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Impact of rain on Daily Bus ridership: A Brisbane Case Study

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Abstract

Weather is one of the most significant elements affecting transit ridership on a daily basis. Until now, there has been limited focus in the literature investigating this issue. Adverse weather conditions impact travellers in choosing travel mode and route, travel schedule, and trip making itself. This paper explores the relationship between adverse weather and transit ridership by analysing the correlation between daily bus ridership and daily precipitation for a three-year period from 2010 to 2012. It is observed from the analysis that wet weather has varying impacts on daily bus ridership. Overall, rainfall negatively affects the daily bus ridership in this region. Morning peak-hours and weekend ridership were found more sensitive to rain than entire day's ridership and weekdays. The study also found a negative correlation between the morning-peak precipitation level and the daily bus ridership, which suggests that a small amount of morning peak-hours rain reduces a significant amount bus ridership for the whole day. The analysis also confirms that summer rain has the most significant effect on ridership compared with the other three seasons. The study findings will contribute to enhancing the fundamental understanding of traveller behaviours, particularly mode choice behaviour under adverse weather conditions.

1. Introduction

Brisbane, the capital of the State of Queensland, is estimated to grow population from 2.7 million in 2006 to more than 4.2 million in 2031 (Connecting SEQ,2013). In order to meet the transport demand of this fast rising and geographically dispersed population, Brisbane is increasingly turning to bus transit, particularly its busway network. More than 25 km of busway has been built to date as a form of bus rapid transit. It comprises grade-separated bus-only corridors, complementing the region's rail network to provide faster and more efficient bus services to residents of South East Queensland. This busway network is the largest form of rapid public transport in Australia. It currently consists of South-East Busway, Northern Busway and Eastern Busway and carries over 70 million passengers each year (Brisbane Metropolitan Transport Management Centre, 2013). Some parts of the busway network carry more than 12,500 passengers per hour, while a typical motorway lane can carry about 2000 people per hour. Additionally, the actual patronage relying on the bus service in peak-hours is higher than CityRail in Sydney (Moore, 2012). Since bus is considered as the primary public transport mode in this region, factors that affect the bus ridership are worthy of investigation.

Transit ridership is influenced directly and indirectly by various factors including, but not limited to, pedestrian walking facilities, land development, car ownership, park-n-ride facilities, parking prices, fares, transit stop facilities, petrol prices, income, congestion level, and so on (Ryan and Diago, 2009; Sarkar, 2002; Cervero, 1993; Filino, 2001; Kuby et al., 2004; Purcher, 204). However, one element that researchers mostly overlook is weather. It affects ridership on a daily basis, influencing almost every aspect of transit service. Adverse weather conditions lead to increased transit travel times and degraded service regularity (Hofmann and O'Mahony, 2005). Transit users are directly affected by weather while waiting or walking to and from the transit stop (Guo et. al, 2007). Transit riders need an extra protection from adverse weather (Sarkar, 2002). Otherwise ridership may be negatively affected by weather conditions (Fielding, 1995; Levine, 1990).

The weather pattern of Brisbane is highly variable by season due to its sub-tropical climate characteristics. Over the past decade, occasional tropical cyclones brought extreme rainfalls and historic floods, although this region observed a drying trend overall (Climate Change Science, 2011). The occurrence of extreme weather conditions has increased recently with more frequent heavier rains for a longer period. Gallant et al. (2007) found the proportion of total rainfall stemming from extreme events has increased since the 1950s.

The main goal of this research is to investigate whether the daily public transport usage in Brisbane is affected by the weather condition, particularly the level of precipitation. A vast amount of research studied weather impacts on vehicle safety, speed and traffic volume (Eisenberg, 2004; Edwards, 1998; Andreescu, 1998; Chung et al., 2006; Prevedouros & Kongsil ,2003; Kyte et al., 2001; Edwards, 1999; Holdener, 1998; Keay and Simmonds, 2005; Hassan and Barker, 1999). Little research analysed the impact of weather on transit ridership providing conflicting results: some studies support the pre-conceived notion that adverse weather affects negatively on public transport, while others suggest the opposite. Majority of those studies were also conducted in the North America. In Australia, several studies explored the weather impact on non-motorised travellers such as cyclists (Phung and Rose, 2008; Nankervis, 1999; Richardson, 2000; Ahmed et al., 2012; Keya, 1992) & pedestrians (Burke et al., 2006). There is virtually no research investigating the impact of weather on transit ridership in Australia.

