COMMUTING DISTANCE AND TRANSPORT ENERGY RESILIENCE:

QUANTIFYING HUMAN COMMUTING DISTRIBUTION TO EXPLORE LOW CARBON POTENTIALS WITH TRANSITION PROJECTS

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Abstract

Human commuting activity plays a significant role in understanding urban transport systems. This paper proposes a novel approach to modelling commuting distance distribution in a concise way. Having studied a small number of training data in New Zealand, it is found that the human commuting distance distribution can be quantified as a simple CDF exponential function with only one parameter to be determined, and the parameter is mainly dependent on the average distance to employment catchment. Besides its good predictability for test data, a Monte Carlo method to calculate the commuting VKT was introduced in the course of validation with considerable approximation to the real VKT observation. Two case studies on how to apply this model are presented to manifest its strength in exploring low carbon potentials in urban transport system, assuming that commuters could cycle to their workplaces in short distance, and an efficient commuting bus line was developed to replace the car driving in long distance. This model is convenient in simulating and predicting commuting distance distribution with limited data availability, and provides a quantitative foundation for analyzing urban transport resilience and emission mitigation.

Introduction

Predicting human mobility has been an essential subject in various research fields including transportation, geography, business and epidemiology etc.(Barthélemy, 2011;Batty, 2008). A body of research have been carried out to unravel the nature of human trajectories and locations thanks to the emergence of big-data and the improvement in technology. A study by (Gonzalez, Hidalgo, & Barabasi, 2008) argues that the distribution of human displacements is well approximated by a power-low as bellows:

$$P(\Delta r) = (\Delta r + \Delta r_0)^{-\beta} \exp(-\Delta r/\kappa) \tag{1}$$

with exponent β=1.75$\pm$0.15 and $\Delta r_0 = 1.5$ km. The research findings indicate that the travel patterns of human beings could be quantified as a spatial probability distribution, the highest probability occurring in a few frequently visited locations. Shi et al.(2008) also employed probability theory and statistics under some hypothesis conditions to simulate residential trip distribution, it was found that the Rayleigh distribution function has a similar pattern with the residential trip distance distribution. Yan, Zhao, Fan, Di, & Wang(2014) proposed a population-weighted opportunities model without any parameters to represent the underlying mechanism that presumably affect human mobility patterns at the city scale. It is found that this model has a good predictability for distance distribution, destination travel constraints and travel flows.

Commuting trip plays a significant role in human mobility, which are highly reliant on motorized travel mode in high-income countries((Poumanyvong, Kaneko, & Dhakal, 2012). The continuous increase in the commuting distance has been a challenging problem for urban smart growth and sustainable development. In developed countries like France, the average distance from home to work has grown by 16 percent over the last decade((Aguilera, 2005). According to OECD(2005), commuting distance has increased in the OECD countries with 1%-16% employees commuting between regions every day. In the case of New Zealand, most commuters do not travel very far to their workplaces, with nearly 47 percent travelling less than

5km and 67 percent travelling less than 10 km (NZ statistics, 2015). However little attention has been paid to the study of commuting distance distribution.

How to model commute activity remains an important issue for planners and policy-makers. Gargiulo, Lenormand, Huet, & Espinosa(2011)proposed a commuting network model with only one parameter based on the conventional gravity law governing commuter's choice for workplace location. An individual-based approach was established by Lenormand,et al.(2012) to overcome the difficulty of doubly-constrained gravity model when no complete matrix of the commuting flows available. It is found that the single parameter of this model follows a universal law that is mainly dependent on the surface area of the geographic units.　Although these models have some strengths in simulating commuting network, the detailed data on the number of commute in and out of a study region are still required for the calibration of parameter. Prior to urban planning or transport project, the travel survey is a pragmatic method to capture the location, distribution and mobility decision, even sometimes the socio-economic situation and personal characteristics are necessary for calibration, which are costly and time-consuming (Michael,2004).

This research was motivated by the need to mathematically characterize the commuting activity in terms of distance-resolved distribution to explore the potential of emissions mitigation in a city. By analyzing the sample travel survey data, it was found that the commuting distance in New Zealand also follows an exponential law and the single parameter has close correlation with the spatial structure of residence and employment. This paper can be divided into three parts. The first part is the model development with the aim to discover a universal law governing commuting distance distribution. The dataset on commuter's trip distribution in Christchurch city was first analyzed with the attempt to develop a distance-resolved commute distribution function. Then the calibration of parameter and associated influencing factors were investigated to finalize the model in a concise way. The second part is the validation analysis to testify the predictability of developed model for test data and VKT data, in which a Monte Carlo method to estimate individual commuting trip assignment were proposed in comparison with real VKT data. The final part is the application and case studies of the developed model in hypothesized transition projects. Assuming that commuters may minimize car driving in accordance with different distance bins, two scenarios were proposed to explore low energy-intensity potentials when car trips are forgone.

1 Model

1.1 Data source and explanation

Commuter flows. All the studied data are drawn from the commuters travel survey by Statistics New Zealand (Statistics New Zealand, 2013). All the information about a commuting OD pair including travel distance, means of travel, number of commuters can be obtained from this database. In this research, the model development was mainly carried out on the analysis for Christchurch city, from which 20 census tracts were randomly selected as the training data to perform model development, and other 15 census tracts were randomly selected as the test data to validate the predictability of the developed model. In addition, the dataset of Dunedin and Waikato were also analyzed to evaluate the universality of proposed approaches.

VKT data: In New Zealand, all the road-going vehicles are required to have regular
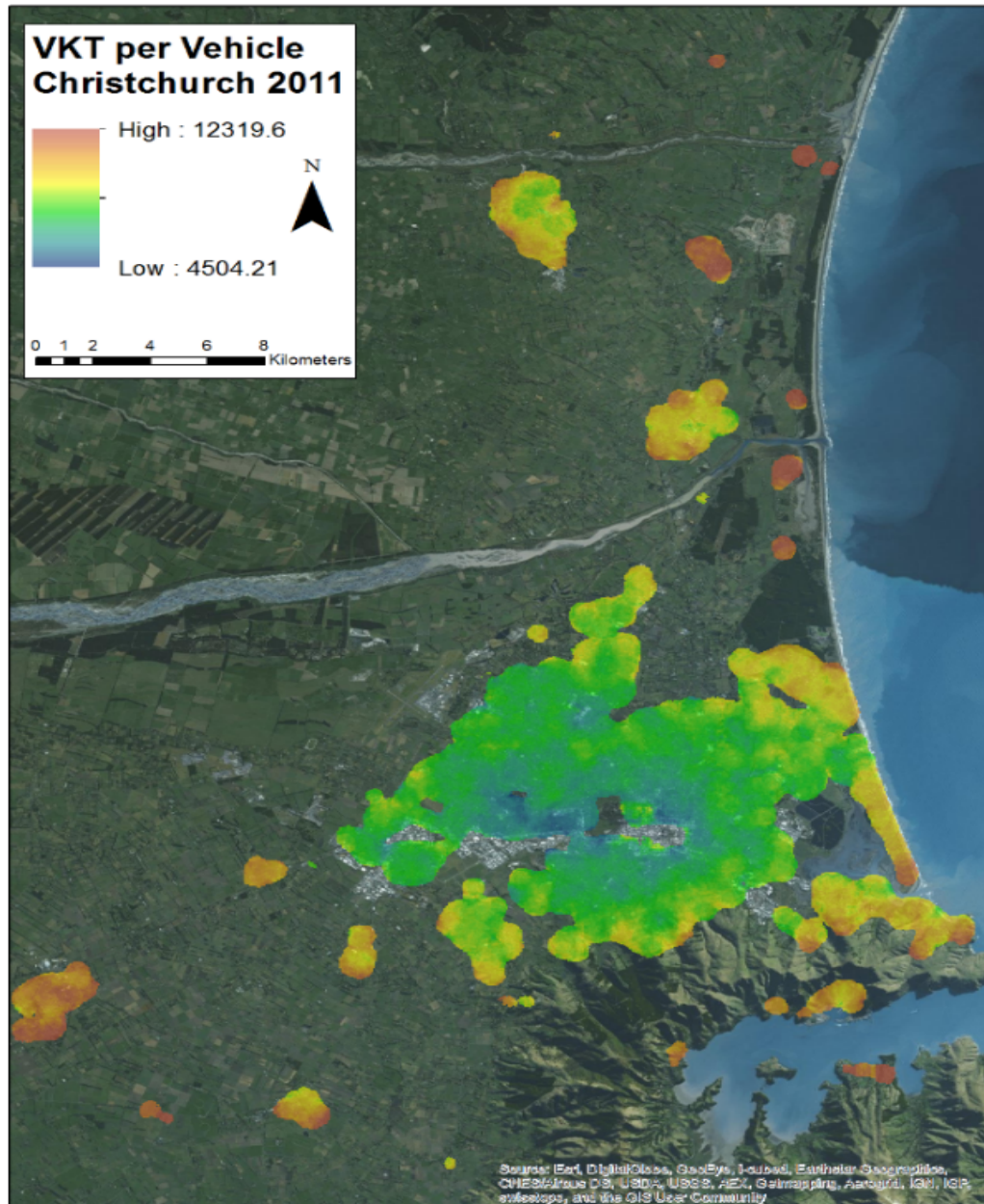
Figure 1 Local average VKT/Vehicle interpolation of Christchurch, 2011.

