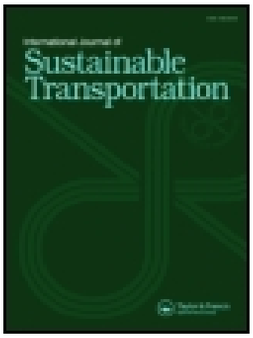

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Estimating Individual Physical Capability (IPC) to make journeys by bicycle

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ABSTRACT

We propose a novel method to estimate capability to make bicycle journeys, specifically considering the individual physical capability (IPC) of entire populations of individuals from all population segments of an area, not just current cyclists. IPC considers the physical constraints on the maximum distance people could cycle given the typical topography of where they live (Distance IPC), and then estimates their ability to make a particular journey (Journey IPC). IPC, when estimated in this way for a particular point in time, may be informed by antecedent behavioural choices and capabilities, and may be a constraint or enabler of subsequent capabilities, potential adaptations and behaviour.

The focus of the present paper is on explaining a generic method of estimating Distance IPC and Journey IPC by constructing an individually based spatially fine-grained model. We show how such an individual-level model may be implemented for a population resident in many small spatial zones by use of spatial microsimulation (population synthesis), to generate the individual attributes required as inputs to the model. We present a case-study for the city of Leeds, UK. We explain the range of data sources used, explore sensitivity of the results to assumptions of the

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model, and illustrate the ability of the model to simulate the effects of policies. Finally, we identify several possible application areas and opportunities to further develop the model.

Key words

Cycling, capability, active travel, spatial microsimulation, accessibility, transport & health.

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1 INTRODUCTION

The objective of the present paper is to develop methods for producing estimates of the capability of a population, living in the small zones that make up a larger area, to make bicycle journeys. We are interested in understanding whether people *could* make bicycle journeys irrespective of current use, focussing on their *individual physical capabilities (IPC)*. IPC considers the physical constraints on the maximum distance people could cycle, and their ability to make a particular journey by bicycle. The methodological justification for the current paper is the continued need to develop improved models of cycling, particularly those considering variations in individuals (Handy et al., 2014; Krizek et al., 2009; Lam and Sumalee, 2013). In addition to the methodological justification, in the field of sustainable transportation there is a range of potential applications of an estimate of capability to complete journeys by cycling, as we illustrate towards the end of the paper.

The paper is structured as follows. In Section 2 we review existing literature which informs construction of the IPC model. The scope of the IPC model and definition of the measures and indicators produced are described in Section 3. Section 4 outlines the modelling process. Section 5 explains the method by which we generate a synthetic population of individuals as input to the IPC model, using spatial microsimulation. Section 6 explains how the model estimates the individual measures and zonal summary indicators of IPC, as defined in Section 3. A case study based on Leeds in the UK is described in Section 7. In Section 8 we illustrate some potential applications of the method, before drawing conclusions in Section 9.

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2 LITERATURE INFORMING CONSTRUCTION OF THE IPC MODEL

We begin by reviewing the various individual aspects of IPC which have been considered in previous work, in order to inform our subsequent development of the IPC model in which several such aspects are integrated.

There has been a great deal of research which has considered the relation between how far people cycle and their travel choices (Dill and Carr, 2003; Ehrgott et al., 2012; García-Palomares et al., 2012; Habib et al., 2014; Landis et al., 1997; Larsen et al., 2013; Parkin, 2004; Parkin et al., 2007; Pooley, 2013; Rybarczyk and Wu, 2010; Stinson and Bhat, 2004; Smith and Kauermann, 2011; Wadud, 2014). In these works, physical capability may be assumed to have been an implicit constraint in the making of choices, but was not considered explicitly.

On the other hand, there exist a number of studies that have explicitly modelled some aspects of IPC, such as: physical capabilities (British Medical Association and Hillman, 1992; Parkin and Rotheram, 2010); variation in fitness across populations (Dickinson et al., 2003; McArdle, 2010; Menghini et al., 2010; Rendall et al., 2011; Rietveld, 2000); environmental factors affecting cycling (Milakis and Athanasopoulos, 2014; Phung and Rose, 2007; Keay, 1992); and the impact of topographic factors on walkability (Klein et al., 2015). In addition, recent work has considered the interaction between distance, environmental factors and perceptions (Yang and Zacharias, 2016). Outside the transport literature, work on physical and physiological constraints has been developed in the sports science literature (e.g. Taylor and Johnson, 2008) and has been applied in studies of working environments (e.g. Mohamed and Alginahi, 2009). Thus, while some aspects of IPC have been considered in the wider literature physical effort is

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generally poorly considered in models used in transport (Parkin, 2008; Parkin and Rotheram, 2010). To this end, Larsen et al. (2013) have called for more accurate measures of the ability to make a journey by bike to be used in transport planning applications. Menghini et al. (2010) argue that further research should investigate the heterogeneity of cyclists in more detail, in this respect. Individual attributes —specifically: age, gender, Body Mass Index (BMI) and levels of physical activity—are known to be key determinants of fitness and thus the capability to cycle (e.g. McArdle, 2010). The Health Survey for England shows considerable variation in these determining factors across the population (Craig et al., 2009). In addition, topography and wind speed also have a significant impact on IPC, yet are rarely considered.

3 DEFINITION AND SCOPE OF THE IPC MEASURES AND INDICATORS THAT WE WISH TO ESTIMATE

The literature reviewed in Section 2 suggests a lack of suitable existing indicators of Individual Physical Capability which capture the heterogeneity of cyclists and non-cyclists across the entire population. A key implication of such evidence of inter-personal variation is that aggregate/mean measures of fitness and physical capability are likely to give us a poor summary of the cycling capability of a population in any area, since we neglect those with poor fitness or limited mobility. These latter people are likely to be of particular interest to policy makers, as they bound the influence of any travel or behavioural change measure. Therefore, capturing individual heterogeneity is a key aspect of our work.

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On the other hand, as our ultimate focus is on transport planning applications, we must understand how capability is also influenced by spatial heterogeneity, such as topographic conditions in the area where an individual resides (where, we suppose, the individual is most likely to make cycling journeys). A difficulty here is that many transport models conventionally use large zones, e.g. UK administrative Wards or Middle layer Super Output Areas. These zone sizes are appropriate for modelling car journeys but not for cycling. Modelled estimates of journeys typically use zone centroids as the origin points for journeys; this introduces error because not all journeys originate at a zone centroid (Iacono et al., 2010). This is particularly important when modelling cycling journeys where many journeys are short, and makes any indicator particularly susceptible to the biases of the Modifiable Unit Area Problem (Openshaw, 1984). Therefore, in addition to modelling heterogeneity in physical attributes, we also require a fine grain level for considering geographic heterogeneity[1].

The proposed model therefore takes into account the twin considerations of individual heterogeneity in capability and spatial heterogeneity. It is able to express IPC as both an individual measure, capturing individual heterogeneity, and as a spatially fine grained zonal summary indicator. In this paper, to refer to the various aspects of IPC, we will adopt the terms defined in Table 1.

The individual measures and zonal summary indicators have narrow temporal scope as they hold all antecedent behaviour and lifestyle choices constant for an instant in time. In the present paper

[1] Such spatially fine grained indicators also have the advantage of facilitating the design of more effective, locally-targeted policy interventions; see: Ballas et al. (2013) and Openshaw (1995).

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our focus will be on estimating IPC at the time at which our survey data on explanatory variables were collected, and so in our case the 'antecedent conditions' refer to those preceding the relevant surveys. However, the same principles could also be applied to explanatory variables generated by a model, forecast or scenario of behaviour at some point in the future (though this is beyond the scope of the present paper). In a different direction, we might also imagine the IPC model being used to generate *inputs* to a model estimating subsequent capabilities, adaptive capacities or behaviours. As we focus on *estimating* (current) IPC in the present paper, it is beyond our scope either to make an explicit consideration either of antecedent conditions to IPC or to develop subsequent models in which IPC may be an input. However, considering these wider possibilities is useful for positioning the scope of our work within the wider field of modelling active travel (Figure 1).

Estimation of the IPC measures and indicators demand a range of individual and geographical data inputs. To establish relevance for policy makers it should be possible to construct an initial version of the IPC measures and indicators from relatively straightforward data sources which keep overall data requirements to a minimum.

For example, though of potential future interest (See Section 8) use of Big Data, and network data to generate a fine grained OD matrix and individual routes are beyond the scope of this paper.

