Modelling the Impacts of Land Use on Transit Utilization in the Central Okanagan

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Abstract

Transit and land use have an intertwined relationship that has been researched for many years; however, this relationship remains abstract and hard to capture. Transit-land use relationship is often described as a chicken-and-egg problem of a two-way nature. By providing suitable access (egress) to (from) transit, land use affects transit utilization and condition transit demand. On the other hand, by ensuring mobility between trip origins and destinations, transit affects land use and condition the spatial distribution of activities and urban development. Much of the complexity in transit-land use interactions can be attributed to passengers' perceptions of various level-of-service and land use factors. It is therefore important to understand such underlying aspects in order to manage the interrelationship between transit and land use. This study explores the relationship between various land use factors and transit mode choice/ridership in the Central Okanagan using two approaches, namely, mode choice and direct ridership modelling. The first method utilizes a trip diary survey and discrete choice modelling to analyze mode choices based on the location of activities and land use patterns. The second method uses a direct ridership model approach that uses spatial analysis and correlations between transit ridership, stop locations and surrounding quantified land uses. As an input for both methods, land use is quantified and defined as number of jobs, school enrolment, and population at a fine-scale (lot level).

Introduction

In 2013, public transit accounted for 4.8% of all trips in Kelowna, BC. Although it is still a small share, 4.8% represents more than double Kelowna's transit modal share in 2007. In Kelowna, transit is looked at as a means of travel that can help alleviate traffic congestion and reduce greenhouse gas emissions. As such, the City of Kelowna has committed millions of dollars for improving transit infrastructure and amenities. Nevertheless, to prioritize and best allocate future transit investments, it is imperative to study the factors that influence transit utilization.

Research has shown a strong association between transit mode choice/ridership and land use (Kemp et al. 1997; Polzin 1999; Guiliano 2004). In spite of the clear recognition of the effect of various land use factors on transit mode choice and ridership, this relationship remains abstract and hard to capture.

In general, there are two approaches to capture the effect of land use on transit utilization. The first is to develop mode choice models to predict travellers' choices at the personal level. The second is to develop designated transit ridership models to forecast boardings and alightings at the stop level. Mode choice modelling has received a lot of attention in the field of transportation planning given its ability to predict individuals' choices in response to policy changes (Bhat 1998; Anggraini et al. 2012). By aggregating individuals' choices, transit modal share can be collectively estimated at the city or the regional level. While useful in estimating aggregate transit modal share, there are several factors that make it difficult for mode choice models to obtain reliable transit ridership forecasts. For example, traditional mode choice models do not adequately account for important land use factors that affect transit ridership. Further, in cases where land use information is incorporated into mode choice models, such data is usually collected at the Traffic Analysis Zones (TAZs) level which implies that the characteristics of land use are uniform within the same TAZ. This unrealistic assumption leads to mode choice models being inaccurate in estimating transit ridership at the stop level (Zhao et al. 2002; Taylor and Fink 2003). Moreover, because of lack of appropriate behavioural data, mode choice models are unlikely developed for small cities and rural communities dominated by the automobile as a mode of travel. Alternatively, direct ridership models are useful for identifying key land use factors for transit utilization and ridership estimation at the stop level. Ridership models are typically based on linear regression. As such, they are much simpler to develop and do not require a large amount of data collection (Horowitz 1984; Boyle 2006; Cardozo et al. 2012). However, it could be argued that the relationship between transit ridership and land is not linear.

Earlier studies have looked at mode choice and transit ridership separately using mode choice and direct ridership models, respectively. It is clear that both approaches have potential for error; however, combining them might provide more insights into the role of various land use variables in altering transit utilization. Unlike previous studies, this paper explores the relationships between land use factors (quantified as the density of population, employment, and enrolment) and transit utilization in the City of Kelowna, using a twofold approach. First, using the discrete choice modelling approach, the influence of land use on human decision-making is investigated at the personal level. Second, a direct ridership model is developed using linear regression. Comparing results from both approaches allowed for a better understanding of the trade-offs and synergies between land use factors and transit utilization, and among the land use factors themselves. As an input for both methods, land use is defined in terms of population, number of jobs, and school enrolment quantified at a fine-scale (lot level).

