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E-bikes and their capability to reduce car CO_2 emissions

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A R T I C L E I N F O

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A B S T R A C T

We estimate the maximum capability to reduce CO_2 by substituting private car travel for e-bike. We use spatial microsimulation (population-synthesis) to simulate the adult population within every small area in England, taking account of area type and geodemographic circumstances of the population. By estimating for individuals the distance they are capable of travelling by e-bike and the extent to which they are capable of replacing private car travel, we find the upper limit on the capability to reduce CO_2 by substituting car travel for e-bike use is 24.4 $MTCO_2$ p.a. (per annum) in England. CO_2 saving capability per person and per small area are highest (over 750 kg CO_2 per person p.a.) for residents of rural areas and the rural urban fringe. e-bikes offer major conurbations more modest CO_2 saving capability per person. We identify areas which are vulnerable to car related economic stress and also have high capability to replace car km with e-bikes, which if supported appropriately could contribute to equitable carbon reduction. Though capable of a very significant contribution to transport carbon reduction, other changes in technology and reduction in demand would also be necessary to reach zero emissions.

Our results are directly relevant to policy actors internationally who require evidence on place-based decarbonisation capability, particularly where car dependence is high. The results highlight how context is important in any attempt to design policy for equitable carbon reduction both to influence discussion on what is possible, as well as practical identification of areas for targeted intervention. Digital indicators covering all zones in a country's geography such as this are also useful because of the rapid digitalisation of policy making. We provide code so that others can produce similar analyses in other countries (https://github.com/DrIanPhilips/e-bikeCarbonReductionCapability).

1. Introduction

The need to address transport's contribution to climate change is well established (Banister, 2011, 2008; IPCC, 2018; Sorrell, 2015). Transport is responsible for 24% of global direct carbon dioxide (CO_2) emissions from fuel combustion, and continues to rise annually (IEA, 2020). As with many developed economies, transport in the UK is responsible for more CO_2 than any other single sector, comprising 24% of the total (113 $MtCO_2$, not including international aviation and shipping), only 4.6% lower than the baseline year of 1990 (BEIS, 2020). UK car CO_2 emissions are responsible for 61% of the sector's emissions (68 $MtCO_2$), and despite increasing sales of hybrid, and electric vehicles, average tailpipe emissions of new cars are still increasing in large part due to increased sales of larger and heavier cars (UKERC, 2019).

Given global and national carbon budgets that have aligned with the goal of limiting global temperature rises to those set out in the Paris Agreement (United Nations, 2015), there is no possibility of transport continuing to lag behind other sectors. The latest budget proposed by the UK Climate Change Committee (CCC) expects transport to reach total decarbonisation (only allowing for some negative emissions by sectors other than surface transport) by 2050, amounting to an annual percentage decline of 4% (CCC, 2020). In the UK, as elsewhere, most efforts to achieve this are overwhelmingly focused on the electrification of passenger cars and light goods vehicles, despite the fact that progress has been admittedly slow so far in most car markets and the associated reduction in motoring costs risks rebound effects exacerbating hypermobility and excess consumption (Urry, 2007, 2010). Consequently, multiple assessments of whole-economy greenhouse gas reduction pathways, including the latest CCC budgets, have concluded that even if there is rapid electrification over the next 10 years, reduction in car use will also be required in order to meet carbon budgets (Brand et al., 2020; Gota et al., 2019; Lefèvre et al., 2021).

Overall, achieving radical reductions in car use will require deep carbon reductions in all locations and a reduction in car use that is

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reflected in national average per capita statistics, not just in a select few inner city locations. Banister and Hickman (2013) have argued that this will involve changes which have major impacts on lifestyles and not simply extrapolating past trends, particularly when seeking decarbonisation strategies. This, in turn, will require targeted interventions that are best based on estimates of the capability for lifestyle change and CO_2 savings as well as an assessment of the equity of distribution of the positive and negative impacts of any change (Lamb et al., 2020; Lucas and Pangbourne, 2014; Mattioli, 2016). This is the approach taken in this paper for e-bikes. We develop small area estimates of maximum capability to reduce car CO_2 emissions in England using e-bikes, to illustrate how much the people in a particular place *could* reduce their car-based transport emissions (i.e. maximum capability for radical change).

1.1. The potential for e-bikes to reduce carbon

E-bikes are promoted as a potential contributor to carbon reduction of land based transport (Bucher et al., 2019; Harvey and Guo, 2018; Jones et al., 2016; McQueen et al., 2019; Popovich et al., 2014). They have a high level of energy efficiency (Berners-Lee, 2019; Weiss et al., 2015). E-bikes are also associated with other transport benefits in terms of health and physical activity (e.g. Langford et al., 2017) amongst the population in general, facilitating active travel for some people with otherwise limited mobility, improvement in local air quality, lower road space requirement than cars and lower cost than cars (Bucher et al., 2019; Fishman and Cherry, 2016; McQueen et al., 2019). In this paper we refer to e-bikes as bicycles with an electrical motor which provides a maximum of 250W assistance whilst the rider is pedalling and does not provide electrical assistance at speeds above 15mph/24kmh. This class of e-bikes is also known as Electric Pedal Assisted Cycles (EPAC).

A number of studies in different countries have estimated the behaviour change potential of e-bikes. Several studies have used revealed uptake data, surveys and engagement with participants in e-bike behaviour change interventions and sharing schemes. Winslott Hiselius and Svensson (2017) surveyed existing e-bike users who on average reduced their transport CO_2 emissions by 272 kg p.a. Berjisian and Bigazzi (2019) summarised several studies and estimated the net CO_2 reduction per e-bike in use was 460 kg p.a. Some studies estimate the car km replaced by e-bikes amongst their study participants (Cairns et al., 2017; Fyhri et al., 2017; Moser et al., 2018). Cairns et al. (2017) found in their 2012-13 study that participants who were of working age living in and around Brighton, UK replaced up to 20% of their car distance travelled with e-bike use.

The previous paragraph indicates potential for CO_2 reduction for e-bikes under various behaviour change programmes, which encourage uptake. However, the steep reductions in car use required by the carbon reduction pathways set out above, have not been achieved before in anywhere other than small localised schemes, let alone at the national level. Such transformations cannot be achieved by incentivising consumer choice driven behaviour change alone, but, require comprehensive system-level change (Shove, 2010; Shove and Walker, 2010). System-level changes will at least partially consist of reductions in the space allocated to cars and where and when they can be used (Anderson et al., 2020; Sorrell, 2015). When active travel is promoted in areas where there are still high levels of car use, segregated cycling infrastructure helps address safety concerns and, for e-bikes, long-distance cycle lanes that extend many miles beyond the built-up area, linking suburbs, towns and cities, will be necessary (Sloman and Hopkinson, 2019). Adeel et al. (2020) point out that reductions in car use and thus CO_2 cannot be achieved by focusing only on short distance urban trips, as 29% of all distance in England is accounted for by a mere 2.4% of journeys (those over 50 miles), with a fifth of all distance accounted for by just those journeys between 8 and 16 miles (13–25 km) which are precisely the journeys that are difficult to serve by walking, cycling or bus modes. Jones et al. (2016a) suggest tax and incentive schemes may help with the relatively high costs of e-bikes and Newsom and Sloman (2019) develop this argument.

