An Exploratory Analysis of Brisbane's Commuter Travel Patterns Using Smart Card Data

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Abstract: Over the past two decades, Location Based Service (LBS) data have been increasingly applied to urban and transportation studies due to their comprehensiveness and consistency. However, compared to other LBS data including mobile phone data, GPS and social networking platforms, smart card data collected from public transport users have arguably yet to be fully exploited in urban systems analysis. By using five weekdays of passenger travel transaction data taken from *go* card – Southeast Queensland's transit smart card – this paper analyses the spatiotemporal distribution of passenger movement with regard to the land use patterns in Brisbane. Work and residential places for public transport commuters were identified after extracting journeys-to-work patterns. Our results show that the locations of the workplaces identified from the *go* card data and residential suburbs are largely consistent with those that were marked in the land use map. However, the intensity for some residential locations in terms of population or commuter densities do not match well between the map and those derived from the *go* card data. This indicates that the misalignment between residential areas and workplaces to a certain extent, shedding light on how enhancements to service management and infrastructure expansion might be undertaken.

1. Introduction

As urban population around the world increases, cities are confronted with issues such as congestion and pollution tied to transport and mobility. Commuting, a significant component of daily travel, is considered to be a major cause of such issues (Antipova, Wang, & Wilmot, 2011). The relationship between commuting patterns and land use has therefore drawn increasing research interests to better understand and ultimately alleviate urban mobility related issues (Liu et al., 2015; Webber & Kwan, 2003). People's commuting patterns are becoming more complex due to both flexible working arrangements as well as more dispersed and polycentric urban form. These commuting patterns not only reflect where people converge over the course of a day and how the intensity of urban activities evolves over time and space, but also reveal the relationship between urban form and flows (Jang, 2010; Liu et al., 2012). However, due to the nature of commuting behaviour in space and over time, traditional data sources such as travel dairies and travel surveys are increasingly insufficient for delineating commuting patterns.

Location based service (LBS) data possesses the advantages in comprehensiveness, consistency, accuracy and timeliness compared to traditional data sources, and have demonstrated its power revealing in commuting patterns (Ahas & Mark, 2005; Ratti et al., 2006). Various technologies have been employed in tracking contemporary commuting patterns, including the use of global positioning systems (GPS) data (Liu et al., 2015), mobile network data (Calabrese et al., 2011), Wi-Fi transmission (Torrens, 2008), and geo-coding of social networking data (Hollenstein & Purves, 2010).

As a type of LBS data, transit smart card data also have received increasing interest in recent years. Despite its potential, however, compared to other LBS data sources, transit smart card data have arguably yet to be fully explored, especially in revealing urban structure through passengers' spatiotemporal dynamics (Bagchi & White, 2005; Ma et al., 2013). To date, most studies have focused on two main aspects of smart card application: journey reconstruction and temporal variation in ridership. In contrast, studies on analysing commuting patterns are still limited (Pelletier et al., 2011). Using smart card records in London, Seaborn et al. (2009) analysed the multi-modal public transport journeys and recommended the elapsed time thresholds for identifying different travel mode transfers. Gong et al. (2012) used 6-days smart card data in Shenzhen, China to analyse the temporal patterns of intra-urban trips and found that the intra-urban trips have significant periodicity with two peak hours over weekdays. Tao et al. (2014) geo-visualised the aggregate flow patterns in Brisbane using one-day's smart card data at a network level and uncovered key pathways of bus passengers and its variations over a one-day period. Overall, studies on transit smart card data have largely concentrated on compact metropolises, such as London, Tokyo, Singapore and Beijing, given that those cities have advanced transit smart card system and large public transport usage.

With the features of big data and LBS data, public transport smart card data can play an important role in exploring passengers' commuting patterns and provide insight into the dynamic urban system. In order to fill the gap and explore the potential of transit smart card data, this study applies Brisbane's *go* card data to delineate and analyse the commuting patterns of public transport passengers. By analysing the spatiotemporal patterns of trip attractors, workplaces and residential locations are identified to understand the dynamics of the urban system.

The remainder of the paper is organized as follows. Section 2 introduces Brisbane as the study area and the features of *go* card data, the transit smart card used in Southeast Queensland. Section 3 describes the methods applied to delineate commuting patterns and identify the workplaces and residential places. Section 4 shows the commuting patterns and urban dynamics, and compares workplaces and residential places against actual urban land uses. Section 5 presents findings and conclusion from this study.

2. Study area and data

2.1 Study area

Brisbane, located in the southeast corner of Queensland, is the capital and most populous city in Queensland, and the third most populous city in Australia. The Brisbane River separates the city into south and north parts, with the city's central business district (CBD) lying in one of the river's bends (Fig.1). Brisbane has an extensive public transport network, containing 461 bus routes (including bus rapid transit services), 11 train lines, 5 ferry lines (Translink, 2012). Although private cars still takes the largest proportion of people's daily travel in Brisbane, the number of public transport passengers is increasing in recent years with public transport facilities becoming more and more convenient (Tao et al., 2014).

