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

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## Abstract

Getting people cycling is an increasingly common objective in transport planning institutions worldwide. A growing evidence base indicates that high quality infrastructure can boost local cycling rates. Yet for infrastructure and other cycling measures to be effective, it is important to intervene in the right places, such as along 'desire lines' of 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 design, features and potential applications of such a tool. The Propensity to Cycle Tool (PCT) is an online, interactive planning support system which was initially developed to explore and map cycling potential across England (see 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'. Scenarios implemented so far include 'Go Dutch' and 'Ebikes', which explore what would happen if English people cycled as much as the Dutch and the potential impact of electric cycles on cycling uptake. The PCT is open source, enabling the creation of additional scenarios by others and its deployment in new contexts. We conclude that new interactive and online tools such as the PCT can provide an accessible and transparent evidence base for developing strategic cycling plans.

# 1 Introduction

Cycling can play an important role in creating sustainable and equitable transport systems. Cycling already provides reliable, healthy, affordable, and convenient mobility to millions of people each day (Komanoff, 2004) 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 of car-dominated transport systems (Han and Hayashi, 2008; Mizutani et al., 2011; Newman and Kenworthy, 1999; Shergold et al., 2012), and the benefits of cycling (De Nazelle et al., 2011; Oja et al., 2011; Tainio et al., 2016), pushing cycling up the transport 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 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 increased share of commute trips made by cycling locally (Heinen et al., 2015). 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).

# 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.

## 2.1 The policy context

A number of factors influence the attractiveness of cycling for everyday trips (Pucher et al., 2010). 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 and allowing cycles to move more freely than motorised traffic (e.g. with early-start traffic lights and barriers passable only by pedestrians and cycles). However, the 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.

Planning new cycle paths requires many decisions to be made, including in relation to the width (Pikora et al., 2002; Wegman, 1979), quality (Heath et al., 2006), directness (CROW, 2007) and geographic location of the 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 this 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.

## 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 knowledge, to help planners prioritise where to invest. This research gap was described by Larsen et al. (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 cost-effective places for investment. With the notable exceptions of Larsen et al. (2013) and Zhang et al. (2014), 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:

- 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' 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) presented an area-based measure of cycling potential that used a regression model to estimate 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. 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) created an individual-based model of cycling potential to prioritise where to build cycle paths to "achieve maximum impacts early on". The 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 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.

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 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 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. (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 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 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). The PAT works by combining geographical data, 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.

## 2.3 Planning support systems

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 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).

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

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

| Tool/method | Scale | Accessibility | Levels of input data | Levels of output | Software licence |
|---|---|---|---|---|---|
| Propensity to Cycle Tool | National: England | Online map-based tool | Area, OD, route, individual | Area, OD, route, route network | R: Open source (AGPL) |
| Permeability Assessment Tool (Payne 2014) | Local: Dublin, Ireland | GIS-based | Area, OD, route | OD, route | ArcGIS: Proprietary |
| Usage intensity index (Zhang et al. 2014) | Local: Belo Horizonte, Brazil | GIS-based | Area, OD, route, individual | Area, individual, route | ArcGIS: Proprietary |
| Prioritization Index (Larsen et al. 2013) | Local: Montreal, Canada | GIS-based | Area, route, point | Area | ArcGIS: Proprietary |
| Cycling Potential Tool (TfL 2010) | Local: London, UK | Static results | Area, individual | Area, population segment | Unknown |
| Bicycle share model (Parkin et al. 2008) | National: England, Wales | Static results | Area, route | Area | Unknown |

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 the future and explore their potential impacts. The results of traditional scenario-based models of the future 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). 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 sometimes seen as ‘black boxes’, closed to public scrutiny (Golub et al., 2013).

## 2.4 Policy context and features of the Propensity to Cycle Tool

The national policy context of the PCT has influenced its design and features. The PCT 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 cycle-friendly infrastructure based on scenarios of the future.

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:

- Estimation of cycling potential at area, ‘desire line’ and route network levels.
- Route-allocation of OD pairs by a routing algorithm specifically developed for cycling. This was done by CycleStreets.net, a routing service 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).

[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.

- 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 via impacts on public health and carbon emissions, enabling interventions to be designed based on specific health and environmental policy goals

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).

# 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 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.

## 3.1 Processing OD data

The central input dataset was a table origin-destination (OD) pairs from the 2011 Census, from the open access file `wu03ew_v2.csv`, provided by the UK Data Service. This captures the number of commuters travelling between Medium Super Output Area zones (MSOAs, average population: 7,800), by mode of travel (see D1, short for Dataset 1, in Figure 1). D1 was derived from responses to questions 40 ("In your main job, what is the address of your workplace?") and 41 ("How do you usually travel to work?") in the English 2011 Census.