inspections for safety (warranty of fitness, WOF). During this inspection the reading on the vehicles odometer is recorded (i.e. Vehicle Kilometer Travelled), along with the registered address and information of fuel type and engine size. Based on the available VKT database, the average annual VKT per vehicle at the census unit level has been calculated by AEMS Lab(Rendall, Page, & Krumdieck, 2015). An example of VKT distribution in Christchurch is shown in figure 1 to illustrate how VKTs geographically differ at the census unit level.

1.2 Data mining

Distance grouping. The distance and number of commuters to destination zones from an origin zone can be obtained from the sample training data. In order to explore the underlying

laws governing distance distribution, all the OD distances were grouped into consecutive distance bins based on interval of 1000m, and then the number of commuters in each distance bin were summed up. Thus the quantity of commuting trips in different distance bins was obtained, then the relative probability of commuter's distance-based distribution and the cumulative probability can be depicted using Origin Software. The distribution of PDF and CDF of Riccarton area and Hornby area are exemplified in figure 2 and figure 3 respectively.
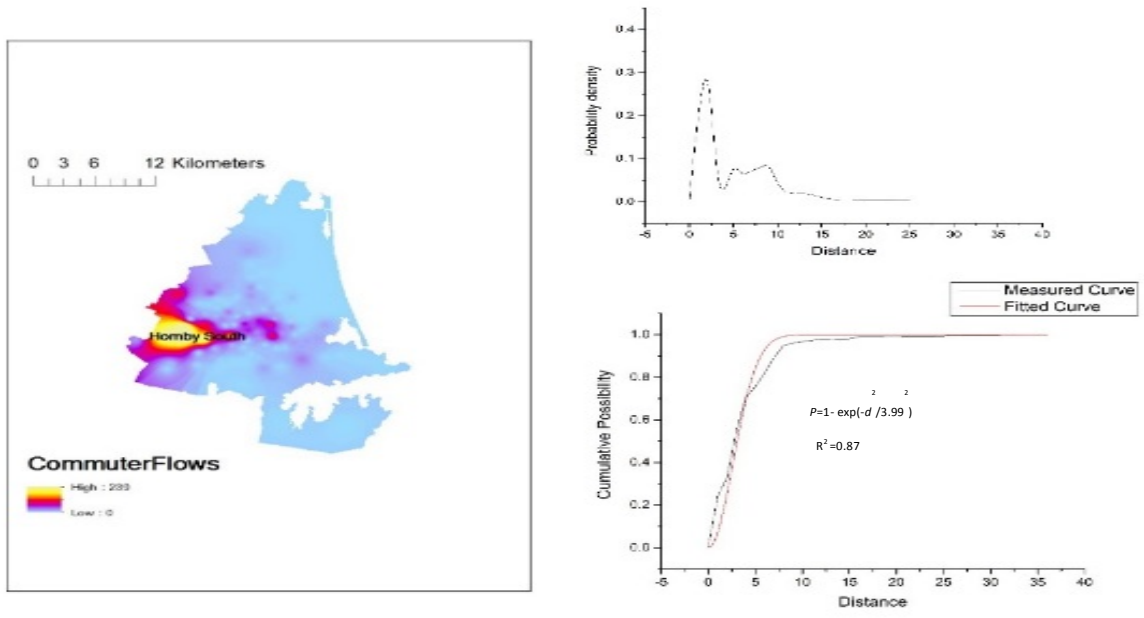

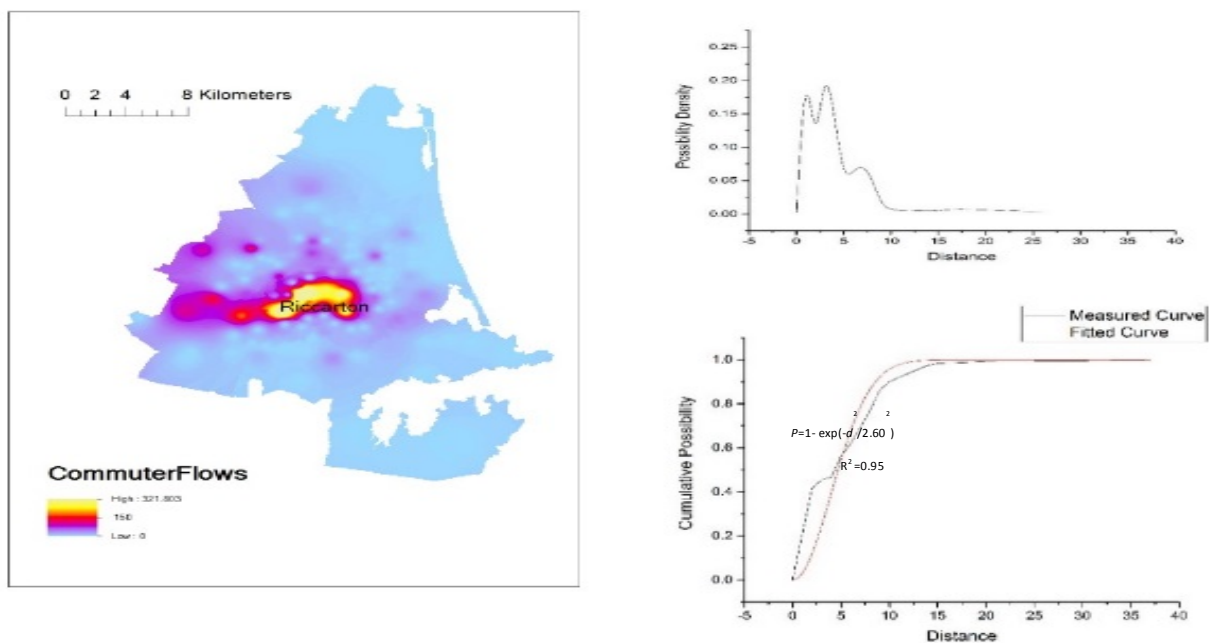Figure 3 Distribution of **Commuter** flows from Hornby North