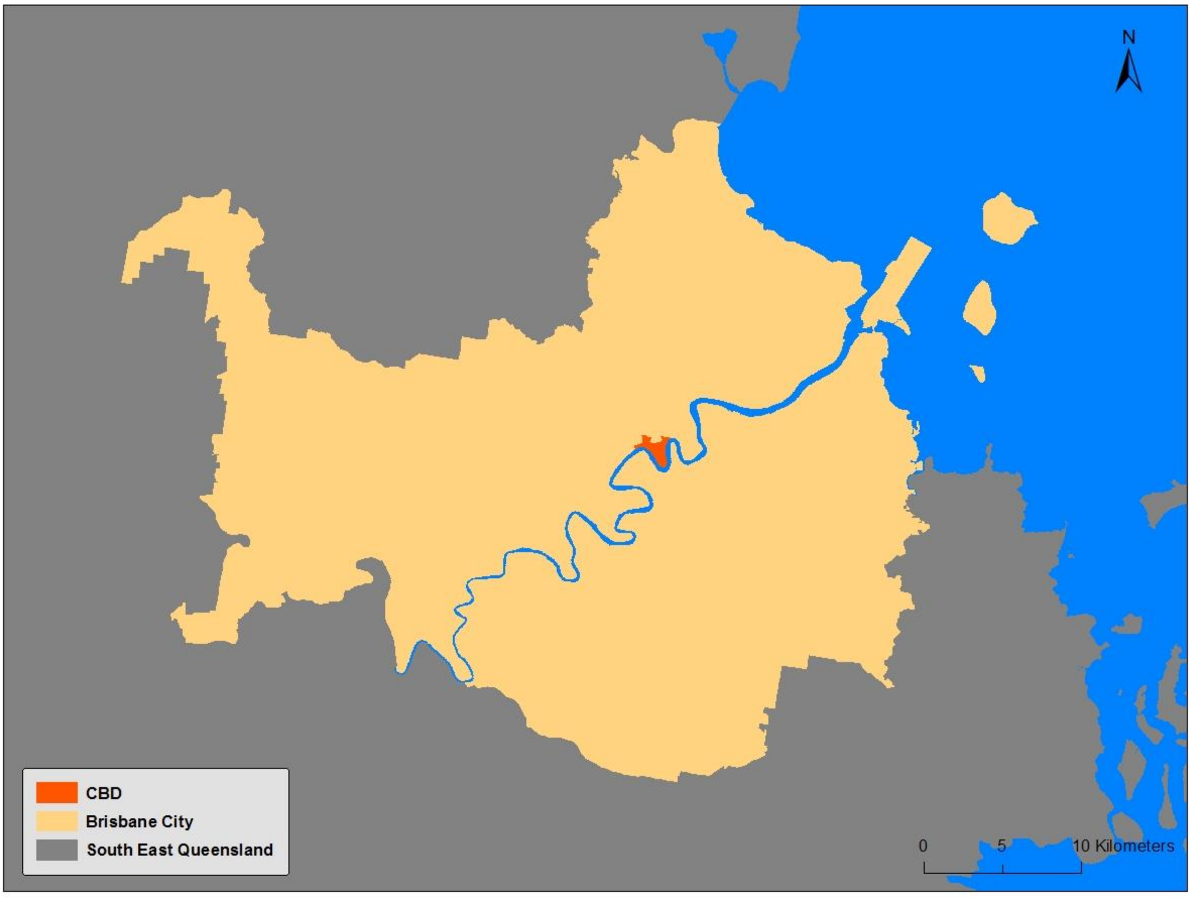


Fig.1. The Case Study Area: Brisbane City

2.2 Go card data

The *go* card was implemented in 2008 to replace independent fare systems on buses, trains, and ferries. As an automatic fare payment media, *go* card requires passengers to touch on their *go* card at a card reader when they get on a public transport, and touch off when they get off. Various pricebased incentives encourage *go* card use, including 80% of paid transit fares (Translink, 2012) and free ride after 9 journeys during a Monday-Sunday week. A journey is made up of one or more trips linking an origin and a final destination, and pricing corresponds to the number of zones travelled rather than trips. Data are collected by *go* cards for each transaction, with one complete record containing user ID, journey ID, route number, boarding stop, boarding time, alighting stop, alighting time, trip ID and card type, amongst other information. In this study, card type is not available due to passenger privacy concern. Table 1 shows the format of each transaction record on *go* card.

Table 1 An example of a trip transaction record on *go* card

User ID	1513EDA290E91F310B301A36DCB62D47
Route No.	116
Boarding stop	Chardons Corner Ipswich Road [BT004914]
Boarding time	2013/3/4 9:40:47
Alighting stop	Adelaide St adj City Hall (Stop 19) [BT0019_1]
Alighting time	2013/3/4 10:02:22
Journey ID	2013030609152235000847855
Trip ID	1
Card type	N/A

In this study, *go* card records were collected from Translink, the agency of Department of Transport and Mains Roads in Queensland, for five consecutive weekdays, from 4th to 8th of March 2013. Over 3.1 million trips were generated in the five days, with each weekday generating more than 600,000 trips or over 450,000 journeys by more than 250,000 passengers using *go* card.

3. Methodology

3.1 Reconstructing commuting journeys

Using the trip transaction data from the *go* card, data identifying each journey information, including origin and destination, as well as journey start and finishing time were reconstructed by combining trips with a same journey ID. Furthermore, by relating each boarding and alighting stop ID with General Transit Feed Specification (GTFS) data — which record a series of information about public transport stops including stop name, ID code and their geographic coordinates (Table 2) — the geographic coordinates of each origin and destination were produced. As such, the reconstructed journey data contains the time and geographic coordinates of each origin and destination of the passengers; this dataset was also used to generate the number of passengers at each stop location at different times during a day.

Table 2 An example of the GTFS Data

Stop_ID	Stop Name	Latitude	Longitude	Type
5602	Mains Rd at Robertson	-27.56422	153.065322	Bus
10885	Old Cleveland Rd near Caradoc St	-27.517190	153.183770	Bus
C8	Coomera station, platform 1	-27.852792	153.317715	Train
6663	Bulimba ferry terminal	-27.45035	153.052243	Ferry
C15	Indooroopilly station, platform 1	-27.503101	152.975944	Train
⋮	⋮	⋮	⋮	⋮

3.2 Geo-visualising commuting patterns

Commuting patterns, discerned from consistent spatiotemporal patterns, can reflect common diurnal activities and their spatial characteristics (Calabrese et al.,2012). Drawing on commuter journeys generated from March 4th to March 8th, 2013, the average number of alighting passengers at each stop over the five-day period was calculated (Table 3). Using passenger numbers at alighting stops as the indicator of daily activities has the advantage that alighting stop is close to the destination of a journey, which can reflect the purpose and feature of a travel (Kwan et al., 2007). To complement, the passenger number of alighting stops can help understand the intensity of land use and its evolution on course of a day.

Table 3 Number of Alighting Passengers at Different Times

Stop name	4:00- 4:59	…	9:00-9:59	…	17:00-17:59	…	sum
Hamilton Rd at Chermside	0	…	18	…	14	…	220
⋮	⋮	…	⋮	…	⋮	…	⋮
Yeronga station, platform 1	0	…	16	…	191	…	742
North Quay Stop 111 near Adelaide St	0	…	37	…	6	…	271
⋮	⋮	…	⋮	…	⋮	…	⋮

An Inverse Distance Weighting (IDW) method was applied to interpolate the number of alighting passengers spatially. IDW, as a deterministic method for spatial interpolation, predicts values in the study area based on the principle that things that are close to one another are more alike than those that are farther apart (Gong, Mattevada & O'Bryant, 2014). Compared to other methods, IDW generates spatially continuous surface without empty values.

3.3 Extracting journey-to-work data

As one of the most significant components of any urban traffic patterns journeys-to-work data can be identified based on the features of commuting patterns (Long & Thill, 2015). By identifying journey destinations at different time of a day, workplaces and residential places can be discerned from the *go* card data. With reference to Liu et al. (2012) and Long, Zhang & Cui (2012), three criteria were applied to extract journey-to-work patterns.