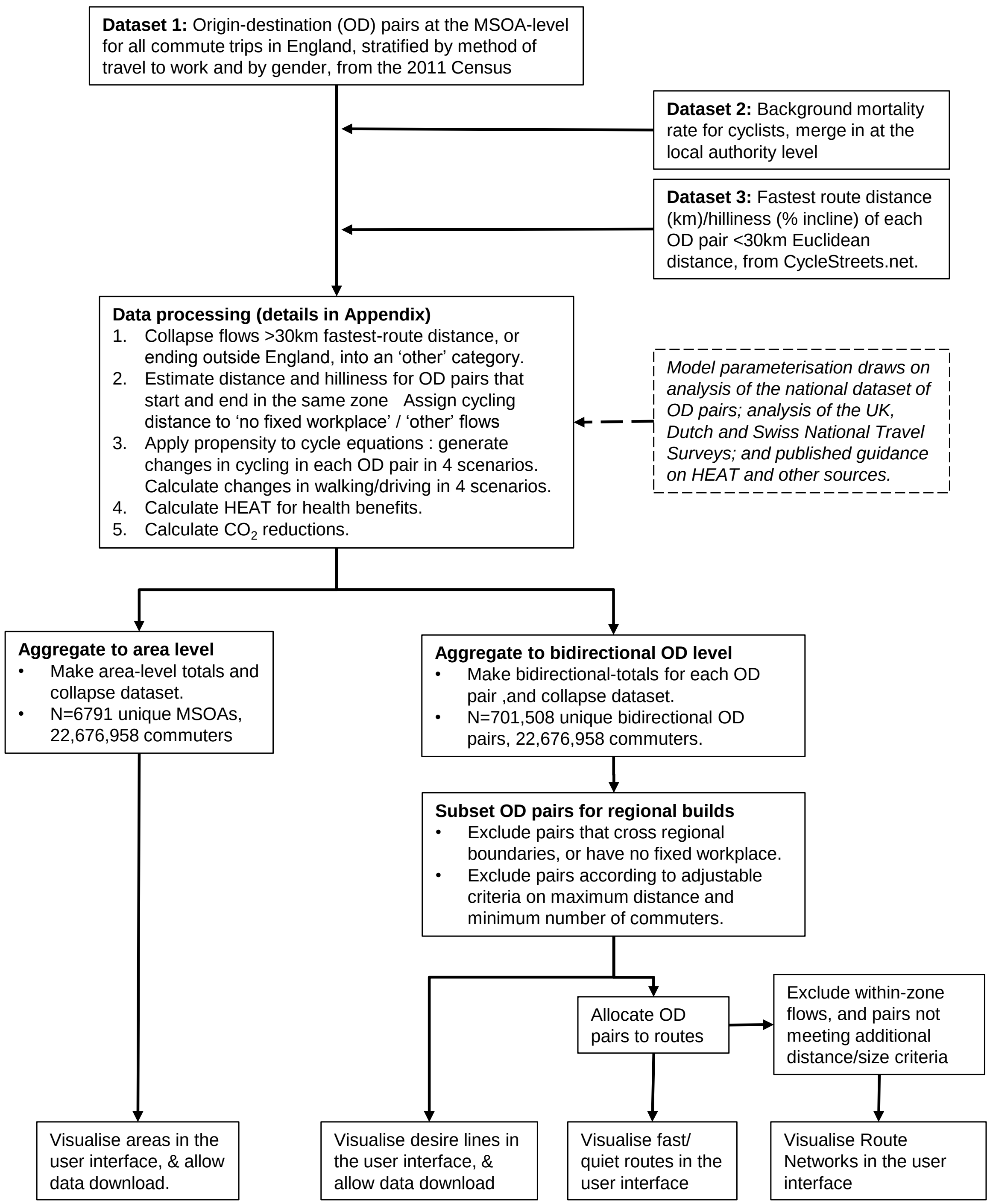


Figure 1: Flow diagram illustrating the input data and processing steps used to create the input data used by the PCT. The abbreviations are as follows. HEAT = Health Economic Assessment Tool, OD pair = origin-destination pair, MSOA = Middle-Layer Super Output Area

The R package **stplanr** was developed to assign additional variables to D1 (Lovelace et al., 2016). This method used the population-weighted centroid of each MSOA to assign geographic coordinates to the OD data, allowing them to be plotted on a map. CycleStreets.net was used estimate of the distance and hilliness (the average gradient, in %) for each OD pair (see D3 in Figure 1). Other input datasets included mortality data per local authority (D2) and an estimate of the gender composition of cyclists in each OD pair (D4) (see the Appendix for further details).

Table 2: Sample of the OD input dataset, representing the number of people who commute from locations within and between administrative zones (MSOAs)

| Area of residence | Area of workplace | Total no. commuters | No. cycle commuters |
|---|---|---:|---:|
| E02002361 | E02002361 | 109 | 2 |
| E02002361 | E02002363 | 38 | 0 |
| E02002361 | E02002367 | 10 | 0 |
| E02002361 | E02002371 | 44 | 3 |
| E02002361 | E02002377 | 34 | 0 |
| E02002361 | E02002382 | 7 | 0 |

### 3.2 Modelling cycling potential

The scenario-based ‘cycling futures’ were based on a baseline estimate of the proportion of trips made per OD pair, as a function of route distance and route hilliness. This was generated using a logistic regression model operating at the individual level. This captured ‘distance decay’, the non-linear impact of distance on the likelihood of cycling (Iacono et al., 2008) and the interaction between distance and hilliness (see Figure 2). This model of current cycling levels formed the basis of three scenarios (Government Target, Go Dutch and Ebikes) (see the Appendix).

