A small area estimation of the capability of individuals to replace car travel with walking, cycling and e-bikes and its implications for energy use

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Abstract

The negative impacts of excessive car use are well documented and this illustrates the need to reduce car use. Mode shift from car use to walking, cycling and e-bike use is one of many possible solutions, addressing for some locations the multiple negative impacts of car use including transport energy demand and associated CO_2 emissions. Walking is the most sustainable and equitable travel mode. Cycle use is also sustainable and may be provided equitably. E-Bikes are a smart technology often overlooked due to the hype around e-cars, and are potentially a sustainable and more equitable means of reducing transport energy demand than e-cars.

Recently fine scale data has become available on total car use in the UK and also the distance individuals in these same small areas are capable of travelling by walking, cycling and e-bike use. Bringing these two data sets together allows us to address these questions: What car travel distance can be transferred to walking and walking, cycling and e-bike use? What is an estimate of the CO_2 reduction potential by substituting car travel for walking and walking, cycling and e-bike use? This data fusion allows production of novel spatial indicators. The utility of these indicators is to provide fine scale information on the potential for transport energy demand reduction. Quantifying the benefits of reducing car based travel demand at the local scale is useful to policy makers to identify specific locations where large reductions in emissions per person may be achieved by shift to active modes, and it can be used to target resources and policy interventions. The method is applied to a case study in the UK.

Introduction

The contribution of transport to energy demand and CO_2 emissions is well documented. The argument for policies focussed on total energy demand reduction is well established (Sorrell, 2015). There are also well established arguments for an urgent and radical reduction in CO_2 emissions (IPCC, 2018).

However we are in uncertain times. We are unsure about the speed at which technological innovation can be deployed to reduce transport emissions and also unsure of the decarbonisation efficacy of new transport technologies. We are unsure about future desired travel demand resulting from new transport technologies and new mobility services (Lyons, 2016; Marsden et al., 2018; Marsden and McDonald, 2017). Because of this uncertainty, there is a need to calculate the upper bound on the capability to reduce transport carbon emissions using a combination of existing technologies and reducing total demand. Walking and cycling are existing low energy transport modes and potentially equitable (particularly walking). E-bikes, even if battery charging is considered, are a far lower energy electric mode than cars.

Understanding the capability of people to reduce high energy car kilometres travelled with walking, cycling and e-bikes (subsequently referred to as active modes in this paper), can contribute to solving the problem of decarbonising the mobility system. Furthermore, spatially fine grained analyses will be particularly useful to planners and policy makers because they indicate where people with capability to change and where those in need of assistance are located. Spatially fine grained indicators are more likely to be effective and equitable, because they better consider people's geographical context.

The paper is structured as follows. Spatially fine grained indicators are developed to help planners and policy makers ad-

Table 1. Data sources.

Data source	Information provided	Link
Health Survey for England 2013	Linking variables Physical activity BMI Weight	UKDS (safeguarded access to microdata) https://www.ukdataservice.ac.uk/
SRTM	Digital elevation model for deriving height and slope	NASA https://www2.jpl.nasa.gov/srtm/cbanddataproducts.html
Meridian	Roads dataset linked to SRTM to extract the slope of each road	Ordnance Survey https://digimap.edina.ac.uk/webhelp/os/data_information/os_products/meridian_2.htm
UK census 2011	Age and gender Economic activity Education Limiting long term Illness	Nomis https://www.nomisweb.co.uk/census/2011
UK National Travel survey	Vehicle km travelled grouped by trip length	https://www.gov.uk/government/collections/national-travel-survey-statistics
*MOT project (data accessed via UK Driver Vehicle Licencing Agency and Department for Transport)	Vehicle miles travelled and emissions factors	https://www.abdn.ac.uk/ctr/research/currentbr-research-projects/mot/ Wilson et al., 2013 – vehicle miles travelled Chatterton et al., 2015 – emissions factors

dress the following questions: What car travel distance can be transferred to active modes? What is an estimate of the CO_2 reduction potential for car travel distance to be transferred to active modes? In section 2 we describe the data and methods used, in section 3 we present the results, In section 4 we present the conclusions; implications for policy makers and areas for further work. The present analysis covers all small areas in England, thought the methods could be applied elsewhere if suitable data is available.

