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Estimating Incoming cross-border Trips through Land use data resources - A case of Karachi City

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Abstract

A multitude of studies have been motivated on the association between land use, urban settings and transport infrastructure to assist policy makers in sustainable planning. Alike, incorporation of cross-border trips have been an integral part of transportation demand models through external surveys. The present study seeks to explore the Incoming Cross Border Traffic (ICBT) into a study area based on the characteristics of a study area that attracts cross-border trips from outside region. This paper presents an analysis of cross-border trips in Karachi Metropolis, largest city of Pakistan, through Household Individual Survey (HIS-2010) and land use data from alternative resources. Results reveal that land use particulars, socioeconomic characteristics and travel attributes of individuals significantly influences cross-border trips and this effect varies spatially. Work, shopping and Education trips are discussed through separate models in this paper with a number of practical insights to policy makers for sustainable development of city. This study contribute in elucidating travel behaviour through land use parameters and also persuade professionals to integrate estimation of cross-border trips by socioeconomic parameters, in transport forecasting models.

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Keywords: Cross-border trips; study area; land use parameters; travel demand models; Open source data, Geographically Weighted Regression (GWR)

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1. Introduction

Travel demand forecasting models are generally built on household travel survey (HTS) data which is largely collected within a study area (for details see[1,2]). Household travel surveys are focal point of research, to measure and understand individual travel behavior and major trends changes in society[3]. HTS contains precise household information, personal and activity-travel details for individuals living in a study area. Since they enclose information on trips undertaken by residents only, secondary surveys are often conducted to estimate Cross Border Trips. A typical study area may attract none or some amount of cross-border travel depending on the size and attractiveness of the study area defined[4].

Transportation planning in small areas have gradually gained some attention of policy makers and transport planners as a high fraction of population (40 – 70%) lives in small counties[5]. Similarly, cross-border trips have long been part of transportation planning models however, only in the last decade econometrics and employment data have been used to forecast cross-border trips.

To date, up to the best of our knowledge, relatively little work has been done in applying open source data to estimate cross-border trips. This research aims to use crowdsourcing data from Open Street Map (OSM) and Google services.

This paper is structured as follows. We discuss literature review in section 2. We describe data sources and study area in section 3. Methodology is discussed in section 4. We explain the model results and discussion in section 5. Finally conclusion is in section 6.

2. Literature Review

2.1. Land use and transport interaction

A multitude of studies have been motivated on the association between land use, urban settings and transport infrastructure to assist policy makers in sustainable planning. Travel behaviour largely depends on land use patterns and its accessibility[6]. Numerous studies have associated an increase in the urban density with reduction in Vehicle Miles Travelled (VMT) and emissions[7,8]. Another study determined that mixed and compact land use reduce travelling during peak hours[9].

Geographically Weighted Regression (GWR) [see section 4.3 for its explanation] has been widely utilized to identify spatial variation in geographical data. A couple of studies have effectively explained geographical variation through GWR models. Lee et al. (2014) studied variation in recreation demand for Texas, USA and ascertained that leisure demand varied over space[10]. Choi et al. (2014) performed spatial analysis for activity travel pattern for Seoul Metropolitan Area and showed positive association between activity-travel behaviour and geographical characteristics[11]. Chow et al. (2006) explained a GWR based transit ridership model and showed that the model performs better than a linear regression explained transit ridership model[12]. Qiu et al. (2011) enlightened the American College Test score's connection with related factors[13]. Tsai et al. applied GWR in exploring Public Transport and Land use interactions and recommended to use GWR models over simple regression as relationship between travel demand and land use is heterogeneous over space[14].

2.2. Incoming Cross border Trips

A trip is labelled here as an "***Incoming Cross border Trips (ICBT)***" only 'if the destination zone of a trip is inside and household location of trip maker is outside the study area' respectively.

ICBT are subjected to boundary problems of the study area and are therefore not discussed in literature in detail. This is possibly linked to lack of awareness outside the study area. Furthermore, the high cost to obtain such a data (from surveys) makes it more difficult. A number of previous studies have tried to address this issue by estimating the Average Daily Traffic (ADT) and through trips at external stations of a study area. However, these models are not well-known due to limited predicting accuracy such as that of Pigman[15].