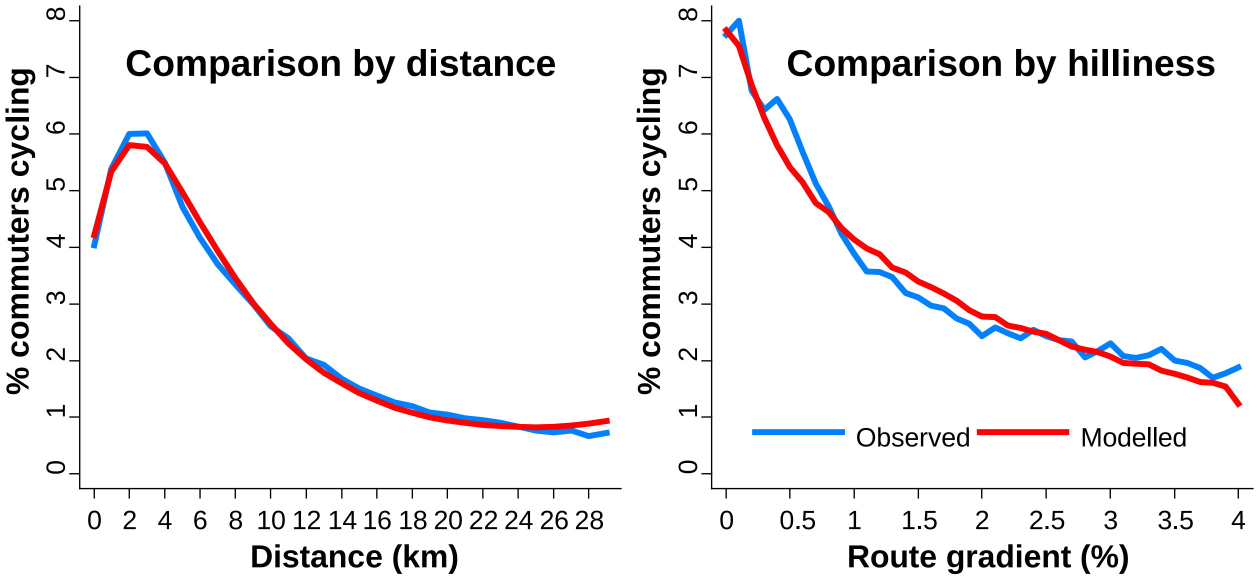


Figure 2: The relationship between distance (left) and hilliness (right) and cycling mode share in England based on the the National Travel Survey. The plots show actual (blue) vs predicted (red) prevalence of cycling to work among 17,896,135 English commuters travelling <30km to work.

### 3.3 Senarios of cycling uptake modeled

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. The second two are 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. This scenario represents a doubling of the level of of cycling in England (Department for Transport, 2014).Although substantial in relative terms (rising from 3% to 6% of commuters), the rate of cycling under this scenario remains low compared with countries such as the Netherlands or Denmark. Growth in cycling is not uniform in this scenario, in either absolute or relative terms. Areas with many short, flat trips and a below-average current rate of cycling are projected to more than double. Conversely, areas with above-verge cycle use and many long-distance hilly commuter routes will experience less than a doubling. Government Target thus generates a slight reduction (but not elimination) of local variation in cycle use that reflects constraints other than distance and hilliness. This scenario is designed to indicate where investment might have the greatest short-term impact.

- Gender Equality. This scenario illustrates the increase in cycling that would result if women 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, women cycle at least as much as men (Aldred et al., 2016; Pucher et al., 2010). This scenario has the greatest relative impact in areas where the rate of cycling is highly gender-unequal.

- Go Dutch. 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 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). As such, whereas the Government Target and Gender Equality scenarios take current levels as a starting point, the predicted levels of cycle use in Go Dutch are unrelated to current levels, and are constrained only by local trip distance distributions and hilliness.

- Ebikes. This scenario models the additional increase in cycle use that would be achieved through the widespread uptake of electric cycles. Electric assist cycles enable longer journeys and reduce the barrier of hills. This scenario is currently implemented as an extension Go Dutch but could be implemented as an add-on for other scenarios.

Additional scenarios could be developed (see Discussion). If deployed in other countries, the PCT will likely benefit from scenarios that relate to both the current policy context and long-term aspirations. OD data must be available for scenarios to be generated in new places, however, as the scenarios primarily operate at the OD level. The estimated changes in the number of cyclists are then aggregated up to the level of areas and allocated to the route network, allowing health and other impacts to be related to transport infrastructure.

## 3.4 Estimation of health impacts

The World Health Organisation'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). To allow for the fact that cycling would in some cases replace walking, because the model assumes all modes are equally likely to be replaced by cycling, HEAT estimates of the increase in premature deaths to the reduction in walking were also included (see the Appendix).

