A NEW Travel Demand Model for Outdoor Recreation Trips

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1. INTRODUCTION

Travel to outdoor recreational spaces has increased significantly in the last decade. According to a report from the Natural England (2016), the total number of outdoor recreational trips has risen from 2.86 billion (2009-2010) to 3.4 billion (2017-2018) in England, generating more than 20 billion pounds just in expenditures. Hence, it is not a surprise that there is a growing interest in understanding the outdoor recreational travel behaviour. Natural England has funded the DEFRA (Department for Environment, Food & Rural Affairs) and Forestry commission to conduct a survey, called Monitor of Engagement with the Nature Environment (MENE) since 2009. This survey has provided robust evidence for the study of travel demand for outdoor recreational trips. The aim of this research is to build a new travel demand model for outdoor recreation activities, based on the conventional transport modelling method. The new model can be used to estimate travel demand for any outdoor recreational destination. The model results can assist planners in assessing interventions of land use and landscape regarding their effects on outdoor recreation activities and associated benefits.

Why is understanding travel to outdoor recreational sites important? Besides the age-old belief that outdoor activities are good for the body and spirit, in recent years, there has been a growing evidence base showing that outdoor recreation is closely associated with human health and wellbeing (Bateman et al., 2014; Fuller et al., 2007; Tzoulas et al. 2007). This evidence appears to have started to influence how people perceive the benefits of outdoor recreation. In a systematic survey on Monitor the Engagement with the Natural Environment (MENE) that has been going for nine years, the proportion of outdoor recreation visits where health and exercise were cited as a motivation rose from 34 per cent in 2009 to 50 per cent in 2018.

On the other hand, relative to other primary disciplines that shape land use and the landscape, such as traffic engineering and estate finance, the effects of specific land use planning or landscape design interventions that aim to improve outdoor recreation activities remain poorly quantified. This puts those who wish to promote such projects at a disadvantage when debating short-term funding priorities and longer-term management of outdoor recreation spaces in the context of land use planning and landscape design. The literature review for this research shows that one particular weak link that leads to this disadvantage is the poor understanding of how and why people travel to outdoor recreation destinations. This appears to be a field of research work that has fallen through a long-standing gap between transport planning and environmental studies.

The aim of this study is to develop a new travel demand model that can represent and predict travel to individual outdoor recreational sites. The new model draws upon ideas from mainstream transport modelling that underlies transport and land use planning in representing how frequently people travel, where they choose to go, and what means of transport they adopt. The model links the geographical distribution of visits to key land uses, landscape design and urban design features at a local level, such as the distribution of population among neighbourhoods, the location of recreational sites, transport accessibility and environmental characteristics, to the outcomes of travel decisions. The resulting quantification of the impacts of policy interventions is expected to make a significant improvement to the empirical basis for decisions on investment, regulation, and planning of outdoor recreation sites. More specifically, this research aims to address four main research questions: First, why do we need another travel demand model? Secondly, how to build the new model for outdoor recreational travel? Thirdly, is the estimation accurate enough? And to what extent can the new model be transferred to destinations outside the case study area?

2. LITERATURE REVIEW

2.1 Travel demand modelling for outdoor recreational trips

In transport travel demand modelling, it is conventional practice to apply discrete choice models (DCMs) to understand and predict a wide range of choices, such as how people choose among alternative destinations for jobs, homes, shopping, personal services etc (Boyce & Williams, 2015). However, it has rarely been used to understand and model travel to outdoor recreational spaces. Mainly because this group of trips is unlikely to take place in the peak time periods, during when congestion would be the most likely to happen.

Although outdoor recreation trips were seldom mentioned in the transportation modelling, the studies of outdoor recreation in the environmental and economic fields were not rare. Research using discrete choice method focuses on a single habitat/site for their economic interests. For example, the freshwater or coastline recreations are among the most extensively studied areas (Table 2-1).

A common weakness of such studies is the lack of transferability, as it makes the method difficult to apply for land use planning. One reason for the lack of general outdoor recreational activities studies is that there was no existing data regarding general outdoor recreation before the Monitor of Engagement with the Nature Environment (MENE) survey. The MENE survey is a questionnaire-based survey conducted by Natural England since 2009. The survey is about how and why people engage with England's natural environment, collects information about the ways that people engage with the natural environment such as visiting the countryside, enjoying greenspaces in towns and cities, watching wildlife and volunteering to help protect the natural environment. Fieldwork started in March 2009 with around 800 respondents interviewed every week across England using an in-home interview format. Every year, at least 45,000 interviews are undertaken. This is the only and most comprehensive survey regarding outdoor recreational trips. This dataset also included primary empirical evidence to build up the new model in this research.

A study carried out by Sen et al. (2013) as part of the UK National Ecosystem Assessment (NEA) project was the only research built on the MENE data. The model has applied a different modelling theory—the variation of the Poisson regression, the Negative Binomial Regression (NBR).

Table 2-1 Discrete Choice Modelling-based Outdoor Recreation Studies

Author	Recreation type	Model
Parsons and Kealy (1992)	Fresh-water recreation at Wisconsin lakes	Nested logit
Feather (1994)	Fresh-water at Minnesota lakes	Standard logit
Shaw and Ozog (1999)	Five sites in Maine, three in Nova Scotia, New Brunswick, and Quebec, Canada	Nested logit
Kling and Thomson (1996)	Sports fishing in California	Nested logit
Parsons and Hauber (1998)	Recreational fishing in Maine	Nested logit
Parsons, Plantinga, and Boyle (2000)	Fishing lakes in Maine	Nested logit
Jones and Lupi (1997)	Recreational fishing in Maine	Nested logit
Parsons, Massey, and Tomasi (2000)	Beach recreation in Delaware, New Jersey, Maryland, and Virginia	Nested logit
Peters, Adamowicz, and Boxall (1995)	Fresh-water fishing in Southern Alberta, Canada	Standard logit
Hicks and Strand (2000)	Publicly accessible recreation beaches along the western shore of the Chesapeake Bay in Maryland	Standard logit

2.2 Application of the negative binomial model in the UK National Ecosystem Assessment (NEA) outdoor recreation model

The Poisson and Negative Binomial Regression is a prevalent method in the environmental economics field. For example, Jones et al. (2010) has estimated the number of informal recreational visits to woodland area. Martinez-Espineira et al. (2008) looked at trips to the Gros Morne National Park in Canada. Shreshta et al. (2007) studied nature-based recreation in public areas of the Apalachicola River region in the United States, and Bowker et al. (2007) estimated the economic value of recreational trails in the Virginia Creeper Rail trail. All of these studies were based on on-site observation and applied either the Poisson distribution or the NBR. The only general outdoor recreation research was conducted by Sen et al. (2011, 2014) from the Centre for Social and Economic Research on the Global Environment (CSERGE), University of East Anglia. This study is part of UK NEA, the first analysis of the UK's natural environment in terms of the benefits it provides to society and continuing economic prosperity (Bateman et al., 2014).

The modelling method was applied in the UK NEA's study for the negative binomial model (Sen et al., 2014). The model was used to predict the number of visits made from each outset location to any given recreational site. The number of visits is assumed to depend on several explanatory variables, including land covers of the destinations and alternatives. The alternative was represented using a 10km buffer area around the origin, travel time, demographic information such as the percentages of retired people, the proportions of non-white ethnicity, total population and median of income. Random intercepts are used to catch unobserved correlations; for example, people from the same place may or may not have emotion attached to certain greenspaces.

The use of this forecasting model is a planning tool for examining the consequences of implementing alternative polices. It is not difficult to see that the strengths of the UK NEA's NBR model. Firstly, unlike previous studies which focused on a single site or habitat, this framework can be applied to estimate recreational demand and values for any spatial unit and habitat mix. Secondly, this model has incorporated environmental characteristics, which are rarely considered by travel forecasting modelling. Thirdly, the applications of the UK NEA's model have revealed that forecasting outdoor recreational trips through environmental characteristics can provide planners with empirical evidence of how people are using green spaces. This kind of model did not exist before, but it is valuable because it can assist decision-makers by estimating the changes in value arising from different scenarios at the national level. It is also able to optimise the location of the proposed green space at the local planning level by forecasting the number of visits to the new site.

However, some weaknesses of this method are evident too. First, it is not theoretically consistent to study choice behaviour purely based on a statistical method such as the NBR model (Boyce & Williams, 2015). Studies relying on the statistical method are usually location-dependent and are difficult to transfer to different places. Forecasting travel demanding should be a part of the studies of human choice behaviour. Also, the NBR is a zonal model, which means it can only be operated at a zonal level. It is more likely to suffer biases caused by variations among the individuals within each zone.

