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MODELLING EXTERNAL-INTERNAL TRIPS AT TRAFFIC ANALYSIS ZONES USING OPEN-SOURCE DATA

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INTRODUCTION

External trips are an important part of a travel demand model for a particular study area. These trips are broadly divided into two categories as through (External-External) trips and External-Internal (E-I) trips. Usually, planning agencies use data from the external surveys which provide the information of travellers entering and leaving the study area. The most common techniques for conducting external survey includes roadside interview and vehicle license plate survey at the positions (stations) where traffic enters and leaves the study area. These stations are referred to as external stations.

Although the information obtained using the above methods for external survey are accurate to estimate the external trips, however, they also have many potential drawbacks. For instance, roadside interview creates disruption in traffic flow by stopping the drivers for interview and also for other drivers which are not interviewed. Additionally, the drivers may also consider being stopped for a survey as a breach of their privacy. Most importantly, both of these methods are quite expensive and time consuming. As an alternative, previous research have developed various statistical models to estimate external trips. However, their major focus remained on estimating through trips and distributing them (at external stations) thus producing through trips tables. E-I trips have only been estimated at external stations i.e. the external station from where the trip entered and exited the study area.

This research contributes to the work on external trips by distributing the E-I trips within a particular study area. Additionally, we have also included trips by non-residents that originate and end inside the study area (as a part of the complete tour). To estimate E-I trips, we developed a set of models explained in section 1 and 2.

The first model is a Geographically Weighted Regression (GWR) model that identifies the potential parameters for estimating the destination of external trips within a particular study area. The second model is stepwise regression model which is estimated using the parameters obtained from the first model. We particularly concentrated on the parameters that can be easily obtained from open source platforms for numerous reasons: (1) They contain rich data that can provide valuable information. (2) Such an information addresses the problem of data unavailability and (3) open source information is extremely valuable for the outside-study-area where little is known otherwise. We produced separate models for work, shopping and total trips. These models were developed and validated by defining smaller sections of Karachi city as our study areas. Model evaluation shows that our models performed well especially for separate trip purposes. The transferability of the models to other regions is still to be considered in further studies.

There are only a handful of studies available that explicitly focus on external trips to and from a particular study area. The work by Modlin (1974) has been considered as pioneer in this regard. He developed a set of equations to first estimate and then distribute through trips at external stations. Modlin (1982) updated the equations and identified average daily traffic (ADT), percentage of trucks and population within a study area as significant variables for through trips. Although this model has been widely used, it lacks the outside world information such as attraction points and their connectivity with the study area and the geographical characteristics of the study area. Horowitz and Patel (1999) developed an analytical model to explain through trips by introducing the outside world parameters in the form of catchment areas. Anderson and Abdullah (2005) also developed a set of regression equations to determine through trips for a small study area. Anderson (2005), in a subsequent study, estimated external trips through a spatial economic model using Huff's probability contour method. The model defined the distance and population of cities near external stations of the study area as spatial and economic indicators respectively.

Han and Stone (2008) followed the work of of Anderson, Modlin and Horowitz. They defined the catchment area based on the size of the study area. Their model also included explanatory variables that represent geographic and economic conditions of the study area. Qian et al (2012) utilized sector wise employment within study area as explanatory variables to estimate external trips in small and medium cities in the US through regression models. Martchouk and Fricker (2009) in a recent study proposed to estimate through trips using logit models as it would ensure that the sum of all distributed trips from each external station is 100%. Talbot et al. (2011) also estimated through trips for Texas region by a set of logit models and showed that the model predictions fit the observations reasonably well. Khan and Anderson (2014) recently modelled through trips from traffic count data (of all links present in the network) by reverse assigning the trips to external zones using all or nothing assignment. They compared the model results with the Bluetooth based origin-destination data and found that the model has performed well.

All the above studies focused on small (population < 50,000) or medium (population <2,00,000) cities in U.S. Furthermore, they focused on trips irrespective of trip purpose. The majority of the models discussed above either estimate external-external trips or external-internal trips at external station (i.e. the point from where they enter or leave the study area). Therefore a methodology is still required to determine the destination of external-internal trips within a particular study area. We preferred Geographically Weighted Regression (GWR) as it examines the spatial relationship between explanatory variables, which, we believe, has a strong contribution in the destination of E-I trips (Fotheringham *et al.*, 2002). A number of studies have applied GWR to study transportation and land use interaction, yet, it has not been used to model external trips.

