Associations Between Health and Active Transportation

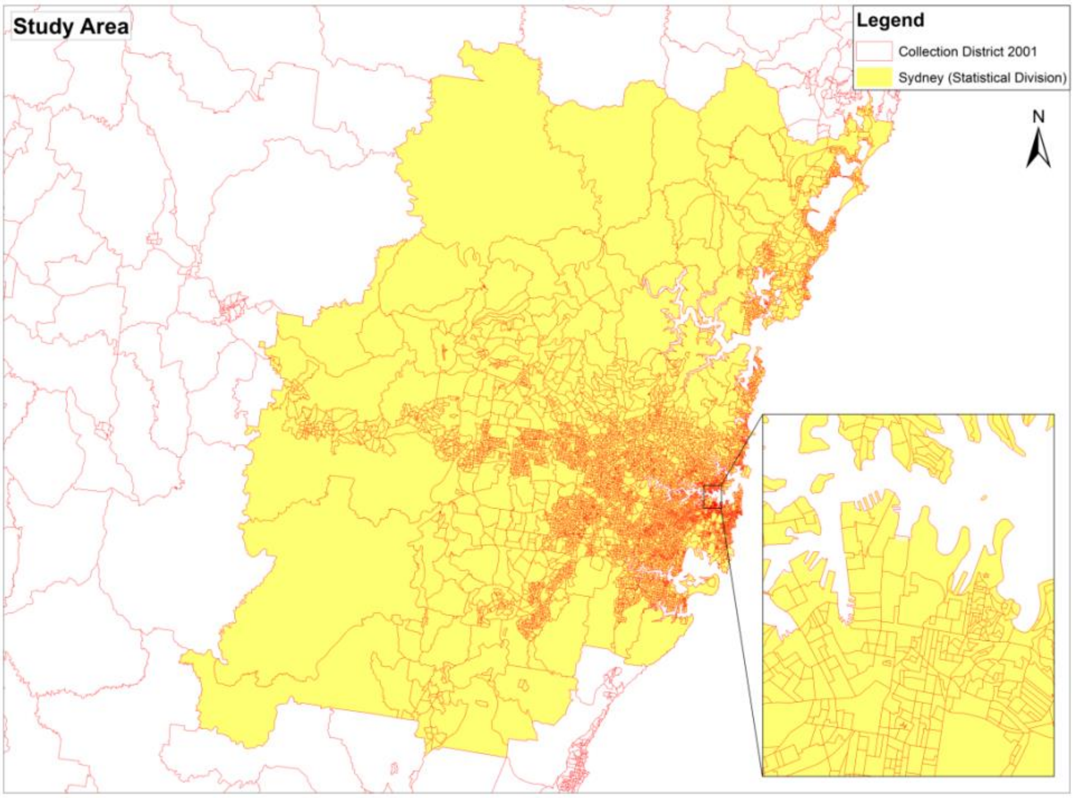
Nima Amini (n.amini@unsw.edu.au)

ABSTRACT:
The relationship between health and transportation variables are explored at collection district level. While this research is on-going, this paper presents the data gathered, the transportation variables developed and the initial results using a binary logit model. Significant correlation was found between walkable road density and body mass index.

INTRODUCTION:
Active transportation is defined as any form of human-powered transportation. Active transportation has a number of benefits including transportation , environmental, economical and health. Health benefits [1] include improved psychological factors, for example increasing community connectedness through increased social interactions. In addition, reduced use of motor vehicles will result in reduced exposure to particulate and noise pollution for drivers and people who spend time close to traffic corridors. Finally increased physical activity can result in reduction in obesity and chronic diseases. There is evidence to suggest that inactive lifestyle is becoming the main cause of increase in obesity [2]. The beneficial effects of physical activity on chronic diseases have also been documented [3]. The focus of this paper is on the health benefits of physical activity due to transportation.

Statistical models are used to assess the health of surveyed individuals in relation to the transport characteristics of the neighbourhood in which they reside. Figure 1 shows the neighbourhood areas selected at collection district (or SA1) level in the study area of the Sydney Statistical Division.

