ASSESSMENT OF PERSONAL TRAVEL ADAPTIVE CAPACITY USING A PARTICIPATORY SURVEY APPROACH

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ABSTRACT

Fuel supply issues have the potential to cause significant travel behaviour change as pressure on oil production spare capacity increases into the future. Transportation planners need information on the transport options available to people and their ability to change to reduce fuel demand. This paper investigates a new transport parameter, travel adaptive capacity, the capability to reduce fuel demand without reducing participation in activities. An online survey, the Travel Adaptive Capacity Assessment (TACA), was used to capture travel activities in a normal week. The interactive survey asks for selection of up to three possible alternatives for each trip including modes, destinations and doing the activity without travel. We propose that these alternatives an be used to calculate travel adaptive capacity (TAC). The survey was conducted in the city of Christchurch and the small rural town of Oamaru, New Zealand. The survey results show a surprisingly high adaptive capacity for a cohort with normally very high level of personal automobile use. We report statistical relationships between adaptive capacity and transport, demographic and geographic factors.

INTRODUCTION

Prominent petroleum geologists over the past decade have presented the evidence that oil supply will peak before 2015 and go into decline beyond 2020 (Bakhtiari, 2004; Campbell and Laherrere, 1998; Deffeyes, 2001; Hirsch et al., 2005; BITRE, 2009). In 2010 the International Energy Agency concluded that total world oil production reached its peak in 2006 at an average of 70 million barrels per day (mbpd) (IEA, 2010). The IEA predicts oil demand to increase toward 90 mbpd by 2035, but any production increase would have to come from unconventional, more costly sources, and the most likely scenario for crude oil is a plateau around 68-69 mbpd, then continuous decline of several percent per year. Even maintaining the production plateau would require more than $8 trillion investment in new resource extraction over the next 25 years.

We have published a meta analysis method to include all expert analysis and produce a probability space for future oil supply (Saunders et al., 2006; Dantas et al., 2007; Krumdieck et al., 2010). The latest geological resource publications were used to produce the oil supply probability distribution shown in Figure 1. The analysis makes it quite clear that all petroleum geology experts agree that the available fuel will decline significantly within the lifetime of the current vehicle fleet. Personal transport in all developed countries is dependent on conventional oil. Furthermore, the existing transport systems were designed and developed in an era of low cost fuel. There is an urgent need for transportation engineering and urban planning research into the issue of fuel energy constraints on personal transport activities.

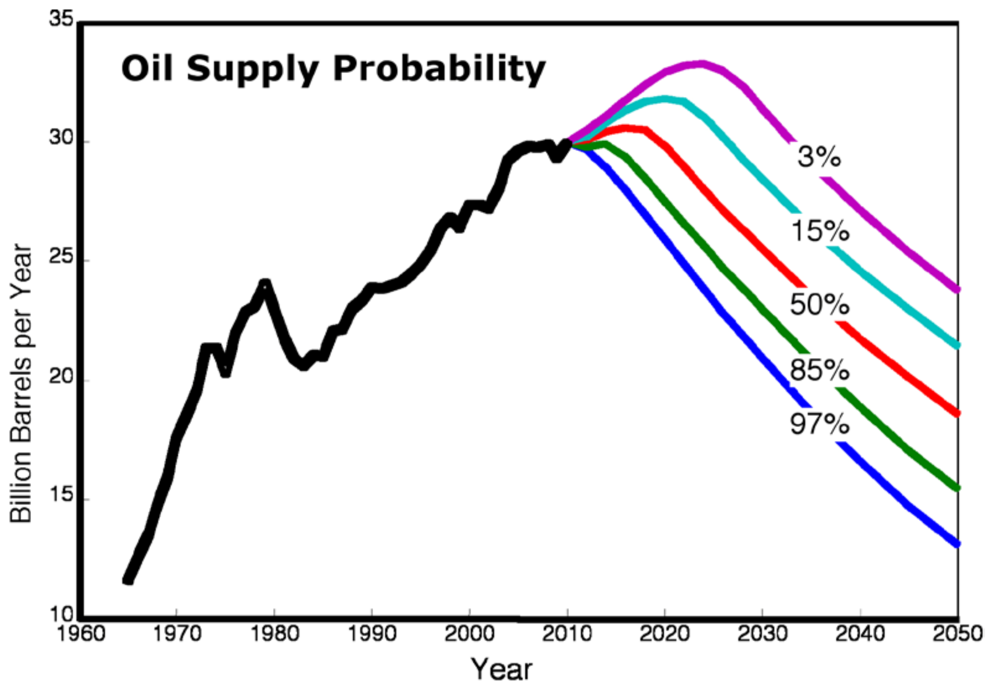


Figure 1. Probability distribution of future oil supply from petroleum geology meta-analysis.

Information about possible alternative modes or *travel adaptive capacity* (TAC) would be valuable for management and planning in the era of contracting fuel supply. Information about current travel alternatives could be used in developing policies, transport system changes and urban transition plans that allow greater adaptive capacity, thus improving resilience to fuel constraints. The term "adaptive capacity" has been widely used in environmental and social fields. It is defined as a potential ability to deal with a range of pressures (Füssel and Klein, 2006; Smit and Wandel, 2006; Preston and Stafford-Smith, 2009). Adaptive capacity includes adaptability, coping ability, management capacity, stability, robustness, flexibility and resilience (Smithers and Smit, 1997; Jones, 2001; Tompkins and Adger, 2004). The available infrastructure, built environment and managerial ability are key factors in adaptive capacity.

Transportation research studies have traditionally focused on alternatives to car use, and the reasons why people are reluctant to use these alternatives (Graham-Rowe et al., 2011). The main motivations for research on alternatives to private vehicles have been to reduce congestion, pollution and travel costs (Van Exel and Rietveld; 2009; Gärling et al. 2000). Analysis of why people do or don't have travel options has largely been limited to questions such as "list the reasons…", or in an interview the participant is given options on what policy/infrastructure changes would make them "get out of their cars and onto public transport" (Mackett, 2009; Kingham et al. 2001; Lyons et al., 2002).

Several studies have looked at travel behaviour change during fuel crisis events or price spikes (Smith and Kauermann, 2011). Understanding the adaptive capacity of travel options in order to reduce fuel consumption will become increasingly important as public and private investment becomes focused on climate change mitigation and oil price pressures. A rigorous survey and analysis method is needed to quantify local travel options, the potential for change, and what factors affect access to options in all urban forms. There is no reported methodology for addressing the issue of oil supply reduction over the lifetime of transport infrastructure and urban form, with the possible exception of a recent study by our group for the Dunedin City Council (Krumdieck, 2010). It may be possible to use existing data about alternatives to gain some insight into the ability to adapt to reduce fuel demand. However, a survey approach that directly assesses the adaptive capacity of a given urban area would be of great benefit to urban land-use and transport planners.