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4 OUTLINE OF MODELLING PROCESS

The method we propose uses data about individuals' physical attributes to estimate two metrics: maximum possible trip length (distance IPC and the summary indicator zone distance IPC) and capability to make a specific journey (journey IPC and the summary indicator zone journey IPC). Figure 2 gives an outline of the model used to estimate IPC and derive related indicators. The estimation process is rather nuanced, since it depends on individual demographic attributes, derived attributes of these individuals, geographical factors of an area, and their complex interactions. The dashed boxes in Figure 2 list data used in the case study, which is discussed in Section 7.2.

There is a practical barrier to calculating this model for an entire population: geo-referenced data on the health and fitness of individuals are not placed in the public domain for reasons of confidentiality (Hermes and Poulsen, 2012). This type of data is sometimes referred to as spatial micro-data. For this reason we generate a synthetic population of individuals, using spatial microsimulation. This precursor to estimating the metrics and indicators is shown at the top of Figure 2. The spatial microsimulation process is described in Section 5.

5 SPATIAL MICROSIMULATION: GENERATING A POPULATION OF INDIVIDUALS FOR WHOM IPC CAN BE MEASURED

Spatial microsimulation is a proven technique used in geography and spatial analysis to conduct *What-if* policy analysis (Ballas et al., 2013; Tanton and Edwards, 2012). It has been used to generate synthetic populations in, among other areas, activity based models of transport demand

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(Beckman et al., 1996; Guo and Bhat, 2007; Frick and Axhausen, 2004), the study of social policy and inequality (Bonsall and Kelly, 2003), and the analysis of commuter fuel poverty (Lovelace and Philips, 2014).

We explain the basic principles of spatial microsimulation below. For those wishing to build and apply the model, software and further literature are available (Ballas et al., 2005; Harland, 2013; Philips et al., 2017). The general principle of spatial microsimulation is to link two types of data. The first type is aspatial, anonymous micro-data about individuals from a survey. An example of this would be the Health Survey for England[2]. Other countries conduct large panel surveys and release anonymised individualised data[3] which may be suitable for applying this model more generally. This data is rich in attributes, but we do not know where the people live. The second type of data is the national census. It has fine spatial detail but has a smaller range of attributes than a survey, for example it does not collect data on physical activity or Body Mass Index (BMI). The census publishes count data such as the number of males and females living in a zone or the counts of people by age group.

Some attributes are common to both the survey data and the census, such as age group and gender. In the literature these are called *constraint* or *linking* attributes. Age group and gender are highly correlated to fitness and BMI (McArdle, 2010) which are only found in the survey

[2] http://discover.ukdataservice.ac.uk/series/?sn=2000021

[3] E.g. US PUMS: http://www.census.gov/acs/www/data_documentation/public_use_microdata_sample/

GESIS: German microdata services http://www.gesis.org/en/services/data-analysis/official-microdata/

Australian health survey: http://www.abs.gov.au/ausstats/abs@.nsf/Lookup/4324.0.55.001main+features12011-12

Spanish health survey: http://www.msssi.gob.es/en/estadEstudios/estadisticas/solicitud.htm

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(they are called *unconstrained attributes*). The common constraints and the correlations to unconstrained attributes allow the linking of spatial and aspatial data (Williamson, 2012). There are several spatial microsimulation algorithms that are able to make this linkage. Simulated annealing based combinatorial optimisation, it has been found, performs well particularly when small zones are required (Harland et al., 2012; Williamson, 2012), such as is the case for UK census Output Areas.

Figure 3 shows a simple example of a spatial aggregate constraint dataset and a sample population table. The steps of the simulated annealing algorithm are shown. In the diagram, the algorithm begins by selecting individuals at random from the sample population and setting a *temperature* (number of iterations). The algorithm checks how the attribute counts fit the attributes in the census table by summing the counts of each attribute measured by the Total Absolute Error (TAE). The algorithm attempts to reduce the error by replacing an individual at random and does this for '*m*' iterations. Improvements are accepted, but if there is no improvement then a poorer result might be accepted. This is more likely if the temperature is high, e.g. if there are still a lot of iterations to run. This procedure gives a better chance of finding an overall combination of individuals to form the synthetic population with zero TAE. In the simple example in Figure 3 TAE is reduced to zero, with the same number of old and young people as in the aggregate table. The use of multiple constraints captures the joint distribution of attributes found in the real population.

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6 ESTIMATING THE IPC MEASURES AND INDICATORS

We now estimate the IPC measures and indicators using a synthetic population, as described in Section 5. In this section the parameters are linked to the model stages shown in Figure 2 as follows: Equations 1--4 explain the derivation of pedalling power; Equation 5 deals with geographic factors; Equations 6 and 7 with estimating the maximum distance an individual can cycle each day (distance IPC); Equation 8 describes estimation of distance to activity; Equation 9 describes estimation of journey IPC for an individual and Equation 10 describes how journey IPC is summarised for each zone to produce the zone journey IPC indicator (the % of the population of each zone with IPC to complete a specified journey by bicycle on a daily basis).

6.1 Individual attributes and linking attributes

Individual attributes are: Body Mass Index (BMI), height, weight, physical activity (based on survey reported vigorous activity), age, gender, and residential location. These individual attributes are simulated for every member of the population using spatial microsimulation techniques. The individual attributes age and gender are also *linking attributes* for spatial microsimulation (see Section 5). We appreciate that actual data availability may vary between locations and applications. We account for this by using a restricted group of datasets, as explained in Section 3.

6.2 Derived attributes

Figure 2 shows that from *Individual attributes* we calculate *Derived Attributes.* The derived attributes discussed in this section and the geographical factors discussed in the next section are needed to estimate distance IPC.

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6.2.1 Fitness using the measure VO_2max

Fitness is a key determinant of the maximum distance a person can travel by bicycle. VO_2max measured in ml of oxygen uptake / kg of body weight / minute is a commonly used measure of cardio-vascular fitness (McArdle, 2010). It is a measure of the maximum rate at which a person's body can make use of oxygen to convert chemicals in the body into energy. In our study it was estimated using the regression model calibrated in the study by Wier et al. (2006). This study involved 2417 respondents, with a BMI ranging from severely underweight (16) to extremely obese (48), and with VO_2max ranging from very unfit (15) to very fit (66). The final model had an R^2 of 0.8. The coefficients are shown in Table 2.

A particular advantage of the chosen study is that it is transferable to the general population, rather than being only applicable to a particular segment of it. In contrast the 2008 Health Survey for England carried out a VO_2max, test with only a sub-group of respondents(Craig et al., 2009) and it deliberately excluded obese individuals. Other empirical studies tend only to study particular population segments (e.g. Hulens et al., 2003).

6.2.2 Pedalling power

Equations 1--4 in this section will explain how pedalling power can be estimated. Not all the energy used by a person on a bike can be used to turn the cranks, nor can a person work at their VO_2max for more than a couple of minutes. Pedalling power, measured in Watts, is the portion of a person's energy expenditure (per second) which contributes to applying force through the cranks of the bicycle.

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When cycling, some of the energy expended is used to power the metabolic systems (metabolic power consumption), and some is available to move the body. Jones and Poole (2004) explain that this can be estimated as follows. For any individual, their total oxygen uptake depends only on their cardio-vascular fitness (as measured by their VO_2max) and their mass, and does not additionally depend on other environmental factors (e.g. location). Jones and Poole estimate that an oxygen uptake of 10 ml/min can produce 1 Watt of output power. Therefore, we may suppose that the total power output O_i (in Watts) for any individual i is given by:

$$O_i = \frac{VO_{2\max i} \times Mass_i}{10} \quad [1]$$

Some of O_i lifts the legs against gravity to the top of the pedal stroke. This is referred to as the Baseline Power Requirement b_i in Equation 2. There are differences in the Baseline Power Requirement of overweight (e.g. BMI >25) and non-overweight people, who are otherwise physiologically similar (Lafortuna et al., 2006). As Jones and Poole, (2004) estimate that a healthy weight individual has a 50 W Baseline Power Requirement, a simple estimation to take some account of the effect of either obesity or being underweight on the Baseline Power Requirement for individual i in Watts is shown in Equation 2. Using Equation 2, the Baseline Power Requirement estimate is 96 W for the most obese individual in the sample with a BMI of 48 and 30 W for the most underweight individual with a BMI of 15.

$$Baseline\ Power\ Requirement_i = b_i = \frac{BMI_i}{25} \times 50 \quad [2]$$

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A person cannot work at their maximum rate for long enough to make most transport journeys. Equation 3 estimates the rate at which a person can work for the duration of a journey, and yet not be too tired to then complete normal day to day activities such as employment and domestic tasks. We refer to this rate here as the *upper threshold*. This upper threshold l_i is expressed as a proportion of VO_2max, and is related to Body Mass Index BMI_i and the number of minutes of vigorous exercise per week q_i (Bircher and Knechtle, 2004; Kim et al., 1991; Cerretelli et al., 1975 and Farrell et al., 1993). Equation 3 shows that obese people (BMI > 30) and severely underweight people (BMI < 19) cannot work as close to their maximum exertion as fit healthy weight people (19 ≤ BMI ≤ 25) who do large volumes of vigorous exercise. Upper threshold estimates are based on the mean of the estimates from Jones and Poole (2004) and Pringle and Jones (2002).