Figure 2 Distribution of commuter flows from

Curve fitting. As for the possibility density distribution, it looks like a multiple peak distribution, which is difficult to fit with an explicit mathematical function. The cumulative density curve, by contrast, exhibits a goodness of regularity and can be fitted with a statistics function (see figure 2 and 3). After a number of fitting trials for different regions, it was revealed that the exponential function family (e.g. Gamma, Rayleigh and simple exponential) best fit the cumulative possibility distribution (R^2>85%). Whereas the Gamma function takes a complicated form with two parameters to be determined, the Rayleigh CDF function was employed in this paper to represent the commuting distance distribution owing to its simple form with only one parameter to be determined(see equation (2)).
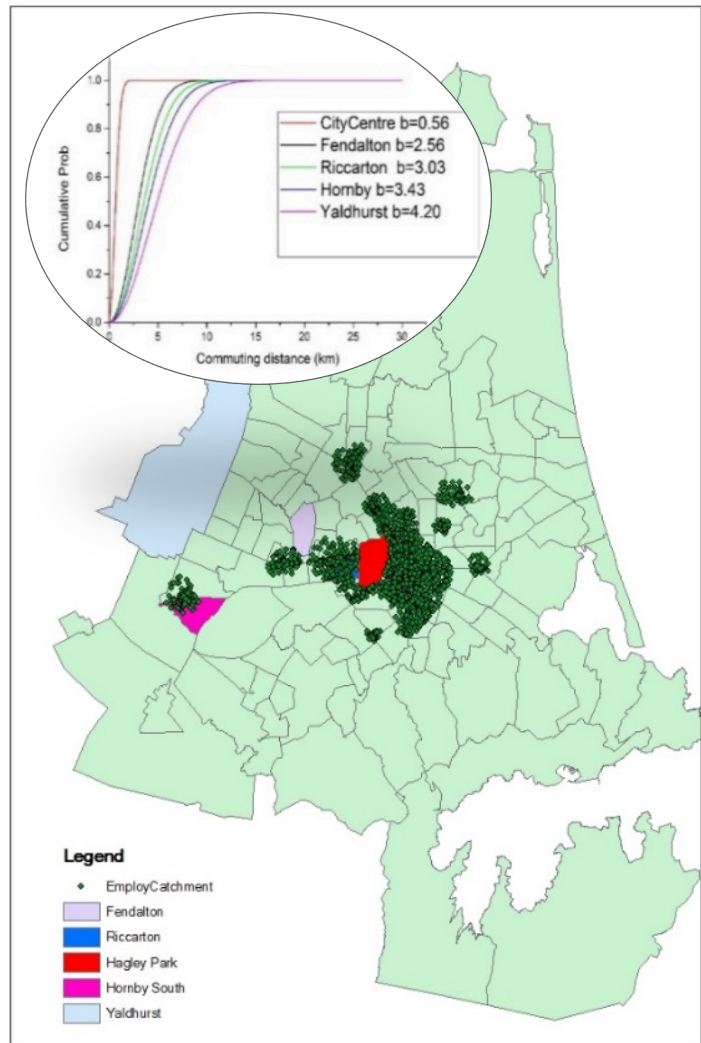

Figure 4 Variation of parameter in different census tracts

$$F(d) = 1 - \exp\left(-d^2/2b^2\right) \tag{2}$$

A series of simulated curves for some census tracts are exemplified in Fig 4, it can be seen that the degrees of skewness of curves are varying with different regions, indicating that each origin zone generate distinctive commuting distance distribution. Unsurprisingly, the city center has a higher proportion (nearly 90%) in short distance (<5km) than other areas. Therefore, it was proposed that the parameter could be used as a characteristic value to quantify the spatial distribution of commuters from an origin region. Given the value of parameter, the proportion of commuters within a certain distance interval can be calculated following the law of Rayleigh distribution. But how to identify the value of parameter? If this parameter could be derived from tangible variables such as distance, time or density? The next paragraph presents the procedures to address these problems.

Parameter analysis. First, 20 census tracts were randomly selected as the training data (see table 1), with regional attributes such as residence population, employment opportunity, number of workplace being considered. A number of research (Van Acker & Witlox, 2011; Rouwendal & van der Vlist, 2005)suggested that the commuting activity is a multi-dimensional

complex system influenced by a wide range of factors such as land use, demography, economic situation, personal preference, etc. Some variables with measurable dimension, for example, the distance and population are easy to obtain, while other subjective factors such as previous experience of long-distance commuting and the economic incentives (e.g. higher income) that are positively related to commuting distance(Sandow & Westin, 2010), are difficult to obtain or quantify. To avoid the effect of subjective factors, a couple of easy-to-capture variables such as the average distance to all employment facilities in a city, local population and employment opportunity as well as the number of workplaces in each origin zone were adopted as the explanatory variables to analyze their relationship with the value of parameter. Besides, according to Salze et al. (2011), the distance to major urban poles plays a significant role in affecting commuters spatial accessibility to facilities on the regional scale. Therefore the average distance to the key employment places were also included into the above explanatory variables. The information on the major job markets (i.e. employment catchment) can be either obtained from official data, or be identified by the combination of workplace location with associated job opportunities (see figure 5).

It was revealed by SPSS statistics analyst that only three predictors exert influences on the value of parameter, with the average distance to key employment places being the most significant sensitivity factor with nearly 80%
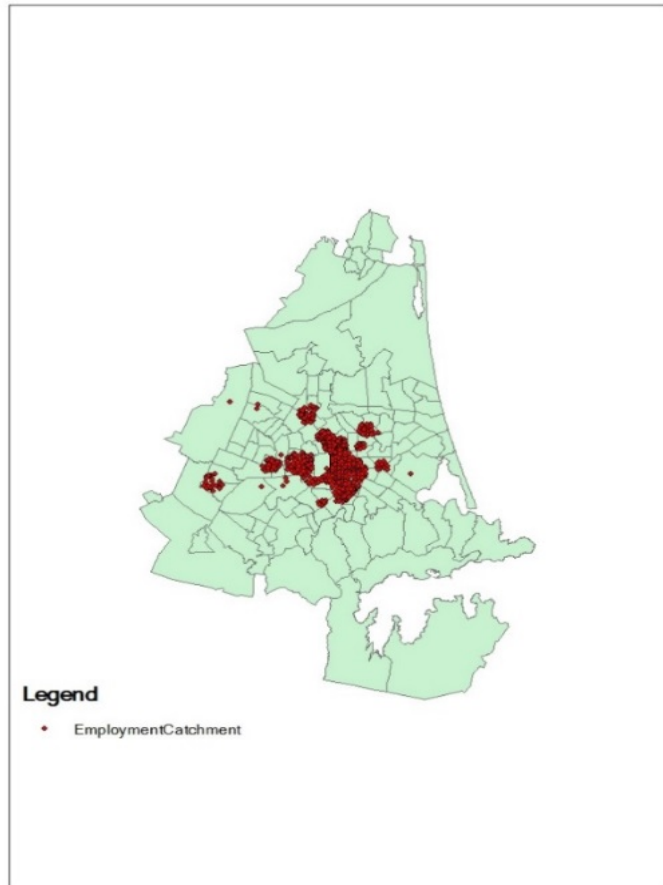

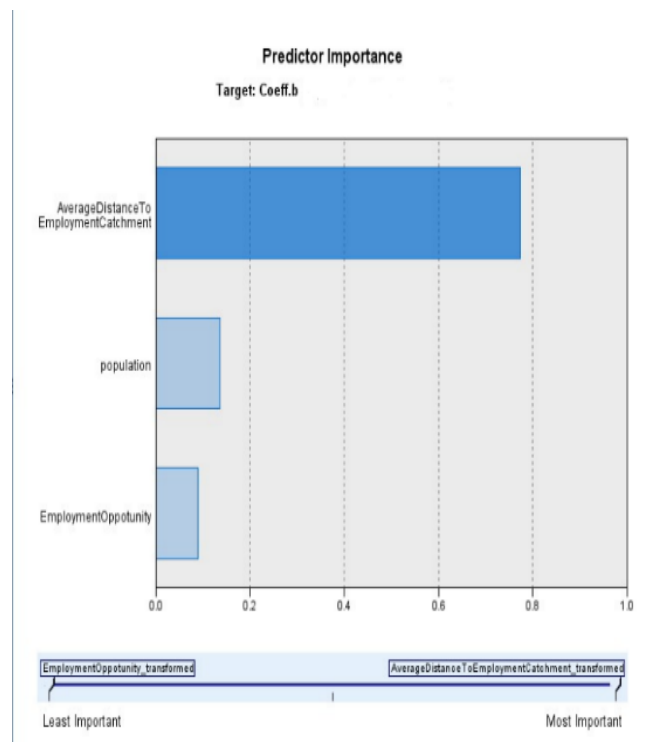**Figure 5 Employment catchment of Christchurch city**