Criterion 1: Alighting time is between 6 am and 10 am

Although various jobs require different start times, it is assumed that the majority of work journeys commence between 6 am and 10 am (Bittman & Rice, 2002; Lee & Hickman, 2014).

Criterion 2: Interval between alighting time and next boarding time is longer than 4 hours

As Australian Bureau of Statistics (ABS) indicates, the daily average work time for full time employee in Australia is around 8 hours (ABS, 2014). However, the work hour for part-time workers would be shorter. Therefore, we choose to use a 4-hour interval to capture the return journeys between home and work by both full-time and part-time workers.

Criterion 3: There are 4 or more journeys that meet criteria 1 and 2 in the five weekdays

Considering that journeys for other purpose may also meet Criteria 1 and 2, the third criterion was introduced to ensure that the most frequent journeys between work and home were captured. While some daily journeys for recreational or other purposes may satisfy the first two criteria, they are less likely to occur as repeatedly as journey-to-work. So as to eliminate the journeys with other purposes, a daily journey that meets first two conditions must be generated at least four times within the five day interval.

Once a journey-to-work has been identified, the origin and destination of the journey can be used to reflect the residential and job locations, with boarding stops reflecting places around residential areas and alighting stops reflecting places around work areas (Lee & Hickman, 2014; Liu et al., 2012; Long & Thill, 2015) .

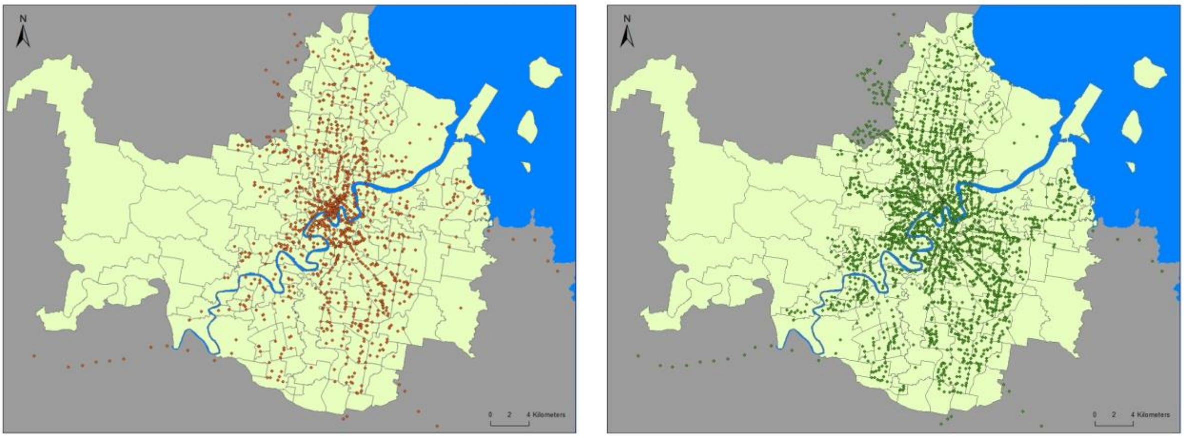
There are some limitations using the three criteria to identify journey-to-work data. On the one hand, the three criteria applied above can also lead to extracting journey-to-school data, given the similar features between these two types of journeys and on the absence of the card type which could be used to differentiate student card users. Our analysis also shows a large number of journeys to universities in Brisbane. This limitation can be override in future study when the type of card data can be used to differentiate between student and full fare paying commuters. On the other hand, the effects of Park-n-Ride (Parkhurst, 2000) facilities in Brisbane were not accounted for in this study. Given that commuters can also drive or cycle to, or be dropped off at a Park-n-Ride site in a number of locations including Ferny Grove, Eight Mile Plains, and other rail and bus termini, the intensity data at those locations can be biased. According to South East Queensland household travel survey conducted in 2011, less than 12% of passengers use park-and-ride in their normal journey.

Nevertheless, this important facility should be considered in future research which would offer valuable information to understand multi-modal transport usage. Furthermore, shift workers and other non-traditional working hours were absent from the data. While the percentage of trips in this category is likely to be marginal, further research may be useful in redressing this off-peak inadequacy.

4. Results and Discussion

4.1 Commuting patterns of public transport passengers

Brisbane is a relatively centralised city with a clearly defined CBD and a transport structure that reflects the city's axial growth over time. This is reflected in the public transport pattern and as Figure 2 indicates, the distribution of workplaces is considerably more compact than the residential locations, reflecting the suburban nature of residential housing.



A. stops around workplaces B. stops around residential places

Fig.2. Stops Around Job-housing Locations in Brisbane City

The number of public transport passengers is highest along Brisbane's major public transport corridors, including the radial rail lines and bus routes. Figure 3 illustrates the spatial distribution of public transport passengers. This map was generated based on the number of commuters at each alighting stop using IDW (Fig.3). From this distribution, the degree of land use intensity as well as the usage of different kinds of public transport can be identified. Figure 4 provides an overview of the most significant stops.

