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Estimating car ownership and transport energy consumption: a disaggregate study in Nelson Mandela Bay

C J Venter, S O Mohammed

PROF CHRISTO VENTER is an Associate Professor of Transportation Engineering in the Department of Civil Engineering at the University of Pretoria. His teaching, research and consulting activities focus on public transport, transport planning, travel demand modelling, and social aspects of mobility. He is registered as a professional civil engineer.

Contact details:
Associate Professor
Department of Civil Engineering
University of Pretoria
Pretoria
South Africa
0002
T: +27 12 420 2184
F: +27 12 362 5218
E: christo.venter@up.ac.za

SEMIRA MOHAMMED is currently a researcher at the CSIR Built Environment (Council for Scientific and Industrial Research) where she has been working for the last eight years. She completed her BSc Civil Engineering degree at the University of Asmara, Eritrea, and her MSc Transportation Planning at the University of Pretoria, South Africa. She has been involved in a number of research projects ranging from traffic management to passenger transport, with emphasis on transport energy, the environment and road safety.

Contact details:
Researcher
Built Environment Unit
CSIR
PO Box 12417
Hatfield, Pretoria
0028
South Africa
T: +27 12 841 3991
F: +27 12 841 4044
E: smohammed@csir.co.za

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This paper investigates energy consumption patterns by households and individuals during travel on a typical day. A methodology is developed to estimate trip-by-trip energy consumption using standard 24-hour travel survey data, and applied to the Nelson Mandela Metropolitan Area using their 2004 household travel survey. Baseline energy consumption patterns by different modes, times of day, and user groups are established. Across the population, energy use is very skewed: 20% of people consume about 80% of transport energy, mainly due to the disproportional contribution of car use to energy expenditure. We then estimate a disaggregate vehicle ownership model and link it to a model of household transport energy consumption to explore the underlying socio-economic and land use variables driving energy consumption. Land use factors (especially job accessibility) significantly affect energy use, but do so differently for low and for high-income households, suggesting that accessibility-enhancing land use and transport measures could have unintended consequences for overall energy and environmental management.

INTRODUCTION

Transport energy consumption is emerging as a major area of public and political concern worldwide. The transport sector is a significant consumer of energy – estimates for Cape Town, for instance, indicate that transport accounts for just over half of all energy consumed in the city (SEA 2003). Given that about 97% of transport energy in South Africa comes from liquid fuels, of which the lion's share is refined imported crude (Cooper 2007), concerns centre around energy security, the exposure of the economy to international oil price volatility, and the environmental impacts of transport fuel use.

Potential strategies to reduce the transport sector's dependence on oil include technological improvements such as increasing the energy efficiency of the vehicle parc, behaviour change, reducing the demand for travel by individual commuters, or shifting towards less energy-intensive modes of travel (Vanderschuren *et al* 2008). Behavioural change objectives are being pursued through the various public transport upgrading and travel demand management strategies being implemented in South African cities (DOT 2007). What complicates these efforts is the extent to which energy concerns are interwoven with many other social and economic goals, from urban restructuring and poverty relief to industrial development. There is thus increasing interest in understanding the drivers of energy use, and their linkages with other urban processes. Local empirical studies of transport energy consumption have tended to focus at the city or provincial level (e.g. Cooper 2007; SEA 2003; Maré & Van Zyl 1992), typically using aggregate fuel sales data. Goyns (2008) analysed fuel consumption and emissions in Johannesburg for a sample of instrumented vehicles under various vehicle, driving and traffic conditions, but could not link it to demographic or land use variables. Goyns's work showed that, as travel demand and conditions vary at a fine grain across space and time, patterns of transport energy consumption vary considerably at the intra-metropolitan level. A greater understanding is needed of the relationships between transport energy consumption and the socio-economic, land use, and transport supply characteristics in cities before the energy and sustainability impacts of urban management policies can be predicted; and before effective policies and interventions can be fashioned that are aimed specifically at addressing energy concerns.

With that in mind, the paper aims to answer the following questions:

- Can detailed and disaggregate information on transport energy use be derived from available travel survey data?
- Which socio-economic and land use variables significantly influence energy consumption in personal transport?

- How do these variables affect household car ownership and transport energy use?
- What are the implications for urban policy and management?

The data is taken from the Nelson Mandela Metropolitan Area Travel Survey (NMMM 2004) conducted in 2004, supplemented by transport supply data. The study is restricted to personal surface transport modes and excludes freight and commercial transport. The focus is furthermore on the end-user consumption of energy only, in terms of the marginal amount of fuel (in the case of road transport) or electricity (in the case of rail) consumed by a traveller during each trip. Full accounting of energy use could include the energy used in the construction of infrastructure and the manufacture of vehicles, but such life-cycle assessments (e.g. Chester & Horvath 2008) fall outside the scope of this paper.

The following section provides a brief introduction to previous work on the relationships between transport energy, land use, and travel behaviour, followed by a description of the research design and methodology used. The final sections describe the results of the analysis, including two disaggregate models estimated on car ownership and energy use. Lastly, conclusions are drawn as to the meaning of the findings for strategies to reduce or manage energy use in the passenger transport sector.

TRANSPORT ENERGY CONSUMPTION, LAND USE AND TRAVEL BEHAVIOUR

The links between land use, travel behaviour and energy consumption

Relationships between land use and energy use have been studied widely internationally. The earliest studies focused on urban density. In perhaps the most well-known (although not uncontested) work, Newman and Kenworthy (1989) measured per capita petroleum consumption and population densities in a number of large cities around the world, and found a clear negative relationship between the two. Car usage was lower and provision of public transport higher in the cities with the highest densities. Others have argued that the transport policy environment accompanying higher densities – including parking management and fuel pricing – often contribute as much to the achievement of high public transport shares as density *per se* (e.g. Gomez-Ibanez 1991).