Figure 6 Correlation analysis between explanatory variables and the parameter

incidence (see figure 6). Different from some previous conclusions(Levinson,1998;Schwanen, Dieleman, & Dijst, 2004), the accessibility to all workplaces, local population density and employment opportunity seem to contribute little to affecting commuting distance distribution. Accordingly, the average distance to employment catchment (i.e. the key employment places) was employed as the primary component in this paper to determine the value of parameter. The algorithm of computing average distances to each workplace point situated in employment catchment area is shown as below:

$$\overline{d} = \frac{1}{m \times n} \sum_{j=0}^{m} d_{ij} \tag{3}$$

Where $\overline{d}$ is the arithmetical mean distance to each employment facility for origin household i, d_{ij} is the minimum network distance between origin *i* and workplace *j, m* is the total number of workplaces in the whole city, *n* is the number of household in the study region. For the sake of simplification, all the households in an origin zone can be aggregated into one point (e.g. the centroid of study region, see Figure 7) provided the study area is not very large. Thus equation (3) can be simplified as equation (4):

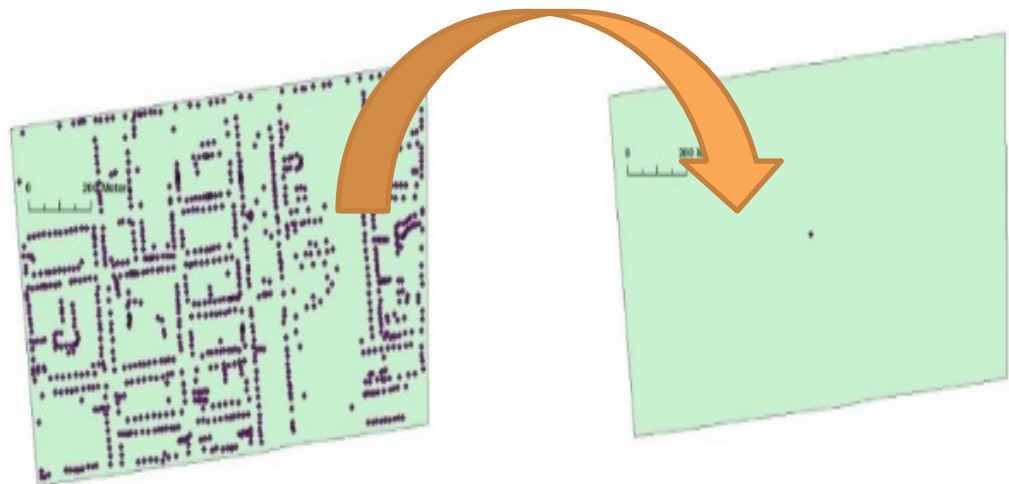$$\overline{d} = \frac{1}{m} \sum_{j=0}^{m} d_{ij} \tag{4}$$

Figure 7   Simplification of Residence distribution in Riccarton

Each $\overline{d}$ of sample census was calculated and plotted as scattered diagram to illustrate the relationship between the parameter and distance, with the value of $\overline{d}$ being log-transformed to even out the variation distribution. It is found that the parameter has an approximately linear correlation with logged average distance to employment catchment (Figure 8). So it is safely to suppose that the value of parameter can be derived as the function of average distance to employment catchment, as shown in equation (5).

$$b = \alpha \ln (\overline{d}) + \beta \qquad \textbf{(For Christchurch, α=3.5109, β=-2.8343)} \tag{5}$$

A tentative hypothesis was then formulated that the commuting distance distribution characteristic value (i.e. parameter) might be predicted by the geographic data only. In other words, given the spatial distribution of residence and employment in a city, the commuting distance distribution for each origin zone could be derived with limited sample travel survey. To

testify this hypothesis, two types of data were utilized to validate the predictability of the developed model: one is the randomly selected 15 census tracts in Christchurch as the test data and the other one is the available VKT data.

Table 1 Training data profile in Christchurch

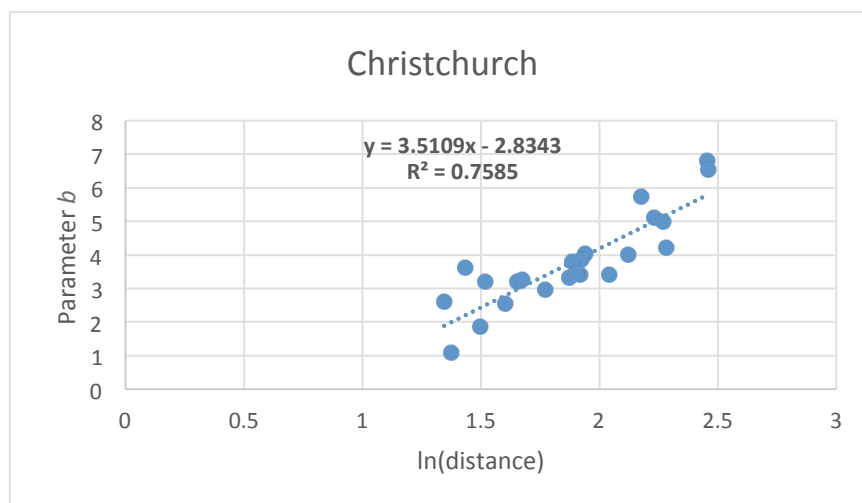| Name of Census	Parameter *b*	Average distance to employment catchment (km)
Hagley Park	1.068	3.952
Riccarton	2.6	3.839
Hornby North	3.42	7.709
Avonhead	3.32154	6.494
Hornby South	3.99	8.342
Ilam	2.9594	5.885
Burnside	3.396	6.819
Linwood East	4.03	6.943
Papanui	3.18669	5.224
Belfast	6.81583	11.654
Yaldhurst	4.199	9.816
Avondale	5.11165	9.292
Fendeltan	2.56227	4.975
Wigram	3.86598	6.843
Bishopdale	3.8072	6.584
Holmwood	1.88	4.464
Bromley	4.9964	9.679
Opawa	3.43882	6.698
St. Alban East	3.2086	4.567
Parklands	6.55716	11.718

Figure 8. Parameter value as the function of average distance to employment catchment
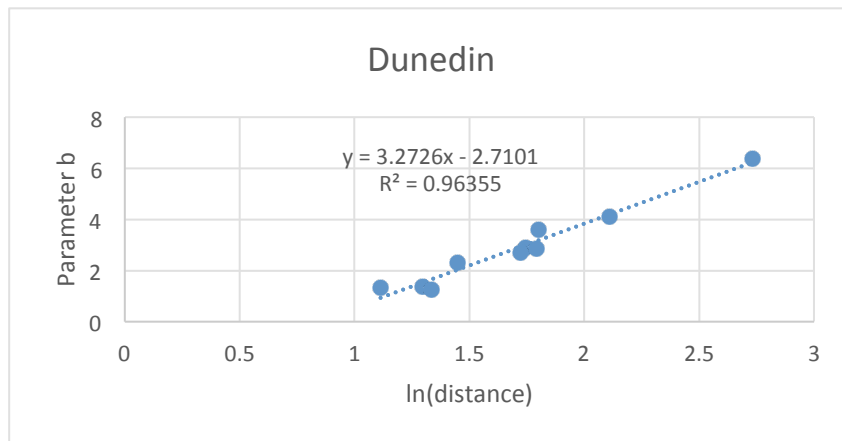
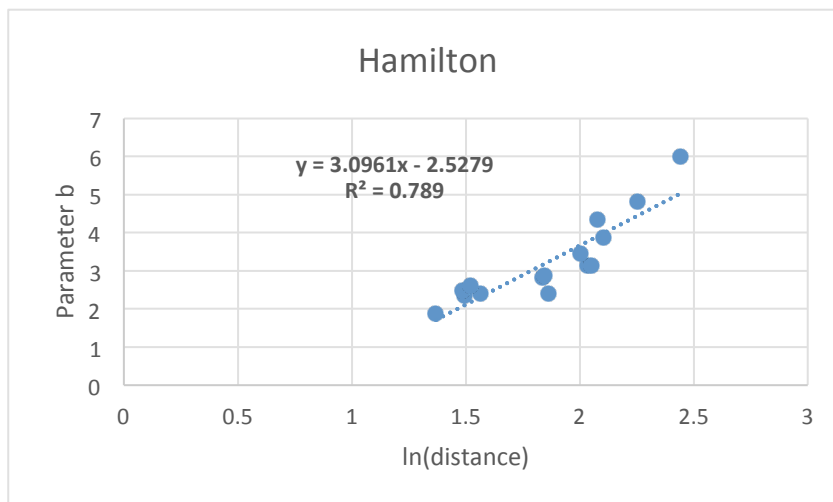**Figure 10. Regression result of sample census tracts in Dunedin**

