Integrating the energy costs of urban transport and buildings

Bruno Osório[1 a], Nick McCullen[a], Ian Walker[b], David Coley[a]

[a]Department of Architecture & Civil Engineering of the University of Bath (UK)
[b]Department of Psychology of the University of Bath (UK)

Abstract

We cannot effectively reduce the carbon-related urban energy use without first having a good method for measuring it at an effective scale. Most prior research has usually considered the energy consumption of buildings and transport separately, but urban energy use is better understood when both uses of energy are considered together. This paper introduces a new energy use metric that combines the energy consumption of both buildings and transport. Estimates are calculated from readily available data and the simplicity of the methodology enables its replicability. This is attractive for policy-makers and planners by delivering them tools of more direct control of local-level policies. Using a LSOA geographic level and mapping the results produces helpful insights into energy consumption patterns and how the two uses of energy can be combined to support mitigation measures. When applying the methodology to a case study in the United Kingdom, maps produced show, amongst other things, how rural commuter belts are disproportionately energy-hungry when assessed per capita. Urban living is revealed as most energy efficient at this level. The integrated modelling approach demonstrated here improves the understanding of consumption patterns to enable better planning of strategies to reduce energy demand and its negative impact.

Keywords: Energy consumption, Buildings, Transport, GIS, Urban spaces

1. Introduction, scope and purpose

Industrialisation and subsequent urbanisation has resulted in a continuous growth in the number of people living in cities, and this increase is expected to continue [1, 2, 3]. This growth is leading to ever increasing global energy demand [4, 5], with a large fraction of final energy being used in cities and other urban areas. Considering that energy supply is largely obtained from fossil fuels [6], cities and overall urban areas are a major source of CO_2 and other greenhouse gas (GHG) emissions [6, 7, 8]. As a result of this, urban mitigation policies are urgently needed [8, 9, 10] to reduce the negative consequences of those emissions, such as climate change and air pollution. To design and implement such mitigation strategies and reduce carbon-based energy dependency of cities, an accurate understanding of urban energy consumption is required. Identifying patterns of energy consumption will allow the analysis and modelling of urban energy demand, in order to devise better energy planning and management strategies [11, 12, 13].

Buildings and transportation are the leading contributors to energy demand [14, 15, 16] and associated carbon emissions. For example, in the European Union of 27 members (EU-27), transport and buildings represented more than 50% and 33% of the total energy consumption, respectively, in 2011 [17]. Given the impracticality of quantifying actual energy consumption values of every urban component (i.e. each building and vehicle), estimates are produced. At present, different approaches are employed to estimate energy consumption, but no definitive solution has yet been found, particularly when looking at large regions. A common approach to estimate urban energy consumption is using models, for both buildings and transport [12, 18, 19, 20, 21, 22, 23, 24, 25], representing the complex dynamics of the real world. However, although they theoretically allow very detailed estimates to be made, these models are usually

[1]Corresponding author.
E-mail addresses: b.osorio@bath.ac.uk (B. Osório), n.j.mccullen@bath.ac.uk (N. McCullen), i.walker@bath.ac.uk (I. Walker), d.coley@bath.ac.uk (D. Coley)

very complex and require large bulks of input data that are not generally available for the majority of cities or urban areas, limiting the large-scale application of the modelling procedure to other geographic areas.

This paper introduces a unified methodology to estimate the total energy consumption costs in urban spaces. Therefore, the methodology combines the operational energy consumption of both buildings and transport into an energy use metric, considering that both are significantly interdependent given that the mobility of the buildings' users and respective travel distances are influenced by the urban spatial layout, i.e. the arrangement of the built environment, affecting, for example, the transport carbon footprint [26]. At the same time, transport networks also have an effect on the operational energy consumption of both buildings and transport [27] by moving individuals and goods between places [28]. Since mitigation strategies are primarily interested in reducing carbon-based energy consumption and its negative impacts, the simultaneous study of the operational energy consumption of both buildings and transport can help planners to avoid unintended outcomes of one-sided strategies.

The introduced methodology seeks also to prevent another major difficulty when estimating urban energy consumption: defining city boundaries. The use of distinct urban/rural boundaries result in different energy estimates. For example, the administrative boundaries of many cities, especially large cities, generally do not encompass the whole urbanised area of a city, since administrative definitions are slow to follow the change over time of urban boundaries [29, 30, 31]. The resulting energy consumption estimates may lead planners and policy-makers to develop biased and ineffective actions to reduce and mitigate carbon-related energy demand [30]. For that reason, in this paper a large scale geographical unit – Lower layer Super Output Area (LSOA) – is used so that the boundaries of cities and urban areas are not predefined and a bias is not added to the analysis. At the same time, the use of the fine-grain detail LSOA units enables to have a better understanding of the energy internal dynamics of cities and urbanised areas, in addition to the regional dynamics and between cities.

The work presented here focusses on urban areas and seeks to feed into policy concerning working and living patterns (rather than global commerce), and so the analysis on the example data was restricted to the operational energy of buildings and commute transport by road and rail. However, the proposed methodology easily allows the inclusion of other factors such as the transport of goods to urban areas and leisure travel. This flexibility of the procedure will prove advantageous to many of the models and approaches used to estimate energy consumption found in the literature. Furthermore, the use of readily available official government data sources and the straightforward simplicity of the methodology makes it easy to replicate to other regions. It can therefore be employed by planners and policy-makers (and even other users) aiming to design effective mitigation strategies to reduce carbon-related energy consumption by buildings and transport. On this account, the benefits of the introduced energy use metric are (but not restricted to): (i) integration of both buildings and transport energy consumption; (ii) use of large scale geographic units, LSOAs, to avert defining city boundaries; (iii) simplicity and replicability of the procedure; (iv) use of official available information, thus considered reliable sources. Overall, the methodology outlined here demonstrates a new, simple alternative approach to estimate energy that uses relevant available data, combines buildings and transport and has the prospect of being replicable, providing additional tools to planners and policy-makers. The energy use metric is aimed to the end-user and local councils and so it is assumed that the operational energy of buildings and commute transport energy are the main variables over which authorities and urban planners have more direct control through policies.