Secondly, the environmental characteristics of sites were defined by linking their one km square grid cell locations to habitat proportions derived from the 25m resolution UK-wide Land Cover Map 2000 data. The land cover map is produced by the Centre for Ecology and Hydrology. This is a digital map of Great Britain derived from satellite imagery since 1990. Land Cover Map was derived from image segments and was assigned land cover values according to the pixel distributions within. The apparent weakness of this data is its poor accuracy at the local level. The proportion of land cover at regional level seems correct. However, when zoomed to the neighbourhood level, land shapes, particularly of the open space in the cities, were very easily only partially recognised, and the detailed land cover types were mistaken. Thirdly, the UK NEA's model includes only land-cover data but has not mentioned anything regarding land use. Land-use data is more relevant than land-cover data when planning decisions were made. This weakness significantly limits the application of the model.

Travel time in studies carried out by Sen et al. were calculated using the Ordnance Survey Meridian road network, and average road speeds from Jones et al. (2010). The study by Jones et al. (2010) assigned a speed to a type of road (e.g. Motorway, A-road, B-road and minor road), and it also discriminated the differences between urban and rural contexts. The road network was converted into a regular grid of 100 x 100-metre cells with each cell containing a value corresponding to travel-time-per-unit distance. The resultant travel time map is used to calculate the minimum travel time between any outset location and any destination site (Sen et al., 2011). The noticeable problem with this method is that the assumption disregards travel mode and road congestions, which are considered essential when estimating the cost of travel.

As a result, although the UK NEA's model gives a fair estimation on trip accounts at the national and regional scale, it faces various challenges when estimating trips to an individual outdoor recreational site for the reasons discussed above. Consequently, it is not expected to be used in making estimations of visits to a single destination. In conclusion, there is a distinct gap in our knowledge and analysis of outdoor recreational travel. Building a new travel demanding model for outdoor recreational trips will be necessary to fill this gap.

3. MODEL CALIBRATION

3.1 Introduction to study area

The study area used for model calibration involves two ceremonial counties in the North-West Region. It covers all of the Cheshire county and six of the ten districts in the Greater Manchester area (Table 3-1). The boundary of the case study area was drawn as shown in Figure 3-1 for two reasons: firstly, this coverage facilitates in-depth studies in green space scenarios. Secondly, 3501 interviewees from the MENE data were collected within this boundary. This has given us sufficient samples to carry out further analysis and training the new model.

Table 3-1 Upper Tier Local Authorities Included in Research Area

Upper Tier Local Authorities
Cheshire:
Cheshire East
Cheshire West & Chester
Halton
Warrington
Wirral
Greater Manchester:
Bolton
Bury
Manchester
Salford
Trafford
Wigan

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Figure 3-1. Case study area.

3.2 Data collection and preliminary analysis

The variables included in the preliminary analysis (Table 3-2) were decided based on an extensive literature review of previous studies. Various data were collected for this area to build the new model, includes demographic data from the Office for National Statistics; origin and destination information from the MENE survey; travel time captured from Google directions API; and environmental characteristics derived from combining data from OpenStreetMap, the Generalised Land Use Database (GLUD) and the MENE survey.

3.2.1 Travel Profile

In previous studies, the disutility of travel to outdoor recreational sites was commonly investigated using one or more of following three aspects: travel time (e.g., Jones et al., 2010; Sen et al., 2014), travel distance (e.g., Bestard & Font, 2010; Herriges & Phaneuf, 2010) and costs (e.g., Bowker et al., 2007; Francis & Martínez-espiñeira, 2012). Travel cost was normally calculated by multiplying travel time by single unit time cost. Studies have different preferences on the value of single-unit time cost, and no agreement has been reached as to what value should be used for outdoor recreational trips (Fezzi et al., 2012; Hagerty & Moeltner, 2005). Therefore, in this research, travel time and travel distance were the only variables tested.

Table 3-2 Variables tested in this Study

Variables
Travel Profile:
Mode
Time
Distance
Environmental Characteristics:
Land use
Land Cover
Demographic:
Population
Percentage of retired population
Percentage of non-white ethnicity
Income

Before either travel time or travel distance can be extracted, the locations of origins and destinations needed to be identified. This was achieved based on the MENE survey. The starting point of each trip is the individual's residential neighbourhood which was recorded in the survey. The finest level of information available in England is called the Lower Super Output Area (LSOA). The population weighted centre of each LSOA area represents the origin for people who say their trip started from home. Destinations of the sampled trips have been documented and geocoded (X, Y coordinates) by the MENE survey team too. The scatter plot graph of the destinations is shown in Figure 3-2. This is an image of outdoor recreational destinations spotted by people living in the study area (Figure 3-1). Therefore, small and informal green spaces are only identified as destinations where they are close to the study area. Outside the North-West region, only major natural spots in England have emerged on the map, for example, the Lake District, York Moors National Park, and Cornwall.

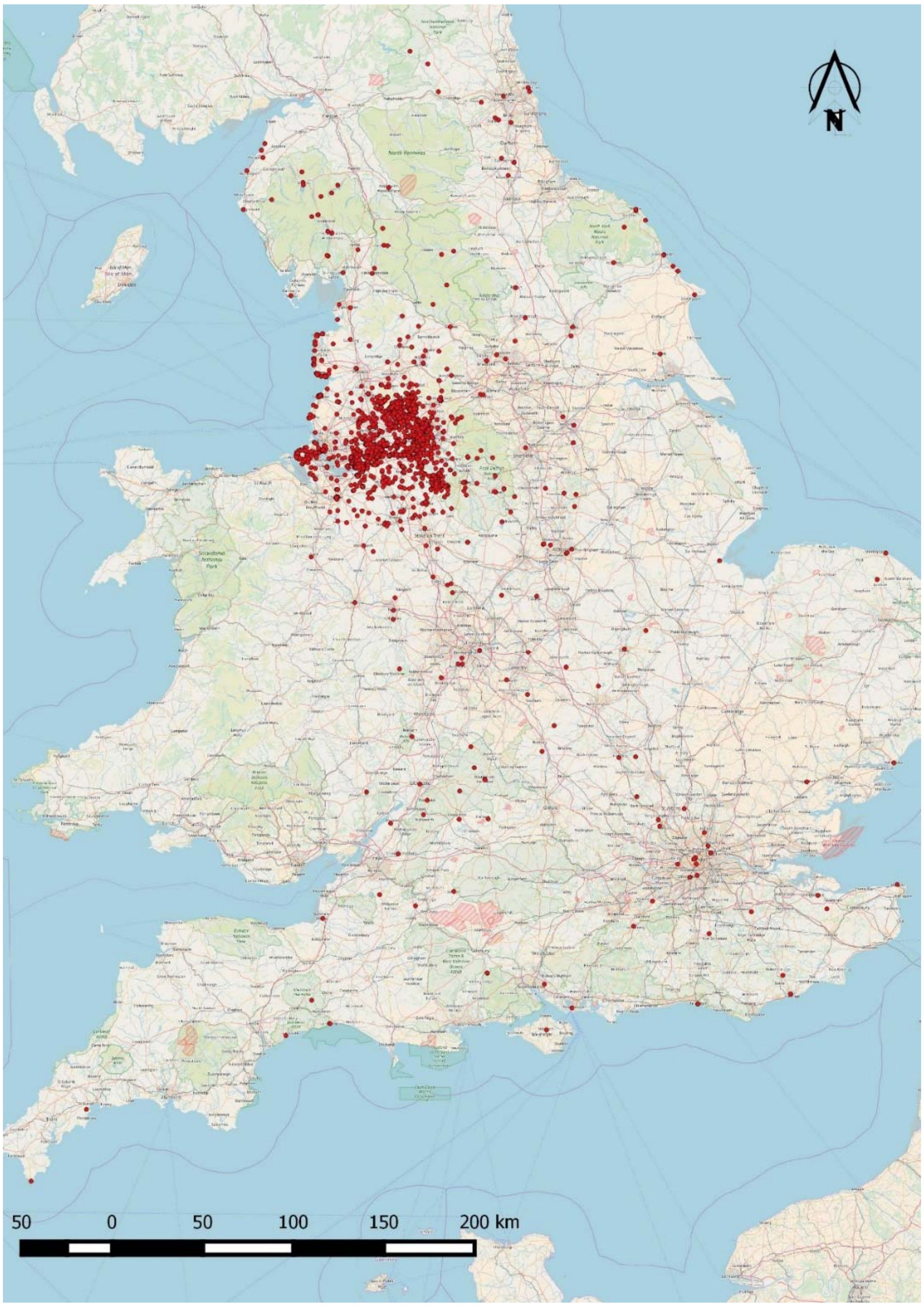

Figure 3-2. Scatter plot of destinations.