Trip duration was estimated as a function of the 'fastest' 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.

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. The assumed age and sex profile of new cyclists also varied between scenarios. The net change in the number of deaths avoided for each OD pair was equal to the number deaths avoided due to cycle commuting minus the number of additional deaths due to reduced walking. Note that this approach means that in 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.

## 3.5 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 visualisation of the OD data builds on published work on cartographic visualisation (Rae, 2009; Wood et al., 2010).

Desire lines allocated to the route network are illustrated in Figure 4. This shows two route options: the 'fastest' route, which represents an estimate of the route taken by cyclists to minimise travel time and the 'quietest' route which 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., 2012; Ehrgott et al., 2012). Of the available routes provided by CycleStreets.net ('quietest', 'balanced' and 'fastest'), the 'fastest' option was used (see cyclestreets.net/journey/help for more information). This option was chosen because when

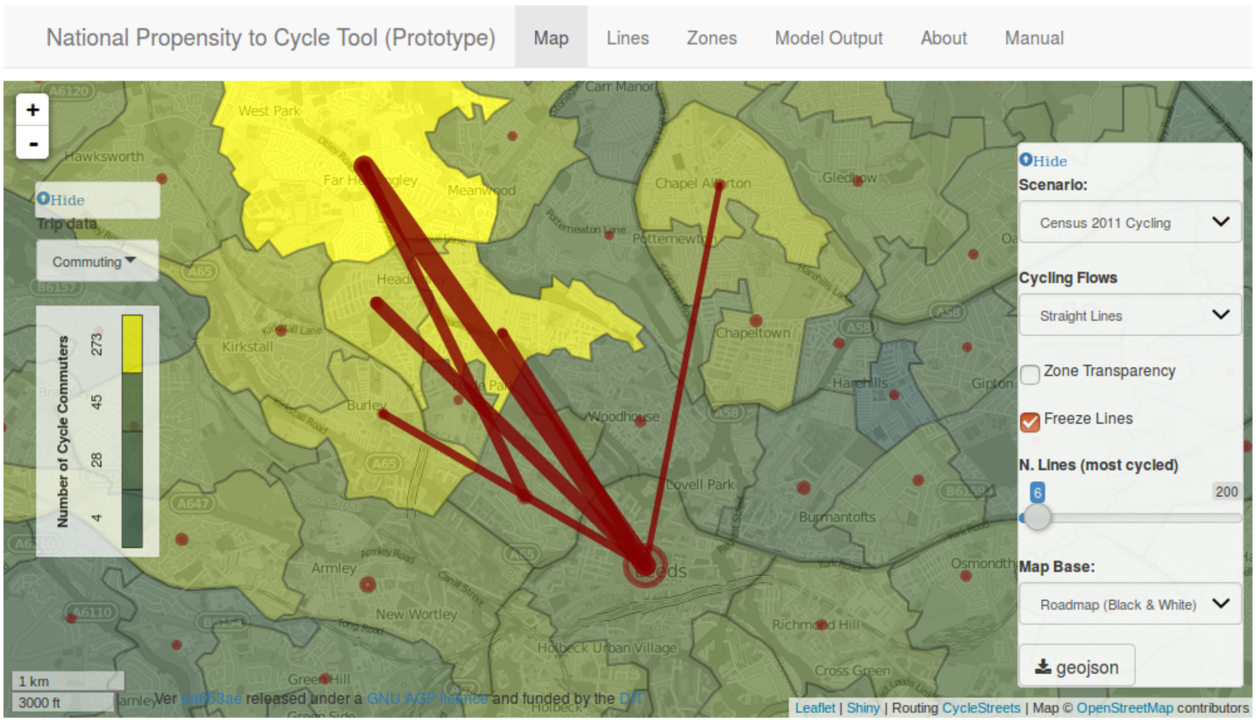


Figure 3: Overview of the PCT map interface, showing area and OD-level data. The zone colour represents the number of people who cycle to work in each administrative zone. The lines represent the top 6 most cycled commuter routes in Leeds (moving the slider 'N. Lines (most cycled)' increases the number of lines). Width is proportional to the total number of cycle trips. Note the use of population-weighted (as opposed to geographic) centroids for the point of departure and destination and the variable width of the centroids, which are proportional to intra-zonal (within zone) flow.