MATERIAL AND METHODS

This study uses a new Travel Adaptive Capacity Assessment (TACA) survey for a particular cohort in a given urban form (Watcharasukarn et al., 2010). This paper presents the results of the TACA survey and subsequent analysis for quantifying travel adaptive capacity. Travel adaptive capacity in this study is defined as the maximum potential to reduce private transport fuel consumption through changing transport mode, car-pooling, and participating in the activity without traveling. One survey cohort was the students and staff at the University of Canterbury in Christchurch, and the other was randomly selected residents of the rural town of Oamaru. The objective of this research was to investigate the perceived alternatives people have when their usual mode of personal vehicle is not available. Specifically, we investigated:

1) How the options of travel alternatives are affected by urban form
2) What specific factors are the most influential on specific adaptability alternatives.

To answer these questions, this paper documents the data collected from the surveys, then undertakes a Multinomial Logit analysis of the results to ascertain which factors are the most influential for transport alternatives.

TACA survey method

Details of the survey design and validation are available elsewhere (Watcharasukarn, 2010). The on-line TACA online survey tool[1] was used to capture individual travel activities in a normal week, as well as the alternative travel options perceived by the survey participants. An interviewer assisted the participants by entering in data, operating the map function of the survey if needed, clarifying the meaning of questions and prompting the participants to recall their typical travel activities. The surveys were carried out at three times over the course of a year. At the University of Canterbury (UC) in Christchurch, 323 participants were surveyed and 120 in Oamaru. The survey in the two areas achieved response rates of roughly 23.6% for UC and 13.8% for Oamaru. A representative geographical distribution of participant primary residences in the survey areas was gained as shown in Figure 1a) Christchurch and 1b) Oamaru.

For each trip, participants first name the activity and select a trip purpose category from a drop-down list. The participants were asked to describe their activity in their own words as it helps memory (Stopher, 1992). Departure and arrival time, origin, destination, mode, and route are recorded. The online survey tool links in with Google maps, allowing participants to easily locate the origin and destination, and define the route taken. If the participants do not have a habitual pattern of travel activities in a week, for example a real estate agent, they are asked to try to recall their travel schedule from the previous week. All participants are asked to provide any one-off activities they engaged in over the previous week as representative of travelling to errands, social engagements or entertainment activities.

Participants are asked to rate the importance of each activity, which is defined as the impact to the household wellbeing if they could not carry out the activity. The importance is selected from a selection of three levels, essential, necessary and optional. The transport mode for the journey is selected from a drop-down list that includes the private vehicles they entered earlier in the vehicle information section plus walk, bike, bus etc. The participants indicate vehicle occupancy if they travelled by car or motorbike. For each trip, the participants are asked: “If you couldn’t use your normal mode, how many other ways could you travel?”. The participants then select up to three alternatives from a list, ranking the responses in order of preference.

CALCULATIONS

The travel adaptive capacity (TAC) is the ratio of cumulative energy intensities, E_i, for each mode, i, in each distance bin, d_j, to the total distance travelled in the current activity system as given in Eq. (1). TAC can be calculated for the normal travel activity and for the indicated alternatives. The energy intensity for each mode is 1.0 for individual vehicle mode, 0.5 for vehicle passenger, 0.25 for bus and 0.0 for non-motorized transport (NMT).

$$\mathrm{TAC} = \Sigma E_i d_j / \Sigma d_j \qquad (1)$$

[1] available at www.aemslab.org.nz

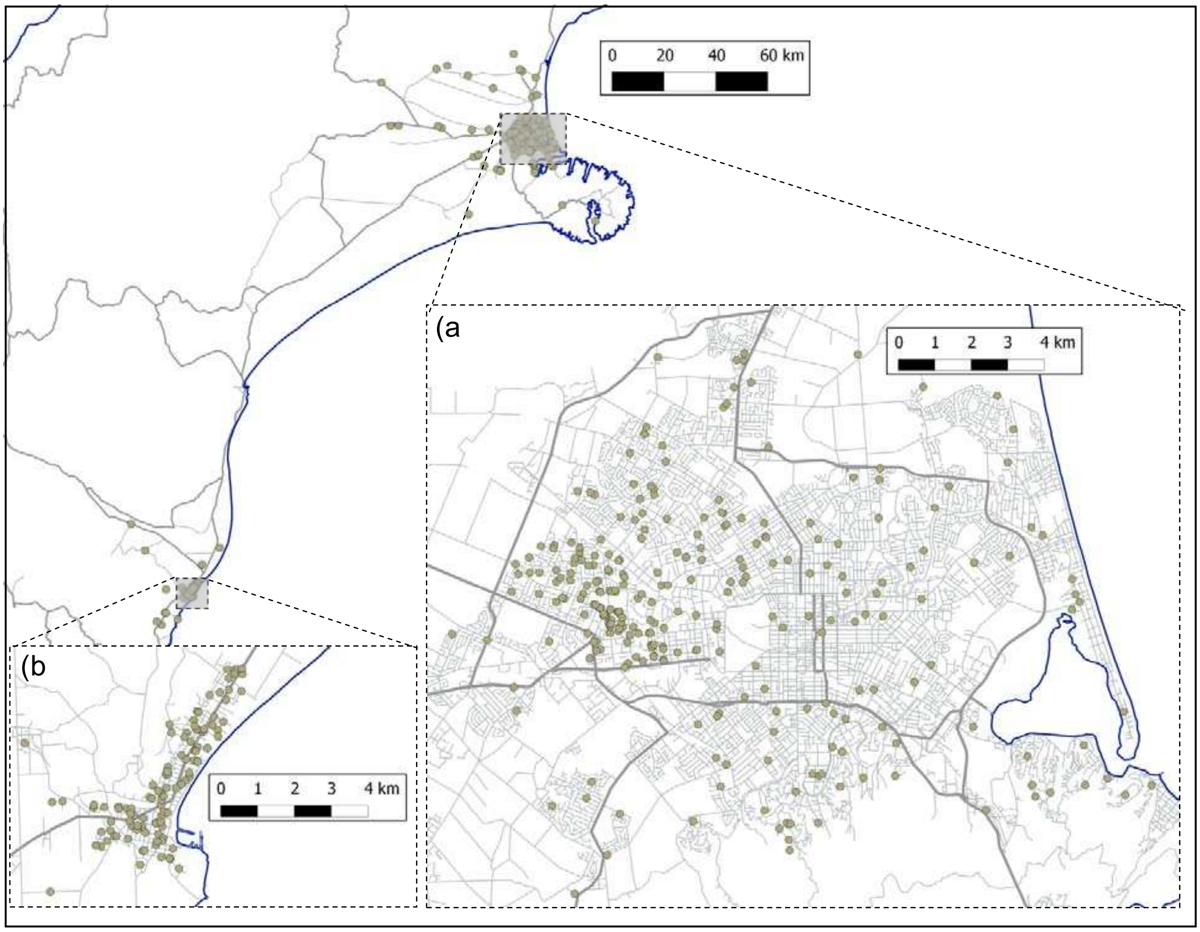


Figure 1. Geocoded residential locations of survey participants in (a) Christchurch, (b) Oamaru.