There are some spatially explicit studies which consider the maximum potential to replace car travel for all purposes with active travel (Philips et al., 2013, 2018; Rendall et al., 2011) though less work has been done specifically relating to e-bikes on this point. Bucher et al. (2019) examine potential for e-bikes in a spatially explicit manner for Swiss municipalities, but only focus on commuting. Goodman et al. (2019) estimate CO_2 savings for the journey to school and suggest measures considering all trip purposes as an area for further work. Other studies conclude on the potential for e-bikes only in terms of broad area-type or context, rather than at a spatially disaggregated scale. For example, studies in Sweden and the Netherlands found e-bike users reduce their car use more in rural areas than in urban areas (Sun et al., 2020; Winslott Hiselius and Svensson, 2017). Jones et al. (2016a) suggest policy makers should promote e-bikes where conventional cycling and walking are too challenging.

Explicitly examining constraints on capacity to make journeys in terms of the physical ability of individuals and the tools available (e.g. e-bikes) is well established (Hägerstrand, 1970). Providing policy stakeholders with estimates of where and how much e-bikes can contribute to carbon reduction is relevant and timely, whether or not the policy stakeholders have radical or more modest policy levers open to them. We present a spatially fine-grained estimate of the maximum capability to reduce transport CO_2 using e-bikes for every neighbourhood (Lower Super Output Area[1]) in England. We do this to provide the following insights to policy stakeholders:

- Estimates of maximum carbon reduction capability are useful in discussions of transport carbon budgets
- Per person estimates for small areas aid policy makers who may want to promote e-bikes in specific places with the specific policy objective of carbon reduction.
- Results placed in context of social indicators help policy makers consider the equity and social and distributional impacts of environmental policies.

The paper continues as follows; Section 2 describes the methods, Section 3 presents results and we summarise and present conclusions in Section 4.

2. Methods and data

We estimate the upper limit on the capability to travel by e-bike and replace car travel, and from that the maximum capability to reduce CO_2 emissions. We used spatial microsimulation (also known as population synthesis) to generate a synthetic population of individuals.

Spatial microsimulation links small area census data to anonymous individual survey data to simulate a population of individuals for every small area in the study area. Once generated, synthetic individuals' attributes were used to estimate the capability of individuals to travel by e-bikes to reduce car use, taking account of the distribution of car distances travelled in those areas, but also the fact that some people in an LSOA are fitter than their neighbours, so can ride further. This consideration of within-area heterogeneity is an advantage of spatial microsimulation over aggregate techniques which would simply assume every individual in an area has the same level of fitness (Hermes and Poulsen, 2012; Philips et al., 2017). The interpretation of results occurs at the small area level or by summarising an indicator for a segment of the synthetic population. It is important to note that though we generate synthetic individuals to consider within-area heterogeneity, we do not

[1] LSOA Lower Super Output Area. UK census data dissemination spatial unit. https://www.ons.gov.uk/methodology/geography/ukgeographies/censusgeography.

Table 1
Data sources used.

Attribute	Data source
Base population	(Census data)
Age	UK census: https://www.nomisweb.co.uk/census/2011
Gender	UK census: https://www.nomisweb.co.uk/census/2011
Education	UK census: https://www.nomisweb.co.uk/census/2011
Economic activity	UK census: https://www.nomisweb.co.uk/census/2011
Health attributes	(Health survey for England)
Body Mass Index	Health survey for England: UK Data Service (safeguarded access to microdata) https://www.ukdataservice.ac.uk/
Frequency of exercise	Health survey for England individual anonymised records UKDS (safeguarded access to microdata) https://www.ukdataservice.ac.uk/
Physical capability to travel by e-bike	
Hilliness of roads	SRTM digital elevation model: NASA https://www2.jpl.nasa.gov/srtm/cbanddataproducts.html Roads dataset linked to SRTM to extract the slope of each road: Ordnance Survey Meridian 2 data https://digimap.edina.ac.uk/
Bicycle availability	UK national travel survey individual anonymised records UKDS (safeguarded access to microdata) https://www.ukdataservice.ac.uk/
Car use and trip length distribution	
Car availability	UK national travel survey individual anonymised records UKDS (safeguarded access to microdata) https://www.ukdataservice.ac.uk/
Car km travelled per person	Vehicle km travelled (Cairns et al., 2014; Wilson et al., 2013) Car trip length distribution age, gender and geo-demographic classification UK national travel survey individual anonymised records UK Data Service (safeguarded access to microdata) https://www.ukdataservice.ac.uk
Distribution of car trip distances (based on age gender and area type)	UK national travel survey individual anonymised records UKDS (safeguarded access to microdata) https://www.ukdataservice.ac.uk
Capability to reduce CO_2 emissions	
mean CO_2 emissions per km for cars registered in each LSOA	LSOA car emissions factors (Chatterton et al., 2015)
Life cycle emissions of e-bikes	Data from ECF (2011)

hope to create an exact replica population (Clarke, 1996). We report results at LSOA resolution because LSOAs have been constructed to preserve some socio-demographic similarity between the inhabitants (Cockings et al., 2013). There are 32844 LSOAs in England with between 1000 and 3000 inhabitants.

Spatial microsimulation is a well-established data fusion tool for small area estimation which considers differences between people within the same area and is long established as a geographical analysis tool for policy planning and analysis (e.g. Ballas et al., 2005). Microsimulation was originally proposed by (Orcutt, 1957) and has a well-documented history (Birkin and Clarke, 2011; Hermes and Poulsen, 2012). There are a number of reviews illustrating the range of applications and algorithms for implementation (Hermes and Poulsen, 2012; O'Donoghue et al., 2014; Tanton, 2014). For an introductory text see Tanton and Edwards (2013). Some software, tutorial texts and a number of code libraries are available for those wishing to construct synthetic populations (e.g. Ballas et al., 2005; Harland, 2013; Kavroudakis, 2015; Lovelace, 2014; Smith, 2021).

In transport studies, population synthesis has been used extensively to model demand as part of predictive activity-based transport models (e.g. Barthelemy and Toint, 2015; Frick and Axhausen, 2004; Guo and Bhat, 2007; Ma et al., 2014; Müller et al., 2010) building on earlier work by Beckman et al. (1996). In the transport domain, spatial microsimulation has also been used, though somewhat less often, for the estimation of other metrics such as social inclusion (Castiglione et al., 2006; Bonsall and Kelly, 2003; Lovelace and Philips, 2014) and physical capability to commute in the event of a disruptive shock (Philips, 2014; Philips et al., 2017).

The data sources, population attributes and indicators estimated in our e-bike analysis are shown in Table 1. Data processing and simulation were carried out using the R language (https://www.r-project.org) in Rstudio. To aid reproducibility, the code used is available at https://github.com/DrIanPhilips/e-bikeCarbonReductionCapability An overview of the modelling process is shown in Fig. 1.

2.1. Base synthetic population and health attributes

To generate the synthetic population we have to join data which is spatially fine grained (census data) but only has aggregate counts, with individual data which for privacy reasons has spatial information removed (health survey data).

Our synthetic population requires base demographic attributes available in both the census and the Health Survey for England (HSE) such as age, gender, economic status and education which we call "constraint attributes". Spatial microsimulation allows us to make small area estimates by linking on constraint attributes (Tanton and Edwards, 2013). We also require estimates of health attributes such as Body Mass Index (BMI), and the frequency of vigorous physical exercise which are only available in the HSE. We call these "non-constraint attributes".

