The Propensity to Cycle Tool: An open source online system for sustainable transport planning

~~14 September 2015~~

1 ~~Abstract~~

Abstract

~~Encouraging cycling , as part of a wider sustainable mobility strategy,~~ Getting people cycling is an increasingly common objective in transport planning institutions worldwide. ~~Emerging evidence shows that providing appropriate high-quality~~ A growing evidence base indicates that high quality infrastructure can boost local cycling rates. ~~To maximize the benefits and cost-effectiveness of new infrastructure~~ Yet for infrastructure and other cycling measures to be effective, it is important to ~~build~~ intervene in the right places~~. Cycle paths, for example, will have the greatest impact if they are constructed~~ , such as along 'desire lines' of ~~greatest~~ high latent demand. This creates the need for tools and methods to help answer the question 'where to build?'. Following a brief review of the policy and research context related to this question, this paper describes the design, features and potential applications of such a tool. The Propensity to Cycle Tool (PCT) ~~seeks to inform such decisions by providing an evidence-based support tool that models current and potential future distributions and volumes of cycling across cities and regions. This paper describes this model and its application to case study cities in England . Origin-destination (OD)data,~~

~~combined with quantitative information at the level of administrative zones, form the basis of the model, which estimates cycling potential as a function of route distance, hilliness and other factors at the OD and area level. Multiple scenarios were generated and interactively displayed. These were: 'Government Target', in which the rate of cyclingdoubles in England; 'Gender Equality', in which women cycle as much as men;~~ is an online, interactive planning support system which was initially developed to explore and map cycling potential across England (see www.pct.bike). Based on origin-destination data, it models and visualises cycling levels at area, desire line, route and route network levels, for current levels of cycling, and for scenario-based 'cycling futures'. Four scenarios are presented, including 'Go Dutch' ~~, in which English people cycle~~ and 'Ebikes', which explore what would happen if English people cycled as much as ~~people in the Netherlands; and 'E-bikes', an exploratory analysis of increasing the distance people are willing to cycle due to new technology. The model is freely available online and can be accessed at . This paper also explains how the PCT's open sourceapproach allows it to be deployed in new cities and countries~~Dutch people and the potential impact of electric cycles on cycling uptake. Health and carbon impacts from each scenario are reported at the local level for each scenario. The PCT is open source, enabling the creation of additional scenarios by others and its deployment in new contexts. We conclude that the ~~method presented has potential to assist with planning for cycling-dominated cities worldwide, which can in turn assist with the global transition away from fossil fuels~~PCT illustrates the potential of online tools to inform transport decisions and raises the wider issue of how models should be used in transport planning.

1 Introduction

Cycling can play an important role in ~~making transport systems more sustainable , healthy and equitable . This mode of transport already provides fast~~creating sustainable and equitable transport systems. Cycling already provides reliable, healthy, affordable, and convenient mobility to millions of people each day (Komanoff, 2004) ~~. Mounting evidence of~~ and is one of the fastest growing modes of transport in some large, cosmopolitan cities such as London, New York and Barcelona (Fishman, 2016). There is mounting evidence about the external costs ~~associated with~~ of car-dominated transport systems (e.g. Han and Hayashi, 2008; ~~Mizutani et al., 2011; Newman and Kenworthy, 1999;~~ Shergold et al., 2012), and the benefits of cycling (~~De Nazelle~~ De Nazelle et al., 2011; Oja et al., 2011; ~~Woodcock~~ Tainio et al., ~~2013)has pushed~~ 2016), pushing cycling up the transport ~~agenda. Cycling is increasingly central to sustainable transport strategies, as illustrated, for example, by funding for cycling policies[1] and the global proliferation of publicly subsidized 'bike share' schemes (O'Brien et al., 2014).~~ [1] ~~Emerging evidence illustrates that~~ policy agenda. In this context there is growing interest, and in some cases substantial investment, in cycling infrastructure, including in countries with historically low rates of cycling.

Providing high-quality infrastructure ~~is an effective way of promoting cycling as a safe, accessible and convenient transport option for people of all ages and abilities~~ can play a key role in promoting cycling uptake (Parkin, 2012). Off-road cycle paths, for example, have been found to be associated with an uptake of cycling for commuting (Heinen et al., 2015). ~~Thanks to various designs of modified cycles (e.g. quadricycles and handcycles), cycling can also provide an efficient means of self propulsion for people who would have to depend on motorised modes or other people (Aldred and Woodcock, 2008).~~ Overall there is growing evidence linking cycling infrastructure to higher rates of cycling (Buehler and Dill, 2016). But where should this infrastructure be built? This paper seeks to demonstrate the potential of online, evidence-based tools to help answer this question, with reference to the Propensity to Cycle Tool (PCT). The PCT is an online planning support system funded by the UK's Department for Transport to map cycling potential (Department for Transport, 2015).

[1] ~~Several examples of multi-million Euro projects are provided by the , the and the . There has been little academic research on the proportion of transport budgets allocated to cycling worldwide, hence the use of resources from NGOs here.~~

[1] ~~An interactive web map associated with O'Brien et al. (2014) illustrates the distribution of many of the largest bike share schemes worldwide. See .~~

~~Within this fast-moving policy context, the question of where to construct new cycle infrastructure is of strategic importance. In response, professional transport planners and consultancies have developed new methods for identifying cost-effective infrastructure interventions, such as Aecom's proprietary Permeability Assessment Tool (Payne, 2014). Yet geographically specific prioritisation of new infrastructure is seldom raised in academic research on cycling and active travel more widely. The design (Heath et al., 2006; Transport for London, 2014; Welsh Government, 2014)and geographic location (Aultman-Hall et al. , 1997; Minikel, 2012) of cycle paths are important factors influencing~~

2 The Propensity to Cycle Tool in context

The PCT was developed in the context of growing policy interest directed towards cycling, alongside two branches of academic research: a) methodological developments for estimating cycling potential and b) Planning Support Systems (PSS). The subsequent overview of this policy and academic landscape places the PCT in its wider context and explains the design of its key features.

2.1 The policy context

A number of factors influence the attractiveness of cycling ~~and the rate of cycling~~ for everyday trips (Pucher et al., 2010). ~~Through the case study of~~ There is a wide range of interventions related to infrastructure that can be grouped under the banner 'space for cycling' (Parkin, 2015). These include reducing speed limits, implementing car free zones, early-start traffic lights and barriers passable only by pedestrians and cycles. However, the ~~PCT, this paper explores the ability of strategic transport planning support tools to assist the decision-making process so that cycling investment is spent effectively~~intervention that has received the most attention has been the construction of new cycle paths. In the UK context, devolved transport budgets mean that local authorities have some control over the design and implementation of cycling networks, a potentially powerful policy lever to get people cycling.

~~The Propensity to Cycle Tool (PCT) is an interactive map-based 'planning support system' (Geertman and Stillwell, 2009). As with other previously documented online systems (e.g. Sinnott~~ Planning new cycle paths requires many decisions to be made, including in relation to the width (Pikora et al., ~~2014), the PCT provides a range of information to the user to inform evidence-based policy (Pettit~~ 2002; Wegman, 1979), quality (Heath et al., ~~2013). The PCT differs from previous planning support systems, in its:~~

~~Focus on future scenarios of cycling. Estimation and visualisation of information at the zone and 'desire line' level. Route-allocation of cycling 'desire lines' from origin destination data ('OD pairs'), enabling specific routes to be identified for improvement.~~

~~The PCT was commissioned by the UK's Department for Transport to identify "parts of the country Englandwith the greatest propensity to cycle " to help prioritise strategic investment in active travel (Department for Transport~~ 2006), ~~2015). Part of the contract involved user testing sessions. Feedback from over 70 practitioners and policy-makers provided: (i) confirmation of the tool's utility for decision-making; (ii) input into the tool's user interface; and (iii)ideas for future development.~~

~~The PCT is the first online and interactive planning support system to focus explicitly on cycling. The computer code underlying the PCT is open source, enabling the methods described in this paper to be reproduced. With access to appropriate data (described in the next section) and R programming skills,~~ directness (CROW, 2007) and geographic location of the ~~PCT can be deployed in new contexts. The codebase underlying the PCT is publicly available at under the conditions of the MIT license. The aggregate level OD model underlying the PCT was written in R (R Core Team, 2015). The interface was written in **shiny**, an R package for creating online web applications for data visualisation~~

~~(Chang et al.,~~ paths. Yet while much guidance has been produced regarding the physical design of cycle paths (e.g. Transport for London, 2015~~).~~ ; Welsh Government, 2014), little work has explicitly tackled the question of where high quality infrastructure should be built (Aultman-Hall et al., 1997; Minikel, 2012). Within this policy context, the PCT focuses explicitly on the question of *where* to build rather than *what* to build, although it does provide evidence on potential capacity requirements across the route network.

~~The PCT is a *strategic* transport planning tool. Its policy-relevance stems from its ability to develop, compare and visualise various scenarios for cycling futures at city to national levels. Unlike 'microscopic' transport models such as SUMO and PTV VISSIM, which simulate vehicular traffic in real time (Behrisch et al. , 2014; Krajzewicz~~

2.2 Research into cycling potential

The growing evidence base regarding the impact of infrastructure on cycling raises the question of how to 'operationalise' this body of knowledge, to help planners prioritise where to invest. This research gap was described by Larsen et al. ~~, 2014), the PCT is scalable to the national level. The PCT isalso able to estimate cycling potentialat relatively fine-grained (and flexible) levels of geographic resolution.~~

~~Unlike McCollum and Yang (2009) and other national-level scenario-based approaches, the PCT allows estimation of where new cycling trips are most~~ (2013), who identified an "absence of research into how to systematically prioritise and locate facilities that are to be built". There is, however, an emerging literature exploring cycling potential. This links to the question of 'where to build' because areas and routes with the highest potential are likely to be ~~generated given predetermined overall increases in cycling. This makes the tool especially well-suited to local-level analysis of the impacts of achieving a target level of cycling (typically measured as a proportion of all trips) . For example, our 'Government target' scenario assumes a doubling in the level of cycling in England (DfT~~ cost-effective places for investment.

With the notable exceptions of Larsen et al. (2013) and Zhang et al. (2014)~~. The PCT provides a method to answer the question: if cycling increases by 'x' nationally or regionally, how much is cycling likely to increase locally? More specifically: along which routes would the new cycle trips plausibly occur?~~ , this body of research has not provided systematic or quantitative evidence for transport planners. The methods broadly fit into three categories depending on the level of the input data used:

~~This ability to model propensity to cycle at the OD level is one important, and novel, feature of the PCT. An 'OD pair' in this context can be represented visually as a 'desire line'. This is a straight line connecting the origin (O) with the destination (D) (Chan and Suja, 2003). These concepts are related to the common T_{ij} matrix notation in transport modelling, which represent the number of trips between OD pairs (Ortúzar and Willumsen, 2001; Simini et al., 2012). The model simulates the proportion trips made by cycle between OD pairs, enabling visualisation of cycling~~

- Area-based measures are based primarily on data at the level of administrative zones. Outputs from these measures can assist with the location of site-specific transport infrastructure such as cycle parking.

- Individual-based measures are based on individual level survey data, typically a household travel survey. These are not always geographically specific and tend to be used to identify and categorise demographic groups in relation to cycling, such as near-market or as warranting tailored interventions, such as targeted cycle training schemes.

- Route-based measures use origin-destination data which can be used to create 'desire lines' ~~, whereas previous approaches to modelling cycling potential have tended to focus only on area-based measures.~~ and (using route allocation) estimates of existing and potential demand at each point on the road network.

This work is reviewed in relation to the PCT below and summarised in Table 1.

Parkin et al. (2008) ~~, for example, used a multiple~~ presented an area-based measure of cycling potential that used a regression model to estimate ~~levels of commuter cycling at an area level. Similarly local survey data has been used to identify areas with high numbers of 'potentially cyclable trips ' in London (Transport for London, 2010). However, neither analysis identified the travel corridors along which these simulated cycle trips would be made.~~

~~More localised approaches, which use information about the route network and the trajectories of cyclists using GPS data, also have great potential for creating an evidence-base for prioritising investment in cycle paths locally (Broach et al. , 2012; Ehrgott~~ the proportion of commuter trips cycled across wards in England and Wales. Factors associated with lower levels of cycling included road defects, high rainfall, hills and a higher proportion of ethnic minority and low-income inhabitants. Parkin et al. ~~, 2012). However, a key limitation of many models is that the results are not presented in a form that is dynamic or accessible to transport planners. By allocating the results of an individual-level regression model to the route network, a method presented by~~ concluded that policy makers must engage with a mixture of physical and social barriers to promote cycling effectively, with the implication that some areas have lower barriers to cycling — and hence higher propensity to cycle — than others.

Zhang et al. (2014) ~~was able to prioritise routes~~ created an individual-based model of cycling potential to prioritise where to build cycle paths to "achieve maximum impacts early on". The ~~PCT differs by operating at the OD level for scalability.~~

~~Results for each scenario are pre-calculated, enabling the outcome to be displayed rapidly; calculating the results 'on-fly' would lead to an unresponsive interface. The user is not required to specify any numerical parameters to interact with the PCT. The only software needed for users to run the PCT is a web browser, reducing a key technological barrier to transport planning. The PCT's open source approach reduces two additional barriers~~

~~to effective use of transport planning software: cost and access to source code. The PCT is part of a wider trend in transport research towards greater transparency in software development and collaboration (Novosel et al., 2015; Tamminga et al., 2012). Thisopen source approach~~outputs of this model were aggregated to the level of 67 statistical zones in the study area of Belo Horizonte, Brazil, and used to generate a 'usage intensity index' for potential cycle paths. This, combined with ~~the widespread availability of OD data (as discussed in the next section), should make the PCT easy to deploy in new contexts.~~

3 ~~Data~~

~~The PCT relies on two key input datasets:~~

~~*Origin-destination* (OD) data relating the number of trips taking place between administrative zones. These can be represented as straight 'desire lines' or allocated to the route network. *Geographical data* providing the coordinates of trip origins and destinations.~~ survey data on cyclists' stated preferences on whether people would cycle were infrastructure provided along particular routes and origin-destination data on travel to work, was used to rank key routes in the city in terms of their cycling potential.