Literature Review

Over the years, the concept of travel as a "derived demand" has been accepted as a fundamental tenet of transportation research. This means that travel is a burden undertaken by travellers to engage in activities that require physical presence in space and time, not for the sake of travel per se (Meyer and Miller 2001). As such, transportation demand models assume that travel-related choice processes (e.g. destination choice, mode choice, route choice, etc.) involve an associated utility (disutility) to be maximized (minimized) by travellers (McFadden 2000; Mokhtarian and Salomon 2001). As generally defined, utility is a measure that reflects one's satisfaction from undertaking a particular trip between an origin and a destination using a certain mode on a particular route. Extensive academic literature has looked at the intricacies of travel-related choices and suggested many ways to define and measure travellers' utilities (Ben-Akiva and Lerman 1985; Ben-Akiva and Bierlaire 1999; Ortuzar and Willumsen 2011).

Continuously, individuals make decisions, some of which may be considered once in a lifetime and others of which are being made on daily basis. For example, one may make decisions about where to live and work (or go to school), where to pursue various activities (e.g. shopping, social, recreational, errands, etc.), and which mode and route to take for travel. The decision-making process underlying mode choice decisions is complex and depends on many different factors. Such factors encompass characteristics of the travellers (who make choices), the land use system (where activities are located and organized), and the transportation system including different modes of travel (through which activities are linked). According to (Kemp et al. 1997), the mode choice process is best described as a hierarchy of interrelated choices that progress from macro lifestyle choices (e.g. home location ,work location, vehicle ownership, etc.) to micro mode choices (e.g. car, transit, cycle, walk, etc.) for specific trip purposes (e.g. work, non-work, etc.). This implies that the micro mode choice decisions of individuals, which collectively determine transit modal share, are the result of a broad range of long- and short-term hierarchical choices.

At the "macro" end of the spectrum, various land use factors work to influence transit mode choice decisions. Research has shown that population and employment densities are the most important land-use predictors of transit mode choice (Kockelman 1995; Cervero 2004). This finding is further supported by (Chatman 2008) who found an inverse relation between automobile use and activity density defined as the number of local desirable non-work activity locations. In addition to density, having a rich mix of activities (also known as diversity) is key to transit mode choice decisions (Dittmar and Poticha 2004). People can complete a number of activities in one transit trip (i.e. trip chaining) if different activities are located within walking distances at destination. Therefore, the pattern and location of activities, and the distance between them, are important considerations for transit mode choice.

Direct ridership models differ from mode choice models in that they only consider the aggregate demand at a node on the transit network rather than the attributes of individual trips. For the purpose of forecasting ridership, direct ridership models offer much greater spatial resolution than a traditional mode choice model. In addition, given that they are based on linear regression, they are much easier to implement than microsimulation. While these simple models cannot replace more sophisticated approaches, they can still be useful for ‘sketch planning’ or the preliminary assessment of alternatives (Upchurch and Kuby 2014). Table 1 shows results from a sample of studies using linear regression for direct ridership forecasting indicating the number of independent variables used and the overall goodness of fit.

Table 1. Results from Studies Using Linear Regression

Region	Independent Variables	R-Squared
Jacksonville (Chu)	15	0.54
San Diego (Ryan & Frank)	7	0.33
Oregon (Schlossberg et al.)*	19	0.53

*Schlossberg et al. estimated three separate models. The one presented in this table is for Medford, OR, and was chosen because of its similarity to Kelowna.