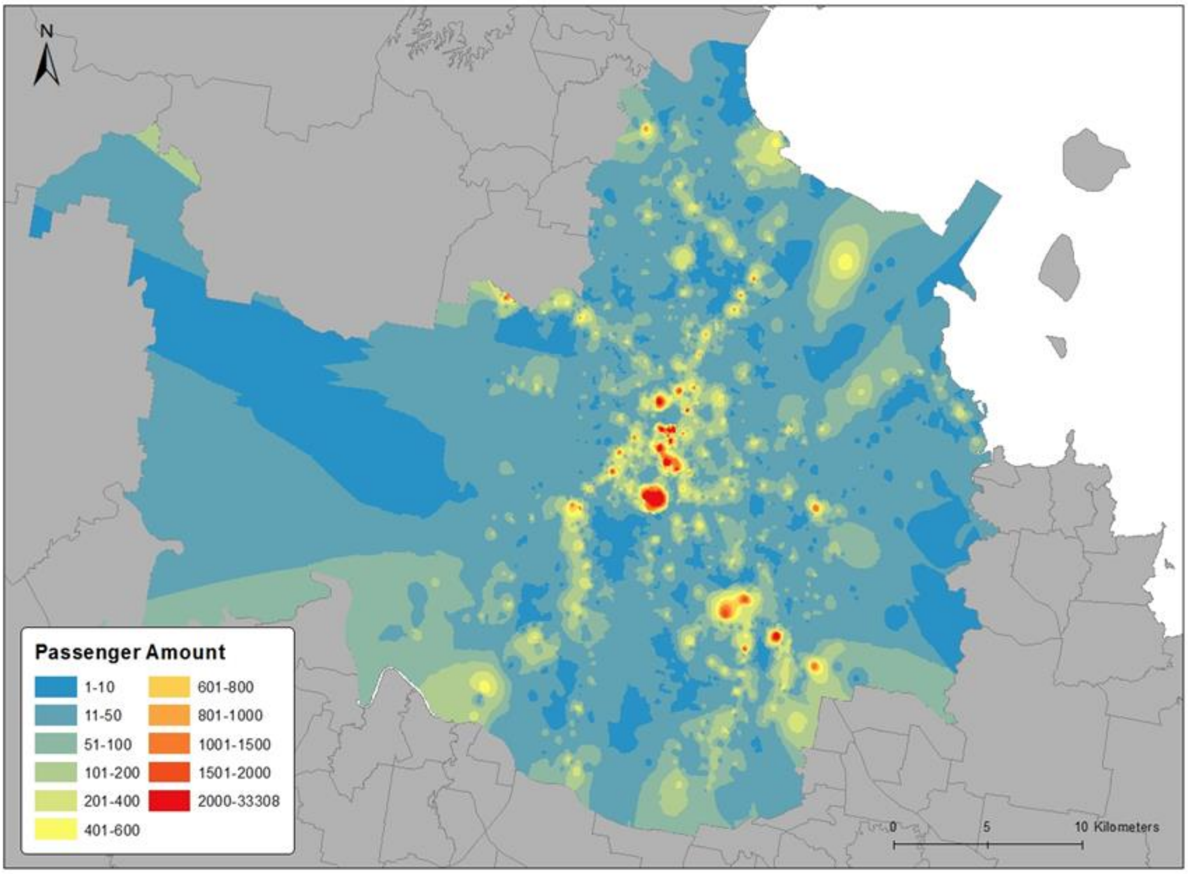


Fig.3. Commuting Patterns Based on Average Daily Alighting Passengers Number from Mar 4th to Mar 8th, 2013

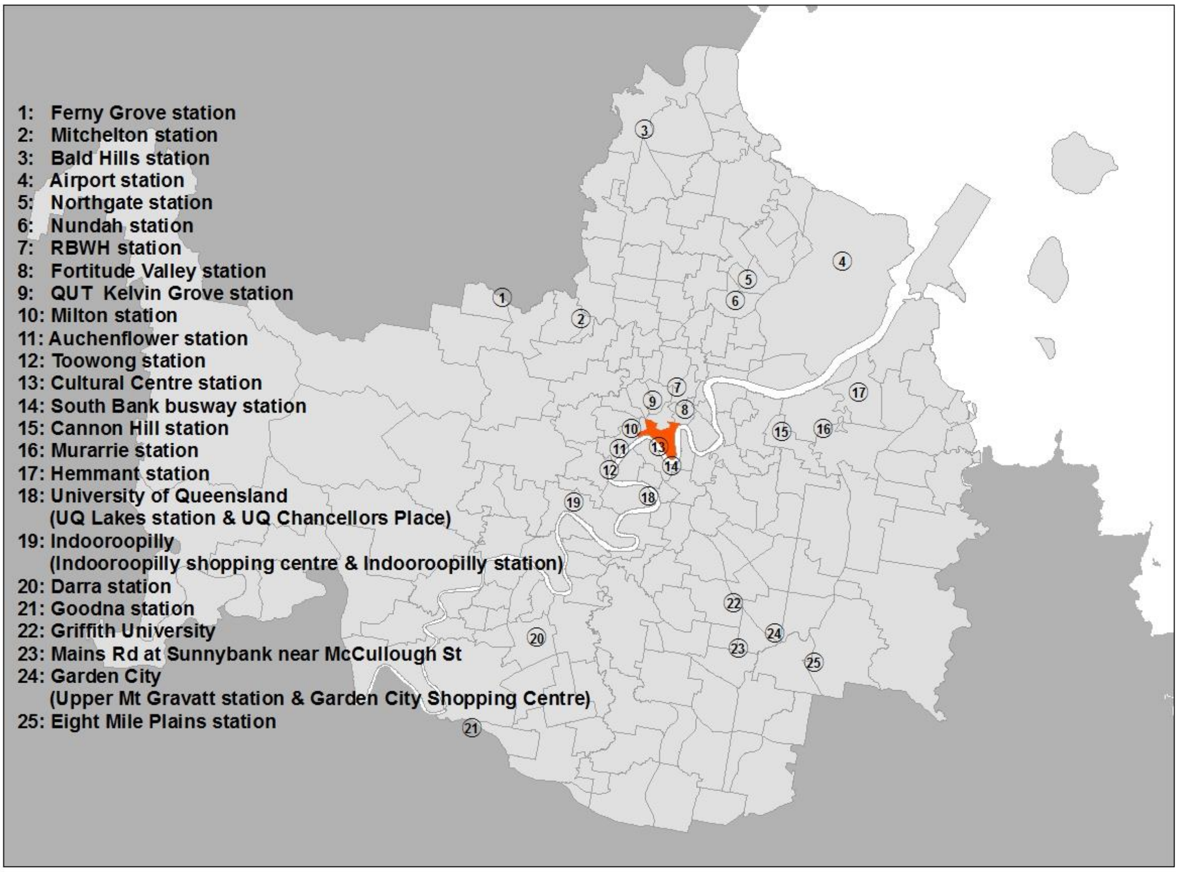


Fig.4. Significant Stops in Brisbane

A number of distinctive features on the commuting patterns can be identified. The five most populous areas attracting large number of commuters were identified, which include The University of Queensland (UQ), the CBD (also termed the City), South Brisbane, Queensland University of Technology (QUT) Kelvin Grove campus and the Garden City — a large shopping centre and transport interchange in the south side of the city. Except for the Garden City, the other four areas present a relatively concentrated spatial pattern. The CBD and South Brisbane, located on the opposite sides of a curve along the Brisbane River, are within close proximity to each other. The UQ's St. Lucia campus and QUT's Kelvin Grove campus have attracted a large number of student commuters. Spatially, the two universities are not close to each other, but their distances to CBD are similar.

There is a linear high intensity commuting pattern running from north to the south of Brisbane via the CBD, reflecting the large number of commuters travelling by rail along fixed routes. The highlighted train corridor on Figure 3 shows that rail service plays a more important role than other transport modes such as bus or ferry in residents' daily commuting, and the distribution of rail commuters amongst all train stations is relatively balanced with no significant central stations with higher or lower usage.