Our constraint attributes, age, gender, economic activity and education are correlated with BMI, and the frequency of vigorous physical exercise. This correlation relationship allows estimation of non-constraint attributes for each individual in each LSOA. The simulation algorithm creates base and health attributes by cloning individual records into LSOAs to match constraint counts. Spatial microsimulation captures the variation in non-constraint attributes (e.g. BMI and frequency of exercise) within each combination of constraints (Tanton and Edwards, 2013). In this step we simulate approximately 43 million adults within the 32844 LSOAs in England. We used a simulated annealing algorithm implemented using openly available spatial microsimulation research software (Harland, 2013; Harland et al., 2012). This algorithm has been shown to work well at simulating populations in small areas (Harland et al., 2012; Voas and Williamson, 2001).

2.2. Physical capability to travel by e-bike

Capability to travel by e-bike is the distance a person is physically capable of travelling by e-bike on a daily basis accounting the physical effort of the rider and the motor assistance they receive. It also accounts for hilliness, the weight of the bike, rider and items they are carrying.

In the base population with health attributes, each individual has attributes for age, gender, Body Mass Index and frequency of exercise. From this it is possible to derive the rider pedalling power using the calculations described by Philips et al. (2018), and using the R code which we have made available. The rider power plus the EPAC motor assistance gives the propulsion power of the rider on the e-bike. Our estimates are based on EPAC e-bikes, which offer a maximum power assistance of 250W whilst the rider is pedalling, and the motor only provides assistance up to 25km/hr. This type of e-bike can be ridden in the UK and EU under the same highway rules as a bicycle. Assistance ratios may vary between countries (Liu and Suzuki, 2019). We assume a maximum assistance ratio of 3:1, where 3 Watts of motor assistance are

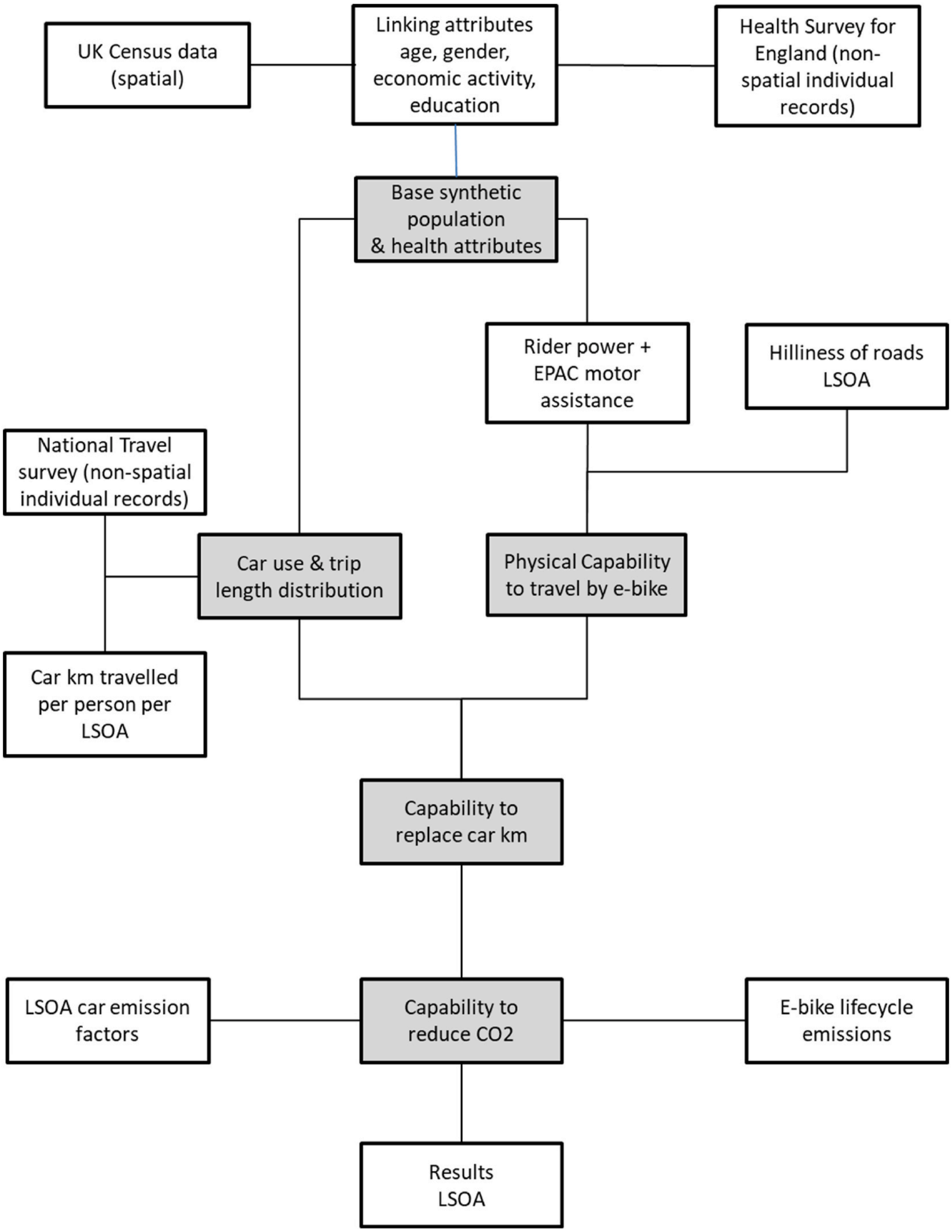

Fig. 1. Spatial microsimulation model overview. The main steps in the process of estimating e-bike CO_2 reduction capability are shown in grey and are described in subsections in the text. Data sources feeding each step are also shown.

available for each 1 Watt of rider power up to 25 km/hr and up to 250W of motor power. We also attach a value for the hilliness of roads in the vicinity of each LSOA, because hilliness is a determinant of how far people can travel by active modes.

Philips et al. (2018) assume a physical upper limit on the time people are capable of walking or cycling every day for utility purposes of 1 h in a morning and 1 h in an evening. The calculations by Philips et al. (2018) assume the individual is not already a regular cyclist, and for each individual they estimate a rate of exertion which can be repeated each day without risk of injury. A recent Swiss e–bike study by Bucher et al. (2019) also assumed a 1 h trip limit by e-bike. We make the same assumption.

We make the assumption that individuals are carrying 15 kg (equivalent to carrying a small child, shopping or day to day items). The power and details of the bicycle weight and rider plus the 15 kg they are carrying, are passed to code which calculates the speed of travel and then the distance the individual is capable of riding using the equations described by Wilson (2004). Our code repository shows how these are implemented. To calculate the maximum capability to travel by e-bike we assume that everyone has access to an e-bike. To facilitate some comparison, we also estimate the maximum distance each individual is capable of travelling by walking and by conventional bicycle. Calculations for the distance people are able to travel by conventional bicycle follow similar assumptions as for e-bikes above, but with pedalling power based purely on the rider. We also assume an e-bike weighs 20 kg, but a bicycle weighs only 15 kg to take some account of the extra weight

Table 2
CO_2 savings capability per year when replacing car use with e-bikes, walking and cycling.

	cars LIFE-CYCLE emissions & e-bikes LIFE-CYCLE e emissions		cars TAIL-PIPE emissions & e-bikes LIFE-CYCLE emissions		
	Maximum capability to replace CO2 from private car km with active modes. Totals for England in million tonnes p.a.	Mean Tonnes CO2 reduction per person p.a.	Maximum capability to replace CO2 from private car km with active modes. Totals for England in million tonnes p.a.	Mean Tonnes CO2 reduction per person p.a.	Mean capability to replace car km travelled per person p.a.
Everyone has an e-bike	24.4	0.58	14.3	0.34	2578
Everyone has a bike	15	0.35	8.7	0.21	1568
Those with a bike cycle & those without a bike walk	8.5	0.2	5	0.18	884
Net e-bike carbon reduction capability compared to bikes: e-bike carbon reduction capability minus carbon reduction capability if everyone had a bike	9.4	0.23	5.6	0.13	1694
Net savings from e-bikes over and above current capability for savings if those with a bike cycle & those without a bike walk	15.9	0.38	9.3	0.16	1010

of motor and battery. Walking distance is estimated using an adapted version of Naismith's rule (Naismith, 1892) used by Philips et al. (2018).

