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Modelling urban carbon emissions for multiple sectors in high spatial resolution for achieving sustainable & net-zero cities

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ABSTRACT

Many largescale initiatives and networks have been established to support city efforts and leadership in decarbonisation. An essential first step in these initiatives is developing a Baseline Emissions Inventory (BEI) to understand drivers of current emissions and provide a benchmark that progress can be measured against. There has been increasing interest in emission inventory methods. However, previous research has focused on single sectors, has neglected emissions other than CO_2, or has not followed a spatial approach. The latter is particularly important to support policy planning and decision-making. This study investigates the development of a novel BEI for a medium-sized city in Ireland to address the methodological knowledge gap in existing literature for a detailed methodology using mainly open-source and spatially resolved data for developing a multi-sectoral BEI in high spatial resolution. Greenhouse Gas (GHG) emissions including CO_2, CH_4, and N_2O, represented as kilotonnes CO_2-equivalent (ktCO_2-eq), were modelled for the Residential; Transport; Commercial & Industrial; Public; Agriculture, Land Use & Fishing (ALUF); and Waste sectors. Total annual emissions were 987 ktCO_2-eq, with emissions per capita of 4.7 tCO_2-eq. The Residential sector accounted for 34 % of emissions followed by the Transport (29 %), Commercial & Industrial (22 %), Public (7 %), ALUF (6 %), and Waste (2 %) sectors. The fine-resolution spatial outputs facilitate the investigation of socioeconomic factors alongside GHG emissions helping to elucidate local drivers and produce equitable mitigation strategies. The findings will contribute to effective policy development and the methodologies, developed in accordance with the Global Covenant of Mayors, can be replicated by cities globally.

1. Introduction

As Greenhouse Gas (GHG) emissions and urbanisation rates continue to rise, so too does the importance of cities within the global challenge of decarbonisation. At present, urban areas account for 55 % of the global population and by 2050, it is expected that this figure will reach 68 % (United Nations, 2018). Projected future urbanisation will exacerbate the impact that anthropogenic GHG emissions are having on global warming (Magazzino et al., 2024; Nyhan, 2015; United Nations, 2018). In response to accelerating urbanisation and climate change impacts, global GHG emissions need to be rapidly reduced towards net zero. This is particularly true for urban areas which contribute between 67 % and 72 % of GHG emissions worldwide (Gouldson et al., 2016; IPCC, 2023; Lamb et al., 2021; United Nations Environment Programme, 2021).

Many global cities recognise their responsibility to decarbonise, and this has led to largescale initiatives and networks with shared climate action goals (Croci et al., 2017; Kona et al., 2018; Saad et al., 2021). These initiatives are aligned with the Paris Agreement which sets out that emissions need to reach net zero by 2050 and limit increases in global temperature to within 2 °C and ideally within 1.5 °C above pre-industrial levels within this century in order to avoid the worst impacts of climate change (Chen et al., 2019; GCoM, 2024; Melica et al.,

Abbreviations: GHG, Greenhouse Gas; ICLEI, International Council for Local Environmental Initiatives; EU, European Union; GCoM, Global Covenant of Mayors; SECAP, Sustainable Energy and Climate Action Plan; SDGs, Sustainable Development Goals; BEI, Baseline Emissions Inventory; kt, Kilotonne; CO_2-eq, CO_2-equivalent ALUF, Agriculture Land Use and Fishing; CSO, Central Statistics Office; SA, Small Area; SEAI, Sustainable Energy Authority of Ireland; BER, Building Energy Rating; EPC, Energy Performance Certificate; OSM, OpenStreetMap; CIBSE, Chartered Institution of Building Services Engineers; UCC, University College Cork; ED, Electoral Division; EPA, Environmental Protection Agency; SD, Standard Deviation.

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2018). C40 Cities was initially formed in 2006 by the mayors of 40 megacities worldwide and consists of 96 member-cities aiming to halve their emissions by 2030 (C40, 2024). Another network, the International Council for Local Environmental Initiatives (ICLEI), connects 2500 local governments in over 125 countries globally (ICLEI, 2024). These two global networks, in partnership with the United Cities and Local Governments and the United Nations Secretary General, launched The Compact of Mayors in 2014, which later merged with the European Union's (EU's) largest network, The Covenant of Mayors, to form The Global Covenant of Mayors for Climate and Energy (GCoM). Accordingly, 11,500 GCoM member cities have pledged to reduce their emissions and implement additional climate policies though Sustainable Energy and Climate Action Plans (SECAPs) (Chen et al., 2019; GCoM, 2024).

Research methods and tools have been progressed to expedite the development of SECAPs including methods for assessing energy consumption and resultant emissions from buildings (Saad et al., 2021; Zanni et al., 2015), emissions inventory tools (ECOSPEED, 2024; L'Association pour la transition Bas Carbone, 2024;Netherlands Enterprise Agency, 2024), climate action prioritisation tools (Saad et al., 2021), socioeconomic models (Pan et al., 2019), geographical information system-based policy supports (Gagliano et al., 2015), harmonised GHG emissions databases (Kona et al., 2021), and unified SECAP data tools for policy recommendations (Dimitropoulos et al., 2023). Past EU initiatives including the Cleaner Energy Saving Mediterranean Cities were established to support the EU's Mediterranean and East European partner nations in sustainable energy and climate action plans (EU Neighbours, 2024).

An essential first step in initiatives focused on urban decarbonisation is the preparation of a Baseline Emissions Inventory (BEI) so that progress in emissions reductions can be measured against a benchmark (GCoM, 2024; Ghaemi & Smith, 2020). Accordingly, research demonstrating the development of emissions inventories, and methods on how to develop them, have increased in recent years (Chen et al., 2019). 'Bottom-up' and 'top-down' approaches have been applied, with the former referring to aggregating emissions sources within a boundary whereas the latter includes apportioning national emissions (O'Regan & Nyhan, 2023). Three prevailing methods for urban GHG emissions accounting have been identified in the literature (Arioli et al., 2020; Fang et al., 2017) including input-output analyses (Dias et al., 2018; Fang et al., 2017; Fry et al., 2018; Mi et al., 2019), life-cycle analyses (Cellura et al., 2018; Dias et al., 2018; Qi et al., 2018), and studies following IPCC or similar guidelines (Cellura et al., 2018; Sówka & Bezyk, 2018). Arioli et al. (2020) investigated 40 studies applying different methods to quantify GHG emissions at the city scale. The majority (38 %) of these studies employed IPCC national guidelines to model urban GHG emissions while other studies applied personalised (23 %) and hybrid life-cycle analysis (LCA) (23 %) methods. Regional models, input-output analysis, eddy covariance and LCA methods were used by 5 %, 5 %, 5 %, and 3 %, respectively. These methods are only recently being adopted for city-scale GHG emissions accounting, and they observed that only 5 % of the reviewed studies included some form of sensitivity or uncertainty analysis. In their review of GHG emissions accounting studies that apply a life-cycle assessment method, Ghaemi and Smith (2020) documented that just 1 out of 28 case studies published between the years 2006 and 2019 conducted a sensitivity analysis in their study. However, many emerging urban energy models, which form the basis of SECAPs and BEIs, have incorporated a spatial dimension of continuously increasing resolution into their analyses. This approach has been shown to advance model relevance and accuracy, particularly in urban areas with diverse energy demand, density, and infrastructure (Aryanpur et al., 2021; Horak et al., 2022). Furthermore, higher-resolution spatial differentiation enables socially equitable and context-specific energy policy interventions such as energy poverty assessments or district heating strategies, respectively (Horak et al., 2022; Kelly et al., 2020).

Consequently, emissions inventory studies integrating a spatial dimension are accumulating in the literature. At a national level, a study in Poland and Ukraine used residential energy demand to approximate disaggregated fuel usage and model residential sector emissions, in CO_2-equivalent (CO_2-eq), at a 2 km × 2 km resolution (Danylo, Bun, See, & Charkovska, 2019). GHG emissions from the transport sector were examined by Puliafito et al. (2015) for Argentina, at a 9 km × 9 km grid resolution and also hourly by Pla et al. (2021) for Valencia at the street level. Charkovska et al. (2019) modelled GHG emissions including methane (CH_4) and nitrous oxide (N_2O) for the agricultural sector in Poland at a 0.1 km × 0.1 km spatial resolution, using the Intergovernmental Panel on Climate Change (IPCC) recommended approach. Gao et al. (2022) modelled carbon dioxide (CO_2) and air pollution emissions for five sectors across China at a 10 km × 10 km spatial resolution. Boychuk and Bun (2014) followed IPCC guidelines to develop a GHG emissions inventory for the energy sector (which includes emissions from energy use across multiple sectors) in western Ukraine and spatially mapped the results at a 2 km × 2 km grid-cell resolution. At the city-wide scale, using visible infrared imaging and statistical data, Zhao et al. (2018) modelled the spatial distribution of CO_2 from residential energy usage at a 0.5 km × 0.5 km grid-cell resolution for cities in China. Lorenzo-Sáez et al. (2020) examined energy and emissions from buildings, at the building-unit level in Quart de Poblet, Spain. Chuai and Feng (2019) modelled energy-related emissions from residential, commercial, industrial, and agricultural activity at 0.3 km × 0.3 km resolution for Nanjing City, China. Marchi et al. (2023) developed a GHG emissions inventory and investigated the spatial distribution of emissions at a 10 m × 10 m resolution for the energy, waste, and agricultural sectors in Grosseto, Italy.

Although a BEI is a prerequisite for joining global urban decarbonisation initiatives and networks, detailed methodologies for developing urban BEIs are poorly documented (McGookin et al., 2021). Some initiatives have developed guidelines, including the Global Protocol for Community-Scale Greenhouse Gas Emission Inventories (GPC) released in 2014, however, even though this was developed with a focus on city-level GHG accounting and derived from IPCC guidelines, few studies have adopted the methodology (Li et al., 2017) and some that have stated that the guidelines don't account for the level of data availability in some cities (Arioli et al., 2020; Erickson & Morgenstern, 2016). Furthermore, the available IPCC guidelines have been developed for national emissions modelling and are not directly applicable in the context of sub-national or urban BEIs (Chen et al., 2019). A lack of fine scale spatial data (Pulselli et al., 2019; Ulpiani et al., 2023a) and detailed methods for modelling precise emissions outputs can lead to ineffective emissions mitigation strategies and misdirected funding for decarbonisation efforts (Gurney et al., 2021). Hence there is an absence for multi-sectoral BEI guidelines applying a spatial approach and open-source data.

There are three prevailing issues within the current literature that this study seeks to address. These include that *i)* many existing studies focus on a single sector (Boychuk & Bun, 2014; Cai & Zhang, 2014 Charkovska et al., 2019; Danylo, Bun, See, & Charkovska, 2019; Lorenzo-Sáez et al., 2020; Pla et al., 2021; Zhang et al., 2022; Zhao et al., 2018); *ii)* the focus is often limited to CO_2 emissions, neglecting other GHGs; and, *iii)* the inventories are not mapped in high spatial resolution, but instead presented as an aggregate regional total (Cai et al., 2018; Fry et al., 2018, 2019; Gao et al., 2022; Kang et al., 2014).

Some studies include emissions resulting from energy usage across other sectors in their own 'energy' sector (Cai et al., 2019; Gao et al., 2022; Marchi et al., 2023). While this may be a useful approach for analysing urban energy demand, optimal mitigation policies should be sector specific and BEIs should reflect the true emissions from each sector's activity in an urban context so that city authorities and citizens may adopt effective mitigation strategies. Energy activity in sectors concerning stationary combustion and transport have been found to contribute the largest shares of emissions (Lamb et al., 2021; Zhang et al., 2023). Furthermore, studies that have completed multi-sectoral emissions modelling mostly have not modelled these in high spatial resolution (Fry et al., 2018; Kang et al., 2014; Manzanera-Benito & Capellán-Pérez, 2021). Spatial analytics is widely applied in research investigating a range of urban environmental metrics including sectoral emissions, air pollution and urban greenspace (Nyhan et al., 2016; O'Regan et al., 2021, 2022, 2024; Romero et al., 2019; Sabedotti et al., 2023) and has been shown to support policy planning and decision-making (Marchi et al., 2023). Furthermore, the application of spatial analytics to understand urban emissions inventories in tandem with socioeconomics can facilitate more equitable decarbonisation as local insights can inform targeted measures and local climate action plans (Garvey et al., 2022; Li et al., 2022). Hence, there is a knowledge gap in the literature for studies modelling and mapping GHG emissions in high spatial resolution for multiple relevant sectors including the residential, transport, commercial and industry, agriculture and land use, and waste sectors that are directly relevant to urban scale climate action plans and subsequent policy and planning decisions.

As such, this study investigates the development of a novel data-driven multi-sectoral BEI in high spatial resolution, which, for the purpose of this study, is defined at the urban neighbourhood level of approximately 0.3 km^2, for an urban study domain in Ireland (of total area 187km^2). This included modelling and mapping of GHG emissions in high spatial resolution in accordance with the GCoM guidelines. The research also sought to highlight the challenges and associated solutions associated with bottom-up BEI modelling in cities with sparsely available data and subsequently address the methodological knowledge gap in the existing literature for detailed multi-sectoral methodology for developing a BEI in high-resolution using mainly open-source and spatially resolved data.

2. Methods

2.1. Study domain & modelling protocol

In this study, bottom-up geo-referenced open-source datasets were used to model and subsequently map urban GHG emissions to form a multi-sectoral BEI in fine spatial-resolution. The study domain included the municipality of Cork City, located in the southwest of Ireland. Cork City currently has a population of 232,450 people (CSO, 2023a). It is the second largest city in Ireland and its area spans approximately 187 km^2 (Cork City Council, 2020).