Figure 9. Regression result of sample census tracts in Hamilton

2 Validation

2.1 Prediction for test data

The average distance to employment catchment for other 15 census tracts located from city center to suburb area have been calculated with ArcGIS system and then substituted into equation (5) to obtain the value of parameter. Then the cumulative possibility distribution curve of commuting distance for each census tract was fitted with Rayleigh function respectively. The comparison between observed parameter and predicted parameter is tabulated as below (table 2). It can be seen that majority of results are within acceptable error range (<20%) except for Kennedy's Bush (This census is situated in outer suburb area with only 735 population). Similarly the aforementioned approaches were applied to other two cities, Dunedin and Hamilton, to investigate whether commuters in New Zealand follow this universal law in terms of commuting distance distribution. The research findings support that the commuting distance distribution can also be fitted with exponential function and the parameter can be derived from linear regression with good prediction(see figure 9 and 10). The value of α, β in different city are

subjected to city characteristics, fluctuating around 3 and 2 respectively. Much more calibration work need to be carried on for other cities to acquire the detailed value matrix of α, β in New Zealand.

Table 2. Prediction results for test data in Christchurch

Name of census	Observed parameter	Average distance to employment catchment (km)	Predicted parameter	Relative error (%)
Bexley	5.69054	10.04	5.26386159	7.5
Avonside	3.79005	6.539	3.758412718	0.83
Merivale	2.18	4.109	2.127232573	2.42
Beckenham	3.10615	6.232	3.589584281	-15.56
Aidanfield	3.81013	7.54	4.258498059	-11.77
Burwood	4.29927	8.117	4.517386368	-5.07
Northcote	4.02	6.262	3.606444726	10.29
Harewood	4.11514	8.11	4.514357305	-9.7
Spreydon	2.82	4.595	2.519712805	10.65
Sockburn	3.3204	6.717	3.852706286	-16.03
Dallington	4.028189	5.968	3.437613409	14.66
Richmond North	3.46776	4.866	2.720899623	21.54
Broomfield	4.26	8.858	4.824099918	-13.24
Travis Wetland	5.81744	9.175	4.947548037	14.95
Kenneydys Bush	4.55	13.283	6.246590264	-37.29
Lyttelton	6.2618	15.828	6.86203524	-9.59

2.2 VKT validation

This possibility model mainly focused on a quantitative measure to estimate cumulative distance-based distribution without involving directional analysis, consequently the detailed inter-region flows can't be derived from this model immediately. As mentioned in section 1.2, it is quite hard to quantify possibility density distribution of commuting distance. In the absence of data availability, Monte Carlo simulation is an effective approach to approximate the detailed situation about individual commuting trips. The next sections demonstrate the strength of this model in predicting commuting VKT trip distribution in comparison with existing VKT data if no individual home-to-work data available.

2.2.1 Individual-level commuting model

Most of commuting data were only available at an aggregated level, the disaggregated data on the specific location of household and workplace for each individual commuter has been lacking due to confidentiality reasons. Based on the travel survey data, Hu & Wang (2015) established a Monte Carlo methodology to simulate individual resident workers and individual jobs within census tracts to estimate the excessive commuting and optimal commuting respectively, in which the commuting time was used as the impedance for work trip model. Travel distance is an effective variable to measure travel demand since it is easy to be converted into transport energy consumption(Becken & Schiff, 2010). Thus applying Monte Carlo methods with the assistance of ArcGIS techniques and python programming, a distance-based disaggregated commuting model was developed to simulate the actual work trips distribution.
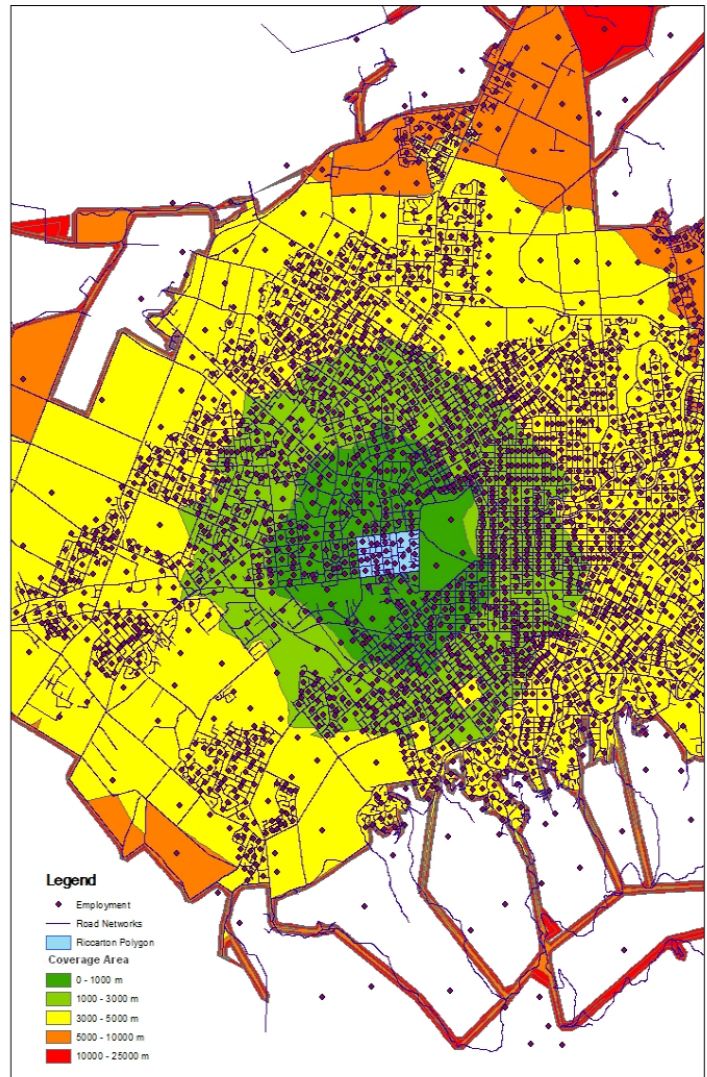

Figure 11. Employment facilities distribution in different distance bins

Study area inputs

- Demographic data: the population of resident living in an origin census.
- Origins: It would be better to iterate all the households in the origin area, but in order to simplify the calculation, each centroid of origin census is regarded as the origin representing local dwelling distribution.
- Destinations: all the employment facility points were mapped into the GIS system.
- Transport networks: the travel impedance in this paper is defined by travel distance. Congestion and trip chains are neglected.

Constant inputs

- Modal split: According to Statistics New Zealand (2013), the car transport remained the dominant travel mode for work trips. The car travel mode share for commuting in

Christchurch is 84%.It is hypothesized in this paper that all the census tracts have the same travel mode split.

- Commuting distribution parameter: all the parameters of census tracts have been calculated based on equation (5).

Methodology

Step 1: For an origin census, the commuter distribution in different distance bins can be determined by inputting demography into equation (6). So the number of commuter working in different distance bins are calculated. In this paper, the distance of 1km, 3km, 5km, 10km and 25km were selected as the critical threshold value for distance bin assignment.

$$P_{cn}=P_i×η×(1\text{-}\exp(\text{-}d_n^2/2\lambda_i^2))\ (d_n = 1\text{km}, 3\text{km}, 5\text{km}, 10\text{km}, 25\text{km} … …) \tag{6}$$

Where P_{cn} is the number of commuters within a certain distance bin d_n. η is the ratio of employed population in origin i, which can be obtained from demographic data.