The tool for generating travel times and distances is the Google Directions API. The API allows the retrieval of predicted journey information, including the assumed shortest route, and trip duration based on selected transport mode. Four different transport modes can be chosen: driving, walking, cycling, and transit (public transport). Within this model, Google generates real-time traffic flow using crowd-sourced data. Google also receives up-to-date public transport timetable and delay information from TfL and Network Rail.

There are very significant differences in the distribution of trips among different groups which were organised by the transport mode.

Figure 3-3 depicts a summary of travel times for a single trip to outdoor recreational sites as recorded in the MENE survey. 75% of cyclists and walkers spend less than 50 minutes going to outdoor green spaces. This is slightly shorter than individuals travelled by car. Three-quarters of people drove less than 80 minutes for outdoor recreation purposes. Medians for these three modes are 9.5, 13.4 and 18.7 minutes respectively. People who chose to use public transportation have made an even more different pattern: the range of time they spend on the journey is broad, from twenty minutes to three-and-a-half hours. The median for transit is 49.3 minutes. Three of these four modes contain significant outliers except cyclists. The longest trip by public transport took more than 10 hours.

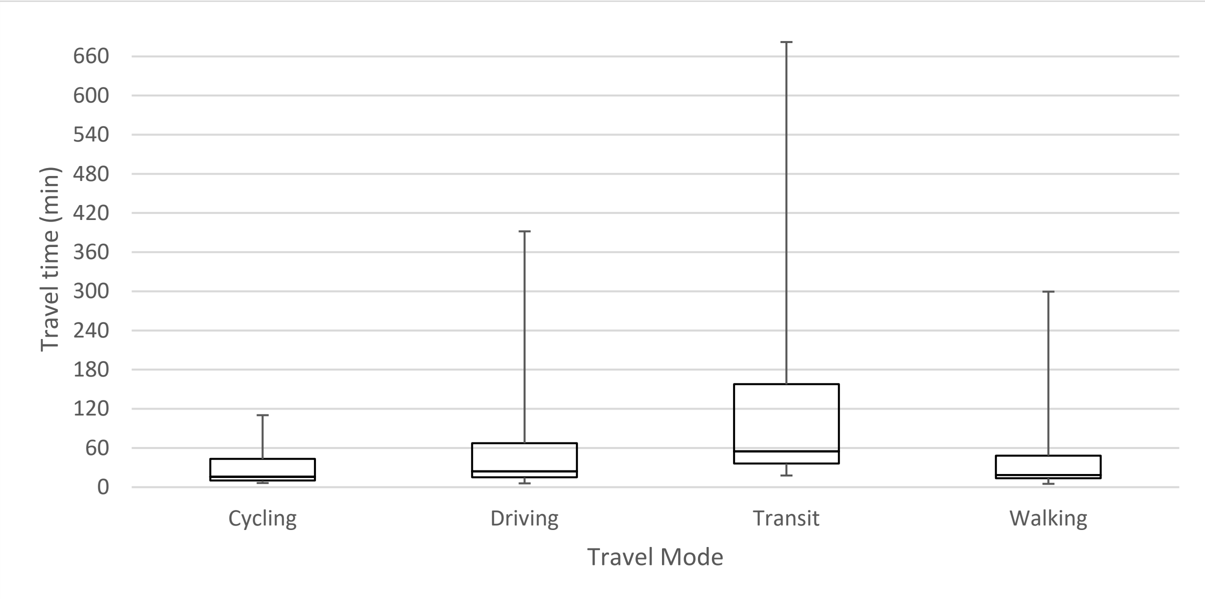

Figure 3-3. Travel time by mode in minutes.

Figure 3-4 illustrates the distribution of the journey distance for outdoor recreations in England, and Figure 3-5 shows the pattern for the case study area. The study area gives a similar travel distance pattern as it is at the national level. Majority people (above 80%) will not go more than ten miles (16 km) for outdoor recreation purposes. Trips these are less than one mile (1.6 km) represent the largest part of both charts (40%).

This data was further divided by different transport modes for analysis. People travelled by different mode, gives us a significantly different pattern in terms of how far/long they would travel for a recreational purpose. For cycling trips (

Figure 3-6), up to 65% people travelled less than five miles (eight kilometres), another 20% to 25% people went more than six miles (9.6 kilometres), but less than 40 miles (64 kilometres); very few people moved beyond this distance by cycling. As to driving trips (

Figure 3-7), only 7% of individuals chose to drive within one mile (1.6 kilometres). Moreover, 45% of people hit between one to five miles for outdoor recreational trips. Another 30% of people would

drive up to 40 miles, and about 20% would drive further than 40 miles, with 5% of individuals going further than 100 miles (160 kilometres). Transit trips give similar patterns to driving tours, as shown in
Figure 3-8. The only difference is fewer people used public transport between one to two miles (3.2 kilometres). In addition, 90% of walking trips are less than two miles (
Figure 3-9), of which 60% are shorter than one mile. Only fewer than 5% of individuals would walk between three to five miles for the recreational purpose. In conclusion, it is necessary to deal with transport modes separately, which has never been done in previous studies.

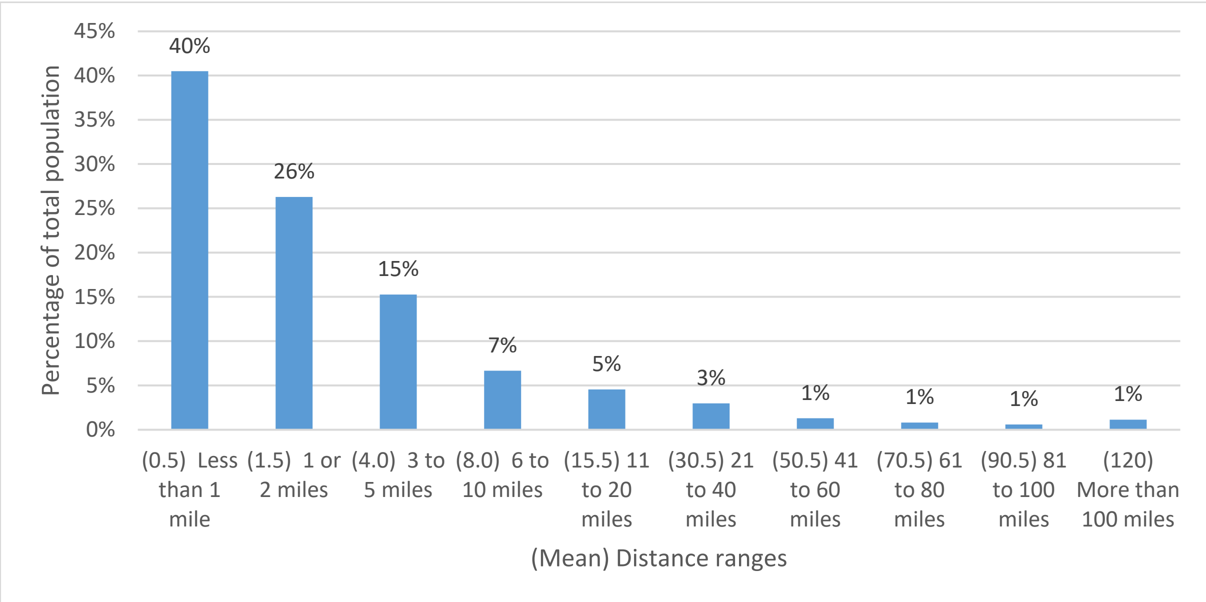

Figure 3-4. Travel distance distribution in England.

