Active Travel England

Data Science for Active Travel Planning

Streets, schemes and networks

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Health benefits of active travel

- Everyday active travel associated with substantial reduction in all cause mortality
- 250k participants aged 40-69 from recruited 2007-2010
- Average follow-up time: 5 years
- Walking and cycling associated with reduced mortality
- Effects especially large for cycling (Celis-Morales et al. 2017)

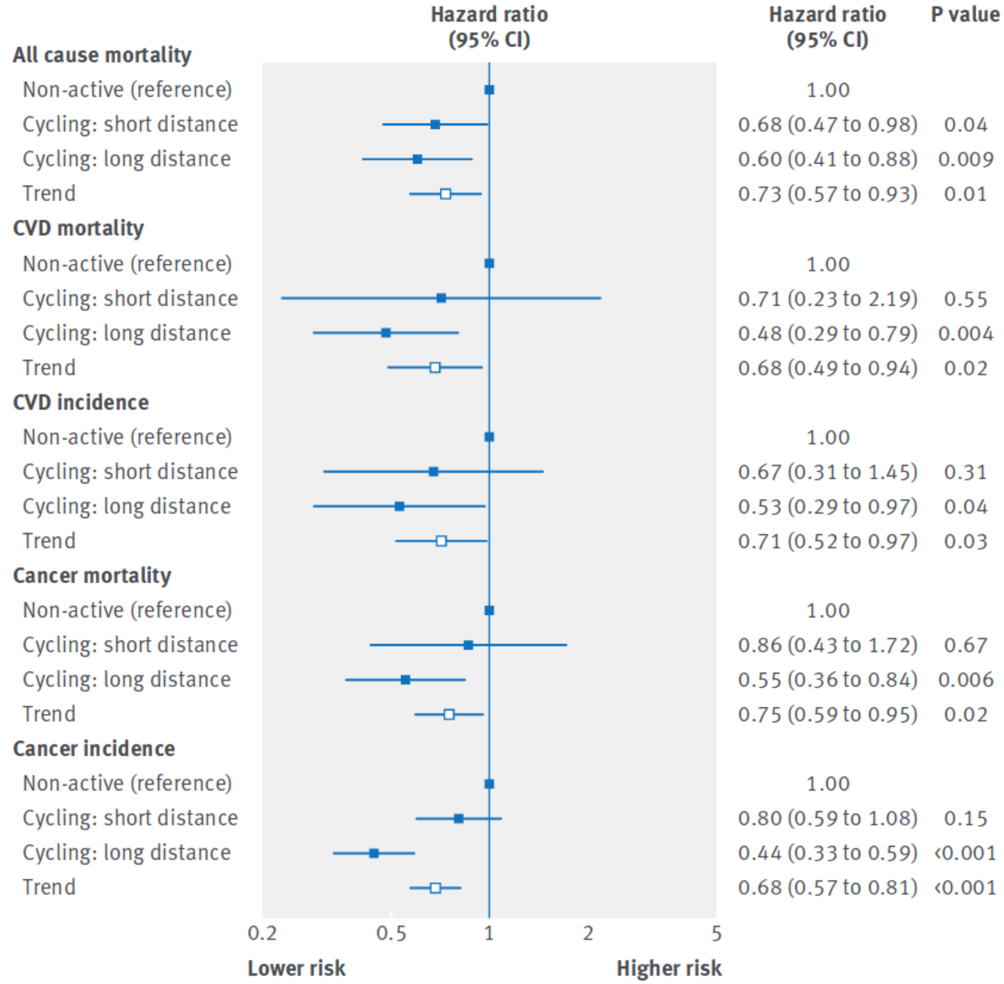

Fig 3 | Hazard ratio for all cause mortality, cardiovascular disease (CVD) incidence and mortality, and cancer incidence and mortality by weekly cycling commuting distance

'Association between Active Commuting and Incident Cardiovascular Disease, Cancer, and Mortality: Prospective Cohort Study'. BMJ https://doi.org/10.1136/bmj.j1456.

Health benefits of active travel

- Major mental health benefits
- Win-win-win solution
- Recent study: According to a partially randomized patient preference design, 141 patients with depression and/or anxiety disorder were randomized
- Clear advantages of active travel interventions supporting social prescribing (Verhoeven et al 2023)


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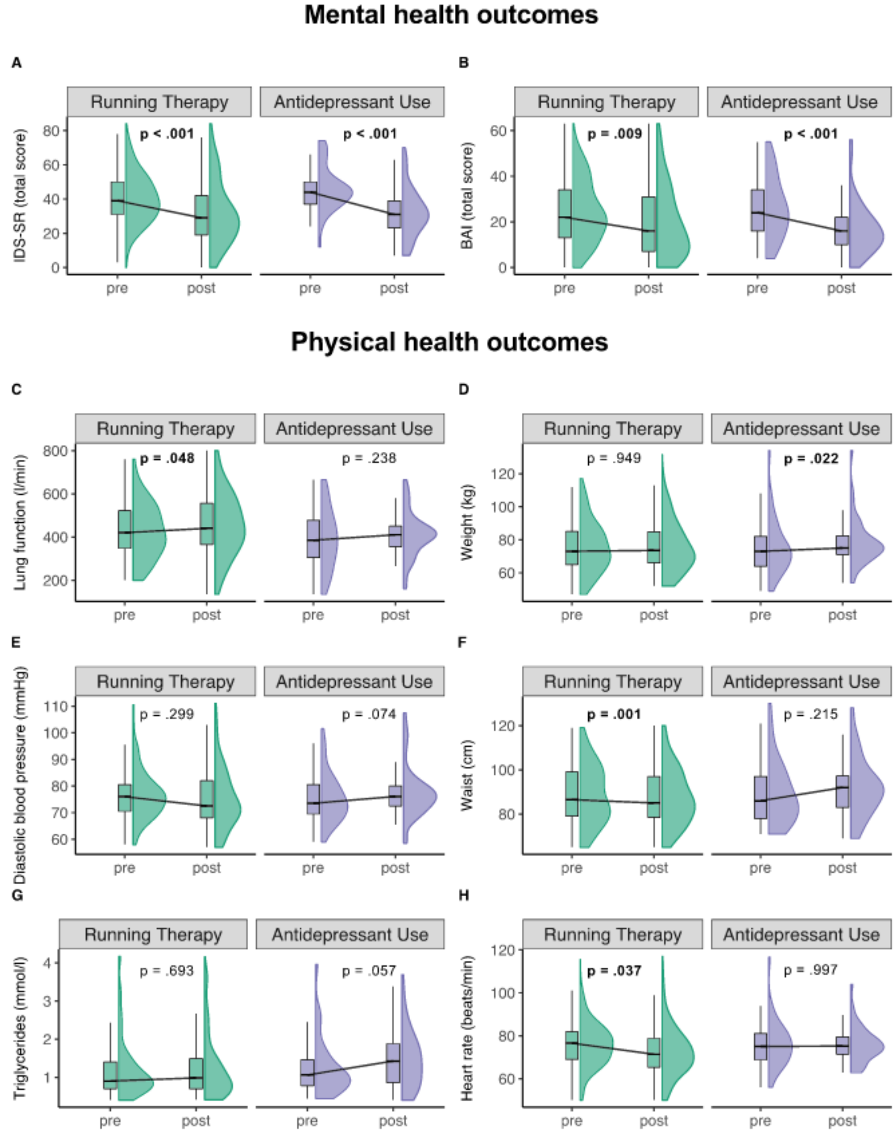
Running as good as pills for treating depression and anxiety, study finds