According to microeconomic theory of choice, individuals choose alternative options that maximize their utility. Random Utility Maximization (RUM) theory considers that the utility of choosing an alternative is composed of two components: systematic utility and random utility (Habib 2011, Train 2003). The systematic utility component, V_j, can be expressed as a linear-in-parameter function of different variables of interest and the random component, ε_j, is expressed in terms of distribution functions. In order to capture the behavioural process of choosing alternative stated adaptation options, we assume that an individual respondent, i, gains utility, U_j, for the option j = 1, 2, 3,...7:

$$U_j = V_j + \varepsilon_j \tag{2}$$

Response options are classified into the following categories, j:

1. None
2. Doing the activity without travelling
3. Getting a ride from someone
4. Biking
5. Walking (NMT)
6. Bus or Park & Ride
7. Others

In order to identify the factors affecting the choice of alternative adaptation options, we further specify the systematic utility components as linear-in-parameter functions of different variables, x_j, and corresponding coefficients/parameters, β_j:

$$V_j = \sum\beta_{0j} + \beta_j x_j \quad (3)$$

Where $\beta_{oj,}$ refers to the alternative specific constant and β_j refers to variable coefficients. The alternative specific constant terms capture the effects of unobserved, but systematic variables. The main challenge of econometric investigation of adaptation behaviour is to estimate the values of parameters corresponding to a range of variables assumed to be influential in the decision making process. For the RUM discrete choice model, the usual assumption is that the random error terms are Type I extreme value distributed. For further assumption of Independent and Irrelevant Distributions (IID) of Type I extreme value errors, the discrete choice probability takes the form of (Ben-Akiva and Lerman,1985):

$$\Pr(j) = \exp(V_i) / \Sigma V_j \quad (4)$$

This is the well-known Multinomial Logit (MNL) model. One basic limitation of MNL is that it assumes independence of the alternative choices and it assumes homogeneous decision makers. Some sort of correlation may be present across the alternatives and there may be considerable heterogeneity across the people who were surveyed. We accommodate heterogeneity and preference correlation by a mixed logit-based approach where the constants of the systematic utility function are considered as random coefficients. This means that we estimate the mean as well as standard deviation of the alternative specific constant terms (Train 2003). We specified an MNL model of adaptation behaviour by using a dataset with 5517 observations. We cleaned the dataset collected through the survey for missing information and modelled the adaptation choice behaviour of trips normally given as automobile either driver or passenger mode. We consider random alternative specific coefficients in order to recognize that there could be considerable heterogeneity across the respondents. The models are estimated by using a maximum simulated likelihood algorithm written in GUASS (Aptech 2009). For the simulated likelihood estimation, a Halton sequence with 1000 iterations is used (Train 2003). The final specification of the adaptation choice model is goodness-of-fit. The goodness-of-fit measures how well the hypothesized model structure fits the observed choice patterns.

$$\text{Goodness-of–fit} = 1 - \frac{\text{Loglikelihood of full model}}{\text{Loglikelihood of null model}} \quad (5)$$

The null model assumes all alternative options are equally likely to all individual respondents. For a discrete choice model, this goodness-of-fit value gives an empirical understanding of how good the model is fitting the reality. For our case this value is 0.22, which is a reasonable value for such a large number of alternatives. It indicates that the hypothesized choice model structure fits the actual stated choice behaviour very well. In terms of parameters, a total of 110 parameters are estimated and over 80 of those are highly statistically significant. Estimating such a huge number of significant parameters by using a relatively small data set is also an indicator of accurate model formulation for stated adaptation choice.

Table 1 presents the estimated model parameters. The specification of adaptation choice model is achieved through testing a series of alternative specifications. The parameters with statistically significant values are retained. Statistical significance is tested by t-statistics, which is the ratio between the estimated mean value and the standard deviation. For 90% confidence limit the critical value of t-statistics is 1.64. We retained some parameters with t-statistics lower than the critical value. This is done because we believe that these correspond to important variables. Also, we believe that if we had larger data sets, these parameters might be significant.

Table 1 Mixed logit model of adaptation option choice.

Loglikelihood of Full Model	-8246.98
Loglikelihood of Null Model	-10735.59
Adjusted Rho-Square Value	0.22

The discrete adaptation choices are modelled considering one alternative as the reference. In our case, the 'Do nothing' option serves as the reference alternative. For all other adaptation options, alternative specific constants are assumed as random parameters. Random parameters capture the heterogeneity across the population and heterogeneity in this regard refers to the systematic variations in adaptation choice behaviour that cannot be captured by available explanatory variables. It is interesting to note that for options "Doing the activity without travelling" and "Getting a ride with someone" the standard deviations of the random parameters are not significant. For these two options there is not heterogeneity across the population. However, for all other options the random parameters are statistically significant meaning that a considerable heterogeneity exists in adaptation choice for the remaining options.

RESULTS

The TACA survey was conducted in two areas on the South Island of New Zealand, the University of Canterbury (UC) as an activity centre in Christchurch, and the small rural town of Oamaru. Christchurch is located on the east coast of the South Island in the Canterbury region. At the time of the survey[2] greater Christchurch had a population of 372,600 and covered an area of 1,493 km^2 with an urban city area of 197.4 km^2 (StatisticsNZ, 2009a; CCC, 2010). The University of Canterbury (UC) had a student and staff population of 24,075 (UC, 2010) and is located approximately 6 km from the Christchurch city centre. The main public transport in Christchurch is served with a diesel bus system provided by local and regional councils, and private operators. Bus fares are standard across the city network and line transfers are available for periods of several hours between trips.

Figure 2 presents a Christchurch map with bus routes from the city centre. In addition to the bus services, the Christchurch City Council has established a network for cycling lanes on roads. The Ministry of Transport (MOT, 2010) has reported that car use remains the dominant form for Christchurch transport with 70% trip mode share as shown in Table 2.

[2] After this survey was completed, a series of destructive earthquakes (4 Sept 2010, 22 Feb 2011, 13 June 2011, 23 Dec 2011) destroyed the central city and several suburbs, substantially altering the population, urban form, activity patterns, housing locations and bus routes.