A BEI for specific sectors including the Residential; Transport; Commercial & Industrial; Public; Agriculture, Land Use & Fishing (ALUF); and Waste Sectors was developed. These sectors were chosen as they have previously been highlighted by existing literature as major contributors to urban GHG emissions (Boychuk & Bun, 2014; Charkovska et al., 2019; Chuai & Feng, 2019; Danylo, Bun, See, & Charkovska, 2019; Gao et al., 2022; Lorenzo-Sáez et al., 2020; Marchi et al., 2023; Pla et al., 2021; Puliafito et al., 2015; Zhao et al., 2018) and are known to generate substantial energy demand within the study domain Curtain and Kavanagh, (2019).

The baseline year of 2018 was used as per national guidelines. In the year 2019, however, the administrative boundary of Cork City expanded, and this new boundary was used for the study to ensure continuity with future emissions inventories. The Cork City BEI was developed in partnership with the city authority, Cork City Council, to directly inform the development of their climate action plan and support their efforts as part of the EU Mission: Climate-Neutral and Smart Cities initiative. This initiative aims to support selected cities in becoming climate-neutral by 2030 and being exemplars of best practice for other cities globally to learn from (European Commission, 2022).

Cork City represents an interesting challenge from an emissions mitigation and urban planning perspective, as despite it being an urban area, it exhibits a high rate of car dependence for travel and most dwellings are detached or semi-detached homes. Furthermore, no previous GHG emissions inventory has been completed for the city using location-specific data to date. Previous estimates of energy demand and GHG emissions within the study domain were computed by applying national emissions per capita to the city's population (Cork City Council, 2020).

Sectoral GHG emissions, including CO_2, N_2O, and CH_4 converted to CO_2-eq emissions, were modelled and mapped in high spatial resolution for Cork City. The choice of these GHGs was based on availability of emissions factors across the six sectors and were converted based on their 100-year global-warming potential. CO_2, N_2O, and CH_4 are the top three contributing GHG emissions in Ireland and globally (EPA, 2022). Energy-related emissions were defined as emissions produced as a result of energy usage in any sector. Non-energy related emissions were considered in the study and these were defined as emissions directly emitted from sector-specific sources including transport, wastewater treatment and agricultural activity.

Irish Central Statistics Office (CSO) data was employed for this research. The CSO conduct the quinquennial National Census of Ireland and collect data and produce statistics about the population and economy. The 2016 Census dataset employed includes variables related to the population, number of dwellings, car ownership, commuting patterns, and accommodation types (CSO, 2017a). Small Areas (SAs), which typically contain 80–120 dwellings each, are the finest geographical units that the CSO collects and publishes data for (CSO, 2017a). 856 SAs were initially identified as being entirely or partially within the new Cork City boundary. From these, 13 were excluded from the analysis since just 10 % of their total area was within the domain boundary. This resulted in a total of 843 SAs for the analysis. For the remaining SAs, it was assumed that the proportion of land within the boundary was representative of the proportion of data to be included in the sectoral emissions analysis of the study domain ((CSO, 2017b).

The emissions modelling framework is shown in Fig. 1. The modelling datasets used and the methodologies applied for each sector within the BEI are described in the following sections. All work was completed using QGIS Version 3.28.1 (QGIS, 2023) and Python Version 3.8.16 (Python Software Foundation, 2023).

2.2. Residential sector

The 2016 Census data were used to compute the total number of dwellings present in each of the 843 SAs within the study domain in the year 2016. Newly constructed buildings in 2017 and 2018 (CSO, 2017a, 2023b) were added to the figures compiled for 2016 to attain the total number of dwellings in each SA and for the entire study domain for the baseline year of 2018 (n = 78,856). The Residential sector energy and emissions were computed based on data from the Sustainable Energy Authority of Ireland (SEAI) which is a governmental organisation responsible for providing dwellings with a Building Energy Rating (BER) (SEAI, 2022a). A BER is equivalent to an Energy Performance Certificate (EPC) which is frequently used in the EU (European Commission, 2023a). BERs of dwellings are based on energy efficiency and are produced on a scale from A to G. They provide a benchmark for space heating, water heating, and lighting based on heating system fuel and household characteristics. The SEAI stores all anonymised BER assessments that have been completed to date and their corresponding SA within the open-source BER Research Tool database. As the CSO datasets do not contain specific dwelling types, the BER dataset was used to create a representative housing stock energy model (SEAI, 2022a). Only BER assessments which were completed in or before the baseline year (n = 40,121) were extracted for the study domain. These individual BER assessments were grouped by dwelling type ('detached', 'semi-detached', 'mid-terrace' and 'apartment') and then further categorised by BER (A to G). Subsequently, assessments were analysed within their dwelling-type categories and this ensured that the dwelling floor areas were considered.

The weighted mean annual energy demand for each dwelling type was determined using methods described in Purcell et al. (2024). This

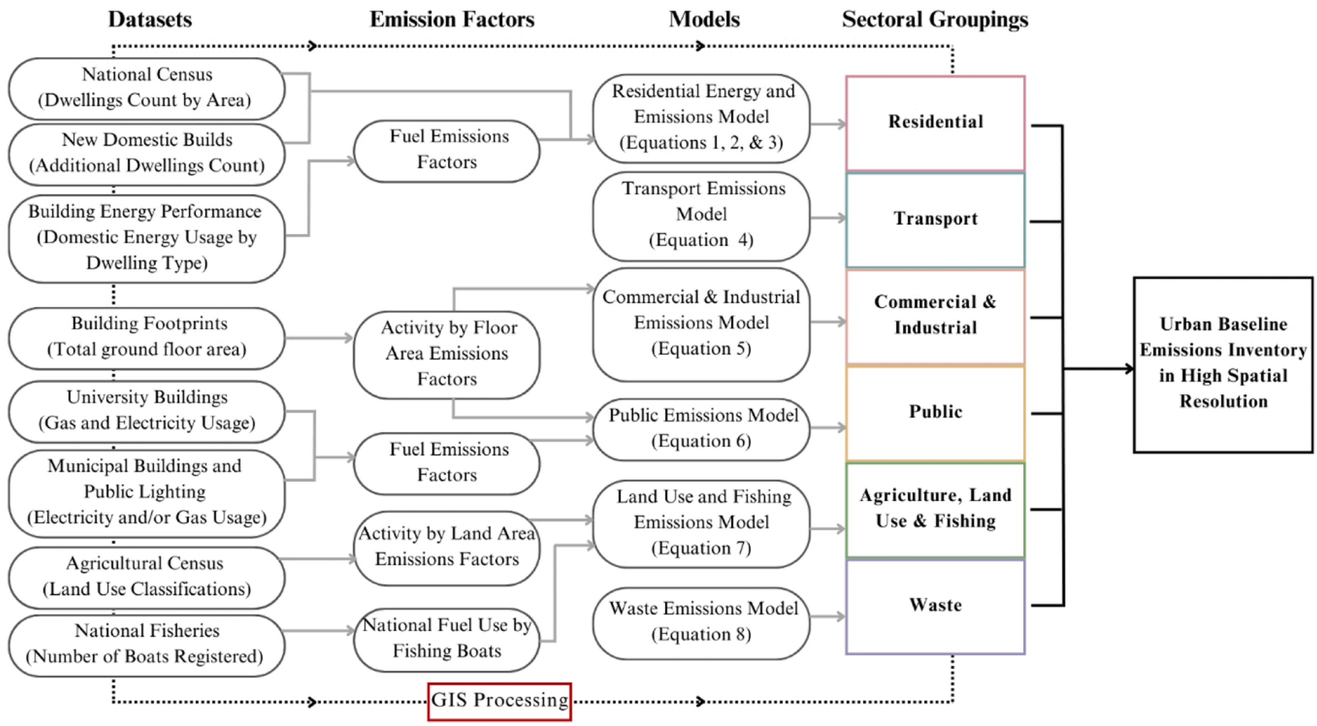

Fig. 1. Emissions modelling framework for the multi-sectoral Baseline Emissions Inventory which was developed in high spatial resolution for an urban area. The framework outlines the open and diverse input datasets, emissions factors, and models applied for each sector within the multi-sectoral model and integrates geo-referenced data and Geographic Information System (GIS) processing across all sectors from the outset.

was computed based on the overall energy demand from all services for each BER sub-group within all dwelling-type categories. The weighted mean was computed as some BER sub-groups had more dwellings than others and some building energy ratings, A-G, were more prevalent in the data (Tsokos & Wooten, 2016; Purcell et al., 2024). It was computed as follows:

$$ED_i = \frac{\sum_j (d_{ij} \times n_{ij})}{n_i} \tag{1}$$

where, ED_i is the weighted mean annual energy demand per dwelling-type category, i; d_{ij} is the BER sub-group energy demand totals for each dwelling type, i, per annum and BER sub-group (A to G), j; n_{ij} is the number of dwellings in the sub-group, j, of the dwelling-type category, i; and, n_i is the number of dwellings in the dwelling-type category, i.

To apply a representative housing stock energy model to the entire study-domain, a model was developed to compute the shares of each dwelling type within every SA. These shares were then applied to the total housing stock in the study domain ($n = 78{,}856$) to determine the number of each dwelling type within each SA. These values were then multiplied by the mean energy demand computed using Eq. (1) for the four dwelling types (kWh/yr) and summed to compute the energy demand within each SA and across the entire study domain.

The mean energy demand computed was distributed over the fuel-share profile for each dwelling-type group to determine the CO_2 emissions resulting from residential sector energy demand. These fuel-share profiles for each dwelling-type category were developed using fuel use data in the BER dataset. Total annual emissions for each dwelling type were computed as a function of energy demand values by fuel and emissions factors (in gCO_2/kWh) (SEAI, 2019; 2022a) as follows:

$$RE_i = \sum_k (RED_{ik} \times EF_k) \tag{2}$$

where, RE_i is the annual residential emissions per dwelling type, i; RED_{ij} is the annual residential energy demand for each dwelling type, i, and fuel type, k (natural gas, heating oil, liquid propane gas [LPG], electricity, and solid multi-fuel); and, EF_k is the emissions factor for each fuel-type, k. Using these totals, the mean CO_2 for each dwelling-type was determined and used to quantify the total residential sector emissions for the study domain. The Residential sector emissions were computed using the following formula:

$$E_{Residential} = \sum_s \sum_i (RE_i \times n_{is}) \tag{3}$$

where, n_{is} refers to the number of dwellings in each dwelling-type category, i, within each SA, s, and all other terms have been defined previously. The residential energy demand and emissions of each SA within the study domain were computed and the distributions of sectoral emissions across the study domain were therefore mapped. Emissions density metrics were computed including CO_2 per km^2, CO_2 per dwelling and CO_2 per person/capita. Further details of the energy demand and emissions mapping methodology are discussed in Section 2.8. A full description of the methodology employed in modelling and mapping residential sector energy demand and emissions can be found in Purcell et al. (2024).

2.3. Transport sector

Transport emissions for the baseline year were computed using the ENEVAL South-West road-link model, which was developed by the National Transport Authority. ENEVAL models GHG emissions, namely CO_2 and CH_4 in addition to other health-relevant air pollutants including particulate matter, hydrocarbons, nitrogen oxides and nitrogen dioxide, on Ireland's road network based on road type, vehicle fleet profiles and traffic flow data. Emissions from aviation, rail and maritime transport were not included in this study and therefore transport sector emissions refer to those from road transport only.

The ENEVAL model output for the road link sections situated within the study domain boundary were extracted and assigned to SAs. The GHG emissions of road links situated in more than one SA were proportionally assigned to SAs based on the share of road segment within them. Subsequently, the resulting GHG emissions of the new road lengths were computed and the total GHG emissions within each SA were computed according to Eq. (4):

$$E_{Transport} = \sum_{s} L_s \tag{4}$$

where, $E_{Transport}$ refers to the emissions from the Transport sector and L refers to the road link emissions computed for each SA, s.

The average annual share of transport modes for each road segment in weekday traffic was also investigated. To enable further insights from road transport emissions, car ownership was also computed and mapped for each SA within the study domain using census data previously described in Section 2.2.

2.4. Commercial & Industrial sector

Statistical energy use data is often used for computing commercial and industrial emissions. However, as a spatial approach was required in this study, commercial surveyed energy use data for Ireland was inappropriate as it omits location information. Furthermore, open-source spatial datasets such as OpenStreetMap (OSM), Google Maps or Google Street View do not contain building energy demand data. Accordingly, this study used OSM building footprint and classification data for modelling emissions from the Commercial & Industrial sector (Geofabrik GmbH, 2018). OSM is a commonly used open-source dataset of building stock profiles (Bernard et al., 2022; Biljecki et al., 2023; Mayer et al., 2023; Schiefelbein et al., 2019; Wang et al., 2022). It is the most widely supported platform of volunteered geographic information (Yan et al., 2020). More than half a billion buildings are mapped in OSM, and it has been shown to quite accurately represent (85 – 90 % of the time) building classifications (i.e. residential or commercial) and building area footprints (Biljecki et al., 2023). To extract the relevant OSM data, the study domain boundary was firstly projected onto the OSM layer and building data including location, floor area and building classification were extracted. There are two important considerations with regards to obtaining a complete building stock profile for a given area. Firstly, some OSM building data may be missing (Biljecki et al., 2023; Möller et al., 2018; Müller et al., 2019) and secondly, while the OSM building footprint data has been found to be reasonably accurate, building heights, which are required to calculate energy demand based on energy benchmark values (in kWh/m^2 by end use or fuel), are generally not included in these data (Biljecki et al., 2023; Katal et al., 2022). To overcome this, and avoid underestimation of sectoral energy use and emissions, for missing building classification data, manual classification of building use was manually performed using Google Maps and Google Street View (Google Maps, 2023; Google Street View, 2023). This resulted in 2611 buildings classified as either commercial or industrial within the study domain. The building floor areas were used to spatially compute the energy demand and emissions from the sector within each SA and throughout the city. Secondly. to account for multi-story buildings, a factor of 1.58 was applied to the floor area of all commercial and industrial units. This factor represented the average number of building stories observed by the SEAI commercial building stock survey (SEAI, 2015). Energy and emission factors (in kWh/m^2) from the Chartered Institution of Building Services Engineers (CIBSE) in the UK were employed (CIBSE, 2021). Fuel use shares for space heating were obtained from the non-domestic BER audits performed by the CSO (CSO, 2019). Total emissions from the Commercial & Industrial sector were computed using the following formula:

$$E_{Commercial} = \sum_{s}\sum_{m}(a_{ms} \times EF_m) \tag{5}$$

where, $E_{Commercial}$ is the total emissions from the sector; a_{ms} is the total floor area for each building classification group, m, per SA, s; and EF_m is the emission factor for the classification group, m.