Locations with higher intensity of commuters identified in the city's southern suburbs reflect the existence of an educational institution (i.e. Griffith University), and transport interchanges along major corridors. But there is also a lack of east-west connectivity. Griffith University station, Sunnybank and Eight Miles Plain are important transit locations for public transport passengers, contributing to the centrality of Garden City to a more influential sub-centre in Brisbane. However, the connection between Garden City and Sunnybank is quite weak (see Figure 3), indicating a weak connection of public transport between the two locations.

The temporal patterns offer additional insight on the use of public transport over the course of the day. By dividing the commuting data into six time periods over the morning and afternoon peak times (i.e., 5:00 to 6:00, 7:00 to 8:00, 9:00 to 10:00 in the morning, and 15: 00 to 16:00, 17: 00 to 18:00 and 19: 00 to 20:00 in the afternoon), the commuting patterns at different time periods were analysed and mapped (Fig. 5). Choosing one hour rather than longer time period as the time interval is because the alighting number and commuting patterns change rapidly in an hour, and longer time period can influence the accuracy in analysing commuting temporal patterns (Tao et al., 2014). Besides, in order to comprehensively show the detailed temporal patterns, the selected six time periods are not continuous, which is also on account of their representativeness and paper size limitation.

In the early morning period (5-6 am), the intensity of commuting was relatively low, with only 373 commuters alighting on average at a public transport station as the highest intensity value. Higher intensity areas between 5 am and 6 am are located in the CBD and South Brisbane areas. On the eastern and western edges of the city, Hemmant and Wacol stations are also significant in drawing passengers in early morning.

7-8 am appears to be the peak hour for journey-to-work trips. As such, the commuter intensity is much higher in most stations, especially in the city area. The Brisbane Central Station (a train station located in the CBD) has the highest number of alighting passengers over 10,000. Other areas, including the three universities (UQ, QUT and Griffith University) are also amongst the higher intensity locations with large number of commuters alighting during this period. Royal Brisbane and Women's Hospital (RBWH) station, close to UQ Herston campus, is another main attractor over this period. After this peak hour, the number of passengers decreases for the 9-10 am period, and again, and passengers' destination concentrates in the aforementioned five primary areas.

From 10 am to 4 pm, passenger volume decreases continuously. Afternoon the trend of passengers is primarily away from the city centre and suburban stations such as Garden City become the core destination for passengers. From 5 pm to 6 pm the afternoon commute reaches its peak. In contrast to the commuting pattern during the morning rush, the destination of journey is quite dispersive. Many parts in Brisbane come active but the largest number of alighting passenger number at any given station is approximately 700. During this period, Garden City, Eight Mile Plains and Ferny Grove, all far from the City area, are the most significant areas. From 7 pm to 8 pm, transport volumes decline, and although Garden City continues to draw some commuting activities compared to other areas, the number declines to 200 or so.

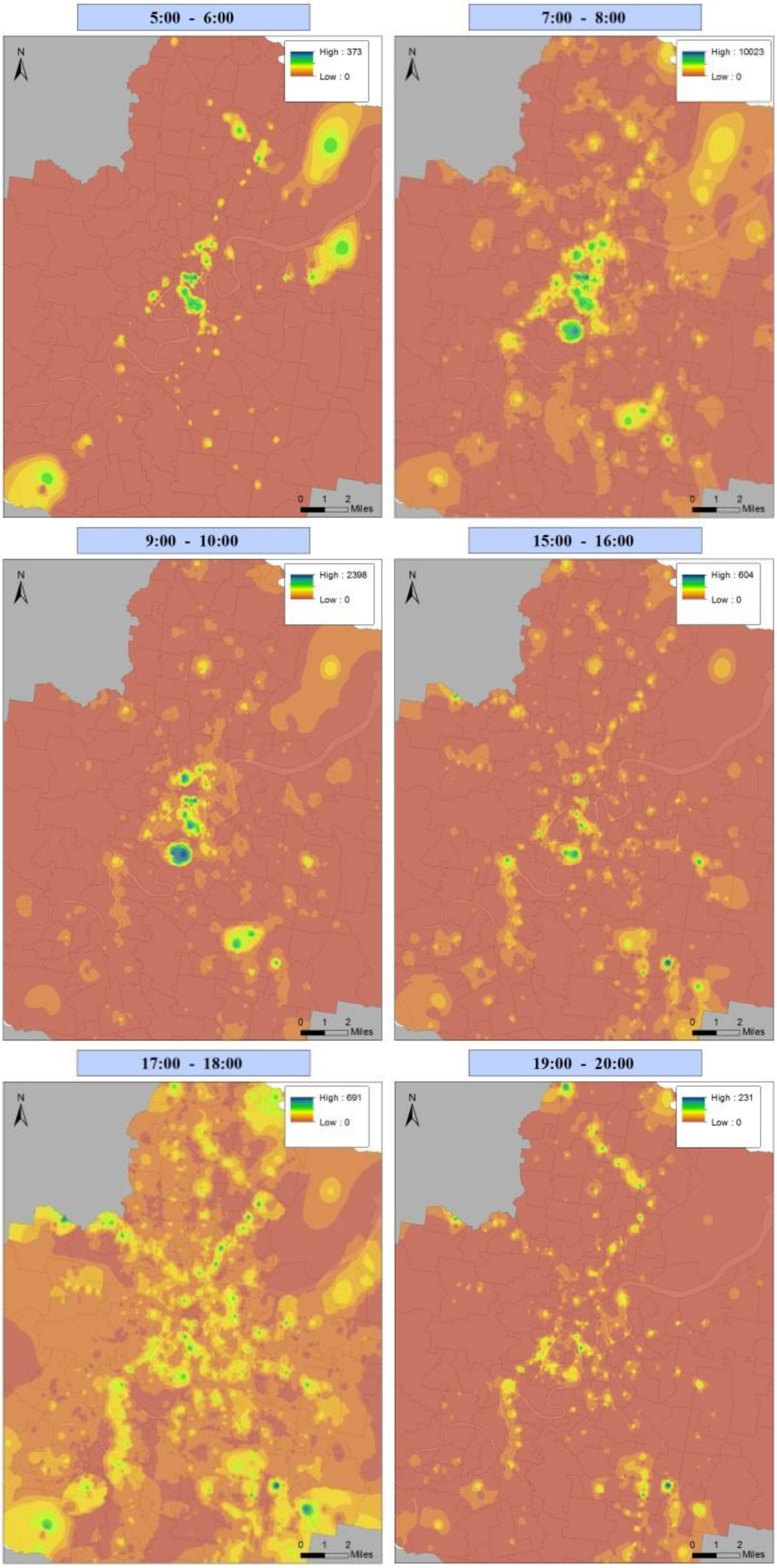

5:00 - 6:00
N
High : 373
Low : 0
0 1 2 Miles
7:00 - 8:00
N
High : 10023
Low : 0
0 1 2 Miles
9:00 - 10:00
N
High : 2398
Low : 0
0 1 2 Miles
15:00 - 16:00
N
High : 604
Low : 0
0 1 2 Miles
17:00 - 18:00
N
High : 691
Low : 0
0 1 2 Miles
19:00 - 20:00
N
High : 231
Low : 0
0 1 2 Miles