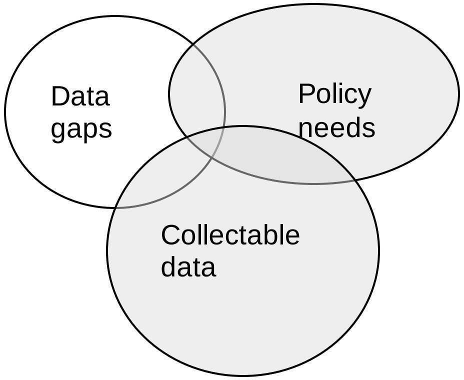
Exercising twice a week improves mood while also boosting physical health but can be harder to sustain than antidepressants, say academics

By Sarah Knapton, SCIENCE EDITOR
7 October 2023 • 8:00am



'Antidepressants or Running Therapy' https://doi.org/10.1016/j.jad.2023.02.064.

What we do in Active Travel England



Infrastructure data
- Existing or (e.g. OSM/OS) **planned** infrastructure
- Geometries (space)
- Lifecycle (time)
  - Completion date
  - Planned infrastructure
  - Dates
- Attribute data
  - Infrastructure type

Behaviour data
- Travel survey data
- Preferences
- Movement data
  - GPS data
  - Point/area counts

Outcomes
- Environmental
- Health
- Economic
- …

Data and Digital (7+2 FTE)

Head of Data and Digital
Lead Developer - Management

Lead Data Engineer

Senior data scientist

Data Scientist (*Statistics and visualisation skills*)