The independent variables commonly used for direct ridership models in the literature can be divided into three categories: attributes of the stop and its position within the network, the built environment surrounding the stop, and the demographics of nearby residents. The level of transit service is often captured by the number of buses per day, average headway, amenities at the stop (such as a shelter or park and ride spots), number of connecting routes (termini and transfer points tend to have higher ridership), or the percentage of regional employment accessible within a given time (Schlossberg et al. 2013). Built form is operationalized through measures of density, diversity, and design: from more macroscale counts of population and employment (Cervero et al. 2010) to microscale features of the pedestrian environment (Chu 2004; Ryan and Frank 2009). Common demographic variables include age, income, vehicle ownership, and ethnicity (Pulugurtha and Agurla 2012).

One of the main challenges for direct ridership models is how the connection between transit service and demand is treated. On one hand, more frequent service may generate higher rates of ridership irrespective of nearby land use; on the other, areas with transit supportive land uses tend to have more service during off-peak hours, which might drive the daily per trip average down. Since transit agencies take demand into consideration when determining the transit supply, including transit service variables in a regression model could lead to biased estimates of their impact on ridership (Kerkman et al. 2015). Conversely, excluding transit service could exaggerate the effects on the built environment on bus patronage. This paper indirectly considers transit service by normalizing the dependent variable (daily boardings and alightings) by the number of buses serving the stop per day.

Table 2. Common Variables in Direct Bus Ridership Models in North America

Region	Dependent Variable	Built Environment	Transit Service	Demographics
Jacksonville (Chu)	Boardings	Count of population Count of employment Pedestrian factor	Transit level of service	Age Income Ethnicity Gender Vehicle Ownership
San Diego (Ryan & Frank)	Boardings + Alightings (log)	Walkability index	Average waiting time	Age Income Ethnicity Vehicle Ownership
Los Angeles (Cervero et al.)	Boardings on BRT	Population density Employment density	Daily buses Number of feeder buses	NA
Charlotte (Pulugurtha & Agurla)	Boardings	Area residential Area commercial Speed limit Presence of median	NA	Income Ethnicity Vehicle Ownership
Oregon (Schlossberg et al.)	Boardings + Alightings (log)	Land use mix Distance to CBD	Job accessibility Average headway	Age Income Education Ethnicity Vehicle Ownership

Final model variables for stop level ridership in North America. Adapted from Kerkman et al. (2015).

Datasets and Preliminary Analysis

The City of Kelowna is selected as a case study for this investigation. Kelowna is the largest city in British Columbia's Okanagan Valley and is home to 123,500 people (City_of_Kelowna 2015). Various sources of data were used in this study. Transit ridership data for September 2014 was obtained from BC Transit, based on Automatic Passenger Counters (APC) for conventional routes and manual counts for community shuttles. A log transformation is applied to correct for the highly skewed distribution of ridership per trip. Information on mode choice, trip length, duration, purpose, etc. was obtained from the 2013 Okanagan Travel Survey, the most recent household-based trip diary survey that was conducted in fall 2013 and covered a sample of residents of the Central Okanagan and the City of Vernon. Land use data was quantified at the parcel level by combining information from census, BC Assessment, Canada Business Points, and enrolment counts from Central Okanagan School District (SD23) among other sources. The resulting estimates of population, employment, and enrolment at each parcel were used to generate the 'activity surface' for the study area. Roadway intersection density was also calculated to provide an additional measure of urban form.

A fine-scale lot level land use data was produced by dividing the study area into a 50×50 m grid. Raster models were built for density of population, employment, and enrolment using the Kernel

Density Function in ArcGIS 10. The area of Lake Okanagan was excluded in density calculations to prevent distorted results near shorelines. Furthermore, the value for activity at each cell in the grid was estimated by combining density of population, employment, and enrolment within a 400 metre radius in order to approximate the walkshed or service area of a bus stop. To move from the raster representation (continuous surface) to the vector one (discrete bus stops), each point was given the activity values of the grid cell they fell within, as shown in Figure 1.