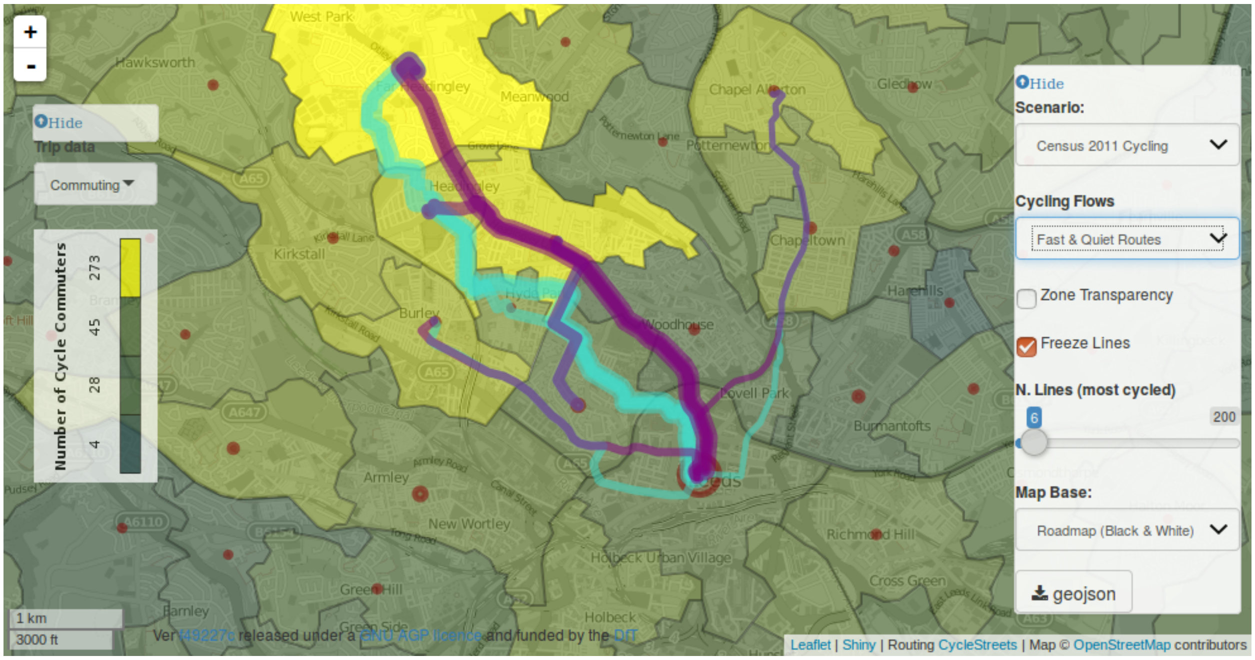


Figure 4: Illustration of desire lines shown in Figure 3 after they have been allocated to the road network by CycleStreets.net. Purple lines are the 'fastest' routes and turquoise routes were the 'quietest' routes.

designing infrastructure, planners should consider cyclists' preference for direct routes (CROW, 2007) and that cycling potential falls quickly with increasing distance.

To generate the Route Network layer, overlapping fast routes were aggregated (see Figure 5). These stages were computationally intensive, leading to a number of steps being taken to make them fast and scalable:

- Adjustable selection criteria were used to sample the lines before route allocation. Parameter setting the Euclidean distance and minimum all-mode number of commutes were set for each build. Note that only between-zone (interzonal) commutes were represented on the route network due to the difficulty of estimating the route taken for a trip that starts and ends in the same zone. Similarly those with no fixed commute were included in area-level data but not in flow-level data.

- Pre-processing of route-allocated lines. This meant that CycleStreets.net was not called for every build. Instead, a pre-generated file of downloaded routes was used.

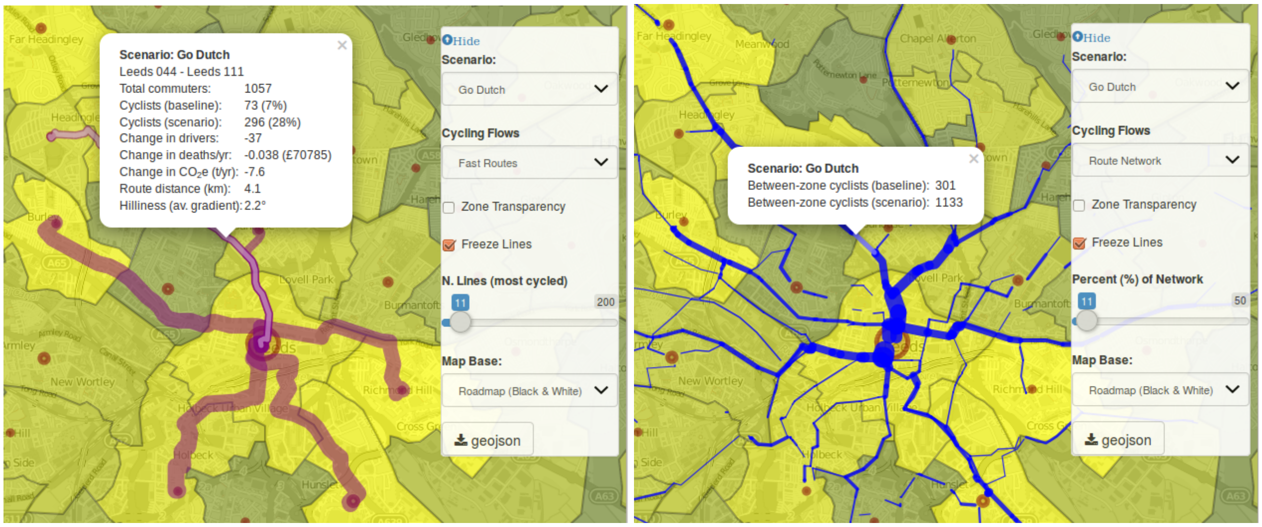


Figure 5: Illustration of route-allocated OD data (left) compared with route network data (right) which was produced by aggregating all overlapping route-aggregated OD pairs, using the 'overline' function from the stplanr R package.