Lead Developer

Software Engineer

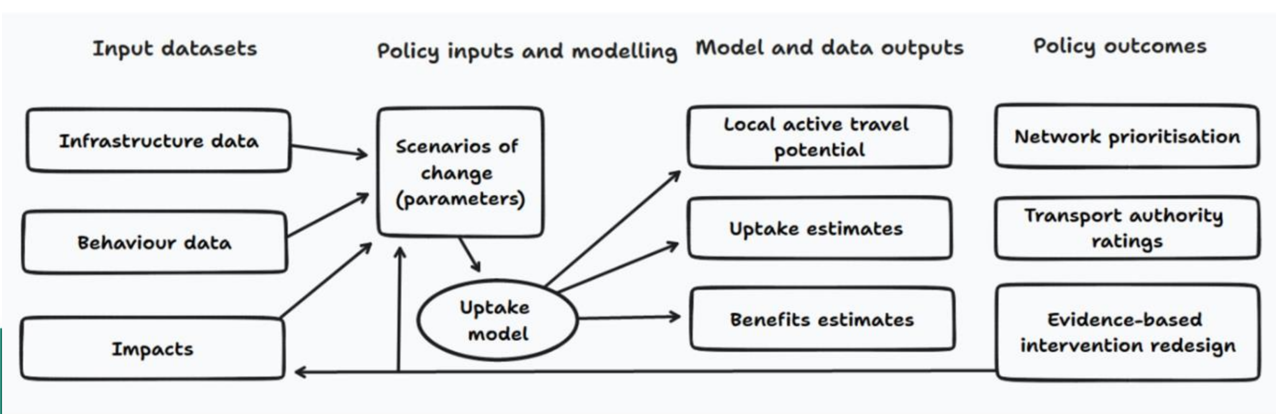
Data scientist

In ATI

Lead Developer

Software Developer

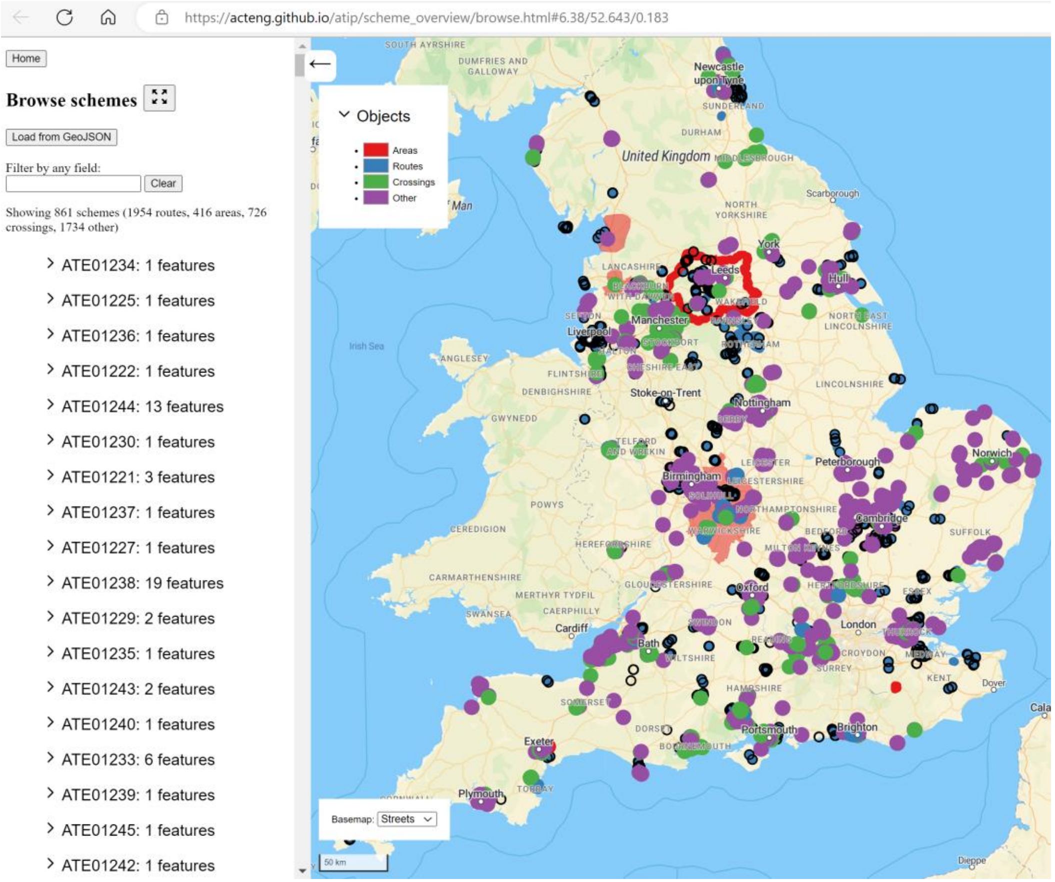
DDAT roles



Stakeholders
- Analysis team
- ATE
- Government
- Public

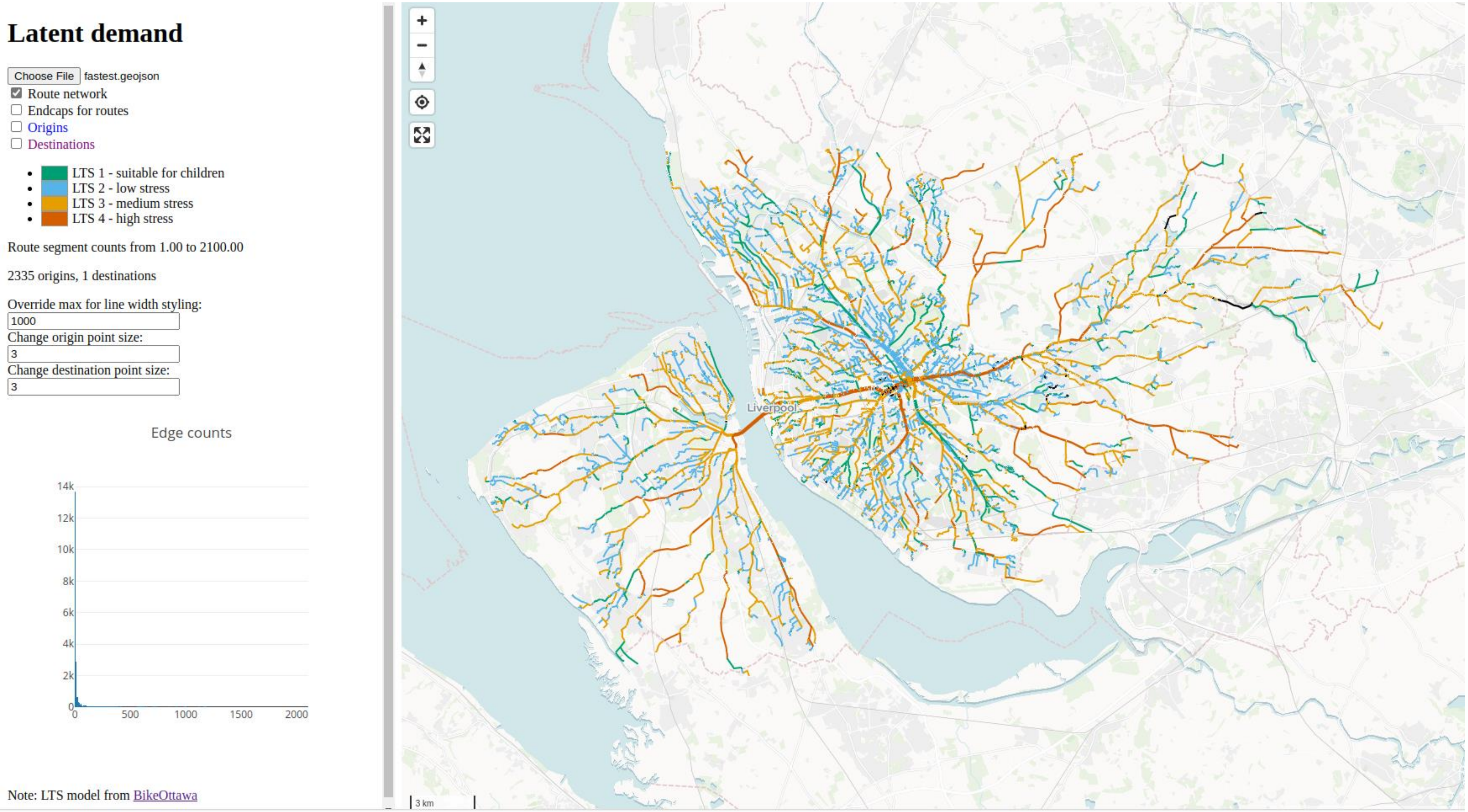
Example project: ATIP

- We now know where schemes are
- Inspectors have a baseline for remote and on site inspections
- Reduced friction between different parts of the transport planning process
- We can do additional analysis, e.g. to identify all schemes in proximity to schools
- **Live Demo!**