Data and Methods

The capability of individuals to travel by active modes was compared to car km travelled by bringing together several data sets (those without an asterisk in Table 1).

To bring together the data sets required to estimate the capability of individuals to travel by active modes, spatial microsimulation was used to generate a synthetic population of individuals. Spatial microsimulation is a well established data fusion tool which considers differences between people within the same area (Tanton and Edwards, 2013). It has been widely used by geographers for policy planning and analysis (Ballas et al., 2005, O'Donoghue et al., 2014). In transport studies, spatial microsimulation is also known as population synthesis – it has been used to generate inputs to some transport models (e.g. Beckman et al., 1996).

Spatial microsimulation draws together multiple datasets to simulate a population of individuals for every small area in the city. Each simulated person has a range of attributes. It begins with census type data to generate individuals with basic characteristics like age group, gender, economic status or geodemographic group. These basic census variables are known as "constraints", because they can be constrained or calibrated to the aggregate counts for each area. The allocation of constraint attributes amongst the simulated population are calibrated to sum to the totals reported in the aggregated data. for example, If the census data states a zone contains ten males and ten females, the sample population will also contain the same numbers of male and female individuals.

We can then link other attributes to the individuals where we know that there is a correlation with the basic characteristics using a variety of spatial microsimulation techniques (Tanton, 2014). These variables may come from survey data of a representative sample of individuals or information about the probability of having a particular characteristic given age group, gender and other census variables. For example the constraints age, gender, economic activity and education are correlated with Body Mass Index (BMI), and the frequency of vigorous physical exercise. The conditional probability of BMI given age, gender, economic activity and education are then used to allocate the value of BMI (Tanton, 2014).

It is then possible using these simulated individual characteristics, to calculate attributes such as physical fitness, capability to make journeys by walking and cycling and likelihood of access to a bicycle. These attributes are correlated to age, gender and other socio-economic attributes found in the census (Philips et al., 2018, 2017). To the individuals in the synthetic population we then appended estimates of annual vehicle km travelled and emissions factors for those vehicles within their residential neighbourhoods using the data in the final row of Table 1 (Chatterton et al., 2015; Wilson et al., 2013).

This gives us a powerful fused dataset of synthetic individuals representing every member of the population of every neighbourhood (Lower Super Output Area[1]) in England. We

1. LSOA Lower Super Output Area. UK census data dissemination spatial unit. Mean 625 households and mean 1500 residents.

are now in a position to see the relationship between how far an individual is likely to travel by car and how far they could travel by active modes. It is important to note we have not had to harvest every bit of data about every individual (which of course is not possible for both ethical and practical reasons). We have instead created a synthetic population who are similar enough to the real population to help us make better decisions.

Not only can we calculate indicators that take account of the variation between different individuals in an area, we can even ask "What-if …". We can ask what-if an attribute were significantly different – due to changed circumstances or policy intervention? for example, how different would the situation be if a policy had been implemented which makes e-bikes available to the residents of a particular area and they use them as much as possible– how much would that affect their ability to reduce their car use? There are many other opportunities to compare the relationship between different attributes at the individual level.

Several indicators were calculated at the individual level. The maximum daily distance individuals could travel every day without risk of injury or over exertion was calculated for every individual using calculations described in (Philips et al., 2018). These calculations took account of individual health and fitness and an individual's weight. From this the power they could produce to propel a bicycle was estimated. The model also considered whether they had access to a bicycle and the hilliness of their residential area. The first indicator calculated was the capability to substitute car km for active travel based on current bicycle availability. Alternative indicators were calculated – what if only walking was available, what if everyone had access to bicycle and what if everyone had access to an e-bike.