- Parallel code. We used the R package **foreach** to make the slowest process in the build script run on multiple computer cores.

The spatial distribution of cycling potential can be explored interactively by selecting the 'top n' routes with the highest estimated cycling demand. Information about the *aggregate cycling potential* on the road network is shown in the Route Network layer. This layer adds together the number of cycle trips for all routes, and relates to the *capacity* that infrastructure may need to handle under different scenarios, as illustrated in Figure 5. Cycling along Otley Road, under the Go Dutch scenario, rises from 73 to 296 along a single route, but from 301 to 1133 in the Route Network.

# 4 Outputs of the Propensity to Cycle Tool

This section describes and illustrates some outputs from the PCT, alongside discussion of how these outputs could be used in transport planning.

## 4.1 Model output tabs

The PCT contains 6 'tabs' (see Figure 3), the first four of which provide region-specific information:

- **Map**: This is the interactive map that shows cycling potential at area, desire-line, route and route network levels under different scenarios of the future, as described throughout this paper. This interactive map is the main component of the PCT, and is the default tab presented to users.

- **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 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.

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

- **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 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.

## 4.2 Trip distance distributions

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 red lines), it is clear that each region has a

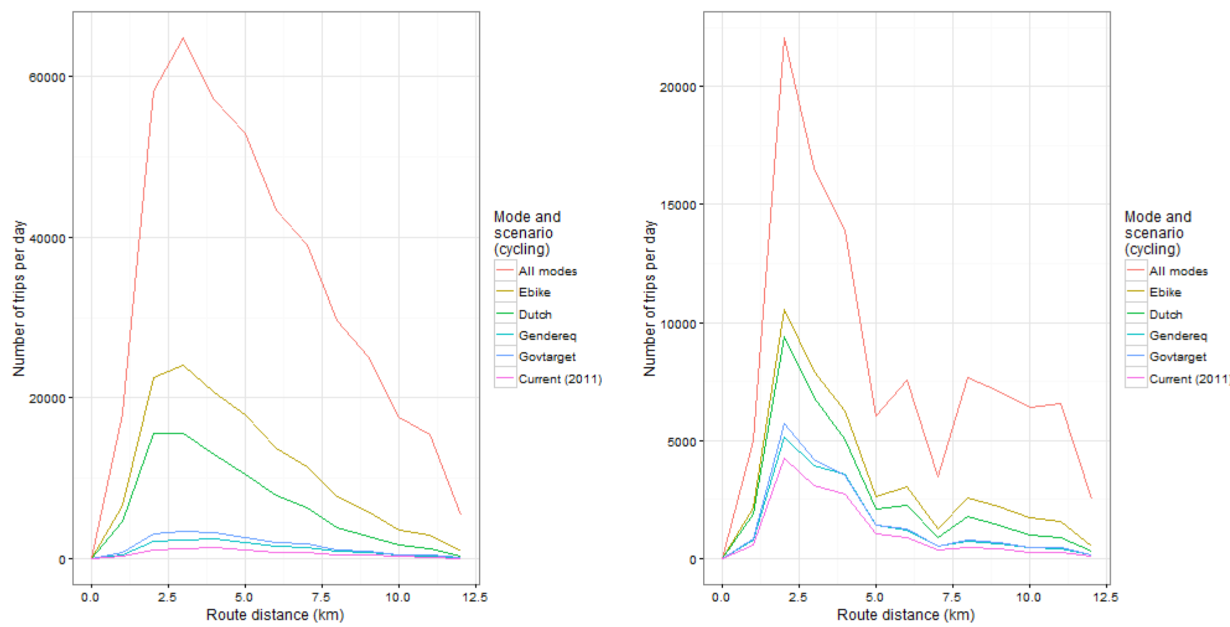


Figure 6: Modal share of trips made by cycling for English commutes in West Yorkshire (left) and Oxfordshire (right) currently and under 4 scenarios of change.

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

Note that although West Yorkshire and Oxfordshire have very different initial levels of cycling, the 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.

## 4.3 The shifting spatial distribution of cycling demand

The difference between the spatial distribution in cycling potential between the Government Target and Go Dutch scenarios is 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 distribution of cycling. As such, cycle commuting is projected to continue to be most common in the North the city. Under Go Dutch assumptions, by contrast, the pattern of cycling shifts substantially to the south of the city. The cycling patterns under the Go Dutch scenario are more representative of short-distance trips across the city overall. In both cases the desire lines are focused around 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 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 to 966). This contrast 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, 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.