$$l_i = \begin{cases} 0.48 & BMI_i \langle 19 \, or \, BMI_i \rangle 30 \\ 0.55 & 25 < BMI_i \le 30 \, and \, q_i \le 75 \\ 0.55 & 19 \le BMI_i \le 25 \, and \, q_i \le 75 \\ 0.6 & 19 \le BMI_i \le 30 \, and \, 75 < q_i < 180 \\ 0.6 & 25 < BMI_i \le 30 \, and \, q_i \ge 180 \\ 0.7 & 19 \le BMI_i \le 25 \, and \, q_i \ge 180 \end{cases}$$

[3]

Equations 1 -3 estimate elements required to estimate pedalling power. In Equation 4 we can now estimate pedalling power W_i in Watts using total power output O_i,(Watts) the estimate of the upper threshold l_i and the Baseline Power Requirement b_i (Watts).

$$W_i = (O_i \times l_i) - b_i$$

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[4]

6.2.3 Physiological constraint on time which individuals are capable of cycling

If we hold antecedent conditions constant and examine IPC at a specific moment in time, the body's cardio-vascular and musculo-skeletal systems determine the limit on the time that a person may be capable of cycling each day without risk of injury.

A cardio-vascular physical limit on time that can be spent cycling is estimated as follows. Sport and exercise science literature on exercise intensity domains (e.g. Jones and Poole, 2004; Pringle and Jones, 2002; Whipp and Rossiter, 2005) suggests the length of time and the power output that a non-athlete individual is physically capable of cycling for. From this work we infer that this limit is one hour for an outward journey to an activity, then after this activity cycling home for one hour. We acknowledge that this does include simplifying assumptions: we have not accounted for variation in the time constraint arising from individual variation in tolerance of different exercise intensity domains. We have also assumed that the activity travelled to is a rest from cycling. We have also assumed that an individual needs to repeat trips daily.

Individuals who are not already regular cyclists may be affected by saddle soreness, muscular and joint pain. Discomfort is likely to be felt within an hour by those beginning cycling. Christiaans and Bremner, (1998) found almost 60% of 453 Dutch volunteers experienced some discomfort during riding on journeys of less than one hour's duration. One hour outward and one hour return travel per day would seem to be an upper limit for the general population to avoid injury (the majority of whom are sedentary and not regular cyclists). Mobility difficulties and

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disability are also considered part of the physical constraint. This is accounted for in the spatial microsimulation process by making use the census attribute *Limiting Long Term Illness*.

6.2.4 Bicycle type and characteristics

The mass of a bicycle, the riding position (which affects aerodynamics) and the friction of tyres affect the speed at a given pedalling power (Wilson 2004). These factors vary between different types of bikes. However to the authors' knowledge there was no detailed, openly available dataset describing the UK bike fleet, its characteristics and its ownership by socio-demographic group, and so we were not able to incorporate this information into our subsequent case study. In the absence of such data, previous research by Parkin (2008) used typical utility bike values based on Wilson (2004) which we have also used.

6.3 Geographic factors

The geographic factors included in the model (see Figure 2) are: gradient, slope profile, wind speed, and route network circuity (an estimate of the ratio of network distance to distance as the crow flies averaged across an area).

6.3.1 Gradient and slope profile

At a given pedalling power speeds are lower as gradient increases. Digital elevation datasets are used to estimate the mean gradient within 5 km of each zone centroid (a possible data source is the NASA SRTM dataset which is freely available with coverage of much of the globe). The method to be described below captures differences in gradient likely to be experienced by trips originating in different zones. We report here this simple approach to accounting for gradient, because this method can be used if reliable network routing data are not available for all journeys

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(e.g. if only origin and not destination data were available or there was a need to minimise computing resources).

The proportion of uphill, flat and down-hill along a given route varies based on location and is associated with gradient (Philips 2014). If route data is not available for all individuals then a simplifying assumption about the slope profile may have to be made e.g. based on the data in Table 3 taken from Philips, (2014). Case studies in other regions may require analysis of gradient. The velocity of the cyclist is calculated for each situation: going up, down and on the flat (using Equation 7 below). For example, a person living where the gradient is 3--4% is assumed to spend 47.5% of their time cycling at their uphill velocity, 5% of the time cycling at their flat velocity (flat is assumed to be terrain with a gradient <0.5%) and 47.5% of their time cycling at their downhill velocity.

6.3.2 Wind speed

Wind speed affects the speed of a cyclist at a given pedalling power. It is difficult to consider wind speed because of its complex continual variation in both magnitude and direction. We use a similar summary wind speed approach to that used by Parkin (2004). The wind power industry has developed datasets of mean annual wind speed above ground. The wind speed at 1.2 m above ground can be estimated. 1.2 m is a height intersecting the torso of most cyclists, which is the part of the body offering greatest contribution to frontal area and wind resistance. The friction of the ground affects the wind speed; the closer to the ground, the lower the mean wind speed. The rougher the ground, the more the wind is slowed. The processes at work are explained in detail in McIlveen (2010). To estimate the wind at 1.2 m above the ground, the logarithmic wind profile is used. It depends on several factors, $h_{1.2j}$ is the wind speed (m/s) at

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1.2 m above the ground in zone *j*, V_{10} is the known reference wind speed at 10 m, *f* is the *roughness length*, a parameter set depending upon the ground cover. This relationship is shown in Equation 5 as follows:

$$h_{1.2j} = V_{10} \frac{\ln\left(\frac{1.2}{f}\right)}{\ln\left(\frac{10}{f}\right)}$$

[5]

This approach is not without issues. Firstly, it is the mean wind speed for an entire year. We acknowledge that wind speed will vary greatly from day to day. Though we have used this approach in the case study it would be possible to use the same equation to estimate IPC on a specific day with specific wind speed data. Secondly, due to turbulence, eddies, funnelling and many complex movements of air around obstacles, localised wind speeds and direction will vary. The prevailing wind direction could be used as a simple proxy, probability of wind direction on a given day could be derived from a wind rose for each location. However neither of these approaches account for the complex micro-effects on wind speed and direction, but they do introduce considerable extra complications to the modelling process. The issue of modelling the effect of wind on cyclists is a complex issue and we acknowledge that our approach is a simple first step in doing so.

6.3.3 Route network circuity.

Circuity is the ratio of journey network distance to Euclidean distance (the latter also known as the distance *as the crow flies*) averaged across an area. Euclidean distances from origins may be

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more easily available than network distances. The circuity factor depends upon the case study area. It may be a single number average for all zones (Ballou et al., 2002; Newell, 1980) or a logarithmic relationship between circuity and journey distance (Levinson and El-Geneidy, 2009). In the case study which is UK based we use the UK estimate of 1.4 given by Ballou (2002).

6.4 Distance IPC (Maximum distance an individual could cycle)

Distance IPC can now be calculated using the individual and derived attributes and the geographic factors described above. Distance IPC for individual *i* resident in zone *j*, s_{ij}^{bike} is calculated in km. It is equal to the velocity of the bike in km/hr, v_{ij}^{bike}, multiplied by the physiological constraint on time which individuals are capable of cycling in minutes $t_{ij.}$ As a result:

$$s_{ij}^{bike} = v_{ij}^{bike} \times t_{ij} \qquad [6]$$

The calculation of velocity *V* is dealt with in Equation 7. A person's velocity V_i can be expressed in terms of pedalling power (Wilson, 2004). In Equation 7, the pedalling power is W_i which was calculated in Equation [4], V_i is the velocity of cyclist *i*, m_i is the mass of the bike and rider, *g* is gravity, *r* is the coefficient of rolling resistance of cyclists' tyres, θ_j is the percentage slope in zone *j*, η_i is the mechanical efficiency of the bike, D_i is the cyclist's aerodynamic drag coefficient, A_i is their frontal area and $h_{1.2j}$ is the wind speed at 1.2 m above ground estimated for zone *j*. In the absence of bike fleet data, the values in Table 4 can be used as a simplifying assumption. The values are used in (Wilson 2004 p139). These are applied to Equation 7. If a

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slope profile assumption is assumed (as discussed in Section 6.3.1), Equation 7 is calculated for each of the uphill, flat and downhill portions of the journey.

$$W_i = \frac{V_i}{\eta}\left\{m_i g\left(r_i + \frac{\theta_j}{100}\right)\right\} + \frac{V_i}{\eta_i}\left\{0.5 D_i A_i \rho \left(V_i + h_{1.2j}\right)^2\right\}$$

[7]

Equation 7 (after Wilson 2004) gives an expression for pedalling power W_i as a cubic function of velocity V_i. We wish to use the inverse relationship, namely to derive a velocity corresponding to a given pedalling power. In all cases we considered, we verified that there was a single positive real root to this cubic equation within a viable range for cycling speeds (i.e. under 40 km/h). This root was analytically calculated using the method originally described in Cardano (1545).