Once estimates for maximum active mode travel distance were obtained, the proportion of car mileage which could be substituted was estimated. The estimation included consideration of the varied length of car trips. Some car trips are very long e.g. a trip from London to Scotland for a holiday, others such as driving to a convenience store may be very short. This estimation included using a cumulative distribution function obtained from the UK National Travel Survey Data. This determined what proportion of car km travelled resulted from trips shorter than the maximum daily travel distance by active modes. Trips shorter than the maximum daily travel by active modes could be substituted for active mode travel. For example, where a person had a maximum daily active travel distance of 10 km this corresponded to being able to replace 19 % of their total car km travelled. Once the distance which could be substituted by each active mode was calculated, potential CO_2 savings were estimated. This was calculated as the distance which could be substituted multiplied by the emissions factor.

Assumptions and simplifications: The maximum daily travel by ebike assumed the power available to each individual was 250 w. Only CO_2 emissions of car use are considered at present – the embedded emissions of car and bike manufacture are not nor at this stage are the upstream emissions from charging. All active mode use is considered as carbon neutral in the present analysis. The physical constraint on the time people are capable of walking or cycling every day for utility purposes is limited to one hour (Philips et al., 2018). Figure 1 provides an overview of the spatial microsimulation process.

Results

POTENTIAL TRANSFER OF DISTANCE TRAVELLED FROM CAR TO WALKING, CYCLING AND E-BIKE USE

The pressing need for reduction in transport emissions may require going beyond behaviour change and planning for a transport system where practices are significantly different (Shove, 2010; Shove and Walker, 2010). It is useful to understand the maximum change possible. The distribution of current vehicle km driven that could be substituted for active modes per annum is shown in Figure 2. E-bikes, because of their greater range, could replace more car km than walking. Substitution by e-bikes shows the case where everyone has an e-bike, substitutable to bike when everyone has access to a conventional bicycle, substitutable car to walk/cycle is the estimate based on current levels of bicycle availability. These cases illustrated in Figure 2 and Table 2 show the maximum possible reduction in car km travelled and car energy used by walking, cycling and e-bikes.

The data plotted in Figure 2 is summarized in Table 2.

ENERGY REDUCTION POTENTIAL OF TRANSFER OF DISTANCE TRAVELLED FROM CAR TO WALKING, CYCLING AND E-BIKE USE

Figure 3 shows that e-bike have greater potential to deliver CO_2 savings based on current car use demand because e-bikes have greatest range. The data plotted in Figure 3 is summarized in Table 3.

A more accurate evaluation of the potential CO_2 savings from e-bike use should be net of the savings possible from walking and the existing bike fleet. It is important not to dismiss existing capability to reduce transport energy demand: Net savings from e-bikes are equal to gross savings from e-bikes minus gross savings from walking or cycling based on current bike availability. The net figure is given in brackets in Table 3.

The total maximum net savings for all LSOAs is 13.4 million tonnes. If we assume national CO_2 emissions of 70million tonnes (DfT NTS). In the scenario what-if everyone had an e-bike, car emissions of CO_2 from km travel could be reduced by 19 % if there is no change in demand.

The curves in Figure 3 suggest there are some places where the net savings from e-bikes are more modest and other places with far greater potential for net savings. The map below illustrates the spatial pattern of this variation. The potential net CO_2 savings per LSOA are more modest in large cities.

Conclusion

POLICY IMPLICATIONS

If the policy objective is to reduce CO_2 emissions, demand reduction should be considered first (e.g Pye et al., 2014; Royston et al., 2018). If demand, particularly for longer journeys is reduced, walking and conventional bicycles would be able to replace a greater proportion of car travel. This would negate the need to produce and consume more e-bikes.