Another potentially useful output is the difference between 'fastest' and 'quietest' routes. Figure 9 illustrates this by showing routes in Manchester with the highest cycling potential under the Government Target scenario. The 'quietest' route is substantially longer: 2.6 km (as shown by clicking on the line). The 'fastest' 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 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 1.4 and 1.6 respectively. We refer to the difference between the 'fastest' and 'quietest'


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

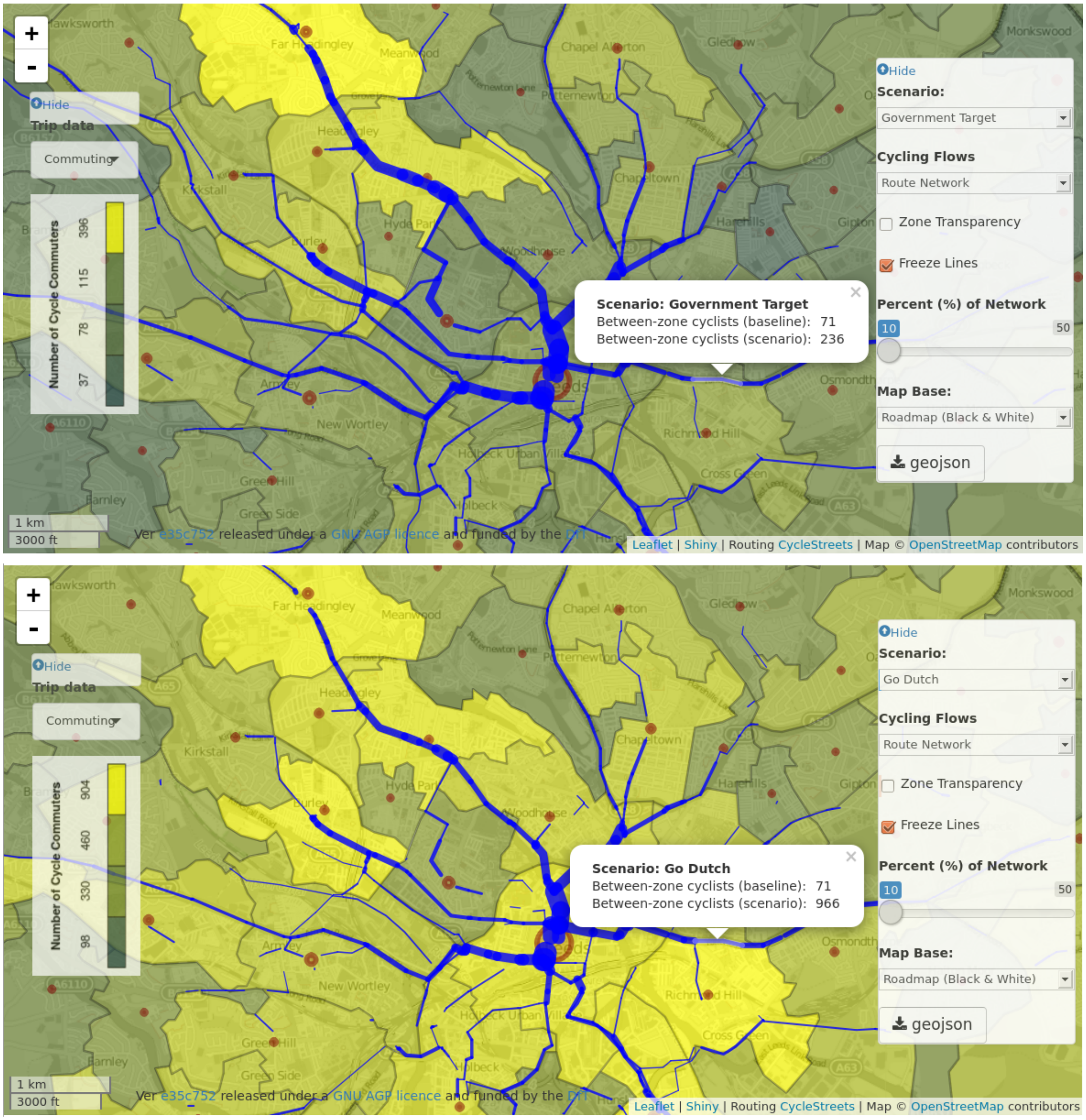


Figure 8: The Route Network layer illustrating the shifting spatial distribution of cycling flows in Leeds under Government Target (top) and Go Dutch (bottom) scenarios.