In recent years, after the pioneer work by Anderson, there has been growing interest in forecasting ICBT by utilizing economic attributes of study area[16]. The study developed a spatial model by taking into account the population and distance of each city compared to all surrounding cities and the trip generating facilities in vicinity area. However, the model does not comment on the extent of distance by which a city may affect ICBT. Qian et al. delved ICBT by employment index, the ratio of local employment to state-wide employment, and found the ICBT to vary for different economic sectors significantly[17]. Furthermore, some studies attempted to model ICBT through comprehensive origin destination surveys, cordon line surveys and by means of econometric analysis[16]. However, the advancements of modelling techniques and the need to comprehensively understand travel behaviour motivates for precise modelling of ICBT.

Bhatta stated that ignoring Intrazonal trips (which is common in most transport models) results in biased model estimation[18]. Greenwald reported strong relationship between intrazonal trips and land use[19]. Similarly, Ewing described mix land use to decrease travel distance[20].

Local attributes strongly influence the destination of a trip, particularly those associated with land use and built environment[21]. However, this is ignored in road-side (where individuals/vehicles are randomly inquired) and cordon line surveys (where individuals/ vehicles crossing a point are counted). Similarly, econometric models, as mentioned earlier, were generalized and overlooked the importance of segregating trips according to trip purpose.

The present study seeks to explore the ICBT into a study area. Since, this information cannot be collected through household survey, alternative data resources are required. Therefore, we have mainly focused on the attributes that can be obtained from open source data. Intrazonal trips are also included in the model estimation. We have applied Geographically Weighted Regression (GWR), as we expect the ICBT to vary spatially.

3. Study Area and Description of Data

Karachi is the biggest city, financial capital, industrial hub and also a population giant of Pakistan. Its population has increased swiftly from 0.2 million in 1947[22] to 18 million in 2011[23] with the growth rate attaining the peak of even 161%[22]. At present Karachi is catalogued into 18 Towns and 6 cantonment areas, a town is then subdivided into Union Councils (UC) which represents the basis for the lowest administrative boundary. Karachi metropolitan area is continuously expanding and its area is now above 3,500km^2. Karachi city consists of 204 UC which also serves as Traffic Analysis Zones (TAZ). For the current study, the analysis is conducted at UC level. Figure 1 shows map of Karachi city. An array of data sources were utilized in this study, with special focus on land use attributes. It comprises of travel demand survey for socioeconomic and travel data, land use information through open source platforms and road network through Open Street Map.

Figure 1. 204 TAZ of Karachi City.

3.1. Household Interview Survey

Household Individual Survey data, collected as part of the “Karachi Transportation Improvement Project (KTIP) – 2030” project[24], is used for this research. The data include travel information of each individual such as trip purpose, car ownership, as well as the socio economic attributes at household level such as income class, household density, number of employed persons, job category and educational qualification. The survey was conducted throughout the year and therefore survey dates are different for each TAZ, similar to the approach followed by Nielsen[1]. The respondents were asked to report their activity of the previous working day and weekend separately as described by Jensen[25]. In addition, cluster sampling was applied to get equal distribution of respondents from all geographical regions with an average sample size of 1.2% of population. The trips obtained from this survey are classified as internal and ICBT through definition of study area (further defined in section 4).

3.2. Land use data

A number of land use parameters were identified and extracted from open source. This included attraction points, and transport network data. ‘Attractions’ for each activity were retrieved from the Radar search function using Google Place Application Programming Interface (API)[26]. Google API allows to inquire for a specific location type within maximum 50km and provides a list of coordinates of up to 200 locations in one page. “School”, “work_places” and “Shopping” are an examples of such keywords to extract educational, work and shopping locations respectively. For a sample of known Point Of Interest (POI) the data seems to be sufficiently accurate. The points were later transferred to TAZs through Quantum GIS application[27]. Once all the points were assigned to respective zones an entropy index was developed for each zone. *The TAZ having highest number of attractions for activity was identified as Central Business District (CBD) for that activity*. Furthermore, *if the residents of a zone made trips to CBD (above a threshold level of 10% of total trips for that activity), then the zone was considered as an attractive zone* and outlier vice versa.