In recent years a significant body of research has emerged around the links between land use and travel behaviour. Travel behaviour – the amounts, types, lengths and modes of travel undertaken by trip-makers with various characteristics – is important as an intermediate factor determining the amount of energy consumed during travel. The range of land use variables examined has also broadened from aggregate density towards more microscopic factors reflecting the quality of the urban environment, including neighbourhood safety, attractiveness for walking and bicycling, block sizes and mixed land uses (e.g. Crane & Crepeau 1998; Zegras 2010). The general conclusion has been that land use variables account for some variation in travel patterns, but that socio-economic characteristics and preferences are at least as important in determining the desire and opportunity for travel (e.g. Ewing & Cervero 2001; Banister 2005). Among the most important socio-economic variables identified were car ownership and employment – travel patterns and distances tend to change significantly once a household owns a motor vehicle.

Models of vehicle ownership

Vehicle ownership models, central to the analysis of transport energy consumption, have a long history. Mokonyama and Venter (2007) provide a brief overview of modelling approaches used in South Africa, and discuss the limitations of conventional ownership models using time-series or income variables only (e.g. Sweet 1988). In short, significant evidence exists of the benefits of using pricing, land use and demographic factors to help explain vehicle ownership. Disaggregate choice models of the kind used in this paper are ideally suited to this task, provided the data is available at the household or individual level. One local application has been found of a logit model used to investigate the choice between petrol and diesel vehicles (Naude 2002), but the model did not go so far as to examine the initial vehicle purchase decision.

Methodologies for studying land use / transport energy relationships

Studies of the effects of urban form on vehicle usage and energy consumption can be divided into aggregate and disaggregate studies. Aggregate studies use spatially defined averages for all variables, with observations usually at the city or metropolitan level. Besides the work by Newman and Kenworthy (1989), recent applications of this approach include comparisons of transport energy consumption across cities in developed and developing countries (Daimon *et al* 2007). A major problem with cross-sectional aggregate approaches is the difficulty in controlling for cultural, political, historical and economic differences. Handy (1996) reviewed many studies, and concluded that aggregate studies are generally not capable of uncovering true relationships between land form measures and travel.

Disaggregate studies, on the other hand, use household observations of vehicle usage and city-wide, zonal or neighbourhood averages for urban form variables. These allow energy use for transport to be compared to characteristics of the household and the residential area (e.g. Golob & Brownstone 2005; Lindsey *et al* 2011). For example, Naess *et al* (1995) used data collected from 321 households in 30 residential areas in Greater Oslo to investigate variations in travel distances, modal splits and energy use, and found that residents of high-density, centrally located communities travel considerably shorter distances and use considerably less energy per capita than those who live in low-density, outer areas. A similar approach is applied in this paper to the Nelson Mandela Bay area.

RESEARCH DESIGN

Background and study area

The study area is the Nelson Mandela Metropolitan Area located in the Eastern Cape Province. It has a population of approximately 1.5 million and a land area of 1 845 square kilometres (NMMM 2004). The metropolitan boundary includes the city of Port Elizabeth, its surrounding low-income residential areas, and the nearby towns of Despatch and Uitenhage. Thirty-four per cent of households have access to one or more cars, very similar to the average of 36% for other metropolitan areas in South Africa (DOT 2005). Nelson Mandela Bay is fairly well served by public transport. Minibus taxis transport about 20% of daily trips, while the Algoa Bus Company, the sole bus operator in the area, serves about 6% of all trips on a fairly extensive bus route network connecting outlying areas with the Port Elizabeth (CBD) Central Business District (NMMM 2005). A single commuter rail line connects the CBD with Uitenhage, but transports less than 1% of trips. The overall split between public and private modes is 40:60 (excluding walking).

Although the modal mix and mode shares in Nelson Mandela Bay are typical of metropolitan areas in South Africa, it has some unique topographical features. These include the coastline which directs growth towards the north and north-west, and the Swartkops River to the north of the metro, both of which might lead to longer travel distances than in other comparable-sized metros.

Travel survey data

In 2004, the Nelson Mandela Metropolitan Municipality undertook a travel survey to determine travel demand characteristics in the area. A total of 2 828 randomly chosen households (10 200 individuals) were included in the survey. The survey included a 24-hour weekday travel diary. As one of the first travel surveys in South Africa that extended beyond peak periods it offered much more complete travel data than traditional survey sources. Data on standard vehicle ownership and demographics was also collected.

To estimate energy consumed for transport, the data on trip distances and public transport occupancies was obtained from secondary sources. Trip distances were extracted from a zonal distance matrix based on shortest route road distances between zone centroids. Public transport occupancy figures were obtained from the municipality's Current Public Transport Record (CPTR), which recorded bus and taxi occupancies by route and time of day.

Land use data and accessibility measures

The land use intensity variables that we used included population density and a job accessibility index. The population density per residence zone was derived from the 2001 national census data.