~~The OD model described in this paper can work for anywhere that has access to such data. Hilliness and route network distance were also included in the regression model. To link the OD and geographic datasets together, *zone ids* are needed in both datasets. An R package,~~ ~~**stplanr**, was developed~~ While the methods presented by Parkin et al. (2008) and Zhang et al. (2014) were developed in an academic context, albeit closely related to policy needs and interests, the Analysis of Cycling Potential (ACP) tool was developed by practitioners (Transport for London, 2010). The ACP combined area and individual-level data to produce a heat map estimating cycling potential across London, UK, for ~~this purpose and other data manipulation challenges.~~

~~Tables 1 and 2 illustrate the two input datasets. Fig. 1 shows the output, straight lines with attributes for each OD pair in both directions. These are also referred to as 'desire lines' when represented as straight lines on the map (Chan and Suja, 2003; see Tobler, 1987~~all trip purposes. The underlying model examined which types of trips are most likely to be cycled, based on the characteristics of observed cycle trips (e.g. time of day, characteristics of the traveller, distance). The ~~visualisation of the OD data builds on published work on cartographic visualisation (Rae, 2009; Wood~~ results of the ACP have informed local cycling schemes, such as where to build new cycle hire stations. The ACP does not use origin-destination data directly or route allocation.

Again working within academia but also closely focused on local planning and policy issues, Larsen et al. ~~, 2010). The model for England described in this paper uses the following open datasets (similar OD datasets are available for cities across the world) :~~

~~OD data representing the~~ (2013) created an area-based 'prioritization index', for Montreal, Canada. This was based on four variables: the area's current level of cycling, its cycling potential (estimated based on the shortest path between the origin and destination of short car trips from a travel survey), the number of ~~trips between origin destination pairs, disaggregated by mode of travel. We used the file `wu03ewSUBSCRIPTNBv2.csv`, obtained from the UK Data Service (see Table 2 for a sample of this dataset)~~[1] ~~This dataset is from the English Census 2011 on travel to work. Note the origin and destination codes in some rows are the same, indicating *intra-zone* travel. The population-weighted centroids of local administrative zones (see Table 1~~injuries to cyclists, and locations prioritised by current cyclists for improvement (Larsen et al., 2013). The method used to combine these four sources was rasterisation, whereby the information was aggregated to the level of evenly spread cells covering the study area. The resulting heat map was used to recommend the construction or upgrade of cycle paths on specific roads.

A more localised approach is the Permeability Assessment Tool (PAT), which was developed

[1] ~~See .~~

by a transport consultancy Payne (2014). The PAT is based on the concept of 'filtered permeability', which means providing a more direct route to people cycling than driving (Melia, 2015). ~~We used 'Medium Super Output Areas' (MSOAs), with an average population of around 7, 800 people~~ The PAT works by combining geographical data, ~~as the zonal system for both origins and destinations. MSOAs were the highest geographical resolution at which the mode-specific OD datawere available. MSOA zone boundaries were provided under the UK's Open Government Licence.~~[1] ~~Route distance, assigned to each desire line using the CycleStreets.net API.~~[1] ~~Hilliness of zones and routes. There are various ways to generate this data, ranging from the simple (e.g. vertical displacement between origin and destination) to the complex (e.g. total amount of climb along the route network in both directions). We calculated mean gradient per MSOA zone using publicly available digital elevation model (DEM)data supplied by NASA.~~[1] including the location of popular destinations and existing transport infrastructure, with on-site audit data of areas that have been short-listed. Unlike the prioritisation index of Larsen et al. (2013), which is primarily aimed at informing a city-wide strategic cycling network, the results of the PAT are designed to guide smaller, site specific interventions such as 'contraflow' paths and cyclist priority traffic signals.

~~Sample of the OD input dataset, representing the number of people who commute from locations within and between administrative zones (MSOAs)id Area.of.residence Area.of .workplace All~~

~~Overview of the PCT map interface. The lines represent trips between origin and destination pairs for Coventry. Width represents the total number of trips. Note the use of population-weighted (as opposed to geographic) centroids for the point of departure and destination.~~

[1] ~~See .~~

[1] ~~To implement this functionality in a generalisable way a custom function, `routeSUBSCRIPTNBcyclestreet()`, was written for the R package **stplanr**.~~

[1] ~~See for the data and the file in the project's repository for the processing algorithm used. "Version 4" of the dataset was used. To allocate this area-based hilliness metric to OD pairs, we calculated the average hilliness of origin and destination zones. This method has the disadvantage that accuracy decreases with increased trip distance.~~

2.1 Planning support systems

~~We used the Census 2011 travel to work dataset for its comprehensive coverage of the population, high geographic resolution and assurances surrounding data quality.~~ The methods and tools for estimating cycling potential outlined in Table 1 were generally created with only a single study region in mind. The benefit of this is that they can respond context-specific to practitioner and policy needs. However, the aim of the PCT was to provide a *generalisable* and *scalable* tool. To do so we drew on the tradition of Planning Support Systems (PSS).

~~A variety of emerging sources can also provide OD data, including 'Big Data' from commercial companies. These alternative sources of OD data include: mobile telephone service providers (Smoreda et al.~~ PSS were initially developed to encourage evidence-based policy in land-use planning (e.g. Klosterman, 1999). The application of PSS to transport planning has been more recent, with a goal of "systematically [introducing] relevant (spatial) information to a specific process of related planning actions" (Brömmelstroet and Bertolini, 2008). The PCT is systematic in its use of national data for all parts of the study region (in this case England) and relates to a specific planning process — the creation of new and enhancement of existing cycle infrastructure.

PSS typically work by presenting evidence about the characteristics and needs of study region in an interactive map. A central objective is to visualise alternative scenarios of cycling uptake and explore their potential impacts. The results of traditional scenario-based models are typically not presented locally at area, let-alone route-specific, levels (Lovelace et al., 2011; McCollum and Yang, 2009; Woodcock et al., 2009). Online PSS can overcome this issue by using interactive maps to show local manifestations of different scenarios (Pettit et al., ~~2013); public transport data (Kitchin,~~ 2013~~); household travel surveys (Transport for NSW, 2014) ; geolocated social media (Stefanidis et al., 2011).~~

3 ~~Data manipulation and modelling~~

2.1 ~~Geographic data~~

~~To ensure reproducibility and enable deployment of the model outside the original case study cities, a systematic data loading method was developed. The computational work to load the various datasets was developed in a series of modular scripts that were subsequently integrated into a single script: `load.Rmd`. This approach ensures that each component of the data (e.g. OD data, administrative zones, topography data)can be loaded separately with a single 'master' script to bring together the diverse data sources.~~[1]

~~Instead of running the model for the entirety of England, the loading script, OD model and output visualisations were run on a region-by-region basis. This was to prevent overloading the computer with national data and to focus attention on the level at which funding is allocated. Using only one regional geographic level could, however, reduce emphasis on 'edge zones' that straddle two or more regions.To overcome this issue it is worth considering using more than one regional geographical system.A modified version of the model could be run at the national level. Another solution to the problem of 'edge zones'is to create buffers around the regions (as discussed below~~). The emergence of libraries for web mapping (Haklay et al., 2008) has facilitated online PSS, offering the potential for public access to the planning process. Transparency is further enhanced by making PSS open source, in-line with a growing trend in transport modelling (Borning et al., 2008; Novosel et al., 2015; Tamminga et al., 2012). In these ways, PSS can make evidence for transport planning more widely available, and tackle the issue that transport models are often seen as 'black boxes', closed to public scrutiny (Golub et al., 2013).

~~The data above were loaded on a region-by-region basis, not for the entire country at once. This was partly because transport decisions (such as where to build new cycle routes)~~

[1] ~~See for a full list of the loading scripts used for the PCT.~~

~~tend to be made at the local level (Gaffron, 2003) and partly to reduce the computational requirements (particularly use of RAM) for scalability. In many cases the choice of region to use is not straightforward, however. This is shown in Fig. 2, which illustrates the decision that must be made between larger and smaller regional units.~~

2.1 National context and features of the Propensity to Cycle Tool

~~The regional units used to iteratively load the geographical data. These were English Local Authority Districts (LADs, above) and County and Unitary Authorities (CUAs, below) levels of transport planning.~~ In addition to the international policy and academic context, the PCT was influenced by the national context. It was commissioned by the UK's Department for Transport to identify "parts of [England] with the greatest propensity to cycle" (Department for Transport, 2015). Thus the aim was not to produce a full transport-land use model, but to provide an evidence base to prioritise where to create and improve cycling infrastructure based on scenarios of the future.

2.2 ~~Variable zone and OD pair selection criteria~~

Local and national cycling targets are often based on a target mode share by a given date.[1] However, there is little evidence about what this might mean in for cycling volumes along specific routes. The PCT tackles this issue by estimating rate of cycling locally under different scenarios and presenting the results on an interactive map. Its key features include:

~~Flows assigned to the transport network were generated when OD pairs were mapped onto the current travel network. This network-level data generation was undertaken~~

- Estimation of cycling potential at area, 'desire line' and route network levels.

[1] The local target in Bristol, for example, is for 20% of commuter trips to be cycled by 2020. Manchester (10% by 2025), Derbyshire (to double the number of people cycling by 2025) and London (to 'double cycling' by 2025) provide further examples of local ambitious time-bound cycling targets.

- Route-allocation of OD (origin-destination) pairs by a routing algorithm specifically developed for cycling. This was done by CycleStreets.net~~(~~, a routing service ~~for planning cycle trips), constituting the most computationally intensive part of the model.~~

  ~~To reduce data processing and visualisation times a sub-sample of OD pairs was used. The aim was to reduce the number of OD pairs whilst retaining the overall travel pattern.To do this a minimum number (labelled `mflow`)of trips between OD pairs was specified. OD pairs with less than `mflow` trips were removed from the analysis.This followed the insight that the distribution of number of commuters per OD pair is skewed: a relatively small number of OD pairs along major travel corridors account for a disproportionately high proportion of travel. In the City of Manchester~~developed by cyclists, for cyclists.

- Visualisation of outputs at multiple geographic levels. The interactive map enables users to examine cycling potential at a very local level (e.g. just a few streets) or at a more regional level (e.g. across a large metropolitan area).

- Public accessibility of results and code. The tool is freely available online and developers are encouraged to modify the PCT (e.g. to create alternative scenarios) by provision of the source code underlying the PCT under the open source AGP License.

- The presentation of estimated benefits under future scenarios, for example ~~, setting `mflow` to 30 reduced the number of OD pairs by 85, yet still accounted for almost 70of commuters. Different values for `mflow` were tested to reach a reasonable balance between comprehensive coverage and speed of saving and loading data . Another way to subset OD pairs is to set the maximum Euclidean (or "crow-flies") distance between ODpairs (labelled `mdist`) . We tested various values for `mdist` and settled on 15 km. This translates to around 20 km on the route networkassuming a *circuity* (Iacono et al. , 2010) value of 1.3. From the Great Britain National Travel Survey, only 1.1of~~

~~cycle commutes in Britain exceed this distance.~~ via impacts on public health and carbon emissions, enabling interventions to be designed based on specific health and environmental policy goals

2.2 ~~The regression model~~

As with any tool, the PCT's utility depends on people knowing how to use it. For that reason training materials and a user manual are being developed to show how the tool can be used (see the 'Manual' tab in Figure 3 and pct.bike/manual.html).

~~Once the input data (discussed in the previous section) has been processed and sub-setted to~~

3 Data and methods

This section describes the data and methods that generate the input data for the PCT. This is summarised in Figure 1 and described in detail in the Appendix. Central to the ~~area of interest, it is passed to a regression model.~~ PCT approach is origin-destination (OD) data recording the travel flow between administrative zones. Combined with geographical data on the coordinates of the population-weighted centroid of each zones, these can be represented as straight 'desire lines' or as routes allocated to the transport network.

~~For all scenarios except *gender equality*, a regression model was used to estimate the potential rate of cycling at the OD level . It does so using Ordinary Least Squares (OLS)to optimize a number of model parameters linking distance (*d*~~

3.1 Processing OD data

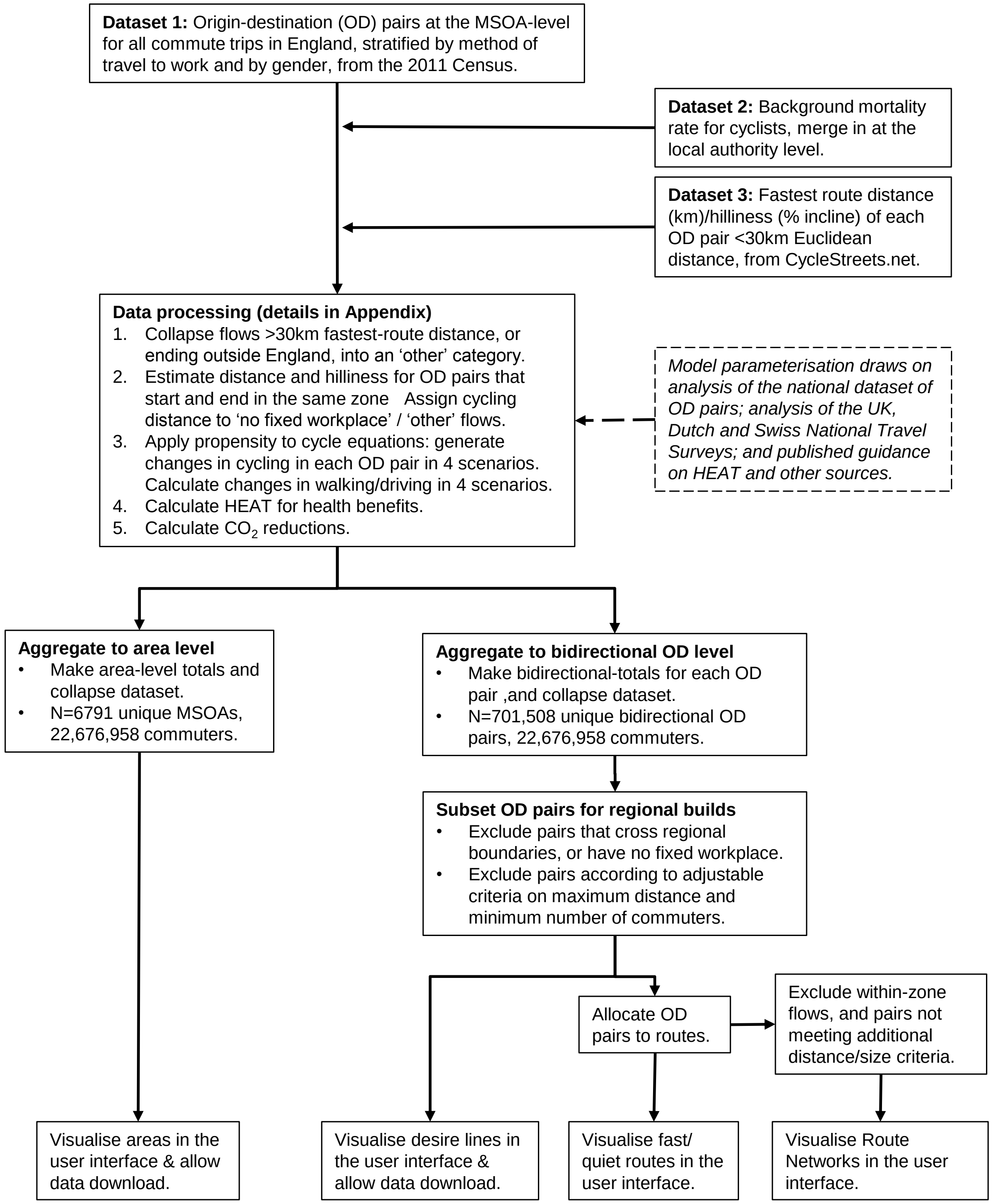

Figure 1: Flow diagram illustrating the input data and processing steps used to create the input data used by the PCT. The abbreviations are as follows. HEAT = Health Economic Assessment Tool, OD pair = origin-destination pair, MSOA = Middle-Layer Super Output Area