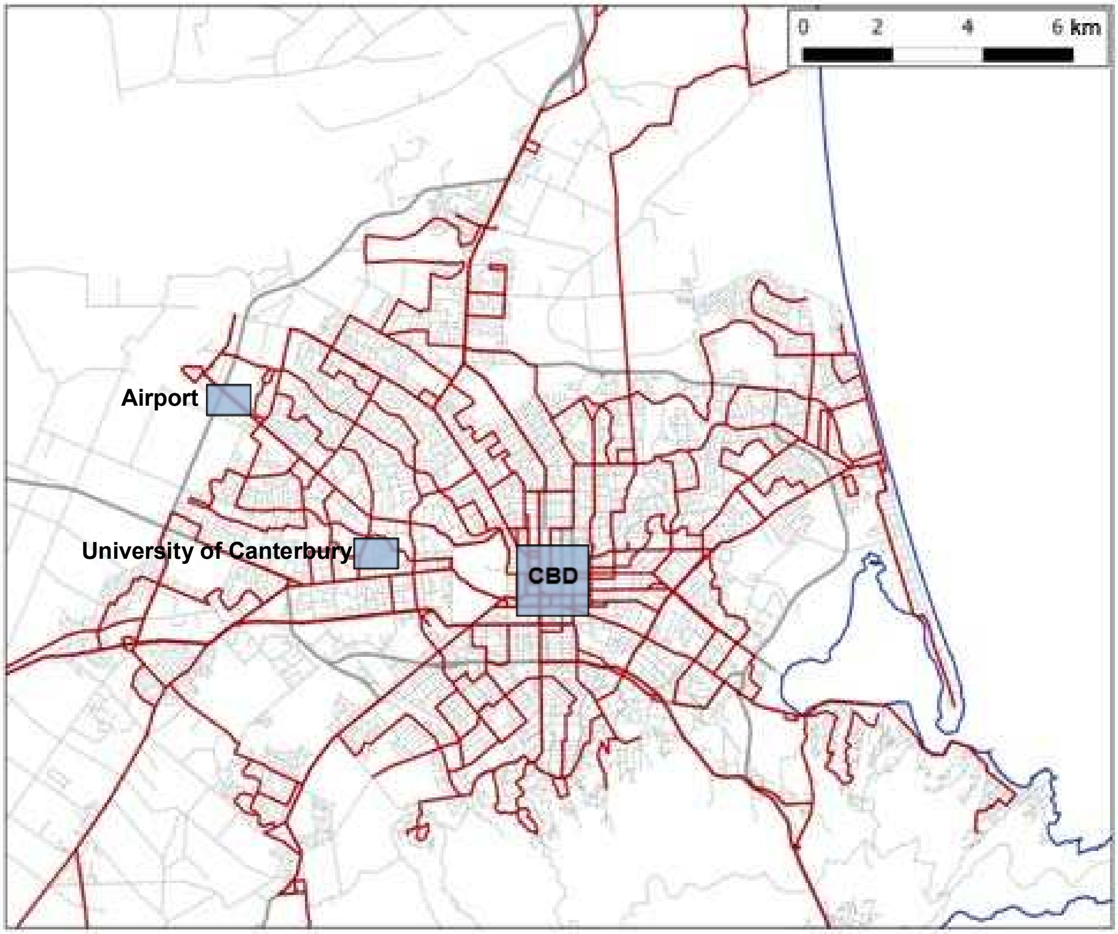


Figure 2. Christchurch area map with bus routes shown and locations of the international airport, University of Canterbury and the central business district (CBD).

Table 2. Mode share of trip legs for three survey areas from government statistics 2003-2007 (MOT, 2010) and from TACA Surveys conducted 2008-2010.

Mode	**Christchurch** MOT	TACA	**Otago Region** MOT	**Oamaru** TACA
Trip legs in sample	*17959*	*6364*	*8816*	*2082*
%household trip legs				
1. Car/ van driver	46%	55%	53%	68%
2. Car/van passenger	24%	7%	23%	7%
3. Pedestrian	23%	14%	20%	18%
4. Cyclist	3%	16%	1%	6%
5. PT (bus/train/ferry)	4%	5%	1%	1%
6. Motorcyclist	0%	0%	0%	0%
7. Other	1%	1%	1%	0%
Total	100%	100%	100%	100%

PT= Public Transport

Oamaru is a small town of population 11,050 located in North Otago, which encompasses covers, an area of 40 km^2. (StatisticsNZ, 2009a). The town of Oamaru has a land area of 40.6 km^2 and is located about 250 km south of Christchurch and 120 km north of the city of Dunedin. Figure 3 shows a street map of Oamaru. The main service and commercial areas are located in the city centre along Thames Street and State Highway 1. Table 3 shows the older population in Oamaru, and the income distributions for the two cities (StatisticsNZ, 2009b). Oamaru is a destination for retirees from other areas.