The paper is structured in the following way: Section 2 introduces the methodological approach by presenting data sources and calculation methods. Section 3 deals with the application of the methodology to a case study, discussing results and causes. Finally, Section 4 is a summary of the previous discussions, and identifies the methodology's limitations and suggests paths for future developments.

2. Methodology

The approach introduced here combines data from both buildings and transport to estimate total energy consumption, thereby developing a new, simple energy use metric. The unfeasibility of estimating the energy consumption of every building and vehicle of a neighbourhood or a large area led to the use of readily available official data to produce a non-detailed energy estimate at large scale. The energy use metric is user-friendly and may be used by policy-makers and planners as an initial estimate to outline strategies to reduce or mitigate carbon-related energy consumption, since the approach combines data from the operational energy consumption of both buildings and commute transport. The proposed methodology is based (and was partly introduced) on previous work [32, 33], and consists of: (i) data selection and aggregation at appropriate scale; (ii) the theoretical energy use metric framework; (iii) data output and presentation. An explanation of each step follows. Additionally, a detailed explanation of the downscaling procedure is presented in §2.4.

2.1. Data aggregation, scaling and units

2.1.1. Data selection and aggregation

Urban energy consumption is primarily due to both buildings (here split into residential and non-residential buildings) and transport (including road and rail transport) [6]. The approach followed here to estimate the energy consumption of those two vectors includes only the operational energy of buildings, as this is immediately related to short-term urban characteristics that can interact with transport, and commute transport carbon footprint, converted to energy use. The use of only buildings' operational energy and commute transport is further justified here as these are urban components over which it is expected for local authorities and planners to have more control to prompt change at short–medium-term. Yet, the flexibility of the approach allows the future inclusion of other urban energy factors, such as the embodied energy of buildings or the transport of goods.

To produce a simple energy metric enabling replication, only available official data is used here. The use of information published by official governing bodies in the UK is perceived as being both reliable and accessible data sources for end users of the research. However, the methodology is robust enough to allow the use of other data sources of varying resolution, if available. Energy consumption values for buildings is derived from sub-regional energy utility data, a procedure found in some previous studies [34, 35, 36]. The Department of Energy & Climate Change (DECC) is the main government institution in the UK publishing energy-related data. Consequently, energy consumption estimates for buildings are based on DECC's tables of sub-regional energy use. This is split by type of building (residential and non-residential) and form of energy (electricity, gas, etc.).

The analysis of transport energy consumption is restricted here to commute transport mainly because of: (i) the availability of reliable data; (ii) the significant proportion of energy consumption this commute transport represents [37, 38] in urban areas – about 4.1% of total energy use and about 14.4% of transport energy use in the UK [39]; (iii) the greater influence (and control) that local governing bodies and planners have to produce actual changes in the system. Commute transport carbon footprint (then converted to energy use) values are derived from the Origin-Destination (OD) matrix table of work commute journeys published by the Office for National Statistics (ONS) and mapped by the DataShine web platform [40]. The information of the OD table allows the calculation of estimates for each mode of transport (car, bus, etc.).

2.1.2. Defining scale, scaling and units

Urban energy use estimates depend on the spatial scale, i.e. how urban areas are delimited in space [41], which depends on data availability [42]. Furthermore, urban boundaries are not always followed by the administrative change of city limits [29, 31]. To prevent deriving unreliable energy consumption estimates, urban boundaries are not defined and rather a Lower layer Super Output Area (LSOA) geographical unit is used that, at the same time, acts as a proxy for large scale analysis.

A LSOA is a geographical unit used for statistical purposes, defined as an area with 1000 to 3000 residents and from 400 to 1200 households [43]. The use of a large scale of analysis enables a better focusing of strategies to modify energy demand, as it is more individual/household-oriented and allows more fine-grained control of the policies implemented by local governments. Regardless of the selected scale, the methodology may be applied at any level of analysis for which data is available, as the main feature of this procedure is combining both buildings and transport energy consumption (see Equation 2).

The use of LSOA units requires the application of a scaling procedure as much of the information used to compute the energy consumption estimates of buildings and transport is not available at LSOA level. Apart from the electricity and gas consumption of buildings (both residential and non-residential), DECC's information (data source for the remaining buildings energy sources) is published at Local Authority (LA) level and ONS' OD matrix table (data source for the commute transport carbon footprint) is published for Middle layer Super Output Area (MSOA) units (a smaller scale than LSOA) [43]. Overcoming the problem of non-standardized energy statistics is carried out by using a *downscaling technique* [44, 45, 46]. Downscaling is commonly used in climate studies and climate projections [47, 48, 49], as it allows a relationship between coarse spatial resolution data and local-scale regions to be established.

The procedure followed here uses a scaling factor (detailed in Section 2.4) to rescale the available data to LSOA resolution. The scaling factor for buildings was derived from the Generalised Land Use Data (GLUD) by LSOA published by the ONS and is based on the Ordnance Survey MasterMap® land features map [50]. These GLUD features assign a different land use to each land parcel of a LSOA unit. Although the latest GLUD information is originally from 2005, the use of alternative data sets – for example, CORINE Land Cover [51, 52] – with different resolutions (usually coarse resolutions) would present a problem [53] as the energy use metric is arranged at LSOA scale. As for transport, the commuting population from the Census dataset published by ONS was considered as the scaling factor to convert the transport energy consumption from MSOA to LSOA geographic level. The use of commuting population instead of total population prevented including a bias into the downscaling procedure, for example the young population (less than 16 years old) are not included in the commuting population.

As mentioned, commute transport data is originally published at MSOA level: commute journeys by mode of travel are released for population-weighted MSOA centroids, thus giving the total number of people commuting between each OD MSOA centroid pair (shown in Figure 1). The data gathered here only used outbound flows, doubling these to obtain return-journey estimates. The following methods of travel are considered: train, bus/coach, motorbike/moped and car.

