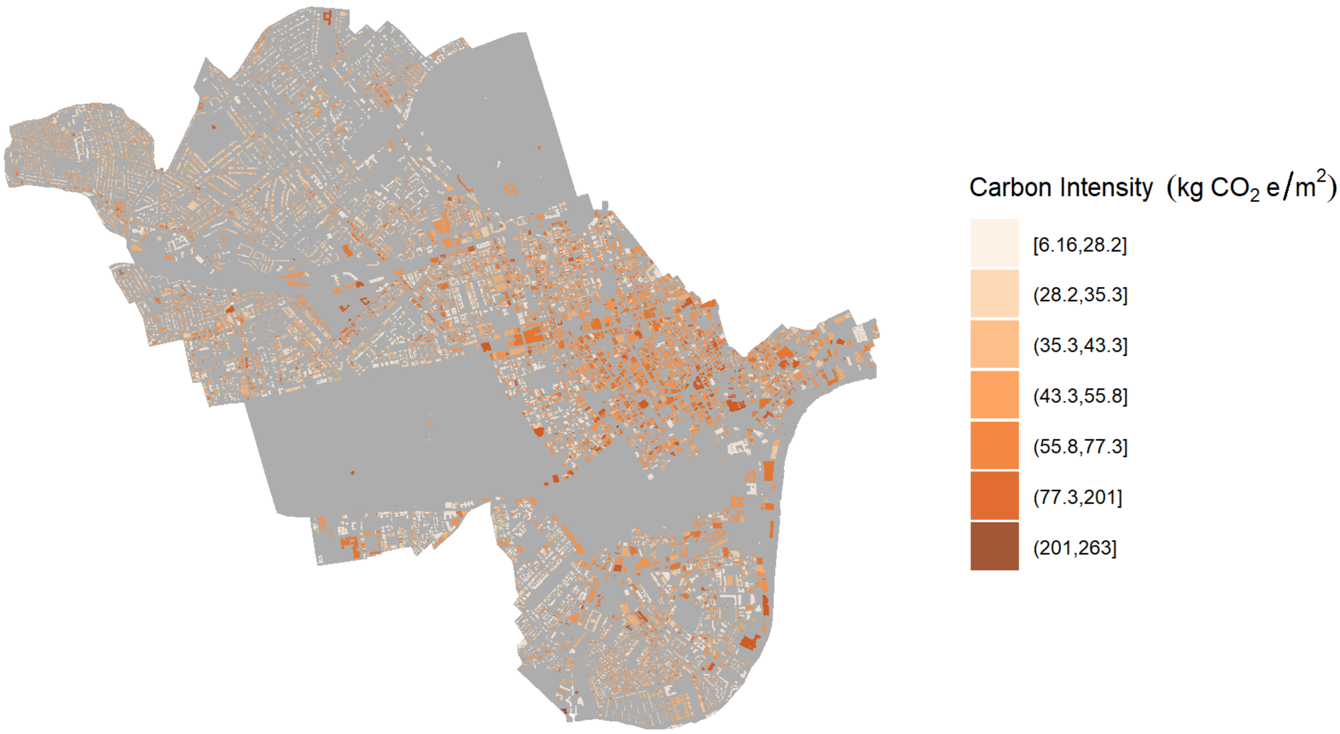

Figure 4.9. Westminster's building polygons with colour indicating the banded total carbon intensity of the building in $kgCO_2e$ per square meter of floor area of the building. Colour classes have been determined by Fisher-Jenks natural breaks. Contains OS data © Crown copyright and database rights, 2021 Ordnance Survey (100025252).