2.3. There are a number of other considerations and assumptions

We have not taken account of the extent to which each area has dedicated infrastructure for active travel as we contend that poor or absent infrastructure and road space allocation primarily for cars does not affect the physical capability to travel by e-bike. There is no doubting that increased dedicated infrastructure could facilitate the actual uptake of such activity, but this is a governance issue and would only be relevant if we were attempting to predict e-bike use under different scenarios of policy implementation. As this is not a predictive modelling exercise, infrastructure provision is not relevant here.

Similarly, we assume that crash risk does not place any additional constraint on capability to travel by e-bike. Schepers et al. (2014) study of EPAC pedalecs (not speed pedalecs) suggests that e-bikers are somewhat more likely to have an injury than cyclists, but that severity is not significantly higher in e-bikers than cyclists. Some studies find older e-bikers are more likely to experience an injury than younger e-bikers (Haustein and Møller, 2016), where others find older e-bikers actively avoid situations such as busy roads to reduce their exposure (Prati et al., 2020). However, in our study we simulate the general population rather than just older people. Most importantly, however, once again we treat any potential constraint on actual uptake which can be alleviated by infrastructure improvements or other policy mechanisms as outside of our simulation. It is a main purpose of results to demonstrate the potential upper levels of e-biking that could be achieved by concerted policy effort if it were deemed desirable to do so.

The infrastructure capacity and the safety issues come together in the question of whether high levels of e-bike use would create a constraint on capability in terms of conflict with other road users. The evidence on e-bike use so far does not seem to suggest this is the case. One European study found that e-bikes have a lower proportion of conflicts with bicycles and pedestrians than cyclists (Petzoldt et al., 2017). Another found that when in conflicts with car users, e-bike users are less likely to be at fault than conventional cyclists (Haustein and Møller, 2016) perhaps explained by Schepers et al. (2014) who make references to conflicts, interactions and crashes occurring because other road users are not familiar with e-bikes. It is therefore plausible that if e-bikes were common-place, familiarity would be increased and conflicts reduced. Indeed, familiarity forms part of the explanation for the sub-linear increase in cycling casualties with increasing numbers (Jacobsen, 2003). Given that some of the solutions for conflicts will depend on the policy decisions related to infrastructure decisions, and given that there is evidence to suggest that a greater critical mass could lead to fewer incidents, we have not factored in conflict between road users as a constraint in our simulation.

2.4. Car use and trip length distribution

We estimate each simulated individual's annual car travel as follows. Using LSOA estimates of annual car distance (km) travelled from (Cairns et al., 2014), we assign the car km travelled by vehicles registered in each LSOA to the members of the simulated population with access to a car. To take some account of within-area variation in car use amongst the simulated population of each LSOA, we weight the car km travelled by age and gender. We used the National Travel Survey (NTS) individual records to derive the weights. Next, we group the anonymous travel diary responses of trip records in the NTS by population subgroup (age, gender and geodemographic group). For each of these population subgroups, we create a distribution table which contains the cumulative proportion of car km travelled arising from trips under 1 km, under 2 km, under 3 km … and so on. We link this distribution information to the simulated population.

2.5. Capability to replace car km with an e-bike

Each member of the simulated population now has an attribute for how far they can travel by e-bike. We can use the trip length distribution information to determine the proportion of their car travel which is made up of trips shorter than their maximum e-bike travel distance. This proportion, multiplied by the annual car km travelled, gives an estimate of the car km which can be replaced by each individual. The code implementing this is available in the Github code repository.

2.6. Car CO_2 emissions, e-bike lifecycle CO_2 emissions and CO_2 reduction capability

To estimate the CO_2 savings a person is capable of making by shifting car km travelled to e-bike, we consider the CO_2 emissions from cars and e-bikes. Car tail-pipe estimates of the per km CO_2 emissions for each LSOA are used (Chatterton et al., 2015) (see data sources in Table 1). We allocate the mean tailpipe CO_2 per km to car km travelled by each individual simulated in that zone. We also estimate car lifecycle emissions per km as does a Canadian study of potential e-bike impacts on CO_2 emissions (Berjisian and Bigazzi, 2019). We add the tail pipe emissions to the estimates of fuel cycle 47 g/km and manufacturing 46 g/km lifecycle estimates for the average European car (source: Carbon Brief, 2019). We make the assumption that e-bikes would be used to replace