The accessibility of a household in a particular zone is generally defined as the ease of reaching opportunities in the surrounding area, and is affected both by the location of the household relative to potential destinations, and the quality of the transport system available. In order to test our hypothesis that the amount of transport energy consumed is affected by the level of accessibility a household enjoys, we constructed an accessibility index for each home zone. A standard gravity-based measure was used (El-Geneidy & Levinson 2007), defined as follows:

$$A_i = \frac{\Sigma d_j \cdot f(w_{ij})}{\Sigma d_j} \quad (1)$$

where:

A_i = accessibility index of zone i to opportunities;

d_j = the amount of job opportunities available at zone j;

$f(w_{ij})$ = an impedance function expressing the increasing difficulty of travelling between i and j as the distance increases;

w_{ij} = the road distance between zones i and j.

We used a locally calibrated impedance function of $f(w_{ij}) = e^{-0.15wij}$ obtained from the trip distribution model of the NMMM strategic transport model; it thus reflects the actual sensitivity of trip makers in the area to travel distance, averaged over trip purpose and income levels (NMMM 2004). Two assumptions are that access to jobs reflects the level of access to other opportunities (including shopping, social, and business opportunities); and that road distance as a proxy for travel friction captures the main effect of interest, even though it ignores congestion.

Table 1 Fuel consumption and energy intensity rates used to estimate energy consumption

Mode used	Fuel consumption (litres/100 veh-km)	Energy intensity (Megajoules/100veh-km)
Walk	0	0
Bicycle	0	0
Motor cycle	2.8	102.8
Bakkie taxi	12.3	451.4
Minibus taxi	14.0	513.8
Commuter rail	---	10.3 (MJ per couch-km)
Bus	47.5	1 833.5
Motor vehicle	10.8	396.4

Note: See text for data sources

Estimating transport energy consumption

The transport energy estimation process requires determining the energy intensity for each individual trip made. Studies have shown that fuel consumption per vehicle-kilometre depends on many factors, including vehicle engine size, fuel type, traffic conditions, environmental conditions and driving style (Goyns 2008; Wong 2000). We used average fuel consumption figures for passenger vehicles and for minibuses as suggested by Schutte and Pienaar (1997), and averaged across petrol and diesel vehicles according to the number of each fuel type registered in the Nelson Mandela Metropolitan Area. The figures for passenger vehicles accord with fuel consumption rates measured by Wong (2000) in coastal regions of South Africa. Sivanandan and Rakha (2003) showed that energy intensity estimates based on an average composite vehicle tend to produce conclusions that are consistent with the explicit modelling of the various vehicle types.

The average fuel consumption estimates for buses were obtained from the Algoa Bus Company. A summary of the final fuel intensity figures (in litres per 100 veh-km) used for each mode in the survey is given in Table 1.

The fuel consumption for each trip made by each individual interviewed during the survey was calculated as:

$$l/person\text{-}trip = \frac{km \times l/veh\text{-}km}{vehicle\ occupancy} \quad (2)$$

where:

$l/person\text{-}trip$ = fuel consumption

km = distance

$l/veh\text{-}km$ = fuel consumption intensity

Trip distances were estimated from the shortest-path route between the origin and destination of each trip. Equation (2) is applicable to all modes of travel, except for passenger rail. Rail transport in Nelson Mandela Metropolitan Area uses electric power. In order to convert the electric power consumption to the same unit as the other modes, the energy consumption and maximum occupancy figures (for 9 M commuter rail trains) suggested by Del Mistro & Aucamp (2000) were used, namely 10.3 MJ/coach-km and 255 passengers respectively. The average occupancy per coach, based on 100% occupancy in peak direction and 20% in the opposite direction, is taken as 60%. Thus the energy consumption per rail passenger trip was calculated as:

$$MJ/person\text{-}trip) = \frac{km \times Mj/coach\text{-}km}{60\% \times maximum\ occupancy\ per\ coach} \quad (3)$$

where:

$MJ/person\text{-}trip$ = energy consumption

km = distance

$Mj/coach\text{-}km$ = energy consumption intensity

Results from Equation (2) were converted to Megajoules (MJ) to enable comparison across different modes using a conversion factor of 36.7 MJ/litre of fuel. The final step was the summation of the energy consumption by trip according to the levels of analysis.

Modelling disaggregate energy consumption: analytical issues

When attempting to model the relationship between transport energy consumption and household, individual or spatial explanatory variables, one is confronted with a number of analytical problems. The first relates to the problem of *self-selection bias*. This kind of problem occurs when cross-sectional data is used to assess how land use variables, such as density or accessibility, influence people's travel behaviour (see Mokhtarian & Cao 2008) or travel energy consumption. Self-selection refers to the fact that households are not randomly distributed across space: households who prefer (or are unable) to own a car may choose to locate in an area that provides opportunities for walking and public transport use. If statistical analysis then identifies a correlation between being located in an accessible neighbourhood and high use of public transport, it is not clear that this behaviour can be attributed to the neighbourhood features rather than to preference variables. In other words, causality is unclear. Methods exist for dealing with problems of simultaneity (see for instance Mokhtarian & Cao 2008), but these require more advanced research designs involving control groups that are not available for this study. We do not correct for self-selection bias here. The results, therefore, must be interpreted with caution: we can, at best, infer association between land use and energy consumption, rather than causality.

A second problem relates to *endogeneity*, in this case with respect to the effect of unobserved taste variations on car ownership and energy use. We expect (and will later prove) that income (and the values and lifestyle choices normally associated with a certain income level) strongly affects the decision to buy a motor vehicle. The same values and preferences also affect the amount of travel undertaken (and therefore the amount of energy consumed). For statistical reasons we cannot specify a single regression model of transport energy consumption containing the household's number of motor vehicles as an independent variable, as this variable may be correlated with the unobserved values and preferences (and thus with the regression model's error term). Instead we develop an instrumental variable, the predicted number of cars in a household, and use this predicted value rather than the observed number of cars owned as the explanatory variable in the regression model (see Zegras 2010).