Where demand cannot be reduced, the analysis presented shows the potential to reduce CO_2 emissions ***if*** journeys by car are substituted for walking, cycling, or e-bike. It is important to note though that there is a risk of e-bike trips replacing conventional cycling trips and this does not lead to a CO_2 saving (Winslott Hiselius and Svensson, 2017). There is also a risk that

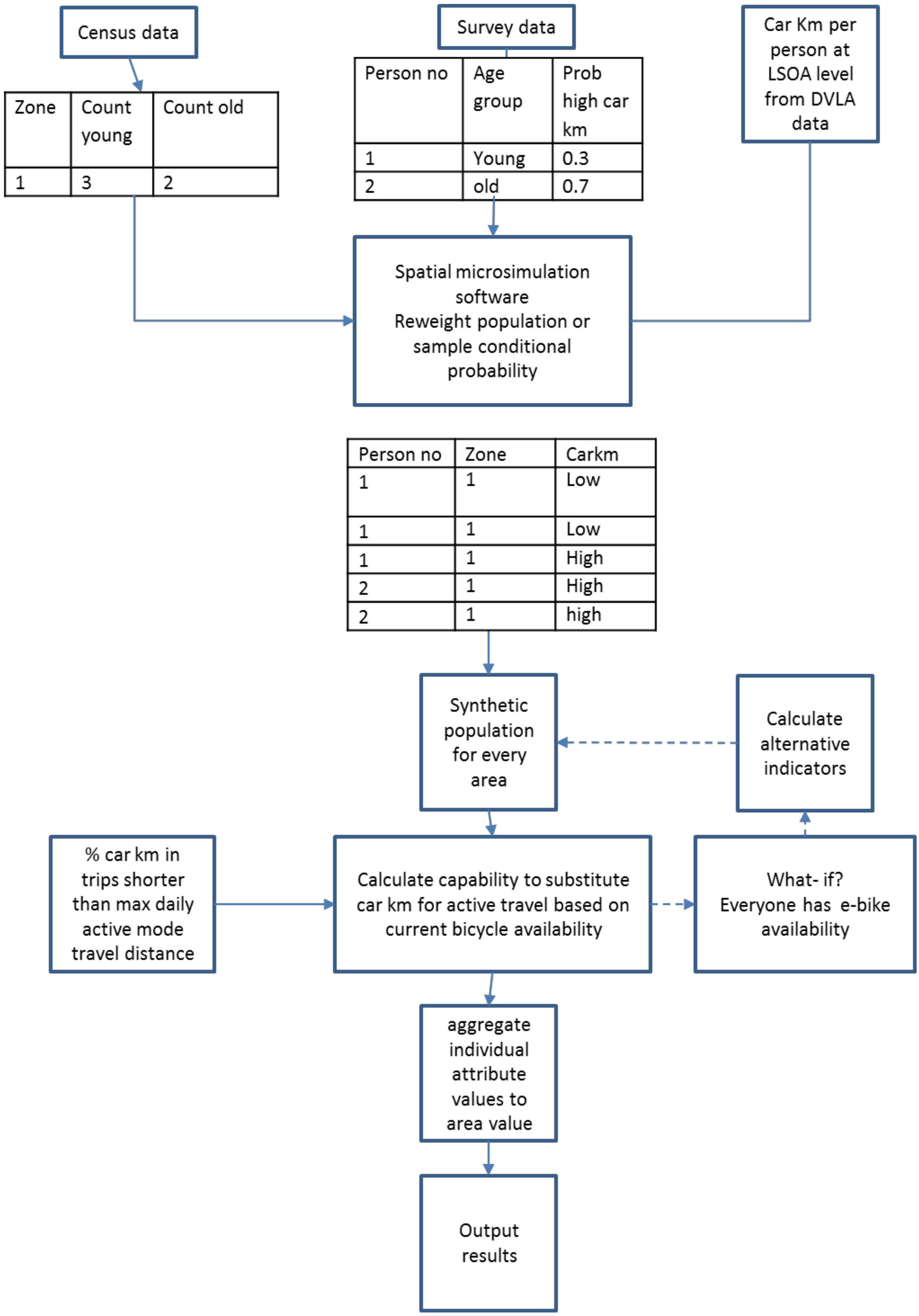

Figure 1. An overview of the spatial microsimulation process.