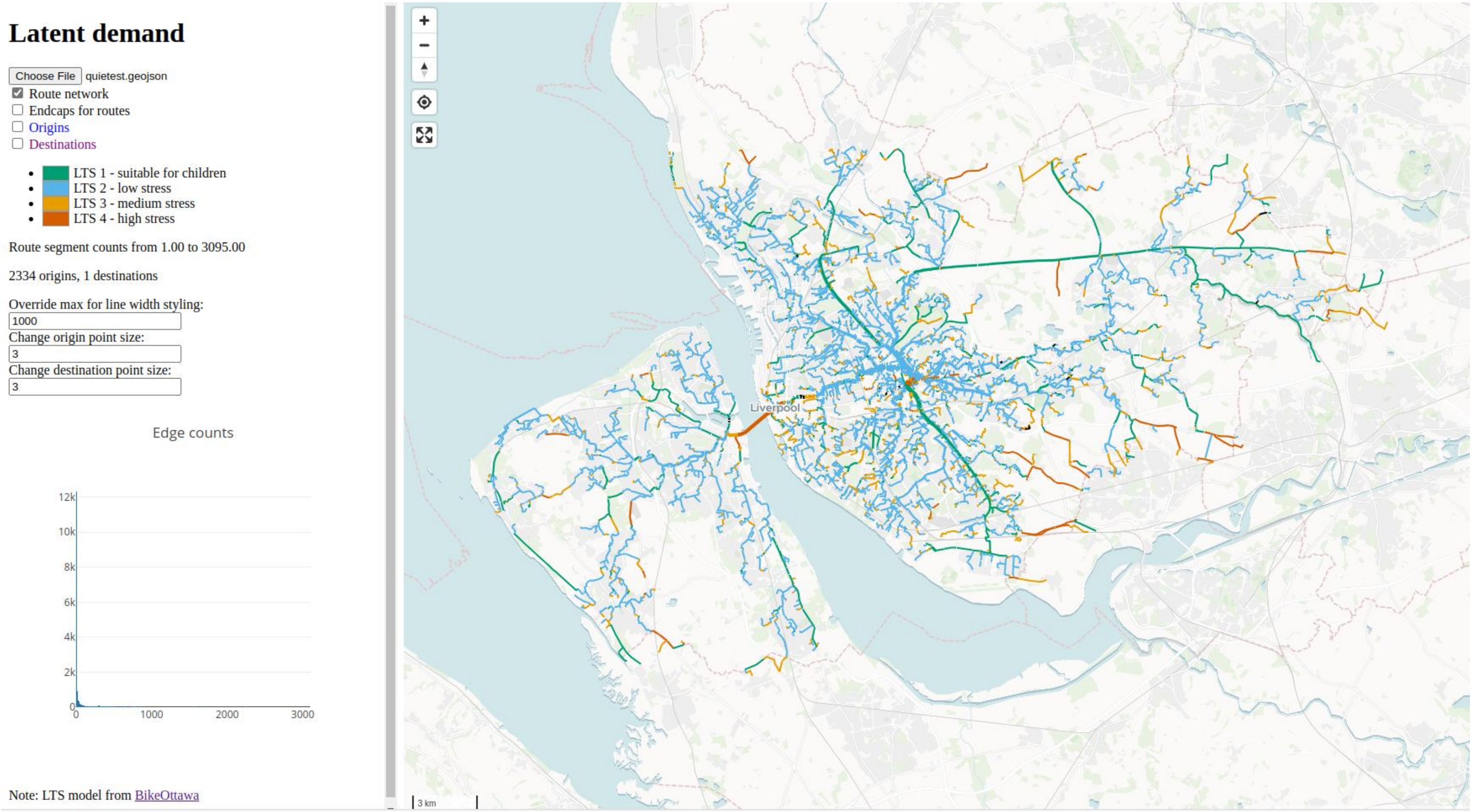
"The inspections team at Active Travel England used ATIP to quickly determine location, context and whether the correct approach was being taken with the proposed scheme assets. Furthermore, ATIP gave the team a chance to assess network cohesion across multiple government programmes and compliance with LCWIP (Local Cycling and Walking Infrastructure Plan) priorities."
Brian Deegan, Director of Inspections, Active Travel England

Safe routes to hospitals?



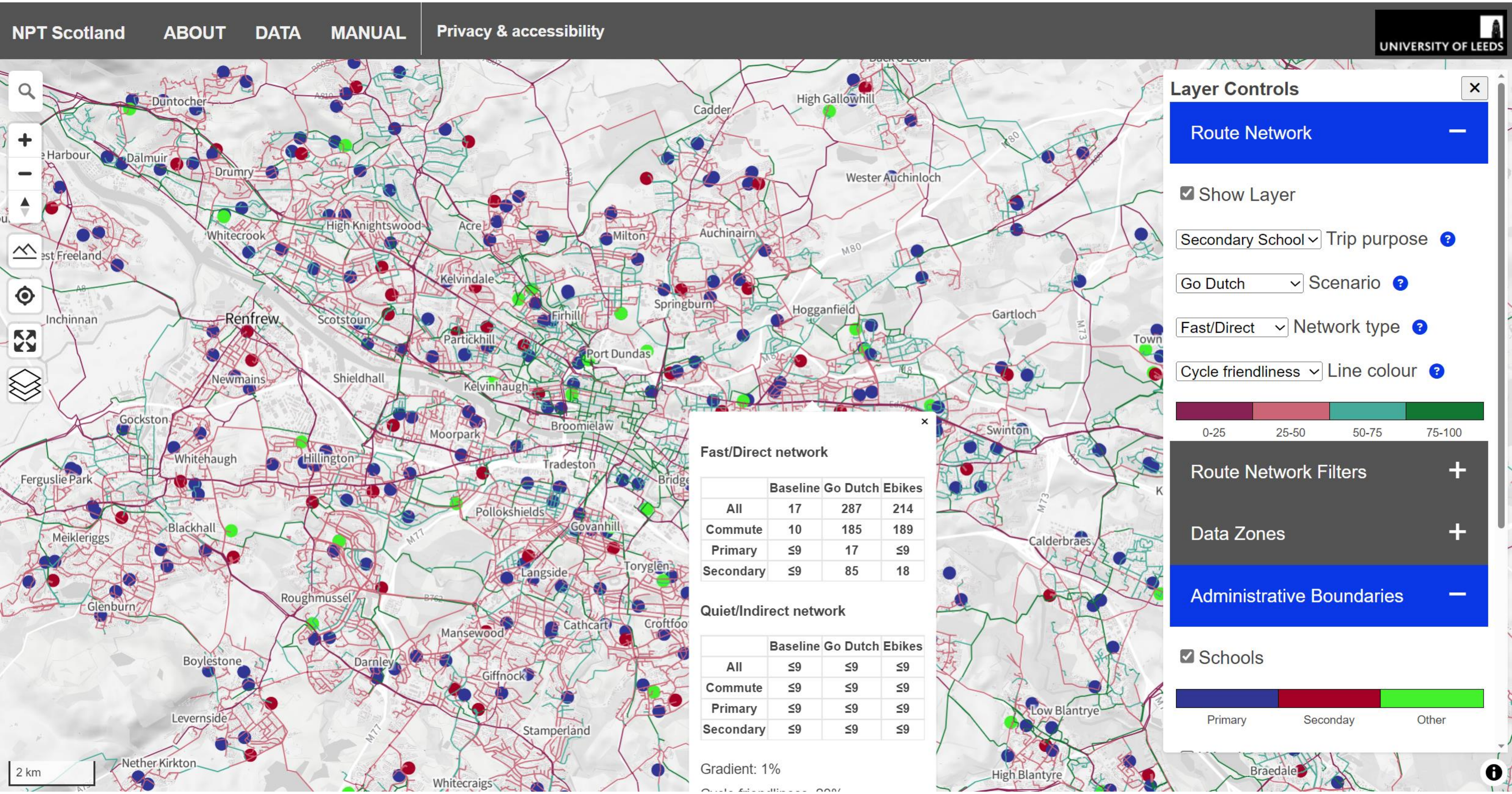
'Fastest' routes to Alder Hey Hospital in Liverpool based on OD data. Source: https://dabreegster.github.io/routing-engines/