Figure 1: Study Area



TRANSPORT VARIABLES:

The main data sources used to develop the transport variables were:

- Australian Department of Agriculture:
  - Landuse (ALUM)
- Australian Bureau of Statistics:
  - Boundaries
  - Population
- NSW Department of Planning and Infrastructure:
  - Public transport stop locations
  - Land zoning
- Land and Property Information:
  - Cadastre
  - Road network
- Bureau of Transport Statistics:
  - HTS 2011
- Walkscore

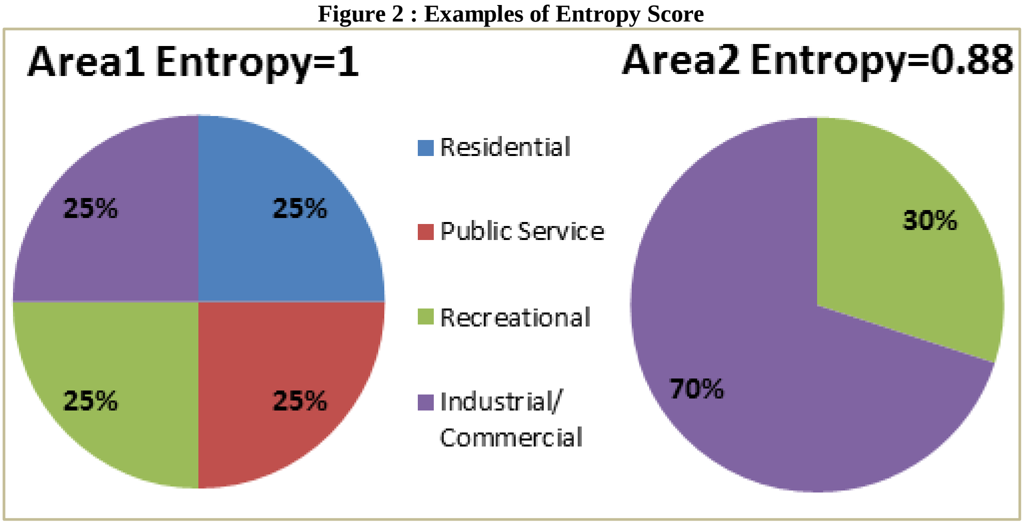
Transport variables are presented below in categories based on the type of transportation factor they represent. The variables were calculated for each collection district. Walkability:

Walkscore.com provides a score of walkability for a given address. The walkscore is based on how close an address is to amenities such as parks, schools, shops, etc, as well as other factors including population and intersection density[4].

Landuse Mix:

Landuse mix was measured using the entropy score. Entropy estimates landuse balance in an area [5, 6] and is affected by the proportions of different landuse types (Figure 2). The highest score of one can be obtained where all landuse types have the same proportions. The lowest score of zero is obtained where only one landuse type dominates an area. It is assumed that an area with good landuse mix (i.e. high entropy score) is conducive to active transport as trip distances are relatively short.

Figure 2 : Examples of Entropy Score



The formula for the entropy score is :

$$\text{Entropy} = -\frac{\sum_n [p_n \times ln(p_n)]}{ln(N)}$$

Where p_n is the proportion of the nth landuse type in the area of interest, and N is the total number of landuse types that exist.

Four landuse types were extracted from the Australian Land Use Management (ALUM) classification, namely: Residential, Commercial/Industrial, Public Service (e.g. office and education) and Recreational. The ALUM dataset did not distinguish between Commercial and Industrial landuse. The landuse areas are based on building foot prints (not Building Floor Area), thus multi-floor buildings are underrepresented and multi-purpose buildings are represented as one landuse. The ALUM dataset was the most suitable landuse data available in NSW for calculation of entropy. It provides an indication of landuse mix, particularly in areas with lower intensity of landuse.

The entropy formula does not consider generation/attraction factors between landuse types (For a more comprehensive list of the issues associated with entropy see Brown, B.B. [5]).For example area 2 (as shown in Figure 2) has a high entropy score=0.88. However, “Commercial/Industrial” and “Recreational” landuse types are both trip attractors and not conducive to walking.

Public Transport Accessibility:

Two variables were developed to show how accessible public transport stops were in each collection district. The first variable was the coverage of public transport stops using a buffer of 420metres around each public transport stop. The proportion of the collection district covered by public transport stops was recorded. The second variable was the density of public transport stops in each collection district.

Road Connectivity:

In order to calculate the walkable road density, Highways and Freeways were distinguished from the other road hierarchies. High speed multi-lane roadways are relatively less conducive to active transport and sometimes an obstacle.

Block length was calculated by dividing the length of walkable roads in each collection district by the corresponding number of intersections.