What the need for an instrumental variable implies is that a separate model of household car ownership choice must first be estimated on the data set, before energy consumption can be modelled. We therefore specify a multinomial logit (MNL) model to capture the household decision of whether to own zero, one, or two or more vehicles, as a function of demographic and spatial variables. Apart from its usefulness in supplying the instrumental variable for the energy use model, the MNL model also provides additional insight into the factors affecting a household's decision of whether or not to buy a car.

A third problem relates to the use of the energy consumption metric as a dependent variable, as the variable is calculated across all persons and households in the sample, and therefore includes many zero observations. In fact, the data shows that 34% of individuals consumed no energy during travel, as their trips consisted exclusively of walking or bicycle trips on the survey day. The data is thus *left-censored*, with many observations clustered at zero, and can not be modelled using a simple linear OLS model for continuous dependent variables. This would produce biased and inconsistent parameter estimates (Washington *et al* 2003). The solution is to use a Tobit model (a model formulation developed specifically to deal with such cases), and estimated Maximum Likelihood methods. The Tobit model is encountered in the travel behaviour literature in the analysis of travel expenditure data, which is frequently left-censored when no money is spent on transport (e.g. Thakuriah & Liao 2005). The paper does not elaborate on the specification or estimation of the Tobit model; suffice to say that Tobit model results and test statistics can be interpreted in the same way as those of ordinary least squares models.

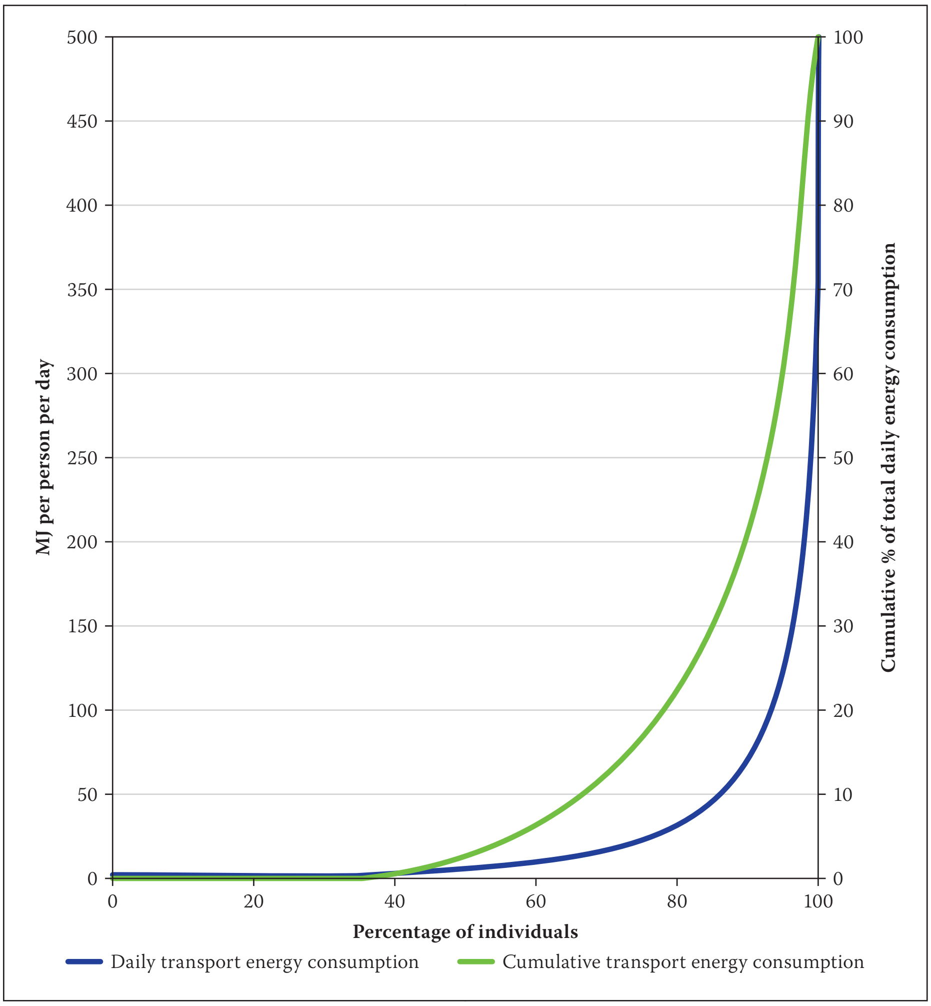

Figure 1 Daily and cumulative daily energy consumption by persons in the sample (unweighted, n = 7 000 persons)

ENERGY CONSUMPTION PATTERNS ACROSS SUB-GROUPS OF THE POPULATION

We look firstly at patterns of daily transport energy consumption by aggregating our trip-level energy consumption estimates by mode used, by time of day, and by zone. We then aggregate across demographic characteristics, such as gender and occupation, in order to examine intergroup differences in energy use.

Transport energy use by mode and time of day

Figure 1 plots the distribution of daily transport energy consumption per person. It is clearly a very skew distribution, with about 34% of individuals in the sample using no fuel, and 83% consuming less than 40 MJ per day to travel (40 MJ is approximately the energy consumed during one 10-kilometre long car trip made by a single occupant). The cumulative distribution in Figure 1 shows that 80% of residents in Nelson Mandela Bay contribute only 22% to the overall energy bill, with the remaining 20% of people consuming 78% of the total.