Route choices and tradeoffs



'Quietest' routes to Alder Hey Hospital in Liverpool based on OD data. Source: https://dabreegster.github.io/routing-engines/

Example project: SchoolRoutes



Network planning tool: https://nptscot.github.io/

Elements of Transport Data Science

- **Areal units**: transport patterns can be understood with reference to zonal aggregates, such as the main mode of travel (by car, bike or foot, for example), and average distance of trips made by people living in a particular zone, covered in Section 13.3
- **Desire lines**: straight lines that represent 'origin-destination' data that records how many people travel (or could travel) between places (points or zones) in geographic space, the topic of Section 13.4
- **Nodes**: these are points in the transport system that can represent common origins and destinations and public transport stations such as bus stops and rail stations, the topic of Section 13.5
- **Routes**: these are lines representing a path along the route network along the desire lines and between nodes. Routes (which can be represented as single linestrings or multiple short *segments*) and the *routing engines* that generate them, are covered in Section 13.6
- **Route networks**: these represent the system of roads, paths and other linear features in an area and are covered in Section 13.7. They can be represented as geographic features (typically short segments of road that add up to create a full network) or structured as an interconnected graph, with the level of traffic on different segments referred to as 'flow' by transport modelers (Hollander 2016)

Another key element: Agents

Source: Geocomputation with R

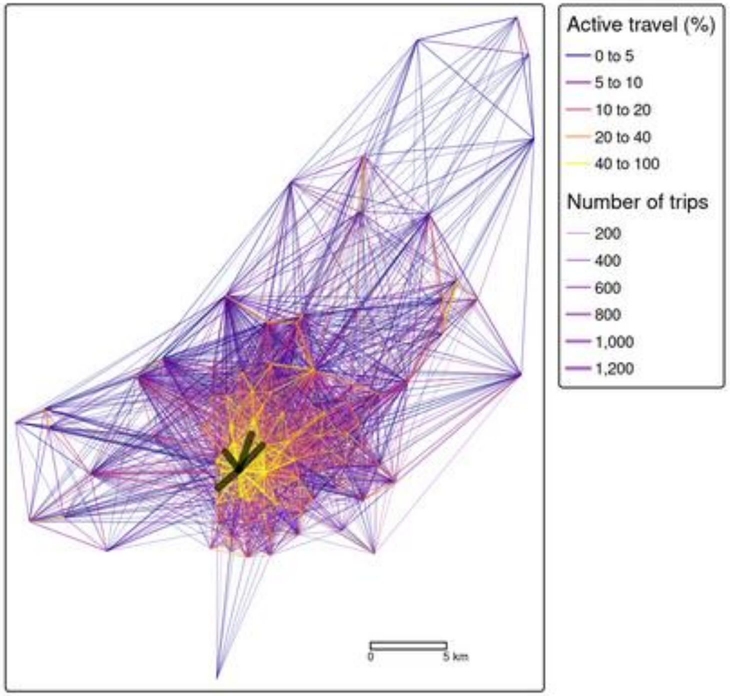


FIGURE 13.3: Desire lines representing trip patterns in Bristol, with width representing number of trips and color representing the percentage of trips made by active modes (walking and cycling). The four black lines represent the interzonal OD pairs in Table 7.1.

Origin-destination (OD) data

```r
od_top5 = bristol_od |>
  slice_max(all, n = 5)
```

o	d	all	bicycle	foot	car_driver	train
E02003043	E02003043	1493	66	1296	64	8
E02003047	E02003043	1300	287	751	148	8
E02003031	E02003043	1221	305	600	176	7
E02003037	E02003043	1186	88	908	110	3
E02003034	E02003043	1177	281	711	100	7

TABLE 13.1: Sample of the top 5 origin-destination pairs in the Bristol OD data frame, representing travel desire lines between zones in the study area.