The central input dataset was a table of origin-destination (OD) pairs from the 2011 Census. This was loaded from open access file `wu03ew`
`SUBSCRIPTNBv2.csv`, provided by the UK Data Service. This captures the number of commuters travelling between Middle Super Output Area zones (MSOAs, average commuter population: 3300), by mode of travel (see Table 2). This dataset was derived from responses to the following questions in the English 2011 Census: “In your main job, what is the address of your workplace?” (question 40) and “How do you usually travel to work? (Tick one box only, for the longest part, by distance, of your usual journey to work)” (Question 41). This dataset was enhanced by merging in information on the gender composition of cyclists in each OD pair (Dataset 1 in Figure 1); data at the area level on the background mortality rate (Dataset 2); and data at the OD pair-level on route distance (km) and hilliness (~~*H*) to the *dependent variable*: the proportion of trips made per OD pair (*pcycle*~~average gradient, in %) (Dataset 3). The ~~concept of ‘distance decay’ (Martínez and Viegas, 2013) was used in the model to describe the (non-linear) relationship between the route distance of OD pairs and the proportion of trips made by cycling. Euclidean distance could be used in contexts where route distance is not known.~~

~~It is well-known that *pcycle* tends to decrease with increasing distance (Iacono~~ latter data was assigned to OD pairs using the ‘fastest’ option on CycleStreets.net, using the R package stplanr (Lovelace et al., ~~2010). Based on this work and exploratory analysis of the data we estimated the *log* of *pcycle* rather than *pcycle* directly. Hilliness was included as a continuous variable in our model and was expected to have a linear impact on *pcycle*. The formula chosen was:~~

$$log(pcycle) = \alpha + \beta_1 d + \beta_2 d^{0.5} + \gamma H$$

2016). See the Appendix for further details.

~~where *d* is distance (km, route distance between population weighted centroids) and *H* is~~

~~the hilliness(average angular degrees of origin and destination zones) per OD pair. The remaining values are scalar coefficients to be estimated. α represents the intercept (the rate of cycling very short trips). β_1 (which must be negative for *pcycle* to tend to zero as distance tends to infinity) and β_2 represent the rate of distance decay. γ represents the impact of hilliness on cycling. A 'quasipoisson' general linear model was used to implement this formula using the base R function `glm`, which predicts $log(pcycle)$ to account for the aforementioned exponential decay.~~

3.2 ~~Zone Buffer~~

3.2 Modelling cycling potential

~~Running the PCT region-by-region means ignoring all the MSOA zones outside the region.If the region is a self-contained transport system this will not create problems. If the region is part of a larger conurbation, however, the clipping could be problematic. To solve this problem we created buffer zones around each region, from which additional zones were sampled in regions in which the number of MSOA zones fell below some threshold, chosen to be 60. For example, this meant that additional zones were selected outside the City of Manchester, which has 57 MSOAs (see Fig. 7 below). This protocol increased the sample size by including all zones whose population-weighted centroid lies inside the buffer, the width of which can also be pre-specified~~The starting point for generating our scenario-based 'cycling futures' was to model current cycle commuting in England. We did this using OD data from the 2011 Census, and modelling cycling commuting as a function of route distance and route hilliness. We did so using logistic regression applied at the individual level, including squared and square-root terms to capture 'distance decay' — the non-linear impact of distance on the likelihood of cycling (Iacono et al., 2008) — and including terms to capture the interaction between distance and hilliness. Model fit is illustrated in Figure 2; see Appendix for details and for the underlying equations. We also developed equations to estimate commuting mode

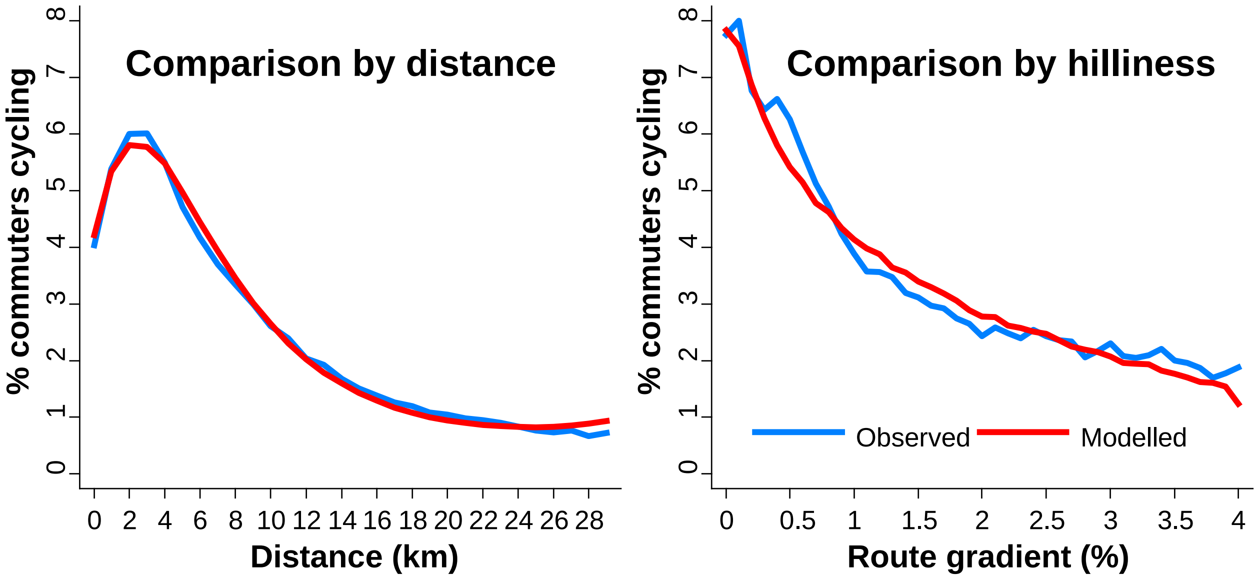

Figure 2: The relationship between distance (left) and hilliness (right) and cycling mode share in England based on the the 2011 Census. The plots show actual (blue) vs predicted (red) prevalence of cycling to work among 17,896,135 English commuters travelling <30km to work.

share among groups not represented in the between-zone ('interzonal') OD data, e.g. those commuting within a specific MSOA (this is within-zone or 'intrazonal' travel), or those with no fixed workplace. This model of current cycling levels formed the basis of three of the four scenarios (Government Target, Go Dutch and Ebikes; see below), with model parameterization drawing additionally on English, Dutch and Swiss travel survey data.

3.3 ~~The Model Output tab~~

~~Users can view a summary of the model via the 'Model Output' tab (Fig. 3). The tab was added in response to feedback during the user testing sessions. The output tab communicates the results of the model, including key statistics, diagnostic plots and model-results on a per-region basis. This means that a different summary document is provided depending on which local authority the user is currently exploring.~~

~~The Output Tab of the Propensity to Cycle Tool~~

4 ~~Model scenarios~~

~~Scenarios were developed to indicate how local cycle use could increase. Current constraints to cycling, including the aforementioned factors of distance and hilliness, can to some degree be overcome by new technology (see the *ebike* scenario below).~~

3.1 Scenarios of cycling uptake

~~The four scenarios developed for the case study cities were developed to explore different cycling futures in England. Because time-scales are not specified, they are not necessarily mutually exclusive.~~ Four scenarios were developed to explore cycling futures in England. These can be framed in terms of the removal of different infrastructural, cultural and technological barriers that currently prevent cycling being the natural mode of choice for trips of short to medium distances. They are not predictions of the future. They are snapshots indicating how the spatial distribution of cycling may shift as cycling grows based on current travel patterns. At a national level, the first two could be seen as shorter-term and the second two more ambitious. The choice of scenarios was informed by a government target to double the number of cycle trips and evidence from overseas about which trips *could* be made by cycling. Summaries of the four scenarios are as follows (see the Appendix for full details):

- Government ~~target (*govtarget*)~~Target. This scenario represents a doubling of the ~~number of cycling trips in England . Although this is a substantial increase~~ level of of cycling in England (Department for Transport, 2014). Although substantial in relative terms, ~~cycle use still remains low in this scenario compared with countries such as the Netherlands,~~ the rate of cycling under this scenario (rising from 3% to 6% of ~~commutes. *govtarget* allows for different rates of growth in different places. Above-average percentage increases (i.e. more than a doubling) are projected in areas~~ commuters) remains low compared with countries such as the Netherlands and Denmark. Growth in cycling is not uniform in this scenario, in either absolute or relative terms. Areas with many short~~(i.e. potentially cyclable)~~ , flat trips and a ~~low~~ below-average current rate of cycling are projected to more than double. Conversely, areas with ~~higher cycle use and a low proportion of short commutes will have below-average growth. *govtarget*~~ above-average levels of cycling and many long-distance hilly commuter routes will experience less than a doubling. Government Target thus represents a slight reduction (but not elimination) of ~~the localised infrastructural or cultural constraints which deter cycle use more in some places than in others. It therefore indicates where investment in increased cycle use might achieve the greatest impact in the short term~~local barriers to cycling. This scenario may be useful for indicating where investment might have the greatest short-term impact.

- Gender Equality~~(*gendereq*)~~. This scenario illustrates the increase in cycling that would result if women ~~cycled as much as men , all other variables being equal~~were as likely as men to cycle a given trip. Specifically, the scenario sets the proportion of female cycle commuters to be equal to the current proportion of males in each OD pair. The scenario is based on the observation that in places where cycling ~~is the norm~~accounts for a high proportion of personal travel, women cycle at least as much as men (Aldred et al., 2016; Pucher et al., 2010). ~~*gendereq* thus represents the elimination of one specific cultural constraint.~~ This scenario has the greatest relative impact in areas where the rate of cycling is highly gender-unequal~~(Fig. 4). In absolute terms, cycling increases most in this scenario where cycling is already a common mode of transport~~.

- Go Dutch~~(*godutch*). While *govtarget* and *gendereq* build on current cycling behaviour, the *godutch* scenario focuses on long-term potential. The 'Go Dutch ' scenario models~~ . While the Government Target and Gender equality scenarios model relatively modest increases in cycle commuting, Go Dutch represents what would happen if English people were as likely ~~to cycle for a given trip (i.e. of the same distance and hilliness) as Dutch people, by applying Dutch distance decay curves to English travel patterns. The scenario represents the elimination of the infrastructural and cultural constraints which currently hold back cycle use in England, including all localised differences. So, unlike the *govtarget* and *gendereq* scenarios, the predicted levels of cycle use in *godutch* are unrelated to current levels, and are constrained only by local trip distance distributions and hilliness.~~ as Dutch people to cycle a trip of a given distance and level of hilliness. This scenario captures the proportion of commuters that would be expected to cycle if all areas of England had the same infrastructure and cycling culture as the Netherlands (but retained their hilliness and commute distance patterns). The scenario level of cycling under Go Dutch is not affected by the current level of cycling.

- ~~E-bikes (*ebikes*)~~Ebikes. This scenario models the additional increase in cycle use that would be achieved through the widespread uptake of electric cycles~~('E-bikes'). E-bikes~~. Electric assist cycles enable longer journeys and ~~make cycling a more viable option for a number of people, including those with low fitness and people with impaired mobility~~reduce the barrier of hills. This scenario is ~~based on the Go Dutch scenario~~currently implemented as an extension Go Dutch but could be implemented as an add-on for other scenarios.

~~These scenarios are described more fully below. They are not intended to be definitive scenarios of cycling futures in England or anywhere else; we encourage users of the PCT to develop new scenarios relevant to new contexts~~Additional scenarios could be developed (see Discussion). If deployed in other settings, the PCT will likely benefit from scenarios that relate to both the current policy context and long-term aspirations.

3.2 ~~Government Target~~Estimation of health and carbon impacts

~~The Government Target scenario (*govtarget*) is~~ An approach based on the ~~UK government's proposed target (as set out in its draft Cycling Delivery Plan (Department for Transport, 2014)) to double cycling in England, from 0.8 billion stages currently to 1.6 billion stages by 2025. However Department for Transport (~~the World Health Organization's Health Economic Assessment Tool (HEAT) was used to estimate the number of premature deaths avoided due to increased physical activity (Kahlmeier et al., 2014)~~says nothing about where these additional trips would come from. The *govtarget* scenario is therefore based on our own assumptions about this. It aims to assist transport planners in identifying where new demand for cycling is likely to be greatest in the near term.~~

~~The key point about this scenario is that cycling does not double in all areas. Instead,~~. To allow for the ~~increase is related to the current commuter trips and the trip distance.~~

~~At the heart of the *govtarget* scenario is the previously discussed regression model (labelled *natmod*) estimating the dependent variable (*pcycle*). The new rate of cycling (*pcycle*(*govtarget*)) is the current rate of cycling plus this model-based estimate:~~ fact that cycling would in some cases replace walking, HEAT estimates of the increase in premature deaths to the reduction in walking were also included (see the Appendix). To model the change in walking, we assumed that within a given OD pair all modes were equally likely to be replaced by cycling. Thus all the non-cycling modes shown in Table 2 experienced the same relative decrease.

$$pcycle(govtarget)_{ij} = (pcycle_{ij} + pcycle(natmod)_d)$$

Trip duration was estimated as a function of the 'fast' route distance and average speed. For walking and cycling we applied the standard HEAT approach. Ebikes are not specifically covered in HEAT Cycling but enable faster travel and require less energy from the rider than traditional bikes. Thus we estimated new speeds and intensity values for this mode, giving a smaller benefit for every minute spent using Ebikes than conventional cycles. For more details see the Appendix.