6.5 Distance to activity

Distance to activity is the distance from the individual's residential location to the activity of interest. The current distance to the activity for an individual derived from secondary data sources is measured as a Euclidean distance between origin and destination points. The model requires this distance to be converted to a network distance. To account for circuity (as defined above), the Euclidean journey distance for person *i* in zone j, X_{ij} is multiplied by the circuity factor *z*. The distance to activity, C_{ij}, accounting for circuity, can be expressed as follows:

$$C_{ij} = X_{ij} \times z$$

[8]

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6.6 Journey IPC (capability of an individual to complete a journey by bicycle)

Journey IPC is estimated by comparing distance IPC calculated in Equation 6 and *distance to activity* estimated in Equation 8. For an individual *i* who lives in zone *j* their journey IPC K_{ij} is 1 if their distance IPC s_{ij}^{bike} .is greater than or equal to the distance to the activity C_{ij}. The relationship can be shown as follows:

$$K_{ij} = \begin{cases} 1 & s_{ij}^{bike} \geq C_{ij} \\ 0 & s_{ij}^{bike} < C_{ij} \end{cases}$$

[9]

The indicator zone journey IPC ($\%K_j$) is derived as a summary of the percentage of individuals with journey IPC; it is still a measure of individual variation and is calculated in Equation 10 as follows. The sum of those individuals with journey IPC equal to 1 is divided by the relevant population of zone *j* (e.g. the relevant population would be employed individuals if commuting were being examined, or children and carers if journeys to school were being examined) and converted to a percentage.

$$\%K_j = \frac{\sum K_{ij}}{relevant\ population\ of\ \ zone\ j} \times 100$$

[10]

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7 CASE STUDY

This section proceeds as follows, first we introduce the case study area. We then describe the specification of the test indicator and data used, before giving the results. Following this, we specify the sensitivity tests carried out before describing the results (including comparisons with the zone journey IPC indicator).

7.1 Description of case study area

The case study of Leeds is included to test the practicalities of implementing the modelling process explained in Sections 4, 5 and 6. Leeds is a city in Northern England with a population of 751,500 (ONS 2015). It is a useful case study because it is contained within a single local authority area and it is of sufficient size as to have significant social and demographic variation. It also has varied topography and it is not dissimilar to the other major cities in the region, Manchester and Sheffield.

7.2 Specification of case study and data used

The construction of the IPC measures and indicators in the case study area required a large number of data sources. The data sources used to construct the case study are shown in the dashed boxes in Figure 2. The requirement in Section 3 to construct the model using data sources available to local practitioners without expensive fieldwork means we rely on secondary data sources and parameter values derived from the literature. The Health Survey for England and the UK census achieve a level of transferability of data to the study area. In the spatial microsimulation, candidate constraint variables associated with BMI and physical activity were identified in the literature (Craig et al., 2009; IPSOS MORI, 2007; McArdle, 2010; NOO,

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2010). We examined these relationships in the 2008 HSE data. Age has a correlation of 0.25 and -0.3 with BMI and physical activity respectively. Analysis of variance (ANOVA) tests of BMI with the categorical variables economic activity and limiting long term illness were significant at the 0.05 level. ANOVA tests of physical activity with economic activity, limiting long term illness, socio-economic status and education were also significant at the 0.05 level.

In terms of circuity we use the UK estimate of 1.4 given by Ballou (2002). We use the parameters describing bike and rider characteristics based on Wilson (2004) because they have been adopted and transferred to other UK studies (e.g. Parkin, 2004; Parkin and Rotheram, 2010). Our case study illustrates distance IPC and journey IPC for one example destination. Potential further applications are discussed in Section 8.

7.3 Results of test indicators.

In Step 1 we estimate distance IPC for each individual and derive the indicator zone distance IPC. The mean zone distance IPC is 4.57 km with a standard deviation of 0.48 km. Zone distance IPC is generally higher in the flatter east of the city than the hillier west. The spatial distribution is shown in Figure 4.

The mean of the zone journey IPC indicator is 57% (the percentage of individuals in a given OA capable of completing, on a daily basis, a specific journey by bicycle, in this case study Leeds city centre). The results of zone journey IPC are summarised in the first row of Table 5. The range in zone journey IPC between Output Areas was 100%. The standard deviation was 30%. The spatial variation in zone journey IPC values is shown in the map in Figure 5.

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Zone journey IPC is generally highest at the centre (81-100%) and lower towards the edge of the city but it is not an even concentric pattern because of the interaction of the factors considered in the model. There are a small number of Output Areas relatively close to the city centre which are not in the highest category, as attributes of individuals in those Output Areas are affecting the indicator value. Note that the pattern of zone distance IPC and zone journey IPC differ considerably because the former is a component influencing the latter.

7.4 Specification of testing sensitivity to modelling assumptions on 5 variables and comparison of the zone journey IPC test indicator with 3 alternative measures

It was possible to quantify some aspects of the zone journey IPC indicator's sensitivity to the modelling assumptions. We carried out the following tests: Altering VO_2max for all individuals by 4.9 (this is 1 SEE in the regression model estimate of VO_2max described in Section 6.2.1), randomly allocating errors in VO_2max according to a normal distribution. Assuming no wind as opposed to the annual mean estimate used in the test indicator. Altering the time people are physiologically capable of cycling for by 10% to 66 minutes. Altering the coefficient of rolling resistance value from the utility bike value shown in Table 3 to 0.003 which is a typical value for a road racing bike (Wilson, 2004). We increased circuity by 0,2 and decreased it by the same amount. We also tested the sensitivity to simultaneous positive errors in VO_2max, Crr, time people are physiologically capable of cycling for, wind, and circuity.

We also compared the zone journey IPC test indicator to three alternative measures. The first alternative measure assumes all individuals are *average*, in that they have the mean weight and

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pedalling power of the micro-data sample. We wished to compare our model of zone journey IPC to a model only considering an *average person* to consider the effect of modelling individual variation. The second alternative measure assumes all individuals can travel 8 km, because Parkin, (2004) notes that it is commonly assumed that journeys up to 8 km are cycleable. The third alternative measure assumes all cyclists can travel at 16 km/hr. The UK Department for Transport accessibility statistics assume that cyclists generally move at 16 km/hr (Department for Transport, 2012).

7.5 Results from sensitivity tests (including comparisons with the zone journey IPC indicator)

The results of the zone journey IPC indicator's sensitivity to the modelling assumptions are summarised for the 2439 Output Areas (OAs) in Leeds in Table 5. Simulating a systematic one SEE error in the estimation of VO_2max has the largest effect of the tested variables (12%). We also note that in the simultaneous positive errors test, errors are smaller than the sum of each individual error.

Table 5 gives an overall summary but importantly there was spatial variation in sensitivity and these variations are shown in Figure 6. Zone journey IPC under sensitivity to a single variable is shown in Figures 6b-h. Reducing VO_2max sees a contraction of the area of highest zone journey IPC and an expansion of the area of lowest zone journey IPC as would be expected. Increasing VO_2max produced the opposite effect. Changing rolling resistance appears to have a slightly greater effect in the east where it is flatter, than the hillier north-west.

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Zone journey IPC under simultaneous positive errors in VO_2max, Crr, the time people are physiologically capable of cycling for, wind, and circuity is shown in Figure 6i. The absolute difference between the indicator and simultaneous positive errors is shown in Figure 6j. The smallest sensitivity occurs closer to the city centre and around parts of two satellite towns, Wetherby and Otley, in the north-east and north-west corners respectively. The largest sensitivities are found closer to the edge of the city and are particularly concentrated in the east. This area is flatter, so an increase in pedal power coming from increased VO_2max, or a reduction in rolling resistance or wind will deliver the greatest increase in potential travel distance.