1. External-Internal Trips Model

Our focus is on estimating the destination of external-internal (E-I) trips within a particular study area. Therefore, we incorporated land-use, socioeconomic and geographic information inside the study area. We first defined the parameters which were created for this study followed by the data compilation from various resources and the research process for this study.

1.1. Concepts and Parameters

A number of parameters have been created in this study to better define the problem where required. This includes Influence Area, Centrality Index and Entropy Index within a study area.

External-Internal Trips - Problem Definition

Formerly, E-I trips have been included in a four step model through survey data. As stated by Ortuzar and Willumsen (2011, p. 201) "The common practice to determine external trips is to take these trips outside the synthetic modelling process: roadside interviews are undertaken on cordon points at the entrance/ exit to the study area". However, here we are estimating the E-I trips at the level of Traffic Analysis Zones (TAZ) within a particular study area; akin to how the internal trips are modelled in the four step model. A typical study area may comprise of a number of TAZ.

Influence Area (IA)

We have defined the Influence Area (IA) as the effective catchment area of a zone for attracting trips. We have developed IAs at zonal level, instead of the study area, because we preferred to estimate the E-I trips for each TAZ separately. The three levels of space can be distinguished as:

1. Study area: Comprises of a number of TAZ and can be of any shape.
2. TAZ: The smallest unit of analysis in this study.
3. Influence Area: A circular region around the centroid of each TAZ. A part of it may be outside the study area specially for those TAZ located around the boundary of the study area. For details see Figure 1.

IA was checked between a radius of (2-7km) and travel times of 10, 20 and 30 minutes from the centroid of its TAZ. A range below 2km was avoided as some zones were having areas around 2km^2. The efficacy of different IAs was checked by estimating regression models. These models predicts total zonal trip attraction. Table 1 presents the results of the estimated regression models under different definitions used for defining IAs. The explanatory variables used here are the number of incoming trips from the defined IA and the intrazonal trips. As observed, an increase in the range of an IA results in a better fit model. However, we defined a 5km range as our IA based on the balance between the data collection efforts and the model performance. Furthermore, the range of IA on the basis of travel time is not considered here because distance seems to be a good indicator (to define IA) in comparison with travel time, as the R.square value remains lower than 0.70 even at the travel time of 30 minute .

Table 1. Model estimation results based on different Influence Area (IA)

Influence Area	Variable	Coefficients	P-value	Adjusted-R^2
2 km	Intrazonal Trips	0.99	0.000	0.47
	Trips from 2km	3.16	0.000	
3 km	Intrazonal Trips	0.34	0.081	0.62
	Trips from 3km	3.33	0.000	
4km	Intrazonal Trips	-3.09	0.000	0.79
	Trips from 4km	3.06	0.000	
5 km	Intrazonal Trips	-0.15	0.131	0.90
	Trips from 5km	2.57	0.000	
6 km	Intrazonal Trips	-2.21	0.000	0.94
	Trips from 6km	2.10	0.000	
7 km	Intrazonal Trips	-1.99	0.000	0.95
	Trips from 7km	1.89	0.000	
10 minute	Trips from 10min	3.00	0.000	0.25
20 minute	Trips from 20 min	1.53	0.000	0.47
30 minute	Trips from 30 min	1.31	0.000	0.68

Centrality Index

The placement of a TAZ within a particular study area may influence its capacity to attract the E-I trips. Therefore, to include this affect, a Centrality Index was developed through the concept of Moment of Inertia. This is shown in equation (1). The Centrality Index ranges from 0 to 1 with TAZs situated at the boundary of study area having centrality index of 0 and centremost TAZs having maximum value of centrality index.

$$Centrality\,\mathrm{I}ndex = [1-(\frac{Y_i - Y\wedge}{\Delta Y})*(\frac{X_i - X\wedge}{\Delta X})] \qquad (1)$$

where,

Y_i and X_i are the x and y coordinates of the centroid of i^{th} TAZ. $Y^{\wedge}$ and $X^{\wedge}$ represent the x and y coordinates of the centroid of the study area respectively. ΔX and ΔY are the ranges of the respective centroid eccentricities. The difference between centroid of TAZ and study area was divided by the total range of study area to scale the length of study area in x and y direction.