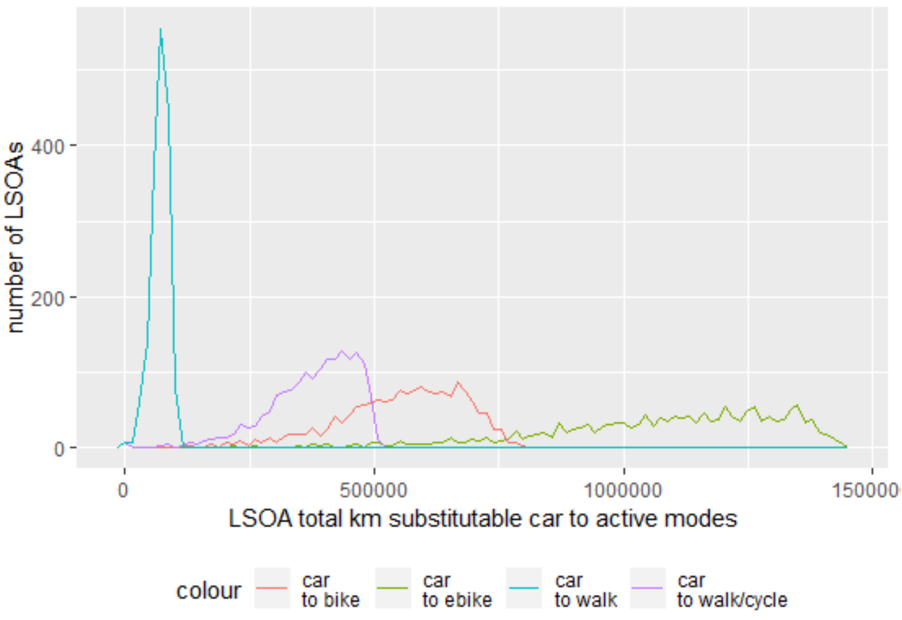

Figure 2. Counts of LSOAs and the maximum number of current vehicle km driven which it is possible to substitute for active modes per annum

Table 2. Maximum anual substitutable km per LSOA from car to active modes.

	If everyone had to walk	Walk or cycle based on current bike availability	If everyone had a bicycle	If everyone had an e-bike
minimum	0	0	0	0
1st quartile	69,422	717,790	1,124,460	2,376,764
median	83,797	817,850	1,462,912	3,224,309
mean	83,386	815,028	1,488,403	3,382,492
3rd quartile	96,594	907,683	1,795,187	4,153,743
maximum	317,360	2,171,687	5,059,177	14,990,543

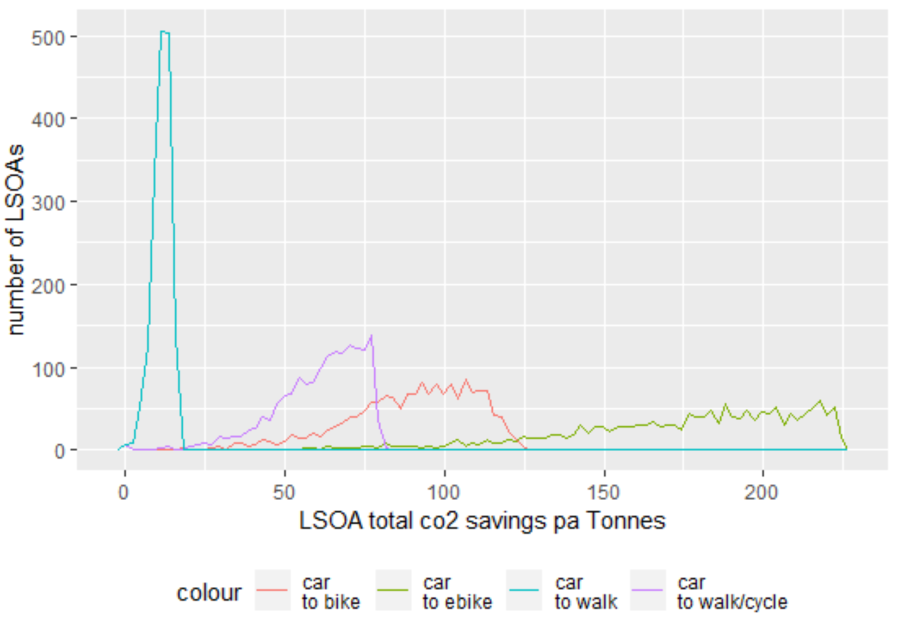

Figure 3. Energy reduction potential of substituting car travel for walking, cycling and e-bikes