Figures 7a, c and e show the results of the three alternative methods specified in Section 7.4. If all individuals were assumed to be *average* in terms of having the mean weight and pedalling power of individuals in the sample population, this results in a mean decrease in zone journey IPC of 5%. If we make the simplifying assumption that all individuals are capable of cycling 8 km (5 miles) the mean difference in zone journey IPC is 17%. If we make the simplifying assumption that all individuals are capable of cycling at 16 km/hr and assume the same physiological constraint on travel time of 1 hour, mean zone journey IPC would be 39% higher (see Table 6).

Figures 7a and c clearly show a concentric ring and Figure 6e shows that in almost all Output Areas 100% of people could cycle to the city centre. Our indicator of zone journey IPC in Figure 5 shows the pattern of journey IPC is not an exact concentric ring; it is influenced by the range of factors considered in the model. Figures 7b, d and f show where the difference between our indicator of zone journey IPC and the comparison is greater than the sensitivity for that OA.

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Figure 7g shows Output Areas where the difference between our zone journey IPC indicator and all three alternative methods is greater than our estimated sensitivity for that OA. Where our estimate is considerably different to these alternative estimates, it suggests that the more individualised procedures are warranted even with our self-imposed restriction of data availability (see Section 2). The conceptual problems of aggregating individual attributes and using an *average person* or assuming all individuals can travel a particular distance were outlined in Section 3.

The maps in Figures 4--7 have policy value because they illustrate measures and indicators of IPC for small areas, and provide policy makers with an understanding of the sensitivity of results in particular OAs. Figure 5 represents the zone journey IPC indicator with no policy intervention, but our model contributes to a process which could also be used to assess the effects of policy interventions. If policy interventions were to impact on key variables, e.g. supposing a health intervention had an effect on the VO_2max of a particular population segment, Table 7 gives an indication of the effect that this could have on zone journey IPC amongst different population segments. The microsimulation approach also means it is possible to examine the factors that have an effect on IPC in a particular area. This would contribute to more targeted policy intervention.

We could simulate the effect of a policy by altering the appropriate individual attributes and recalculating the indicator. For example in Figure 7h we simulated improvements in BMI which might occur in a hypothetical health intervention, e.g. decrease the BMI of people aged 50--59 by 10%, which affects VO_2max which then affects the indicators. Note this is a

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hypothetical intervention, it is beyond the scope of this paper to forecast the effect of specific interventions on BMI. Figure 7h shows the 498 out of 2439 OAs where the impact of the hypothetical policy is greater than the estimate of sensitivity to model assumptions. This method would allow policy makers to identify areas most likely to be affected by real policy interventions whilst also accounting for model sensitivity.

8 Potential applications

The indicators of distance and journey IPC have potential for application in the field of sustainable transportation. These include: estimating walking and cycling targets; estimation of the service area of public transport stops; integration into an accessibility measure which, by considering capability more effectively can be applied to gain greater insights into the health and social constraints on mobility and participation in activities; estimating active mode service areas for public transport nodes; understanding transport based social exclusion and short term disruptions to fuel supply. The model could also be used to control for physical capability in studies of the influence of (perceived) safety as constraints to the spatial limits of cycling travel. There is potential to implement these indicators as part of a *what-if* policy model related to sustainable transport futures. For example Philips et al., 2013 provide a conceptual model of resilience to permanent reduction in fuel supply which provides a context which is described in terms of antecedent conditions and a policy event which would be compatible with the modelling framework shown in Figure 1, though there would be additional issues in modelling the fuel restriction event (e.g. sudden change in travel need). Policies and visions for cycling futures based on capability have potential to feedback more radical options for change (Wang 2015;

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Philips et al., 2013; Banister and Hickman, 2013; Diamond, 2006; Goodwin and Dender, 2013; Tight et al., 2011; Timms et al., 2014; Urry, 2010), driven by the literature on environmental limits on resource use (e.g. Berners-Lee and Clark, 2013; McGlade and Ekins, 2015; Rockstrom et al., 2009).

Also of considerable interest would be the application of the model to consider capability to make multi-leg trips. Distance IPC could be used as a simple measure in this regard, but the model could be refined to make it appropriate for this specific application as follows. We have described above a data constrained implementation of the model without routing data and for single trips. However there are many opportunities to gather full day activity / travel diaries. If this information were available it could be used to produce estimates of total daily travel need and activity locations (possibly using big data). Routing could be done for small samples with the Google-maps API, but for large numbers of routes other APIs such as Routino (https://www.routino.org/uk/) may be more suited (e.g. Bearman and Singleton, 2014). The energy required to complete a specific route or daily set of routes by an individual could be estimated. The IPC measures could be refined to consider whether an individual's *maximum cumulative energy expenditure (MCEE)* is sufficient to fulfil their daily activity requirement. This would build on the Active Mode Accessibility (AMA) work of Rendall et al., (2011) or be applied in a large scale agent based travel simulation such as MATSIM (http://www.matsim.org).

Below we briefly outline the process which would be required to consider multi-leg trips using route data and estimating MCEE. It is beyond the scope of this paper to develop it fully, but we

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highlight it as an area for further work. We could define maximum cumulative energy expenditure MCEE for individual *i* in zone *j*, in relation to their pedalling power W_{ij} and physiological time constraint t_{ij} as follows:

$$MCEE_{ij} = W_{ij} \times t_{ij}$$

[11]

The simple pseudo code below could then be used to estimate whether a person has capability to complete their daily travel activity by bicycle:

Set remaining energy = $MECC_{ij}$

Do while k < = total number of legs

Remaining energy = remaining energy – energy expenditure leg_k

If remaining energy is > = 0

Print 'leg k is possible'

Otherwise

Print 'leg k is not possible'

k = k+1

End while loop

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9 SUMMARY AND CONCLUSIONS

This paper proposed a generic methodology that could be applied to any area to estimate an individual's capability to travel by bicycle. The model of IPC links the complimentary fields of human physiology and active transportation analysis. It considers physical capabilities, individual variation (including cyclists and non-cyclists) and is spatially fine grained. First we generated a synthetic population using spatial microsimulation. We then demonstrated the estimation of the maximum distance an individual could cycle on a daily basis (distance IPC) and the capability of an individual to complete a specific journey (journey IPC). The case study illustrates the implementation of the model using a range of secondary data sets available to practitioners.

We concentrated on constructing indicators which could be produced with secondary data (mindful that few have the resources to conduct large health and active travel surveys) taking a simple approach to representing attributes such as network circuity and gradient (again, mindful that data for more nuanced estimates may not always be available). This is a generic methodology that could be applied to any area, but which could be tailored to the data availability for that area, and almost certainly would need to borrow/transfer values from other studies for some factors (as is conventional in most transportation analyses).

Our case study is intended to be illustrative of our general method. Our sensitivity testing aims to position this work relative to other approaches. We do not claim to have fully calibrated this model, though sensitivity tests suggest that the individualised modelling procedures are not unwarranted because the differences between the zone journey IPC estimate and the

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commonly used assumptions such as that journeys up to 8 km are cycleable (Parkin, 2004) are greater than the sensitivity to systematic 1SEE errors in VO_2max or a 10% error in the time people are capable of cycling or variation if wind speed is not considered at all.

9.1 Implications for Leeds

Whilst the focus of the paper is methodological, the results provide policy relevant implications for Leeds, though we caveat these with the simplifying assumptions and limitations of calibration that we describe elsewhere in the paper.

The result in Figure 4 illustrates the spatial variation in zone distance IPC. Figure 5 shows the considerable variation in zone journey IPC at OA level because of the interaction of health and topography. Not only this, the data underlying these maps are at the individual level, so estimates can be made of the number of individuals, from different population sub-groups, capable of travelling a particular distance or making a particular journey.

These outputs could aid the long term planning of cycling interventions and sustainable transport planning more generally in cities. The approach described in this paper can provide more detailed measures of accessibility by cycling because it accounts for variation in IPC across the population. This is novel. UK local authorities generally use the Journey Time Statistics accessibility measures produced by the UK Department for Transport. These measures focus on what Geurs and van Wee, 2004 term an infrastructure perspective rather than a people perspective. The method presented in this paper could be used to augment the current JTS methodology and provide more detailed accessibility measures to local planning authorities.

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Improved accessibility measures have implications for local transport planners because they aid the development of better spatially targeted health, social inclusion and sustainable transport policies. For example: understanding where IPC is a greater or lesser constraint on cycling can increase the likelihood that selected interventions applied to specific areas are successful. The indicator could be developed to inform cycle interventions and cycle mode share targets by providing a measure of the saturation level that Parkin(2004) described as important.