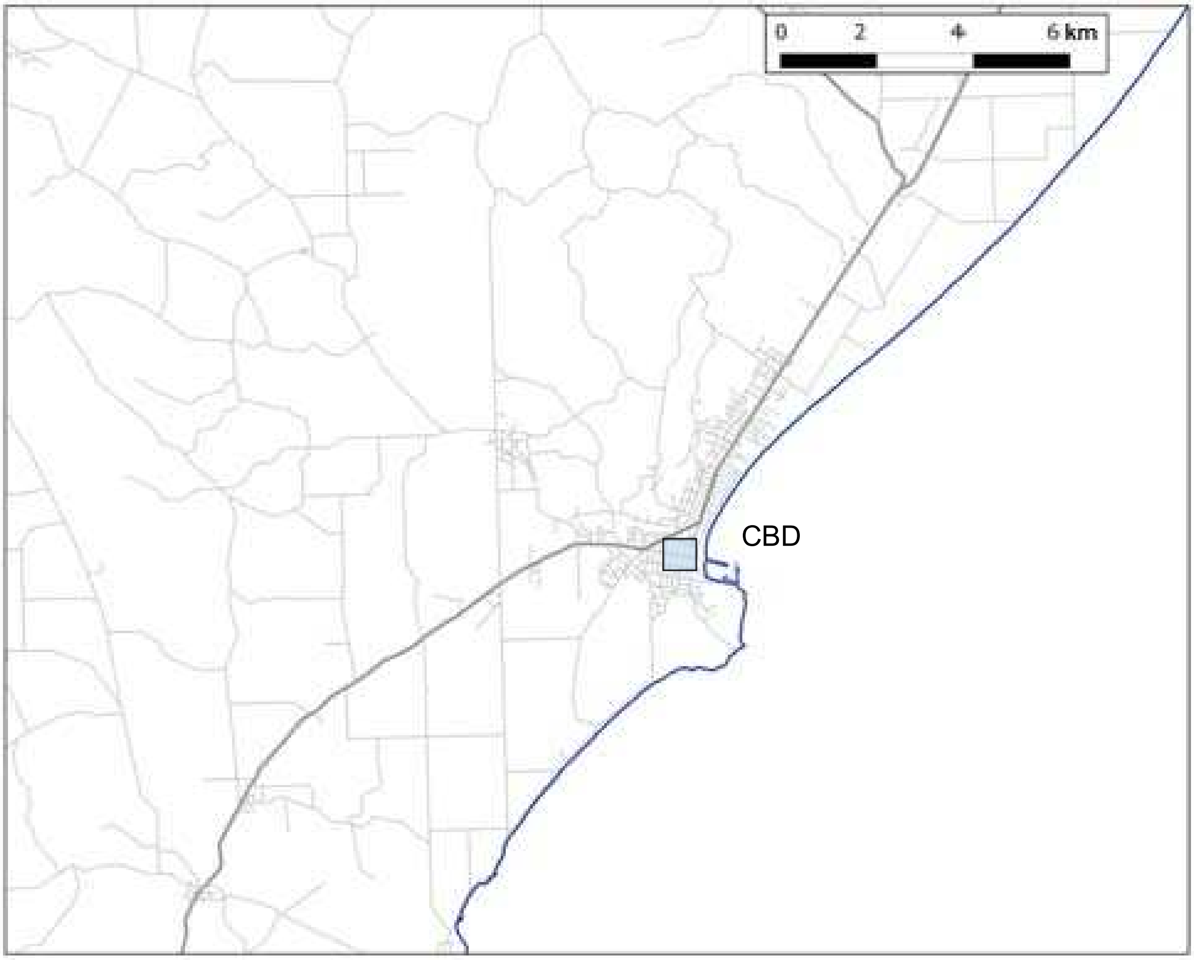


Figure 3. Oamaru and surrounding rural area on same scale map as Fig. 4 Christchurch map.

Table 3. Demographic details for the two study areas (StatisticsNZ, 2006; 2009).

Age Distribution	**0-9**	**10-19**	**20-29**	**30-39**	**40-49**	**50-59**	**60-100**
Christchurch (%)	12.4	13.6	14.7	13.8	14.4	12.4	18.8
Oamaru (%)	11.1	12.3	8.3	9.2	13.3	13.9	31.9
Income x1000 NZD	**< 5**	**5-10**	**10-20**	**20-30**	**30-50**	**> 50**	**not stated**
Christchurch (%)	12.0	7.6	21.1	14.8	21.6	14.8	8.0
Oamaru (%)	8.6	8.5	32.1	15.2	19.7	7.3	8.6

Figure 4 shows the travel demand pattern of the participants at the University of Canterbury and Oamaru. As expected, there are two main differences in the normal travel pattern of Christchurch and Oamaru, the mode of travel, and the distances travelled. Due to the small spatial extent of Oamaru, distances of trips are much shorter than UC, with the exception of trips over 20 km, which represents out of town trips. The proportion of car trips was significantly higher in Oamaru, due to the lack of a bus service. Although some bus trips were recorded for Oamaru, these were long distance intercity trips. The higher age population of Oamaru may also contribute to the low number of trips made by bicycle.

Figure 5 presents the capacity to adapt normal car trips showing only the first alternative selected by the participant when asked the question "If you could not use your normal mode, how many other ways could you travel?" This question is asked for each trip, and the results are presented on a trip basis, and on a distance basis.

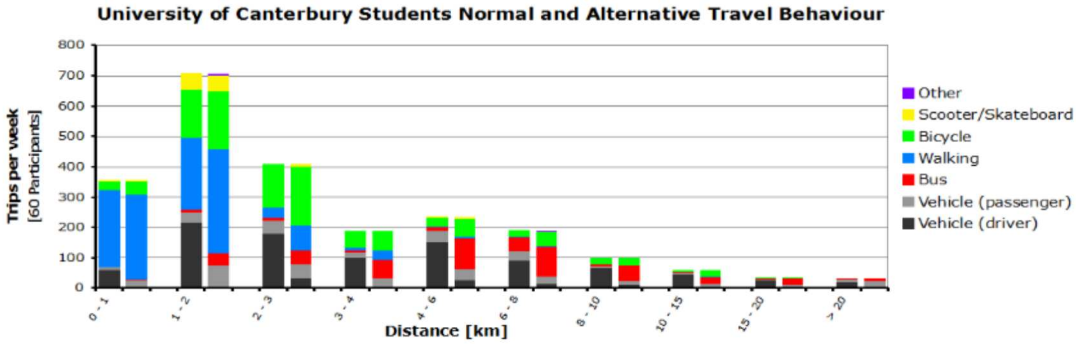
For both Oamaru and UC, the more adaptable trips were shorter distance vehicle trips with options for walking or cycling. This is to be expected, as switching to walking/biking modes is possible when the distances are short. A distinct difference between the two survey groups is level of bus service, and how this greatly impacts the options available. Another interesting finding was the very low numbers of participants who reported being able to do the activity without travel as an option. Both cities have high speed internet, and there has long been an expectation that working or shopping from home using the internet would begin reducing travel demand at some point in the future.

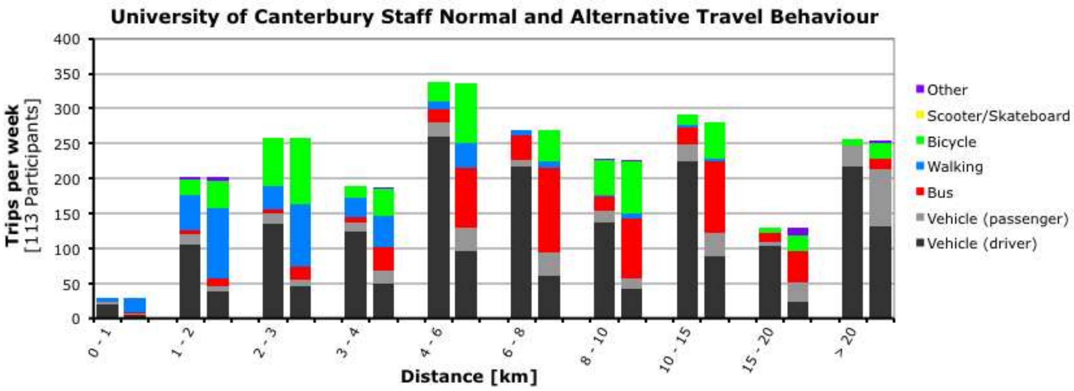
Travel adaptive capacity (TAC)