3.3. Entropy index

Entropy index, as shown in equation 1, was calculated as proposed by Frank[28]. However, due to unavailability of detailed data we have utilized the (unweighted) number of POIs of specific land use type as a replacement for area of each land use type. Entropy Index value of one represents equal share among various land use while a value close to zero identifies zones suitable for specific type of activity only such as industrial and commercial zone.

$$-1*[\left(\frac{b1}{a}\right)\ln\left(\frac{b1}{a}\right)+\left(\frac{b2}{a}\right)\ln\left(\frac{b2}{a}\right)+\left(\frac{b3}{a}\right)\ln\left(\frac{b3}{a}\right)+...+\left(\frac{bn}{a}\right)\ln\left(\frac{bn}{a}\right)]/\ln(n) \tag{1}$$

where, a = cumulative POI for all land use type; from b1 to b(n) are the POIs for each specific type of land use, and n = number of different land use type present.

3.4. Descriptive statistics of parameters

Table 1 shows descriptive analysis of parameters used in estimation process. Although not all of these parameters are used in model estimation to avoid any sort of biasness (as explained later), some variables were important to be calculated in order to understand the underlying basis of results properly as described later. This descriptive analysis is for total 204 zones.

Table 1. Descriptive Analysis of Variables

Type	Variables	Max	Min	Mean
Land Use	Attraction Points	416	5	96
	Entropy Index	0.92	0.18	0.61
	Population	1,48,632	79,244	1,10,112
	Node Count	642	9	179
	Node Density(Node/Km)	461	8	116
	Area	18.05	0.5	2.27
	Centrality (Section)	0.79	0	0.19
	Distance to CBD (km)	18.76	4.87	10.93
	Distance to CBD (education) (km)	17.45	0	11.34
	Distance to CBD (shopping) (km)	6.85	0.48	7.32
	CBD outlier	-	-	-
Socioeconomic	HH Density	4.72	3.08	4.04
	Income (Rs)	27,500	3,250	11,500

	High End Jobs (%)	7.70%	0.30%	3.30%
Travel Attributes	Average Trip Distance (work)	6.99	1.98	4.11
	Average Trip Distance (education)	3.38	0.04	1.49
	Average Trip Distance(shop)	6.85	0.47	2.42
	Trip Rates	2.61	2.07	2.27
	Internal Trips (work)	127369	7182	21347
	Internal Trips (education)	40590	4649	18092
	Internal Trips (shopping)	4589	229	1967

4. Methodology

The methodology aims to expound the ICBT through prominent land use parameters, socioeconomic and travel attributes of its inhabitants with respect to each activity purpose. Travel and socioeconomic attributes obtained from household survey are aggregated at UC level.

4.1. Defining section and centrality

To estimate ICBT, a section (consisting of 57 zones) was selected from total of 204 zones (of Karachi city) to avoid cross-referencing (total tips originating = total trips ending). *Trips ending in zones within this section and made by those individuals living in this section were considered as Internal trips.* Amount of ICBT also varies with the placement of TAZ within a study area. For instance, keeping everything else equal, a TAZ on centre of a study area will attract few cross-border trips as compared to TAZ at the edge of the study area. This is true because most of the potential influence area for attracting will be enclosed in the study area.

Urban geography and location theory defines centrality of land use in terms of attractiveness, for details please refer[31,32]. However, Cutini proposed that centrality changes over time as it shifts towards new development areas[33]. On the same principle centrality index was developed for current study through the concept of Moment of Inertia, as shown in equation 2. It ranged from 0 to 1 with TAZ situated at the boundary of study area having centrality index of 0 and centermost TAZ having maximum centrality.

$$Centrality = \left(\frac{Y_i - Y^\wedge}{\Delta Y}\right) * \left(\frac{X_i - X^\wedge}{\Delta X}\right) \tag{2}$$

where, Y_i = Centroid of TAZ(i) around y-axis; X_i = Centroid of TAZ(i) around x-axis; $Y^\wedge$ = Centroid of section around y-axis; $X^\wedge$ = Centroid of section around x-axis; ΔX = Difference in Maximum and minimum X value and ΔY = Difference in Maximum and minimum Y value

4.2. Process

A four-step procedure was used to estimate ICBT. First all the parameters mentioned in Table 1 were prepared. In Step 2 the correlation between all the parameters was checked, through pairwise regression models, to avoid biasness in results. In Step 3 remaining (uncorrelated) parameters were used in Global regression models to estimate significant effects and in the last step these significant parameters were used in GWR to estimate ICBT. The results of GWR were then plotted using QGIS to find spatial variation.