~~where $pcycle_{ij}$ is the~~ The risk of death varies by gender and increases rapidly with age. This was accounted for using age and sex-specific mortality rates for each local authority in England, for all ages from 16-74 years. The assumed age and sex profile of new cyclists also varied between scenarios. For the baseline and Government Target scenario the age-gender distribution of cyclists recorded in the 2011 Census was used. New cyclists under Gender Equality were assumed to be female, with the age profile of existing cyclists in the 2011 ~~Census proportion of commuters who cycle for an OD pair ij of distance d apart and $pcycle(natmod)_d$ is the proportion of commuters expected to cycle the distance d based on the national-level regression model. The sum of these values can be multiplied by the total number of commuters for all modes $tflow_{ij}$ to convert the proportion into a number of cyclists, i. e. :~~

$$SLC(govtarget)_{ij} = (pcycle_{ij} + pcycle(natmod)_d) * tflow_{ij}$$

~~where $SLC(govtarget)_{ij}$ is the *Scenario-based Level of Cycling* for this scenario for the ij OD pair. An example of this scenario for an imaginary OD pair ab with Euclidean distance 4.5 km is as follows. Based on a representative sample of OD pairs in the UK and under the 'national doubling', assume an additional 5of commuters now cycle for all trips of 4.5km — i.e. $pcycle(natmod)_{4.5} = 0.05$. For our OD pair ab in the Census there are 200 commuters of which 2 are cyclists , $pcycle_{ab} = 0.01$. Applying the scenario adds an additional 5of commuters which represents an additional 10 cyclists , far more than doubling. The same methodology is applied to all distances represented in the OD matrix.~~

~~The approach assumes that cycling potential against a given national increase is always a positive number.~~ Census. New cyclists under Go Dutch and Ebikes were assumed to have the age-gender profile of commuter cyclists in the Netherlands. The ~~larger the increase in cycling for the scenario, the less the current level matters. By contrast, the larger the current rate~~

~~of cycling,~~ inclusion of age specific parameters and mode shift from walking show how the HEAT approach can be applied in a nuanced manner using only routine, publicly available data and provides a valuable evidence source for the development of local business cases.

The net change in the ~~lower the impact this scenario has on the future rate of cycling~~number of deaths avoided for each OD pair was estimated as the number of deaths avoided due to cycle commuting minus the number of additional deaths due to reduced walking. Note that this approach means that for some OD pairs where walking made up a high proportion of trips, additional deaths were incurred. The monetary value of the mortality impact was calculated by drawing on the standard 'value of a statistical life' used by the Department for Transport.

~~Our implementation of the *govtarget* scenario is thus in line with findings from Sloman et al. (2014) and Heinen et al. (2015), who found that it is initially easier to achieve growth in cycle use in places where cyclingis already common. However, with sustained investment in overcoming the infrastructural and cultural constraints which limit cycle use, there is great long-term potential for increased cycling in many areas that currently have a low rate of cycling. This is modelled in the Go Dutch scenario (described after the *gendereq* scenario)~~ We also estimated the reduction in transport carbon emissions resulting from decreased car driving in each scenario. This again relied on the assumption that all modes were equally likely to be replaced by cycling.

3.3 ~~Gender equality~~

~~The next scenario to be discussed is Gender Equality (*gendereq*). In this scenario cycling tends to grow more in areas that already have a high rate of cycling. The scenario recognizes that this disparity is reduced or absent in countries with a high rate of cycling (Fishman et al.,~~ The average CO^2-equivalent emission per kilometre of car driving was taken as 0.186 kg, the 2015 value of an 'average' car (DEFRA, 2015).

3.3 Visualisation, route allocation and network generation

The data analysis and preparation stages described in the previous sections were conducted using the national OD dataset for England as a whole. By contrast, the stages described in this section (route allocation and visualisation) were conducted using a region-by-region approach. The regional focus was selected because transport decisions tend to be made at the local level (Gaffron, 2003). The regional approach also reduced the computational requirements of the data generation process.

Figure 3 shows a visualisation of the output, straight lines with attributes for each OD pair aggregated in both directions. These represent cycling 'desire lines' (Chan and Suja, 2003; Tobler, 1987). The ~~Gender Equality scenario (*gendereq*) builds on such insights and is based *observed level of cycling* (*OLC*)from the 2011 Census~~visualisation of the OD data builds on published work on cartographic visualisation (Rae, 2009; Wood et al., 2010).

~~On average in England around 3/4 of cycle commuters are male, although this varies geographically (Aldred~~

Desire lines allocated to the route network are illustrated in Figure 4. This shows two route options: the 'fast' route, which represents an estimate of the route taken by cyclists to minimise travel time and the 'quiet' route that preferentially selects smaller, quieter roads and off road paths.

Routes generated by CycleStreets.net do not necessarily represent the paths that cyclists currently take; route choice models based on GPS data have been developed for this purpose (Broach et al., ~~2015~~2012; Ehrgott et al., 2012). ~~*gendereq* assumes that gender equality is reached in cycling. A prerequisite is a model-based estimate of the number of male and female cyclists between origin and destinations for the observed data. This involves splitting the number of cyclistsproject by the model, the *Scenario-based Level of Cycling*, into male~~ ~~$(SLC(gendereq)_m)$ and female $(SLC(gendereq)_f)$components:~~

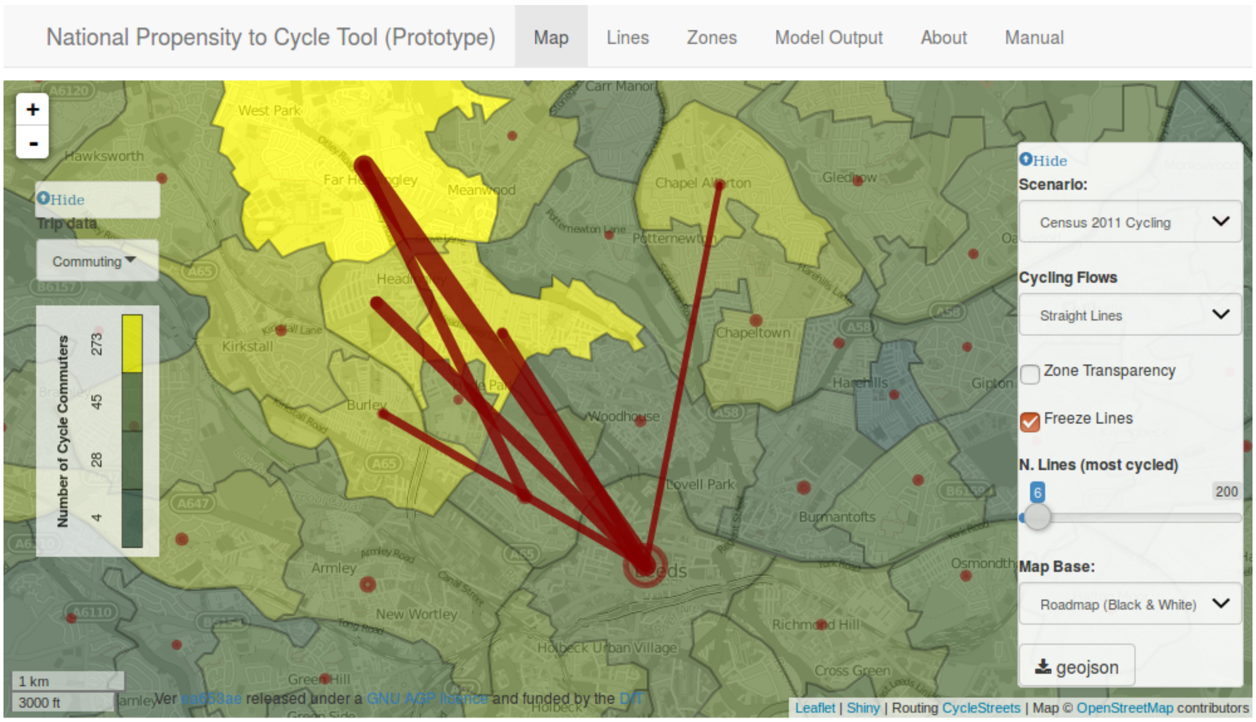

Figure 3: Overview of the PCT map interface, showing area and OD-level data. The zone colour represents the number of residents who cycle to work. The lines represent the top 6 most cycled commuter routes in Leeds, with width proportional to the total number of cycle trips. Population-weighted centroids are represented by circles, the diameter of which is proportional to the rate of within-zone cycling.

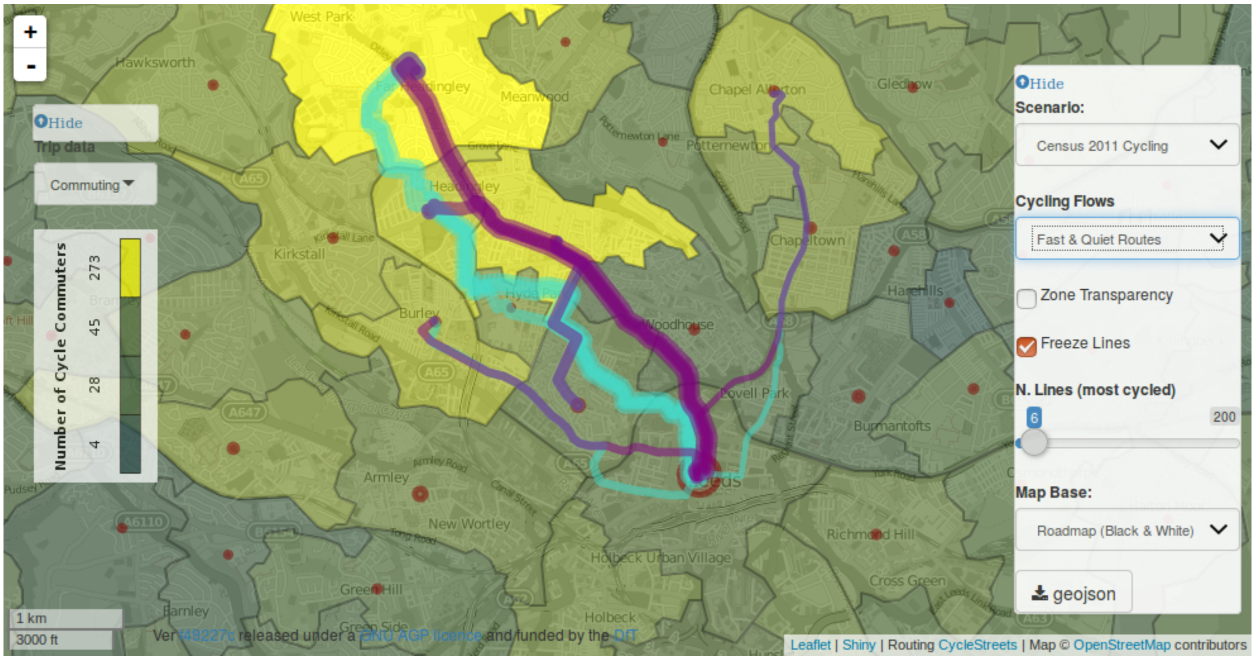

Figure 4: Illustration of desire lines shown in Figure 3 after they have been allocated to the road network by CycleStreets.net. Purple lines are the 'fast' routes and turquoise routes were the 'quiet' routes.

$$SLC(gendereq) = SLC(gendereq)_m + SLC(gendereq)_f$$

Of the available routes provided by CycleStreets.net ('quietest', 'balanced' and 'fastest'; see cyclestreets.net/journey/help for more information), the 'fastest' option was used. This option was chosen because when designing infrastructure, planners should consider cyclists' preference for direct routes (CROW, 2007) and that cycling potential falls quickly with increasing distance.

~~More males cycle to work than females in every Local Authority in England (Fig.~~ The spatial distribution of cycling potential can be explored interactively by selecting the 'top n' routes with the highest estimated cycling demand (see the slider entitled "N. Lines (most cycled)" in Figures 3 and 4). ~~For this reason, the~~ Information about the ~~*gendereqscenario is based on the assumption that the rate of cycling amongst females increases to match the rate of cycling amongst males. Under* gendereq $SLC(gendereq)_m = OLC_m$, *there are no additional*~~

~~*male cyclists. Note that this is not as simple as*~~ $\cancel{SLC(gendereq)_f = SLC(gendereq)_m}$~~*, as the absolute number of female and male cyclists will also depend on the gender split of the total commuting population within each OD pair.*~~[2] ~~*It is the*~~ *aggregate cycling potential* on the road network is shown in the Route Network layer. Because the layer is the result of aggregating overlapping 'fast' routes, and summing the level of cycling for each scenario (see Figure 5), it relates to the ~~*proportionof males and females per OD pair who cycle that becomes equal, as follows.*~~ *capacity* that infrastructure may need to handle. Cycling along Otley Road (highlighted in Figure 5), under the Go Dutch scenario, rises from 73 to 296 along a single route, but from 301 to 1133 in the Route Network. Note that more confidence can be placed in the relative rather than the absolute size of these numbers: the Route Network layer excludes within-zone commuters, commuters with no fixed workplace, and commuters working in a different PCT region because the PCT does not represent these on the travel network (see Figure 1). Route Network values also omit routes omitted due to the adjustable selection criteria: maximum distance and minimum total numbers of all-mode commuters per OD pair. At the time of writing these were set to 20 km Euclidean distance and 10 commuters respectively. This means that routes longer than 20 km or with ten or fewer commuters were omitted. Nationally, the Route Network layer under these settings accounts for around two thirds of cycle commuters.

$$pcycle(gendereq)_f = pcycle_m$$

$$\frac{SLC(gendereq)_f}{tflow_f} = \frac{OLC_m}{tflow_m}$$

$$SLC(gendereq)_f = tflow_f * \frac{OLC_m}{tflow_m}$$

[2] ~~To illustrate this point, consider an OD pair in which the total number of female commuters is larger than the total number of male commuters. In this case, the number of female cyclists would exceed the number of male cyclists in the *gendereq* scenario.~~