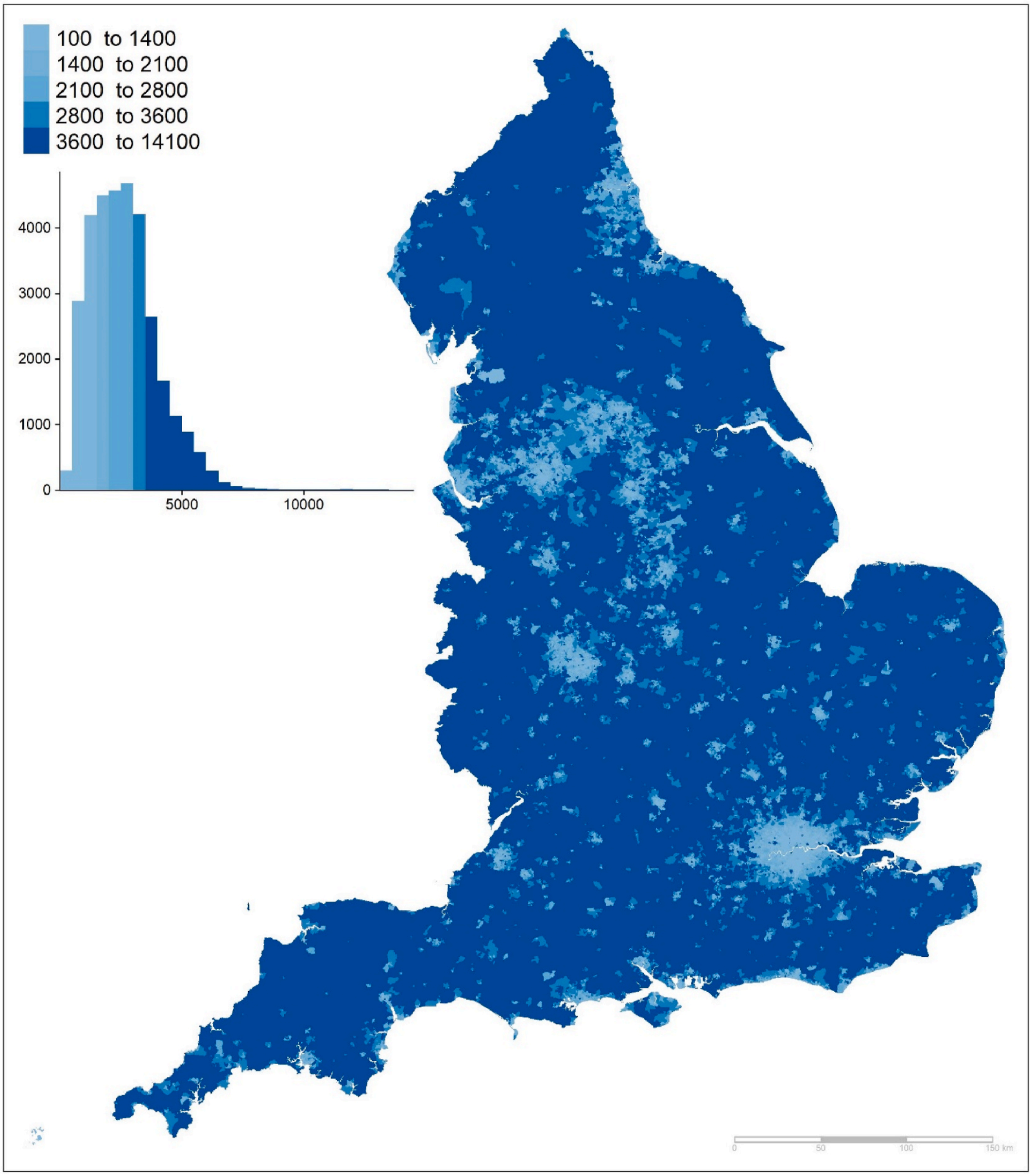

Fig. 2. Capability to replace car km with e-bike use: The mean capability per-person for residents of each LSOA p.a.

distances undertaken by the current car fleet, but, have made no assumptions about what this might mean for future levels of car ownership. For this reason we do not include embedded car emissions savings associated with car fleet renewal.

We account for the life cycle emissions associated with cycling and e-biking. The European Cycling Federation (ECF), drawing on work by (Hendriksen et al., 2008) estimate lifecycle CO_2 per km ridden for cycling (16 g/km for existing bicycles) and e-biking (22 g/km including new e-bike production to provide people with e-bikes). Other studies have also used ECF's estimation (e.g. Jones et al., 2016; McQueen et al., 2020; Nematchoua et al., 2020). These estimates account for the lifecycle CO_2 emissions in battery and bicycle production, they also account for CO_2 emissions to generate the electricity which charges the e-bike.

It is also worth mentioning e-bike batteries. e-bike battery production is included in the lifecycle emissions. In terms of life cycle emissions, minimising the resource consumption is an important first step (Harper et al., 2019), e-bikes require less material and have lower manufacturing emissions than cars, for example an e-bike battery is only 1–2% of the size of an electric car battery meaning less resource use per e-bike. Currently, within the cycle industry there are companies recycling e-bike batteries but this would need to be scaled up. Electrification of heat, cooking and transport raise issues around electricity grids and supplies. E-bike chargers in the home draw relatively low power (500W–1400W) and would run on existing circuits, so would not specifically require upgrades to the domestic electricity grid. Away from the home, dedicated circuits may be required to facilitate charging of larger numbers of e-bikes such as at work places. Where electric car charging infrastructure is being installed, combined e-car and e-bike charging units are available (e.g. https://bike-energy.com/en/#technologie). It is also important to note that the power required to charge an e-bike is significantly lower than for electric cars, particularly the rapid charging of cars.

3. Results

We first briefly present the national level picture, before describing the variations between small areas. The e-bike carbon reduction capability across England is 24.4 million tonnes CO_2 per year considering

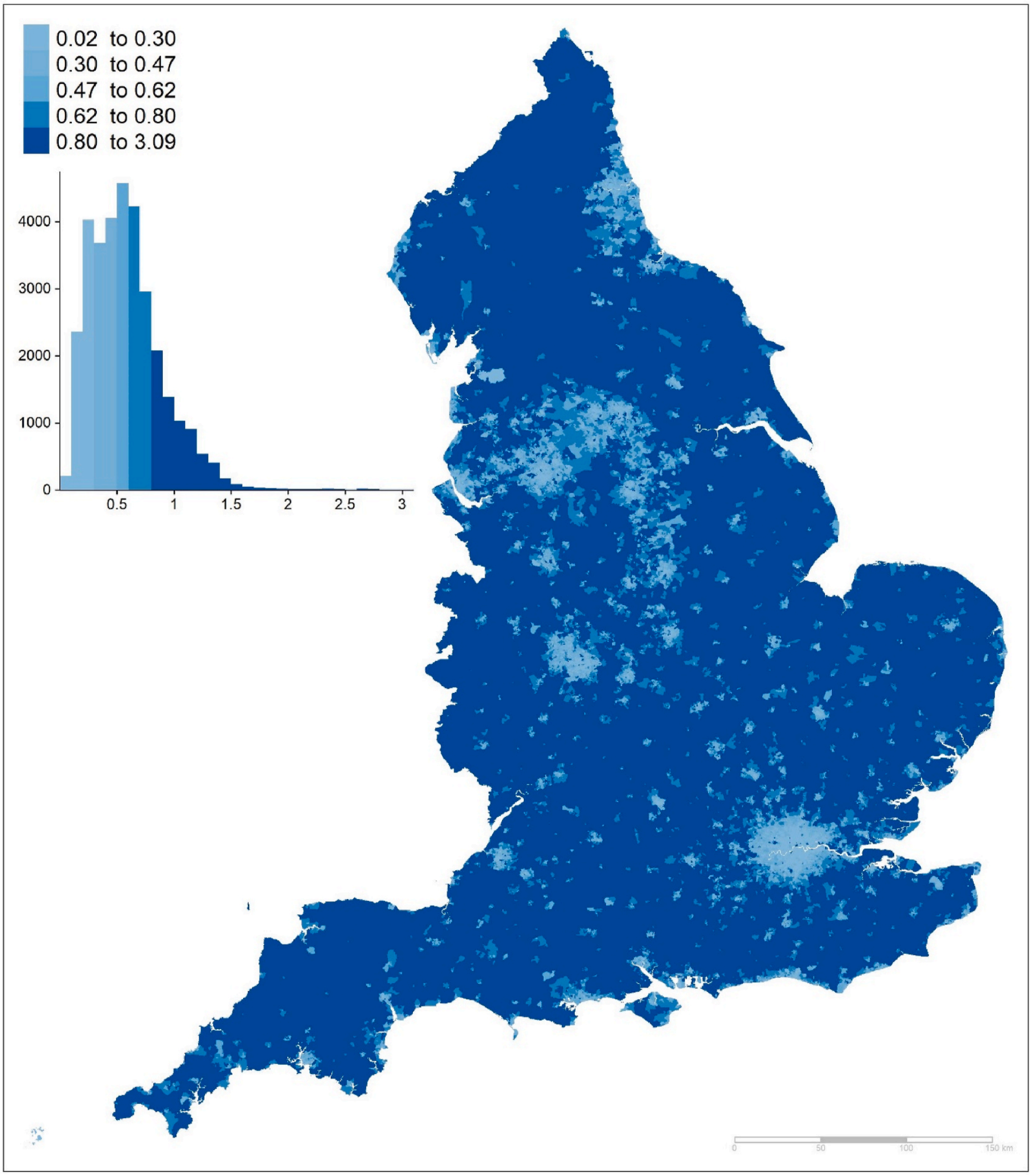

Fig. 3. Shows the carbon reduction capability through switching car km travelled to e-bike use. It shows the mean maximum CO2 reduction capability per person for each LSOA in England considering lifecycle emissions for cars and e-bikes.

lifecycle emissions of both cars and e-bikes, if there is no change in the demand for trips currently undertaken by car. For each individual who uses an e-bike to replace car km to their maximum capability, the mean saving is 0.58 tonnes CO_2 p.a.