Active Transport Mode Share:

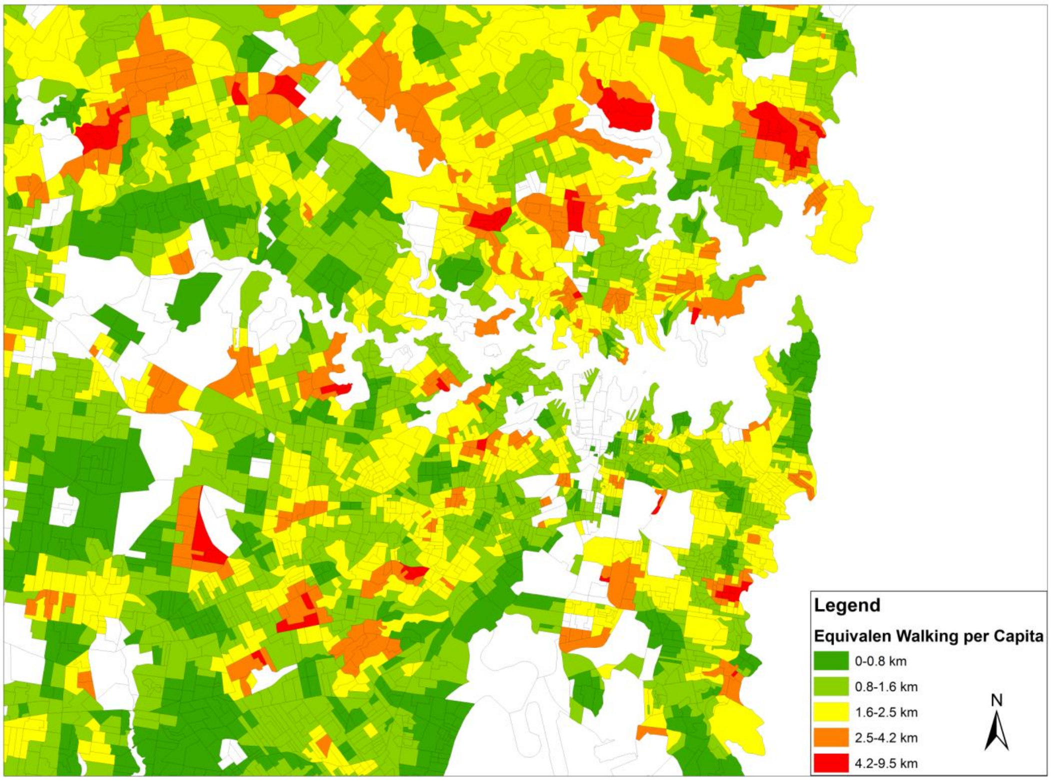
House Hold Travel Survey pooled from 5 waves (i.e. 07/08 to 11/12) were used to develop proxy variables for mode choice and amount of physical activity for transportation in each collection district.

It was found that including all trip origins from a travel zone resulted in large number of car trips in high density zones in areas such as Sydney CBD or Parramatta. This reflected trips coming to the area and not the travel behaviour of residents. It was decided to include trip from travel zones where the person is a resident of that travel zone.

To obtain the amount of physical activity for transportation the length of walk, cycle, and Public transport trips were converted to the equivalent distance walked by each person. The equivalent distance walked for public transport trips was 573metres for each trip[7]. The conversion of cycle distance to equivalent walking distance was obtained by dividing cycle trips by three [8].

Figure 3 shows the relative amount of physical activity for transportation at collection district level. There are hot spots as well as cold spots within the Inner Sydney Area, it will be interesting to examine why these discrepancies exist.

Figure 3: Physical Activity for Transport per Capita (Proxy)



STATISTICAL MODELLING:

Linear regression, binary and ordinal logit models were examined to explain the relationship between health and transport variables. This paper includes the preliminary results from the binary logit model.

A number of health variables were considered as the dependent variable including Self-assessed heath, SF-36 for general health and Body Mass Index(BMI). Table 1 shows the Pearson Correlation between the health variables and transport variables. BMI had the greatest number of variables significant at 0.01 level and the strongest correlation with all transport variables. BMI was selected as the dependant variable.

Table 1: Pearson Correlation of Health and Transport Variables

	Entropy	Walk score	PT Stop Cover	PT Stop Density	Road Density	Highway Density	Block Size	Vehicle (%)	PT(%)	Walk (%)	Bicycle (%)	Equivalent Walk (km)
Body Mass Index	-.045	-.099	-.033	-.045	-.098	-.029	.018	.093	-.103	-.059	-.039	-.058
Self-assessed health	-.016	-.065	-.008	-.035	-.048	-.039	.032	.040	.001	-.049	-.006	-.040
SF-36 general health	-.004	.056	.018	.035	.043	.024	-.028	-.013	.001	.018	-.016	.022

Significant at: 1%, 5% not significant.