2.5. Public sector

Public services energy demand and emissions in this study refer to those resulting from the use of local authority buildings, public lighting (including street lighting and public space lighting), educational institutions, hospitals, and health facilities. Energy demand and emissions were determined using several data sources. These included OSM-derived floor areas and building classifications which were determined as described in Section 2.4; energy demand from gas and electricity use within a large university, namely University College Cork (UCC); and, gas and electrical energy demand from the city authority, including from public lighting within the study domain. As energy demand data could not be obtained from all universities within the study domain, energy demand was predicted based on UCC energy usage rates per floor area for the other university buildings.

For computing all other sources of public sector energy demand and emissions, OSM-derived building floor areas and CIBSE emissions factors were employed. Buildings included law enforcement and judiciary buildings; hospitals and healthcare-related buildings; and educational institutions such as nurseries, schools, and colleges (Geofabrik GmbH, 2018; CIBSE, 2021). Following a manual examination of two major hospitals within the study domain, hospital buildings were estimated to be four stories high. Public sector emissions were thereby modelled using the following formula:

$$E_{Public} = \sum_{s}\left(\left(\sum_{fuel}(LD_{fuel} \times EF_{fuel}) + E_{light}\right)_s + \left(\sum_{m}(n_m \times EF_m)\right)_s + \left(\sum_{fuel}(UD_{fuel} \times EF_{fuel})\right)_s\right) \tag{6}$$

where, E_{Public} is the total Public sector emissions for all SAs, s; LD_{fuel} is the energy demand of local authority buildings per fuel type; EF_{fuel} is the emission factor of the fuel used; E_{light} are the emissions from public lighting; n_m is the number of buildings in the OSM classification group, m; EF_m is the CIBSE emissions factor of the classification group, m; UD_{fuel} is the energy demand for universities within the study domain; and EF_{fuel} is the university energy demand fuel emission factor. All public sector emissions outputs were then spatially combined for subsequent mapping (see Section 2.8).

2.6. Agriculture, Land Use & Fishing (ALUF) sector

To quantify and spatially map emissions from the ALUF sector, land use data from the Census of Agriculture 2020 was retrieved from the CSO through their AgriMap tool (CSO, 2020a). The AgriMap tool presents data at the Electoral Division (ED) level. EDs are the smallest legally defined boundaries in Ireland (CSO, 2017b). SAs are non-legally defined sub-divisions of EDs, existing solely in statistical capacities. The proportion of land classified as farmland within EDs was distributed amongst SAs based on their relative areas. As the Census of Agriculture did not provide sufficient detail for bottom-up emissions modelling in this sector, national emissions were obtained from Ireland's Environmental Protection Agency (EPA). National agricultural emissions were allocated to the SAs based on the share of designated agricultural land within them (EPA, 2022; SEAI, 2022b). SAs containing primarily urban areas were omitted from the analyses as they do not include any agricultural land.

The Irish Fishing Fleet Register and the SEAI provided information on emissions sources from fisheries (DAFM, 2023). Five fishing boats were registered in Cork City, and these were assigned to three SAs located in the Port of Cork. National fuel use data for fisheries were obtained from the SEAI, and these were apportioned to the fishing boats located within the study domain (SEAI, 2022b). Emissions factors were then applied to compute their associated emissions. The total emissions resulting from agricultural, land usage and fishing activity within the study domain was therefore computed according to the following:

$$E_{ALUF} = \sum_s \left(\frac{A_{agri,s}}{A_{agri,nat}} \times E_{agri,nat} \right) + \sum_s \left(\frac{n_{boats,s}}{n_{boats,nat}} \times D_{boats,nat} \times EF_{diesel} \right) \tag{7}$$

where, E_{ALUF} are the total emissions from the ALUF sector; $A_{agri,s}$ is the area of agricultural land, per SA, s; $A_{agri,nat}$ is the total area of land classified for agricultural use nationally; $E_{agri,nat}$ is the total national GHG emissions from agricultural activity; $n_{boats,s}$ is the number of fishing boats registered per SA, s; $n_{boats,nat}$ is the total number of fishing boats registered nationally; $D_{boats,nat}$ is the national diesel use from fishing; and EF_{diesel} is the emissions factor for diesel.

2.7. Waste sector

Waste handling and treatment emissions for Ireland, which were previously computed and presented on a 1 km × 1 km grid resolution, were used in this study (Nielsen et al., 2020; Schmidt Plejdrup, 2022). The gridded emissions were distributed over the SAs within the study domain. Emissions from the Waste sector were computed for each SA and the city using Eq. (8) as follows:

$$E_{Waste} = \sum_s \sum_r (n_{rs} \times r) \tag{8}$$

where, E_{Waste} refers to the total emissions from the Waste Sector; n_{rs} is the number of grid cells with emissions value, r, in small area, s; and r is the value of emissions per grid cell.

2.8. Spatial mapping & statistical analyses

The modelled emissions for all six sectors were aggregated to compute overall emissions within each SA ($n = 843$) and across the entire study domain. Point, line, area, and grid sources of emissions were aggregated to map the resulting combined-sector emissions for the city. The areas of SAs (in km^2) across the study domain differed greatly. The mean SA area was 0.2 km^2 (± 0.6 km^2). Consequently, to standardise emissions and compare between SAs, the emissions density, in CO_2-eq/km^2, for each sector and for all emissions were computed within each SA. Additional sector-specific metrics were also computed and mapped. These included energy demand (in GWh), energy density (in GWh/km^2), CO_2 emissions per capita and CO_2 emissions per dwelling in the Residential sector. Population and dwelling statistics obtained from the 2016 Census and variables relating to the higher contributing sectors, namely the Residential and Transport sectors, were mapped to provide supplementary insights regarding decarbonisation challenges in these sectors. In some instances, choropleth maps were developed for two variables and then merged to form a bivariate map. For the Transport sector, CO_2-equivalent emissions per kilometre of road were computed and mapped in addition to CO_2-equivalent emissions per kilometre of driveable road to account for multiple lanes of certain road links. When mapping the emissions from public services, commercial, industrial, and ALUF activity, many SAs within the city boundary did not contain emissions data for these sectors. As such, these areas were greyed out in sectoral map outputs to differentiate them from SAs that contained low values. The results of the modelled multi-sectoral BEI for Cork City and the mapped distributions of emissions are described in the following section.

3. Results

3.1. Overall emissions

The CO_2-eq emissions for the study domain of Cork City were quantified across six sectors including the Residential; Transport; Commercial & Industrial; Public; ALUF; and Waste sectors. The total emissions for the study domain across all sectors was determined to be 987 ktCO_2-eq. Fig. 2 illustrates the proportional sectoral contributions to the overall emissions. The Residential sector accounted for the largest sectoral share which accounted for 34 % (332 ktCO_2-eq) of emissions. This was followed by the Transport sector and the Commercial & Industrial sector which accounted for 29 % (289.5 ktCO_2-eq) and 22 % (216 ktCO_2-eq) of emissions, respectively. The three smallest sectoral shares of emissions were from the Public (7 %), ALUF (6 %), and Waste (2 %) sectors. 91 % of the overall emissions were energy related, attributable to energy-production and -consumption across all sectors excluding the Waste sector, while the remaining 9 % of emissions were non-energy related and attributable to some Transport, ALUF, and Waste sector emissions. The CO_2-eq emissions per capita were 4.7 tCO_2-eq. The national GHG emissions in the same year were 14.4 tCO_2-eq per capita (EPA, 2022).

The spatial distribution of aggregate emissions for all sectors computed within each SA ($n = 843$) across the study domain are shown in Fig. 3. The spatial density of emissions, in ktCO_2-eq/km^2 per SA are presented. Emissions were highest in the urban centre and surrounding areas while some peaks were observed in satellite towns located in the western, northwestern and southeastern areas of the city. The suburbs and exurbs exhibited lower emissions densities relative to other areas. The mean SA emissions computed ($n = 843$) was 13.7 ktCO_2-eq/km^2 (± 12.3 ktCO_2-eq/km^2) and ranged from 0.8 ktCO_2-eq/km^2 to 127 ktCO_2-eq/km^2 (see Table 1). This wide range may be explained by SA geography and demographics. The SAs which exhibited the highest emissions densities were typically density populated, exhibited high residential and transport emissions, and were small in geographic area.

3.2. Sectoral emissions

3.2.1. Residential

The Residential sector accounted for the largest share of CO_2 emissions equating to 34 % of emissions from all sectors. 78,856 urban dwellings were responsible for 1174 GWh of energy demand and produced a total of 332 ktCO_2. This is equivalent to 1.6 tCO_2 per capita. Energy demand was primarily due to main space and water heating. 41 % of the housing stock were semi-detached dwellings. Terraced, apartment and detached dwellings accounted for 26 %, 19 % and 14 % of the housing stock, respectively. Of these dwelling-types, detached homes produced the highest level of emissions per unit (5.2 tCO_2) while apartments produced the lowest level of emissions per unit (3.2 tCO_2). This is shown in Figure S6 where higher residential emissions, in tonnes CO_2 per dwelling, were observed in the suburban and exurban areas of the city while lower emissions per dwelling were observed in the city centre. Semi-detached and mid-terraced dwellings generated 4.4 tCO_2 and 3.9 tCO_2 per dwelling, respectively. Emissions from heat energy demand were 2.6 times greater in detached houses than apartments.

Fig. 4(a) displays the Residential sector emissions mapped for 843 SAs within the study domain. A similar spatial distribution was observed for the Residential sector as for the aggregated emissions from all sectors (Fig. 3). Elevated levels of Residential emissions are concentrated in the urban centre and neighbouring areas because of increased housing

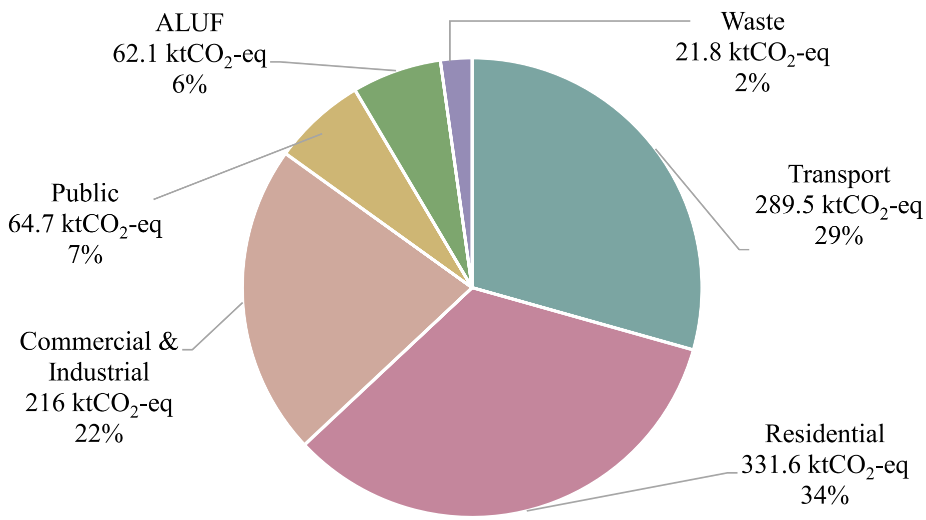

Fig. 2. Baseline Emissions Inventory sectoral contributions for the study domain of Cork City for the baseline year of 2018. Proportions are in kilotonnes of CO_2-equivalent ($ktCO_2$-eq) followed by sectoral proportion (%) of total emissions.