Source: Geocomputation with R: Transportation

Routing

3 types of routing from data science environment: 1) in memory, 2) locally hosted routing engine (e.g. OSRM), 3) remote services (e.g. Google Directions)

Locally hosted routing engines include OpenTripPlanner, Valhalla, and R5 (which are multi-modal), and the OpenStreetMap Routing Machine (OSRM) (which is 'uni-modal'). These can be accessed from R with the packages **opentripplanner**, valhalla, **r5r** and osrm (Morgan et al. 2019; Pereira et al. 2021). Locally hosted routing engines run on the user's computer but in a process separate from R. They benefit from speed of execution and control over the weighting profile for different modes of transport. Disadvantages include the difficulty of representing complex networks locally; temporal dynamics (primarily due to traffic); and the need for specialized external software.

```
routes_short = route(l = desire_lines_short, route_fun = route_osrm,
                     osrm.profile = "bike")
```

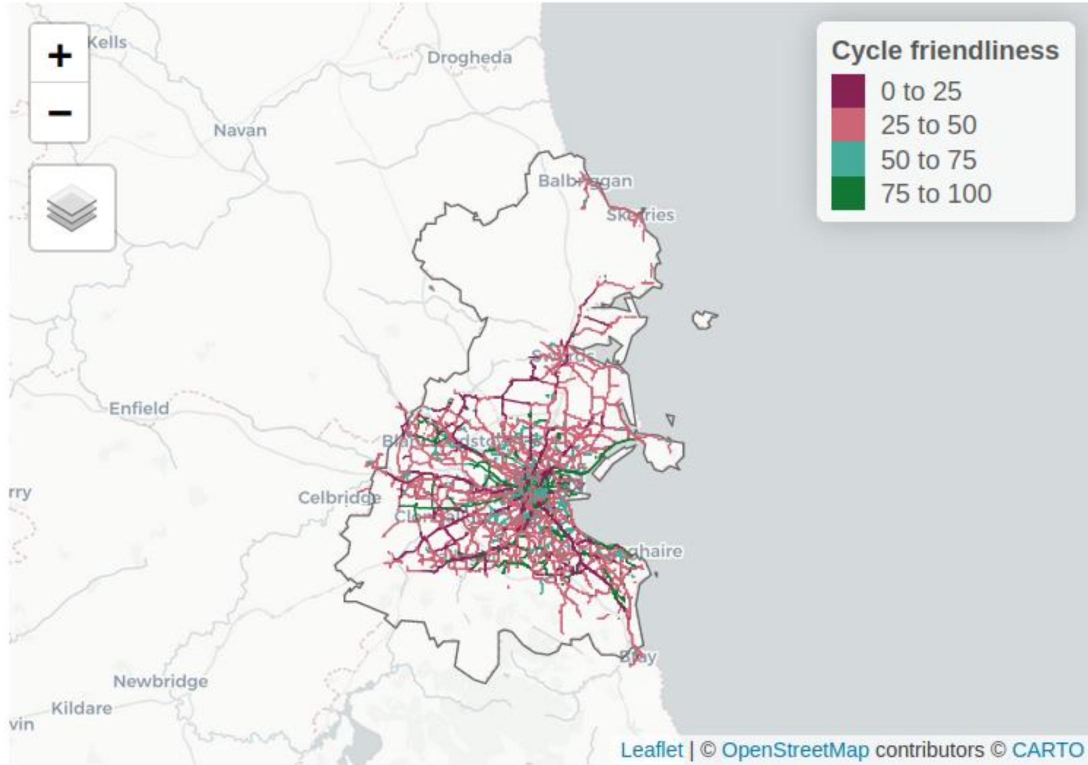
Route network analysis

- What are the key summary statistics we want to know about a route network?
- A question that data science can help answer!

- Network length
- Average flow per link
- Average flow-weighted 'quietness' per link
- Network density
- Network density compared with all available segments
- Distribution of flows
- Spatial inequalities
- Comparisons with other spatially-variable statistics (e.g. population density)
- …
- Source: open CRUSE tool: https://cruse.bike/dublin/route-types

Fastest network

On the fastest network, 29% of the distance cycled occurs in non-hostile segments and 13% in cycle-friendly segments.



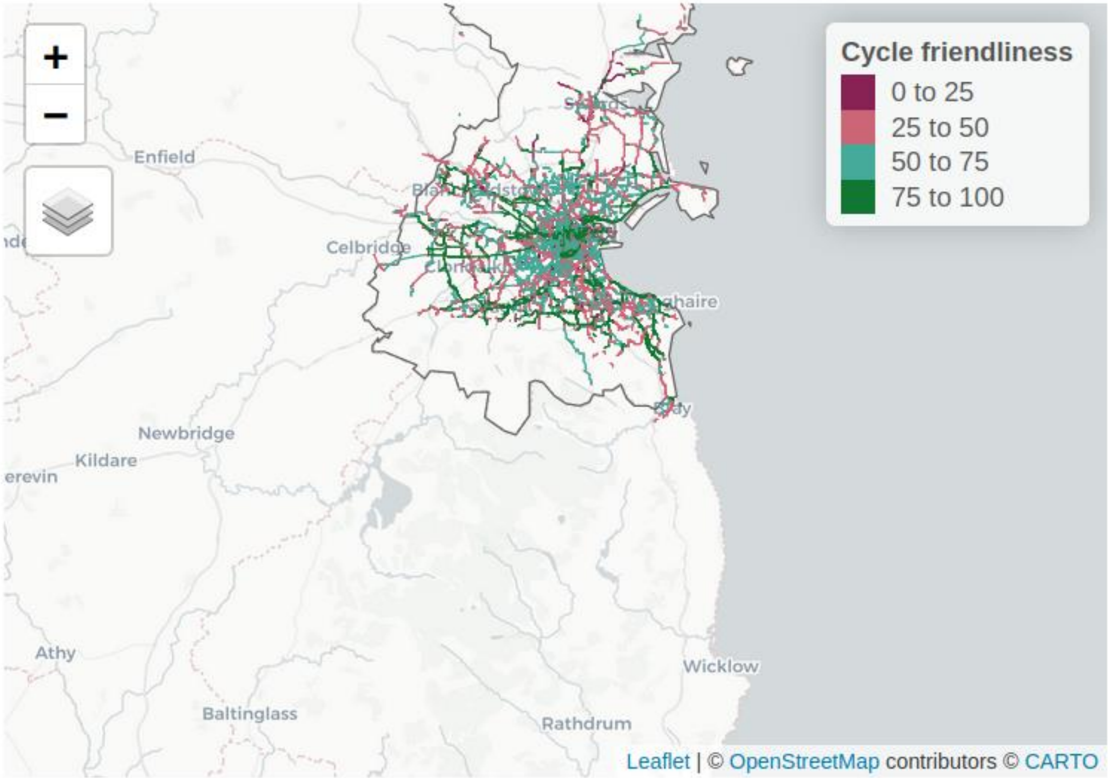
Click here to see the map full screen.

Route network analysis

- What can change?