The reason for this skewness is apparent from Table 2, which shows the distribution of trips by mode in the sample. Almost half of all trips are made on foot or on bicycles. The car is used in a quarter of person-trips, but these trips consume three to five times the amount of energy as trips by motorcycle, minibus taxi or bus. This is due to the car's low occupancy rather than to long trip distances; mean car trip lengths are similar to trip lengths by taxi, and less than trip lengths by bus and train. Surprisingly, the mean energy consumption per bus trip is about 50% higher than that per trip in a minibus taxi. Two reasons account for this: buses have an energy intensity that is more than three times higher than that of minibuses (Table 1); and bus passengers tend to make longer trips than taxi passengers. When controlling for trip distance, however, the energy consumed per bus passenger *on a per-kilometre basis* is about equal to that of a minibus taxi passenger. The higher carrying capacity of buses offsets their higher energy intensity, but perhaps not to the extent expected. Trains are by far the most efficient mode due to their high passenger capacities.

When comparing transport energy consumption across different times of the day, marked differences are observed. As shown in Table 3, average energy use of trips made during peak hours is 60% higher than that of trips made during the rest of the day. Both occupancies and trip distances vary depending on the time of the day. Table 2 shows that only buses are significantly fuller during the peaks than during the off-peaks; minibus taxis have about the same average occupancy throughout the day, while private cars actually have lower occupancy during peaks – an indication that the car trip to work tends to be predominantly single-occupancy. Furthermore, mean trip distances are higher during the peak than the off-peak (Tables 2 and 3), contributing further to peak period energy use.

Table 2 Comparison of transport energy use by travel mode

Mode of travel	Number of person-trips observed	Percentage of trips	Mean energy use (MJ/ person-trip)	Average occupancy (persons/vehicle)		Average trip distance (km/trip)	
				Time of day		Time of day	
				Off-peak	Peak	Off-peak	Peak
Non-motorised	9 785	46.1	0.0	1.00	1.00	1.8	1.9
Motor cycle	50	0.2	5.6	1.03	1.00	5.9	4.7
Motor vehicle	5 333	25.1	25.8	2.02	1.95	8.3	10.2
Minibus taxi	4 751	22.4	4.8	9.30	9.43	8.0	9.5
Bakkie taxi	89	0.4	11.1	4.67	4.87	12.9	10.9
Bus	1 120	5.3	7.1	32.94	44.38	12.3	14.6
Train	57	0.3	1.7	51.0[a]	255.0[a]	32.0	23.8
Other	45	0.2	8.9	2.80	2.81	5.9	7.0

Notes:
Sources: Mean energy use estimated. Average occupancy of motor vehicle trips as reported in survey.
Average occupancy of public transport trips obtained from Current Public Transport Record, 2004.
a = Train occupancies based on national averages. Average occupancy shown per coach.

Table 3 Comparisons of transport energy use by time of day

Period	Mean energy use (MJ/person-trip)	Mean trip distance (km/trip)
Peak period	9.7	6.9
Off-peak period	6.0	5.2
All trips in sample	8.1	6.1

Notes: Peak period is defined as 6:00-9:00 and 15:00-18:00. Off-peak period is all the other hours of the day

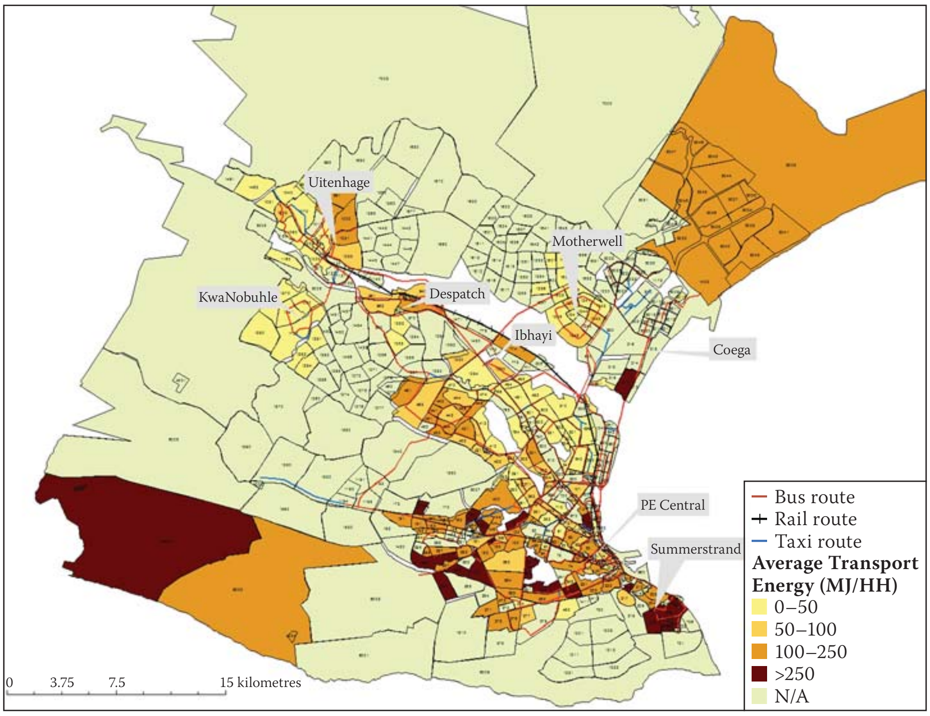

Figure 2 Estimated average daily household transport energy consumed (MJ), shown per transport analysis zone