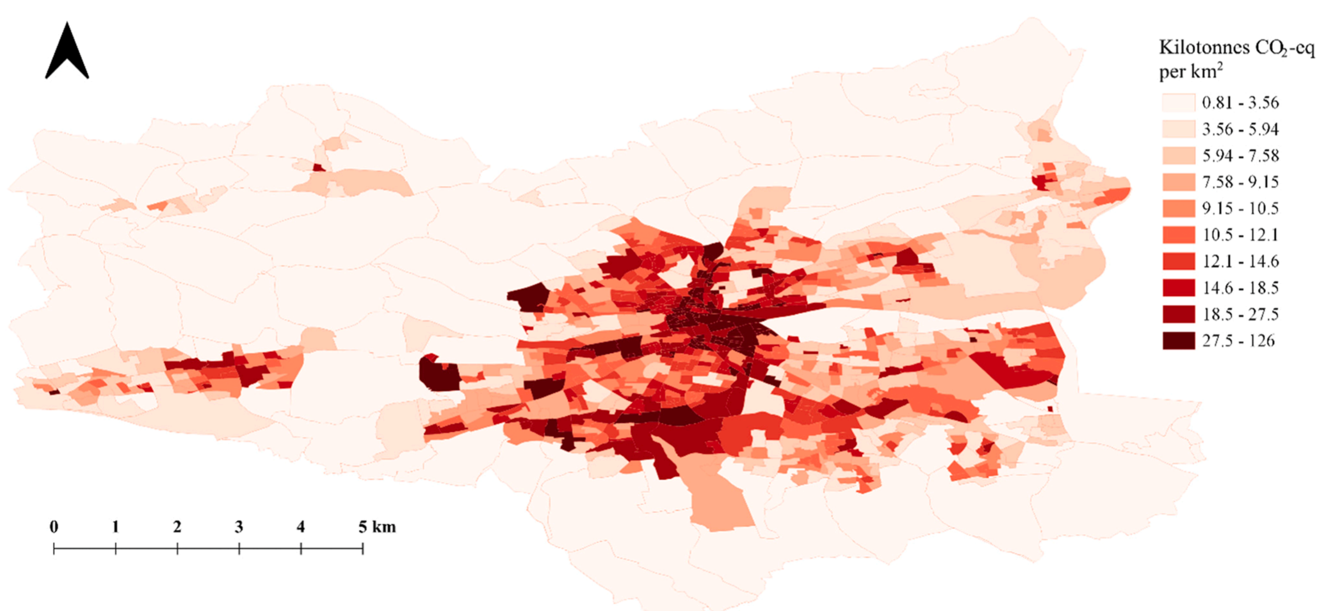

Fig. 3. Spatial distribution of aggregate emissions for all sectors in kilotonnes of CO_2-equivalent per kilometer squared ($ktCO_2$-eq/km^2) per Small Area (n = 843) within the study domain of Cork City.

Table 1
Descriptive statistics of emissions in kilotonnes of CO_2-equivalent per kilometer squared ($ktCO_2$-eq/km^2) for each sector (Residential; Transport; Commercial & Industrial; Public; ALUF; and Waste) and for the aggregate emissions for all sectors. The minimum, maximum, mean, median and standard deviation (SD) were computed over all Small Areas (SAs) (n = 843) within the study domain of Cork City.

	Emissions Density ($ktCO_2$-eq/km^2)						
	Residential	Transport	Commercial & Industrial	Public	Agriculture, Land Use & Fishing	Waste	All Sectors
Min	0.1	0.0	0.0	0.0	0.0	0.0	0.8
Max	106.1	47.3	38.4	48.1	0.9	3.8	126.6
Mean	8.5	3.0	1.5	0.6	0.1	0.2	13.7
Median	7.2	1.5	0.0	0.0	0.0	0.0	10.5
SD	8.5	4.4	4.2	3.5	0.2	0.5	12.3

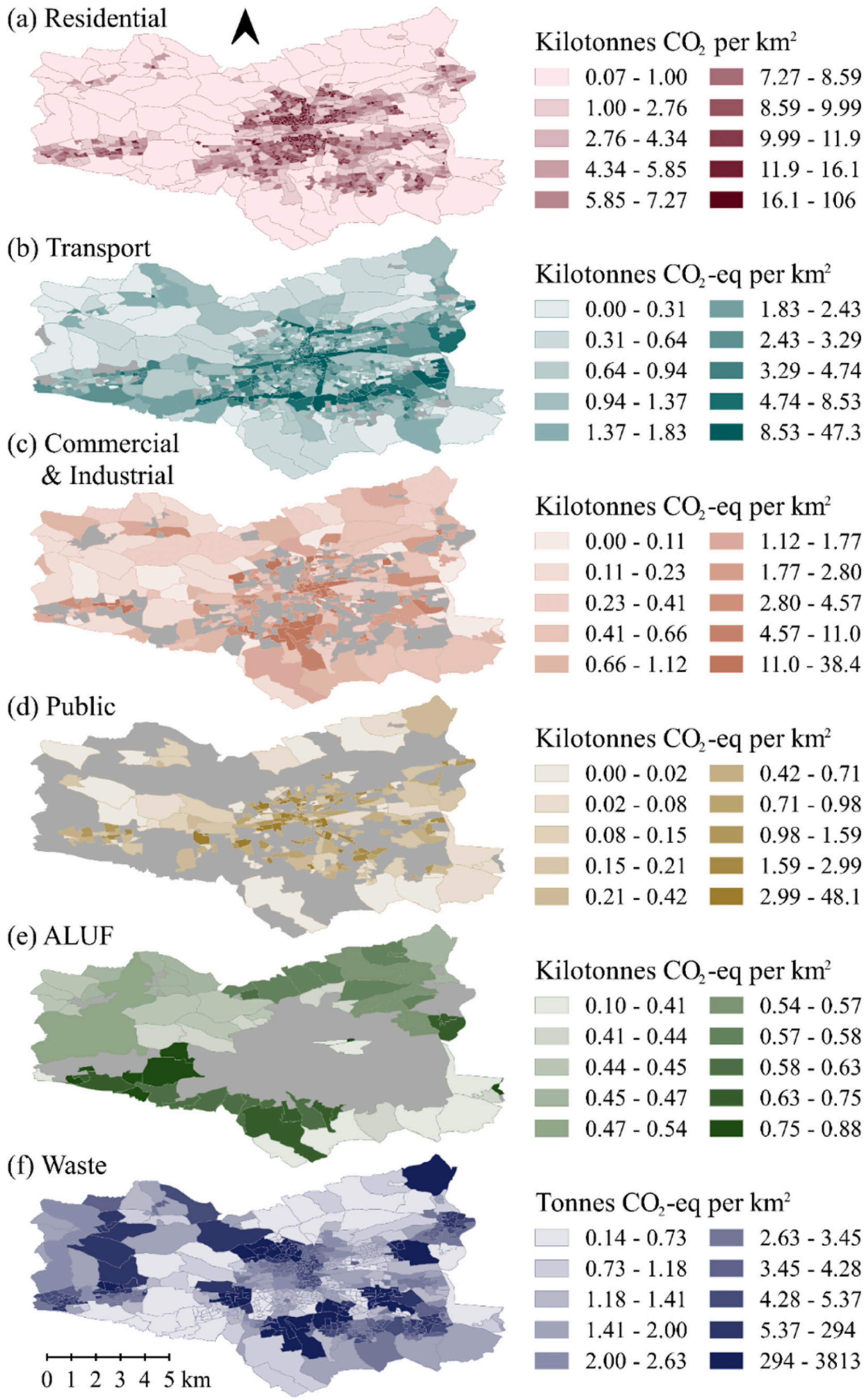

Fig. 4. Spatial distribution of emissions within the study domain of Cork City for the (a) Residential; (b) Transport; (c) Commercial & Industrial; (d) Public; (e) ALUF; and (f) Waste sectors. Emissions were mapped in tonnes or kilotonnes of CO_2-equivalent per kilometer squared (CO_2-eq/km^2) for all sectors except the Residential emissions, which were mapped in kilotonnes of CO_2 per kilometer squared (ktCO_2/km^2). Emissions were mapped at the Small Area (SA) ($n = 843$) level where data was available within each sector. SAs in grey represent areas that contained no sectoral emissions or areas where data was unavailable.

density in these areas. The mean Residential emissions computed across all SAs ($n = 843$) was 8.5 ktCO_2/km^2 ($\pm$ 8.3 ktCO_2/km^2). SA emissions ranged from 0.1 ktCO_2/km^2 to 106.1 ktCO_2/km^2. When emissions per capita were mapped across the study domain, no discernible spatial pattern was observed (See Figure S5).

3.2.2. *Transport*

The Transport sector accounted for 29 % or 290 ktCO_2-eq of the total modelled emissions for Cork City. These transport emissions were equivalent to 1.4 tCO_2-eq per capita. Private vehicles accounted for the greatest share (87 %) of road transport emissions. This was followed by Large Goods Vehicles (9 %), Heavy Goods Vehicles (HGVs) (4 %) and buses (1 %). The spatial distribution of emissions from road transport, in $ktCO_2$-eq/km^2, is shown in Fig. 4(b). Emissions are highest in the congested city centre and roads emanating to the north and south of the city centre. They were also highest along major commuter roads in the east of the city. The mean Transport emissions computed across all SAs which contained road links (n = 740) was 3.4 $ktCO_2$-eq/km^2 (± 4.6 $ktCO_2$-eq/km^2). SA emissions ranged from 1×10^{-3} $ktCO_2$-eq/km^2 to 47.3 $ktCO_2$-eq/km^2. 103 SAs did not contain any roads and therefore the ENEVAL model did not predict emissions for these areas.

Active transport usage, private vehicle usage and private vehicles ownership were also investigated using census data and these were mapped for all SAs within the study domain (see Figures S19, S20, and S22). Approximately 93,300 private vehicles were owned by those living within the study domain in the year studied. These data were spatially analysed and the contrasting spatial pattern to that of the road transport emissions displayed in Fig. 4(b) was observed. Vehicle ownership rates were highest in the suburban and exurban areas while they were lowest in the urban centre. The mean ownership rate across all SAs was 0.4 vehicles per capita (±0.2 vehicles per capita) while it ranged from 0.03 vehicles per capita in the urban centre to 0.8 vehicles per capita in the suburban and exurban areas. Active transport use, including persons commuting to school, college or work by foot, bicycle, bus, or train, was highest in the core urban area (Figure S19) but generally followed a similar spatial pattern to people in rented accommodation (Figure S16). Private vehicle users were similarly distributed across the study domain with denser populations exhibited by the peripheral urban SAs. The density of commuters in each SA was computed and ranged from 21 – 42,800 people per km^2. Higher numbers of commuters were observed in the city centre and other towns.

3.2.3. Commercial & industrial

The Commercial & Industrial sector contributed 22 % of the city's total emissions. The sector exhibited a total energy demand of 650 GWh and generated 216 $ktCO_2$-eq. Emissions per capita were found to be 1 tCO_2-eq. Heating accounted for the majority of energy demand (466 GWh) and was responsible for most emissions from this sector. This heat energy demand included electric heating (64 %), gas heating (33 %) and oil heating (3 %). Electricity use accounted for the remaining energy demand. Commercial services produced 98 % of the total emissions while industrial activity contributed 2 %. The sub-sectors responsible for most commercial services emissions were offices and retail.

Fuel use shares for space heating were computed for the sector based on the CSO's non-domestic BER data. Some sub-sectors including hotels, nursing homes and schools also employed LPG as a main heating source (12 %, 12 % and 6 %, respectively). Fig. 4(c) displays the spatial distribution of SA (n = 340) emissions from commercial services and industrial activity across the study domain. Similar to the Residential sector, the Commercial & Industrial sector emissions are concentrated in the city-centre and in sub-urban areas in the southern, western, and north-western parts of the city where commercial and industrial estates are located. Many SAs did not contain commercial or industrial activity data, and hence this sector's emissions have not been modelled for these SAs. The mean emissions computed across all SAs (n = 340) for this sector was 3.6 $ktCO_2$-eq/km^2 (± 6.0 $ktCO_2$-eq/km^2). SA emissions ranged from 0.3×10^{-3} $ktCO_2$-eq/km^2 to 38.4 $ktCO_2$-eq/km^2.

3.2.4. Public

Modelled emissions from public services were 64.7 $ktCO_2$-eq, equivalent to 0.3 tCO_2-eq per capita. Public sector emissions resulted primarily from schools, universities, higher education facilities, healthcare settings, hospital buildings, public lighting, and local government buildings. Of these sources, university and hospital buildings accounted for 36 % and 35 % of the sector emissions, respectively. They were followed by schools (10 %), local government buildings (8 %) and other public services (6 %).

The spatial distribution of Public sector emissions is shown in Fig. 4 (d). A large proportion of SAs (n = 585) did not contain activity data from public services or data was not available. SAs with relatively higher levels of emissions were concentrated in the city-centre with a small cluster located in the western part of the city. The mean emissions from public services computed across all SAs (n = 258) was found to be 2.1 $ktCO_2$-eq/km^2 (± 6.1 $ktCO_2$-eq/km^2) while SA emissions ranged from 0.2×10^{-3} $ktCO_2$-eq/km^2 to 48.1 $ktCO_2$-eq/km^2.

3.2.5. Agriculture, land use & fishing (ALUF)

The ALUF sector produced a similar share of emissions to the Public sector. It generated 62 $ktCO_2$-eq which was 6 % of the city's overall emissions and 0.3 tCO_2-eq per capita. Only a negligible proportion of these emissions (0.01 %) were energy related. The spatial distribution of these emissions can be seen in Fig. 4(e). Exurban SAs contributed to most of this sectors' emissions while the urban and suburban SAs did not contribute any emissions as those areas are not typically used for agriculture and food production. It was observed that agricultural and land use emissions were higher in the South-Western region of the city, followed by the North-Eastern areas. Five fishing boats were registered to Cork City, and these were located in the Port of Cork. These can be observed as three isolated SAs contributing emissions in the urban centre. The mean emissions computed across all SAs (n = 80) for this sector was 0.5 $ktCO_2$-eq/km^2 (± 0.1 $ktCO_2$-eq/km^2). This sector exhibited a low range of emissions relative to other sectors, ranging from a minimum of 0.1 $ktCO_2$-eq/km^2 to a maximum of 0.9 $ktCO_2$-eq/km^2.