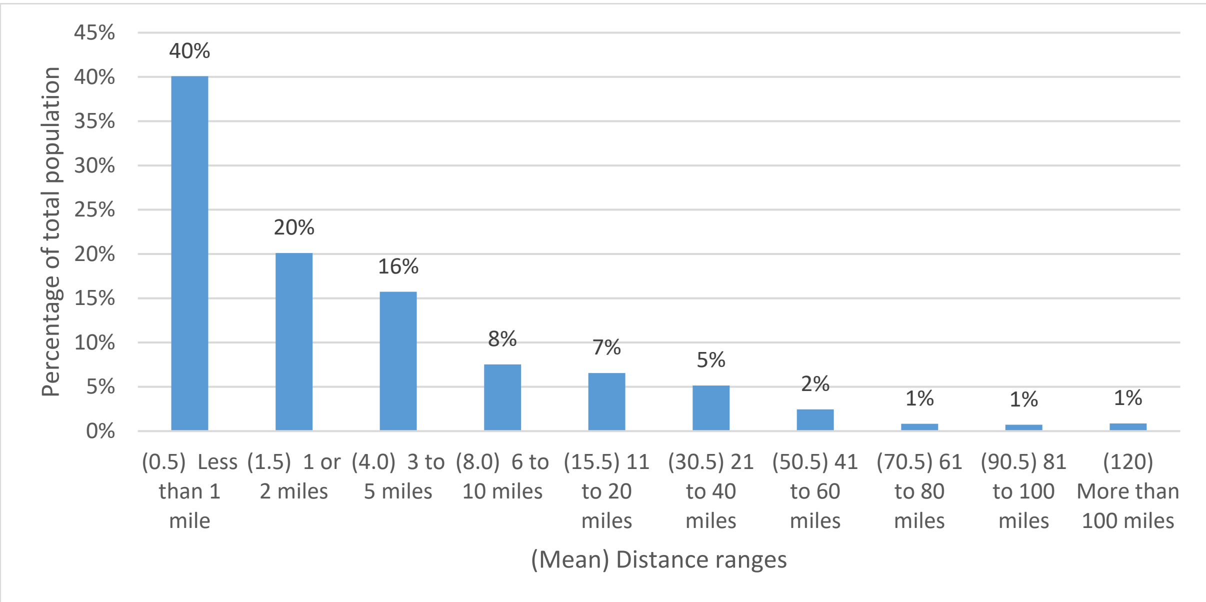

Figure 3-5 Travel distance distribution in the study area.

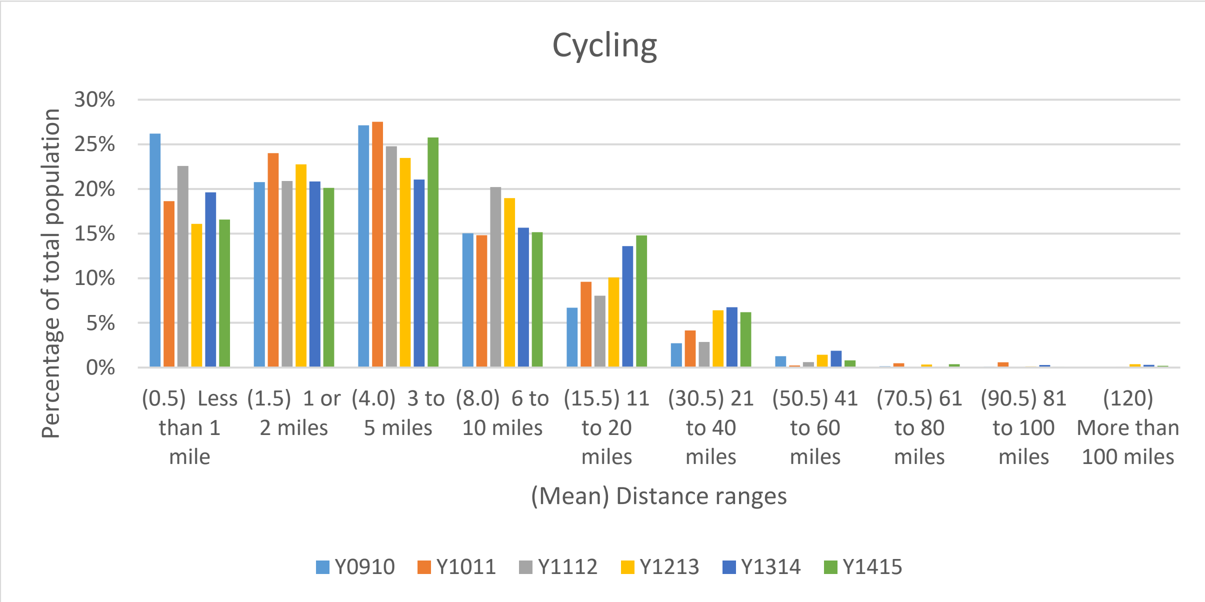

Figure 3-6. Travel distance by cycling.

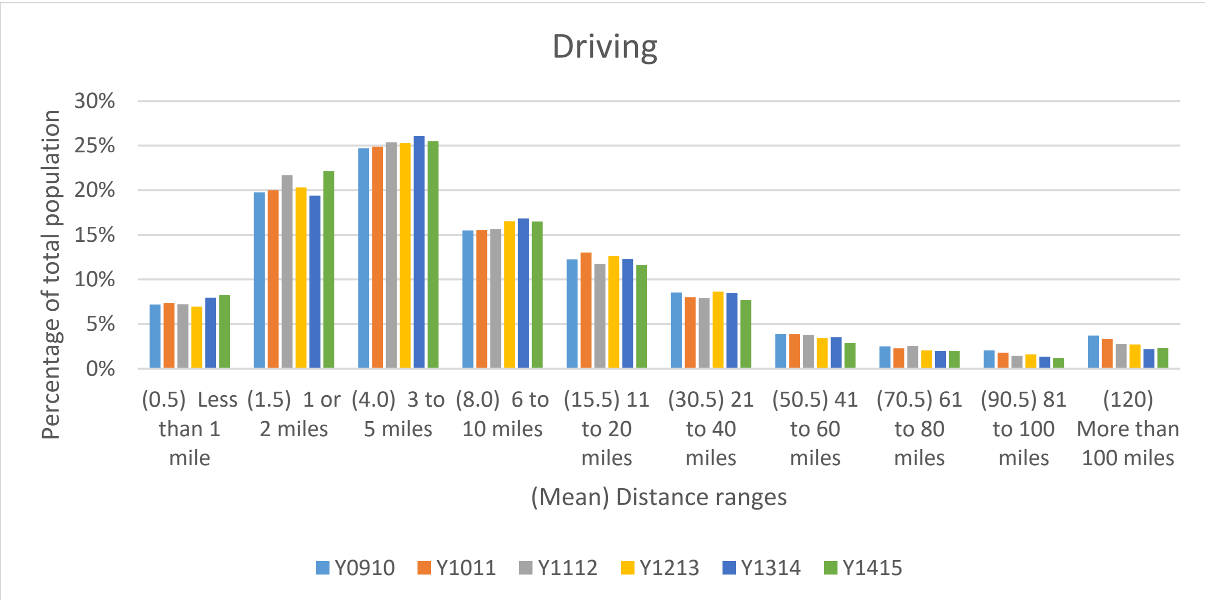

Figure 3-7. Travel distance by driving

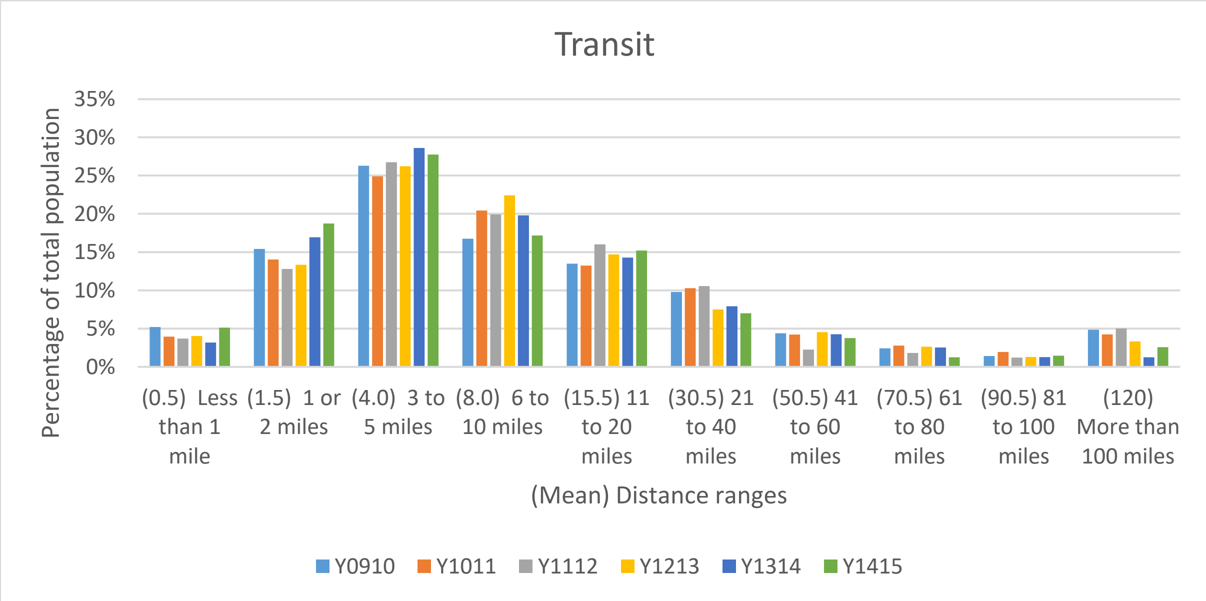

Figure 3-8. Travel distance by transit.