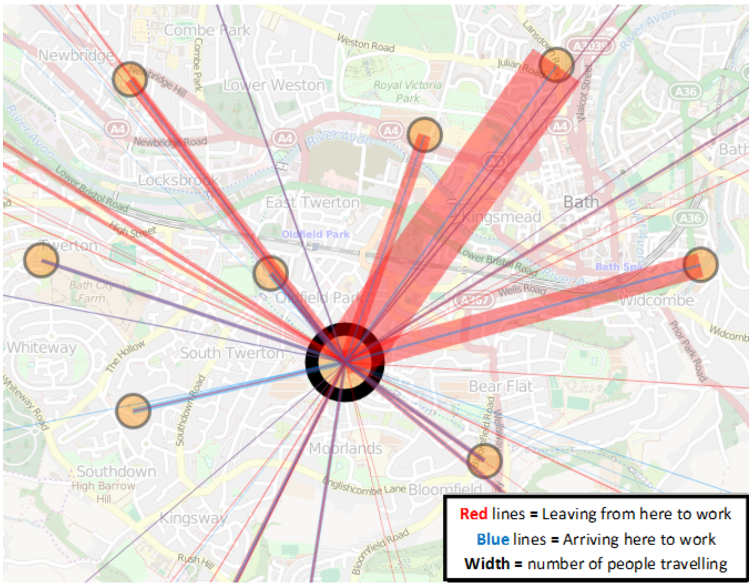

Figure 1: Origin-Destination travel to work flows in the Bath region (yellow circles show MSOA centroids and line thickness represents the number of people commuting)

Source: DataShine [40]

The transport carbon footprint is obtained to the distance between Origin and Destination of each commute trip and converted to energy use (§2.2.2 for more details). The downscaling technique is then applied to calculate the carbon footprint at LSOA scale of both road and rail transport from the MSOA data. The choice of the scaling factor, such as population density, total area, building footprint or other, is very important, since the scaling metric can give different results, leading to different insights in each case and by cross comparison (see Section 3).

To combine the energy consumption of buildings and the commute transport carbon footprint into the same framework, further action is required. DECC's data sets on the operational energy consumption of buildings – including the consumption of electricity, gas, coal and other products by both residential and non-residential buildings – are published in kWh, based on meter readings and hence are point-of-use energy figures [54]. On the other hand, transport carbon footprint was originally obtained in $kgCO_2$. Since the energy metric used herein includes an estimate of both buildings and commute transport, the common SI unit of measurement the megajoule (MJ) is used. The conversion from kWh to MJ is based on the following rate:

$$1kWh = 3.6MJ \tag{1}$$

The conversion of buildings energy values is straightforward (given that source data is made available in kWh), but the conversion of the commute transport carbon footprint is mainly based on fuel conversion factors for each mode of transport and included several steps (detailed in §2.2.2).

2.2. Energy use framework

The new, combined energy use metric approach introduced here is built on the fundamental relationship:

$$E = B + T \tag{2}$$

where E is the Total Energy Consumption, B is the Buildings operational Energy Consumption and T is the commute Transport carbon footprint converted to Energy.

The method produces a unified energy use metric to launch a more empirically-oriented and simple approach to the estimate of total energy use. Follows a description of the calculation of each energy vector.

2.2.1. Buildings: residential and non-residential

The sub-regional energy utility data for buildings published by DECC covers the main forms of energy: electricity, gas, coal, manufactured fuels, petroleum products and bioenergy & waste. With the exception of the latter form of energy, DECC's tables distinguishes each form of energy between domestic (i.e. *residential*) and industrial & commercial (or *non-residential*) buildings. Therefore, the integration of every factor is given by:

$$B = R + N + W, \tag{3}$$

where R is the energy consumption of Residential Buildings and N is that of Non-Residential Buildings and W is the value for Buildings' Bioenergy & Waste.

Residential buildings energy consumption R results from households, essentially the consumption by families of electricity and gas [23, 55]. Based on the collected data published by DECC, that consumption can be described by:

$$R = R_e + R_g + R_c + R_m + R_p, \tag{4}$$

where R_e to R_p are the Residential consumption values for Electricity, Gas, Coal, Manufactured Fuels and Petroleum Products, respectively.

Energy consumption of non-residential buildings N is composed of that from public buildings, corporate offices, factories and other non-residential structures [56, 57]. The consumption of non-residential buildings is broken down in the same way as Equation 4.

Dowscaling.

As some sources (specifically coal, manufactured fuels and petroleum products) of energy consumption of buildings are published by DECC at LA geographic level, a downscaling procedure is applied to adjust the original information to LSOA. Using a scaling factor to estimate the values of each form of energy:

$$E_L = \frac{E_{LA} F_L}{F_{LA}}, \tag{5}$$

where E_L and E_{LA} are the Energy Consumption values by LSOA and LA, respectively, and F_L and F_{LA} are the Scaling Factor values by LSOA and LA, respectively. The actual values used for the scale factors F_{LA} and F_L depend on which metric is chosen to scale with.

As aforementioned, the scaling factor used here is based on the GLUD features published by the ONS and made available at LSOA geographic level. A more detailed explanation of the downscaling procedure can be found in §2.4. For residential buildings R, GLUD's category designated as "domestic buildings" (in m^2) is used as scaling factor, since it refers to the area covered by those type of buildings. As for non-residential buildings N, the land use classification designated "non-domestic buildings" (in m^2) is used as scaling factor. Consequently, the sum of the values of the two factors was used to compute the buildings' bioenergy & waste W consumption at LSOA. The use of the mentioned GLUD's land use categories refers to the fact that these features are directly associated with the estimated energy consumption of each type of building: residential and non-residential.

2.2.2. *Transport: road and rail*

Transport energy use is the other of the two major contributors to the total energy consumption [58, 59]. Here only commute land transport is considered, which primarily consists of road and rail transport [60, 61]. According to that premise and the ONS' commute trips tables, the following is considered:

$$T = Ro + Ra, \tag{6}$$

where Ro is the Road Transport Carbon Footprint and Ra is the Rail Carbon Footprint.

For road transport, ONS' data provides information about the number of people travelling by car, bus/coach and motorbike/moped. To obtain the carbon footprint (then converted to energy use in MJ) of commute transport, all outbound journeys by road and rail transport between every Origin-Destination (OD) MSOA centroid pair in England are considered. Therefore, the calculation of the road transport carbon footprint for any given mode of transport is obtained from:

$$Ro = LD_{OD}C_f PW_d 2 \tag{7}$$

where L is the number of litres of fuel consumed by km, D_{OD} is the Road Distance between an OD pair, C_f is the fuel conversion factor for each mode of transport, P is the number of people commuting by each method of travel, and W_d is the number of working days in UK in a given year; the factor of 2 is used to include the return journey of commuters each day.