3.2.6. Waste

The Waste sector, referring to activity involving waste handling and treatment, contributed the smallest proportion (2 %) of emissions of all sectors studied to the overall emissions for the city. During the baseline year, 22 $ktCO_2$-eq was produced by waste handling and wastewater treatment services. 2 $ktCO_2$-eq of this was from methane. Per capita emissions from the sector were found to be 0.1 tCO_2-eq. The data for this sector was comprehensive across all SAs and the spatial distribution of modelled emissions can be seen in Fig. 4(f). SAs with relatively higher emissions can be clearly observed in waste disposal and wastewater treatment sites. The mean emissions computed across all SAs (n = 843) was 0.2 $ktCO_2$-eq/km^2 (± 0.5 $ktCO_2$-eq/km^2) while it ranged from 0.1×10^{-3} $ktCO_2$-eq/km^2 to 3.8 $ktCO_2$-eq/km^2.

4. Discussion

4.1. Key findings and comparison with other studies

In this study, a novel urban BEI was developed by modelling GHG emissions represented as $ktCO_2$-eq in high spatial resolution for multiple sectors including the Residential; Transport; Commercial & Industrial; Public; Agriculture, Land Use & Fishing (ALUF); and Waste sectors using primarily open-sourced and spatially resolved data. The BEI was developed using a data-driven, energy-demand and spatial mapping approach in line with the requirements of the Global Covenant of Mayors. This fulfils the methodological knowledge gap in the existing literature for a detailed multi-sectoral BEI in high spatial resolution using mainly open-source and spatially resolved data.

In this research, it was observed that the Residential Sector contributed the largest sectoral share of emissions (34 %). This was followed by the Transport (29 %) and Commercial & Industrial (22 %) sectors. The Public, ALUF, and Waste sectors contributed 7 %, 6 %, and 2 %, respectively. In contrast to the EPA's national inventory, which reports that the agriculture sector contributes to the largest share (33 %) of emissions, in the urban study domain of this research, the ALUF only accounts for 6 % of total emissions. This is due to negligible agricultural activity within the city's boundaries compared to nationally (CSO, 2020b). Similar to this study, the EPA reports in their national emissions inventory of Ireland, that the Transport sector contributed the second largest share (20.1 %) of overall emissions while waste, public services and industrial processes accounted for smaller shares of 1.5 %, 1.6 % and 3.8 %, respectively. Using a similar bottom-up approach, comparable results were observed in Ireland's capital city of Dublin in a study of Dublin City's 2016 BEI (Cachia, 2018) whereby residential buildings and road transport were the largest (35 %) and second largest (25 %) sectoral contributors to total emissions, respectively. Waste handling and wastewater treatment contributed 2 % to overall emissions (Cachia, 2018).

As this study is the first to develop an urban BEI in high spatial resolution for the specific Residential, Transport, Commercial & Industrial, Public, ALUF, and Waste sectors, and no previous GHG emissions inventory exists for the study domain, the spatial results are not directly comparable to other studies. The analysis presented here in this study determined that total CO_2-equivalent emissions for Cork City in 2018 were 987 ktCO_2-eq. The combined-sector GHG emissions per capita were found to be 4.7 tCO_2-eq. The national GHG emissions per capita determined by the EPA in the same year were 14.4 tCO_2-eq (EPA, 2022). The large difference (67 % decrease) between this study's result and the national average justifies the need for location specific modelling. This difference can be attributed to differences in urban and rural emissions contributors including low levels of agricultural land and associated activity within the urban study domain.

Estimated per capita emissions of 5.1 tCO_2-eq for Dublin City in 2016 (Cachia, 2018) are comparable to the emissions estimate of 4.7 tCO_2-eq determined for the urban domain in this study. A similar result of 4 tCO_2-eq per capita across all sectors was observed for Grosseto, Italy (Marchi et al. 2023). However, using input-output models, Fry et al. (2018) determined higher emissions in four Chinese cities, namely Chongqing (5.6 tCO_2-eq per capita), Shanghai (6.4 tCO_2-eq per capita), Tianjin (7.3 tCO_2-eq per capita), and Beijing (8.1 tCO_2-eq per capita). However, these emissions included imports and exports for the cities and hence, have included additional 'sectors' in their analysis.

The distribution of sectoral GHG emissions was mapped and examined for the study domain in fine spatial resolution. The mean combined-sector emissions for 843 SAs was 13.7 ktCO_2-eq/km^2. Chuai and Feng (2019) obtained a much lower result (5.7 ktCO_2-eq/km^2) for the mean emissions across their study domain, however, their study included emissions from energy consumption within the residential, industrial, commercial, and agricultural sectors only. Zhang et al. (2018) observed a similar, although slightly larger, range of emissions intensities than ours, from 0.00001 to 160 ktCO_2-eq/km^2 across the city of Xiamen.

4.2. Strengths

This study presents a BEI for a sub-national urban area, namely a medium-sized European city, with emissions modelled in fine spatial resolution at the neighbourhood SA level or for every 80–120 dwellings. A major strength of this study is the input data employed. The sectoral emissions data are modelled primarily using bottom-up unit-level data with a minor share computed through the disaggregation of national emissions source data. For instance, this study adopts an individualised approach for quantifying the residential sector emissions by utilising the BER assessment data measured from existing dwellings within the study domain. Additionally, most of the unit-level data employed is open-source, ensuring that the methodologies developed are replicable for any city or urban area globally where these data also exist. As such, the energy and emissions model outputs produced are specific to the urban population of the study domain, unlike many methods which only model sub-national emissions by apportioning national inventories according to population size or land use (Manzanera-Benito & Capellán-Pérez, 2021; Zhang et al. 2018). Consequently, the insights drawn from the study output can directly inform local climate action plans and facilitate effective targeted emissions mitigation within the study domain (Ghaemi & Smith, 2020). Furthermore, these SAs for which emissions were modelled, are defined neighbourhoods and communities, allowing urban citizens to identify sources of sectoral emissions in their locality, thus encouraging informed citizen climate action. The production of BEI outputs that translate to both study domain inhabitants and policy makers supports effective collaboration and engagement for developing decarbonisation pathways that are fair, just, and equitable.

While some studies have conducted emissions inventories for cities globally (Fry et al., 2018; Kang et al., 2014; Manzanera-Benito & Capellán-Pérez, 2021), few have examined the spatial distribution of emissions resulting from activity within the study domain, which has been shown to have significant positive impacts on urban planning and emissions reduction strategies (Chuai & Feng, 2019). However, location-based activity data are rarely collected at a sub-national, city or sub-city scale (Pulselli et al., 2019), which hinders the development of geo-spatial emissions inventories. This study addresses a methodological knowledge gap in the literature for modelling multi-sectoral BEIs using primarily open-source data and applying spatial approaches from initial data processing to results mapping. This study can act as an exemplar for cities who seek to develop spatially resolved all-sector emissions inventories for their urban domain, notwithstanding challenges related to data availability.

By spatially resolving emissions at a sub-city scale, and aggregating data by statistical area, the modelled output enables policymakers to identify GHG emission hotspots from specific sources and directly inform targeted and localised policy interventions. Furthermore, as socio-economic indicators are collected as part of the census, with the smallest unit of aggregated data being the Small Area, this approach allows for a direct comparison and integration of emissions data with socio-economic factors. This in turn can help elucidate the local drivers of emissions, as demonstrated by Fig. 5 and Figure S23, and support the development of equitable mitigation strategies, which is not possible using input-output models.

Furthermore, the sectoral classification of emissions facilitates the appropriate allocation of funding to decarbonise carbon-intensive sectoral activities within the study domain (Gurney et al., 2021). For example, this may include providing funding for targeted retrofitting schemes, electric vehicle charging infrastructure, commercial clean-energy grants, and recycling incentives.

Maps detailing the spatial distribution of emissions at the SA level across the municipality can be useful for urban citizens. The SAs boundaries of the study domain consist of 80–120 dwellings and, as such, residents may also draw insights from the modelled emissions for their own neighbourhood, area of work, daily commute, or recreational zone.

The methodologies applied in this study are directly applicable to GCoM member cities who are required to develop a BEI as part of their SECAP. The GCoM guidelines recommend an 'activity-based approach' when developing a BEI that relates to the energy consumption of the municipality and as such, this approach has been employed here. This includes the use of emissions factors which incorporate indirect emissions resulting from energy supply to the study domain (GCoM, 2024). The emissions factors described in this paper relate to the study domain's national data, however, this BEI approach may be adopted to cities with missing or out-of-date country-specific factors, by using readily available IPCC emissions factors, which is also recommended by the GCoM.

4.3. Limitations and future research

Our research used the best available data, however, there were some limitations. For the Residential sector, the housing stock model developed was based on the BER energy performance assessments which were available for 51 % of the housing stock. While prior studies have determined the Irish EPC data to hold statistical significance and pass

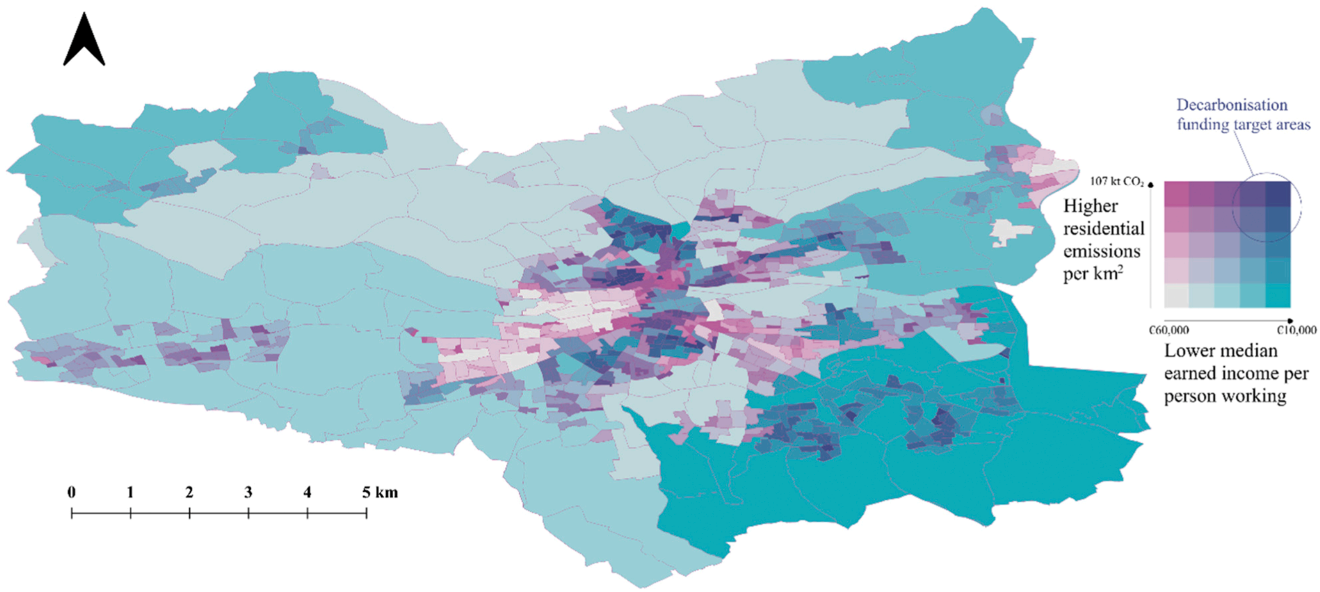

Fig. 5. Bivariate map showing the spatial distribution of emissions from the Residential sector, measured in kilotonnes CO_2 ($ktCO_2$) and median earned income per person working, measured in euro (€). Darker pink colours represented areas of higher emissions while darker teal colours represented areas of lower income. The resultant map and legend shown indicates that areas highlighted in navy are lower income areas with higher levels of residential emissions. Paler grey areas in the study domain indicate areas where median earned income per person is highest and where emissions are lowest.

Eurostat Level 3 validation (Di Zio et al., 2016; Raushan et al., 2024), the robustness of this model could be further improved with more housing stock and energy performance data and by stricter policy regarding mandatory assessments.

Other voluntary rating systems including the Building Research Establishment Environmental Assessment Methodology (BREEAM), Leadership in Energy and Environmental Design (LEED), and WELL Building Standard (WELL) certifications are more established and prevalent globally in terms of completed assessments (Jiménez-Pulido et al., 2022; Sesana et al., 2024). However, at the time of analysis, no certified residential projects were listed under the LEED or WELL databases within the study domain. Although one BREEAM-certified residential project existed, the diverse mix of dwelling types in the study domain made the BREEAM classification system less suitable. As a result, the BER dataset was determined to be the most appropriate source of residential energy performance data for this study.

For the Transport sector, this study focused solely on GHG emissions from road transport, namely private vehicles, buses, and HGVs. Therefore, the results likely represent an underestimation of CO_2-equivalent emissions in this sector. Protocols for attributing international aviation emissions to specific sectors are lacking and widely debated. Furthermore, for cities developing a SECAP, the GCoM guidelines do not recommend the inclusion of aviation and shipping sub-sectors. Future research efforts should consider the inclusion of transport emissions from all relevant modes including rail services.

For the transport sector, this study focused solely on GHG emissions from road transport, specifically private vehicles, buses, and HGVs. Nationally, road transport accounted for 96 % of total transport-related CO_2-equivalent emissions in 2018 (EPA Ireland, 2022) and was therefore the primary focus of emissions reporting in this inventory. The authors acknowledge that this approach results in a slight underestimation of total CO_2-equivalent emissions in the sector. Future research should consider incorporating emissions from other relevant transport modes, such as rail services. Additionally, emissions from international aviation and marine navigation are not included in Ireland's national emissions inventory reporting (EPA Ireland, 2024) and the GCoM guidelines do not recommend their inclusion for cities developing a SECAP (Bertoldi, 2018). Therefore, they were excluded from this study to maintain alignment with national reporting standards and GCoM guidelines.