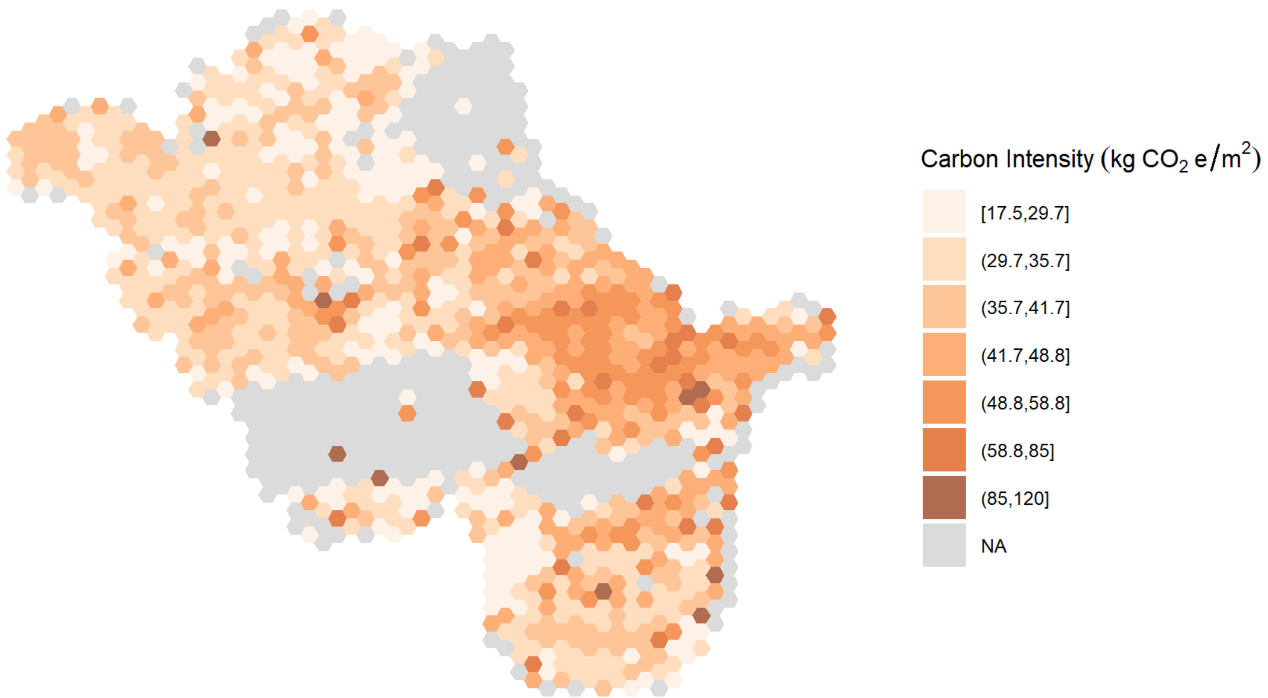

Figure 4.10 Hexbin map of Westminster divided into equally sized hexagons. The colour of each hexagon indicates the combined carbon intensity in $kgCO_2e$ per square meter, calculated by dividing the total carbon emissions by the total floor area of buildings within each hexagon. Colour classes have been determined by Fisher-Jenks natural breaks.

From the final carbon emission calculations, Westminster's buildings are estimated to produce 1,986,195 tonnes of CO_2e annually. This estimate is consistent with previous baseline carbon emission levels published by Westminster City Council, which allocated 1,949,620 tonnes of CO_2e emissions to Westminster's buildings in 2017 (Jones, 2021). Of building carbon emissions, Westminster's baseline attributes 83% of emissions to come from non-domestic buildings. The final results of the model estimates 87% of total emissions to come from non-domestic buildings.

5. Discussion

This work has set out to answer the following question:

- *How can non-spatially referenced data be used to spatially investigate urban building CO_2 emissions?*

Using existing data on building characteristics and energy use, combined with statistical modelling and developing an address-matching methodology to match non-geographically referenced data to individual GIS polygons, a model was created to predict building by building energy use and CO_2 emissions in Westminster. The results correspond well with existing baseline information on the borough's energy and carbon performance, for both energy consumption aggregated at LSOA level, and borough-wide carbon emissions

5.1. Implications

The results of the model can be used by Westminster to communicate to owners how their buildings are performing in relation to others, to incentivise carbon reduction initiatives at a building level. An example where this is already being carried out is in the cities of Boston, Chicago, and New York, which all provide online interactive visualisations which allow the public to compare building's energy performance in the context of their local geographies in an easy-to-understand format (Beddingfield, Hart and Hughes, 2018). The schemes act as capacity building tools, allowing users to independently determine which buildings have the greatest energy saving potential, and supports energy saving projects to be identified by building owners.

The results could not only be used to assess individual building performance, but also in the planning and implementation of low carbon energy systems such as district heating and distributed energy generation. For example, from the results, an area could be identified where all buildings experience high gas demand – these may benefit from shared district heating due to their spatial proximity to each other. An existing example is the London Heat Map, designed to support the planning and design of local low carbon heating projects using publicly accessible online visualisations of energy modelling. The London map is actively being used by both local governments and developers in planning for new developments to assess the feasibility of low carbon, renewable and decentralised energy projects (C40 Cities, 2016; Centre for Sustainable Energy, 2018). The results produced by this study could be used in a similar way, by providing an estimate of energy demand at an even more granular level.