Fig.5. Commuting Patterns at Different Times on Course of a Day

From the series of commuting patterns, the highlighted areas in morning peak hours (7 am to 10 am) are just the most intensive areas in one day's commuting pattern, showing journey-to-work is one of the most important components of daily public transport usage. The city centre absorbs mostly morning commuters, while outer suburbs and various institutions and nodes are sites of journeys beyond the morning and into the evening. The CBD and South Brisbane are the areas most frequently used by commuters in the morning, however, during afternoon and night, the number of alighting passengers declines rapidly. UQ, also among the five main areas in attracting passengers, becomes active later than CBD and South Brisbane but longer than the centre areas, one explanation for this phenomenon might be that university has more flexible time schedule as not all courses are arranged in the morning and some courses are scheduled at noon or in the afternoon. Similar patterns can also be observed around QUT Kelvin Grove campus. The evolution features of passengers' pattern in Garden City area are different. Garden City is continuously attracting passengers from morning peak hours to afternoon peak hours. This indicates a higher level of mixed land use patterns around this area. Besides, the striking contrast between commuting pattern in morning peak hours and that in afternoon peak hours, to a certain extent, reflects the centralization of work places and the decentralization of residential places.

4.2 Identifying workplaces and residential places

While the commuting pattern of public transport passengers can be identified using *go* card data, the relationship between travel pattern and types of urban land use is a key question with regard to spatial mobility. Stops around workplaces and residential places have been identified respectively (Fig.2). On the basis of the number of alighting passengers at each stop, the workplaces and residential places for public transport commuters are delineated using IDW interpolation (Fig.6, Fig.7).

In Figure 6, several workplaces for public transport passengers have been identified. Considering journey-to-school may be also included, educational places are not focused in this part, which include QUT Kelvin Grove, RBWH, UQ (St. Lucia) and Griffith University. It is obvious that the CBD is the core workplace for public transport passenger. Fortitude Valley and South Brisbane also show high intensity employment areas close to the CBD. Following these the rail hubs of Milton station and Toowong station serve as CBD-fringe employment centres. Peri-urban shopping centres such as Garden City, Northgate station and Carindale Shopping centre have suburban dispersal. In general, the workplaces of public transport passengers are quite concentrated spatially, with these three as notable exception.

Compared to the concentrated distribution of workplaces, residential places for public transport passengers are more dispersed. CBD and South Brisbane, the two most significant nodes as commuters' travel destinations, do not show up in residential places map. Instead, seven significant residential places are discerned, which include Bald Hills station, Ferny Grove station, Northgate station, Darra station, Goodna station, Garden City and Eight Miles Plains. Except for Garden city and Eight Miles Plains (bus termini), the other five residential places are based on train stations.