For the Commercial & Industrial and Public sectors, a notable limitation of the OSM dataset employed was incorrect or missing building classifications (Biljecki et al., 2023; Möller et al., 2018; Müller et al., 2019). Even though the authors overcame this with manual verification and/or correction of all building-unit classifications, this work could be made more efficient in the future with the addition of location-based information of non-domestic energy and emissions surveys or an automated verification process.

For the ALUF sector, the subsectors analysed included agricultural and fishing activity only due to data availability. Other studies have classified specific subsectors such as emissions from enteric fermentation, manure management, agricultural soils, fertilizer use, and the burning of agricultural residues, in addition to CO_2 removals by land cover type (Charkovska et al., 2019; Liu et al., 2020; Marchi et al., 2023). Given that this case study is located in an urban environment, where the contribution of ALUF to emissions is limited, such detail was not deemed necessary. A further consideration is the need to assess consumption-based emissions, in conjunction with or instead of production-based emissions in this sector. This approach may more accurately reflect the emissions associated with food consumption within the study area (Wiedmann et al., 2021). Both of these areas offer interesting prospects for future research.

As the study employed a wide range of open and diverse datasets, there are uncertainties surrounding the input data and output results. An analysis of these uncertainties was not conducted in this study and despite this being the standard in the literature (Arioli et al., 2020; Ghaemi & Smith, 2020), future studies surrounding the development of GHG emissions inventories should incorporate some sensitivity and/or uncertainty analyses. Overall, increasing the detail and frequency of unit-level activity data collection across sectors, including activity from sectoral operations and embodied emissions, would improve the accuracy and robustness of emissions inventories, baseline and ongoing, and insights on the drivers of urban GHG emissions (Chancel, 2022).

4.4. Policy implications

The findings of this research will enhance the decision-making capabilities of the study domain municipality. Under Ireland's Climate Action and Low Carbon Development Law 2021, the national objective is to reduce GHG emissions by 51 % in 2030 relative to 2018. Cork City is one of the EU Mission Cities, striving to lead the way on climate action, which means exceeding this national ambition. While emissions are currently much lower than the national average, achieving stringent reduction targets will be difficult. The detailed and spatially resolved outputs highlight some of the key challenges to be overcome.

Most notably, home retrofitting targets and electrification in heating will require new policy interventions to tackle rental properties. The Residential sector emissions were considered in the context of rental and income variables. The density of people in rented accommodation was mapped for each SA (Figure S16) within the study domain boundary and a similar spatial pattern to Figure S15 of population density was observed. Cork City's housing stock is a major source of CO_2 emissions in the city, concentrated in the core urban area and boundary urban areas including Ballincollig, Tower, Blarney, and Glanmire. However, these areas were found to have very high shares of rental properties. It was found that 90–100 % of the population were in rented accommodation in some SAs in these areas. SAs contributing larger shares of emissions while containing high shares of people in rented accommodation (see Figure S23), could be carefully considered in terms of retrofitting schemes and grants. These could consider both tenants and landlords to circumnavigate issues surrounding lack of autonomy. Furthermore, emissions reductions schemes should be equitable and consider that while emissions intensities are highest in urban areas, it is notable that higher emissions per dwelling were exhibited by suburban and exurban detached homes due to larger building sizes and subsequent energy use which has also been observed in the literature (Feng et al., 2021). In this instance, SAs with lower median income but high residential emissions could be identified, as shown in Fig. 5, and targeted decarbonisation subsidies distributed accordingly.

Considering the transport sector, interesting insights were observed when comparing locally produced transport emissions in Fig. 4(b) with active transport users in Figure S19. Levels of emissions produced from road transport were higher in areas where active transport usage was highest, and this indicates that active transport users may be exposed to higher levels of transport emissions in these areas even though they are not responsible for them. Strategies including the pedestrianisation of inner urban areas and implementing greenspace and cycling infrastructure would reduce GHG emissions, improve air quality, and reduce exposure burdens for all urban citizens and active commuters (Pulselli et al., 2019). A barrier to reducing transport emissions, however, is the intensity of emissions observed along the major routes within the urban boundary, including the N8, N20, N27, and N40 (see Figure S1) that connect the nearest motorway, industrial estates, airport, and other areas of relatively high employment. In these areas, pedestrianisation and greenspace measures, which has been shown to positively impact human health (O'Regan et al., 2021), would be insufficient. In these cases, public transport options and their accessibility and frequency should be enhanced. Emissions from the Commercial & Industrial sector were primarily due to energy use, specifically energy demand. Moreover, the distribution of emissions was centred around the central business district in the city centre where most commercial buildings are located. Therefore, decentralised energy options could be considered in response to these results (McGookin et al., 2021). The insights and recommendations made may facilitate local and national climate action plans to be developed in a just, equitable and sustainable manner, which has been emphasised as important by previous studies (Ulpiani et al., 2023b). The BEI will enable the city to actively reduce emissions and achieve its net-zero goals, now that major contributors have been identified, and a baseline has been established to measure progress against.

The BEI and spatial analysis presented in this study fully align with the United Nations Sustainable Development Goals (SDGs), namely SDG 11 and SDG 13 relating to sustainable cities and communities, and climate action, respectively. True to the UN SDG ethos of not leaving anyone behind and protecting the most vulnerable in society, spatially mapped multi-sectoral BEIs can support more effective, targeted, fair, and equitable mitigation policies and climate action plans (Garvey et al., 2022). In addition, the informed decarbonisation pathways that will be developed from the results of this study will also contribute towards SDG 3 related to good health and wellbeing, SDG 7 on affordable and clean energy, and SDG 12 for Responsible Production & Consumption (UN DESA, 2023).

The methods developed herein this study may be applied in any city or urban area even where limited data is available to account for the GHG emissions produced within their domain boundary. BEIs are required by many largescale climate initiatives, including the Global Covenant of Mayors for Climate and Energy and the EU Cities Mission which aims to contribute to the goals of the Paris Agreement. However, detailed guidelines, leveraging diverse open-source datasets, do not currently exist (Chen et al., 2019; European Commission, 2023b; GCoM, 2024; Melica et al., 2018; Ulpiani et al., 2023a) and this research sought to address that major knowledge gap. The methodologies developed can be emulated to examine the distribution of emissions in high spatial resolution and municipalities of cities or large urban areas that have not yet completed a BEI should do so which may support informed policy and decision making (Marchi et al., 2023)

This study presents the first spatial analysis of multi-sectoral city-wide emissions in high spatial resolution for specific sectors including the Residential; Transport; Commercial & Industrial; Public; Agriculture, Land Use & Fishing; and Waste Sectors in the literature. While this study focused on how to model and map a BEI using publicly available data for a medium-sized EU city, future research could conduct a largescale data collection of unit-level activity and location data across multiple sectors to further enhance the accuracy of the methodologies employed. Socioeconomic data may also be incorporated into analyses in order to draw even more valuable insights regarding the emissions-related behaviour of inhabitants within the study domain. Where possible, future research should build on previous research which has focused on the top-down disaggregation of national activity- or emissions-data and instead, apply a bottom-up approach and location-based data and emissions factors to accurately model emissions produced within the study domain as outlined in this study.

5. Conclusions and implications

In order to achieve both local and global climate action targets, advancements in city-level emissions modelling are urgently needed. However, detailed methodologies and guidance for their development remains limited in the literature. Previous research has primarily focused on single sector modelling, CO_2 emissions only, and aggregated or disaggregated regional emissions. To address this knowledge gap, an activity-based multi-sectoral (Residential; Transport; Commercial & Industrial; Public; ALUF; Waste) GHG emissions (CO_2, CH_4, and N_2O) inventory was modelled and mapped in high resolution for a medium-sized Irish city for the year 2018.

A 'bottom-up' approach was primarily used to quantify emissions for each sector in this study. Emissions were quantified in high-spatial resolution at a neighbourhood scale, enabling emissions to be mapped in detail across the city. This study also highlighted the challenges associated with data-availability in urban-scale emissions quantification and subsequently, proposed solutions to overcome these limitations. Furthermore, the use of open-source data enables the methodology employed in this study to be applied to other cities and municipalities globally.

This study highlighted the importance of high-resolution, multi-sector GHG emissions quantification and mapping in supporting effective climate action at an urban scale. Providing a multi-sectoral breakdown of emissions mapped in high-spatial resolution can guide the development of evidence-based policies to reduce GHG emissions and facilitates sustainable urban planning. Key recommendations include:

- Retrofitting schemes and subsidies for the rental market: Address high emissions in areas with a large proportion of rental accommodation by offering incentives for property owners to improve energy performance.
- Place-based decarbonisation strategies for low-income areas: Expand targeted decarbonisation grants, such as those for electrical vehicles and solar panels, to support fair and equitable GHG emissions reduction efforts.
- Expand active and public transport infrastructure: Reduce congestion and emissions by enhancing public transport options, accessibility, and frequency; and pedestrianise urban centres, increase greenspaces and improve cycling infrastructure.
- Decentralise energy options for the city's central business district, focusing on commercial buildings that contribute significantly to the city's GHG emissions.

Implementing these policies would not only lead to a significant reduction in GHG emissions but it can also provide numerous co-benefits, including improved air quality, reduced health risks from harmful exposures for urban residents, and increased safety for active commuters. The methodologies used in this study offer a framework for other cities, advancing both local and global climate goals while supporting a just transition toward fair and equitable cities of the future.

CRediT authorship contribution statement

Lily Purcell: Conceptualization, Formal analysis, Methodology, Software, Visualization, Writing – original draft. **Anna C. O'Regan:** Data curation, Formal analysis, Methodology, Software, Visualization, Writing – review & editing. **Conor McGookin:** Conceptualization, Data curation, Methodology, Validation, Writing – review & editing. **Marguerite M. Nyhan:** Conceptualization, Funding acquisition, Investigation, Methodology, Project administration, Resources, Supervision, Validation, Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Professor Marguerite Nyhan reports financial support was provided by Research Ireland (formerly Science Foundation Ireland) and Cork City Council. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.scs.2025.106370.

Data availability

Data will be made available on request.

References

Arioli, M. S., Márcio de Almeida, D. A., Amaral, F. G., & Cybis, H. B. B. (2020). The evolution of city-scale GHG emissions inventory methods: A systematic review. *Environmental Impact Assessment Review, 80*, Article 106316. https://doi.org/10.1016/j.eiar.2019.106316

Aryanpur, V., O'Gallachoir, B., Dai, H., Chen, W., & Glynn, J. (2021). A review of spatial resolution and regionalisation in national-scale energy systems optimisation models. *Energy Strategy Reviews, 37*, Article 100702. https://doi.org/10.1016/j.esr.2021.100702

Bernard, J., Bocher, E., Le Saux Wiederhold, E., Leconte, F., & Masson, V. (2022). Estimation of missing building height in OpenStreetMap data: A French case study using GeoClimate 0.0. 1. *Geoscientific Model Development Discussions, 2022*, 1–47. https://doi.org/10.5194/gmd-15-7505-2022

Guidebook 'How to develop a Sustainable Energy and Climate Action Plan (SECAP) – Part 2 - Baseline Emission Inventory (BEI) and Risk and Vulnerability Assessment (RVA). *EUR 29412. EN*, (2018)). Luxembourg: Publications Office of the European Union. https://doi.org/10.2760/118857. JRC112986.

Biljecki, F., Chow, Y. S., & Lee, K. (2023). Quality of crowdsourced geospatial building information: A global assessment of OpenStreetMap attributes. *Building and Environment, 237*, Article 110295. https://doi.org/10.1016/j.buildenv.2023.110295

Boychuk, K., & Bun, R. (2014). Regional spatial inventories (cadastres) of GHG emissions in the energy sector: Accounting for uncertainty. *Climatic Change, 124*, 561–574. https://doi.org/10.1007/s10584-013-1040-9

Cachia, R. (2018). *Dublin city baseline emissions report 2016*. Codema, Dublin: codema.ie. Published online atRetrieved from https://www.codema.ie/images/.

Cai, B., & Zhang, L. (2014). Urban CO_2 emissions in China: Spatial boundary and performance comparison. *Energy Policy, 66*, 557–567. https://doi.org/10.1016/j.enpol.2013.10.072

Cai, B., Liang, S., Zhou, J., Wang, J., Cao, L., Qu, S., Xu, M., & Yang, Z. (2018). China high resolution emission database (CHRED) with point emission sources, gridded emission data, and supplementary socioeconomic data. *Resources, Conservation and Recycling,, 129*, 232–239. https://doi.org/10.1016/j.resconrec.2017.10.036

Cai, B., Lu, J., Wang, J., Dong, H., Liu, X., Chen, Y., Chen, Z., Cong, J., Cui, Z., Dai, C., & Fang, K. (2019). A benchmark city-level carbon dioxide emission inventory for China in 2005. *Applied Energy, 233*, 659–673. https://doi.org/10.1016/j.apenergy.2018.10.016

Cellura, M., Cusenza, M. A., & Longo, S. (2018). Energy-related GHG emissions balances: IPCC versus LCA. *Science of the Total Environment, 628*, 1328–1339. https://doi.org/10.1016/j.scitotenv.2018.02.145

C40. (2024). *About C40*. C40.org. Published online atRetrieved from https://www.c40.org/about-c40/.