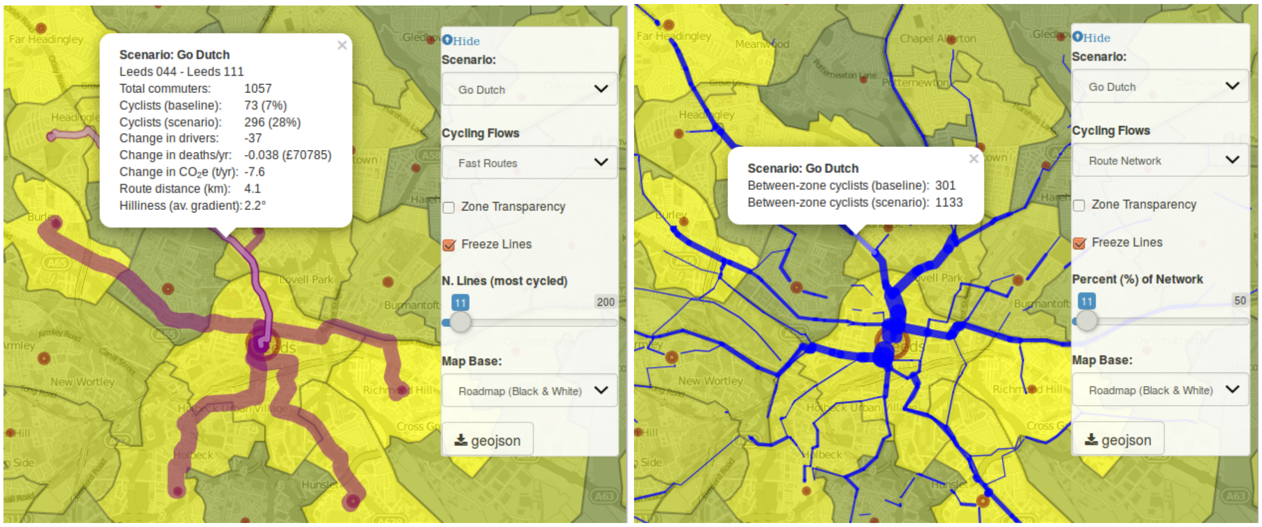

Figure 5: Illustration of route-allocated OD data (left) compared with route network data (right) which was produced by aggregating all overlapping route-aggregated OD pairs, using the 'overline' function from the stplanr R package.

~~OLC_m is the observed number of male cycle commuters (in the 2011 Census in this case), $SLC(gendereq)_f$ is number of female cycle commuters in the gender equality scenario, and $tflow_m$ and $tflow_f$ are the total numbers of males and females in the OD pair respectively.~~

4 Outputs of the Propensity to Cycle Tool

~~$tflow_m$ and $tflow_f$ are both available at the OD level in the 2011 Census, as is the total number of cyclists (OLC). The proportion of cyclists who are male in each OD pair($pmale_(cyclist)$) is not available in the published 2011 datasets. The smallest level at which the gender breakdown of cyclists is currently available is the zone level ('$pmale_{cyclist}(zone)$'), and we assume that all OD pairs have this same proportion of male cyclists. This allows the estimation the number of male cycle commutersas $OLC_m = OLC * pmale_{cyclist}(zone)$, so that~~ This section describes and illustrates some outputs from the PCT, alongside discussion of how these outputs could be used in transport planning. Note that some details of the graphics in the online version may evolve as the PCT develops.

$$SLC(gendereq)_f = OLC * pmale_{cyclist}(zone) * \frac{tflow_f}{tflow_m}$$

4.1 Model output tabs

~~and therefore the total number of trips for gender equality $SLC(gendereq)$ would be~~ Tabs are panels within the PCT that reveal new information when clicked (see the top of Figure 3). Of these, the first four provide region-specific information:

- $$SLC(gendereq) = OLC_m + SLC(gendereq)_f$$

  Map: This interactive map is the main component of the PCT, and is the default tab presented to users. It shows cycling potential at area, desire-line, route and route network levels under different scenarios of the future, as described throughout this paper. 'Popups' appear when zones, desire lines or segments on the Route Network are clicked, presenting quantitative information about the selected element.

- $$SLC(gendereq) = OLC * pmale_{cyclist}(zone) * (1 + \frac{tflow_f}{tflow_m})$$

  ~~Cycling and the gender balance of cycling in England. The choropleth maps illustrate the spatial distribution of the two variables. The scatter plot illustrates the relationship between the two variables cycle commuting (x axis) against the proportion of commuter cyclists who are male (y axis) for all 326 Local Authorities (including Districts) in the UK.~~

  ~~To illustrate how this method works in practice, imagine an OD pair in which 50 from a total of 500 people commute by cycle ($tflow = 500; OLC = 50$). 300 of the total trips in the OD pair are made by males ($tflow_m = 300$) and 200 by~~

~~females ($tflow_f = 200$). In addition, 70of commuter cycling in the wider zone is by males ($pmale_{cyclist}(zone) = 0.70$). This means that an estimated $50 * 0.70 = 35$ cycle commuters are male ($OLC_m = 35$) and 15 are female ($OLC_f = 15$).~~

~~Applying the formulae presented previously:~~

Lines: When lines are displayed on the interactive map, this tab provides the raw data as a table at the OD pair level. Variables shown include the origin and destination zone of the route, current number of commutes by rail, bus, car and bicycle, the increase in cyclists under different scenarios, and geographical data such as straight line distance, hilliness and circuity.

- $$SLC(gendereq)_f = OLC * pmale_{cyclists}(zone) * (1 + \frac{tflow_f}{tflow_m})$$

Areas: This tab is the equivalent of the 'Lines' tab, but with data at the area level.

- $$SLC(gendereq) = 50 * 0.70 * (1 + \frac{200}{300}) = 58.3$$

~~The increase from 50 cyclists to 58.3 represents an increase of 17from the observed rate of cycling in total numbers of cyclists. All of these extra 8.3 cyclists are female, giving a new total of 15 + 8.3 = 23.3 female cyclists (and still 35 male cyclists). Gender equality in cycling has been reached, such that an estimated 11.7of commute trips are made by cycling among both men (35/300) and women (23.3 / 200).~~

4.2 ~~Go Dutch~~

~~The 'Go Dutch' scenario represents the rate of cycling that would occur if people had the same propensity to cycle as the Dutch do, for trips of the same length and hilliness. It is important to note that this is not a 'top down' scenario in which the national~~

~~level of cycling is set to levels found in The Netherlands. The scenario is 'bottom up' because the proportion of trips being cycled is set per OD pair and the end result for any particular region depends on the local distribution of trip distances. Although the Dutch currently cycle far more frequently than the English for short trips, their propensity to cycle still drops rapidly with distance, with relatively few utility trips being made beyond around 15 km.~~

~~Based on these insights, the essence of the 'Go Dutch' scenario is the application of distance decay parameters found in the Netherlands to each OD pair in the study area.~~

~~In contrast to *govtarget* and *gendereq* scenarios, *godutch* is unrelated to the current rate of cycling. The scenario thus represents the elimination of localised constraints which inhibit cycle use more in some area than others. Local cycle use in *godutch* is therefore constrained only by trip distances and hilliness.~~

4.2 ~~E-bikes~~

~~The aim of this scenario was to provide an indication of the rate of cycling increase possible due to the uptake of electric cycles ('E-bikes'). The scenario represents a reduction in the degree to which cycle use is constrained by trip distances. This is the most ambitious and speculative scenario presented in this paper; it builds on 'Go Dutch'.~~

~~The results are~~ **Model output**: This tab includes key statistics, diagnostic plots and model-results on a per-region basis. Since the contents of this tab are created based on the ~~decision to increase by a small amount the β_1 distance decay parameter, that corresponds to distance as a linear term. Specifically, we increased this value by 0.025, as we found this to be sufficiently small to avoid generating an implausibly high rate of cycling but sufficiently large to create a noticeable effect. This allows us to illustrate~~

~~the type of output that will be possible in this model. In future work we plan to update this scenario, basing the changes to the distance decay parameters on real data from the Dutch National Travel Survey. This will build on analysis of the influence of E-bikes on propensity to cycle in the Netherlands that is being undertaken in parallel to the work presented in this paper.~~ data for each regional 'build', it produces a different summary document depending on the region currently being viewed. For each scenario it shows the distribution of cycling by trip distance (see Figure 6), and thereby provides insight into local travel patterns and how they relate to cycling potential in the region overall.

5 ~~Results~~

4.1 Trip distance distributions

~~To demonstrate how the scenarios work in practice and to provide an overview of the results, Fig. 5 illustrates the observed level of cycling (*OLC*, from the 2011 Census)and the scenario-based level of cycling in two Local Authorities (Manchester and Norwich). Note that while Manchester has a much higher total number of trips than Norwich,~~ Figure 6 shows how the proportion of trips made by cycling varies as a function of distance in two regions currently, and under the PCT's four scenarios of change. Examining the distribution of commute trips by all modes (the ~~proportion of those trips that are made by cycling is lower. There is noticeable distance decay for all modes of transport, especially for cycle trips in Norwich, where cycle trips above 7.5 km observed from 2011 census data are comparatively rare~~red lines), it is clear that the two regions have different spatial structures. In Oxfordshire a high proportion of all commute trips are short (under 5km), which helps explain the high rate of cycling there. West Yorkshire, by contrast, has a higher proportion of trips of medium or longer lengths. West Yorkshire also shows a less marked difference in the number of

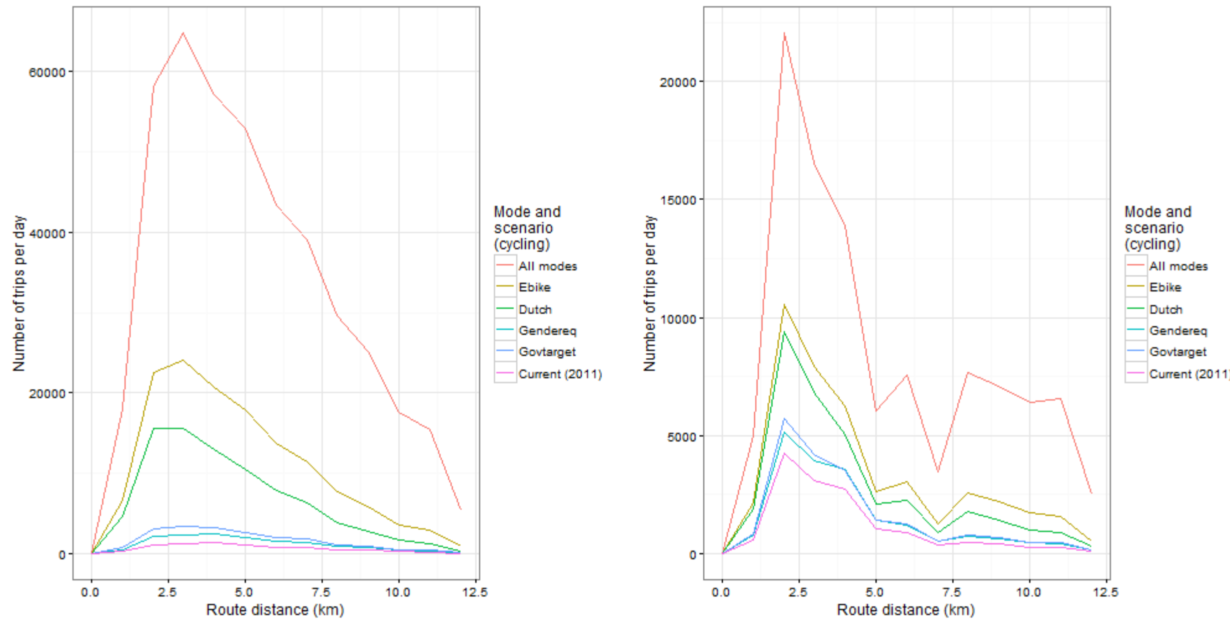

Figure 6: Modal share of trips made by cycling for English commutes in West Yorkshire (left) and Oxfordshire (right) currently and under 4 scenarios of change.

cyclists according to distance than Oxford, as indicated by the comparatively shallow curve for current cycling.

Note that although ~~Manchester and Norwich~~ West Yorkshire and Oxfordshire have very different initial levels of cycling, the ~~final level estimated from the *godutch* and *ebike* scenarios there are similar. This is because trip distance distributions in the two cities are comparable — these~~ estimates under Go Dutch and Ebikes scenarios for each distance band are similar: long-term scenarios are not influenced by the current rate of cycling. ~~Note also that the *govtarget* scenario in Manchester has a considerably higher rate of cycling than the *gendereq* scenario, whereas in Norwich these scenarios are very similar. This is because Manchester is starting from a lower baseline, so a doubling nationwide results in a relatively high absolute increase in cycling locally. In Norwich, by contrast, the current rate of cycling is considerably greater than the national average, so the *govtarget* scenario represents less than a doubling in cycling.~~

~~Results of observed and scenario-based levels of cycling from PCT model runs for the city~~

~~of Manchester (left) and Norwich (right).~~

4.2 The shifting spatial distribution of cycling

The ~~difference between the spatial distribution in cycling potential between the Government Target (*govtarget*) and Go Dutch (*godutch*) scenariosis illustrated in Fig. 6 for Norwich. Note that the top 20 OD pairs in Norwich under *govtarget* assumptions are dominated~~ spatial distribution of cycling potential differs markedly between scenarios, as illustrated in Figure 7 for the city of Leeds, West Yorkshire. The top 6 OD pairs (a low number was used to focus on the city centre) in Leeds under Government Target are strongly influenced by the current ~~rate~~ distribution of cycling, ~~with the most travelled desire lines projected to continue to be found towards the east~~ which is focussed in the relatively wealthy North of the city (~~this can be explained by the location of the University of East Anglia to the east of the city~~see Figure 3 for top 6 flows currently). Under ~~*godutch* assumptions~~the Go Dutch scenario, by contrast, the pattern of cycling shifts substantially to the ~~west~~South. The cycling patterns under the ~~*godutch*~~ Go Dutch scenario are more representative of short-distance trips across the city overall. In both cases the desire lines are focused around ~~Norwich~~ Leeds city centre: the region has a mono-centric regional economy, making commute trips beyond around 5 km from the centre much less likely to be made by cycling.