The procedure for rail transport is similar to Equation 7, but instead of road distance D_{OD} the railway length between the closest train stations of each OD MSOA pair is considered. The distance (in km) between each OD pair (or train stations in the case of Ra) is obtained using a scripted interface to Google Maps on-line IDE tool [62]. The fuel conversion factors for each mode of transport is based on recognised conversion tables [63], giving the values of commute transport consumption in kWh, which is then converted to MJ using Equation 1. Furthermore, it should be noted that, although some commute travels are made outside of the normal working week, it has been assumed that the contribution from this is small and thus only the number of working days W_d is taken into account. Finally, the sum of the values of Rail and Road carbon footprint converted to energy use gives the total Transport Energy Consumption T by LSOA.

The commuting journeys within the same MSOA units are also included in the analysis – a small component of at most 1% of the total. Since it is not possible to obtain the distance between the OD pairs of these trips, an approximation to the radius of each MSOA unit was taken as the commuting travel distance (assuming that each MSOA is roughly circular). From here, the transport energy consumption within each MSOA is obtained and downscaled to LSOA geographic level, and later added to the remaining transport consumption computed using Equation 7.

Dowscaling.

In a similar way to buildings, a downscaling procedure is used to modify the original commute transport data from MSOA to LSOA geographic level. As ONS publishes information about the commuting population at both MSOA and LSOA level, this dataset is used as the scaling factor. The procedure is similar to Equation 5, but replacing LA for MSOA values. A detailed explanation of the downscaling procedure is found in §2.4.

2.2.3. *Total energy consumption*

It is assumed that the total energy consumption estimates given by Equation (2) at LSOA level provides more detailed and further information to policy-makers and urban planners that seek to reduce carbon-related energy demand without having to reduce growth or economic development [64, 65, 66].

Currently, most methods to estimate energy consumption rely on complex methodologies, using physically-based models [6, 67, 68] that require data from different sources with distinct quality criteria and uncertainty levels which may produce in unreliable results. Additionally, a large number of those approaches are not integrative models and are applied to specific cities (or set of cities) [6, 67, 69] and/or typologies of buildings or vehicles that generally are difficult to reproduce and replicate to different regions and scales.

Here is outlined a new energy use metric that follows a simpler and more empirically-oriented procedure which may be replicable to other regions. The simplicity of the introduced methodology relies on the usage of data published by official governing bodies, the premise of the relation between buildings and transport, and the application of simple scaling techniques.

2.3. Data presentation

The introduced methodology requires the use of large amounts of information. A Geographical Information Systems (GIS) framework environment [70, 71] is used to store and manage data, and map the results. GIS benefits multidisciplinary studies by allowing the integration of different source data [72]. It it also useful in planning and decision-making processes by favouring the identification of patterns and adding value to the analysed data [73]. For example, the maps produced provide an important visualisation tool to recognise energy consumption patterns by sector, form of energy and mode of transport, as well as the geographic distribution of energy demand (see Section 3). The analysis of these patterns may then be employed to design better energy use mitigation strategies.

The geospatial data used here to produce the cartographic figures of the energy consumption is based on the Geography Services of the ONS that is built from the boundary-line map created annually by the Ordnance Survey [74]. The use of an ArcGIS framework environment enabled the easy creation of maps showing energy consumption patterns by LSOA.

2.4. Downscaling: issues and procedure

The selection of scaling factors is a complex process and past research has dealt with the many difficulties, problems and approaches [75, 76, 77, 78, 79, 80, 81]. In general, there is no perfect and standardized solution for statistical downscaling, since the process always implies making assumptions of how a given dataset at a coarse-resolution can be converted to larger scales. However, there are ways of minimizing the negative impacts of the downscaling procedure, such as studying correlation links or using multiple linear regression to select the most appropriate scaling factors [82, 83, 84, 85, 86].

Following previous research examining the impacts of key urban characteristics on energy consumption [85, 86, 87], a Pearson's correlation procedure was followed to obtain suitable scaling factors for the downscaling process. This was performed by correlating the measured energy use (dependent variable) with a independent variable from data at MSOA level, for both buildings and transport. Additionally, the scaling factors were selected considering the ease of availability of data and their significance for the energy of buildings and transport, respectively. The independent variables included only non-complex and fundamental indicators such as population, number of households, total buildings footprint, surface area, and other similar variables. Those that explain a higher proportion of the variation of the dependent variable are deemed as better predictors for use in a downscaling procedure.

At MSOA level, it was found that, for example, the commuting population driving a car or van has more impact on the energy consumption of car commute transport than other choices, with a correlation coefficient of $r = 0.874$. Other options (e.g. number of households or total population) show weaker correlation with urban energy use ($r = 0.288$ and $r = 0.263$, respectively). The energy consumption of buildings is complex, and it was found that the majority of the considered variables show weak to moderate correlation with energy, although with different values for residential and non-residential buildings. For example, the correlation between the residential buildings area and the residential buildings energy is $r = 0.358$ (moderate strength), but for non-residential buildings is only $r = -0.007$, revealing very weak correlation. Therefore, a compromise was made by using the buildings footprint, as these demonstrate at least moderate strength correlations with buildings energy.

Consequently, the total buildings footprint and the commuting population by method of travel were selected as scaling factors (as mentioned in §2.2.1 and 2.2.2). The use of different downscaling factors (as total population for buildings energy consumption) would deliver less reliable energy consumption estimates of buildings and transport from MSOA to LSOA geographic levels.

3. Results and discussion

In order to demonstrate the use of the methodology in a practical context the unitary authority of Bath and North East Somerset (BANES) was selected as a case study (Figure 2). This council is located in the South West of the UK and covers an area of 570 km^2. Although not all LSOAs within BANES can be described as urban spaces, for simplicity all units were considered urban.

The results show the total energy consumption (in terms of the relative carbon cost) of both buildings and transport displayed per unit area and per capita, including a selection of their components.