It is important not to dismiss the existing capability of walking and cycling to reduce transport energy demand: Net e-bike CO2 reduction capability is dependent upon the underlying capability to walk or cycle, and suggests we should be careful to assess whether the new technology is necessarily better in all areas (e.g. Berners-Lee, 2019; Kesselring, 2008; Winslott Hiselius and Svensson, 2017). If everyone had access to a bicycle, then the potential reduction in CO2 would be 15 million tonnes pa, which is 61% of the savings capability from e-bikes. Because bicycles do not have the power assistance of the e-bike motor, the distance a person can travel on a bicycle is less than the distance they can travel on an e-bike. At the moment, around 38% of adults in England have a bicycle, although this varies across LSOAs. Walking and cycling (where those who have a bike ride and those who do not walk) have the capability to reduce car CO2 by 8.5 million tonnes p.a. This would give e-bikes a net carbon reduction capability of 16 million tonnes p.a. compared to existing walking and cycling capability. These observations are summarised in Table 2.

Tailpipe CO_2 emissions from all car use in England are approximately 60 million tonnes per year (DfT, 2018). Where only the tailpipe emissions of cars are considered versus lifecycle emissions of e-bikes, the reduction is 14.3 million tonnes.

3.1. Spatial results

e-bike carbon reduction capability per person is highest for residents of rural areas, and lowest for residents of major conurbations. Fig. 2 shows the mean maximum capability per person to replace car km with e-bike use in each LSOA in England. Fig. 3 shows the mean maximum CO_2 reduction capability per person for each LSOA in England considering lifecycle emissions for cars and e-bikes.

Fig. 4 shows the net e-bike carbon reduction capability compared to bikes (e-bike carbon reduction capability minus carbon reduction

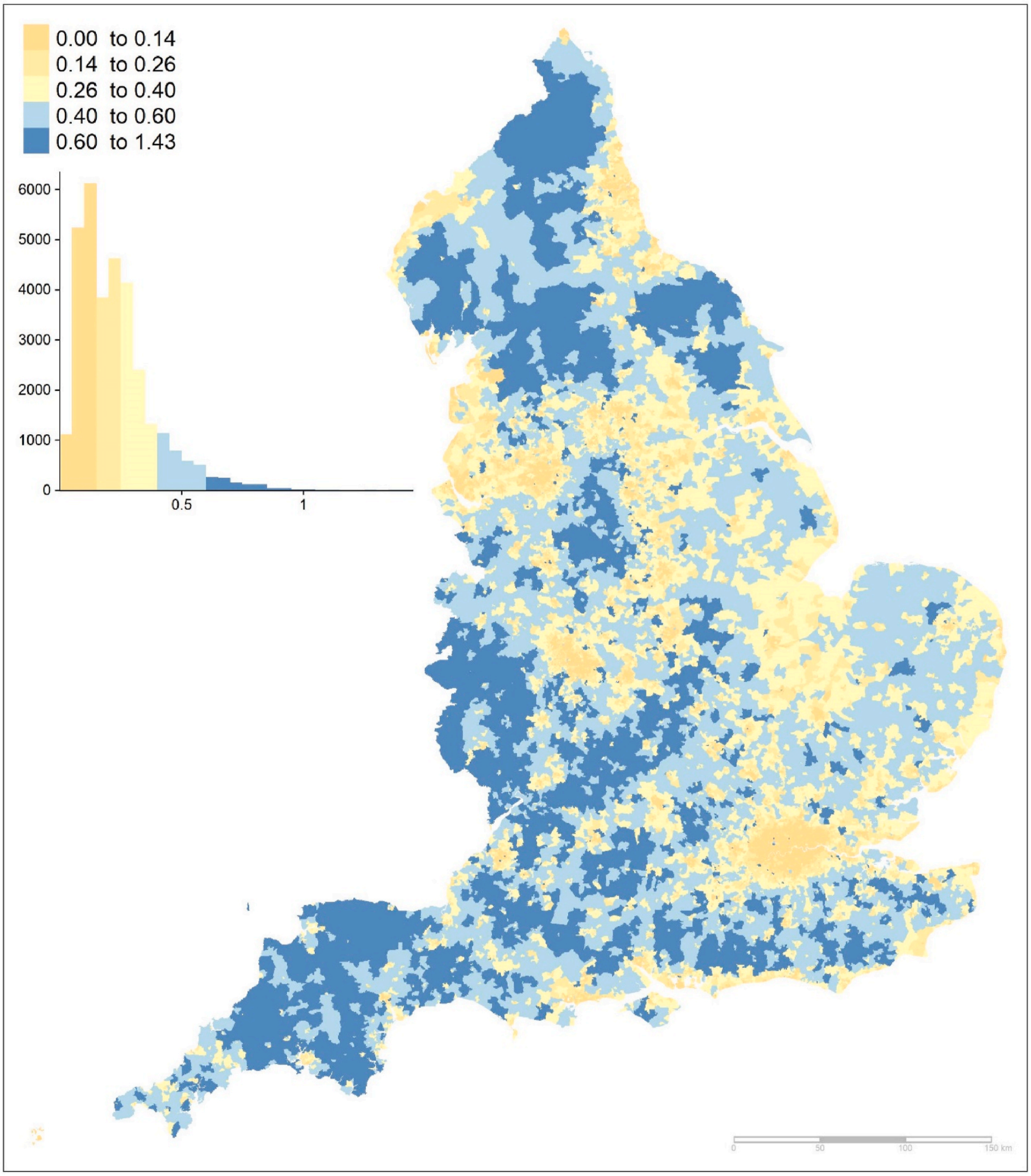

Fig. 4. e-bike carbon reduction capability minus carbon reduction capability if everyone had a bike. Units are the mean tonnes per person per year by LSOA considering lifecycle emissions for cars and e-bikes.

capability if everyone had a bike).

3.2. The results in a rural-urban context

Figs. 3 and 4 show that e-bikes have much larger CO_2 reduction capability than bicycles in rural areas. In rural areas, people drive a greater number of km per year than city residents. In urban areas there is a higher proportion of short car trips because of the relative proximity of activities. The median car trip length in urban areas is 5 km whereas in rural areas it is 10 km (DfT, 2017). These are both shorter than the synthetic population's mean maximum trip distance by e-bike of 20 km (compared to 11 km by bicycle). However, because a greater proportion of rural trips are longer, these areas present larger CO_2 savings per person than urban areas. This implies that e-bike promotion policies would be more effective in rural areas to achieve the goal of carbon reduction.

It follows that, in rural areas, a greater proportion of journeys are possible by e-bike which are not possible by cycling. Fig. 5 shows e-bike carbon reduction capability is 125% higher than for bicycles in rural villages, but only 56% higher in major conurbations. Rural areas have only half the population of major conurbations, but the carbon reduction capability of rural areas (including the rural-urban fringe) is 7.1 million tonnes, slightly higher than the combined carbon reduction capability of all conurbations which is 6.5 million tonnes.

Rural areas have poor public transport compared to conurbations. They are predominantly car dependent. These areas have received less attention than conurbations from new mobility services providers (E.g. Mobility as a Service (MaaS), e-bike sharing schemes). The implication is that there is a large untapped potential for e-bike use in rural and peri-urban areas. Longer distance cycle infrastructure radiating out from urban areas or between smaller towns is not the norm in the UK, however, there are examples of this in other European countries (Sloman and Hopkinson, 2019). These areas may represent potential for business models which generate a genuine reduction in car CO_2.