Entropy Index

To estimate the diversity of land use in each TAZ an entropy index (I) was developed (2), also known as Shannon index, similar to the one developed earlier (Frank *et al.*, 2005). Here, an Entropy Index value of 1 represents an equal share among various land use types (as in mixed land-use) while a value close to 0 identifies the suitability of a TAZ for a specific type of activity only (such as an industrial or a commercial zone).

Due to the unavailability of detailed information such as the surface area of POI, only the number of POIs associated with a specific land use type were used in calculating this index.

$$I = \frac{-1*[\left(\frac{b1}{a}\right)\ln\left(\frac{b1}{a}\right)+\left(\frac{b2}{a}\right)\ln\left(\frac{b2}{a}\right)+\left(\frac{b3}{a}\right)\ln\left(\frac{b3}{a}\right)+...+\left(\frac{bn}{a}\right)\ln\left(\frac{bn}{a}\right)]}{\ln(n)} \quad (2)$$

where, a = cumulative POI for all land use types, b_1 to b_n = number of POIs for each specific type of land use. n = total type of land use involved in estimating *I*.

1.2. DATA COMPILATION

Case Study

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 to 23.5 million in 2013 (Hasan and Mohib, 2003; Express Tribune, 2013). The Karachi metropolis is continuously expanding and its area is now above 3,500km^2. At present Karachi consists of 18 Towns and 6 cantonment areas, a Town is then subdivided into Union Councils (UCs), which represent the basis for the lowest administrative boundary. Karachi city consists of 204 UCs, and the four step model developed for the city used these UCs to define Traffic Analysis Zones (TAZ). Therefore, in this study the analysis was conducted at UC level. An array of data sources were utilized in this study, with a special focus on open-source data to gather information outside the study area. The data consists of the household interview survey for travel and socioeconomic information, land-use attributes and the road network which were obtained through open source platforms, and also geographical parameters which were self produced. The details of these datasets are further described below.

Household Interview Survey Data

Household Interview Survey data, which was collected as part of the Karachi Transportation Improvement Project (KTIP) - 2030 obtained from Japan International Cooperation Agency (JICA) (2012), was used in this study. It was a paper based door-to-door survey of approximately 60,000 households. The dataset contains detailed activity and trip information of the previous weekday and weekend of each member of household above five years in age (at the time of survey). It also contained the travel records of each surveyed individual with trip purpose, travel mode as well as socio-economic attributes such as income class, household size, job category and educational qualification.

Land use Data

Few major land use characteristics were identified on the basis of their availability and usefulness and their information was extracted from open source platforms. The most important amongst them was Points of Interests (POI). POIs for each activity were retrieved from the Radar search function using the Google Place Application Programming Interface (API) (Google Developers, 2015). The Google API allows searching for a specific location type within a range of 5km and (only) provides a list of 200 location coordinates in one go. "Work_places" and "Shopping" are examples of such keywords to extract work and shopping locations respectively. The POI data obtained from Google API was found to be more detailed for Karachi city as compared to POI data on Open Street Map (OSM).

These extracted POIs were assigned to each TAZ using the QGIS function *count points in polygon* (QGIS, 2015). The TAZ having the highest number of POIs for a given activity type was identified as the *Central Business District (CBD)* for that activity. However, the accuracy of POI datasets needs to be thoroughly examined; in our observation, for a sample of known POIs the data seems to be geographically accurate concerning offices, shops and educational institutes.

Network data

The transport network data was obtained from OSM (OpenStreetMap contributors, 2017). We created node count and node density parameters in each TAZ using OpenJump GIS Software (Project, 2008).

Geographic Parameters

As mentioned in the above section, E-I trips also depend on the geographical characteristics of the IA, for instance, the population and the presence of natural borders within the IA.