For this model the BMI was converted to a binary variable by assigning a score of one for BMI ≥ 25 (i.e. overweight or obese), and a score of zero for other BMIs. A number of covariates were examined including those used in similar research area [5, 6, 9, 10] . Covariates such as household income and level of education were not found significant in the binary logit model and as such excluded. Table 2 shows the descriptive statistics of the variables used in the model.

Table 2: Logit Model Predicting Probability of Being Overweight or Obese[1]

	N	Minimum	Maximum	Mean	Std. Deviation
BMI ≥ 25	*1927*	*0*	*1*	*.5366*	*.49879*
Walkable Road Density	*1927*	*.00372*	*2.51175*	*.3290867*	*.23033735*
Age	*1927*	*15*	*75*	*43.19*	*16.596*
Long Term Health Issue	*1927*	*0*	*1*	*.2231*	*.41646*
Gender (Female=1)	*1927*	*0*	*1*	*.5309*	*.49918*
Born in NE Asia	*1927*	*0*	*1*	*.0426*	*.20190*
Has Children	*1927*	*0*	*1*	*.6108*	*.48770*
Relationship Status[2]	*1927*	*0*	*1*	*.5916*	*.49167*

[1] Data filtered by: Number of years at current address ≥ 1
[2] Relationship Status = 1 if married or living with someone in a relationship

INITIAL RESULTS:

Table 3 illustrates the results from a binary logit model predicting the probability of being overweight or obese. The only transport variable used in this model is walkable road density which is negatively correlated. i.e. assuming all the variables are kept constant, an increase in walkable road density is associated with reduction of likelihood of being overweight or obese.

Table 3: Logit Model Predicting Probability of Being Overweight or Obese[1]

	B	S.E.	Wald	df	Sig.	Exp(B)
Walkable Road Density	*-.675*	*.208*	*10.561*	*1*	*.001*	*.509*
Age	.010	.003	9.926	1	.002	1.010
Number of Children	.131	.040	10.934	1	.001	1.140
Relationship Status[2]	.264	.099	7.079	1	.008	1.302
Gender	-.537	.094	32.928	1	.000	.585
Long Term Health Issue	-.356	.115	9.518	1	.002	.701
Born in NE Asia	-1.296	.272	22.694	1	.000	.274
Constant	1.064	.314	11.448	1	.001	2.897

[1] Data filtered by: Number of years at current address ≥ 1
[2] Relationship Status = 1 if married or living with someone in a relationship
Omnibus Tests of Model Coefficients significant to 0.01
Nagelkerke R Square = 0.138

FUTURE DIRECTIONS:

This paper presents the initial results of this study which is in progress. The next steps are to explore other modelling techniques and possibly other variables using the rich set of datasets gathered to date.

Other possible future directions include examining respiratory or psychological relationships with transportation. Inclusion of diet as a covariate may also be examined.

REFERENCES:

1. PHAA, *Policy At a Glance – Low Emissions & Active Transport Policy*. 2011, PHAA's Environmental Health Special Interest Group.
2. Prentice, A.M. and S.A. Jebb, *Obesity in Britain: gluttony or sloth?* BMJ British medical journal., 1995.
3. PAGAC, *Physical Activity Guidlines Advisory Committee Report 2008*. 2008.
4. Walkscore. *Walk Score Methodology*. [cited 2014 February]; Available from: http://www.walkscore.com/methodology.shtml.
5. Brown, B.B., et al., *Mixed land use and walkability: Variations in land use measures and relationships with BMI, overweight, and obesity.* Health & Place, 2009. **15**(4): p. 1130-1141.
6. Kockelman, K., *Travel Behavior as Function of Accessibility, Land Use Mixing, and Land Use Balance: Evidence from San Francisco Bay Area.* Transportation Research Record: Journal of the Transportation Research Board, 1997. **1607**(-1): p. 116-125.
7. Daniels, R., *Explaining walking distance to public transport: the dominance of public transport supply.* 2011.
8. DGAC, *The Report of the Dietary Guidelines Advisory Committee on Dietary Guidelines for Americans*. 2005, Dietary Guidelines Advisory Committee.
9. Frank, L.D., et al., *Many Pathways from Land Use to Health: Associations between Neighborhood Walkability and Active Transportation, Body Mass Index, and Air Quality.* Journal of the American Planning Association, 2006. **72**(1): p. 75-87.
10. Samimi, A., A. Mohammadian, and S. Madanizadeh, *Effects of transportation and built environment on general health and obesity.* Transportation Research Part D: Transport and Environment, 2009. **14**(1): p. 67-71.