Spatial patterns of transport energy use

Figure 2 shows the zonal average household transport energy consumption, plotted on the transport analysis zones used by NMMM. The figure indicates how demographic, spatial and transport supply factors interact to determine energy consumption patterns in the study area. High transport energy consumption is recorded in outlying areas towards the north (around Coega) and south, but these are in fact sparsely populated areas of low significance. Low income residential areas that are well-served by public transport, such as Motherwell, iBhayi and Kwanobuhle, have relatively low transport energy consumption; so do the Despatch and Uitenhage areas which are close to the rail line and to local factory jobs. Higher-income areas such as Bluewater Bay, Summerstrand and the PE central suburbs are located closer to the Port Elizabeth CBD, but have higher energy consumption – this despite having relatively good taxi and bus coverage. The metro's unique topography may also contribute to higher energy consumption across the river to the north, from where residents have longer travel distances to access major work nodes to the south.

Table 4 Comparisons of transport energy use and travel, by gender and occupation

Group	Mean energy use (MJ/person/day)	Mean number of trips (trips/person/day)	Mean daily travel distance (km/person/day)
Gender			
Female	20.8	3.1	18.0
Male	28.9	2.9	19.3
Employment status			
Working outside home	46.9	3.3	27.8
Not working outside home	13.8	3.3	14.7
Scholars and students	8.8	2.7	11.8
All individuals in sample	24.7	3.0	18.6

Notes: 'Working outside home' includes part and full-time workers. 'Not working outside home' includes people working from home, home-makers, unemployed, retired.

Table 5 Estimation results: Multinomial logit model of vehicle ownership choice

Variables	0 vehicles (base)	1 vehicle		2+ vehicles	
		Beta	T-value	Beta	T-value
Household characteristics					
No of workers		0.353	4.69**	0.703	6.79**
HH income (R'000s)		0.149	5.67**	0.264	9.57**
HH size (low income[a])		–0.138	–3.92**	–0.146	–2.50**
HH size (high income[a])		0.001	0.025	–0.047	–0.86
Zone characteristics					
Population density[b]		–0.148	–9.183**	–0.366	–11.945**
Job access index[c]		6.847	4.476**	6.720	3.491**
Constants		–1.003	–5.87**	–1.898	–7.72**
Number of observations	1 648	534		411	
Likelihood ratio test (full model)	Chi-squared = 1 475**				
Adjusted rho-squared	0.314				

** = Significant at 95%
a = Low-income households are below the median income of R2 500 per month; high-income is above
b = Population density of household zone (in 1 000 persons per square kilometre)
c = Accessibility index by road to job opportunities (see text for explanation)

TRANSPORT ENERGY USE BY GENDER AND EMPLOYMENT STATUS

To examine patterns of transport energy use across segments of the population, trip-level consumption figures are aggregated for each individual and grouped by gender and employment status (see Table 4). Gender is considered here as it relates to the different roles played by men and women in society, and has frequently been found to account for significantly different travel patterns across a population (e.g. Turner & Fouracre 1995). In this sample, the mean energy consumption by male travellers is significantly higher than that of women. Men make slightly fewer trips per day than women, but, on average, travel longer distances. This is consistent with previous findings indicating that, compared to men, women tend to make more non-work trips, and tend to visit destinations closer to the home (e.g. Venter *et al* 2007). Men also tend to use cars more: 28% of all trips by men are made by car, compared to 22% for women.

A similar grouping by occupation type shows the importance of employment status as a predictor of transport energy consumption. People who are employed and travel to work consume 47 MJ during travel per day, compared to 14 MJ for unemployed people or homemakers, and 9 MJ for students and scholars. Thus giving one unemployed person a job would tend to increase their transport energy use more than three-fold, everything else being equal, as employment is associated with both longer travel distances and more frequent use of the car. The strength and nature of the income effect on energy consumption is examined further in the following section.

DISAGGREGATE RELATIONSHIPS BETWEEN LAND USE, DEMOGRAPHICS AND TRANSPORT ENERGY CONSUMPTION

The objective here is to assess to what extent energy use during travel is affected by a household or individual's own characteristics (such as income and gender), by zone-level land use characteristics (such as density), and by zone-level accessibility to surrounding opportunities. Some of the variables were already examined in the previous section, but we now include them in a multivariate model to assess the relative strength of each in explaining variations in energy use. Theory suggests that higher incomes are associated with higher energy use, as both car ownership and travel activity tend to increase as incomes grow. Higher densities are associated with lower energy use, all else being equal, because opportunities for walking and reducing trip lengths grow as more activities are available close to home. The influence of accessibility is unpredictable; being located in more accessible areas close to the city centre might lead to reduced trip lengths and thus reduced energy requirements, but it might equally lead to increased trip making as the opportunities for interaction improve.

As explained earlier, we first estimate a model of household vehicle ownership choice to examine the factors driving the decision to purchase a vehicle, and to supply an instrumental variable of predicted car ownership that can be used in the subsequent energy use models.

Household vehicle ownership choice

A multinomial logit (MNL) model of vehicle ownership choice was estimated, using a category-dependent variable with three potential outcomes, namely zero cars (the base case), one car, or two and more cars in a household. Household characteristics tested as explanatory variables included the monthly household income reported by respondents, the number of workers in the household, and household size, which was interacted with income to test the possibility that household size has a differential effect on vehicle ownership depending on socio-economic status. All correlations among explanatory variables are below 0.5, indicating sufficient independence. Zonal population density and job accessibility index variables were included as land use descriptors.