Enhanced understanding of the precipitation factor affecting the choice of public transit mode will assist policy makers, transit authorities, and transport engineers and planners to: *i)* improve the system efficiency and user satisfaction under adverse weather conditions by re-arranging and/or re-scheduling transit service on rainy days; *ii)* design and implement appropriate programs to encourage the use of public transit under adverse weather conditions; *iii)* increase the level of service and infrastructure of transit station to provide extra protection from adverse weather; and, *iv)* promote and improve non-motorised amenities as these are an integral part of transit ridership.

2. Literature review

A few studies have been conducted concerning the impacts of weather variables on transit ridership and majority of them concentrated on the observed ridership changes by different weather conditions. The majority of the research revealed the negative correlation between adverse weather and transit ridership, while some found a positive trend.

The study of Guo et al. (2007) seems the first research in this domain investigating the effect of weather on transit ridership. Their research unveils that precipitation, snow and wind have significant negative impact on transit ridership. This study also reveals that the observed intensity of such weather impacts varied by transit mode, season, and day of the week. For instance, the degree of sensitivity to weather is more prominent on bus than other public transit modes. The weather impact is more significant on weekends than weekdays. They also shed light on the fact that discretionary trips are more sensitive to weather conditions than mandatory trips (i.e., commuting trips).

A recent study by Stover et al. (2012) examined the effects of weather on bus ridership in Pierce County in the state of Washington, USA, for a three-year period from 2006 to 2008. They considered four weather variables (wind, temperature, rain, and snow), and analysed their effect on bus ridership in four seasons (winter, spring, summer & autumn). The study shows that rain is the only variable having a significant effect on ridership in all four seasons. Compared with the average ridership, the occurrence of rainfall led to a decrease in bus ridership by 5.05% in winter, 9.73% in spring, 7.36% in summer, and 5.97% in autumn.

Kalkstein (2009) encompassed several weather variables into a single class, named air mass. It syndicates various weather factors and explains that from the perspective of human perception, rather than numbers and digits. The outcome of this research coincides with previous studies that precipitation reduces transit ridership. Additionally, similar to Guo et al. (2007), the study identified that air mass has more impacts on transit ridership in weekends than weekdays due to increased numbers of discretionary travellers.

Changnon (1996) investigated the effects of summer precipitation on weekdays in Chicago urban area. The study found that the ridership decreased by 3 to 5% on a rainy day. Interestingly, a major reduction in ridership occurred by raining in midday (6%) compared with morning (3.3%) or afternoon (1.9%) rain. This result suggests the nature of discretionary passengers, who are more likely to avoid travel on public transport on rainy days.

Hofmann and O'Mahony's (2005) investigated the impact of adverse weather on bus performance measures such as ridership, frequency, headway regularity, and travel time in Dublin, Ireland. The study analysed electric magnetic strip card data and found that the electric card users prefer alternative transport modes than bus on rainy days. Overall, a slight decrease of the bus ridership was found on rainy days but the significance of the result was unclear.

Contrary to the aforementioned studies, some researchers associated adverse weather with a positive trend in public transit use. Mostly this issue is linked with commuter’s response to severe weather condition. Khattak (1991), in a behavioural travel survey conducted in Chicago, identified that commuters diverts from car to transit during extreme weather. Diversion also occurred from other modes including walking and cycling. Consistent with this study, Khattak et al. (1995) also found that commuters switch from car to public transport during adverse weather in San Francisco Bay Area.

The findings of these two surveys are not spatially dependent. The Belgium study of Khattak and de Palma (1997) coincides with their findings. A substantial number of automobile users (54%) responded that they changed their travel mode, departure time, and/or route choice during bad weather conditions. Among the commuters who changed their travel pattern in adverse weather, 27% of respondents indicated that weather was either “very important” or “important” factor in determining what mode of transportation to use. Additionally, according to the transit agency in Brussels, a higher level of transit ridership was identified during adverse weather and unexpected delays on major routes.

The impact of adverse weather is not limited to public transit ridership and it significantly affects cycling and walking as well. Rose et al. (2011) found significant effects of precipitation on the cyclist volume in Portland, Oregon, USA and Melbourne, Australia. According to their model, 1 mm increase of precipitation reduced the cyclist volume by 4% to 5% in Portland and 4% in Melbourne.