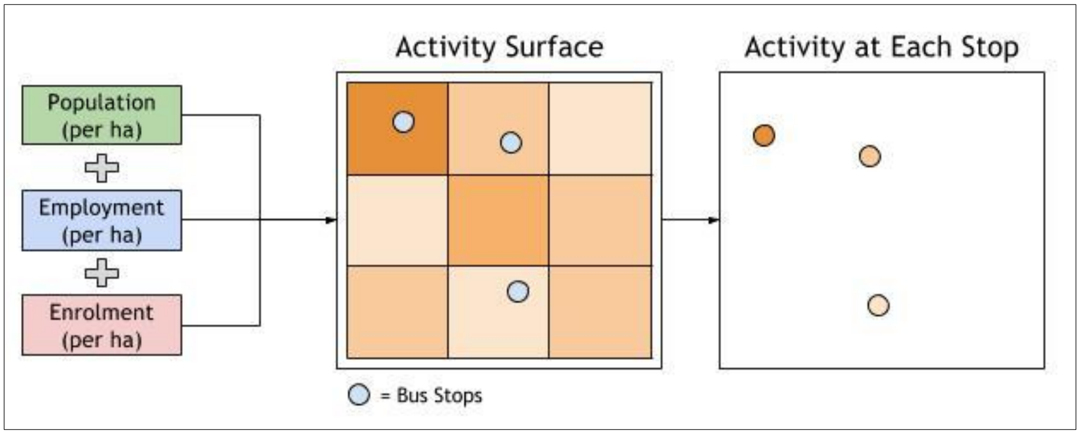

Figure 1. Overview of Method

The final activity surface for the City of Kelowna, showing the density of population, employment, and enrolment per hectare is shown in **Error! Reference source not found.**. A general 'hourglass' pattern can be seen with concentrations of activity along the Highway 97 corridor. The cluster of activity in the top right represents the UBC Okanagan campus. The resulting dataset was then used for all subsequent models (i.e. mode choice and ridership models).

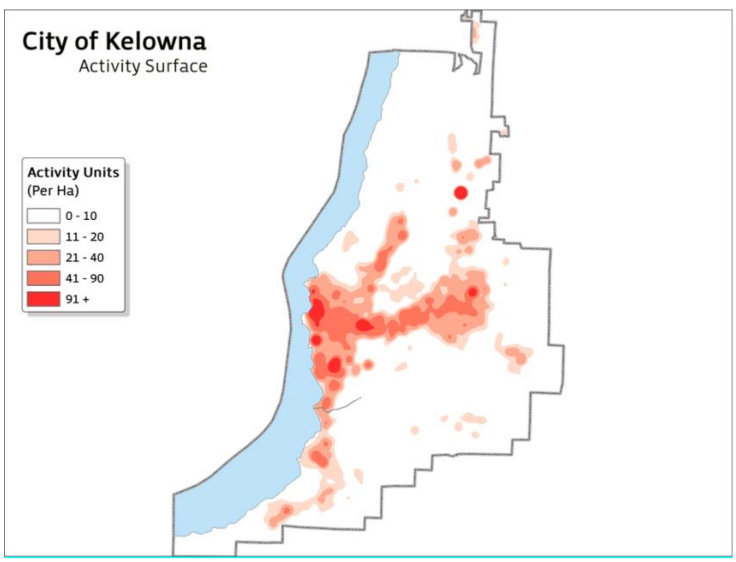

Figure 2. Density of activity (sum of population, employment, and enrolment) per hectare in the City of Kelowna

To check for multicollinearity between the independent variables, the relationships between the different components of activity (i.e. population, employment, and enrolment) were assessed. As shown in **Error! Reference source not found.**, none of individual components of activity are significantly correlated with each other. This reflects a general lack of land use mix at a pedestrian scale in the Central Okanagan.