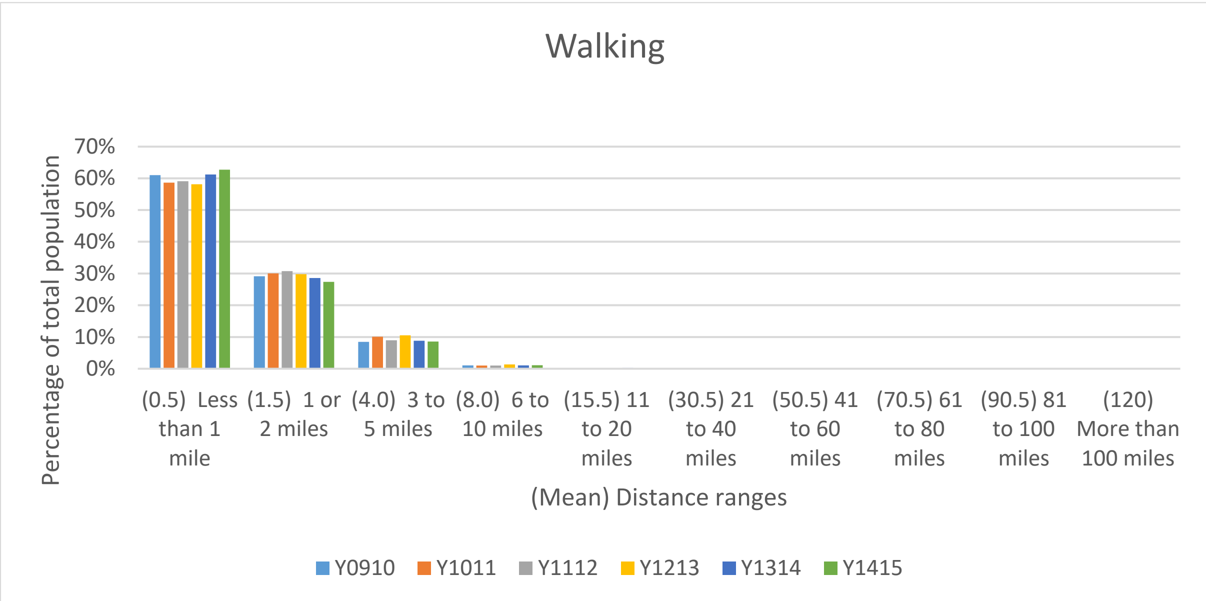

Figure 3-9. Travel distance by walking.

3.2.2 Land Uses and Environment Characteristics

In recent studies the crucial role of environmental characteristics has been highlighted, however, different studies have examined environmental attributes through various forms. Land use and land cover are the most frequently used. Land use is the function of the land. Land cover focuses more on the physical characteristics of the area. However, it is remarkably difficult to get land cover information with precision. On the other hand, land use is more directly connected to planning strategies than land cover. Research using land cover will have to transfer land cover to land use, in order to be applied in the urban planning process. Therefore, environmental characteristics in this research are in the form of land use, derived through combing information from the OpenStreetMap (OSM), the Generalised Land Use Database (GLUD) the MENE survey. A statistics summary of explanatory variables which were used in this study is shown in Table 3-3 and Table 3-4 below

Table 3-3 Dummy Variables

Variable	Description	Number of observed trips
WOODLAND	A woodland or forest (including community woodland	109
FARMLAND	Farmland or destinations locate on anything related to agriculture in the OpenStreetMap.	97
MOUNTAIN	A mountain, hill or moorland	60
WATER	A river, lake or canal	163
VILLAGE	A village	89
PATHS	A path, cycleway or bridleway	170
COUNTRYPARK	A country park	150
PARKINCITY	A park in a town or city or destinations locates on anything related to park on the OpenStreetMap.	373
ALLOTMENT	An allotment	13
PLAYGROUND	A children's playground	97
PLAYFIED	A playing field or other recreation area or destinations located on anything related to sports pitches on the OpenStreetMap.	148
IFGREEN	Any other green spaces in and around town and city	353
BEACHNCOAST	A beach and Other coastline	63

Table 3-4 Travel Time and Area Variables

Variable	Description	mean	Std. dev	median	Range
TIME (minutes)	Traveling time from Origins to Destination in minutes	27.67	36.72	15.83	0.10-510
BUILDINGS(%)	Coverage of non-domestic buildings	0.03	0.05	0.02	0.00-0.41
DBUILDINGS(%)	Coverage of domestic buildings	0.05	0.04	0.05	0.00-0.20
DGARDEN(%)	Coverage of Domestic gardens	0.15	0.12	0.14	0.00–0.61
GREENSPACES(%)	Coverage of green spaces	0.54	0.27	0.51	0.02–1.00
ROADS(%)	Coverage of roads	0.09	0..07	0.09	0.00-0.32
RAILS(%)	Coverage of rail	0.01	0.01	0.00	0.00-0.12
PATHS(%)	Coverage of path	0.01	0.01	0.01	0.00-0.07
WATER(%)	Coverage of Water	0.05	0.10	0.01	0.00–0.88
AREA(km^2)	Area of destinations	0.50	0.44	0.35	0.00-1.00

3.2.3 Other

The third group of variables that have been included in previous outdoor recreation studies is demographic characteristics. For instance, age, income, ethnicity, sex, education level and household size are the most mentioned variables in earlier studies. However, results are not consistent across different studies. For instance, Shreshta (2007) suggested education level was a significant predictor of recreation trips to the Apalachicola River region in Florida. However, Tuffour (2012) found that education attainment is insignificant for the Gros Moren national park in Canada. Following the latest study of general recreational trips by UK NEA (Sen et al., 2013, 2014), the demographic variables tested in this research include percentages of retired people, proportions of the non-white population, the median of income and population, and test was in the trip generation stage.

Another popular variable which was frequently used in other studies is activity. For instance, Bowker (2007) used a dummy variable, which equals to one when an individual went to Virginia Creeper Rail Trail for biking, zero for any other activities and found the trail is apparently unattractive to bikers. Herrings and Phaneuf (2010) used a dummy variable indicating ownership of hunting or fishing licenses, and found it significantly increases the likelihood of taking a trip to any site on the Iowa Wetland. The way this study to include activity was grouping the observations by different activity (e.g. walking a dog, playing with child/children, eating out), and training a model for each activity.

3.3 Model Training Process

The model training process was formed by two stages (Figure 3-10). Firstly, define the model structure. The data was firstly run through a multinomial logit model and then tested in the nested logit models. When tested in the nested logit model, two types of structure were applied (Figure 3-11 and Figure 3-12): the first one was based on the assumption that the individual chose the travel mode before the destination. Secondly, the other way around. The better structure was decided on the basis of the restriction of the nested logit model (Train, 2009) that parameters associated with different levels should not increase under progression towards the top of the tree. The tests using nested logit model also investigated whether the Independence of irrelevant alternatives (IIA) assumption is validly held in the multinomial logit test.