The ~~equivalent results are shown for the city of Manchester in Fig. 7. This shows that Manchester has a poly-centric structure, favouring the construction of cycle routes between the various sub-centres, not just in radial routes to a single centre. Note in both scenarios the large increase in the~~ same scenario is illustrated in Figure 8 with the Route Network layer. This shows how the shift in cycling to become more evenly spread across the city translates into estimates of cyclist flows on specific road segments. The number of commuter cyclists expected on York Road, highlighted with a popup, more than triples (from 71 to 236) under Government Target and increases more than 10 fold under Go Dutch (from 71

Figure 7: Model output illustrating the top ~~20~~ 6 most cycled OD pairs in ~~Norwich~~ Leeds under the Government Target and Go Dutch scenarios.

to 966). This contrasts with Otley Road (highlighted in Figure 5), which 'only' triples under Go Dutch. These results suggest that as cycling grows, policy interventions in Leeds should shift from routes in the Northwest of the city, the area with the highest current level of cycling~~between *govtarget* (which represents only a doubling nationwide) and *godutch* scenarios (which represents a more ambitious plan for cycling uptake).~~ , to routes that have low current rates of cycling but high potential, such as York Road to the East. Cycle paths built to help achieve ambitious targets, as represented by the Go Dutch scenario, should be of sufficient width to accommodate the estimated flows: the number of cycle commuters would be expected to increase more than ten-fold on York Road under this scenario and infrastructure design should adapt accordingly.

~~Model output illustrating the top 20 most cycled OD pairs in Manchester under Government Target and Go Dutch scenarios.~~

~~As described earlier, Cyclestreets. net was used to allocate OD pairs to the travel network. 'Fastest' and 'quietest' routes were estimated by the service and~~ Another potentially useful output is the difference between ~~these routescan be important from a transport planning perspective. Fig. 8~~ 'fast' and 'quiet' routes. Figure 9 illustrates this by showing ~~route~~ routes in Manchester with the highest cycling potential under the ~~*govtarget*~~ Government Target scenario. The '~~quietest~~quiet' route is substantially ~~further, with a distance of 2.8~~ longer: 2.6 km (as shown by clicking on the line). The '~~fastest~~fast' route is more direct (with a route distance of 2.3 km) but passes along Trinity Way (the A6042), a busy dual carriage way. The ~~PCT (with the 'Straight Lines' option) tells us that~~ Euclidean distance associated with this OD pair is 1.6 km (this can be seen by clicking on a line illustrated from the 'Straight Lines' layer inn the PCT's interface), resulting in circuity values of ~~1.44 and 1.75~~ 1.4 and 1.6 respectively. We refer to the difference between the '~~fastest~~fast' and '~~quietest~~quiet' routes as the 'quietness diversion factor' ($qdf = 1.2$ in this case).

Dutch evidence suggests that cyclists are generally unwilling to take a path that is more than

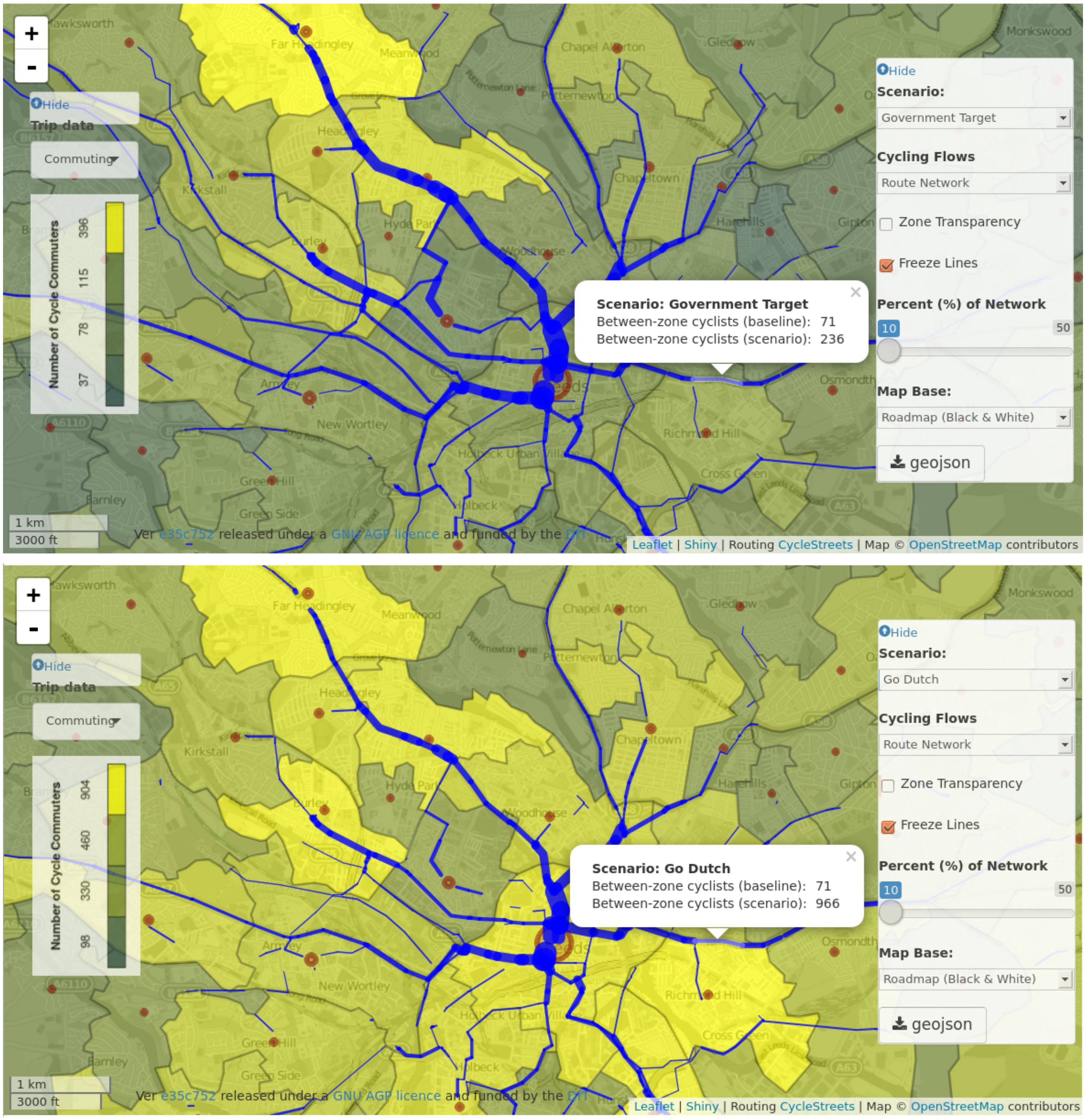

Figure 8: The Route Network layer illustrating the shifting spatial distribution of cycling flows in Leeds under Government Target (top) and Go Dutch (bottom) scenarios.

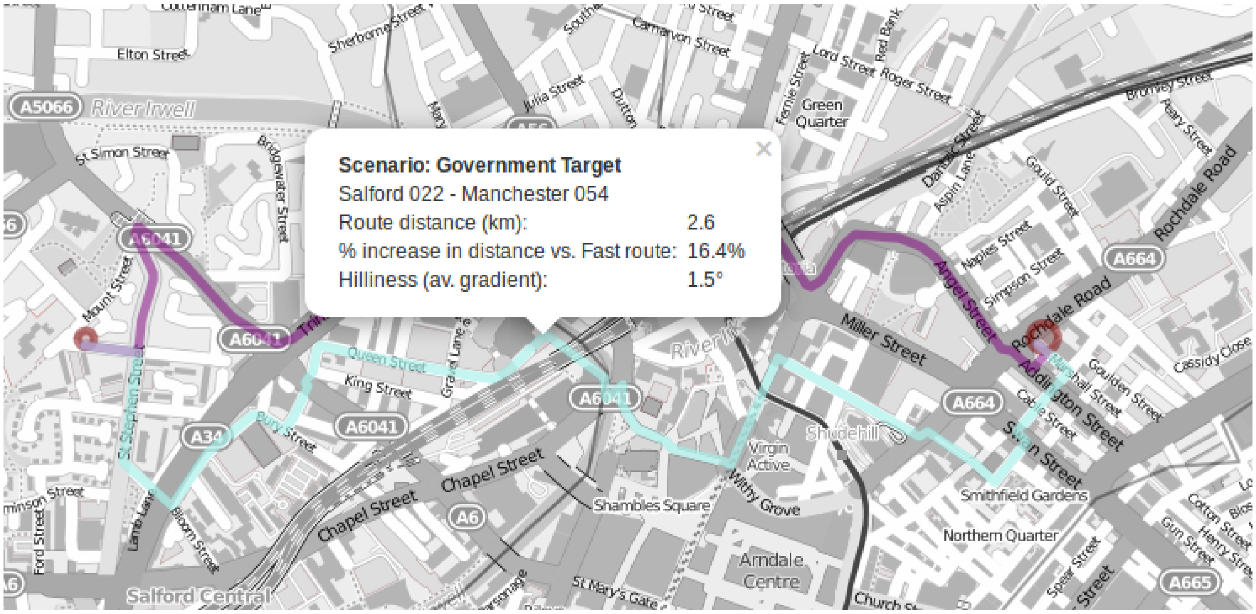

Figure 9: Close-up of ~~the 'fastest~~a 'fast' and ~~'quietest'routes from CycleStreets.net of~~ quiet' route in the ~~OD pair with highest cycling potential~~ PCT under the ~~*govtarget*~~ Government Target scenario in Manchester. This provides an indication of the local ~~'~~'quietness diversion factor'.

around 1.3 to 1.5 times the length of the 'crow-flies' Euclidean distance~~(defined as *q* above)~~. The same research suggests ~~target~~ that circuity values for "for cycle provision should be 1.2" (CROW, 2007). This suggests that high quality cycle infrastructure along the ~~Trinity Way route would be much better used by commuters~~ 'fast' route shown in Figure 9 would be more attractive than an alternative quiet route that ~~diverges greatly~~ greatly diverges from the shortest path. ~~The decline in cycling propensity with distance supports this approach. The faster decline for~~ Previous work indicates that women and older people ~~, combined with their~~ have a greater preference for ~~protected infrastructure, highlights the importance of providing direct and safe routes~~ off-road routes and shorter routes (Garrard et al., 2008; Woodcock et al., 2016, see Appendix 8), suggesting the 'fast route' option could be favourable from an equity perspective. This example illustrates how the PCT could be used to provide evidence on how to encourage cycling amongst groups who currently cycle the least.

5 ~~Discussion~~

~~The flexibility~~ Figure 9 demonstrates another feature of the PCT~~methodology enables its use for applications that go beyond those described in this paper. Because the underlying methods and computer code are transparent and open source, it is possible to use the PCT as a platform for further research and planning applications. This flexibility has been demonstrated by the tool's ability to be deployed in any Local Authority (or other administrative area)in England. Extensibility has been demonstrated by the addition of new scenarios. Three user testing sessions have helped identify shorter-term changes to the interface (such as 'freeze scope') and longer-term needs (such as the use of additional data sources~~'s interactive map: the ability to turn the transparency of the colours representing the area level of cycling on or off, allowing users to see the basemap more clearly. Three basemaps are available on PCT, and choosing the appropriate one can show how latent demand for cycling relates to current cycle infrastructure (with the OpenCycleMap basemap), small-area deprivation (with the Indices of Multiple Deprivation 'IMD' layer) and road width for space re-allocation for cycle and walking paths (with the satellite basemap).

~~Planners can use the different scenarios to consider short , medium, and long-term potential for cycling locally and along specific routes, in combination with local knowledge. In the PCT can therefore shed light on the following question, previously raised by Sloman et al. (2014) and Aldred and Jungnickel (2014): Should cycling investment prioritise areas of relatively low current propensity but high potential, or those of relatively high current propensity but lower potential?~~

4.1 Visualising Health and Carbon Benefits

~~In the Netherlands (representing long-term ambition for cycling) , cycling is equally common among males and females. Cycling levels are also even between different socio-economic groups, although ethnic and religious differences exist (Fishman et al., 2015). Demographics~~

~~should therefore play less of a role in estimating cycling potential for strategic purposes than for identifying 'quick-win' policies based on current propensities. Based on this understanding,~~ The health benefits of cycling do not necessarily rise in direct proportion to the number of people cycling: longer trips lead to a greater health benefit than short ones and older people benefit more from increased physical activity. Further, health benefits along desire lines with a low pedestrian mode share can expected to be greater.

This is demonstrated in the data presented by the PCT. The economic value of health benefits reported for the 4.1 km route in Figure 5 (above) is estimated to be £70785, based on the HEAT methodology described in the previous section. Exploration of this variable for other areas shows that, when health savings are the main criteria, longer desire lines would be favoured, as opposed to focussing on the more immediately obvious metric of focussing on the number of additional trips cycled. Future versions of the ~~PCT has the ability to represent different scenarios of change. An indication of how the pattern of cycling could shift to new transport corridors in the hypothetical future represented by 'Go Dutch' was illustrated with examples from Norwich and Manchester. These show that as cycling grows, its spatial distribution will shift, to areas with high latent demand. This feature of the PCT was described as 'very useful'by transport planners during user testing, coinciding with the finding that 'visioning' has great potential to improve transport planning for the long-term (Tight~~ PCT could allow users to select the top routes ranked by health and carbon benefits.

5 Discussion

We have outlined a method for modelling and visualising the spatial distribution of cycling flows, currently and under various scenarios of 'cycling futures'. Inspired by previous approaches to estimating cycling potential (Larsen et al., ~~2011).~~

~~The results of user testing indicated the utility of~~ 2013; Zhang et al., 2014) and by online, interactive ~~and open source web applications for cost-effective allocation of investment. Local Authority transport planners working in active travel said that the tool could be useful for setting local targets or implementing locally-specific policies. To follow-up on such feedback, modifications of the methods described in this paper are planned, to help determine the suitability of localised cycling targets in relation to investment options.~~[2] ~~Moreover, as illustrated by the *govtarget* scenario, the method can be used to~~ planning support systems (PSS) (Pettit et al., 2013), the PCT tackles the important yet largely unresolved issue of how to create a systematic evidence base to prioritise where to build new cycle paths and identify areas to prioritise for localised interventions. By showing potential health-related benefits the tool provides various metrics for transport planners, going beyond the number of additional trips. Illustrative uses of the PCT demonstrated the potential utility of the tool, for example by showing settings in which the spatial distribution of cycling demand is likely to shift as cycling grows.