Therefore, two parameters to represent the geographical characteristics were developed. First was the *population in IA*. It was used to distinguish densely populated built-up areas from other open spaces. The second parameter *percentage of border in IA* was introduced to incorporate the differentiation between a boundary (such as the boundary of a typical TAZ or the study area) and a border (hard boundary) within the IA of a zone. The latter here anticipates the presence of a natural barrier to travel near the study area such as the sea or a mountain. The maximum value of *percentage of border in IA* was found to be 12%, which implies 12% of the area in the IA of a TAZ is sea/mountain area. Figure 1 illustrates the relationship between TAZ, IA and the parameter *percentage of border in IA* through an imaginary study area. Here, the *percentage of border in IA* for all TAZs except TAZ 1 will be 0.

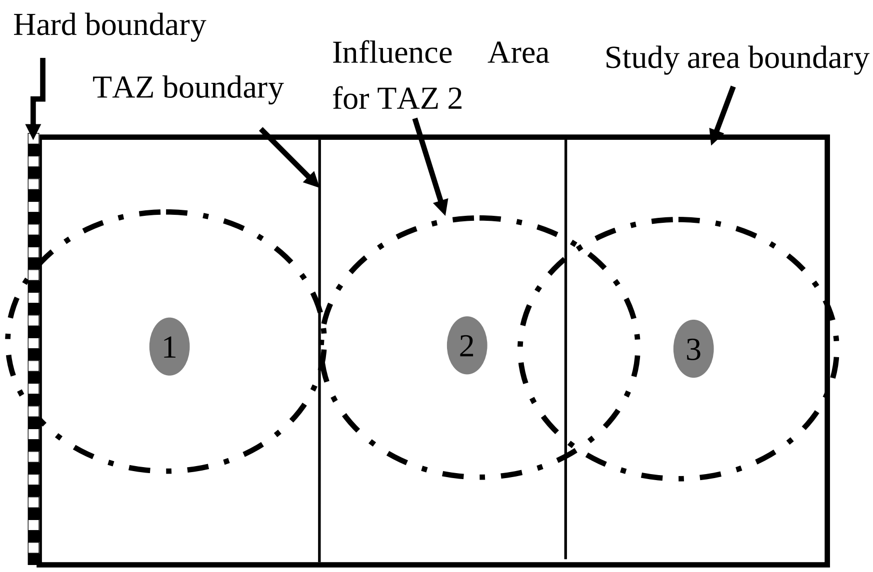

Figure 1: Relationship between TAZ, IA

1.3. RESEARCH PROCESS

The flowchart in Figure 2 illustrates the research process adopted for this study. The research process was categorized into two phases. First, we defined the Influence Area (IA) and developed the required parameters within IA (as described above). The second phase was estimating E-I trips. For this, we primarily checked the multicollinearity between all the explanatory variables and then used uncorrelated variables in the estimation process. We initially applied a GWR model to analyse the variation of parameters within the study area. Based on the results obtained from the GWR model we developed a stepwise regression model.

We further fitted the results of the stepwise regression model on another study area for validation of the estimated model. We defined the first and second study areas as training and validation study area, respectively. There were in total 57 and 86 TAZs, areas of 130km^2 and 175km^{2,} and populations of 6.2million and 8.3million in the training and validation study areas, respectively. Figure 3 illustrates both training and validation study areas.