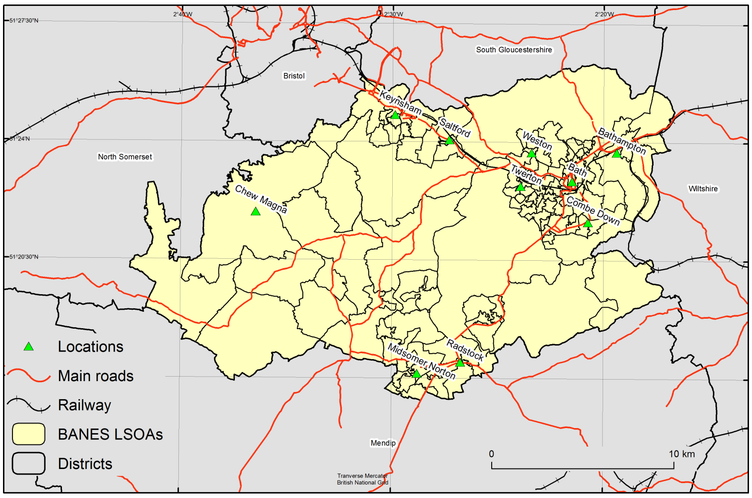

Figure 2: BANES: main locations, roads and railway networks
Based on: Ordnance Survey, OpenStreetMap (cartography)

3.1. *Buildings*

Figure 3 shows three major areas with higher energy consumption estimate per unit area for residential buildings: 1) the city of Bath and immediate surroundings in the East region of the local authority (BANES) limits – the main consumption area; 2) the civil parishes of Keynsham and Saltford in the North; and 3) a conurbation formed by Midsomer Norton, Radstock and Peasedown St John in the South.

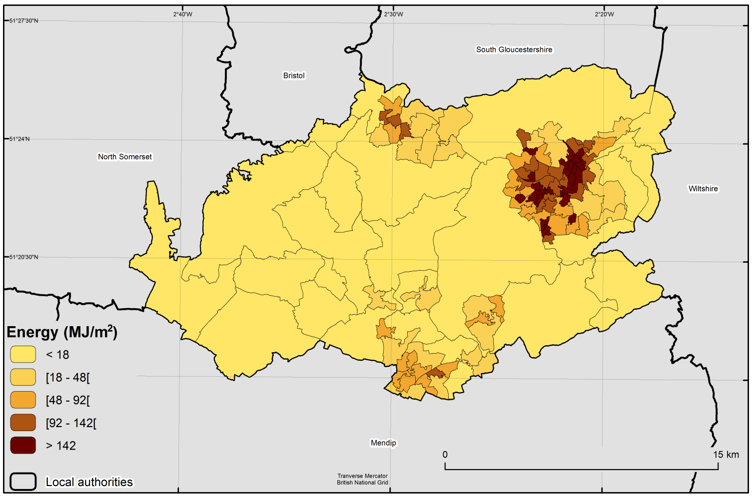

Figure 3: Energy consumption of residential buildings by LSOA per unit land area in BANES (2013)
Based on: DECC (data); Ordnance Survey (cartography)

As expected when looking at energy per unit surface area, the areas with the highest consumption are located in the city, primarily following a North-East to South-West direction passing through the city centre. Moving away from the city centre, the dwindling of consumption is recognizable – less than 18 MJ per m^2. The high energy consumption LSOAs in the city are directly related to their energy requirements, since there is a higher density of people and businesses located here than in the closest but mostly rural outskirts.

In contrast, a different picture emerges by analysing per capita consumption. The energy consumption per capita of buildings (Figure 4) gives contrasting results. The lower consuming LSOAs are mostly located in the three regions that present highest values in Figure 3. However, exceptions are observed: LSOAs presenting high energy consumption by both surface unit and per capita can be identified as the main centres of the three mentioned regions. Ultimately, considering both maps together, it becomes clear that areas with high population density, i.e. smaller LSOAs, as they are based on approximately equal population (Figure 5), demonstrate lower use of energy per capita, excluding the cited centres. These centres can be identified mostly in the city region and in the Midsomer Norton conurbation, which demonstrate high energy consumption by both area (m^2) and population (per capita). Further study is needed to understand the reasons, but these areas also reveal potential to target strategies to reduce energy consumption for BANES.

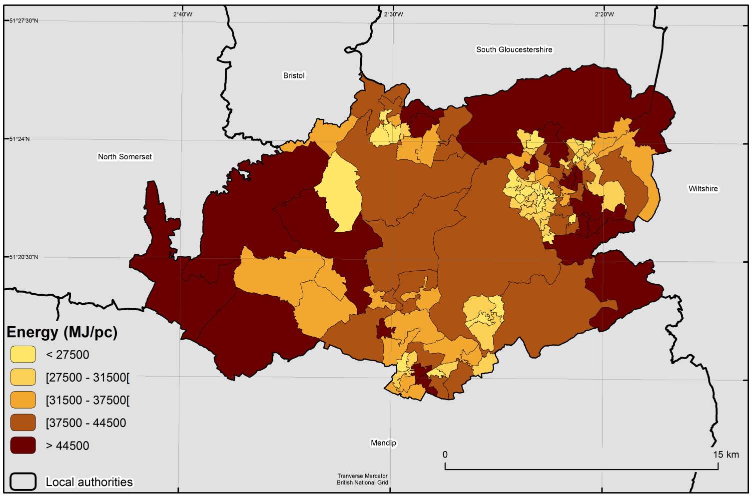

Figure 4: Energy consumption of buildings by LSOA per capita in BANES (2013)
Based on: DECC (data); Ordnance Survey (cartography)

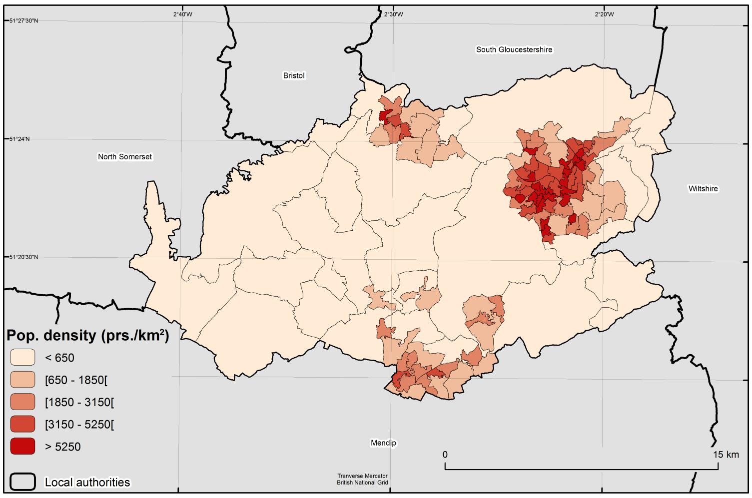

Figure 5: Population density by LSOA in BANES (2011)
Based on: ONS (data); Ordnance Survey (cartography)