Locally targeted interventions could account for the most specific constraints such as health and circuity. A visual comparison of Figure 6(a) and Figure 6(g) shows that a reduction in circuity has an influence on capability. This has implications for the routing of cycle infrastructure in the case study city and in turn accessibility. The hypothetical health policy summarised in Table 6 implies that were a policy targeted at a specific group of individuals successful, it could have a considerable effect on IPC. Figure 6(c) and 6(c) also suggests where interventions improve fitness (e.g. result in increased VO_2max) would improve distance and journey IPC. The implication is that for some in these affected zones, an intervention would be needed to help people gain the capability to make the cycling journeys that provide the combined transport and health benefits of cycling. Though further calibration would be needed it shows that the method presented could be used to identify groups in specific locations which could make planning targeted health and sustainable transport interventions more effective.

9.2 Further calibration

To calibrate the model, further primary data collection may be required. Further studies of the rate of exertion and power output of non-regular cyclists would allow refinement of the

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pedalling power calculation and the physiological constraint on time available for cycling amongst different subsections of the population. We acknowledge that using the Dutch study of cyclist discomfort (Keytel and Noakes, 2002) may have some limitations, but again there is no comparable study on UK participants. This would be an area for future research which would contribute to refinement of the model. Primary data may also be usefully gathered on the state of the bike fleet that are *in the shed*. For example, data improvements could be made by assessing the level of maintenance and mechanical efficiency of cycles, the type of bicycle (which affects the aerodynamics of the rider) and the type of tyres used which affects rolling resistance.

Further work combining route estimation and day to day variation in wind speeds and direction would be complex, but if required for a specific application may give a more detailed picture of the day to day variation in capability to travel by bicycle. Additionally, for applications where detailed origin and destination data are available, network modelling of journeys by every individual from every Output Area to every activity may help reduce the sensitivity associated with circuity. A further simplifying assumption about the network in the model presented in the case study is that cyclists do not have to stop at junctions to wait for motor vehicles to pass. However, useful further work may include estimation of the effect of starts and stops on rider exertion which could be calculated based on the work of Parkin and Rotheram (2010).

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9.3 Expanding the model

The model could be expanded to include social factors which influence the time available for travel such as household constraints. Bicycle availability could also be considered. The model may also be expanded to consider walking trips and give an overall IPC to travel by active modes (e.g. Philips, 2014). A further limitation comes from the ability of combinatorial optimisation based spatial microsimulation to provide all the necessary individual attributes shown in Figure 2. It is appreciated that in some future study areas not all attributes may be available in a single representative survey. A more flexible method of spatial microsimulation may be required. This would have to retain the ability to simulate populations accurately for small zones but also allow inclusion of attributes from more than one source (Philips et al., 2017).

This modelling process may be of considerable interest to policy makers and those lobbying for more sustainable transport systems as there are a range of potential applications (See section 8). The model is constructed to allow simulation of the effects of policies on IPC which could be developed beyond the illustration given in the case study. We have both presented a means of estimating IPC to make journeys by cycling for whole populations as well as highlighting challenges and opportunities for further work. A number of simplifying assumptions have been made in estimating IPC, but, having made the calculations and presented them clearly, this allows for other researchers to make different assumptions and to understand the impacts of those choices which will aid the development of the model for specific applications.

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Table 1. Individual measures and corresponding zonal summary indicators used to express IPC.

Individual measure	Definition	Corresponding zonal summary indicator	Definition
Distance IPC	Distance in km that an individual is physically capable of travelling by bicycle on a daily basis	*Zone distance IPC*	The mean distance in km that residents of the given zone are capable of travelling by bicycle on a daily basis
Journey IPC	A categorical variable set to 1 if an individual is capable of completing a specific journey by bicycle on a daily basis and zero otherwise	*Zone journey IPC*	The percentage of individuals in a given zone capable of completing a specific journey by bicycle on a daily basis

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Table 2. Regression estimate of VO_2max (Source: Wier et al., 2006)

Attribute	Beta
Constant	57.402
Age (years)	-0.372
gender (M=1, F=0)	8.596
Self reported physical activity (PASS Physical Activity scale)	1.396
Body Mass index, BMI (Kg/m^2)	-0.683
Standard Error of Estimate (SEE) ml/kg/min (95%ci)	±4.9

Sample size; n male = 2417, n female = 384. VO_{2max} range = 15-66, BMI range 16-48.

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Table 3. Proportion of near flat route length in cells with different mean road gradient used to estimate slope profile (slope in %).

Area of sample	Mean slope	Proportion of network in sample area with slope < 0.5%[a]	Proportion of network in sample area with slope < 1%[b]	Assumed slope profile
Vale of York	< 1%	25%	33%	37.5% up, 37.5% down 25% flat
Doncaster urban area	1- 2%	17%	46%	41.5% up, 41.5% down 17% flat
Harrogate urban area	2 -3%	7%	18%	46.5% up 46.5% down 7% flat
North West Leeds	3-4%	5%	13%	47.5% up 47.5% down 5% flat
Keighley	4-6%	5%	12%	47.5% up 47.5% down 5% flat

[a]The force due to rolling resistance of a person on a utility bike with 95kg total mass is greater than the force of gravity on gradients of less than 0.5%

[b]On a mountain bike the force due to rolling resistance with 95kg total mass is greater than the force of gravity on gradients of less than 1%

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Table 4. Constants used in the calculation of bicycle velocity

Constant	Suggested value (after Wilson 2004)
g= acceleration due to gravity	9.8 ms^{-2}
r= coefficient of rolling resistance	0.008
η= the mechanical efficiency of the bicycle	0.95
D= aerodynamic drag coefficient	1.2
A= frontal area of rider and machine	0.5m^2
ρ= density of air (kg/m^3)	1.226kg/m^3

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Table 5. Summary of zone journey IPC indicator's sensitivity to the modelling assumptions across 2439 Output Areas in Leeds

Zone journey IPC (%)	min	max	median	mean	std.dev
Test indicator zone journey IPC	0	100	66	57	30
VO_2max all individuals minus 4.9	0	97	46	45	29
VO_2max all individuals plus 4.9	0	100	79	67	30
VO_2max error normal distribution	0	100	66	58	31
No wind	0	100	69	60	28
Alter Time t_{ij} *to 66 minutes*	0	100	71	61	29
Set Crr to 0.003	0	100	70	60	28
Circuity = 1.2	0	100	73	64	28
Circuity = 1.6	0	100	55	51	32
Simultaneous positive errors (VO_2max +4.9, wind = 0, circuity =1.2 time=66, crr 0.003)	0	100	79	75	19

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Table 6. Summary of comparison tests and hypothetical policy simulation across 2439 Output Areas in Leeds

Zone journey IPC (%)	min	max	median	mean	std. dev	Absolute difference between test indicator and alternative	% of population
Test indicator	0	100	66	57	30	-	57
Alternative measure 1; all individuals are *average*	0	100	100	52	50	5	52
Alternative measure 2; all individuals travel 8km	0	100	100	74	44	17	74
Alternative measure 3 all individuals travel at 16km/hr	0	100	100	96	19	39	96
Hypothetical policy; BMI reduced by 10% for 50-59year olds	0	100	100	64	29	7	64

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Table 7. Variation in zone journey IPC with key parameters.

gender & age group	Pedal Power (W)	ΔVO_2max -4.9	ΔVO_2max +4.9	Zone distance IPC(km)	ΔVO_2max -4.9	ΔVO_2max +4.9	Zone journey IPC(%)	ΔVO_2max -4.9	ΔVO_2max +4.9
Male 16-24	150	130	170	12.00	10.99	12.93	89	86	91
Female 16-24	70	55	86	8.16	7.04	9.24	66	55	74
Male 25-34	124	104	145	10.36	9.20	11.41	83	77	87
Female 25-34	67	50	83	7.85	6.60	8.98	62	49	72
Male 35-54	91	71	111	8.51	7.35	9.60	67	56	76
Female 35-54	43	28	58	5.93	4.59	7.16	39	24	53
Male55-64	57	38	76	6.36	5.06	7.49	42	26	56
Female55-64	18	8	32	3.84	2.70	5.06	13	5	25
Male 65+	57	38	77	6.58	4.97	8.01	45	24	60
Female 65+	11	3	23	2.90	1.08	4.11	7	0	16