Step 2: generate distance-based coverage areas of origin i where the employment facility points in different distance bins are included. An example of employment geographical distribution in different coverage areas is illustrated in figure 11.

Step 3: randomly select a workplace j in a coverage area for a commuter k living in origin i until the commuters limit in this coverage area is reached. Then all the OD distance pairs in a coverage area can be calculated by GIS.

Step 4: randomly assign a travel mode for each OD distance pair following the travel mode split (The travel mode assignment was implemented in python script to ensure the overall statistics in line with the required travel mode split). If the travel mode is assigned as 'car', this OD pair is then recorded as a commuting VKT element.

Step 5: Average all the commuting VKT elements to get the aggregated VKT result for origin i.

Step 6: Repeat the above steps for numerous times until the result tends to stability. Figure 12 shows the steady convergence of simulated commuting VKT of Riccarton area after 1000 iterations.
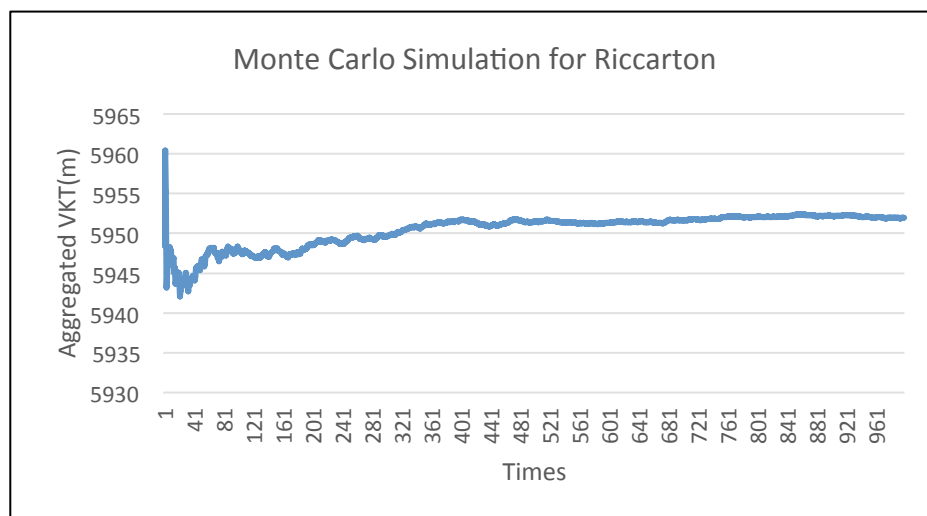

Figure 12. A change curve of accumulative average commuting VKT with iteration times

2.2.2 Real Commuting VKT extrapolation

Because the available VKT data is simply on the annual driving distance for individual registered vehicle, it is still in question to obtain the breakdown of VKT data for specific trip purpose at census unit level. Therefore some extrapolations based on literature reviews and travel survey were conducted to estimate the actual VKT data for commuting trips. According to MOT(2015), on average the work-related trip (travel to main job or other jobs and travel on employers business) accounts for about one third of all household driving time and distance. Accordingly with the obtained annual VKT per vehicle for each census tract (see figure1), the extrapolated one-way commuting VKT can be computed as follows:

$$VKT_c = (1/3{\times}VKT_{avg})/250(working days)/2(back\ and\ forth) \qquad (7)$$

The comparison between simulated Commuting data and observed commuting data was plotted in figure 13 to illustrate the variation trend with different census tracts. It is shown that both curves are almost parallel to each other, with slightly lower values in simulated commuting VKT data. The average relative error is no more than 20%, which supposedly result from the less rigorous computation in equation (7) or the homogeneous assumption for modal split of each census tract. It would be better to validate the developed model with realistic commuting data, nonetheless this model could be used as an alternative measure to estimate distance distribution in the absence of detailed travel survey.
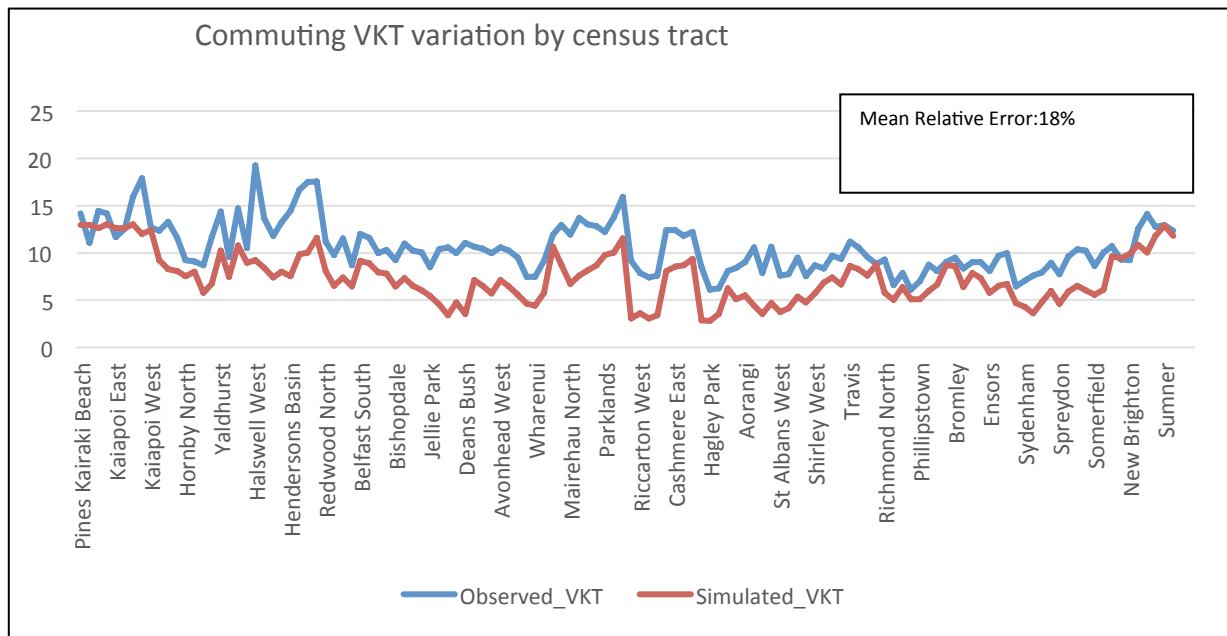

Figure 13. Comparison between simulated VKT and observed VKT

In summary, this model can be mathematically expressed in the following equations

$$\begin{cases} P_i = 1\text{-exp } (-d^2/2\lambda_i^2) \\ \lambda_i = \alpha \ln (\bar{d}_{ij}) + \beta \\ \overline{d_{ij}} = \frac{1}{m \times n} \sum_{i=0}^{m} d_{ij} \end{cases} \qquad (8)$$

Where P_i is the proportion of commuters from origin *i* within a specified distance *d*, the value of λ is determined by the average distance to key employment places $\bar{d}$, which is calculated by d_{ij}. And d_{ij} is the distance from origin *i* to a workplace *j* in employment catchment. The employment catchment can either be obtained from official data (if any) or be depicted based on the integration of employment opportunity and distribution.