Cities and towns (urban areas which are not conurbations) have an even higher overall carbon reduction capability (10.8 million tonnes)

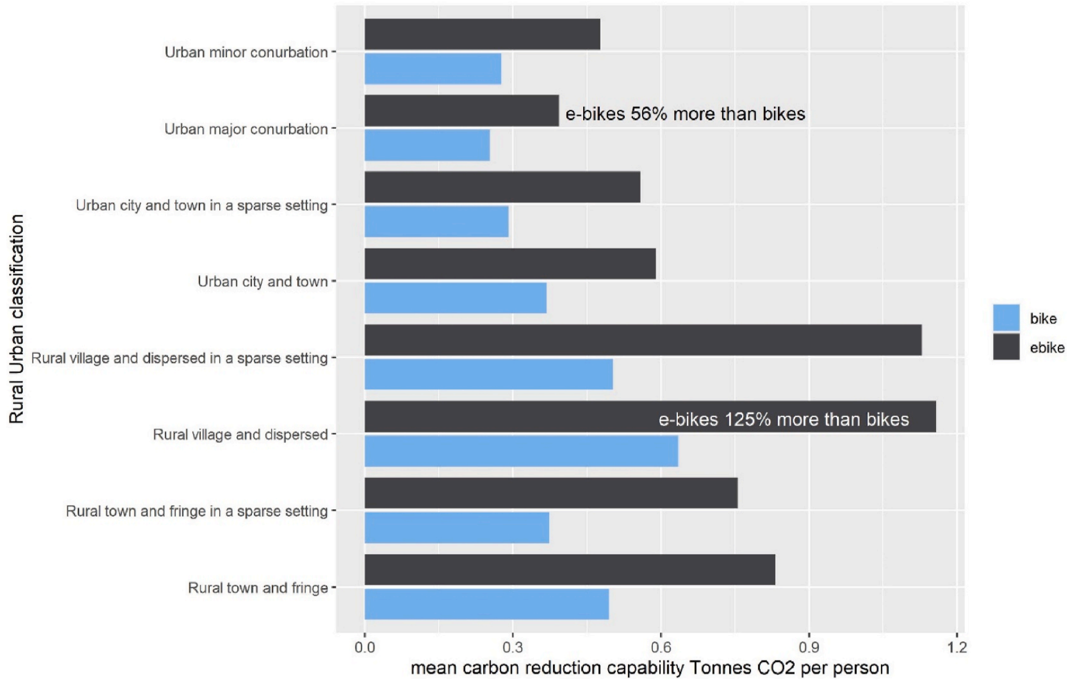

Fig. 5. e-bike carbon reduction capability in different area types (the Rural Urban Classification). E-bikes have the highest net carbon reduction capability in rural areas when compared to bicycles.

than either rural areas or conurbations, but a lower per person capability than rural areas. These settlements are more car dependent than conurbations with less comprehensive public transport. Funding for active travel has been far more modest outside of major conurbations in England. A scheme to promote cycling demonstration towns in non-metropolitan areas was evaluated as being successful (Sloman et al., 2017). Sun et al. (2020) find in a behavioural study in the Netherlands that people who adopt e-bikes in rural areas are more likely to reduce their car use than those in urban areas. Investment in e-bikes in rural areas and towns may also improve accessibility as a co-benefit to CO_2 reduction.

3.3. The results in a socio-economic vulnerability context

There are strong arguments that an effective transition to a low carbon transport system should be equitable and transport CO_2 reduction policies should be progressive (Berners-Lee, 2019; Lucas and Pangbourne, 2014). Mattioli et al. (2019) constructed a spatial indicator of vulnerability to transport fuel price increases in England at the same spatial resolution as our estimates of carbon reduction capability. The indicator of vulnerability considered car use, cost of motoring fuel, income and accessibility by public transport. Replacing car trips with e-bike trips would reduce total travel cost including the reduction in fuel costs. Though we do not consider it in detail in this paper, there could also be savings associated with maintenance, tax, insurance and depreciation if a car could be replaced with an e-bike. We compared CO_2 reduction capability in LSOAs with transport vulnerability in Fig. 6, to gain some indication of whether this may be progressive in policy terms.

Firstly, the dark green group shows LSOAs which have both high vulnerability to transport cost increases and are in the highest quartile of CO_2 reduction capability. Income in these LSOAs is slightly lower than the national average, but car km travelled per person is double the national average – being in areas furthest from cities and having poor public transport accessibility. This group of over 3400 LSOAs may be usefully targeted by policy makers wishing to promote e-bikes to both reduce CO_2 emissions and reduce economic stresses of car dependence.

There are however just over 900 LSOAs which are highly vulnerable and which are in the lowest quartile for capability for e-bike carbon reduction. In these areas car use and income are less than half the national average. Physical capability and hilliness are close to the national average. As Mattioli et al. (2019) observed, there is a north-south divide in England in terms of transport economic vulnerability. This pattern is also seen here – 10% of the LSOAs with high vulnerability and low e-bike carbon reduction capability are in London and the South East whereas 80% are in the Midlands and North.

*There are a further 1035 LSOAs which are not economically vulnerable, but which have a high potential to reduce car km and car CO_2 by adopting e-bikes. These LSOAs are found in the extended travel to work areas of the major conurbations particularly around London. This group may be targeted with progressive policies aimed at curbing excess demand as well as instigating change in areas with high adaptive capacity in terms of relative affluence. In planning for equitable carbon reduction it is important to consider not only those who struggle to access necessary activities and services, but also those with the highest demand (*Chatterton et al., 2019*).* Finally there are just under 4000 LSOAs in inner London and other urban centres where there is low transport economic vulnerability and low e-bike CO2 reduction capability.

4. Conclusion

We have presented an indicator of the maximum theoretical capability to reduce transport carbon emissions by replacing car use with e-bikes. This is not a predictive model, but an exercise in identifying where to target resources to have the best chance of reaching the carbon reductions implied by the Paris Agreement. Deep reductions need to be achieved by 2030, well before most countries are able to decarbonise their car fleets and it is now widely accepted that unprecedented reductions in car use are going to be needed alongside the transition of vehicle technology.

Our micro-simulation of England finds that the maximum total capability to reduce car CO_2 emissions using e-bikes is 24.4 million tonnes per annum. Although the CO_2 intensity of the car fleet will improve as it moves towards electrification, this is progressing too slowly to avoid the need for parallel reductions in car use and the