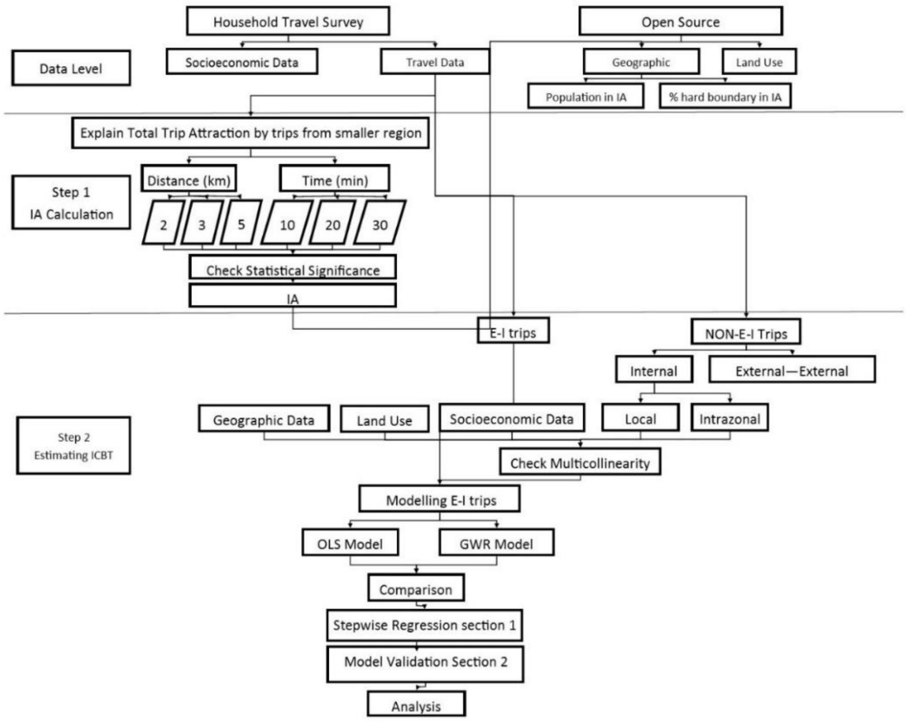

Figure 2: Research process

Figure 3: Training and Validation Study areas

2. RESULTS

2.1. UNIVARIATE ANALYSIS

Table 2 reports the descriptive analysis of the variables used in the model development procedure for the training and validation study areas. Column L.DC represents the level of data collection.

Table 2. Descriptive analysis of variables

Type	Variables	L. DC *	Training study area			Validation study area		
			Max	Min	Mean	Max	Min	Mean
Land Use	Attraction Points	T	416	5	96	313	4	82
	Entropy Index	T	0.92	0.18	0.61	0.97	0.18	0.61
	Population (100k)	T	149	79	110	149	15	98
	Area	T	18.1	0.5	2.3	11.5	0.3	2.1
	Centrality	SA	1.0	0.2	0.8	1.0	0.2	0.8
	Distance to CBD (work) (km)	SA	18.8	4.9	10.9	20.7	5.1	11.8
	Distance to CBD (shopping) (km)	SA	6.9	0.5	7.3	16.8	0.0	7.0
	Node Count	T	642	9	179	753	19	165
	Node Density (/km2)	T	461	8	116	362.9	2.54	112
Socioeconomic	HH Density	T	4.7	3.1	4.0	4.6	2.9	3.9
	Median Income (1000k Rs)	T	37.5	6.25	15.6	32.5	4.75	15
Geographic	Population in 5km (1000)	IA	6,243	1,064	3,683	6,243	434	3,631
	Border share in 5km (%)	IA	11.5	0	0.6	0.068	0	0.002
Travel Attributes	Average Trip Distance (work)	T	7.0	2.0	4.1	9.4	1.6	4.7
	Average Trip Distance(shop)	T	6.9	0.5	2.4	8.3	0.1	2.6
	Trip Rates	T	2.6	2.1	2.3	2.7	2.0	2.3
	Internal Trips (work)	T	1,27,369	7,182	21,347	31,562	869	9,855
	Internal Trips (shopping)	T	4,589	229	1,967	4,306	145	1,791

* T = attributes measured at TAZ; SA = Attributes measured with respect to Study Area; IA = attributes measured within IA. Internal trips = Trips made by persons living within the study area.

2.2. SPATIAL DISTRIBUTION OF EXTERNAL-INTERNAL TRIPS

Geographically Weighted Regression (GWR) was applied to estimate the distribution of work and shopping trips separately. The *centrality* of a TAZ was found to have an overall negative effect on work E-I trips (β= [-22561, -2277]). This suggests, keeping everything else constant, a TAZ in the centre of the study area will attract less external-internal (E-I) trips as compared to a TAZ located at the boundary of the study area (see Section 3). For the parameters in the IA, the p*ercentage of border and population* were found significant for work and shopping trips, respectively. Table 4 describes the results of the GWR model for work trips.