In addition to creating an evidence base for planning specific routes and area-based interventions, the long-term Go Dutch and Ebikes scenarios could be used for 'visioning' transport futures (Hickman et al., 2011). The PCT could also: help translate national targets into local aspirations ~~. However, the implementation of the PCT~~ (as illustrated by the Government Target scenario); inform local targets (e.g. by indicating what the potential in one region is relative to neighbouring regions); support business cases (by showing that there is high cycling potential along proposed routes); and help plan for capacity increases in cycling along the route network via the network analysis layer. Ongoing case study work with stakeholders will establish and develop these uses. Future developments will be facilitated by the open source code underlying the PCT (see github.com/npct), making it easy for others to use the project as a basis for further work (Lima et al., 2014).

[2] ~~Targets have proliferated in recent years. For instance, an official target to reach 10of trips made by bicycle has been made by authorities in Dublin, Leicester and across all of Scotland over various time-scales (Beatley, 2012). A mode share of "20by 2020" has been set for several cities including San Francisco and Orlando.~~

As with any modelling tool, the approach presented in this paper ~~does have some~~ has limitations: the reliance on Census OD data from 2011 means that the results are ~~not up-to-date; there are no scenarios representing specific infrastructure interventions;~~ limited to commuting and may not encapsulate recent shifts in travel behaviour, and the user interface is constrained to a few~~discrete~~ , discrete, scenarios. These limitations ~~open-up the potential~~ suggest directions for future work, including: ~~using more up-to-date~~ use of new sources of OD data~~; creating a version of the model to represent the impact of specific improvements to the route network (e.g. by modifying the 'quietness diversion factor', described above);~~ , and the implementation of continuous variables to define future scenarios. ~~Wider extensions of the model that could build on the framework presented here include:~~

~~Additional 'output tabs' in the~~ There is often a tension between transparency and complexity in the design of tools for transport planning. Excessive complexity can result in tools that are 'black boxes' (Saujot et al., 2016). In a context of limited time, expertise, and resources, Saujot et al. caution against investing in ever more complex models. Instead, they suggest models should be more user focussed. The PCT's ~~user interface, to estimate the quantitative benefits of cycling uptake at the local (and potentially route-allocated) level. Benefits estimated could includehealth savings through increased physical activity to feed into models such as HEAT (Fraser and Lock, 2011). Geographically specific energy and carbon savings of cycling uptake could also be estimated (Lovelace et al., 2011).~~ open source, freely available nature will, we believe, facilitate the future development of the PCT organically to meet the needs of its various users. For instance, we envision that stakeholders in local government modifying scenarios for their own purposes, and that academics in relevant fields may add new features and develop new use cases of the PCT. Such enhancements could include:

- ~~Deployment of the PCT for entire countries. This would depend on having appropriate OD data and could could build on emerging 'Big Data' sources for origin-destination flows (Alexander et al., 2015~~Additional scenarios to illustrate a wider range of 'cycling futures', including medium-term and local targets such as 'Go York' (where 12% of commuters cycle to work).

- ~~International comparisons of cycling potential. This could include include an exploration of the relationship between places of high potential and investment. We have already begun this by using Dutch distance decay functions in an English context, but more could be done by fully implementing the model in different country contexts. The extension of the model to cover variation between different demographic groups. This could be done using the method of spatial microsimulation, which enables the use of additional individual-level variables, such as access to a cycle, to inform more targeted interventions~~ Use of individual level data to estimate cycling potential and impacts. The use of synthetic 'spatial microdata', for example, could enable analysis of outcomes by a much wider range of predictors (Lovelace et al., 2014). These could include the impacts of physical fitness and access to high quality pedal cycle on cycling potential.

- Additional purposes of trips in the model. An 'education layer' would enable prioritisation of 'safe routes to school', building on methods analysing 'school commute' data (Singleton, 2014). ~~The extension of the tool to enable the estimation of cycling demand following new developments, such as high-density housing, a new school or local job creation.~~

  ~~The PCT's open source licence allows others to modify it for their own needs. We actively encourage practitioners to 'fork' the project (Lima~~ Other data sources to include more trip types include mobile telephone providers (Alexander et al., ~~2014), to modify the scenarios, input data and display of the results to suit local contexts. This could, for example, help to visualise city-level targets for the proportion cycling by a certain year and which will vary considerably from place to place in ways not yet well understood. Modifying the code base would also allow transport planners~~

~~to decide on and create the precise set of online tools that are most useful for their work. Building on participatory models at the macro-level (Macmillan et al., 2014), extensions to the model could include using the PCT methodology to enable public engagement in the strategic planning process around sustainable transport.~~ 2015) and outputs from traditional transport models.

- Deployment of the PCT for new cities, regions or countries. This depends on the availability of appropriate OD data, perhaps from sources mentioned in the previous point. Such work could also facilitate international comparisons of cycling potential.

Transport ~~policy~~ planning is a complex and contested field (Banister, 2008). ~~Therefore~~ When it comes to sustainable mobility, policy, politics, leadership and vision are key ingredients ~~for sustainable urban mobility~~ that computer models alone cannot ~~provide~~ supply (Melia, 2015). The approach described here can, however, assist in this wider context by providing new tools for ~~assessing the best available evidence . The PCT thus supports informed and open decision making. A more specific limitation of the PCT is its current lack of inclusion of detailed cycle route quality data (e.g. width and bumpiness of path), which could help planners assess the scale of changes needed to enable substantial uptake. Future versions of the tool could make use of data derived from new network assessment technologies (Joo and Oh, 2013).~~ exploring the evidence at high geographical resolution and envisioning transformational change in travel behaviours.

~~The flexibility of the approach outlined in this paper means that PCT can be seen not only as a tool but as a framework for strategic transport planning. Under this interpretation the case study of cycling in England is just one of many potential applications. Still, a number of the lessons learned throughout the development and user testing of the tool are generalisable internationally. Indeed, one of~~ By providing transport authorities, campaign groups and the public with access to the same evidence base, we hypothesise that tools such as the PCT can encourage informed and rigorous debate, as advocated by Golub et al. (2013). In conclusion, the ~~major motivations for writing this paper is to showcase the method for use by others to avoid 'reinventing the wheel' to solve such a ubiquitous and embedded problem as the un-sustainability of current travel patterns.~~

~~Future work will focus on enabling practitioners to add new features to the PCT. This is based on the understanding that the people who best understand the requirements of transport planners are the transport planners themselves. By reducing barriers to entry in scenario-based transport modelling, the PCT methodology can empower decision-makers, planners and citizens to supplement their understanding of transport systems with evidence and plausible visions of the future.~~ PCT provides an accessible evidence base to inform the question of where to prioritise interventions for active travel and raises more fundamental questions about how models should be used in transport planning.

~~The PCT is highly policy relevant. By identifying specific routes where intervention is expected to be most effective, it can help to build business cases for further investment and policy change. Moreover, by highlighting the importance of 'arterial' routes to key destinations, the PCT can help rejuvenate long-standing debates such as the re-allocation of road space away from private cars (Black et al., 1992; Jones, 2014; Sharples, 2009). In conclusion, new tools such as the PCT can inform the decision of where to construct new cycling infrastructure and, more widely, strengthen the evidence-base needed for a transition towards sustainable transport systems~~

Author contribution statement

The PCT was built as a collaborative effort. The Principal Investigator of the project was JW, and the initial concept for the project came from JW and RL in response to a call from the Department of Transport. AG led the creation of the model underlying the PCT, and the generation of estimates of cycling levels, health gains and carbon impacts in each scenario. JW and AG led the development to of the methods for calculating health impacts.

JW, RL, AG, and RA contributed to the development of the cycling uptake rules. RL led the processing of these modelled estimates for spatial visualisation in the online tool and coordinated the development of the online tool. RA led the coordination of policy implementation and collection of practitioner feedback. AA led on the user interface, with contributions from all authors. NB led the deployment of the PCT on a public facing server. AG led the writing of the appendix. RL led the writing of this manuscript, with input from all authors.

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References

~~Aldred, R., Jungnickel, K., 2014. Why culture matters for transport policy: the case of cycling in the UK. Journal of Transport Geography 1–22.~~

~~Aldred, R., Woodcock, J., 2008. Transport: challenging disabling environments. Local Environment 13, 485–496.~~

Aldred, R., Woodcock, J., Goodman, A., ~~2015. Does more cycling mean more diversity in cycling~~2016. Does More Cycling Mean More Diversity in Cycling? Transport Reviews ~~1–17.~~

36, 28–44. doi:10.1080/01441647.2015.1014451

Alexander, L., Jiang, S., Murga, M., Gonz, M.C., 2015. Validation of origin-destination trips by purpose and time of day inferred from mobile phone data. Transportation Research Part B: Methodological 1–20. doi:10.1016/j.trc.2015.02.018

Aultman-Hall, L., Hall, F., Baetz, B., 1997. Analysis of bicycle commuter routes using geographic information systems: ~~implications~~ Implications for bicycle planning. Transportation Research Record: Journal of the Transportation Research Board 1578, 102–110. doi:10.3141/1578-13

Banister, D., 2008. The sustainable mobility paradigm. Transport Policy 15, 73–80. doi:

~~Beatley, T., 2012. Green urbanism: Learning from European cities. Island Press.~~ DOI: 10.1016/j.tranpol.2007.10.005

~~Behrisch, M., Bieker, L., Erdmann, J., Knocke, M., Krajzewicz, D., Wagner~~ Borning, A., Waddell, P., ~~2014. Evolution of SUMO's Simulation Model. Traffic and Transportation Simulation 64.~~

~~Black, J.a., Lim, P.N., Kim, G.H., 1992. A traffic model for the optimal allocation of arterial road space: a case study of Seoul's first experimental bus lane. Transportation Planning and Technology 16, 195–207. doi:~~Förster, R., 2008. UrbanSim: Using simulation to inform public deliberation and decision-making, in: Digital Government. Springer, pp. 439–464.

Broach, J., Dill, J., Gliebe, J., 2012. Where do cyclists ride? A route choice model developed with revealed preference GPS data. Transportation Research Part A: Policy and Practice 46, 1730–1740. doi:10.1016/j.tra.2012.07.005

Brömmelstroet, M. te, Bertolini, L., 2008. Developing land use and transport PSS: Meaningful information through a dialogue between modelers and planners. Transport Policy 15, 251–259. doi:10.1016/j.tranpol.2008.06.001

Buehler, R., Dill, J., 2016. Bikeway Networks: A Review of Effects on Cycling. Transport

Reviews 36, 9–27. doi:10.1080/01441647.2015.1069908

Chan, W.-T., Suja, T., 2003. A Multi-Criteria Approach in Designing Bicycle Tracks, in: Map Asia Conference.

~~Chang, W., Cheng, J., Allaire, J.J., Xie, Y., McPherson, J., 2015. shiny: Web Application Framework for R.~~

CROW, 2007. Design manual for bicycle traffic. Kennisplatform, Amsterdam.

~~De Nazelle~~ De Nazelle, A., Nieuwenhuijsen, M.J., Antó, J.M., Brauer, M., Briggs, D., Braun-Fahrlander, C., Cavill, N., Cooper, A.R., Desqueyroux, H., Fruin, S., 2011. Improving health through policies that promote active travel: ~~a~~ A review of evidence to support integrated health impact assessment. Environment international 37, 766–777.

DEFRA, 2015. DEFRA Carbon Factors: UK Government conversion factors for Company Reporting, 2015, V2.0.

Department for Transport, 2015. Response to the consultation on the draft Cycling Delivery Plan. Department for Transport, London.

Department for Transport, 2014. Cycling Delivery Plan: Draft. Department for Transport.

Ehrgott, M., Wang, J.Y.T., Raith, A., Houtte, C. van, 2012. A bi-objective cyclist route choice model. Transportation Research Part A: Policy and Practice 46, 652–663. doi:10.1016/j.tra.2011.11.015

Fishman, E., ~~Böcker, L., Helbich, M., 2015. Adult Active Transport in the Netherlands: An Analysis of Its Contribution to Physical Activity Requirements. Plos One 10, e0121871. doi:~~

~~Fraser, S.D.S., Lock, K., 2011. Cycling for transportand public health: a systematic review of the effect of the environment on cycling. European journal of public health 21, 738–43~~2016. Cycling as transport. Transport Reviews 36, 1–8. doi:10.1080/01441647.2015.1114271

Gaffron, P., 2003. The implementation of walking and cycling policies in British local authorities. Transport Policy 10, 235–244. doi:10.1016/S0967-070X(03)00024-6

~~Geertman, S., Stillwell,~~ Garrard, J., ~~2009. Planning Support Systems: Content, Issues and Trends, in: Geertman, S.~~ Rose, G., Lo, S.K., 2008. Promoting transportation cycling for women: The role of bicycle infrastructure. Preventive Medicine 46, 55–59. doi:10.1016/j.ypmed.2007.07.010

Golub, A., Robinson, G., Nee, B., ~~Stillwell, J.(Eds.), Planning Support Systems Best Practice and New Methods SE - 1, The GeoJournal Library. Springer Netherlands, pp.1–26~~2013. Making accessibility analyses accessible: A tool to facilitate the public review of the effects of regional transportation plans on accessibility. Journal of Transport and Land Use 6, 17–28. doi:10.5198/jtlu.v6i3.352

Haklay, M., Singleton, A., Parker, C., 2008. Web Mapping 2.0: The Neogeography of the GeoWeb. Geography Compass 2, 2011–2039. doi:10.1111/j.1749-8198.2008.00167.x

Han, J., Hayashi, Y., 2008. Assessment of private car stock and its environmental impacts in China from 2000 to 2020. Transportation Research Part D: Transport and Environment 13, 471–478.

Heath, G.W., Brownson, R.C., Kruger, J., Miles, R., Powell, K.E., Ramsey, L.T., Services, T.F. on C.P., 2006. The effectiveness of urban design and land use and transport policies and practices to increase physical activity: ~~a~~ A systematic review. Journal of Physical Activity & Health 3, S55.