Table 5 shows the parameter estimates and the t-values for each coefficient, as well as the goodness-of-fit statistics. Almost all coefficients are significant, and the adjusted rho-squared value of 0.31 is good for disaggregate choice models. Household income and the number of workers show a positive and strong relationship to vehicle ownership – this can be expected and agrees with evidence from previous studies. Household size has an interesting differential effect on the likelihood of buying a car, depending on the income. For low-income households, an increasing household size is associated with a lower likelihood of buying a car, even controlling for the level of income itself. Increasing household sizes indicate the presence of either more children or dependent elderly people in the family, who represent a competing claim on household resources, leaving less for the purchase and maintenance of a vehicle. Amongst high-income households, however, the number of people in the household has no statistically significant relationship with the number of vehicles – evidently, once incomes are high enough, children's impact on household resources is not significant enough to affect vehicle purchase decisions.

The density of people in a household's neighbourhood has a negative association with the likelihood of buying a vehicle, as was expected. This strong relationship is, however, not necessarily an indication that land use by itself influences car ownership – the problem of self-selection bias described above prevents us from drawing any conclusions regarding causality. A look at population density figures for NMMA confirms that the highest density zones are found in lower income townships like Ibhayi and Motherwell. It is likely, therefore, that households who cannot afford to buy a vehicle locate in higher density residential areas for a host of reasons, including historical or community ties, housing affordability, and, perhaps, the nearby location of social and educational opportunities.

The accessibility index, as a measure of relative location on a metro-wide scale, is significant and positive. The more accessible a home is via the road network, the more likely the household is to own one or more vehicles. The implication is, once again, not necessarily one of causality. The result might as well be an outcome of historic settlement patterns typical to the South African city: higher income households have historically had the opportunity to locate in more central, more accessible places with good road networks, and are also more likely to afford and own more vehicles. It is important to note that there is at this stage no evidence that city-scale accessibility patterns influence vehicle ownership decisions – a more detailed investigation, controlling for socio-economic variables and preferably using time-series data, is needed to examine such a question.

Table 6 Estimation results: Tobit models of transport energy consumption

Variables	Household model		Individual model	
	Beta	T-value	Beta	T-value
Household characteristics				
No of workers	15.181	6.45**		
HH size	2.865	3.19**		
Expected vehicles owned[a]	104.54	20.83**	38.32	27.7**
Individual characteristics				
Gender (1 = male)			3.605	2.67**
Age			0.593	10.41**
Employed (1 = employed)			31.07	16.68**
Studying (1 = scholar/student)			–10.48	–4.17**
Zone characteristics				
Population density[b]	0.964	1.67	–0.066	–0.33
Job access index[c]				
Low-income HH[d]	–31.304	–0.55	97.68	4.53**
High-income HH[d]	–263.73	–4.06**	–0.186	–1.09
Constants	–34.971	–5.92**	–44.02	–12.80**
Number of observations	2 593		7 000	
Number (%) of zero observations	363 (14%)		2 380 (34%)	
Likelihood ratio test (full model)	Chi-squared = 1 201**		Chi-squared = 3 039**	

** = significant at 95%
Dependent variable = Megajoules of transport energy consumed per day (per individual/household)
Empty cells denote variable not used in model
a = Estimated as 0*P(0) + 1*P(1) + 2.3*P(2+), where the values of P(*n*), the probability of owning *n* vehicles (calculated from the MNL model estimated above), and the value 2.3 is the mean number of vehicles owned by all households in the sample who own two or more vehicles.
b = Population density of household zone (in 1 000 persons per square kilometre)
c = Accessibility index by road to job opportunities (see text for explanation)
d = Low-income households are below the median income of R2 500 per month; high-income is above

Household transport energy consumption

Table 6 presents the results of a Tobit model of transport energy consumption estimated at the household level, and using household characteristics and spatial properties of the household's home zone as independent variables. Household income is omitted from the model due to its high correlation with the expected vehicle ownership variable.

Parameter estimates are largely significant and of the expected sign, and the model performs well according to the likelihood ratio test. The positive signs of the household variables indicate that, all else being equal, households consume more transport energy if they have more workers or more people in the household overall. More workers mean more work trips – which we already showed tend to be energy intensive – while bigger households make more trips overall. Expected vehicle ownership dwarfs all other variables in the model (looking at the t-values), confirming that this is the single most important driver of household transport energy use (Goyns 2008).

The land use variables show interesting results. Population density of the home zone is insignificant: by itself it does not explain household transport energy consumption. Read in conjunction with the previous model's results, this implies that the density effect is indirect rather than direct: lower density is associated with higher car ownership, thus indirectly affecting travel patterns via mode use; but once the car is bought, lower population density is not associated with more trip-making. This is consistent with the findings of Mirrilees (1993) that factors such as the distribution and distances between different land uses, the location of services with respect to one another, and vehicle ownership play a larger role in transport energy demand than urban density.