3.2. *Transport*

Estimates of transport energy consumption are based on the conversion of the carbon footprint of outbound commuting travels (i.e. all trips from each MSOA centroid to work locations plus the return trip) to MJ units, as these are an important source of CO_2 emissions [88]. Figure 6 shows that the highest road transport consumption is located in the same three regions as for building energy consumption, although the importance of Keynsham-Saltford area and Midsomer Norton conurbation is higher than for buildings. This means that it is from these three regions (and respective LSOA units) that most commuting flows in BANES have their origin. The outskirts of the city region and partly the Midsomer Norton conurbation are especially significant, demonstrating an important prevalence of outbound commuting trips. The location of the higher value LSOAs in the outer boundaries of the city region demonstrates that these regions act as commuter satellites to the city centre. Additionally, some closer areas to the centre also show high commute road transport energy consumption values, revealing the main residential LSOAs of the region. Ultimately, the LSOAs with higher energy consumption values indicate where people use more (and may be more dependent on) road transport (primarily car), which underlines the need of mitigation actions to reduce car use for those areas.

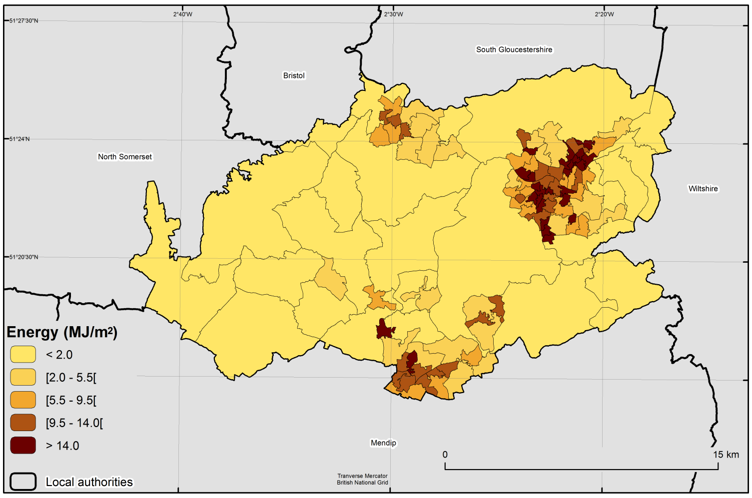

Figure 6: Energy consumption of commute road transport by LSOA per unit land area in BANES (2011)
Based on: ONS, DataShine (data); Ordnance Survey (cartography)

The results of the energy consumption per unit area for car commute travel and total commute transport (not shown) demonstrate similarities with Figure 6: highest consuming LSOAs are located in the three main regions with a few discrepancies. Furthermore, LSOA units showing higher energy consumption related to car travel represent the areas that are more dependent on cars, which could indicate the absence or the lack of bus services. This also raises concerns about the accessibility of places located outside the major urban spaces. Lower energy consumption areas show less use of road transport which could be associated with people working close to their home.

BANES is served by three train stations: Bath Spa, Oldfield Park and Keynsham. Figure 7 shows that the city's train station (Bath Spa) attracts more people, mostly living in the city centre or outer surroundings, both in the North and South of the city centre. As anticipated, the energy consumption of commute train transport is concentrated in the LSOAs near to a train station (Figure 7).

The results for the total commute transport (road and train transport) energy consumption per capita (Figure 8) show a different picture. The consumption is essentially divided into three regions, from lower to higher consumption values: i) the city of Bath and outskirts; ii) most of the Keynsham-Saltford area, some LSOA units in the Midsomer Norton conurbation and most of East BANES; and iii) West BANES, part of Central BANES and the majority of the Midsomer Norton conurbation. Accordingly, West and Central BANES comprise larger LSOAs but less energy efficient, and thus relying more on fossil fuel-based carbon consuming transport. This may denote isolation and/or unavailability of alternative forms of transport for the local populations.

3.3. Total energy consumption

Figure 9 demonstrates the main approach in this paper: the combination of energy consumption of both buildings and (commute) transport. The combined energy use metric offers new insights of the consumption patterns which are

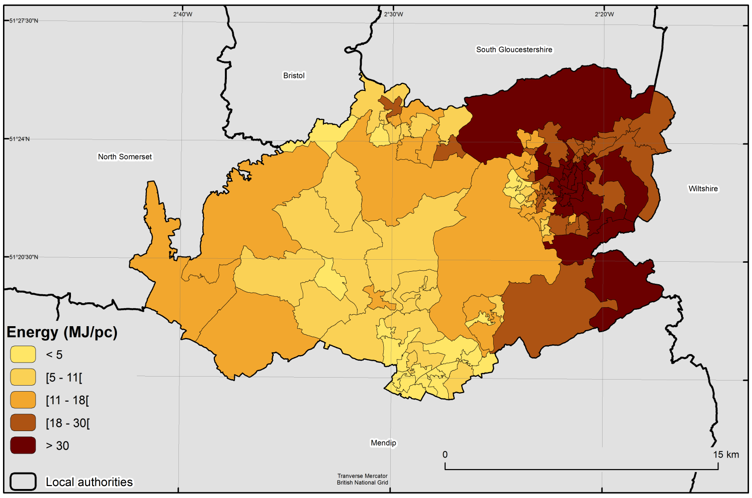

Figure 7: Energy consumption of commute train transport by LSOA per capita in BANES (2011)
Based on: ONS, DataShine (data); Ordnance Survey (cartography)