Application

This research has a positive significance for urban planning, transportation management and travel demand prediction. For instance, when it comes to urban resilience or active transport system, a pressing problem is to learn about how many trips would be generated in different distance bins during urban development. For a particular area or planned area, it can be inferred from equation (8) that the less the $\overline{d_{ij}}$ is, the higher likelihood the short commuting distance occurs. As such this model provides a convenient tool for urban transport planners to assess how commuting distances vary with the layout of employment location or population migration. From the perspective of human beings adaptation to possible energy disruption, using techniques of ArcGIS system, the next section presents two transition projects applying the above model to explore low carbon commuting potentials in Christchurch, for which two scenarios were developed with the hypothesis **I**: Commuters can shift their car trips within short distance (<5km) into cycling or walking; and hypothesis **II**: a commuting shuttle bus line was developed to replace car trips in long distance. It is envisioned that commuters would minimize car trips to access their workplaces with alternative mode choices, but the land use and spatial structure remain unchanged.
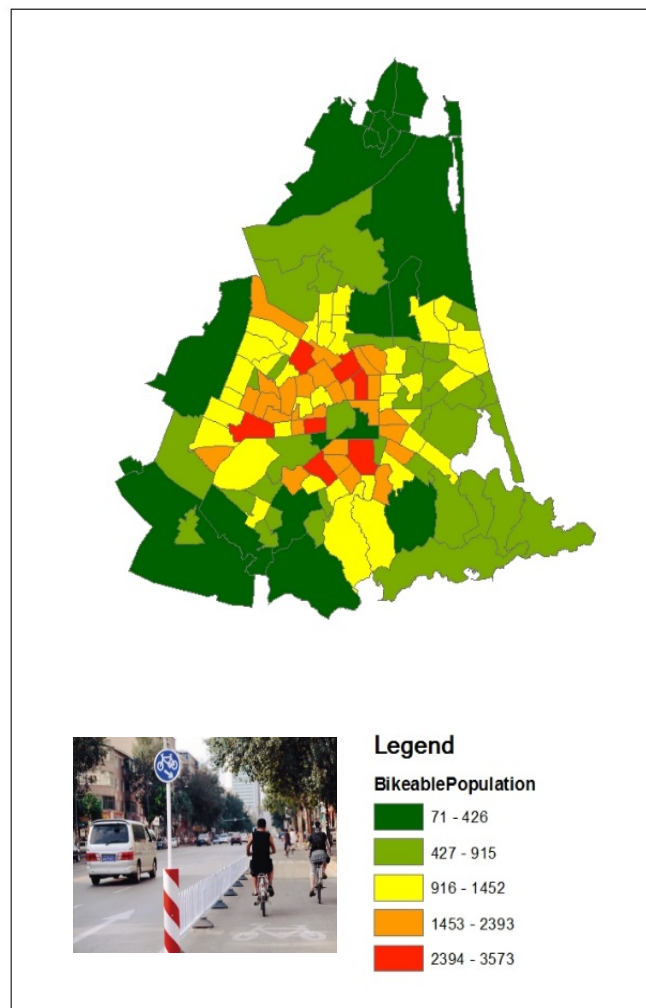

Figure 14. Ranking of Cycleable commuting areas in Christchurch

Scenario 1: Mode shift in short distance

It is assumed in this paper that the short distance car-driving to workplace would not be necessarily required if the cycling-friendly infrastructure were available and pro-bike policies were implemented. The threshold for viable cycling distance is defined as 5 km, and the average ratio of commuters of a census is set as 70% of local resident (Statistics New Zealand, 2013). Through calculating the average distance to employment catchment with the assistance of GIS network analyst, all the parameter values for each census tract have been obtained, then the population that could travel to their workplaces by walk or bike was computed according to the exponential distribution law as equation (9) exhibits.

$$P_{ic}=P_i \times 0.7 \times (1-\exp(-5^2/2\lambda_i^2)) \tag{9}$$

Where P_{ic} is the quantity of bikeable commuters potentially generated from origin i, P_i is the overall population in origin i, λ_i represents the characteristic value of commuting distance distribution for origin i. The distribution of people who could cycle to their workplaces was mapped in Figure 14, which shows the relative cycle-commuting potentials in different parts of Christchurch. Obviously the periphery areas are less likely to adapt to cycling work trips due to the longer commuting distances, whereas living in the proximity to city center can contribute to reducing commuting distance. For dark red areas in figure 14, the possibility of cycling mode share might increase if the cycling infrastructure in these areas are improved with favorable policies (e.g. a physical segregation between cycle way and driving road, as shown in figure).

Scenario 2: Commuting shuttle bus line development

For long distance commutes, the only way to substitute car driving is the development of transit network system with high frequency services and wide coverage for residents. This model also has the strength to capture long-distance distribution, thereby facilitating the operation or optimization of public transport system.   In the case of Christchurch, there is only one bus line (Orbiter route) operating with a high frequency service, and only 1 percent of people travelling to work by bus from surrounding districts(StatisticsNZ,2016). As a strategy to improve public transport and enhance environmental performance, a commuting shuttle bus line with regular service frequency was proposed using this model to meet resident's long-distance commuting demand.

Apart from the key employment places, the demand points where commuters have long distance work trips also need to be identified. This model can facilitate finding out these demand points. From the figure 4, it can be inferred that the proportion of long-distance (>5km) commuters is likely to increase with the increment of parameter λ_i. It is revealed by calculation that the value of P within 5 km is less than 0.5 when parameter is greater than 4.0. Therefore in consideration with the economy of bus service, the selection criteria for demand points is defined as below:

      (1) The Population of census tracts>2000

      (2) The parameter λ_i >4.0

After selecting the demand points in conformity with the above criteria, all the candidate stops then were identified (see figure17). So a preliminary commuting bus route was developed with a variety of ArcGIS techniques (Owing to the limitation of space, the detailed procedures are omitted). If the bus line can serve commuters with higher frequency and lower price, the

possibility of car driving to work would be decreased as the result.

Given the commuting distance distribution with travel mode share in different distance bins, the current total energy use for a study region in terms of the one-way home-to-work journey can be calculated as bellows:

$$E_i = \sum_{j=0}^{n} e_m * d_{ij} \qquad (10)$$

Where e_m is the energy intensity of transportation tools((Newman & Kenworthy, 1999), d_{ij} is the distance to destination j, n is the number of employment facilities for origin i. The current regional Commuting Transport energy use for one-way work trips was calculated and mapped in figure 15. It can be seen that the major high energy consumption censuses are situated in suburb areas, which result from the large population or longer commuting distance.

Assuming those commuters who currently drive long distance to work could access to this bus service by walk, and commuters in short distances can ride a bike as the alternative means of travel to their workplaces, the consumption of transport energy should theoretically drop down.

Mode=bike   if d_{ij} <=5 km
Mode=bus   if d_{ij} >5km and in the vicinity of bus stops
Mode=car   if else

Recalculate the energy use with equation (10), the regional commuting energy use after mode shift was mapped in figure 16 and figure 17 respectively. At first glance, there is no much disparity in energy consumption distribution between figure 15 and figure 16, especially for the dark red areas. A reasonable explanation is that resident living in these suburb areas have relatively higher proportion of longer commuting distances, which makes it impossible to choose cycling as the travel mode. Nevertheless the total energy consumption still might be reduced 33% simply by mode shift into cycling. It can be seen from the figure 17 that the greened areas expand considerably compared to figure15 and figure 16, both regional transport energy use and total energy use are obviously improved by nearly 75 percent of reduction. Hence the low carbon potential of Christchurch development could be realized by mode shift only provided the improved cycling and transit infrastructure are available as well as favorable policies are implemented. In other words, the Christchurch city itself has a good potential to low carbon travels with the urban form and land use remained constant, some minor adjustments in transport system of Christchurch may contribute to reduction in transport energy use.
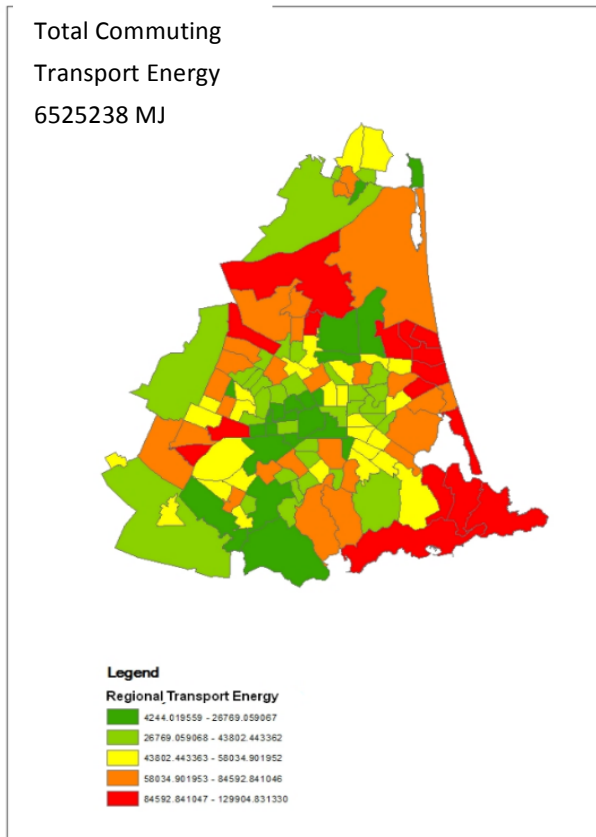
Total Commuting
Transport Energy
6525238 MJ