4.3. Geographically Weighted Regression

Geographically Weighted Regression (GWR) was introduced by Fotheringham to estimate global trends and minimize the residuals assigning spatial weights[34]. It is a kind of regression model where parameter estimates vary geographically. Equation 3 shows a general GWR equation. For details on GWR modelling the reader may refer to[34,35]. GWR was developed by Tomoki Nakaya and is available at https://geodacenter.asu.edu/gwr_software. We have used its version 4.0 for current study.

$$Y_i = \beta_0(i) + \beta_1(i)X_{1i} + \beta_2(i)X_{2i} + ...\beta_n(i)X_{ni} + \varepsilon i \tag{3}$$

Where, β = parameter estimates; i = weight assigned to location and ε = error term

5. Results and Discussion

GWR was applied for estimating the generation of work, education and shopping trips. 57 TAZs (constituting the section area mentioned in 4.1) were used in model estimation with an average area of 2.27km^2 and standard error of 0.35. Table 2 shows the model estimates for ICBT for work, shopping and education purposes. As shown in Figure 2, R^2 values for work (0.93), education (0.76) and shopping (0.67) trips were higher in GWR than global regression as compared to simple regression. Akaike Information Criterion (AIC) was used as the model fit criteria. Lower value of (AIC) denotes better model. The R_i^2 value along with parameter estimates for GWR model for work, education and shopping trips is shown in Figure 2.

Table 2. GWR model criteria for Work, Educaton and Shopping trips

Parameters/ Trips	Work		Education		Shopping	
Diagnostics	OLS	GWR	OLS	GWR	OLS	GWR
Residual SS	2.90E+09	1.80E+09	7.03E+08	2.64E+08	7.20E+07	6.01E+07
R2	0.88	0.93	0.37	0.76	0.61	0.67
Adjusted R2	0.86	0.90	0.29	0.57	0.56	0.58
Effective Parameters	6	9.5	7	20.38	7	10.37
(AICc/classic AIC)	1190.04	1174.15	1111.48	1109.03	976.30	975.66

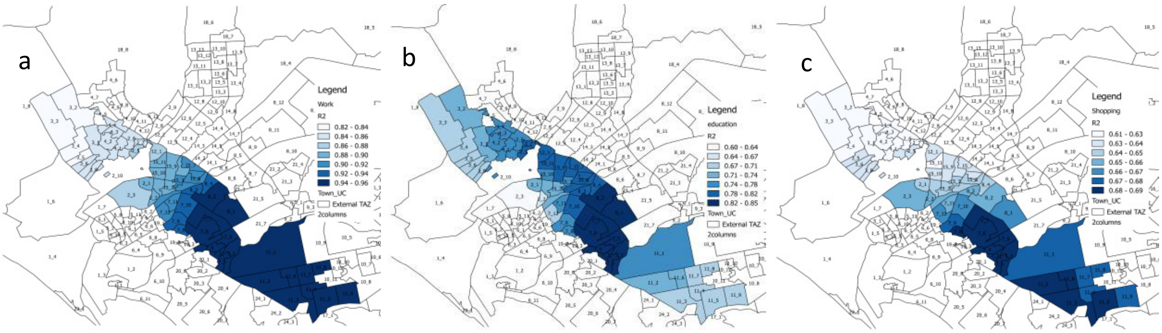

Figure 2. Local R^2 values for (a) Work; (b) Education; (c) Shopping trips.

5.1. Experimental results

The southern part of city is an industrial area (Entropy 0.18 – 0.36) therefore the coefficient for internal trips is higher for work trips as it represents commercial/ industrial zone. Alternatively, the north-western area is a suburb region of low to medium income (mean Rs.6,250; study area mean Rs.11,100) therefore it does not show high attractiveness for ICBT for work purpose. The region in the center of the city is close to CBD and thus has higher attraction power. Similarly, an increase in distance from CBD will result in higher ICBT (as the utility to reach to CBD becomes low). Centrality of TAZ was found to have a negative effect overall. Attraction power of area for ICBT (/km^2) varies spatially, that depends on TAZ and its neighboring TAZ trip attraction rate. Table 3 shows the distribution of parameter estimates of ICBT for work, education and shopping purpose.