Table 3. Correlations between Components of Activity

	Dwellings	Population	Employment	Enrolment
Dwellings				
Population	**0.95**			
Employment	-0.01	-0.16		
Enrolment	0.00	-0.02	0.01	

n=578, bolded values are significant below p>0.05

Next, correlations between the boardings and alightings per trip for each bus stop and the different components of activity were explored. The initial results are presented in **Error! Reference source not found.** below. There are significant positive correlations between the employment density, enrolment, and ridership; however, there is a slightly negative, though insignificant, relationship between population density and ridership. This counterintuitive result runs contrary to much of the established literature, but may be explained by the low variation in population density throughout the region. Half of the bus stop walksheds in the City fall within the range of 4 to 10 dwellings per hectare. If the individual bus network tiers (i.e. frequent versus local routes) are considered separately, there is a small positive correlation for dwelling density and boardings on the local transit network. Also absent is the relationship between intersection density and ridership which was found by (Ryan and Frank 2009).

Table 4. Correlations between Walkshed Activity and Ridership

	Dwellings	Population	Employment	Enrolment	Activity	Intersections
Boardings	**0.08**	-0.02	**0.44**	**0.31**	**0.51**	-0.04
Alightings	0.00	-0.10	**0.40**	**0.25**	**0.42**	-0.11
Total	**0.10**	-0.01	**0.48**	**0.29**	**0.54**	-0.03

n=474, bolded values are significant below p>0.05

One potential explanation for the null relationship between population density and ridership could be the overwhelming influence of stops at UBC Okanagan and Queensway Exchanges. Both are in the bottom quartile of nearby population density: yet they account for nearly a third of daily boardings and alightings. Table 5 shows the correlation results after excluding these outliers. Dwelling density becomes weakly correlated with ridership, and population is weakly correlated with boardings (p= 0.1). This discrepancy, particularly given the strong relationship between dwelling and population density (r= 0.95) shown in Table 3, suggests that dwelling density is a more reliable indicator of transit supportive land uses than population density in Kelowna, which is plausible given the wide range of household sizes among neighbourhoods of detached housing the city.

Table 5. Correlations between Activity and Ridership (Excluding UBCO and Queensway)

	Dwellings	Population	Employment	Enrolment	Activity	Intersections
Boardings	**0.15**	0.06	**0.35**	**0.18**	**0.37**	-0.07
Alightings	0.06	-0.04	**0.32**	**0.13**	**0.28**	-0.13
Total	**0.18**	0.07	**0.41**	**0.16**	**0.41**	-0.05

n=462, bolded values are significant below p>0.05

To test whether the relationship between nearly population and ridership is stronger at higher densities, the process was repeated for bus stops above the median for population density (17 persons per hectare). Similar results are observed: population density failed to reach significance at the 90% confidence level.

Mode Choice and Ridership Modelling

A sample of 12,052 all-purpose trips (representing a total of 368,081 trips) having both their origin and destination in Kelowna were extracted from the 2013 Okanagan Travel Survey. To investigate the effect of various land use factors on travellers' perception and transit mode choice behaviour at the personal level, two mode choice models were developed, as shown in Table 6.

Model 1 accounts for the individual effect of population, employment, and enrolment densities (as indicators for the pattern and location of activities) on transit mode choice. In addition, the model is sensitive to the travel time and distance between activity locations. It seems that, the most important land use predictor of transit mode choice is enrolment density at both trip ends given its high magnitude and statistical significance. This might be related to the high percentage of students using public transit in Kelowna. The model also shows that population density at trip origin positively affect transit mode choice, and is more important than population density at trip destination. This can be observed from the positive parameter estimate associated with population density at origin, being lower in magnitude at trip destination. Ensuring higher population densities at trip origins increases transit mode choice and reduces automobile use. Interestingly, the model shows that employment density is of no importance to transit mode choice at both trip origin and destination given its low parameter value and being statistically insignificant.

Model 2 accounts for the combined effect of the above mentioned variables (i.e. diversity or mixed land use) on transit mode choice. The model is also sensitive to the travel time and distance between activity locations. The model indicates that land use diversity is equally important for transit mode choice at both trip ends. In other words, transit mode choice is expected to increase on the expense of car use if a good mix of activities is concentrated around transit stops at both trip origins and destinations.