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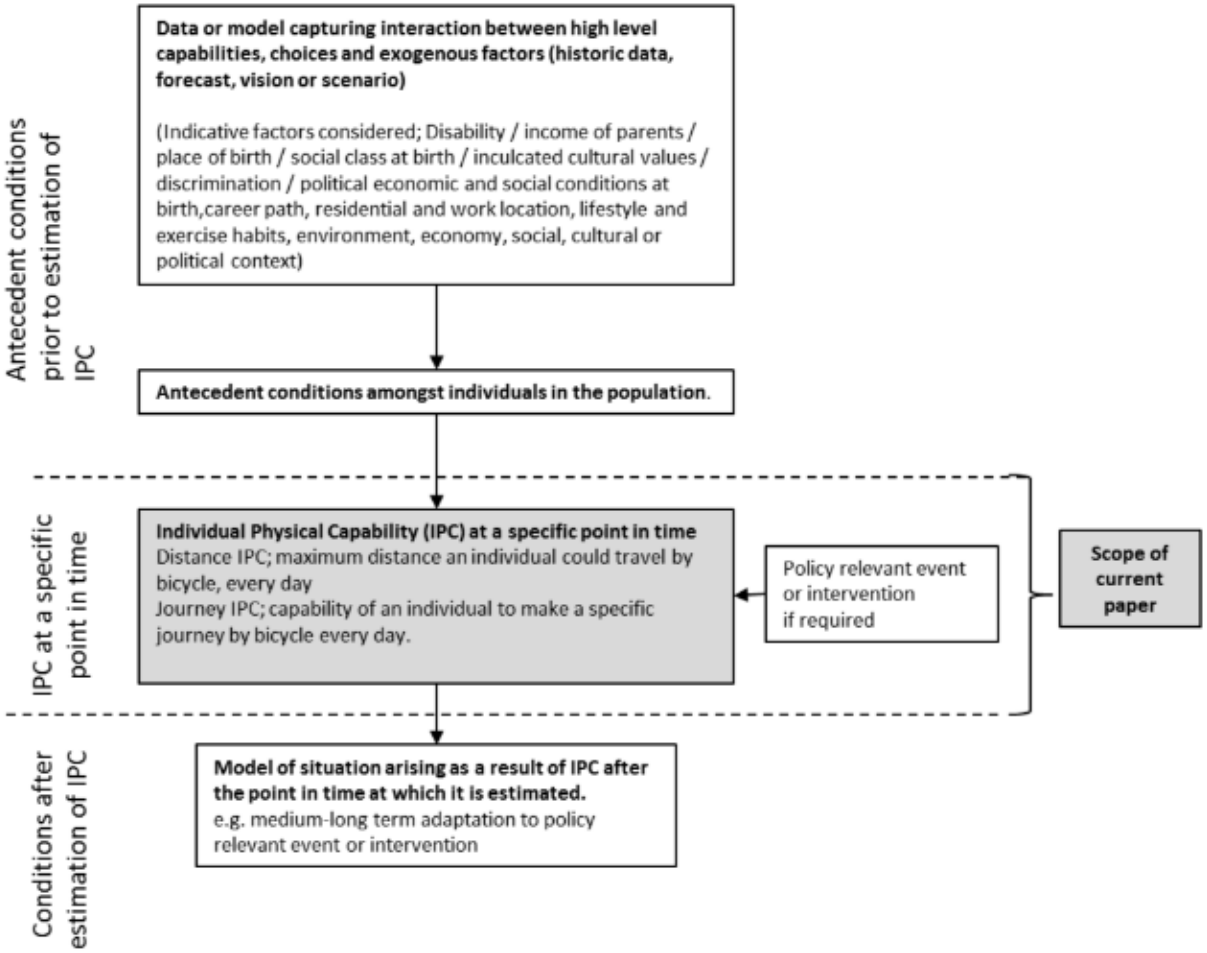

Figure 1. A simplified representation of how the estimation of IPC at a particular point in time is related to and distinct from antecedent conditions and conditions after the estimation of IPC

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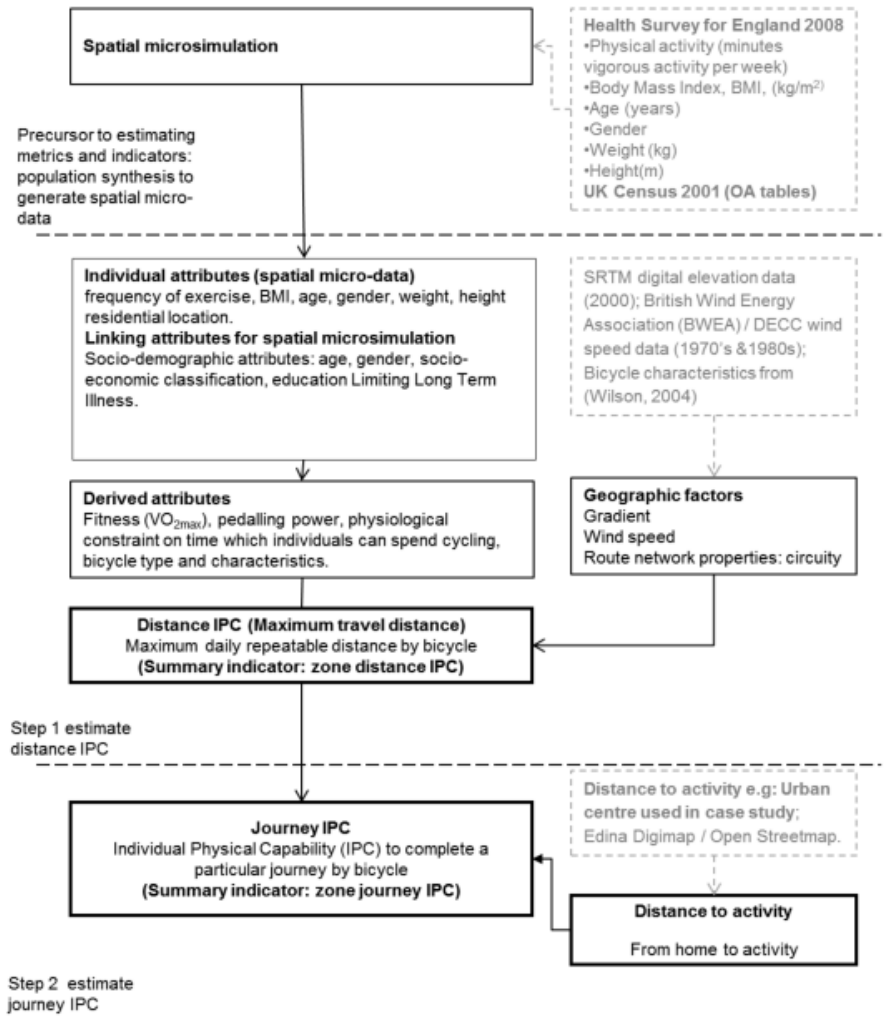

Figure 2. Model outline to estimate IPC metrics and indicators for a synthetic population of individuals. Data sources used in the case study in Section 7 are shown in the boxes with dashed outlines.

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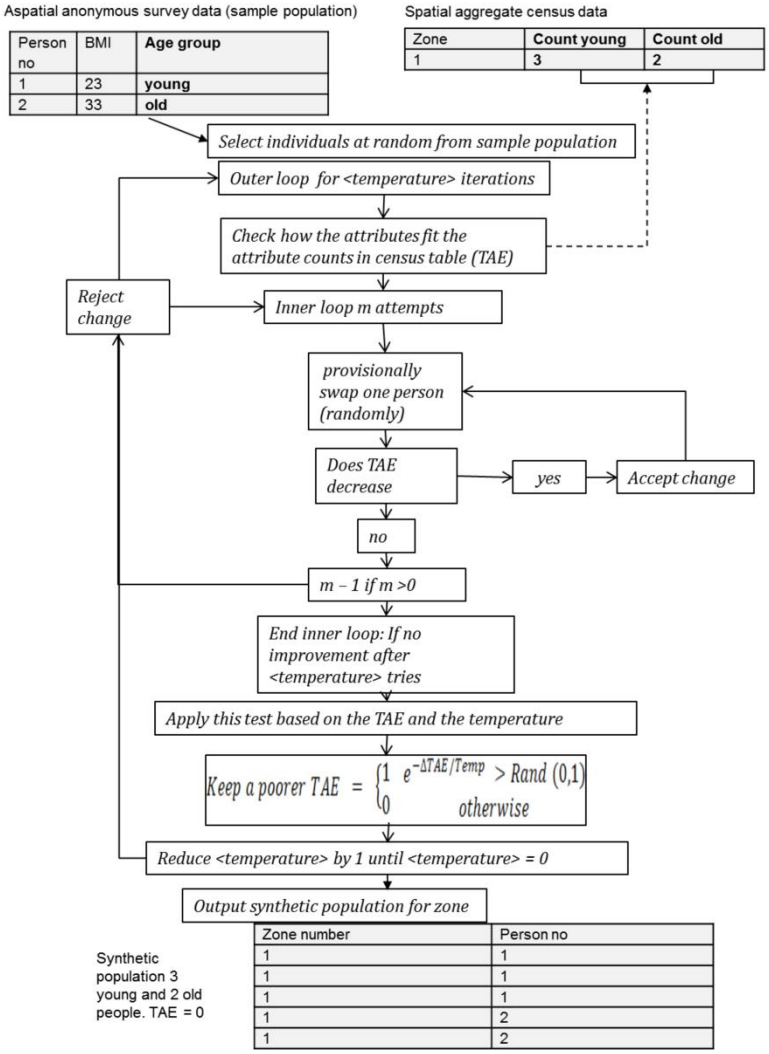

Figure 3. The basis of simulated annealing combinatorial optimisation based spatial microsimulation (after Harland 2013).