Table 3: Geographically Weighted Regression model results for work trips

Trip	Predictor	OLS	GWR					
	Variable	β	Global (β)	Min	Lower Quartile	Median	Upper Quartile	Max
Work	Intercept	-11102	14161	-	-	-	-	-
	Intrazonal Trips	-0.0226	-	-0.27	-0.16	-0.03	0.03	0.08
	Internal Trips	0.9472	-	0.22	0.49	0.99	1.16	1.22
	POI	12	-	0.4	6	9	14	21
	Area	2180	-	7,69	1,263	1,825	2,770	3,978
	Distance To CBD	-306	-	-1,457	-1,305	-952	-545	68
	Border in IA	-29,993	-	-3,20,342	-239164	-172337	-119597	-94,485
	Population in IA	0.0019	-	0.0001	0.0011	0.0014	0.0018	0.0021
	Centrality	2,706	-	-22,561	-18,170	-14,689	-7,982	-2,277
	R2 (Adjusted) (OLS: 0.92; GWR: 0.95)							
	Effective Parameters (OLS:9 ; GWR: 16.75) AIC (OLS:1158.37; GWR: 1143.75)							

2.3. MODEL VALIDATION

In order to validate the results obtained from the GWR model we developed a stepwise regression model for the training study area and applied the same model on the validation study area. Three models were developed and validated for Work, Shopping and Total trips, respectively (Table 4). Internal Trips were found significant for all three models; however, the coefficient was highest for work trips. The model for work and shopping trips showed better fitting compared to the model for total trips. This is because these activities trips have different underlying principles, for instance shopping activity is flexible in terms of space and time unlike work activity.The results suggests E-I trips should be modelled separately for each trip purpose.

Table 4.Regression Model Fitting for Work, Shopping and Total Trips

Parameter	Work	Shopping	Total Trips
Internal Trips	1.08	0.36	0.67
Area	1353.14		3403.52
Dist. CBD	-615.18		
Centrality	3848.66		36868
POI		11.36	
ln (Pop. in IA)			-3633.72
Population			0.18
R^2 (Training study area)	0.94	0.8	0.9
R^2 (Validation study area)	0.94	0.73	0.74

3. DISCUSSION AND CONCLUSION

Unlike previous models, this research does not assess external-internal (E-I) trips at external stations; instead it estimated them at the level of TAZs within the study area. Therefore, instead of variables used in the previous studies for estimating E-I trips, this study developed new parameters that would fit the purpose. We particularly focused on open source data to easily obtain relevant information associated to the outside world with an emphasis on land use and geographic information. We also reformed some conventional terms and indexes such as the CBD and entropy index to fit our needs.We first fitted a GWR model to identify the potential parameters for the E-I trips. We discarded those parameters whose coefficients varied from positive to negative across the study area and were symmetric around 0. Although GWR models are not transferable to other regions, they were applied to identify explanatory parameters significant for determining E-I trips. These identified variables were then used in developing stepwise regression models, for instance Centrality Index was created to describe the shape of the study area. In our case, the negative effect of centrality was caused by the fact that Karachi city does not have the CBD in the centre of the city, like some European cities, but contains a number of Outlying Business Districts (OBD) spread across the city. The stepwise regression models provided a good fit for both the training and validation study area. We focused on work and shopping trips as they constituted a major share of total trips in our dataset. The models for work and shopping trips provided better fit than the model for total trips for the validation study area. Therefore, we recommend that E-I trips shall be modelled with respect to trip purpose instead of just considering them as total trips. The high value of R^2 shows that land use characteristics have significant explanatory power in determining E-I trips. The method is also cost-effective as compared to expensive road-side surveys. Although we identified two variables representing outside world characteristics, none of these variables were found to be significant in the stepwise regression model. Therefore, it is recommended to develop and examine some other parameters to include this information in the model. We successfully tested and validated the model for Karachi city; however, further studies are required to test its effectiveness for study areas of different shape and size.

In this study, we investigated E-I trips through land use features, geographic attributes, travel and socioeconomic parameters. We estimated E-I trips at the TAZ level of the study area. We applied Geographically Weighted Regression (GWR) to identify various factors that are important in estimating E-I trips. We then estimated stepwise regression model for predicting and validating E-I trips. Our results emphasize to model E-I trips by trip purpose rather than just considering total trips. Further research work shall focus on the shape and size of the study area and characterisitics in its periphery to check the transferability and consistency of results with other locations and extend the analysis to other trip purposes such as education, medical, social, and leisure trips.

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