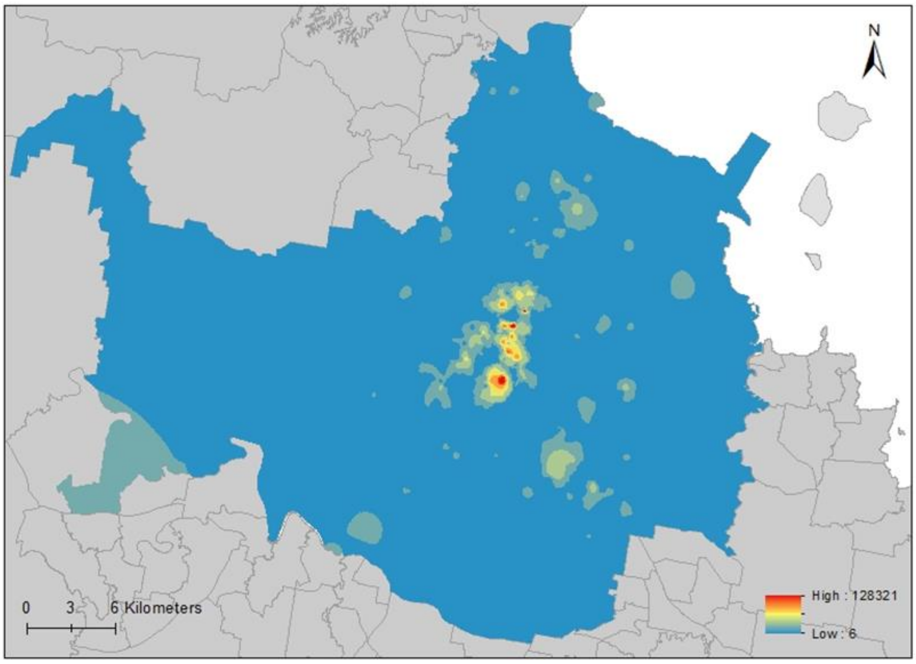


Fig.6. Interpolated Workplaces for Public Transport Passengers

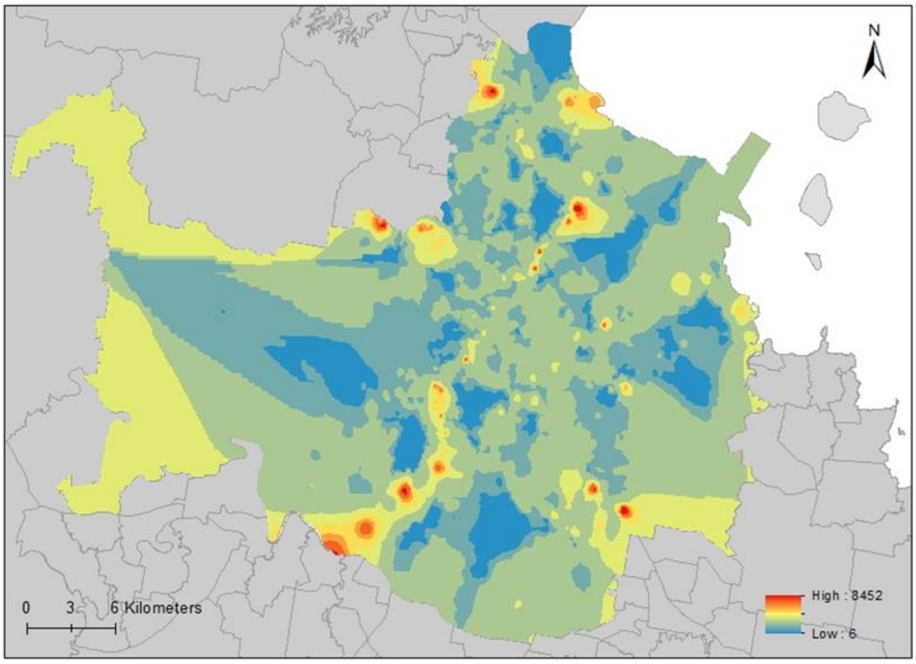


Fig.7. Interpolated Residential Places for Public Transport Passenger

4.3 Comparing workplaces and residential places to land use maps

Although workplaces and residential places have been identified in this study based on the commuting patterns and the travel behaviour features, it is unclear whether the land use pattern identified through *go* card data correspond to actual land uses. Brisbane City Council publishes its land use map annually, and by comparing land use against commuting patterns this relationship can be discerned (Fig.8, Fig.9).

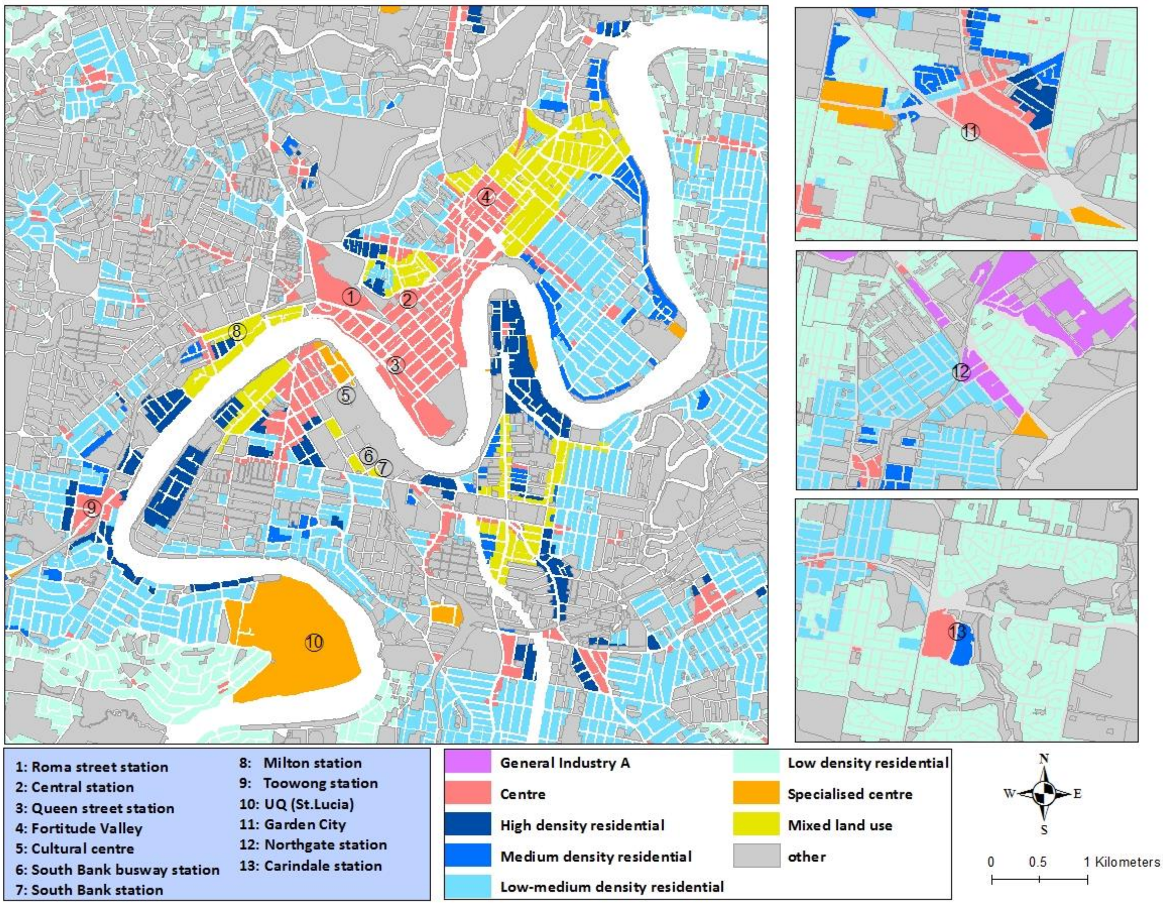


Fig.8. Land Use Type around Identified Workplaces

From the map of land use around the significant workplaces, the identified workplaces are associated with three kinds of land use — Centre, Mixed land use and Industry, each with distinct features. The CBD, where Roma street station, Central station and Queen Street station are located, has the Centre land use. South Brisbane, including Cultural Centre, South Bank busway station and South Bank station, is different from the CBD. The land use type around Cultural Centre falls under the designation of Centre and Specialised centre, but is Mixed land use around the other two stops. Toowong station, Fortitude Valley, Garden City and Carindale station are all classified as Centre land uses. Milton station, close to CBD is located in mixed land use area. Darra station, far from CBD, is the only identified workplace located around Industry areas.

The identified residential places correspond well to the residential land use category on the actual land use map, but the density of residential places and neighbourhood features are not coincident. Most identified residential places are located around low-medium or low density residential land use, which include Northgate station, Ferny Grove station, Bald Hills station and Eight Mile Plains. Nundah station and Darra station are located closely to medium density residential land use. Garden City stands out as unique, located around various density residential land use types. High density, medium density and low density residential land use types are all found in Garden City residential area.