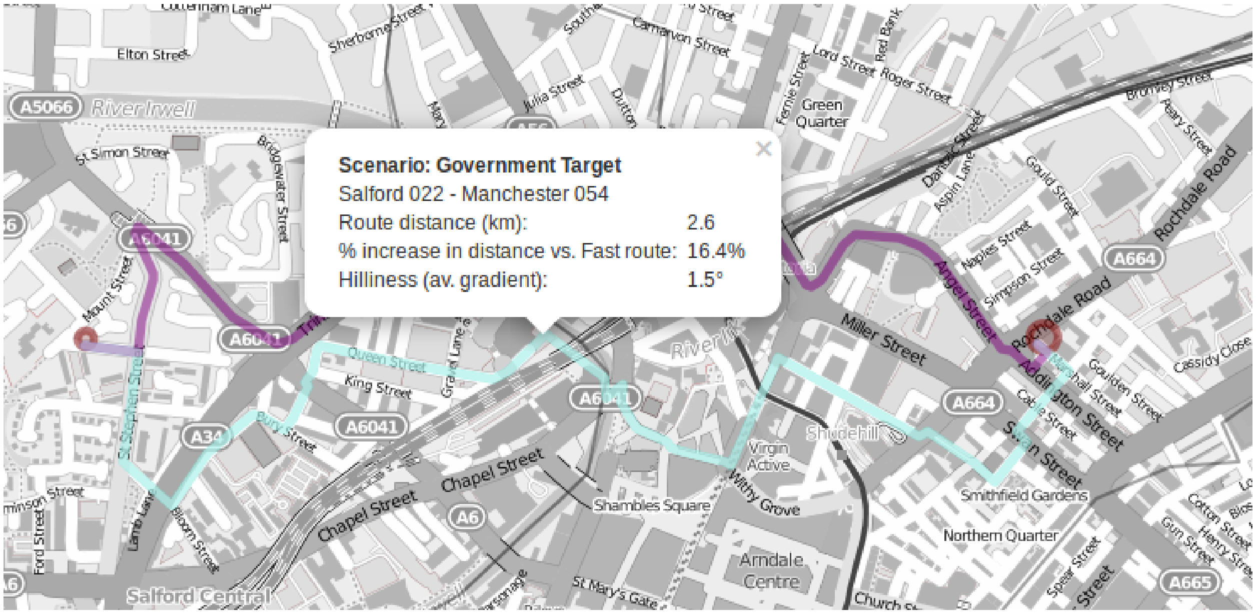


Figure 9: Close-up of the 'fastest' and 'quietest' routes from CycleStreets.net of the OD pair with highest cycling potential under the Government Target scenario in Manchester. This provides an indication of the local 'quietness diversion factor'

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 around 1.3 to 1.5 times the length of the 'crow-flies' Euclidean distance (defined as $q$ above). The same research suggests that circuity values for "for cycle provision should be 1.2" (CROW, 2007). This suggests that high quality cycle infrastructure along the 'fastest route' shown in Figure 9, or a more direct route that does not adhere to the current transport infrastructure, would be more attractive than an alternative quiet route that diverges greatly from the shortest path. Previous work indicates that this is likely particularly true for women and older people, for whom distance is a greater deterrent to cycling than for young men (Woodcock et al., 2016, see Appendix 8). Combined with their greater preference for segregated infrastructure reported by these groups, this highlights the importance of providing direct and safe routes to encourage cycling amongst groups who currently cycle the least.

Figure 9 demonstrates another feature of the PCT'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).

# 5 Discussion

We have outlined a method for estimating 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., 2013; Zhang et al., 2014) and online, interactive 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. Illustrative use cases of the PCT demonstrated the potential utility of the tool by showing that the spatial distribution of cycling demand is likely to shift as cycling grows. For example, the output of the PCT suggests that the 'centre of gravity' for cycling in the city of Leeds will shift towards areas with high numbers of short distance trips but low current rates of cycling.

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; Tight et al., 2011). The PCT could also: help translate national targets into local aspirations (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 use the project as a basis for further work (Lima et al., 2014).

As with any modelling tool, the approach presented in this paper has limitations: the reliance on Census OD data from 2011 means that the results are not up-to-date, and the user interface is constrained to a few, discrete, scenarios. These limitations suggest directions for future work, including: use of new sources of OD data, and the implementation of continuous variables to define future scenarios.

There is often a tension between transparency and complexity in the design of tools for transport planning, and the latter 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 'bottom-up'. The PCT's open source, freely available nature will, we believe, facilitate the future development of the PCT in an organic way that meets the needs of its users. We envision stakeholders with the capacity participating in the development of the tool, for example modifying scenarios for their own purposes, and academics adding new features and developing new use cases of the PCT. Community-led enhancements could include:

- 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).
- The extension of the model to cover variation between different demographic groups. This could be done using spatial microsimulation, which enables the use of additional individual-level variables, such as access to a cycle and physical fitness, to inform more targeted interventions (Lovelace et al., 2014).
- The incorporation of changes in land-use and transport since the Census 2011, to explore the dynamics of cycling potential, such as the impact of new residential and commercial

developments. This work could build on recently developed GIS for transport planning (Farrell et al., 2015).

- 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). Other data sources to include more trip types include mobile telephone providers (Alexander et al., 2015) and traditional transport models.
- Deployment of the PCT for in 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 planning is a complex and contested field (Banister, 2008). When it comes to sustainable mobility, policy, politics, leadership and vision are key ingredients that computer models alone cannot supply (Melia, 2015). The approach described here can, however, assist in this wider context by providing new tools for exploring the evidence at high geographical resolution and envisioning transformational change in travel behaviours.

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 PCT provides an accessible evidence base to inform the question of where to construct new cycling infrastructure and raises more fundamental questions about how models should be used in transport planning.

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