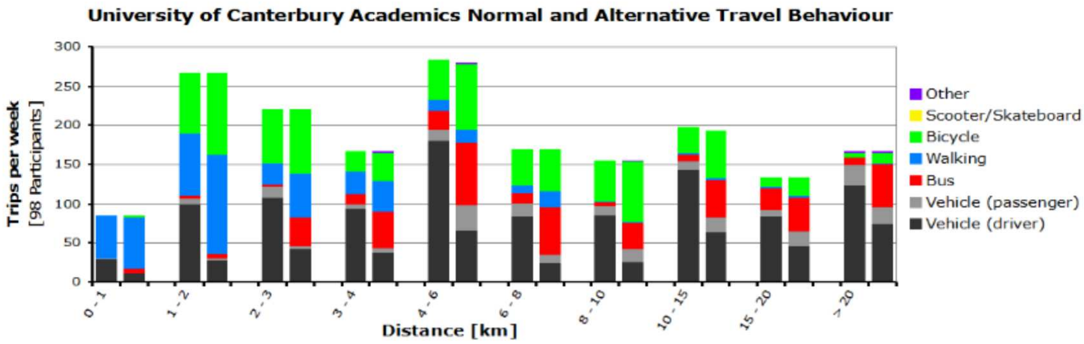
The travel adaptive capacity (TAC) for fuel use was calculated from the survey data for each trip which included distance and the relative energy intensity of the alternative mode chosen as given in Eq.(1). The normal travel behaviour has a TAC based on the proportion of activities and distances travelled that currently do not require fuel or that have lower fuel intensity. The TAC represents the ability to carry out current activities while reducing fuel use. The university student participants have the highest TAC for their current travel behaviour as shown in Table 4.

The university general staff have by far the highest current energy use and also the lowest TAC. The staff include secretaries, administrators, librarians and technicians. Their jobs may require early arrival at work compared to other groups and may have less flexibility. They also tend to live further from the university, with 56% higher vehicle distance travelled per week than the university academics.

The results of the statistical analysis for all the participants examining a range of factors is shown in Table 5. It is interesting to note that for options "Doing the activity without travelling" and "Getting a ride with someone" the standard deviations of the random parameters are not significant. This implies that for these two options there is not considerable heterogeneity across the population. However, for all other options the random parameters are statistically significant indicating that a considerable heterogeneity exists in adaptation choice. Household socioeconomic as well as personal attributes affects adaptation choices. The results show that travel distance affects different adaptation options differently.


University of Canterbury Students Normal and Alternative Travel Behaviour
Trips per week
[60 Participants]
Distance [km]
0 - 1
1 - 2
2 - 3
3 - 4
4 - 6
6 - 8
8 - 10
10 - 15
15 - 20
> 20
Other
Scooter/Skateboard
Bicycle
Walking
Bus
Vehicle (passenger)
Vehicle (driver)


University of Canterbury Staff Normal and Alternative Travel Behaviour
Trips per week
[113 Participants]
Distance [km]
0 - 1
1 - 2
2 - 3
3 - 4
4 - 6
6 - 8
8 - 10
10 - 15
15 - 20
> 20
Other
Scooter/Skateboard
Bicycle
Walking
Bus
Vehicle (passenger)
Vehicle (driver)


University of Canterbury Academics Normal and Alternative Travel Behaviour
Trips per week
[98 Participants]
Distance [km]
0 - 1
1 - 2
2 - 3
3 - 4
4 - 6
6 - 8
8 - 10
10 - 15
15 - 20
> 20
Other
Scooter/Skateboard
Bicycle
Walking
Bus
Vehicle (passenger)
Vehicle (driver)

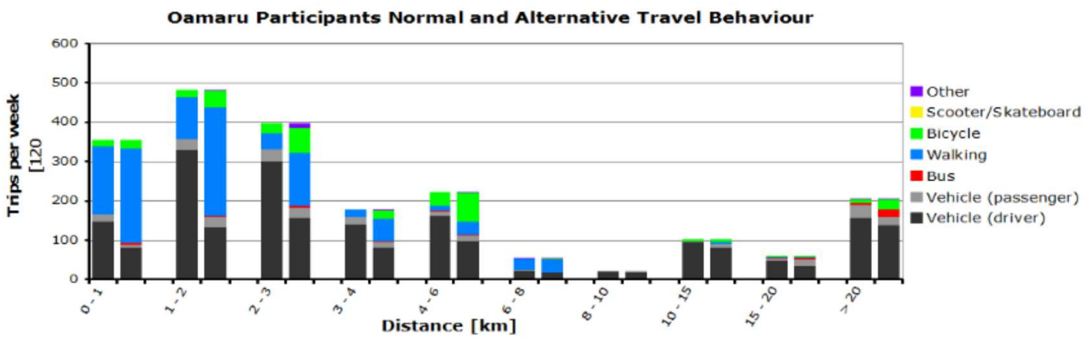

Oamaru Participants Normal and Alternative Travel Behaviour
Trips per week
[120
Distance [km]
0 - 1
1 - 2
2 - 3
3 - 4
4 - 6
6 - 8
8 - 10
10 - 15
15 - 20
> 20
Other
Scooter/Skateboard
Bicycle
Walking
Bus
Vehicle (passenger)
Vehicle (driver)

Figure 4. The normal weekly travel patterns and alternative travel patterns for the three groups of UC people surveyed and Oamaru participants.