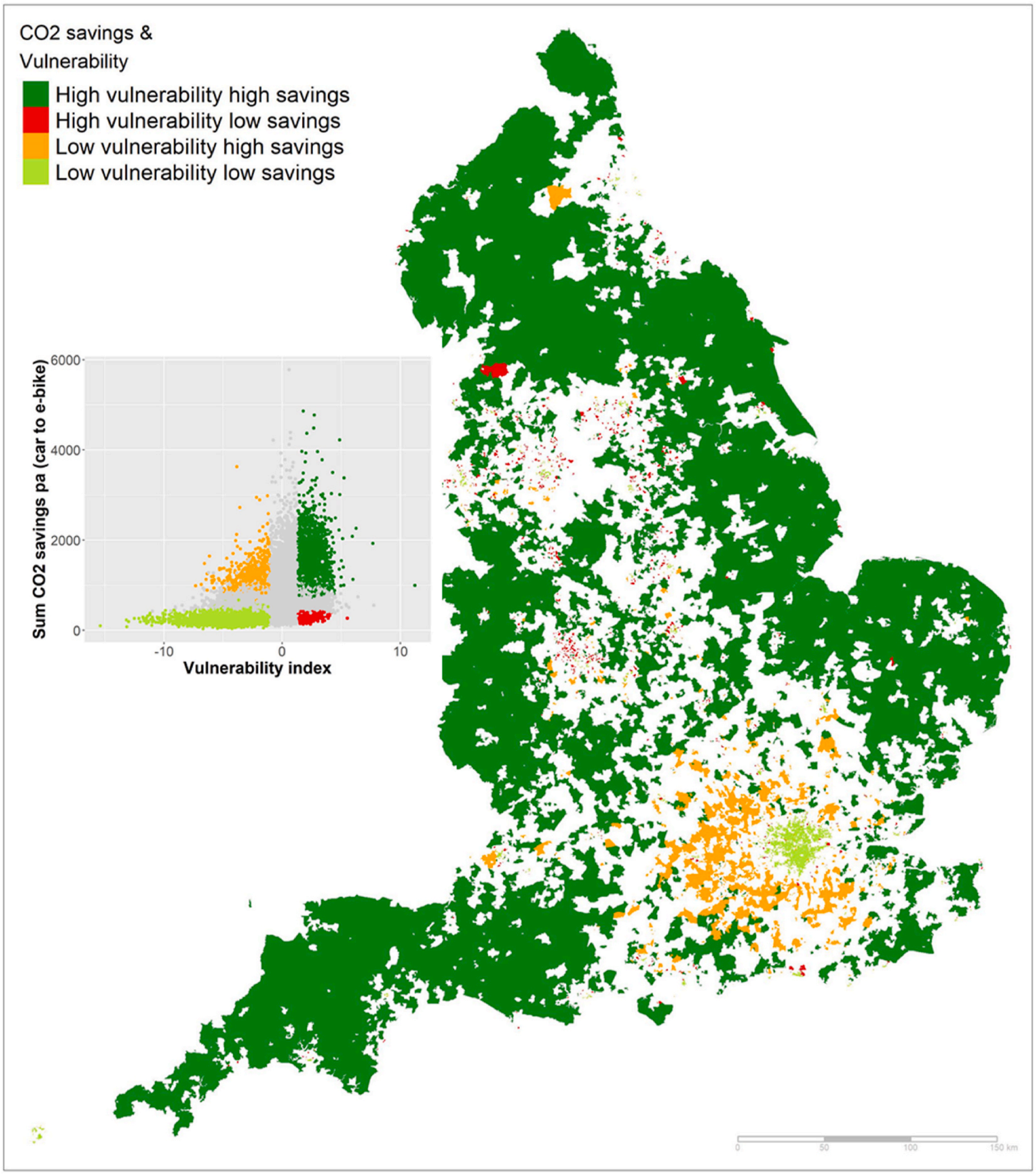

Fig. 6. Relationship between capability to reduce car CO2 using e-bikes and vulnerability to motor fuel price increases.

simulation is an attempt to quantify the scale of carbon reductions if a switch to e-bikes were to happen in the near-term. Mass uptake of e-bikes could make a significant early contribution to transport carbon reduction, particularly in areas where conventional walking and cycling do not fit journey patterns and bus provision is relatively expensive, inflexible and, certainly in the UK, has diminished over recent decades.

Many policy stakeholders only have levers available to them to try to encourage some people in some places to use e-bikes. For this reason, we presented per person averages for small areas. This helps identify where any successful intervention is likely to be most effective. Rural areas have the greatest capability per person for CO_2 reduction. Conversely, funding *for active travel has been far more modest outside of major conurbations in England.* Most bike share and e-bike promotion schemes are focussed on "urban transport" - and this is generally conflated with cities rather than towns and rural areas. 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. E-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 conventional cycling are more likely to be viable. We have found that a significant portion of car travel demand (and related CO_2) for travel originating in residential locations away from cities could be replaced with e-bikes. Much of the demand originating outside cities has its destination within cities. This has negative effects e.g. traffic collisions and air quality (Barnes et al., 2019; Graham et al., 2013).

In addition to being able to achieve early reductions and target otherwise challenging communities for transport decarbonisation, e-bikes have the potential to offer an equitable solution to carbon reduction. In our case study, there are over 3400 LSOAs which are both vulnerable to motoring price rises and which have a high capability to reduce car dependence with e-bikes. These areas may usefully be targeted by policy makers wishing to promote e-bikes to both reduce CO_2 emissions and reduce economic stresses of car dependence.

E-bike ownership and use is lower in the UK than in many other European countries. Austria, Belgium, Netherlands and Germany have so far experienced sales per person an order of magnitude higher than the UK (Newsom and Sloman, 2019). These countries have higher rates of conventional cycling than in the UK, but are finding that e-bikes are extending the proportion of trips and kilometres undertaken by non-car modes particularly in rural areas due to the fact that they are suitable for longer journeys, more hilly terrain and can enable different socio-demographic groups to take up cycling (Sun et al., 2020; Winslott Hiselius and Svensson, 2017). Adopting policies from these countries may increase e-bike use. Newsom and Sloman (2019) argue that a principal reason for higher e-bike use in Europe rather than in the UK is the widespread use of e-bike incentive schemes. Infrastructure interventions such as building cycle ways, and traffic signal optimisation to favour cyclists through "green-waves" (Pucher and Buehler, 2008) also encourage active travel. Changing legal policy such as introduction of 'strict liability' is also proposed as a way to enhance active travel (Pooley et al., 2011). The potential for traffic calming as well as e-bike use is seen as part of the pathway to a more sustainable transport future by Pucher and Buehler (2017). Traffic restraint in English city centres is currently being discussed based on experiences in Europe (Reid, 2020). The interventions described above could have positive effects and may help improve "societal readiness" so that it becomes acceptable to implement more radical transport carbon reduction measures. In order to reach carbon reduction targets, other measures will also be needed. Demand reduction should be considered first (Pye et al., 2014; Royston et al., 2018). If demand, particularly for longer journeys (e.g. over 20 km, the mean maximum trip distance by e-bike) is reduced, e-bikes would be able to replace an even greater proportion of car travel.

Although this case study has been based on England, the issues of urgency, equity and the need to achieve reductions in all areas, not just urban centres, applies everywhere. Metrics for describing the maximum capability for change have widespread applicability across countries and jurisdictions in order to facilitate back-casting and the development of radically different pathways to meet our carbon budget targets (Tight et al., 2011; Timms et al., 2014). In addition, disruption caused by the Covid pandemic presents an opportunity to plan for carbon reduction with many countries pledging green recovery strategies which may often be targeted at poorer and vulnerable areas (Marsden et al., 2020).

Furthermore, it is important to develop methods and share code to produce place-based decarbonisation indicators which generate estimates for every zone within a country. Policy makers increasingly look to data science for answers to policy questions. If place-based transport decarbonisation indicators are not available, there is a risk that important equity issues and decarbonisation potential will be overlooked.

Dynamic scenarios of car emissions under different fleet evolution pathways, and changed trip distributions post-covid are beyond the scope of this paper, but, could be areas for future research. Infrastructure emissions are beyond the scope of this paper, but could be significant when comparing car dependent scenarios with new road building versus car demand reduction scenarios with construction of less carbon intense e-bike infrastructure.

In the present paper we consider direct substitution of trips. Further work could usefully investigate the synergistic potential of e-bike journeys to public transport hubs then public transport to leverage further capability for carbon reduction. There are other issues beyond the scope of this paper which should also be considered in terms of the practical feasibility of major change from car to walking, cycling and e-bikes including congestion effects and road safety effects, battery type and electricity charging source, diet and food source of people using active travel (Fishman and Cherry, 2016). There will be combined effects such as changing demand for infrastructure and energy in other aspects of life as the e-bike influences day to day routines and practices. The dynamics of these related effects would also be a useful area for further research.

Author statement

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