Unlike work and shopping trips, the results show ICBT for education were decreased (in some region), with increase in educational places with values ranging between -113 to +205, as shown in Table 3. A possible decrease in ICBT with an increase in educational places is due to congestion as all primary, secondary and high school follow same timings. Similarly, higher coefficient of education places in high income areas explains its association with quality of education. ICBT were found to decrease with increase in population for densely populated areas and vice versa. Low populated areas have less facilities and therefore growth in population will also result in schemes having better services thus increasing ICBT. Centrality had positive effect on ICBT especially for 'well-developed' zones. The significant effect of distance to CBD was found to be constant irrespective of location (global effect) for education and shopping trips.

The attraction influence of shopping locations was found to marginally vary between 28 and 32 trips per location. Moreover, this influence attenuates as distance to CBD increases. ICBT for shopping were higher for high income zones. This perhaps demonstrates the presence of high-end shopping malls in posh areas where a certain percentage of visitors also accounts for window shopping.

ICBT for shopping were higher for zones with high number of internal trips. It denotes the presence of marketplace in the zone. Likewise, ICBT were reduced if resident go to CBD (CBD outlier) for shopping. However, this reduction was low for suburb areas. The coefficient for centrality shows that ICBT will decrease.

Work, education and Shopping purpose were separately modelled as they possesses different characteristics. Work trips are regular in daily agenda and considered more important as compared to shopping and education.

Table 3. Variation in β Estimates of ICBT for Work, Shopping and Education purposes

	Predictor Variable	OLS	GWR					
		β	Minimum	Lower Quartile	Median	Upper Quartile	Maximum	Global (β)
Work	Internal Trips	0.7	0.49	0.51	0.52	0.74	0.86	-
	Attractions	24	20	30	32	35	37	-
	Centrality	18,856	-51,671	-50,878	-46,974	-25,430	-11,193	-
	Area	2,879	18,55	2,763	3,904	4,266	4,520	-
	Distance from CBD	-101	715	873	917	964	1095	-
Education	Internal trips	0.33	0.07	0.16	0.40	0.45	0.56	-
	Attraction points	-26	-113	-80	-60	38	205	-
	CBD outlier (1/0)	1050	-3384	-301	361	2961	5682	-
	Population	-0.0002	-0.09	-0.07	-0.02	0.05	0.17	-
	Centrality	-885	-4528	-3623	-1722	1400	5634	-
	Distance from CBD	-621.02	-	-	-	-	-	-606.5
Shopping	Internal Trips	0.42	0.24	0.24	0.28	0.50	0.61	-
	Attractions	28	27	28	28	29	29	-
	Median Income Group	179	137	157	195	220	273	-
	CBD outlier (1/0)	-1,647	-2,609	-2,139	-1,958	-1,570	-1,471	-
	Centrality	1,479	1,115	2,373	2,638	4,123	7,441	-
	Distance from CBD	68.02	-	-	-	-	-	-223.74

6. Conclusion

In this paper, we have investigated Incoming Cross Border Trips (ICBT) through land use and socioeconomic parameters. ICBT are usually modelled through external surveys and economic parameters. Our study contributes by successfully applying alternative land-use attributes (such as POIs) based on the crowdsourcing resources. This study applied geographically Weighted Regression (GWR) model to estimate ICBT.

GWR models significantly explained ICBT for Work, Educational and Shopping trips. ICBT depend on a number of land use, socioeconomic and travel attributes and the influence of these attributes may vary from region to region. The main benefit of GWR is modelling these attributes' effects in space. The results also showed opposing effects of parameter over space. For instance, increase in attraction points may increase or decrease ICBT for two different locations in space, depending on the attractiveness for activities, as in case of education trips.

Analysis of results provided useful insight related to travel behaviour and can assist policy makers in effective management of urban-transport planning. This study focused on open source data to gather information outside the study area hence reducing the need to conduct expensive external surveys. This study also calls for further research through more experiments to check the consistency and transferability of results and calibration with other study area.

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