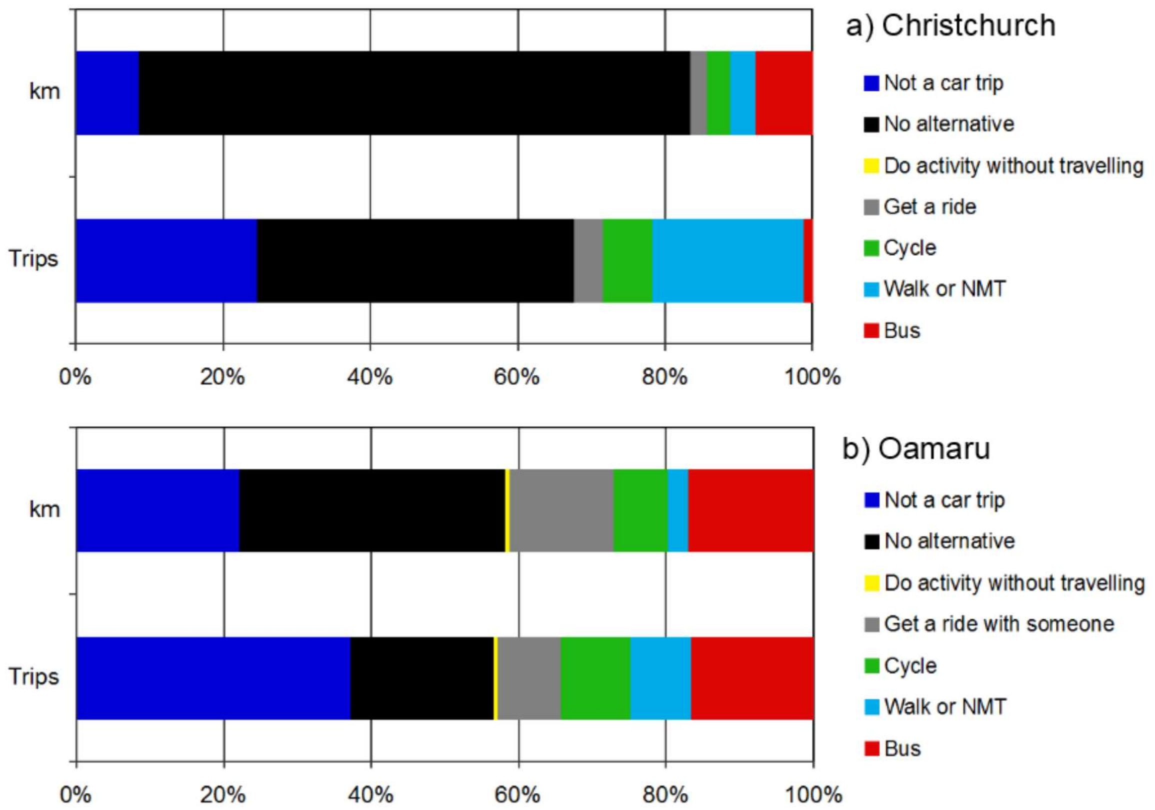


Figure 5. The travel adaptive capacity in distance [km] and number of trips for a) University of Canterbury and b) Oamaru TACA survey participants.

Table 4. Travel adaptive capacity (TAC) for fuel use reduction while maintaining activities.

	Normal TAC [%]	Alternative Mode TAC [%]
Oamaru	18	36
Christchurch	25	58
UC Students	37	74
UC Staff	18	51
UC Academics	29	57

The different demographics between Christchurch and Oamau are evident in the trip purpose results. The education purpose has a much higher percentage of trips among the university participants than in the rural town with a high percentage of retired people. Fig. 6 shows the percentages of trips by purpose for both cities and the importance rankings given by the participants for each trip. The importance, or essentiality, of different trips is a new concept in transport. Considering the issue of oil supply, the percentages of trips that people rank as optional would be a useful parameter in evaluating the potential for energy savings by reducing trips. The results are not surprising in that work, education and seeking medical attention are ranked as the most important trips. The more surprising result may be the 25% of social visit, entertainment and recreation purpose trips that were ranked as essential. 35-45% of shopping trips were also rated as essential to wellbeing.

Travel Factors	**Activity w/o travel**		**Get a ride**		**Bike**		**Walk (NMT)**		**Bus**		**Other**	
Est = estimate *t-Stat* = t-statistic	*Est*	*t-Stat*	*Est*	*t-Stat*	*Est*	*t-Stat*	*Est*	*t-Stat*	*Est*	*t-Stat*	*Est*	*t-Stat*
Alternative Specific Constant	8.13	3.44	9.47	11.59	9.85	13.22	5.78	7.07	5.66	7.13	4.94	2.63
Standard Deviation	-0.30	-0.70	0.01	0.08	0.46	2.56	0.51	2.30	0.85	3.66	-0.54	-0.7
Auto Driver			0.86	4.33			-0.83	-5.49	-0.66	-4.55		
Distance less than 3 km							3.18	12.26	-0.78	-5.86		
Distance 3 - 6 km					0.28	2.71	1.62	6.57				
Essential Work Activity			0.28	1.85	0.52	3.74	0.44	2.71	0.45	3.17		
Essential Educational Activity			1.19	3.56	1.33	4.36	0.93	2.71	1.05	3.26		
Essential Shopping Activity			-0.56	-1.83	-1.51	-3.88	-1.1	-4.41	-0.39	-1.39		
Essential Social/Entertaining	1.58	2.47	0.50	2.10								
Necessary Shopping Activity							-0.81	-2.77	0.61	2.60		
Necessary Social/Entertaining					-0.33	-1.35	-0.43	-1.75	-0.27	-1.20		
Logarithm of Age in Years	-3.11	-5.00	-2.36	-11.7	-2.31	-12.98	-1.56	-9.16	-0.81	-4.18	-1.36	-2.96
Gender: Male	1.64	3.50										
Income less than $30,000			-0.65	-3.6	0.22	1.27	0.73	4.63	1.09	6.98		
Income: $40,000-$50,000			0.71	3.95	-0.31	-1.42					2.19	7.28
Income: $50,000-$70,000	-1.83	-2.90	-0.14	-0.96	0.14	1.09	0.22	1.41	0.24	1.84		
Number Household Vehicle			0.12	3.08								
Household Size	-0.65	-4.10	-0.27	-6.28	-0.18	-4.88	-0.14	-3.37	-0.21	-5.99		
Full Time Worker	1.62	2.97	-0.84	-4.5	0.62	4.06	0.82	5.07			0.66	1.85
Part Time Worker			-0.48	-2.59			0.23	1.64	-0.6	-3.52		
Resident of Oamaru			-1.2	-6.53	-0.70	-4.44	-0.21	-1.37	-4.18	-13.84	0.63	1.53
General University Staff	1.07	2.51	0.16	1.12					-0.42	-3.66		
After two trips of the day			-0.29	-1.59								
Vehicle Occupancy											-0.20	-1.20
Travel Time in Minutes	-0.02	-1.30			-0.04	-8.25	-0.07	-6.48	-0.01	-4.01	-0.01	-1.11
After two trips of the day					-0.22	-1.26	-0.74	-3.19	-0.38	-2.17	-2.91	-4.86
Monday							-0.33	-1.74			-3.68	-4.15
Friday					-0.34	-2.41			0.20	1.51		
Weekends					-0.77	-6.47	-0.36	-3.08	-0.52	-4.69		

Table 5. Results of statistical analysis of participants in the TACA surveys.