Table 6. Individual and Combined effect of
Population, Employment, and Enrolment Densities on Mode Choice

		Model 1		Model 2	
Number of observations		11,837		11,837	
Null Log-Likelihood		-13,004.274		-13,004.274	
Final Log-Likelihood		-5,097.123		-5,180.927	
Rho-Square		0.608		0.602	
Variable	Mode	Coefficient	t-stat	Coefficient	t-stat
Alternative Specific Constant	Auto Driver and Passenger	Fixed	---	Fixed	---
	Public Transit	-4.010	-23.45	-4.740	-36.05
	Cycle and Walk	-0.68	-7.62	-0.65	-8.76
Population per Hectare at Origin	Auto Driver and Passenger				
	Public Transit	0.010	3.44		
	Cycle and Walk	0.006	2.95		
Population per Hectare at Destination	Auto Driver and Passenger				
	Public Transit	0.006	2.15		
	Cycle and Walk	0.006	3.17		
Employment per Hectare at Origin	Auto Driver and Passenger				
	Public Transit	0.002	1.25		
	Cycle and Walk	0.003	3.81		
Employment per Hectare at Destination	Auto Driver and Passenger				
	Public Transit	0.0003	0.25		
	Cycle and Walk	0.004	5.31		
Enrolment per Hectare at Origin	Auto Driver and Passenger				
	Public Transit	0.013	17.90		
	Cycle and Walk	0.006	5.17		
Enrolment per Hectare at Destination	Auto Driver and Passenger				
	Public Transit	0.013	17.66		
	Cycle and Walk	0.005	4.24		
Activity per Hectare at Origin	Auto Driver and Passenger				
	Public Transit			0.009	15.22
	Cycle and Walk			0.004	6.24
Activity per Hectare at Destination	Auto Driver and Passenger				
	Public Transit			0.009	14.73
	Cycle and Walk			0.004	7.06
Travel Time	Auto Driver and Passenger	-0.141	-9.1	-0.157	-10.6
	Public Transit	-0.0352	-8.23	-0.0296	-7.1
Travel Distance	Cycle and Walk	-0.864	-27.6	-0.883	-28.9

To investigate the effect of land use factors on transit ridership, direct ridership forecasting models were developed using linear regression. The models utilized stop level ridership data and nearby land use information. Boardings and alightings were investigated separately using a series of regression models to capture the effect of land use on transit ridership at trip origins and destinations explicitly. In each investigation, the first three models (Models 1a, 1b, and 1c) were a stepwise process where the components of activity were added sequentially to test their individual significance. The second direct ridership model (Model 2) included only the sum of activity per hectare for comparison. It appears that keeping the different components of activity separate leads to a significantly more predictive model than summing them into a single measure.

As seen in Table 7 and Table 8, population per hectare has a null relationship with ridership, though the addition of employment and enrolment density significantly improved the explanatory power of the model. The models also show that employment density at both trip ends is the strongest land use predictor of transit ridership given its high magnitude and statistical significance. The previous findings appear to contradict the mode choice model where population density was a strong predictor of mode choice and density of employment was insignificant at both origin and destination. Given that mode choice models are more related to passengers' behaviour, a possible explanation for this disagreement between the two models could be attributed to passengers' perception of the qualities that entail population density (not population density per se). Research has shown that population density is not just related to population per unit area, but rather it is a comprehensive definition that reflects the versatile integration of urban structure and efficient use of the potential of a city (Khodabakhshi 2011). These qualities might be missing or even different in employment density. For example, one could argue that travellers associate high employment density with poor neighbourhood design and less social aspects compared to high population density (i.e. surrounded by offices *vs.* surrounded by people). Further investigation is required to determine whether this is an artefact of the model specification or possibly due to the urban form of Kelowna where many centres of employment lack a supportive pedestrian environment.