Table 3. Potential gross CO_2 savings (Tonnes per annum) per LSOA by substituting car km to active modes.

	If everyone had to walk	Walk or cycle based on current bike availability	If everyone had a bicycle	If everyone had an e-bike
minimum	0	0	0	0
1st quartile	11	114	179	378 (net 264)
median	13	130	233	512 (net 382)
mean	13	130	238	540 (net 410)
3rd quartile	15	145	287	664 (net 519)
maximum	52	349	917	2,717 (net 2,368)

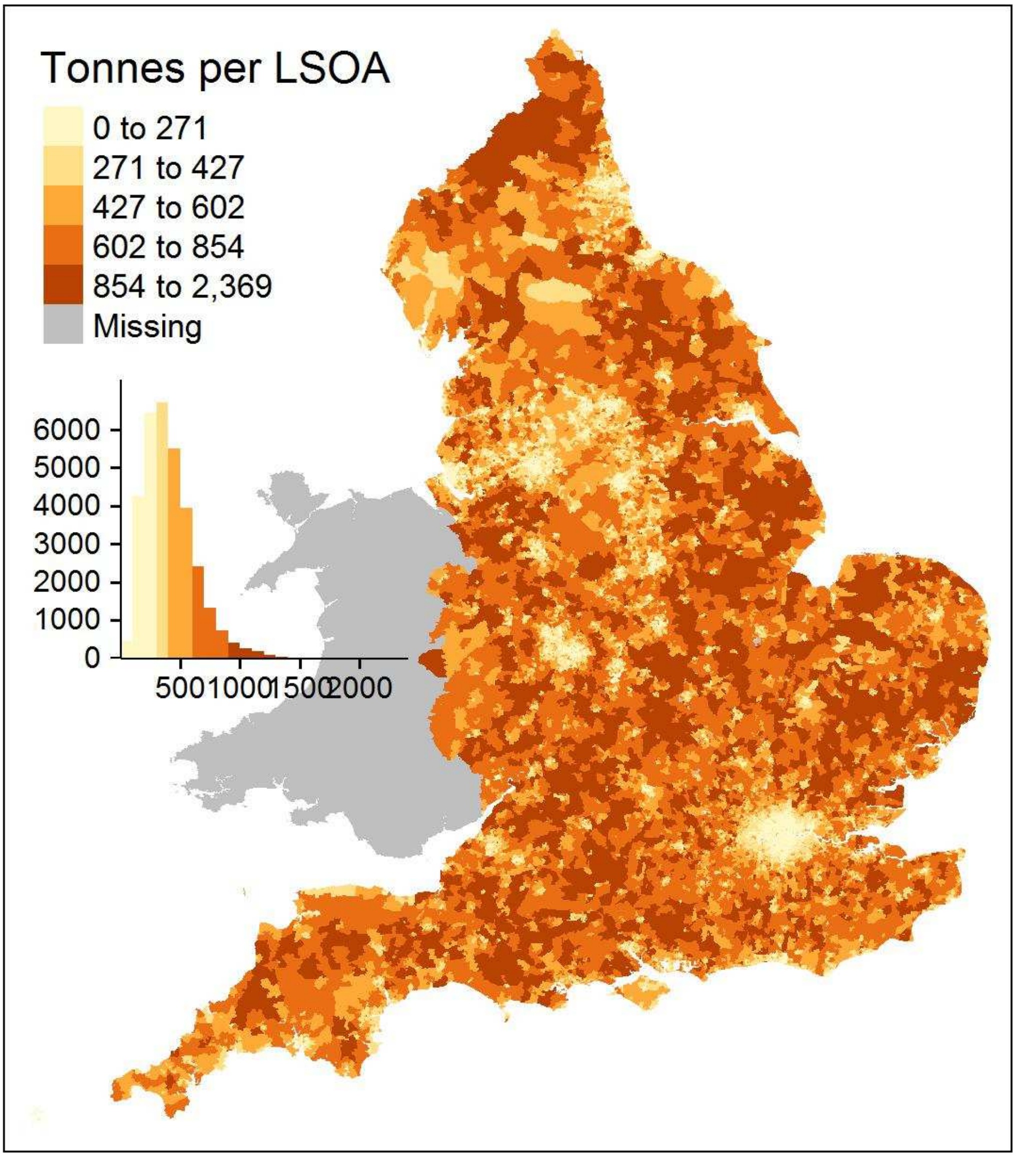

Figure 4. Maximum possible CO_2 savings pa per LSOA by e-bikes given no change in demand.

energy consumption by current pedestrians of cyclists could increase if they switch to e-bike use.

Figure 4 shows that LSOAs outside large cities have the higher potential for reducing CO_2 emissions by promotion of e-bike use. This is important to note because most bike share and e-bike promotion schemes are focussed on "urban transport" – and this is generally conflated with cities rather than smaller towns. E-bike schemes in large cities may have co-benefits such as reducing motor vehicle traffic flows, but the focus of this paper is to illustrate the potential CO_2 savings.

However bike sharing schemes in cities where there are already highly developed transport infrastructures might encourage mode shift from public transport to e-bikes rather than out of cars. Also, in cities, distances to services are generally lower than elsewhere, so this means that walking and cycling are likely to be viable. Again excessive e-bike promotion might cause mode shift from these already sustainable modes. Bike sharing services and MaaS with a bike sharing component are typically promoted in cities due to high population density increasing the likelihood of commercially viable services.

If the objective is as stated through this paper is to reduce CO_2 emissions, then the greatest savings from e-bikes may occur where sharing schemes are not currently seen as commercially viable. The results would suggest that If a non-commercial, public funded e-bike scheme were considered the start point for action is outside of large cities. They would likely have a limited number of e-bikes and they would be able to act in a small number of LSOAs). The results suggest an initial set of candidate areas. The