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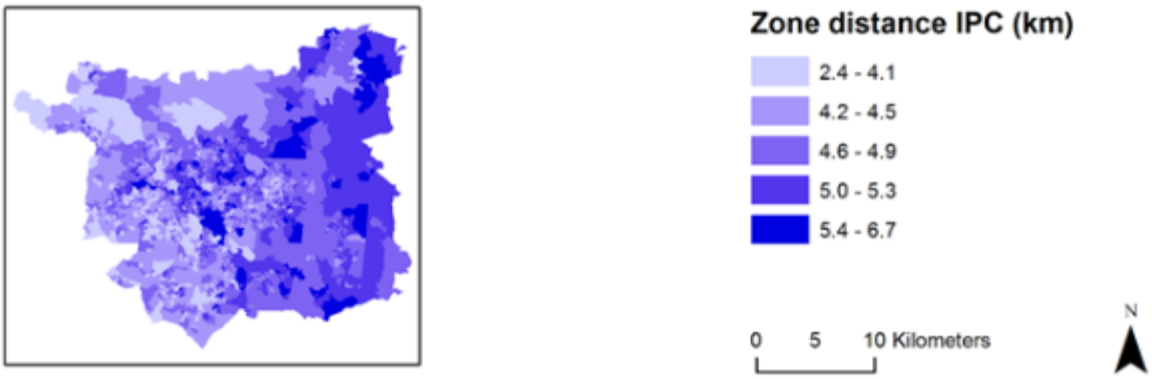

Figure 4. Distance IPC is the mean maximum distance that all individuals in an Output Area are capable of travelling by bicycle on a daily basis given their home location (this is the result following Step 1 in Figure 2).

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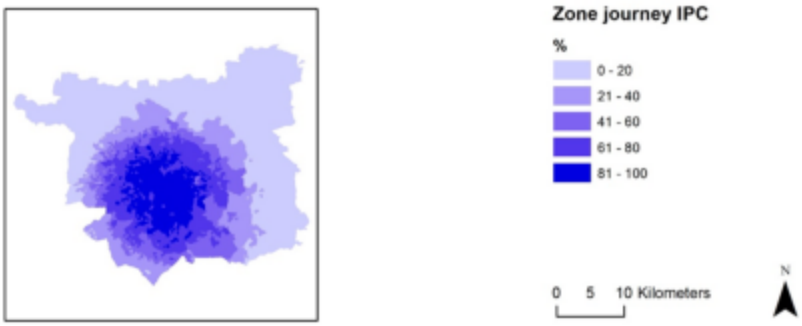

Figure 5. Zone journey IPC is the percentage of individuals in a given zone capable of completing a specific journey by bicycle on a daily basis (the result following Step 2 in Figure 2)

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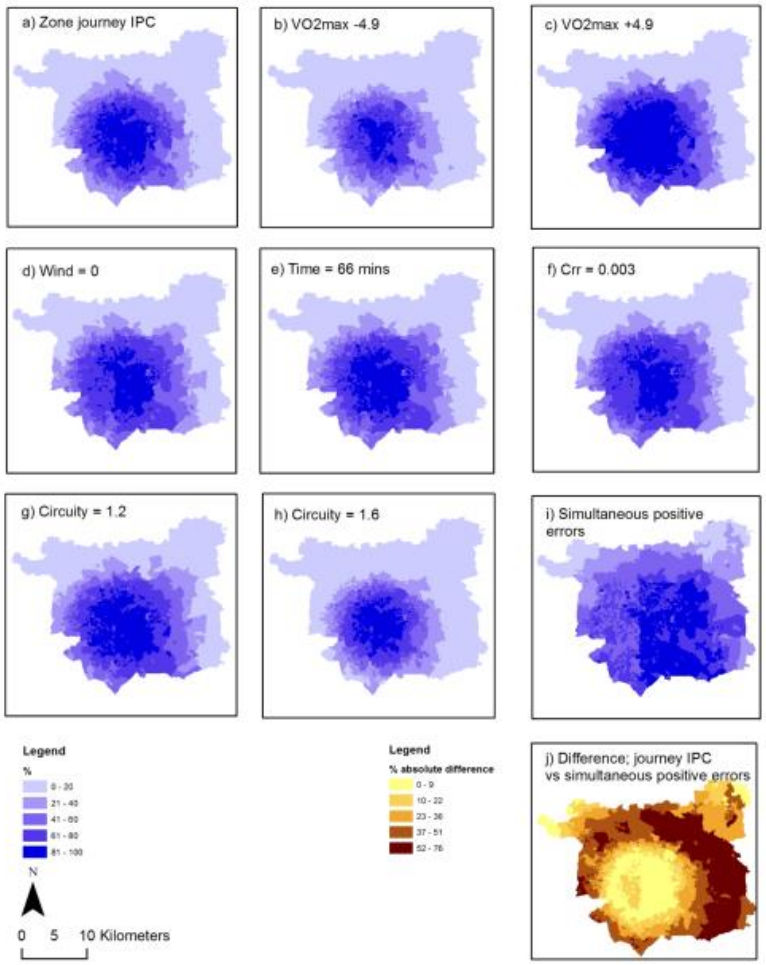

Figure 6. Spatial variation in zone journey IPC value (a) as variables are manipulated in sensitivity tests (b) – (i) and spatial pattern of difference between zone journey IPC and simultaneous errors (j)

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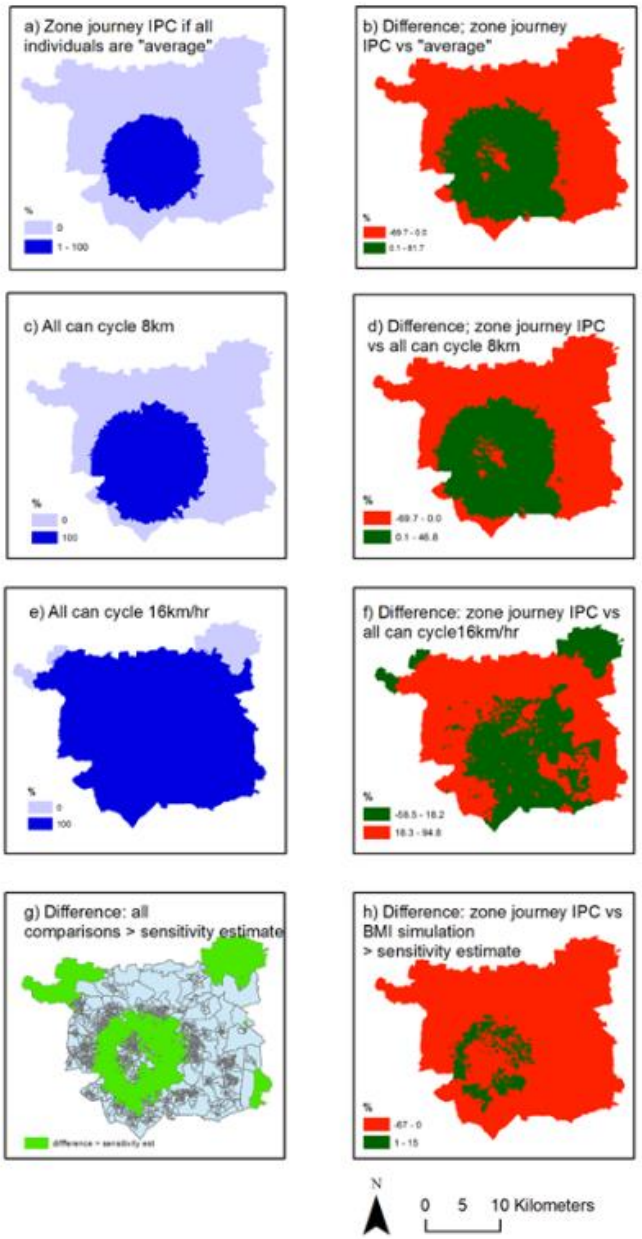

Figure 7. Spatial variation when comparing zone journey IPC with alternative models