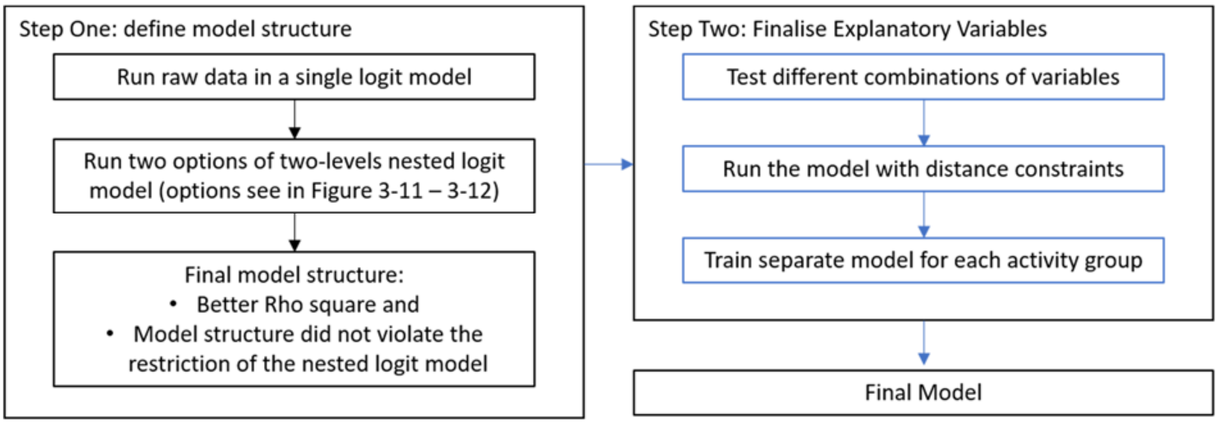

Figure 3-10 Model Training Process

The second stage of building up the new model is finalising the explanatory variables. This was done by testing different combinations of variables through the same model structure. The ultimate variable combination was judged by the best statistical model results (i.e. Rho square). The second test was implemented distance limits for each travel mode when considering the alternatives of destinations. The results showed little difference by putting this constrains. The last experiment was grouping observations by activity group and train a model for each group. The experiment was informational because it shows the variations of preferred destinations for groups of people who chose different activities at some level. For example, the top three walking (without a dog) destinations are beach and coast, park in the city and mountain. For people who walked a dog, they tend to go to country parks more than mountains. Unfortunately, due to the limited sample size, none of above models was converged. It would need more observations for all groups to make the activity models robust enough to be implemented. For this reason, the activity feature will not be presented in the final model, but this could be a direction to work on in the future. Due to length constraint, there will be no further details presented in this paper, but all the results of above experiments are available on request.

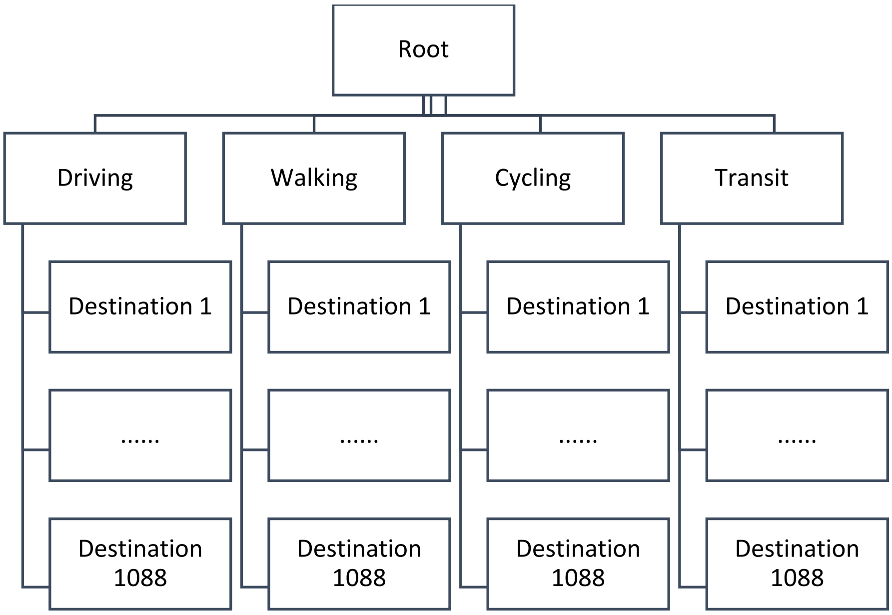

Figure 3-11 Nests structure for travel mode choice first nested logit model. "......" (Ellipsis) means Destination 2 to Destination 1087.

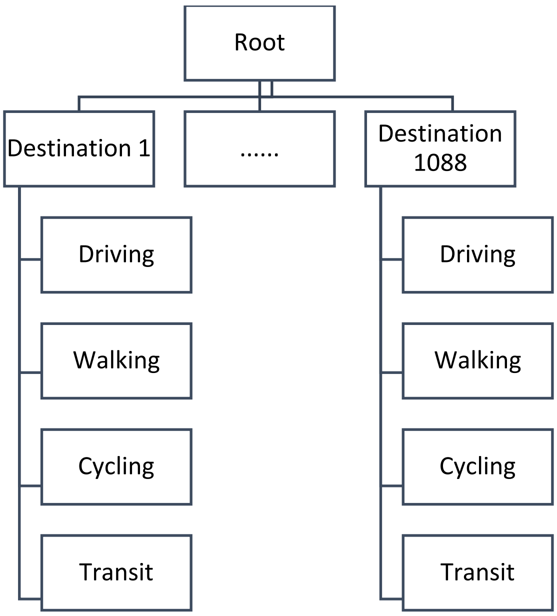

Figure 3-12 Nests structure for destination choice first nested logit model. "......" (Ellipsis) means Destination 2 to Destination 1087.

Table 3-5 Activities Regrouping

New activity group (Number of observations)	Activities in the MENE report
Walking, not with a dog (1030)	Walking, not with a dog
Walking with a dog (760)	Walking with a dog
Informal sports and Play (839)	Field sports, Playing with children, Running, Informal games and sport, Road cycling
Others (989)	Eating or drinking out, Fishing, Horse riding, Off-road cycling or mountain biking, Off-road driving or motorcycling, Picnicking, Appreciating scenery from your car, Swimming outdoors, Visiting beach, sunbathing or paddling in the sea, Visiting an attraction, Water sports, Wildlife watching, Any other outdoor activities

3.4 Final model

The final model structure is presented in Figure 3-13, it is formed by three parts: Trip generation, Modal choice and Trip distribution.

3.4.1 Trip generation

This research first ran a log-linear regression to investigate the correlation between a number of trips generated by each origin zone (LOSA) and its demographic and land use explanatory variables. Same as reviewed in Section 2, the effects of demographic variables in particular were neither clear nor significant. Therefore the trip generation function was stick with the conventional trip rate based function, without further user class splits.

Table 3-6 Log Linear Regression Results

Name	Value	Std err	t-test	p-value	
Intercept	-19.00	9.98	-1.91	0.06	.
Population	0.00	0.00	3.70	0.00	***
Retired	0.00	0.00	-0.66	0.51	
Income	-0.26	0.15	1.79	0.07	.
Non-white	0.00	0.00	-1.42	0.16	
Water	0.20	0.10	2.05	0.04	*
Domestic buildings	-0.19	0.13	-1.39	0.16	
Nondomestic buildings	0.39	0.29	1.35	0.18	
Roads	0.38	0.14	2.79	0.01	**
Paths	0.38	0.70	0.55	0.59	
Rails	0.25	0.34	0.73	0.47	
Greenspaces	0.20	0.10	2.04	0.04	*
Domestic Garden	0.25	0.13	1.97	0.05	*

Significant. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1
Residual standard error: 0.476 on 727 degrees of freedom
Multiple R-squared: 0.06786, Adjusted R-squared: 0.05247

The trip generation calculates the total number of trips generated from each origin, multiplying the mean of trips per person per year by the population of the corresponding zone. It can be written as:

$$T_j = T_i / Pop_i \times Pop_j \qquad \text{Equation 1}$$

Where T_j is total number of trips generated from origin zone *j*. T_i is the total number of trips in region *i* as recorded in the MENE data, Pop_i is the population of region *i*, Pop_j is population of neighbourhood *i*, and all the population numbers come from the 2011 census data.