5.2. Next steps

The next steps for Westminster in using the results produced by this study is to place them into the borough's context. Communicating the results through interactive visualisations that are easy to explore can enable city stakeholders to gain a better understanding of how buildings consume energy. The results can also be used by policymakers to quantify how much energy use intensity will need to decrease across the borough in order to meet the council's 2040 targets, as well as analysing different pathways to reach these targets and assessing feasibility, as it is likely that not all buildings have the same emissions reduction potential (Lloyd-Jones *et al.*, 2008). From this, buildings can be identified which need to be prioritised for the maximum emission reduction impact.

The results of this study allow for the communication of energy consumption data to Westminster's building owners as well as occupiers. While the communication of building emission data may encourage building occupiers to reduce individual energy consumption through behaviour change, previous studies have found that occupant behaviour change alone does not result in significant reductions in building energy consumption (James and Ambrose, 2017). The greatest energy consumption reduction was instead seen when properties underwent a combination of energy saving retrofits and behaviour change interventions. However, Westminster faces the challenge of landlord-tenant split incentives as a barrier to retrofitting, as many of Westminster's properties are tenant-occupied. Landlords carry most of the responsibility to pay for energy efficiency upgrades, while tenants will be the ones directly benefiting from lower energy costs as a result (Bird and Hernández, 2012). The results of this study should therefore be combined with policies that incentivise landlords to carry out energy-efficiency measures in the borough, for example by providing economic aid to carry out improvements. An existing example is Melbourne's 1200 Buildings scheme, which provides grants and guidance to building owners to aid retrofitting projects (C40 Cities, 2012).

Significant funding for grants, and tax incentives such as tax rebates on rental income (UK Green Building Council, 2013), however, are reliant on wider UK Government schemes, and are difficult to implement at local authority level. While the benefits of energy efficiency improvements are well established (James and Ambrose, 2017; Brown *et al.*, 2018), UK public spending to encourage retrofitting has been limited, with multiple schemes being abandoned before being realized (Tingey *et al.* 2021). Most recently, the government scrapped its Green Homes Grant Scheme, which was part of the UK's green recovery strategy following the Covid-19 pandemic, only six months after its launch. The scheme was put in place to offer grants to homeowners for the installation of insulation and low-carbon heating (Harvey, 2021).

Considering the recent IPCC report (2021), the UK Government still needs to take drastic action to reduce the energy consumption of buildings across the country in the context of its wider carbon reduction targets. However, Tingey et al. (2021) argued that local authorities play an equally, if not more important, role in enabling energy efficiency upgrades. Examples include developing localised retrofit programmes which work together with local businesses to deliver retrofits to homeowners at reduced costs (Tingey *et al.* 2021). Another example explored by Westminster is to encourage landlords through financial incentives such as Council

Tax relief for properties above a certain EPC rating, making the properties more desirable for renters, which in turn may increase rental prices (WCC communication, 2021). As local authorities oversee planning applications in the area, they are also positioned to facilitate projects that reduce the energy demand of existing buildings. Equipped with the results of this study, Westminster City Council can make spatially informed decisions on development projects which are well integrated within the borough's existing building energy context – whether these are small-scale energy retrofits, or larger energy saving schemes such as district heating.

Further, the methodology can be used to explore different carbon reduction scenarios, for example modelling how energy use would change if every domestic building improved their EPC rating by one band. Scenario modelling can be used to quantify emission reduction potential, as well as incentivising private stakeholders by quantifying and communicating the economic savings potential of retrofitting. Additionally, scenario modelling can be used to analyse the impact of wider efforts of decarbonising the UK's electricity grid and encouraging a shift from gas to electric heating. While the current carbon emission factor for electricity is higher than that of gas, this is projected to decrease rapidly as the UK shifts to a cleaner electricity mix. By 2040, the Department of Business, Energy and Industrial Strategy, predicts an electricity emission intensity of only 0.067 kgCO_2e per kWh, a 68 % reduction from the current value (Department for Business, Energy, and Industrial Strategy, 2019). Taking these factors into consideration, the results can be used to predict future emissions and assess different scenarios, such as if consumption values stay the same, or the effect of replacing all gas heating in Westminster with electric heating.

Westminster's 2040 targets are a decade ahead of the targets set out in the London Plan (2021), which aims for London to be net-zero by 2050. The novelty of combining multiple datasets with no reference between them to create detailed spatial insight on consumption for targeted action could therefore be used as a precedent on how to address building carbon emissions in the rest of London. The methodology used for this study could easily be adopted for other cities in the UK. The data challenges presented and resolved within this work are common to other countries, for example as highlighted by the works of Kontokosta et al. (2015) and Mastrucci et al. (2014). Disseminating the presented methodology, and local variations in data availability through knowledge sharing schemes such as C40 cities would assist in reducing global energy consumption and place Westminster at the forefront of global greenhouse gas reduction efforts.