Table 7: Results of Linear Regression (Log of Boardings Per Trip)

	Model 1a		Model 1b		Model 1c		Model 2	
Variable	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Constant	-1.1787	**(14.21)**	-1.6026	**(19.04)**	-1.6836	**(21.06)**	-1.8419	**(28.25)**
Population per Ha	-0.0014	(0.44)	0.0037	(1.25)	0.0041	(1.45)*		
Emp. per Ha			0.0168	**(10.77)**	0.0167	**(11.37)**		
Enrolment per Ha					0.0132	**(7.80)**		
Activity per Ha							0.0140	**(12.89)**
F-Value			**116.01**		**60.78**			
F-Value (2)					**19.40**			
R-Squared	0.0004		0.198		0.290		0.260	

n=474, bolded values are significant below p>0.05. *Value is approaching significance at p=0.15 (2) in comparison to Model 2

Table 8: Results of Linear Regression (Log of Alightings Per Trip)

Variable	Model 1a Coefficient	Model 1a t-stat	Model 1b Coefficient	Model 1b t-stat	Model 1c Coefficient	Model 1c t-stat	Model 2 Coefficient	Model 2 t-stat
Constant	-0.9097	**(11.18)**	-1.2771	**(15.07)**	-1.3429	**(16.31)**	-1.5607	**(22.98)**
Population per Ha	-0.0069	**(2.16)**	-0.0024	(0.81)	-0.0021	(0.75)		
Emp. per Ha			0.0146	**(9.27)**	0.0145	**(9.58)**		
Enrolment per Ha					0.0107	**(6.15)**		
Activity per Ha							0.0113	**(9.97)**
F-Value			**85.92**		**37.87**			
F-Value (2)					**30.94**			
R-Squared	0.0098		0.163		0.225		0.174	

n=474, bolded values are significant below p>0.05. (2) in comparison to Model 2

Although the current direct ridership models fail to explain as much of the variation in stop level ridership as previous studies, this is to be expected given their simplicity. Unlike the models shown in Table , demographic or transit service variables are not included as independent variables. (Schlossberg et al. 2013) reported that land use explained 17% of the variance in their sample of ridership, which is comparable to the results shown here. The weak relationship between ridership and population density, together with the strong correlation with employment density highlights the need to consider the characteristics of destinations in addition to residences in transit planning.

Though this analysis represents a good initial step towards a direct ridership model, there remains significant room for improvement. More nuanced measures of proximity should be considered, either through altering the parameters of the kernel density function or utilizing spatially weighted regression as in (Pulugurtha and Agurla 2012). Though demographic variables were purposely excluded in this version, their inclusion in future iterations could greatly increase the predictive power of the model. Finally, though this model attempts to reduce the endogeneity problem between transit supply and potential demand by normalizing the number of boardings and alightings per trip, this may have led to biased parameter estimates if the relationship between potential demand and service level varies significantly across the city. A more sophisticated approach might incorporate interactive terms (Cervero et al. 2010) or the two-stage method outlined in (Kerkman et al. 2015).

Conclusions

This paper explored the effect of density and diversity indicators on transit utilization using two approaches, namely, mode choice and direct ridership modelling. The developed mode choice models investigated the effect of density of population, employment, and enrolment on decision-making in terms of mode choice. The direct ridership models considered the same indicators at the bus stop level to estimate transit ridership. Both approaches gave interesting insights into the relationship between land use and transit utilization.

The mode choice models highlighted the importance of population density at transit trip origins, being of lower importance at trip destinations. In addition, the results showed that minimizing travel time/distance between activity locations increases transit modal share on the expense of auto use. Though the mode choice models found no significant relationship with employment at the trip origin or destination, further investigation is required to determine whether this is a result of the employment distribution in Kelowna. Interestingly, the direct ridership models showed different results as they emphasized the role of employment density. Both approaches showed a highly significant relationship between enrolment density and transit utilization which is to be expected given the demographics of current transit users in the city. The results of both methods suggest that keeping the components of activity separate, rather than summing into an aggregate measure leads to significantly more explanatory models.

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