The estimates for the job accessibility variables show that, indeed, a household's location relative to job (and by implication other opportunities in the surrounding metro area) does affect the amount of transport energy consumed, even after controlling for vehicle ownership. The effect differs, however, across households. In order to account for a potential accessibility/income relationship suggested by the MNL model, the accessibility index was interacted with a household income dummy which categorised the household as either below or above the median income level for the area. The parameter estimates show that a household's accessibility significantly affects transport energy consumption *only if the household is high-income*: richer households tend to consume less transport energy if they live in more accessible places. This suggests that, once a vehicle is available, households benefit from being located in more central, accessible places by gaining the ability to reduce their travel distances and, by extension, their transport energy consumption. Low-income households do not gain this benefit from being located in accessible places (as indicated by the non-significant parameter estimate). The reason is probably that low-income households are more likely to have low transport energy consumption levels anyway – being more likely to walk or use public transport – so that any additional gains in travel distances do not impact energy expenditures significantly.

Individual transport energy consumption

The results of the transport energy consumption model estimated at the individual level indicate similar findings (see Table 6). Once again, expected household car ownership is the strongest predictor of energy use. Personal characteristics also explain energy use: all else being equal, being male, being older, and being employed raises a person's energy expenditure, while being a student or scholar reduces energy use (relative to being unemployed). These findings are consistent with the results of the bivariate analyses presented earlier.

Population density is again non-significant. However, the interacted access index variable reverses its significance and sign: persons living in *low-income* households are now *more* likely to have higher energy expenditures, while no effect is found among high-income persons. What this might indicate is that accessibility is associated with increased travel activity among lower-income people, as one might expect if there was significant latent or suppressed demand for travel among low-income persons, which is released once travel becomes easier or less expensive due to improved accessibility. This interpretation matches the general finding regarding the differential benefits of accessibility suggested by the previous model: that accessibility plays a different role for different people, depending on their socio-economic status and the extent of mobility they already enjoy. Among high-income (car owning) people, higher levels of access are associated with travel activity *savings* and a *reduction* in energy use; among lower-income people, higher access is associated with *increased* motorised travel and *higher* energy expenditures.

CONCLUSIONS: IMPLICATIONS FOR URBAN MANAGEMENT

Methodologically the study demonstrated the feasibility of using travel survey data to establish disaggregate patterns of transport energy consumption at the individual, household or neighbourhood levels. This provides opportunities for using existing travel data sources for establishing baseline data to monitor impacts and changes over time. Marginal methodological improvements might come from improved data collection (especially the inclusion of vehicle size and fuel type data in questionnaires), and marrying travel route information with more accurate link-level speed information to improve the accuracy of vehicle energy consumption estimates.

Our results clearly showed how skewed energy expenditure is across the population. Car users, although they make only 25% of trips, contribute 70% of the passenger transport energy consumption in metropolitan Nelson Mandela Bay. The strong influence of car ownership and income level on energy consumption is a common finding globally. From the urban policy perspective this highlights the challenges inherent in addressing urban sustainability issues. If the objective were simply to reduce transport energy use, the largest pay-off would come from reducing private vehicle use through, for instance, the pricing of low-occupancy car travel. However, energy reduction goals are traded off against other policy objectives such as job creation. Workers spend three times more energy travelling daily than the unemployed; should residential and work locations remain fixed, employment gains will result in significant increases in South Africa's energy needs, unless a significant proportion of such travel can be shifted to non-motorised modes or to rail.

What might transport interventions do to energy consumption? Compared to the difference between cars and non-car modes, the difference in energy use between road-based public transport modes is relatively small. So is the average difference between peak and off-peak travel (although this difference might be larger in cities with higher congestion levels than NMMM). More specifically, on a per-passenger-kilometre basis, the energy consumption of minibus taxi trips is similar to that of bus trips, due to the high energy efficiency of small vehicles and the relatively low occupancy of metropolitan bus services. This suggests that – in energy terms – little can be gained from travel demand management (TDM) strategies such as peak spreading, or from public transport interventions such as bus rapid transit (BRT), unless they are coupled with appreciable increases in bus occupancy, introduction of more fuel efficient vehicles, significant speed gains by avoiding congestion, and a significant amount of switching from car (rather than taxi) to BRT. The predominant focus of first-generation BRT schemes on replacing minibus-taxi services is likely to do little for energy and environmental concerns unless they delay the car purchase decision among medium-income *future* car owners. This is a challenging proposition given the sensitivity of car ownership to income growth.

A significant element of the urban sustainability agenda is concerned with changing the density and form of land use in cities. Our findings suggest that such efforts will have a variety of impacts on travel behaviour, energy consumption and sustainability – and not all of it in a desirable direction. High neighbourhood densities are correlated with lower car ownership (and thus with reduced transport energy use), but the data does not allow us to establish causality – in other words to conclude that densification strategies would necessarily lead to better sustainability outcomes. Further research using time-series data (perhaps using repeated panel surveys) is needed to allow researchers to tease out the effects of density (and other land use factors) from other historic and taste-based variables.

Metropolitan-wide accessibility – the ease of reaching job (and other) opportunities within a reasonable travel time – does seem to affect travel behaviour and transport energy consumption. An important finding is that this relationship appears to depend on the socio-economic status of a household or individual. Among high-income households, better accessibility is associated with lower travel. It is likely that access-enhancing strategies, such as those promoting mixed-use developments in accessible, centrally located nodes, would reduce driving distances and the energy and environmental costs of travel. However, the same accessibility improvements could have the opposite effect on lower-income (non-driving) households, as the time or cost savings brought about by the access improvements could be converted into increased travel, releasing some of the pent-up demand for mobility. This is where coordination between land use and transport is key: attractive, upgraded public transport should then be available to capture this additional demand in energy-efficient ways. Otherwise, uncoordinated land use measures could have unintended consequences and contribute to deteriorating sustainability outcomes in our cities.

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