Acuto (2016) argued that in order to lead the fight against climate change, cities must collect and share data which is both "granular and globally relevant" (Acuto, 2016, p.613). This study has demonstrated that cities have the potential to do exactly that - produce granular and spatial insights on building-level carbon emissions, even when this data is not directly available. The approach of matching non-spatial energy and building data with spatial information presented here has the potential to allow cities to take a data-driven approach to efficiently target emission reduction activities. If more cities begin producing and reporting data on building carbon emissions and initiatives to reduce emissions, this may encourage a culture of inter-city knowledge sharing and co-operation in limiting the devastating consequences of climate change (IPCC, 2021).

5.3. Limitations

Due to the lack of comprehensive energy and building data, this report has made several assumptions to predict building energy consumption, and the results are not without errors. From the regression results presented in Tables 4.3 and 4.4, the coefficients of determination (R^2) of the final models suggests that the predictors selected for the model can only partially explain the variation in energy use, with the gas model performing better than the electricity model. This is likely because in addition to physical building characteristics, domestic energy consumption is influenced by complex factors such as the habits and preferences of individuals, which cannot be captured by quantifiable measures. Interestingly, when aggregating the domestic estimates up to LSOA level, the predictions for electricity are more in line with real consumption than gas. This may be because while gas consumption is primarily used for heating, the need for which can be highly varied across an area due to local effects such as the orientation of buildings, electricity use is likely to be less affected by spatial variations. Further, the energy use intensities used to estimate energy consumption and emissions of Westminster's non-domestic stock are derived from national data, which may not consider regional variations in energy consumption due to factors such as climate. As there is no comprehensive available data on non-domestic energy consumption from buildings it is also difficult to validate the predictions made for that portion of Westminster's buildings. Nonetheless, when taking the sum of all the predicted emissions across the borough, these estimates correspond well with Westminster Council's own published statistics on building emissions.

To improve the predictions of building-level energy consumption, there is a need for more granular and detailed information on both building characteristics and energy use. As improved data becomes available, the methodology can be adapted to make better predictions. Despite the limitations, the above results have shown that it is possible to predict building CO_2 emissions with limited data, which can be used as an outset from which cities can begin to address building carbon emissions and prevent the irreversible consequences of a climate change as outlined in the latest IPCC report (IPCC, 2021).

6. Conclusion

Climate change is already in full effect, and to prevent the irreversible effects of a complete climate breakdown, urgent and drastic action need to be taken to limit global warming to 1.5 °C. Westminster City Council has set the ambitious target of becoming a climate neutral city by 2040, however targets alone will not cut emissions. WCC needs take rapid action to curb the borough's carbon emissions, which are dominated by buildings. However, translating reduction targets to action is difficult without knowing how individual buildings consume energy and contribute to emissions. A lack of comprehensive data on energy consumption in buildings provides a significant challenge in knowing where emission reduction activities should be targeted. Further, the sparse data that is available on individual buildings is not spatially referenced, making it difficult to analyze building performance in relation to one another on a spatial scale. While a lack of comprehensive and usable data highlights the need for more transparency on how buildings in use energy use, a systemic change in how energy consumptions statistics are disclosed is likely to happen over time. In the face of the climate crisis, however, there is not much time. In absence of better data, this research has set out to create a model that spatially investigates CO_2 emissions from Westminster's buildings, by combining statistical modelling and non-spatially referenced data with spatially referenced GIS polygons. The result is a prediction of annual carbon emissions for almost every building in Westminster.

While the methodology used makes a significant number of assumptions to predict energy use in buildings, and is not free of errors, when aggregated upwards, the results align well with previously established emission statistics. The results can be useful to plan feasible large scale energy initiatives such as district heating and distributed generation, but can be used further to generate a culture of accountability and encourage individuals to take action to improve the efficiency of their buildings. The results are a first step towards a spatial approach to

Westminster’s decarbonisation strategy, and the methodology is robust to be applied and improved as new and better data becomes available. Further, the methodology can be applied to cities across the UK with the same data challenges, and even internationally, given similar data. To conclude, the model created for this work has the potential to provide cities with a methodology to produce a spatial overview of building carbon emissions, which in turn can be used to identify steps that need to be taken to reach carbon targets, and work towards the global climate goal of limiting atmospheric heating to 1.5 degrees.

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