Chancel, L. (2022). Global carbon inequality over 1990–2019. *Nature Sustainability, 5* (11), 931–938. https://doi.org/10.1038/s41893-022-00955-z

Charkovska, N., Horabik-Pyzel, J., Bun, R., Danylo, O., Nahorski, Z., Jonas, M., & Xiangyang, X. (2019). High-resolution spatial distribution and associated uncertainties of greenhouse gas emissions from the agricultural sector. *Mitigation and Adaptation Strategies for Global Change, 24*, 881–905. https://doi.org/10.1007/s11027-017-9779-3

Chen, G., Shan, Y., Hu, Y., Tong, K., Wiedmann, T., Ramaswami, A., Guan, D., Shi, L., & Wang, Y. (2019). Review on city-level carbon accounting. *Environmental Science & Technology, 53*(10), 5545–5558. https://doi.org/10.1021/acs.est.8b07071

Chuai, X., & Feng, J. (2019). High resolution carbon emissions simulation and spatial heterogeneity analysis based on big data in Nanjing City, China. *Science of the Total Environment, 686*, 828–837. https://doi.org/10.1016/j.scitotenv.2019.05.138

CIBSE. (2021). *Energy benchmarking tool [dataset]*. Retrieved from https://www.cibse.org/.

Cork City Council. (2020). *Cork city development plan 2022 - 2028 stage 1: pre-plan consultation issues paper*. corkcity.ie. Published online atRetrieved from Https://consult.corkcity.ie/en/.

Croci, E., Lucchitta, B., Janssens-Maenhout, G., Martelli, S., & Molteni, T. (2017). Urban CO_2 mitigation strategies under the Covenant of Mayors: An assessment of 124 European cities. *Journal of Cleaner Production, 169*, 161–177. https://doi.org/10.1016/j.jclepro.2017.05.165

Central Statistics Office (CSO). (2017a). *Census 2016 small area population statistics [dataset]*. cso.ie. Published online atRetrieved from https://www.cso.ie/en/census/census2016reports/.

Central Statistics Office (CSO). (2017b). *Census 2016 boundary files [dataset]*. cso.ie. Published online atRetrieved from https://www.cso.ie/en/census/.

Central Statistics Office (CSO). (2019). *Non-domestic building energy ratings Q4 2018*. cso.ie. Published online atRetrieved from https://www.cso.ie/en/releasesandpublications.

Central Statistics Office (CSO). (2020a). *Census of agriculture 2020*. cso.ie. Agrimap 2022 [dataset]Published online atRetrieved from https://visual.cso.ie/?body=entity/ima/coa.

Central Statistics Office (CSO). (2020b). *Environmental Indicators Ireland 2020 [dataset]*. cso.ie. Published online atRetrieved from https://www.cso.ie/en/releasesandpublications/.

Central Statistics Office (CSO). (2023a). *Press statement census of population 2022 - summary results cork [dataset]*. cso.ie. Published online atRetrieved from https://www.cso.ie/en/csolatestnews.

Central Statistics Office (CSO). (2023b). *New dwelling completions*. cso.ie. Published online atRetrieved from https://www.cso.ie/en/statistics/.

Curtain, K., & Kavanagh, S. (2019). *Report on baseline energy balance, renewable energy potential and register of opportunities*. energycork.ie. Published online at https://www.energycork.ie/index.php/portfolio/corks-energy-master-plan/.

Danylo, O., Bun, R., See, L., & Charkovska, N. (2019). High-resolution spatial distribution of greenhouse gas emissions in the residential sector. *Mitigation and Adaptation Strategies for Global Change, 24*, 941–967. https://doi.org/10.1007/s11027-019-9846-z

Department of Agriculture, Food and the Marine (DAFM). (2023). *Irish fishing fleet register [dataset]*. gov.ie. Published online atRetrieved from https://www.gov.ie/en/.
Di Zio, M., Fursova, N., Gelsema, T., Gießing, S., Guarnera, U., Petrauskienė, J., Quensel-von Kalben, L., Scanu, M., ten Bosch, K. O., van der Loo, M., & Walsdorfer, K. (2016). Methodology for data validation 1.0. *Essnet Validat Foundation.* ec.europa.eu. Published online atRetrieved from https://ec.europa.eu/eurostat/documents/7755309/7769541/Methodology_for_data_validation_V1.0_REV-2016-06_FINAL.pdf/ed7abb5d-6f1f-4e92-9a72-40d8a7fe0b85.
Dias, A., Lemos, D., Gabarrell, X., & Arroja, L. (2018). Comparison of tools for quantifying the environmental performance of an urban territory. *Journal of Industrial Ecology, 22*(4), 868–880. https://doi.org/10.1111/jiec.12614
Dimitropoulos, N., Milioni, E., Lampkowski, M., Sarmas, E., Kapsalis, P., Marinakis, V., & Doukas, H. (2023). A web-based service supporting local governments in SECAP implementation activities. In *2023 14th International Conference on Information, Intelligence, Systems & Applications (IISA)* (pp. 1–7). IEEE. https://doi.org/10.1109/IISA59645.2023.10345905.
ECOSPEED. (2024). *ECOSPEED Software Solutions*. Published online at https://ecospeed.eu/.
EPA. (2022). *Ireland's provisional greenhouse gas emissions 1990-2021 [dataset]*. epa.ie.. Published online atRetrieved from https://www.epa.ie/publications/monitoring–assessment/.
Erickson, P., & Morgenstern, T. (2016). Fixing greenhouse gas accounting at the city scale. *Carbon Management, 7*(5–6), 313–316. https://doi.org/10.1080/17583004.2016.1238743
EU Neighbours (2024). CES-MED cleaner energy saving mediterranean cities. Published online at south.euneighbours.eu. Retrieved from: https://south.euneighbours.eu/.
European Commission. (2022). *Representation in Ireland*. ec.europa.eu. Published online atRetrieved from https://ireland.representation.ec.europa.eu/news-and-events/.
European Commission, 2023a. Certificates and inspections. Published online at energy.ec.europa.eu. Retrieved from: https://energy.ec.europa.eu/topics/energy-efficiency/.
European Commission. (2023b). *EU mission: Climate-neutral and smart cities*. research-and-innovation.ec.europa.eu. Published online atRetrieved from https://research-and-innovation.ec.europa.eu/.
Fang, K., Dong, L., Ren, J., Zhang, Q., Han, L., & Fu, H. (2017). Carbon footprints of urban transition: Tracking circular economy promotions in Guiyang, China. *Ecological Modelling, 365*, 30–44. https://doi.org/10.1016/j.ecolmodel.2017.09.024
Feng, K., Hubacek, K., & Song, K. (2021). Household carbon inequality in the US. *Journal of Cleaner Production, 278*, Article 123994. https://doi.org/10.1016/j.jclepro.2020.123994
Fry, J., Lenzen, M., Jin, Y., Wakiyama, T., Baynes, T., Wiedmann, T., Malik, A., Chen, G., Wang, Y., Geschke, A., & Schandl, H. (2018). Assessing carbon footprints of cities under limited information. *Journal of Cleaner Production, 176*, 1254–1270. https://doi.org/10.1016/j.jclepro.2017.11.073
Gagliano, A., Nocera, F., D'Amico, A., & Spataru, C. (2015). Geographical information system as support tool for sustainable energy action plan. *Energy Procedia, 83*, 310–319. https://doi.org/10.1016/j.egypro.2015.12.185
Gao, Y., Zhang, L., Huang, A., Kou, W., Bo, X., Cai, B., & Qu, J. (2022). Unveiling the spatial and sectoral characteristics of a high-resolution emission inventory of CO_2 and air pollutants in China. *Science of The Total Environment, 847*, Article 157623. https://doi.org/10.1016/j.scitotenv.2022.157623
Garvey, A., Norman, J. B., Büchs, M., & Barrett, J. (2022). A "spatially just" transition? A critical review of regional equity in decarbonisation pathways. *Energy Research & Social Science, 88*, Article 102630. https://doi.org/10.1016/j.erss.2022.102630
Geofabrik GmbH. (2018). *OpenStreetMap data extracts [dataset]*. Retrieved from Http://download.geofabrik.de/.
Ghaemi, Z., & Smith, A. D. (2020). A review on the quantification of life cycle greenhouse gas emissions at urban scale. *Journal of Cleaner Production, 252*, Article 119634. https://doi.org/10.1016/j.jclepro.2019.119634
Google Maps. (2023). *Cork* [dataset].. Retrieved from https://www.google.com/maps
Google Street View. (2023). *Cork* [dataset]. Retrieved from https://www.google.com/maps/.
Gouldson, A., Colenbrander, S., Sudmant, A., Papargyropoulou, E., Kerr, N., McAnulla, F., & Hall, S. (2016). Cities and climate change mitigation: Economic opportunities and governance challenges in Asia. *Cities, 54*, 11–19. https://doi.org/10.1016/j.cities.2015.10.010
Gurney, K. R., Liang, J., Roest, G., Song, Y., Mueller, K., & Lauvaux, T. (2021). Under-reporting of greenhouse gas emissions in US cities. *Nature Communications, 12*(1), 553. https://doi.org/10.1038/s41467-020-20871-0
Horak, D., Hainoun, A., Neugebauer, G., & Stoeglehner, G. (2022). A review of spatio-temporal urban energy system modeling for urban decarbonization strategy formulation. *Renewable and Sustainable Energy Reviews, 162*, Article 112426. https://doi.org/10.1016/j.rser.2022.112426
International Council for Local Environmental Initiatives (ICLEI). (2024). *ICLEI – Local governments for sustainability*. Retrieved from https://iclei.org/.
IPCC. (2023). Summary for Policymakers. In , *Climate Change 2023: Synthesis ReportContribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team]* (pp. 1–34). Geneva, Switzerland: IPCC. https://doi.org/10.59327/IPCC/AR6-9789291691647.001.
Jiménez-Pulido, C., Jiménez-Rivero, A., & García-Navarro, J. (2022). Improved sustainability certification systems to respond to building renovation challenges based on a literature review. *Journal of Building Engineering, 45*, Article 103575. https://doi.org/10.1016/j.jobe.2021.103575
Kang, J., Zhao, T., Liu, N., Zhang, X., Xu, X., & Lin, T. (2014). A multi-sectoral decomposition analysis of city-level greenhouse gas emissions: Case study of Tianjin, China. *Energy, 68*, 562–571. https://doi.org/10.1016/j.energy.2014.01.023
Katal, A., Mortezazadeh, M., Wang, L. L., & Yu, H. (2022). Urban building energy and microclimate modeling–From 3D city generation to dynamic simulations. *Energy, 251*, Article 123817. https://doi.org/10.1016/j.energy.2022.123817
Kelly, J. A., Clinch, J. P., Kelleher, L., & Shahab, S. (2020). Enabling a just transition: A composite indicator for assessing home-heating energy-poverty risk and the impact of environmental policy measures. *Energy Policy, 146*, Article 111791. https://doi.org/10.1016/j.enpol.2020.111791
Kona, A., Bertoldi, P., Monforti-Ferrario, F., Rivas, S., & Dallemand, J. F. (2018). Covenant of mayors signatories leading the way towards 1.5° global warming pathway. *Sustainable Cities and Society, 41*, 568–575. https://doi.org/10.1016/j.scs.2018.05.017
Kona, A., Monforti-Ferrario, F., Bertoldi, P., Baldi, M. G., Kakoulaki, G., Vetters, N., Thiel, C., Melica, G., Lo Vullo, E., Sgobbi, A., & Ahlgren, C. (2021). Global Covenant of Mayors, a dataset of greenhouse gas emissions for 6200 cities in Europe and the Southern Mediterranean countries. *Earth System Science Data, 13*(7), 3551–3564. https://doi.org/10.5194/essd-13-3551-2021
L'Association pour la transition Bas Carbone. (2024). *Le bilan carbone®*. Published online at https://abc-transitionbascarbone.fr.
Lamb, W. F., Wiedmann, T., Pongratz, J., Andrew, R., Crippa, M., Olivier, J. G., Wiedenhofer, D., Mattioli, G., et al. (2021). A review of trends and drivers of greenhouse gas emissions by sector from 1990 to 2018. *Environmental Research Letters, 16*(7), Article 073005. https://doi.org/10.1088/1748-9326/abee4e
Li, Y., Du, W., & Huisingh, D. (2017). Challenges in developing an inventory of greenhouse gas emissions of Chinese cities: A case study of Beijing. *Journal of Cleaner Production, 161*, 1051–1063. https://doi.org/10.1016/j.jclepro.2017.06.072
Li, Z., Wang, F., Kang, T., Wang, C., Chen, X., Miao, Z., Zhang, L., Ye, Y., & Zhang, H. (2022). Exploring differentiated impacts of socioeconomic factors and urban forms on city-level CO2 emissions in China: Spatial heterogeneity and varying importance levels. *Sustainable Cities and Society, 84*, Article 104028. https://doi.org/10.1016/j.scs.2022.104028
Liu, H., Yan, F., & Tian, H. (2020). A vector map of carbon emission based on point-line-area carbon emission classified allocation method. *Sustainability, 12*(23), Article 10058. https://doi.org/10.3390/su122310058
Lorenzo-Sáez, E., Oliver-Villanueva, J. V., Coll-Aliaga, E., Lemus-Zuniga, L. G., Lerma-Arce, V., & Reig-Fabado, A. (2020). Energy efficiency and GHG emissions mapping of buildings for decision-making processes against climate change at the local level. *Sustainability, 12*(7), 2982. https://doi.org/10.3390/su12072982
Marchi, M., Capezzuoli, F., Fantozzi, P. L., Maccanti, M., Pulselli, R. M., Pulselli, F. M., & Marchettini, N. (2023). GHG action zone identification at the local level: Emissions inventory and spatial distribution as methodologies for policies and plans. *Journal of Cleaner Production, 386*, Article 135783. https://doi.org/10.1016/j.jclepro.2022.135783
Magazzino, C., Cerulli, G., Haouas, I., Unuofin, J. O., & Sarkodie, S. A. (2024). The drivers of GHG emissions: A novel approach to estimate emissions using nonparametric analysis. *Gondwana Research, 127*, 4–21. https://doi.org/10.1016/j.gr.2023.10.004
Manzanera-Benito, G., & Capellán-Pérez, I. (2021). Mapping the energy flows and GHG emissions of a medium-size City: The case of Valladolid (Spain). *Sustainability, 13*(23), Article 13181. https://doi.org/10.3390/su132313181
Mayer, K., Haas, L., Huang, T., Bernabé-Moreno, J., Rajagopal, R., & Fischer, M. (2023). Estimating building energy efficiency from street view imagery, aerial imagery, and land surface temperature data. *Applied Energy, 333*, Article 120542. https://doi.org/10.1016/j.apenergy.2022.120542
McGookin, C., Gallachóir, B.Ó., & Byrne, E. (2021). An innovative approach for estimating energy demand and supply to inform local energy transitions. *Energy, 229*, Article 120731. https://doi.org/10.1016/j.energy.2021.120731
Melica, G., Bertoldi, P., Kona, A., Iancu, A., Rivas, S., & Zancanella, P. (2018). Multilevel governance of sustainable energy policies: The role of regions and provinces to support the participation of small local authorities in the Covenant of Mayors. *Sustainable Cities and Society, 39*, 729–739. https://doi.org/10.1016/j.scs.2018.01.013
Mi, Z., Zheng, J., Meng, J., Zheng, H., Li, X., Coffman, D. M., Woltjer, J., Wang, S., & Guan, D. (2019). Carbon emissions of cities from a consumption-based perspective. *Applied Energy, 235*, 509–518. https://doi.org/10.1016/j.apenergy.2018.10.137
Möller, B., Wiechers, E., Persson, U., Grundahl, L., & Connolly, D. (2018). Heat Roadmap Europe: Identifying local heat demand and supply areas with a European thermal atlas. *Energy, 158*, 281–292. https://doi.org/10.1016/j.energy.2018.06.025
Müller, A., Hummel, M., Kranzl, L., Fallahnejad, M., & Büchele, R. (2019). Open source data for gross floor area and heat demand density on the hectare level for EU 28. *Energies, 12*(24), 4789. https://doi.org/10.3390/en12244789
Netherlands Enterprise Agency. (2024). *Regionale klimaatmonitor*. Published online at https://klimaatmonitor.databank.nl.
Nielsen, O., Plejdrup, M. S., Bruun, H. G., Gyldenkærne, S., & Christensen, J. H. (2020). *MapEIre: National mapping of greenhouse gas and non-greenhouse gas emissions sources project*. Ireland: Environmental Protection Agency. IBSN: 978-1-84095-901-7.
Nyhan, M. M. (2015). Coping with air pollution in an age of urbanisation. *Angle Journal*. Retrieved from http://anglejournal.com/article/2015-06-protecting-urban-populations-from-air-pollution-in-an-age-of-global-urbanisation/.
Nyhan, M. M., Sobolevsky, S., Kang, C., Robinson, P., Corti, A., Szell, M., Streets, D., Lu, Z., Britter, R., Barrett, S. R. H., & Ratti, C. (2016). Predicting vehicular emissions in high spatial resolution using pervasively measured transportation data and microscopic emissions model. *Atmospheric Environment, 140*, 352–363. https://doi.org/10.1016/j.atmosenv.2016.06.018
O'Regan, A. C., Hunter, R., & Nyhan, M. M. (2021). Biophilic cities - quantifying the impact of Google Street view derived exposures to greenspace on socio-economic