Heinen, E., Panter, J., Mackett, R., Ogilvie, D., 2015. Changes in mode of travel to work: ~~a~~ A natural experimental study of new transport infrastructure. International Journal of Behavioral Nutrition and Physical Activity 12, 81. doi:10.1186/s12966-015-0239-8

~~Iacono, M., Krizek, K.J., El-Geneidy, A., 2010. Measuring non-motorized accessibility: issues, alternatives, and execution~~ Hickman, R., Ashiru, O., Banister, D., 2011. Transitions to low carbon transport futures: Strategic conversations from London and Delhi. Journal of Transport Geography~~18, 133–140~~, Special section on Alternative Travel futures 19, 1553–1562. doi:10.1016/j.jtrangeo.2011.03.013

~~Jones, I., 2014. Road space allocation: the intersection of transport planning, governance and infrastructure.~~ Iacono, M., Krizek, K., El-Geneidy, A., 2008. Access to Destinations: How Close is Close Enough? Estimating Accurate Distance Decay Functions for Multiple Modes and Different Purposes 76.

~~Joo~~ Kahlmeier, S., ~~Oh~~Kelly, P., Foster, C., ~~2013. A novel method to monitor bicycling environments.Transportation Research Part A: Policy and Practice 54, 1–13. doi:~~Götschi, T., Cavill, N., Dinsdale, H., Woodcock, J., Schweizer, C., Rutter, H., Lieb, C., 2014. Health economic assessment tools (HEAT) for walking and for cycling, Methods and User Guide. World Health Organization Regional Office for Europe, Copenhagen, Denmark 2014.

~~Kitchin~~ Klosterman, R.~~, 2013. Big data and human geography: Opportunities, challenges and risks. Dialogues in Human Geography 3, 262–267~~E., 1999. The What If? Collaborative Planning Support System. Environment and Planning B: Planning and Design 26, 393–408. doi:10.1068/b260393

Komanoff, C., 2004. Bicycling, in: Cleveland, C.J. (Ed.), Encyclopedia of Energy. Elsevier, New York, pp. 141–150. ~~doi:~~

~~Krajzewicz, D., Erdmann~~ Larsen, J., ~~Härri, J., Spyropoulos, T., 2014. Including Pedestrian and Bicycle Traffic in the Traffic Simulation SUMO, in : 10th ITS European Congress. Helsinki, p. 10.~~ Patterson, Z., El-Geneidy, A., 2013. Build it. But where? The use of geographic information systems in identifying locations for new cycling infrastructure. International Journal of Sustainable Transportation 7, 299–317.

Lima, A., Rossi, L., Musolesi, M., 2014. Coding Together at Scale: GitHub as a Collaborative Social Network. arXiv preprint arXiv:1407.2535.

Lovelace, R., Ballas, D., Watson, M., 2014. A spatial microsimulation approach for the analysis of commuter patterns: ~~from~~ From individual to regional levels. Journal of Transport Geography 34, 282–296. doi:http://dx.doi.org/10.1016/j.jtrangeo.2013.07.008

Lovelace, R., Beck, S.~~B.M.~~, Watson, M., Wild, A., 2011. Assessing the energy implications of replacing car trips with bicycle trips in Sheffield, UK. Energy Policy 39, 2075–2087. doi:

~~Macmillan, A., Connor, J., Witten, K., Kearns, R., Rees, D., Woodward, A., 2014. The societal costs and benefits of commuter bicycling: simulating the effects of specific policies using system dynamics modeling. Environmental health perspectives 122, 335–344. doi:~~

~~Martínez, L.M., Viegas, J.M., 2013. A new approach to modelling distance-decay functions for accessibility assessment in transport studies. Journal of Transport Geography 26, 87–96. doi:~~10.1016/j.enpol.2011.01.051

McCollum, D., Yang, C., 2009. Achieving deep reductions in US transport greenhouse gas emissions: Scenario analysis and policy implications. Energy Policy 37, 5580–5596. doi:10.1016/j.enpol.2009.08.038

Melia, S., 2015. Urban Transport Without the Hot Air, Volume 1: Sustainable Solutions for UK cities.

Minikel, E., 2012. Cyclist safety on bicycle boulevards and parallel arterial routes in Berkeley, California. Accident Analysis & Prevention 45, 241–247.

~~Mizutani, F., Suzuki, Y., Sakai, H., 2011. Estimation of social costs of transport in Japan. Urban Studies 48, 3537–3559.~~

~~Newman, P., Kenworthy, J., 1999. Costs of automobile dependence: global survey of cities. Transportation Research Record: Journal of the Transportation Research Board 17–26.~~

Novosel, T., Perković, L., Ban, M., Keko, H., Pukšec, T., Krajačić, G., Duić, N., 2015. Agent based modelling and energy planning–Utilization of MATSim for transport energy demand modelling. Energy.

Oja, P., Titze, S., Bauman, A., DeGeus, B., Krenn, P., Reger-Nash, B., Kohlberger, T., 2011. Health benefits of cycling: ~~a~~ A systematic review. Scandinavian journal of medicine & science in sports 21, 496–509. doi:10.1111/j.1600-0838.2011.01299.x

~~Ortúzar~~ Parkin, J.~~de D., Willumsen, L.G., 2001. Modelling transport. John Wiley; Sons,~~

2015. Planning and design approaches for cycling infrastructure.

~~O'Brien, O., Cheshire~~ Parkin, J. ~~, Batty, M., O'Brien, O. , 2014. Mining bicycle sharing data for generating insights into sustainable transport systems. Journal of Transport Geography 34, 262–273. doi:~~(Ed.), 2012. Cycling and sustainability, 1. ed. ed, Transport and sustainability. Emerald, Bingley.

Parkin, J., Wardman, M., Page, M., 2008. Estimation of the determinants of bicycle mode share for the journey to work using census data. Transportation 35, 93–109. doi:10.1007/s11116-007-9137-5

Payne, S., 2014. Removing barriers to direct access. Get Britain Cycling 4, 6–8.

Pettit, C.J., Klosterman, R.E., Nino-Ruiz, M., Widjaja, I., Russo, P., Tomko, M., Sinnott, R., Stimson, R., 2013. The online what if? Planning support system, in: Planning Support Systems for Sustainable Urban Development. Springer, pp. 349–362.

Pikora, T.J., Bull, F.C.L., Jamrozik, K., Knuiman, M., Giles-Corti, B., Donovan, R.J., 2002. Developing a reliable audit instrument to measure the physical environment for physical activity. American Journal of Preventive Medicine 23, 187–194. doi:10.1016/S0749-3797(02)00498-1

Pucher, J., Dill, J., Handy, S., 2010. Infrastructure, programs, and policies to increase bicycling: An international review. Preventive Medicine 50, ~~S106 – S125~~S106–S125. doi:

~~R Core Team, 2015. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria.~~ DOI: 10.1016/j.ypmed.2009.07.028

Rae, A., 2009. From spatial interaction data to spatial interaction information? Geovisualisation and spatial structures of migration from the 2001 UK census. Computers, Environment and Urban Systems 33, 161–178. doi:10.1016/j.compenvurbsys.2009.01.007

~~Sharples, R., 2009. Reducing road capacity to change travel behaviour, in: 32nd Australasian Transport Research Forum. Australasian Transport Research Forum,~~

~~Auckland, New Zealand.~~ Saujot, M., Lapparent, M. de, Arnaud, E., Prados, E., 2016. Making land use – Transport models operational tools for planning: From a top-down to an end-user approach. Transport Policy 49, 20–29. doi:10.1016/j.tranpol.2016.03.005

Shergold, I., Parkhurst, G., Musselwhite, C., 2012. Rural car dependence: ~~an~~ An emerging barrier to community activity for older people. Transportation Planning and Technology 35, 69–85.

~~Simini, F., González, M.C., Maritan, A., Barabási, A.-L., 2012. A universal model for mobility and migration patterns. Nature 8–12. doi:~~

Singleton, A., 2014. A GIS approach to modelling CO2 emissions associated with the pupil-school commute. International Journal of Geographical Information Science 28, 256–273. doi:10.1080/13658816.2013.832765

~~Sinnott, R.O., Bayliss, C., Bromage, A., Galang, G., Grazioli, G., Greenwood, P., Macaulay, A., Morandini, L., Nogoorani, G., Nino-Ruiz, M., Tomko, M., Pettit, C., Sarwar~~ Tainio, M., ~~Stimson, R., Voorsluys, W., Widjaja, I., Others, 2014. The Australia urban research gateway. Concurrency and Computation: Practice and Experience 27, 358–375. doi:~~

~~Sloman, L., Taylor, I., Wilson~~Nazelle, A.~~, King, N., Goodwin, P., Anable, J. , Davison, S., Crawford, M., Cope, A., Adcock~~J. de, Götschi, T., Kahlmeier, S., ~~2014. Finding the optimum: revenue/capital investment balance for sustainable travel. Department for Transport.~~

~~Smoreda, Z., Olteanu-Raimond, A.-M., Couronné~~Rojas-Rueda, D., Nieuwenhuijsen, M.J., Sá, T.~~, 2013. Spatiotemporal data from mobile phones for personal mobility assessment. Transport survey methods: best practice for decision making. Emerald Group Publishing, London.~~

~~Stefanidis, A. , Crooks, A., Radzikowski~~H. de, Kelly, P., Woodcock, J., ~~2011. Harvesting ambient geospatial information from social media feeds. GeoJournal 78, 319–338~~2016. Can air pollution negate the health benefits of cycling and walking? Preventive Medicine.

doi:10.1016/j.ypmed.2016.02.002

Tamminga, G., Miska, M., Santos, E., Lint, H. van, Nakasone, A., Prendinger, H., Hoogendoorn, S., 2012. Design of Open Source Framework for Traffic and Travel Simulation. Transportation Research Record: Journal of the Transportation Research Board 2291, 44–52. doi:

~~Tight, M., Timms, P., Banister, D., Bowmaker, J., Copas, J., Day, A., Drinkwater, D., Givoni, M., Gühnemann, A., Lawler, M., Macmillen, J., Miles, A., Moore, N., Newton, R., Ngoduy, D., Ormerod, M., O'Sullivan, M., Watling, D., 2011. Visions for a walking and cycling focussed urban transport system. Journal of Transport Geography 19, 1580–1589. doi:~~10.3141/2291-06

Tobler, W.R., 1987. Experiments in migration mapping by computer. The American Cartographer 14, 155–163.

Transport for London, ~~2014. London cycling design standards. Transport for London, London~~ 2015. London Cycling Design Standards (LCDS).

Transport for London, 2010. Analysis of Cycling Potential. Transport for London.

~~Transport for NSW, 2014. Household Travel Survey Report: Sydney 2012/13.~~ Wegman, F.C.M., 1979. Urban planning, traffic planning and traffic safety of pedestrians and cyclists, in: Contribution to the OECD-Symposium in Safety of Pedestrians and Cyclists, Paris.

Welsh Government, 2014. Guidance Active Travel (Wales) Act. Welsh Government, Cardiff.

Wood, J., Dykes, J., Slingsby, A., 2010. Visualisation of ~~Origins, Destinations and Flows with OD Maps~~origins, destinations and flows with OD maps. The Cartographic Journal 47, 117–129. ~~doi:~~

Woodcock, J., ~~Givoni, M., Morgan~~Aldred, R., Goodman, A.~~S., 2013. Health Impact Modelling of Active Travel Visions for England and Wales Using an Integrated Transportand Health Impact Modelling Tool (ITHIM). PLoS ONE 8. doi:~~, Lovelace, R., Ullrich, A., Abbas, A., Berkoff, N., 2016. National Propensity to Cycle Tool Project: Summary Report. Department for Transport.

Woodcock, J., Edwards, P., Tonne, C., Armstrong, B.G., Ashiru, O., Banister, D., Beevers, S., Chalabi, Z., Chowdhury, Z., Cohen, A., Franco, O.H., Haines, A., Hickman, R., Lindsay, G., Mittal, I., Mohan, D., Tiwari, G., Woodward, A., Roberts, I., 2009. Public health benefits of strategies to reduce greenhouse-gas emissions: Urban land transport. The Lancet 374, 1930–1943. doi:10.1016/S0140-6736(09)61714-1

Zhang, D., Magalhaes, D.J.A.V., Wang, X.(., 2014. Prioritizing bicycle paths in Belo Horizonte City, Brazil: Analysis based on user preferences and willingness considering individual heterogeneity. Transportation Research Part A: Policy and Practice 67, 268–278. doi:10.1016/j.tra.2014.07.010

Table 1: Summary of tools and methods to prioritise where to invest in cycling.

Tool/method	~~Bicycleid~~ Scale	~~Area.of .residence~~ Accessibility	~~Area.of .workplace~~ Levels of input data	~~All~~ Levels of output	~~Bicycle~~Software licence
~~920573 E02002361 E02002361 109 2920575 E02002361 E02002363 38 0920578 E02002361 E02002367~~ Propensity to Cycle Tool	~~10~~ National: England	~~0920582~~ Online map-based tool	~~E02002361~~ Area, OD, route, individual	~~E02002371~~ Area, OD, route, route network	~~44~~ R: Open source (AGPL)
Permeability Assessment Tool (Payne 2014)	~~3920587~~ Local: Dublin, Ireland	~~E02002361~~ GIS-based	~~E02002377~~ Area, OD, route	~~34~~ OD, route	~~0920591~~ ArcGIS: Proprietary
Usage intensity index (Zhang et al. 2014)	~~E02002361~~ Local: Belo Horizonte, Brazil	~~E02002382~~ GIS-based	~~7~~ Area, OD, route, individual	~~0 Sample of the 'cents' input dataset, representing the geographical location of the population-weighted centroids of MSOA zones described in Table 1.~~ Area, individual, route	~~geo~~ArcGIS: Proprietary
~~SUBSCRIPTNBcode MSOA11NM coords. x1 coords.x2 geoSUBSCRIPTNBcode~~ Prioritization Index (Larsen et al. 2013)	~~MSOA11NM~~ Local: Montreal, Canada	~~coords.x1~~ GIS-based	~~coords.x21708~~ Area, route, point	~~E02002384~~ Area	~~Leeds 055~~ ArcGIS: Proprietary

Table 2: Sample of the OD (origin-destination) input dataset, representing the number of people who commute from locations within and between administrative zones (MSOAs). Note 'Car' refers people who drive as their main mode of travel per OD pair, rather than people who travel to work as a passenger in a car.

		Number of commuters by main mode				
Area of residence	Area of workplace	Total	Cycle	Walk	Car	Other
E02002361	E02002361	109	2	59	39	9
E02002361	E02002362	7	1	0	4	2
E02002361	E02002363	38	0	4	24	10
E02002361	E02002364	15	1	0	10	4
E02002361	E02002366	29	1	10	11	7