information in this paper provides useful information but planners must further refine their set of target areas by asking: what social, demographic and attitudinal effects would impact behaviour change programmes or schemes to provide or incentivise e-bike use? Information from behaviour change studies would be a useful start point, for example, a UK study of e-bike use suggested a 20 % reduction in car km travelled by participants (Cairns et al., 2017).

If equitable mobility and CO_2 reduction are joint objectives, then as well as considering the points above, the results should also be contextualised in terms of economic vulnerability arising from car dependence (e.g. Mattioli et al., 2017) – Those areas with high vulnerability and high potential for CO_2 savings should be prioritised.

LIMITATIONS FURTHER WORK

The present paper estimates the maximum capability to reduce CO_2 emissions using active modes. It contributes to understanding the potential for reducing emissions from car use, but, there are other issues beyond the scope of this paper which should be considered in terms of the practical feasibility of major change from car to walking, cycling and e-bikes including congestion effects and road use safety effects, battery type and electricity charging source, diet and food source of people walking and using a conventional bicycle (Fishman and Cherry, 2016).

In the present paper, all active modes were considered not to have associated emissions per km of travel. This relies on the assumption that people do not eat extra calories in order to walk or cycle – most people in the UK consume an excess of calories so may not need to eat more to walk or cycle for utility trips. E-bikes if recharged using renewable sources would not generate CO_2, but some emissions are likely. The production related emissions of bikes and e-bikes could be considered. Leading from this, an interesting area of further work would be to compare the lifetime emissions of electric cars against those for e-bikes.

The spatial microsimulation process itself may be further refined, considering individual level factors in greater detail, by incorporating further data on current travel behaviours.

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