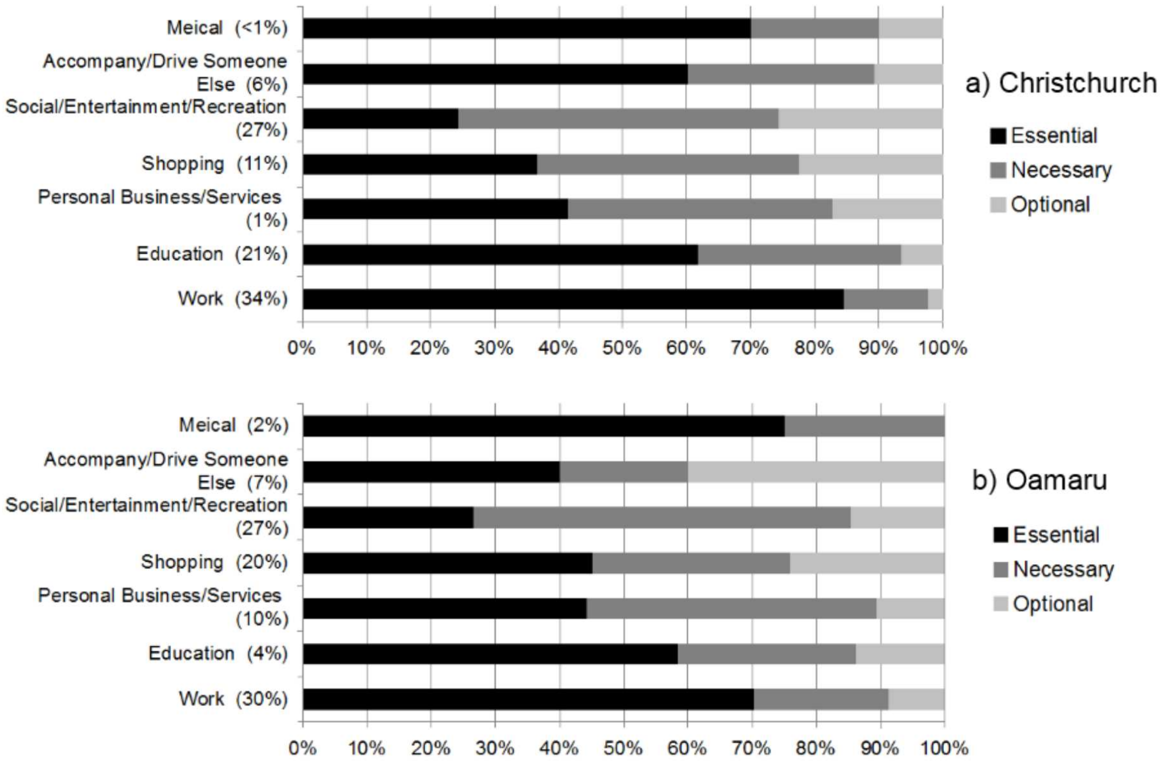


Figure 6. Participants gave the purpose of each trip and selected a level of importance of the trip to the household wellbeing.

DISCUSSION AND CONCLUSIONS

This paper presents a survey method and statistical study of travel adaptive capacity. The survey is unique in that it works more like a personal transport audit with a focus on activity participation and provides feedback to the participant. The concept of travel adaptive capacity is a new contribution to the field that will gain importance as oil supply issues continue to generate pressure for change on personal vehicle travel. The data collected by the TACA survey for normal weekly travel behaviour agrees reasonably well with the data from the conventional travel survey conducted by the government. Differences in the mode shares likely arise from the 30% university student participants in Christchurch and the targeting of homeowners rather than whole households in Oamaru.

We propose that the travel adaptive capacity for a particular cohort of people is an important transport engineering characteristic of the urban form and transport infrastructure. The logic for this hinges on the principles of risk assessment. Engineering assessment of the risk associated with a certain aspect of infrastructure does not need to predict future behaviour in order to be useful in making decisions about priorities for improving resilience or reducing risks. In the same way, information about the travel adaptive capacity provides part of the picture of the vulnerability to future oil supply issues. There is no way to verify that the alternatives to normal vehicle trips indicated in the TACA survey would represent an actual behaviour change in the event of an oil shortage or in response to a fuel price rise.

The TACA survey method was developed to fill a critical knowledge gap in urban development and transport planning regarding the adaptive capacity of the urban form and the population living and working within that urban form. There is now little doubt that transport fuel supply will continue to be expensive and increasingly insecure within the planning timeframe for city councils. This will most likely put increasing pressure for fuel demand reduction on the automobile mode choice. Currently available travel survey data is collected for the purpose of traffic flow and congestion management and does not provide information about how future travel demand might adapt under increasing fuel supply pressure.

The bulk of research into travel behaviour change has focused on the motivating factors or the barriers to reducing the car mode share for commuting. Peak oil and climate change risks provide motivation for choosing lower energy modes. There is little research in the transport field investigating the travel adaptive capacity. It is virtually impossible to conduct a controlled experiment where participants are subjected to a fuel price spike or fuel shortage. It is also impossible to conduct a survey asking people what they would do in such situations, as they do not have a preference for a highly undesirable situation. The TACA survey can probe the relative adaptability by asking a simple question in relation to each private vehicle trip: "do you have an alternative mode?'. This survey design avoids any suggestion of why the car would not be available. Our previous research showed that people mentally provided their own situation based on past experience, often a dead battery or other mechanical breakdown of the car. Thus, the data collected in the TACA survey represents a reasonable and physically possible adaptive capacity that is independent of any particular motivation.

A case study was conduced in Christchurch and Oamaru in New Zealand. Our analysis confirms that the TACA survey can be used to give an assessment of the adaptive capacity and thus the vulnerability of people in different urban forms. The TACA survey can be used to look at the ability of workers to reach a particular organization or of customers to access market places without cars. The statistical analysis showed that the adaptive capacity varies with different demographic factors. Young people were by far the most adaptable, having the least energy intensive normal travel behaviour as well as the highest adaptive capacity for active modes and public transport. This could be due to their relative physical ability, and because it is only a few years since the students gained their drivers licenses, so they would have recent experience with alternative modes. Distance was verified as the main factor in adaptability of trips to non-motorized transport, with 3km representing a definite upper limit for both active mode and accessing public transport. Oamaru had no bus service, and this was the most important factor in the small town having a much lower travel adaptive capacity than the much larger city of Christchurch. In general, the level of adaptive capacity to substitute car trips was surprisingly high, considering how difficult it seems to be to "get people out of their cars" as reported in the travel demand literature.

The results of this study show that Oamaru is more vulnerable to peak oil than Christchurch. Taking the 97% probability future oil supply from Fig. 1, we can see that Oamaru's current TAC of 38% would be exceeded in 2030. The University of Canterbury cohort in Christchurch could adapt according to the reported TAC of 58% until 2050, assuming that at least half of the bus routes could be converted to electricity over that period. We know that there are investments in transportation infrastructure and urban development policies that could make a city more adaptable to fuel use reduction. The TAC assessment provides an indication of the urban areas that need more aggressive investment and planning to increase their travel adaptive capacity.

Finally, we reiterate that understanding the *ability* of people to use less fuel is vital for long-term planning of urban development and transportation infrastructure. Peak oil represents a risk management issue for all city councils, schools, service providers and business owners. Travel adaptive capacity is the best measure currently available to assess the readiness and resilience to fuel supply issues. The TACA survey provides a reasonable way to assess the travel adaptive capacity for a whole town or a particular activity system. Our future work involves conducting more TACA surveys, particularly in areas that have a more car-dominated urban form, like Auckland. We are also continuing to explore using the TAC data to develop log-term adaptation models, which can be used for oil supply decline planning. We think the most important thing to do is to use the TACA data to identify neighborhoods, organisations and demographic groups who are at most risk of transport poverty as fuel prices continue to rise and fuel supply becomes increasingly insecure.

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