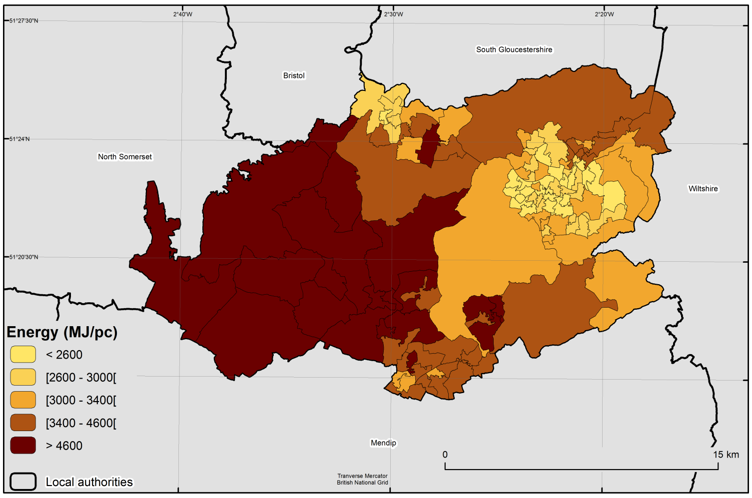

Figure 8: Energy consumption of commute transport by LSOA per capita in BANES (2011)
Based on: ONS, DataShine (data); Ordnance Survey (cartography)

not entirely evident when analysing buildings and transport alone (Figures 4 and 8, respectively). This information will allow a better understanding of consumption patterns by planners and policy-makers to support the outline of actions to improve energy efficiency or mitigate and reduce energy use.

The results here show that, with some exceptions, most of the lower energy consumption LSOAs are located in the West boundary of city region and partly in the remaining two identified urban regions (Figure 9). However, the number of LSOAs with lower consumption, and also their spatial distribution, does not exactly match the separate consumption of buildings and transport alone introduced in the respective individual maps. Although total energy and buildings consumption show similarities, the differences demonstrate the significance of Figure 9 and thus of the combined approach proposed in this paper and given by Equation 2. The highest energy consumption LSOA units are mainly clustered in the main centres of the three mentioned urban regions and some of their outer boundaries, North-east BANES and the majority of West and Central BANES. The high energy consumption of the outskirts areas of the city region indicates that these LSOAs demonstrate dormitory town characteristics (see Section 3.4), i.e. large energy use of buildings and outbound commute transportation. Overall, the identification of high energy consumption areas

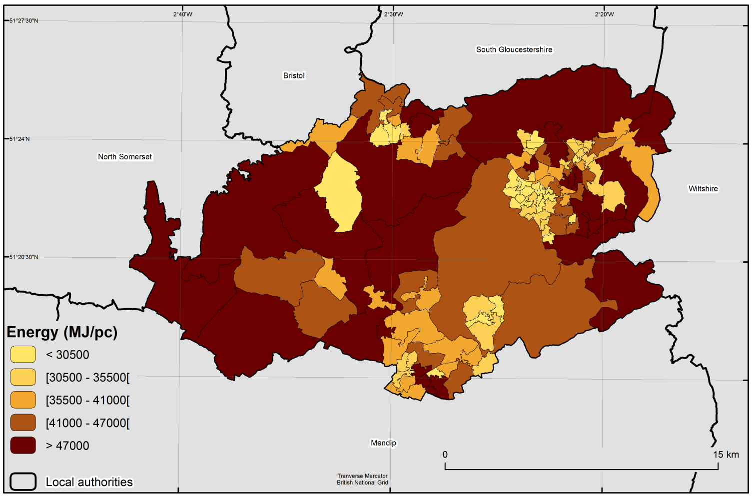

Figure 9: Total energy consumption by LSOA per capita in BANES (2013)
Based on: DECC, ONS, DataShine (data); Ordnance Survey (cartography)

(LSOA units) provides valuable information to planners and policy-makers of where (and on what) to implement the different actions aiming at mitigating or reducing carbon-based energy use. Maps of the consumption of, for example, electricity and gas by buildings (not shown) provide information about the locations that may be subject to mitigation actions or energy efficiency improvement measures. The identified consumption patterns dissimilarities between buildings and commute transport also reveals that these mitigation strategies should be designed with different focus and objectives.

3.4. Discussion

The research in this paper introduces a unified means of analysing and presenting estimates of total energy consumption based on a simple approach and using available data. A case study is presented to demonstrate the implementation of the approach and its significance to estimate energy consumption at a large scale of analysis, as well as using readily available data. The maps produced allow the identification of consumption patterns, presented with respect to different scaling metrics, which can inform strategies for efficiency measures in both buildings and transport. Presenting the outcomes per capita and by land unit area allows a different analysis of the results, as the first provides information on efficiency and the second shows the areas with more total energy consumption.

One of the main aims when devising the methodology was to ensure that it may be replicated to other regions/areas, guaranteeing its applicability and relevance to planning. For the pilot case study of BANES, the results show that high energy consumption per unit area of both buildings and transport (excluding train) is focused on three major urban areas. The per capita analysis tells a different, more complex story: smaller LSOAs have low energy consumption, including those within the mentioned three regions, but with the exception of the main centres of these urban regions. High consumption is primarily located in North-east, Central and West BANES and some outskirts of the city, although more clearly attributable to buildings. As this per capita analysis is directly related to people, it is likely to be more useful for policy development, since the locations of high and low consumption are recognised. Ultimately, the combined energy use metric provides new information on consumption patterns that are not obvious when analysing buildings and transport alone (Figures 4 and 8, respectively), as for example the spatial distribution of high and low consumption values.

The analysis of commute transport suggests that LSOAs with higher energy consumption per unit area may have more reliance on fossil fuel-based transport, mostly due to car use. This can indicate that these areas display dormitory town characteristics [89, 90, 91], where people work in a different area (LSOA) than their place of residence. On the other hand, the analysis of commute transport energy consumption per capita indicates that most of the larger surface area LSOAs located in Central and West BANES have higher consumption. The city region demonstrates lower consumption, though parts of the remaining two urban regions in most maps also show low consumption. Nevertheless, further work to analyse the energy consumption of commute transport can look into the consumption patterns from the city centre to outskirts areas introduced in previous work [32]. This can provide additional information about the road network accessibility of those outskirts, which may in turn influence strategies for mitigating the carbon emissions from transport

The results also show that the average proportion of the commute transport in the total energy consumption of BANES is about 9.3%, a figure slightly above the 4.1% mentioned by other authors [39]. Although 4.1% refers to all England and is obtained at a different scale of analysis – NUTS level 4 against LSOA (in this research) –, the difference indicates that a probable underestimation of the commute transport energy use has been considered by authorities, as well as the use of a different method to calculate commute transport. This shows the importance of studying energy consumption at more fine-grained scales (as LSOA) to obtain a better description of the urban consumption. This knowledge will help to devise more focused strategies related to energy consumption and efficiency.