Quietest network

Under the baseline scenario, 69% of the distance cycled on the quietest network occurs in non-hostile segments and 32% in cycle-friendly segments.



Click here to see the map full screen.

Active travel planning: details matter

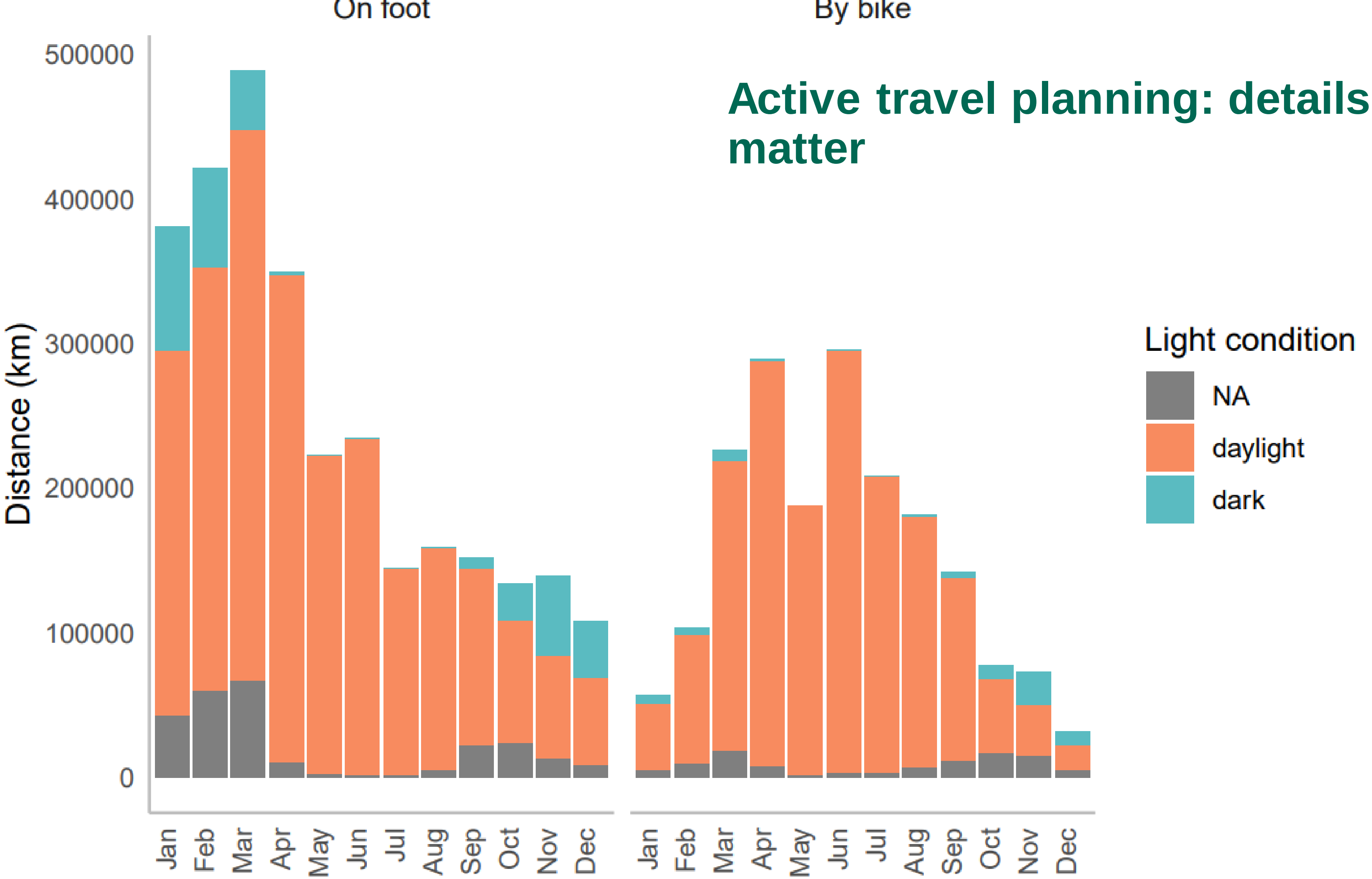


Figure 2: Distance (km) travelled by Strava users per month and light condition, City of Glasgow

Research by Eugeni Vidal, SATURN project. Source: https://github.com/saturnlighting

Table 4: Standardized estimates and standard errors of associations between crime, night lighting, their interaction, other relevant spatial factors and distance (km) on foot and by bike in the daylight and dark.

	Daylight		Dark	
	km on foot	km by bike	km on foot	km by bike
Crime	-0.36 ***	-0.36 ***	-0.35 ***	-0.57 ***
	-0.08	-0.08	-0.08	-0.11
Light	0.52 ***	0.60 ***	0.55 ***	0.71 ***
	-0.1	-0.11	-0.1	-0.14
Crime*Light	0.23 *	0.21 *	0.28 **	0.21
	-0.09	-0.1	-0.1	-0.13
Income	1.02 ***	0.56 ***	1.15 ***	0.73 ***
	-0.08	-0.08	-0.08	-0.1
Access	0.28 ***	0.04	0.24 ***	0.15
	-0.06	-0.07	-0.06	-0.09
Density	-0.07	-0.18 **	-0.09	-0.07
	-0.08	-0.07	-0.08	-0.1
Recreational	-0.01	-0.23 **	-0.12	-0.27 **
	-0.13	-0.07	-0.08	-0.09
Commercial	-0.15 *	-0.09	-0.1	-0.12
	-0.08	-0.08	-0.08	-0.11
Industrial	-0.13	-0.02	-0.24 ***	-0.16
	-0.07	-0.08	-0.06	-0.09
Infrastructure	0.92 ***	0.83 ***	0.96 ***	0.95 ***
	-0.12	-0.12	-0.13	-0.16
Quietness	0.43 ***	0.44 ***	-0.03	0.25 **
	-0.06	-0.07	-0.07	-0.09
Gradient	-0.35 ***	-0.41 ***	-0.36 ***	-0.47 ***
	-0.06	-0.06	-0.07	-0.09
N	746	746	746	746
sigma	1.44	1.53	1.51	2.02
logLik	-5836.8	-5606.53	-4341.55	-2449.17
AIC	11701.6	11241.07	8711.1	4926.33
BIC	11766.2	11305.67	8775.7	4990.94

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

What else can transport data science + geocomputation do?