and health factors in three urban areas. *Environmental Science & Technology, 55*(13), 9063–9073. https://doi.org/10.1021/acs.est.1c01326
O'Regan, A. C., & Nyhan, M. M. (2023). Towards sustainable and net-zero cities: A review of environmental modelling and monitoring tools for optimizing emissions reduction strategies for improved air quality in urban areas. *Environmental Research, 231*(3), Article 116242. https://doi.org/10.1016/j.envres.2023.116242
O'Regan, A. C., Grythe, H., Hellebust, S., Lopez-Aparicio, S., O'Dowd, C., Hammer, P. D., Sousa Santos, G., & Nyhan, M. M. (2024). Data fusion for enhancing urban air quality modeling using large-scale citizen science data. *Sustainable Cities and Society, 116*, Article 105896. https://doi.org/10.1016/j.scs.2024.105896
Pan, H., Page, J., Zhang, L., Chen, S., Cong, C., Destouni, G., Kalantari, Z., & Deal, B. (2019). Using comparative socio-ecological modeling to support climate action planning (CAP). *Journal of Cleaner Production, 232*, 30–42. https://doi.org/10.1016/j.jclepro.2019.05.274
Pla, M. A. M., Lorenzo-Sáez, E., Luzuriaga, J. E., Prats, S. M., Moreno-Pérez, J. A., Urchueguía, J. F., Oliver-Villanueva, J. V., & Lemus, L. G. (2021). From traffic data to GHG emissions: A novel bottom-up methodology and its application to Valencia city. *Sustainable Cities and Society, 66*, Article 102643. https://doi.org/10.1016/j.scs.2020.102643
Puliafito, S. E., Allende, D., Pinto, S., & Castesana, P. (2015). High resolution inventory of GHG emissions of the road transport sector in Argentina. *Atmospheric Environment, 101*, 303–311. https://doi.org/10.1016/j.atmosenv.2014.11.040
Pulselli, R. M., Marchi, M., Neri, E., Marchettini, N., & Bastianoni, S. (2019). Carbon accounting framework for decarbonisation of European city neighbourhoods. *Journal of Cleaner Production, 208*, 850–868. https://doi.org/10.1016/j.jclepro.2018.10.102
Purcell, L., O'Regan, A. C., McGookin, C., & Nyhan, M. M. (2024). Modelling & spatial mapping of residential-sector emissions for sub-national & urban areas. *MethodsX, 12*, Article 102617. https://doi.org/10.1016/j.mex.2024.102617
Python Software Foundation. (2023). *Python* [Software]. Retrieved from https://www.python.org/.
QGIS. (2023). *QGIS geographic information system version 3.28.1 [Software]*. QGIS Association. Retrieved from http://www.qgis.org.
Qi, C., Wang, Q., Ma, X., Ye, L., Yang, D., & Hong, J. (2018). Inventory, environmental impact, and economic burden of GHG emission at the city level: Case study of Jinan, China. *Journal of Cleaner Production, 192*, 236–243.
Raushan, K., Mac Uidhir, T., Llorens Salvador, M., Norton, B., & Ahern, C. (2024). A data-driven standardised generalisable methodology to validate a large energy performance certification dataset: A case of the application in Ireland. *Energy and Buildings, 323*, Article 114774. https://doi.org/10.1016/j.enbuild.2024.114774
Romero, Y., Chicchon, N., Duarte, F., Noel, J., Ratti, C., & Nyhan, M. M. (2019). Quantification and spatial disaggregation of air pollution emissions from ground transportation in a developing country context: Case study for the Lima metropolitan area in Peru. *Science of the Total Environment, 698*, Article 134313. https://doi.org/10.1016/j.scitotenv.2019.134313
Saad, S., Lahoud, C., Brouche, M., Hmadi, M., Ghandour, M., & Mourtada, A. (2021). Advanced tool for elaborating a sustainable energy and climate action plan at municipalities level. *Energy Reports, 7*, 51–69. https://doi.org/10.1016/j.egyr.2021.09.049
Sabedotti, M., O'Regan, A. C., & Nyhan, M. M. (2023). Data insights for sustainable cities: The impact of Google Street view-derived urban greenspace on Google air view-derived pollution levels. *Environmental Science & Technology, 57*(48), 19637–19648. https://doi.org/10.1021/acs.est.3c05000
Schiefelbein, J., Rudnick, J., Scholl, A., Remmen, P., Fuchs, M., & Müller, D. (2019). Automated urban energy system modeling and thermal building simulation based on OpenStreetMap data sets. *Building and Environment, 149*, 630–639. https://doi.org/10.1016/j.buildenv.2018.12.025
O'Regan, A. C., Byrne, R., Hellebust, S., & Nyhan, M. M. (2022). Associations between Google Street view-derived urban greenspace metrics and air pollution measured using a distributed sensor network. *Sustainable Cities and Society, 104221*. https://doi.org/10.1016/j.scs.2022.104221
Global Covenant of Mayors for Climate and Energy (GCoM) (2024). Retrieved from: https://www.globalcovenantofmayors.org/.
Schmidt Plejdrup, M. (2022). Spatial Results. Published online at au.dk. Retrieved from: https://projects.au.dk/mapeire/spatial-results/download.
SEAI. (2015). *Extensive survey of the commercial buildings stock in the Republic of Ireland. Insights Paper*. seai.ie. Published online atRetrieved from https://www.seai.ie/publications/.
SEAI. (2019). *Energy in Ireland 2019 report*. seai.ie. Published online atRetrieved from https://www.seai.ie/publications/.
SEAI. (2022a). *National building energy rating research tool [dataset]*. Retrieved from https://ndber.seai.ie/BERResearchTool/ber/search.aspx.
SEAI. (2022b). *National energy balance [dataset]*. seai.ie. Published online atRetrieved from https://www.seai.ie/data-and-insights/.
Sesana, M. M., Salvalai, G., Della Valle, N., Melica, G., & Bertoldi, P. (2024). Towards harmonising energy performance certificate indicators in Europe. *Journal of Building Engineering, 95*, Article 110323. https://doi.org/10.1016/j.jobe.2024.110323
Sówka, I., & Bezyk, Y. (2018). Greenhouse gas emission accounting at urban level: A case study of the city of Wroclaw (Poland). *Atmospheric Pollution Research, 9*(2), 289–298. https://doi.org/10.1016/j.apr.2017.10.005
Tsokos, C., & Wooten, R. (2016). *The joy of finite mathematics. chapter 8 – basic statistics* (pp. 265–327). Academic Press. https://doi.org/10.1016/B978-0-12-802967-1.00008-5. ISBN 9780128029671.
Ulpiani, G., Vetters, N., Melica, G., & Bertoldi, P. (2023a). Towards the first cohort of climate-neutral cities: Expected impact, current gaps, and next steps to take to establish evidence-based zero-emission urban futures. In *Sustainable Cities and Society, 95*, Article 104572. https://doi.org/10.1016/j.scs.2023.104572
Ulpiani, G., Vetters, N., & Maduta, C. (2023b). Towards (net) zero emissions in the stationary energy sector: A city perspective. *Sustainable Cities and Society, 97*, Article 104750. https://doi.org/10.1016/j.scs.2023.104750
United Nations. (2018). *World urbanization prospects 2018*. New York: Department of Economic and Social Affairs, Population Division. Published online at Population. UN.org. Retrieved from https://population.un.org/wup/Publications.
United Nations Environment Programme. (2021). *Emissions Gap Report 2021: The heat is on - A world of climate promises not yet delivered*. ISBN: 978-92-807-3890-2.
UN DESA (United Nations Department of Economic & Social Affairs). (2023). *The United Nations Sustainable Development Goals*. Retrieved from Https://sdgs.un.org/goals.
Wang, C., Ferrando, M., Causone, F., Jin, X., Zhou, X., & Shi, X. (2022). Data acquisition for urban building energy modeling: A review. *Building and Environment, 217*, Article 109056. https://doi.org/10.1016/j.buildenv.2022.109056
Wiedmann, T., Chen, G., Owen, A., Lenzen, M., Doust, M., Barrett, J., & Steele, K. (2021). Three-scope carbon emission inventories of global cities. *Journal of Industrial Ecology, 25*(3), 735–750. https://doi.org/10.1111/jiec.13063
Yan, Y., Feng, C. C., Huang, W., Fan, H., Wang, Y. C., & Zipf, A. (2020). Volunteered geographic information research in the first decade: A narrative review of selected journal articles in GIScience. *International Journal of Geographical Information Science, 34*(9), 1765–1791. https://doi.org/10.1080/13658816.2020.1730848
Zanni, D., Righi, A., Dalla Mora, T., Peron, F., & Romagnoni, P. (2015). The energy improvement of school buildings: Analysis and proposals for action. *Energy Procedia, 82*, 526–532. https://doi.org/10.1016/j.egypro.2015.11.865
Zhang, G., Ge, R., Lin, T., Ye, H., Li, X., & Huang, N. (2018). Spatial apportionment of urban greenhouse gas emission inventory and its implications for urban planning: A case study of Xiamen, China. *Ecological Indicators, 85*, 644–656. https://doi.org/10.1016/j.ecolind.2017.10.058
Zhang, N., Luo, Z., Liu, Y., Feng, W., Zhou, N., & Yang, L. (2022). Towards low-carbon cities through building-stock-level carbon emission analysis: A calculating and mapping method. *Sustainable Cities and Society, 78*, Article 103633. https://doi.org/10.1016/j.scs.2021.103633
Zhang, L., Niu, M., Zhang, Z., Huang, J., Pang, L., Wu, P., Lv, C., Liang, S., Du, M., Li, M., & Cao, L. (2023). A new method of hotspot analysis on the management of CO2 and air pollutants, a case study in Guangzhou city, China. *Science of the Total Environment, 856*, Article 159040. https://doi.org/10.1016/j.scitotenv.2022.159040
Zhao, J., Chen, Y., Ji, G., & Wang, Z. (2018). Residential carbon dioxide emissions at the urban scale for county-level cities in China: A comparative study of nighttime light data. *Journal of Cleaner Production, 180*, 198–209. https://doi.org/10.1016/j.jclepro.2018.01.131