4. Conclusions, limitations and future work

Measuring energy consumption is essential for better planning and policies [57, 92, 93] to mitigate and reduce the negative consequences of carbon-based energy demand [6, 9, 10]. The recognition of consumption patterns will allow better management and planning of that demand [12, 13].

This paper introduces a new energy use metric that combines the energy consumption of both buildings and transport. The estimates calculated are derived from readily available data published by official government bodies (assumed as reliable sources) and integrate the operational energy of buildings and commute transport energy. The use of official sources such as the Census dataset to derive energy consumption (in the case of commute transport energy) is considered to ensure better results, as it covers the full population of the case study. Moreover, the approach aims at the end-user and local authorities and thus the energy consumption of both buildings and commute transport are considered the main measures over which local councils and planners have more direct control and can influence through policies to reduce energy use. Therefore, the simplicity of the methodology enables its replicability beyond the presented case study and so it can be attractive tool for policy-makers and planners. Mapping the results also produces helpful insights into energy consumption patterns to support the development of mitigation measures, which benefits from the use of a large geographic scale.

The limitations of the methodological approach arise mostly from data unavailability and the assumptions that had to be made. For example, the commute road distance is obtained between the Origin-Destination (OD) MSOA centroids and not the actual OD locations (§2.2.2). The information about every commute trip is not available at such large scale, necessitating such an assumption. Considering that the average diameter of a MSOA unit is 4 km and the average commute trip is 5.8 km (according to the National Travel Survey by the Department for Transport [94]), the average commute distance between OD MSOA centroids is believed to be between 4 and 8 km (based on the average radius value of the two to four contiguous MSOA units). By way of illustration, if considering both the direct (centroid–centroid) and road distances for actual journeys between a single BANES' MSOA to 10 other BANES' MSOAs, the analysis shows that the average OD road distance between MSOAs is 80% of the direct distance between their centroids. However, after downscaling the car transport energy consumption to LSOA level based on those distances and the respective commute population, and including the energy consumption related to buildings and the other transport modes of travel, the total energy consumption is similar if using direct or road distances (with ratio of 0.99). This means that the uncertainty in the total energy resulting from the assumption of using direct rather than actual road distances is only around 1% in this instance, which is satisfactory given the data availability restrictions of detailed information.

Further assumptions are related to fuel conversion factors, used to obtain the energy consumption of each commute travel mode. Although based on acknowledged conversion tables [63], average values were used to simplify the methodology, as producing a simple and repeatable procedure was a central aim of this work. An illustrative example is the use of a combined average of conversion values for petrol and diesel cars, where data is not readily available at MSOA resolution and such an assumption has to be made. Nevertheless, the difference between the individual conversion factors is less than 5%, which is considered as an acceptable error influencing the final energy consumption by MSOA, given the other uncertainties.

The assumptions include also the use of the same conversion factors for all commute trips by travel mode, independently of car, bus or train type. Therefore, MSOAs with higher proportion of, for example, urban luxury cars (with a consumption of 0.8 kWh per km [63]) would have bigger car transport energy consumption than other units with a higher proportion of city economy car (0.42 kWh per km [63]). In this research, a combined average of petrol plus diesel conversion values was used (0.52 kWh/km, somewhere in between the extremes) to convert the energy consumption by transport. This assumes a lower proportion of luxury cars in each MSOA unit, and thus a smaller impact on the final energy consumption. Similarly to other assumptions, this is essentially due to the unavailability of information about the car type used for commuting. Furthermore, all energy estimates published by official sources (as DECC's [54]) are modelled and, in the case of the transport sector, based on standard vehicle emissions and conversion factors provided by the industry. Still, it is believed that the use of average conversion factors to obtain commute transport energy makes a reasonable compromise between the lower and upper limits of those energy conversion values. Nothing in the methodology precludes more refined data to be included in the analysis were it to be available in particular cases. Consequently, the methodological approach introduced in this paper seeks to address also the limitations of the source information, as well as the unavailability of detailed data, to produce a more consistent energy estimate at large geographical scale that is replicable by various stakeholders.

The integrated energy use metric presented here suggests potential future developments to deal with the limitations of the work. First, replicating the work across the UK would enable the analysis of consumption patterns at LSOA scale and assess the reliability of the approach. Furthermore, the analysis of all transport energy consumption (and not only commuting transport) may provide additional understanding of the ratio of commute energy use to all transport and to total energy use at urban scale. For example, leisure transport is also a highly energy demanding sector [95, 96] – accounting for as much as 31% [97] – and thus should also be subject to policies to reduce energy consumption. Additional future work might also include estimating energy consumption over a period of time, allowing to evaluate its growth and assess the impacts of consumption mitigation policies meanwhile implemented.

The analysis of the case study reveals that the high density areas as the LSOAs located in the city region have lower energy consumption per capita, except for the main centres. This agrees with some authors [4, 98, 99, 100] who relate higher densities with shorter travel distances (and so lower energy consumption). However, other authors [101, 102, 103] challenge those findings, as the analysis of the energy consumption of transport (but also of buildings) should take into consideration the full characteristics of cities (or urban spaces) that is given by the urban form itself. Understanding the relationship between urban form and energy use, and how the first affects the second, can provide a better knowledge of the energy consumption process within the urban areas [33, 104], and support the design of better strategies. It is also important to note that the introduced methodology does not consider human preferences and wellbeing. Though the results suggest that higher population density areas favour lower energy consumption, this may not correlate with better well-being of the populations. In fact, some authors refer to the overall decrease of the quality of life and the environment resulting from the concentration of people in cities and general urban areas [105, 106, 107], and may even increase energy demand of buildings and carbon emissions [108, 109, 110], among other consequences brought by intensification measures.

In summary, the results presented here using this unified but flexible approach highlight the possibility of using easily available data to estimate energy consumption patterns in urban areas. Simultaneously, these consumption figures can identify potential target areas for urban-scale interventions aimed at improving energy efficiency and reducing carbon-based energy use at the city level.

Competing interests

The authors declare that they have no competing interests.

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