Figure 15. Transport energy distribution of status of quo

Total Commuting
Transport Energy
4387023 MJ
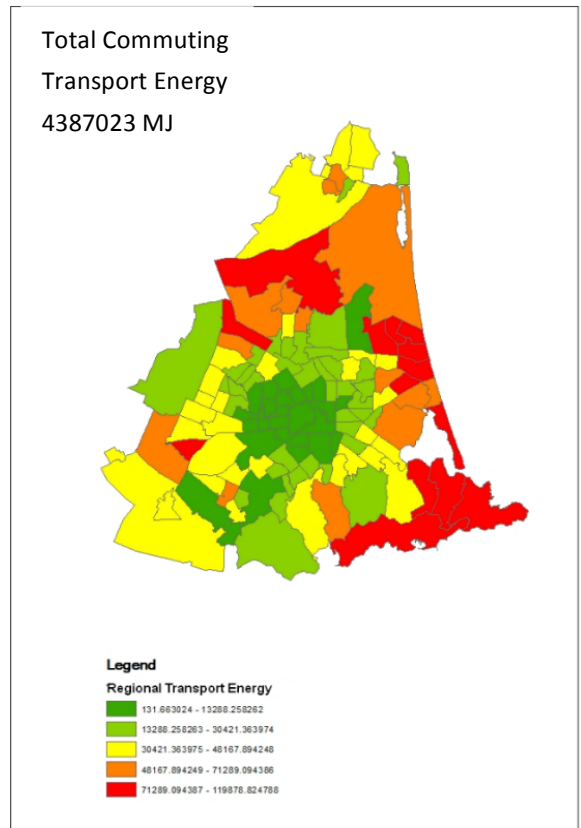
Figure 16. Transport energy distribution after mode shift to cycling

Total Commuting
Transport Energy
2193193 MJ

Figure 17. Proposed commuting Bus line development and resulting transport Energy distribution

Scenario	Energy Reduction
Mode shift to cycling	33%
Mode shift to cycling + bus	67%

Conclusion

This research studied the commute travel patterns in New Zealand with the intention to discover a universal law governing commuting distance distribution and investigating the determinant behind. Based on the training data from the commuter flows of sample census tracts, the fitting analysis demonstrate that the cumulative possibility distribution of commuting distance has an obvious regularity and the exponential function family can fit it well. In this paper, the Rayleigh function was employed to quantify the commuting distance distribution as it takes a simple form with only one coefficient to be determined, which to some extent facilitate the following regression analysis. Then the average distance to employment catchment, through the analysis to data pertinence, was specified as the single predictor variable to affect the value of parameter. Consequently a set of simultaneous equations in representative of commuting distribution were developed, for which only a few measurable factors are required including population, employment opportunity and geographical distribution of household and workplace. In order to validate the predictability of model, two types of data were analyzed: one is the validation for test data with nearly 80 percent of accuracy, the other one is a Monte Carlo simulation to approximate disaggregated commuting OD pairs by private car in comparison with the available VKT data. The results display little differences between the simulated commuting VKT data and the real data. Finally two applications of this model were presented to explore the low energy-intensity transport potentials of Christchurch city. If the land use and spatial structure of Christchurch remain unchanged, a 30% reduction of transport energy consumption may be achieved just by mode shift to cycling for work trips, and a highly efficient transit system could reduce up to 70 percent of current transport energy use. Under the circumstances where the requirement for precision is not that rigorous, this model has potential implications for evaluating the proportion of commuters in different distance bins and facilitating the analysis for urban resilience and adaptation to climate change or oil shortage.

References

Aguilera, A. (2005). Growth in commuting distances in French polycentric metropolitan areas: Paris, Lyon and Marseille. *Urban studies, 42*(9), 1537-1547.

Barthélemy, M. (2011). Spatial networks. *Physics Reports, 499*(1), 1-101.

Batty, M. (2008). The size, scale, and shape of cities. *science, 319*(5864), 769-771.

Becken, S., & Schiff, A. (2010). Distance models for New Zealand international tourists and the role of transport prices. *Journal of Travel Research*.

Gargiulo, F., Lenormand, M., Huet, S., & Espinosa, O. B. (2011). A commuting network model: going to the bulk. *arXiv preprint arXiv:1102.5647*.

Gonzalez, M. C., Hidalgo, C. A., & Barabasi, A.-L. (2008). Understanding individual human mobility patterns. *Nature, 453*(7196), 779-782.

Hu, Y., & Wang, F. (2015). Decomposing excess commuting: a Monte Carlo simulation approach. *Journal of Transport Geography, 44*, 43-52.

Lenormand, M., Huet, S., Gargiulo, F., & Deffuant, G. (2012). A universal model of commuting networks. *PloS one, 7*(10), e45985.

Levinson, D. M. (1998). Accessibility and the journey to work. *Journal of Transport Geography, 6*(1), 11-21.

Michael Wegener. (2004). Overview of Land-use Transport Models. Retrieved from:

http://www.spatialcomplexity.info/files/2013/11/MW_Handbook_in_Transport.pdf

MOT (2015). Ministry of Transport, Driver Travel--New Zealand Household Travel Survey 2011 – 2014. Retrieved from: http://www.transport.govt.nz/assets/Uploads/Research/Documents/Drivers-2015.pdf

Newman, P., & Kenworthy, J. (1999). *Sustainability and cities: overcoming automobile dependence*: Island Press.

NZ Statistics (2013). Car, bus, bike or train: What were the main means of travel to work?

NZ Statistics (2015). Commuting Patterns in New Zealand: 1996–2006. Retrieved from:http://www.stats.govt.nz/browse_for_stats/Maps_and_geography/Geographic-areas/commuting-patterns-in-nz-1996-2006/distance-travelled-by-commuters.aspx#

OECD, 2005. Employment Outlook. OECD, Paris.

Poumanyvong, P., Kaneko, S., & Dhakal, S. (2012). Impacts of urbanization on national transport and road energy use: Evidence from low, middle and high income countries. *Energy Policy, 46*, 268-277.

Rendall, S., Page, S., & Krumdieck, S. (2015). Voila! A new measure of oil vulnerability for cities.

Rouwendal, J., & van der Vlist, A. (2005). A dynamic model of commutes. *Environment and Planning A, 37*(12), 2209-2232.

Salze, P., Banos, A., Oppert, J.-M., Charreire, H., Casey, R., Simon, C., . . . Weber, C. (2011). Estimating spatial accessibility to facilities on the regional scale: an extended commuting-based interaction potential model. *International journal of health geographics, 10*(1), 1.

Sandow, E., & Westin, K. (2010). The persevering commuter–Duration of long-distance commuting. *Transportation Research Part A: Policy and Practice, 44*(6), 433-445.

Schwanen, T., Dieleman, F. M., & Dijst, M. (2004). The impact of metropolitan structure on commute behavior in the Netherlands: a multilevel approach. *Growth and change, 35*(3), 304-333.

Shi fei, Lu Zhenbo. (2008). Research on trip distance distribution model and parameter. Journal of Traffic and Transportation Engineering. Vol.8, Apr. 2008. (in Chinese)

Statistics New Zealand, 2013. Retrieved from: http://www.stats.govt.nz/datavisualisation/commuterview/index.html#

Van Acker, V., & Witlox, F. (2011). Commuting trips within tours: how is commuting related to land use? *Transportation, 38*(3), 465-486.

Yan, X.-Y., Zhao, C., Fan, Y., Di, Z., & Wang, W.-X. (2014). Universal predictability of mobility patterns in cities. *Journal of The Royal Society Interface, 11*(100), 20140834.