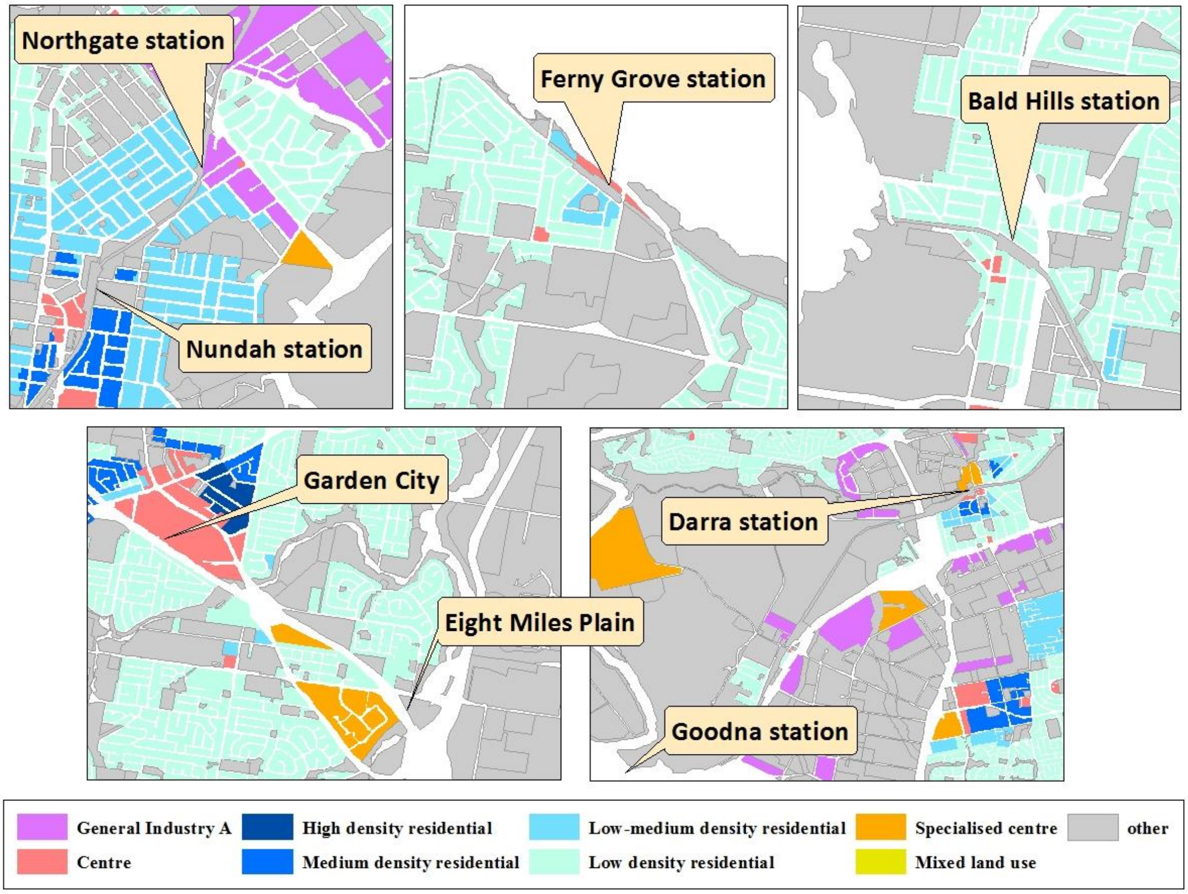


Fig.9. Land Use Type around Identified Residential Places

The three types of land uses identified as employment centres are verified as the areas having working place features from the land use map. On the one hand, the result shows that the identified workplaces on the basis of *go* card data are reliable. On the other hand, the results reveal the job features around the workplaces. Although centre, mixed land use and industry land use all have the features of employment centre, the corresponding job features are different. Centre land use and mixed land use belong to the employment centre in the tertiary sector, while the industry land use reflects employment centre in secondary sector. Only one identified work place (Northgate station) locates in the industry land use, indicating most of workers using public transport are related to service sector. This leads to further questions regarding why service employment is more amenable to public transport, with possible answers ranging from non-traditional hours tied to shift work to a lack of centrality in Industrial locations. In the land use map, Centre or Specialised Centre land uses are found around the identified residential places except for Northgate station. The residential density, to a degree, is related to the scale of centre land use. Higher density residential places are found close to larger scale of centres.

5. Conclusion

Using five consecutive weekdays' smart card data, this study identifies the relationship between the commuting patterns of public transport passengers in Brisbane and established land use patterns. The key origin and destination locations of public transport passengers in Brisbane were determined, and their spatiotemporal features were analysed. In addition, according to the travel features, journey-to-work was extracted and the workplaces as well as residential places identified.

The dynamic commuting patterns show that journey-to-work is a major component of public transport usage on weekdays. The most significant of these locations draw passengers throughout the course of a day, including the CBD, South Brisbane, UQ (St. Lucia), QUT Kelvin Grove and Garden City, with each showing respective characteristics. The CBD and South Brisbane show typical features of workplaces, with a crescendo during morning peak hours and declining dramatically after that time. UQ (St. Lucia) and QUT Kelvin Grove reflect the features of a university, the period drawing passenger is longer than that in the CBD and South Brisbane. Garden City, with mixed land use type and multiple urban functions, has a relatively less fluctuated number change.

The key contribution of this paper lies in the analysis of the relationship between commuting patterns and established land use patterns. The fact that most workers taking public transport live away from city centre is illustrated. The centralization of workplaces and the decentralization of residential places have been established from different perspectives. For most residential areas, train service plays a more important role in passengers' job-housing journey compared to other public transport modes.

Compared to actual land use type, the locations of the identified workplaces and residential places are consistent with those in the land use map, which indicate the methods of using smart card data to discern workplaces and residential places are reliable. The land use types around identified work places show that most of public transport commuters are working with service based business. In addition, it is found that the density of residential places aligns most strongly with the scale of centre or mixed land uses. Generally, the larger scale of centre or mixed land use, the denser of residential land use locates.

This study has shown the relationship between commuter patterns and land use types, which informs a clearer understanding of both how smart card data can inform land use transformations (e.g. rezoning), and how transport connectivity might be optimised to better connect various parts of a city. In the future, multiple data sources, such as census data and travel surveys, can be integrated with such transit smart card records to enrich information on public transport passengers, providing more accurate and detailed residential and workplaces information, and at a fraction of the cost of stand-alone surveys. Smart card data have the advantage of being dynamic and continuously updated, identifying potential changes in service, logjams, and new service opportunities.

Like other LBS data, smart card data can also make a great contribution on urban analytics and travel behaviour analysis. Although other LBS data have been widely used in study on urban structure, sub-urban interactions and predicting traffic flow, application of smart card data is relatively limited. Exploring the potential of smart card data will not only help advance our understanding of urban development, but also benefit the development of more feasible and effective city plans.

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