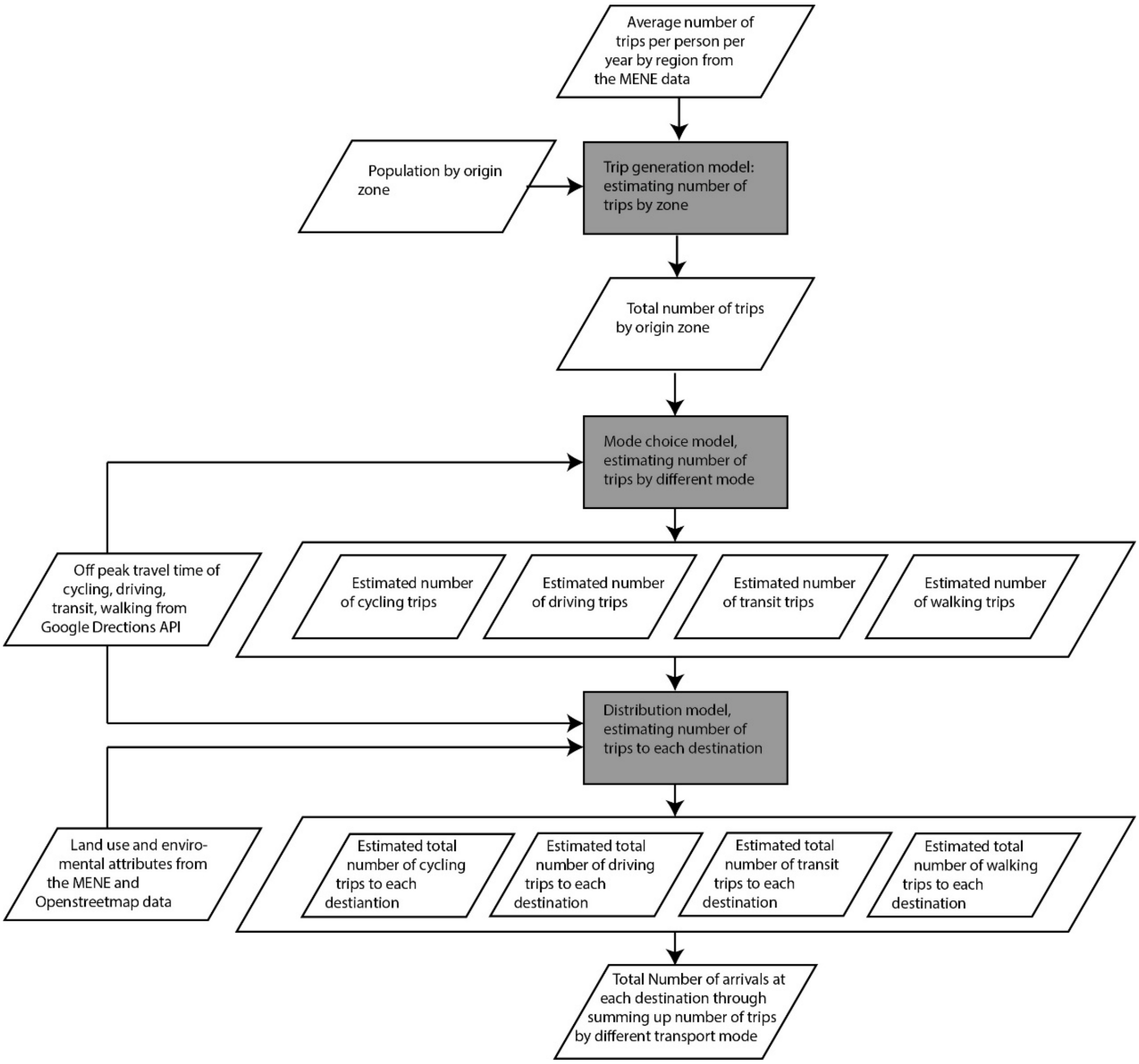

Figure 3-13 Schematic representation of modelling procedure

3.4.2 Modal choice model

The first step estimates the total number of trips generated by each transport mode. This was achieved through a standard logit model taking a flowing format:

$$P_{ni} = \frac{e^{V_{ni}}}{\sum_l e^{V_{nl}}} \qquad \text{Equation 2}$$

P_{ni} represents the probability of individual *n* choosing transport mode *I* to travel to the known destination observed by the MENE survey. The utility function is:

$$V_{ni} = a + \beta x_{ni} \qquad \text{Equation 3}$$

Where a is the constant, and β is the correlation coefficient to be estimated. X_{nk} denotes travel time from LOSA where individual *n* lives to the destination *k* through transport mode *i*. In our case, there are four different transportation modes: cycling, driving, transit and walking. Model results are shown in the following table:

3.4.3 Distribution model

When we know a total number of trips generated by each mode from origin *j*, the next stage is to estimate the number of trips to each individual site through the distribution model:

$$P_{nk} = \frac{e^{V_{nk}}}{\sum_m e^{V_{nm}}} \qquad \text{Equation 4}$$

P_{nk} represents the probability of individual *n* choosing destination *k* from *m* alternatives; the utility function is written as:

$$V_{nk} = \beta_{TRAVELTIME}TRAVELTIME_{nk} + \beta_{ALLOTMENT}ALLOTMENT_{nk} + \beta_{BEACHNCOAST}BEACHNCOAST_{nk} + \beta_{PATHS}PATHS_{nk} + \beta_{COUTRYPARK}COUTRYPARK_{nk} + \beta_{FARMLAND}FARMLAND_{nk} + \beta_{INGREEN}INGREEN_{nk} + \beta_{MOUTAIN}MOUTAIN_{nk} + \beta_{PARKINCITY}PARKINCITY_{nk} + \beta_{PLAYFIELD}PLAYFIELD_{nk} + \beta_{PLAYGROUND}PLAYGROUND_{nk} + \beta_{VILLAGE}VILLAGE_{nk} + \beta_{WATER}WATER_{nk} + \beta_{WOODLAND}WOODLAND_{nk} \qquad \text{Equation 5}$$

There is no green spaces information in some of the LOSA zones based on either the MENE survey or OSM map. This does not necessarily equal no green space in the LOSA area. However, the green space (if there is any) could not be identified for outdoor recreational purposes. In other words, in some LOSAs, the area of green space does not equal zero, but the green space will not attract any outdoor recreational trips. Therefore, a size parameter S_k^{α} is introduced, and the final probability function can be written as:

$$P_{nk} = \frac{e^{V_{nk} * S_k^{\alpha}}}{\sum_m e^{V_{nm} * S_j^{\alpha}}} \qquad \text{Equation 6}$$

Where S_k is the green space area of destination *k*, α is parameter which needs to be estimated practically. In this research, the α is set to be 0.4. Model results are shown below (Table 3-8 - Table 3-11).

Table 3-7 Mode Split Model

Name	Value	Robust Std err	Robust t-test	p-value
ASC_Car	0	fixed		
ASC_Cycling	-1.92	0.136	-14.19	0.00
ASC_Transit	-1.36	0.157	-8.66	0.00
ASC_Walking	1.74	0.175	9.96	0.00
B_TIME	-0.03	0.00496	-6.05	0.00
Number of estimated parameters:	4			
Number of observations:	2401			
Null log-likelihood:	-3445.722			
Init log-likelihood:	-3445.722			
Final log-likelihood:	-1815.574			
Likelihood ratio test:	3260.297			
Rho-square:	0.473			
Adjusted rho-square:	0.472			
Final gradient norm:	1.94E-03			
Diagnostic:	Convergence reached...			
Iterations:	8			
Significant. codes: ‘*’ > 0.05				

Note: where ASC_Car is the constant for the car, the same applies to the other modes, constant for a can is fixed to be zero by default, B_TIME is the calibrated parameter for travel time.

Table 3-8 Distribution Model Results for Cycling Trips

Name	Value	Std err	t-test	p-value	
ALLOTMENT	-4.22	2.23	-1.89	0.06	*
AREA	1.12	0.364	3.06	0.00	
BEACHNCOAST	1.34	1.55	0.86	0.39	*
PATHS	1.72	0.689	2.49	0.01	
COUNTRYPARK	2.85	0.878	3.25	0.00	
FARMLAND	0.274	1.1	0.25	0.80	*
IFGREEN	0.872	0.618	1.41	0.16	*
MOUTAIN	6.02	1.59	3.80	0.00	
PARKINCITY	-0.458	0.756	-0.61	0.54	*
PLAYFIELD	0.562	0.754	0.75	0.46	*
PLAYGROUND	-0.543	0.998	-0.54	0.59	*
TIME	-0.161	0.0307	-5.25	0.00	
VILLAGE	0.489	1.26	0.39	0.70	*
WATER	1.97	0.897	2.19	0.03	
WOODLAND	-1.31	1.21	-1.08	0.28	*
Number of estimated parameters:	34				
Number of observations:	71				
Null log-likelihood:	-212.697				
Init log-likelihood:	-212.697				

Final log-likelihood:	-35.319
Likelihood ratio test:	354.755
Rho-square:	0.834
Adjusted rho-square:	0.674
Diagnostic:	Convergence reached...
Iterations:	15
Significant. codes: ‘*’ > 0.05	