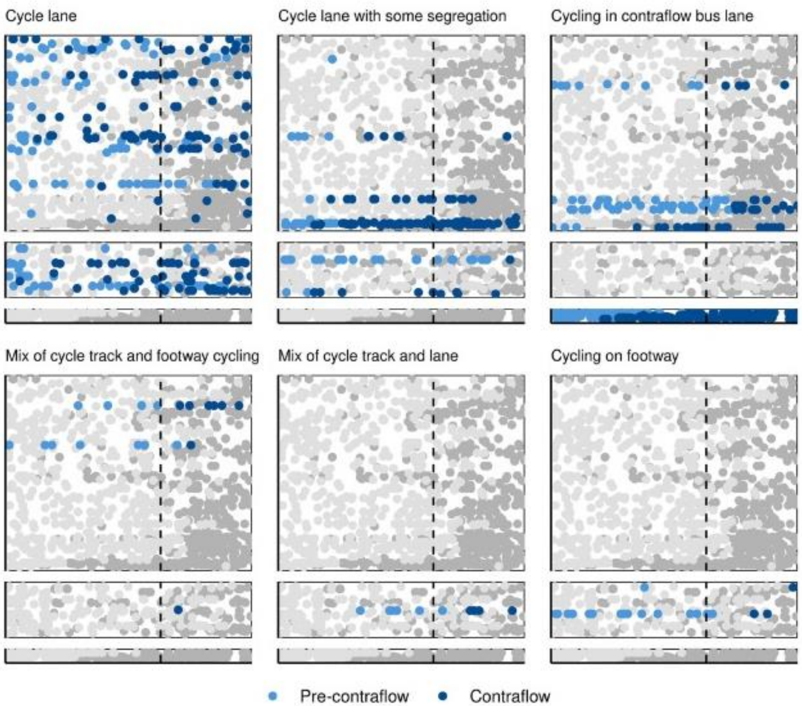


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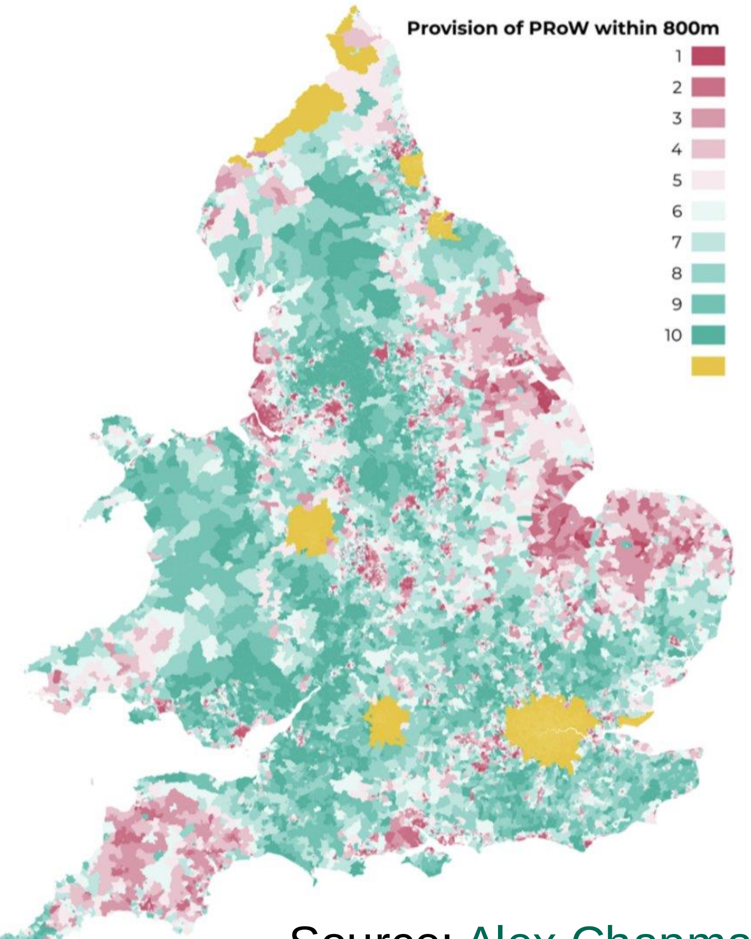
Fig. B1. **Dot visualisation of all crashes involving pedal cycles within 10 m of a road segment by unique road segment (vertical position); date of crash (horizontal position); crash segment status (colour); and significant change to road segments (pane).** Top visualisation represents all crashes. Lower visualisations highlight crashes by additional cycling infrastructure mentioned in Traffic Regulation Order. The seven contraflow removed crashes have been omitted to aid visualisation.

Source: Caroline Tait ([2023]) Accident Analysis & Prevention

MAP 1: LENGTH OF PUBLIC RIGHT OF WAY WITHIN 800M OF A POSTCODE, GROUPED INTO LOWER LAYER SUPER OUTPUT AREA (LSOA) DECILES. AREAS WITH MISSING DATA ARE SHOWN IN YELLOW, WHERE DECILE 1 (PINK) REPRESENTS THE LOWEST LEVELS OF PROW PROVISION.



Source: Alex Chapman

Source: Authors' analysis of local authority public rights of way datasets

10x your impact

- Programming: an area where 10x speed-ups are possible
- Communication: key
- Packaging: build foundations
- For others to build on

SPLINK
Data linkage at scale

release v3.9.8 | downloads/month 121k | API documentation

Fast, accurate and scalable probabilistic data linkage

Splink is a Python package for probabilistic record linkage (entity resolution) that allows you to deduplicate and link records from datasets that lack unique identifiers.

CRAN 3.0.0 | R-CMD-check passing | downloads 77K | lifecycle stable | Peer Reviewed | JOSS 10.21105/joss.01181 | codecov 52%

stats19

stats19 provides functions for downloading and formatting road crash data. Specifically, it enables access to the UK's official road traffic casualty database, STATS19. (The name comes from the form used by the police to record car crashes and other incidents resulting in casualties on the roads.)

A full overview of STATS19 variables be found in a document provided by the UK's Department for Transport (DfT).

fespuny / SplineHazardRegression

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