Table 3-9 Distribution Model Results for Driving Trips

Name	Value	Robust Std err	Robust t-test	p-value	
ALLOTMENT	-0.119	0.189	-0.63	0.53	*
AREA	0.358	0.0253	14.18	0.00	
BEACHNCOAST	1.73	0.138	12.54	0.00	
PATHS	-0.305	0.0868	-3.51	0.00	
COUNTRYPARK	0.973	0.0869	11.20	0.00	
FARMLAND	0.231	0.109	2.11	0.03	
IFGREEN	0.205	0.0775	2.64	0.01	
MOUTAIN	1.01	0.145	6.96	0.00	
PARKINCITY	0.137	0.0802	1.70	0.09	*
PLAYFIELD	0.265	0.0876	3.02	0.00	
PLAYGROUND	0.517	0.0981	5.27	0.00	
TIME	-0.0507	0.00487	-10.42	0.00	
VILLAGE	0.437	0.107	4.08	0.00	
WATER	0.304	0.0857	3.55	0.00	
WOODLAND	0.14	0.108	1.30	0.19	*
Number of estimated parameters:	34				
Number of observations:	995				
Null log-likelihood:	-2980.754				
Init log-likelihood:	-2980.754				
Final log-likelihood:	-2115.341				
Likelihood ratio test:	1730.825				
Rho-square:	0.29				
Adjusted rho-square:	0.279				
Diagnostic:	Convergence reached...				
Iterations:	8				
Significant. codes: ‘*’ > 0.05					

Table 3-10 Distribution Model Results for Transit Trips

Name	Value	Robust Std err	Robust t-test	p-value	
ALLOTMENT	-0.844	0.802	-1.05	0.29	*
AREA	0.6	0.255	2.35	0.02	
BEACHNCOAST	2.93	0.563	5.20	0.00	
PATHS	-0.0112	0.389	-0.03	0.98	*

COUNTRYPARK	0.273	0.474	0.58	0.57	*
FARMLAND	-0.374	0.536	-0.70	0.49	*
IFGREEN	0.847	0.334	2.54	0.01	
MOUTAIN	0.713	0.998	0.71	0.47	*
PARKINCITY	0.792	0.319	2.48	0.01	
PLAYFIELD	0.054	0.43	0.13	0.90	*
PLAYGROUND	1.21	0.31	3.90	0.00	
TIME	-0.038	0.00842	-4.51	0.00	
VILLAGE	1.21	0.525	2.30	0.02	
WATER	0.484	0.373	1.30	0.19	*
WOODLAND	-1.01	0.648	-1.56	0.12	*
Number of estimated parameters:	34				
Number of observations:	84				
Null log-likelihood:	-251.642				
Init log-likelihood:	-251.642				
Final log-likelihood:	-126.278				
Likelihood ratio test:	250.728				
Rho-square:	0.498				
Adjusted rho-square:	0.363				
Diagnostic:	Convergence reached...				
Iterations:	13				
Significant. codes: '*' > 0.05					

Table 3-11 Distribution Model Results for Walking Trips

Name	Value	Robust Std err	Robust t-test	p-value	
ALLOTMENT	0.502	0.552	0.91	0.36	*
AREA	0.642	0.131	4.91	0.00	
BEACHNCOAST	2.6	0.419	6.20	0.00	
PATHS	0.406	0.169	2.40	0.02	
COUNTRYPARK	0.7	0.225	3.10	0.00	
FARMLAND	0.45	0.346	1.30	0.19	*
IFGREEN	0.794	0.134	5.92	0.00	
MOUTAIN	1.21	0.463	2.62	0.01	
PARKINCITY	1.02	0.146	6.99	0.00	
PLAYFIELD	0.393	0.173	2.26	0.02	
PLAYGROUND	0.238	0.166	1.43	0.15	*
TIME	-0.0844	0.0049	-17.24	0.00	
VILLAGE	0.12	0.292	0.41	0.68	*
WATER	0.59	0.216	2.73	0.01	
WOODLAND	-0.66	0.32	-2.06	0.04	
Number of estimated parameters:	34				
Number of observations:	1251				
Null log-likelihood:	-3747.661				
Init log-likelihood:	-3747.661				
Final log-likelihood:	-526.683				
Likelihood ratio test:	6441.956				

Rho-square:	0.859
Adjusted rho-square:	0.85
Diagnostic:	Convergence reached...
Iterations:	13
Significant. codes: '*' > 0.05	

4. MODEL VALIDATION

The model was validated in two parts. In the first part, the new model was applied on a nature reserves inside the model calibration area - Wigg Island. The estimation from the new model was compared with the observations collected by the visitor counter in Wigg Island (Table 4-1). In the second part, the application of the new model is extended to the area outside the model calibration zone, specifically, the ten English National Parks. In Table 4-2 the model results are then compared with the total number of visits to each of the ten National parks, which are reported in the final report of valuing England's national parks report (2013).

The new model makes decent estimations on Wigg Island, with a 0.5% difference compared with the visiting accounts reported by the people-counting monitors. When the model was applied to make estimation for trips to English national parks, it shows more robust estimations for those parks inside or close to North-West region, except the Lake District, where the visiting account was hugely underestimated. On the other hand, results for those National Parks further away from the North-West region are less accurate. This is partly because the new model has been trained on baseline data selected from individuals who live in the North-West region; people who live in other regions might behave differently.

Table 4-1 Simulation Results of Wigg Island.

Wigg Island	Number of visits per year
Cycling	5,705
Driving	20,968
Transit	721
Walking	31,810
Total	59,204
Observed data	59,474
Residual	0
Difference (ratio)	0.5%

The overall new model has great potential for estimating the travel demand for outdoor recreational trips. It offers robust estimations on the destinations inside or close to the model calibration area. The model has a limitation regarding behaviours of people from all regions. However, it does not overthrow the fact that this new model has shown great potential to forecast the travel demand for any outdoor recreation destination. And it is particularly robust in the area where the data used for calibration were collected.

Table 4-2 Estimated Number of Trips to National Parks per Year

National Park	Cycling	Driving	Transit	Walking	Modelled all modes	Reported Total	Difference (Million)	Ratio
The Broads	151,381	1,863,687	135,374	3,267,444	5,417,886	6,308,000	-0.89	14%
Dartmoor	184,91	1,549,036	26,963	866,851	2,461,341	2,052,000	0.41	20%
Exmoor	8,399	1,271,069	14,441	351,354	1,645,264	1,060,700	0.58	55%
Lake District	114,027	4,122,801	122,738	3,174,067	7,533,633	12,960,630	-5.43	42%
New Forest	69,649	1,976,648	112,908	1,615,912	3,775,117	3,161,000	0.61	19%
North York Moors	112,127	1,723,576	164,126	3,216,395	5,216,225	5,099,650	0.12	2%
Northumber-land	8,324	477,277	4,429	787,927	1,277,957	1,290,200	-0.01	1%
Peak District	256,352	4,935,201	212,598	3,319,431	8,723,582	7,950,000	0.77	10%
South Downs	765,317	25,600,699	716,058	9,654,425	36,736,500	44,316,000	-7.58	17%
Yorkshire Dales	88,735	853,617	64,879	1,862,422	2,869,653	3,117,000	-0.25	8%

5. CONCLUSION

The unique feature of this research is that the new model provides the first quantitative insights into the effects on green spaces resulting from planning and design decisions of location, size, land use, environmental characteristics and transport connections. There was no similar kind of model existing in the transportation field. This new model developed through this research provides a new method for assessing the impacts of alternative urban development and green space designs.

Secondly, the new model has a very systematic and rigorous calibration and validation process. The new model was built upon reviews of previous studies as well as experiments, where three different forms of DCMs have been designed and tested on an expanded database. During the model-calibration process, this research has incorporated, for the first time, a wide range of data in modelling trips to green spaces, establishing entirely new methods for forecasting travel to green spaces by combining data sources on transport, census, land use and natural environment. All of these data are published data, enabling this method to be transferred to any site in England easily. Regarding the validation process, the new model was tested on independently observed data that had not been used in model calibration.

From the application point of view, the new model could be applied to alternative land use and green space scenarios, and it provides new information to the valuation of green spaces. It can provide empirical evidence of how much the outdoor recreational demand will be affected by adding new green space and changing characteristics of green space. It could be used to provide guidance on how green space should be designed and located to obtain greater health and well-being gains for the population.

One primary challenge in this research is to obtain detailed observations for validation. It is rare to find origin-destination surveys or even systematic arrivals for greenspace sites. Therefore, it might be challenging to find validation data for different sites in the UK. New social media data may offer some potential in filling this gap. It would, thus, seem necessary to develop a new research agenda to collect such information to strengthen the empirical basis of the model.

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