The recent study of Tin tin et al. (2012) analysed the influence of weather variables on hourly and daily cycle volumes in Auckland, New Zealand. Their study shows that 1 mm increase in rainfall reduces the hourly cycle volume by 10.6% and the daily cycle volume by 1.5%. This study result is consistent with the findings of a previous survey by Nicholson and Kingham (2003) that observed lower likelihood of cycle commuting on a cold and wet day than on a warm and dry day. Likewise, Moreno and Nosal (2011) found that precipitation has a direct and lagged effect on bicycle ridership. They found the cyclist volume in Montreal, Canada, is significantly affected by the precipitation in the current and previous three hours. However, a few studies have identified different types of cyclist user groups (utilitarian and recreational) react differently to weather conditions. Thomas et al. (2009), Brandenburg et al. (2007), and Keay (1992) found that recreational cyclists were more sensitive to weather conditions than utilitarian cyclists.

A study by Montigny et al. (2011) investigated the correlation between weather conditions and the amount of walking in nine different cities in the USA and Europe. The study revealed that a 5^{0}C increase in temperature increases the pedestrian volume by 14%. Similarly, shifting from snow to dry weather was related with 23% increase in the pedestrian volume. Aultman-hall ei.al (2009) analysed one year automated hourly pedestrian data related with weather parameters including temperature, humidity, wind and rain in downtown Montpelier, Vermont. This study revealed that precipitation and cold weather reduced the average hourly pedestrian volume by almost 13% and 16%, respectively.

3. Study area

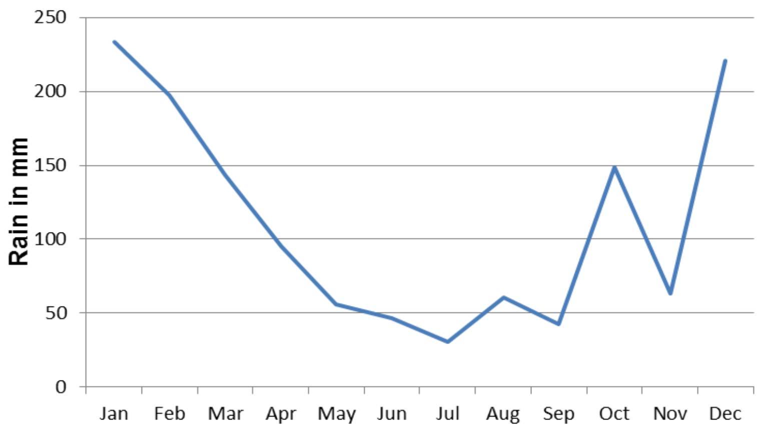
Brisbane is located in the south east corner of Queensland. The South-East Queensland (SEQ) region includes 11 regional and city councils (SEQ regional plan 2009-2031, 2011). Among them, the city of Brisbane, comprising 189 suburbs, occupies 5.9% of SEQ and only 0.1% of Queensland in terms of land area. However, it supports nearly one third of SEQ's population and one quarter of Queensland's total population (QTT, 2011). Likewise, Brisbane comprises significant economic drivers of the region as well as the whole of Queensland, including the CBD, adjacent employment area, and the region's principal airport and seaport.

Public transport in Brisbane is provided by TransLink, Division of the Queensland Department of Transport and Main Roads, which splits its network into 23 travel zones. Brisbane city encompasses five of these zones. In order to deliver bus services to Brisbane area, TransLink works with Brisbane Transport, and Brisbane Bus Lines (TransLink, 2012).

TransLink operates a total of 394 routes that originate from within the Brisbane City Council region (study area). For the years 2010, 2011 and 2012, the estimated total patronage for Brisbane's bus service was 77.2 million, 75.9 million and 77.8 million, respectively. The patronage decline in 2011 is explained by the impact of floods in January 2011 and the change of multi-trip ticket type (TransLink authority annual report, 2010-2011).

Brisbane is known as the “sub-tropical” capital of Queensland. The climate of Brisbane is characterised as warm temperate, with a fully humid precipitation and hot temperature in summer (Kottek et al. 2006). Generally, there are four distinct seasons observed in Brisbane. Summer is from December to February (typically high heat, humid and wet); winter from June to August (typically dry, low humid and cold); autumn from March to May; and spring from September to November. Brisbane has an average daily temperature range from 14.9^{0}C to 24.9^{0} C and on average it receives 1,165 mm of rainfall each year (QTT, 2011).

Figure 1: Average monthly precipitation (2010-2012), Brisbane station



4. Data

Two data sets were used for this analysis: daily bus ridership data from TransLink and daily precipitation data from Bureau of Meteorology, Climate Data Services (2013). Both datasets were collected for a three-year period from January 1, 2010 to December 31, 2012. Bus ridership data comprises the daily sum of all passengers for 24-hr period, provided by two ticket types; paper ticket and electronic ticket, which is also known as “*go*-card”. The database contains approximately 231 million ridership records for three years including weekends and other holidays.

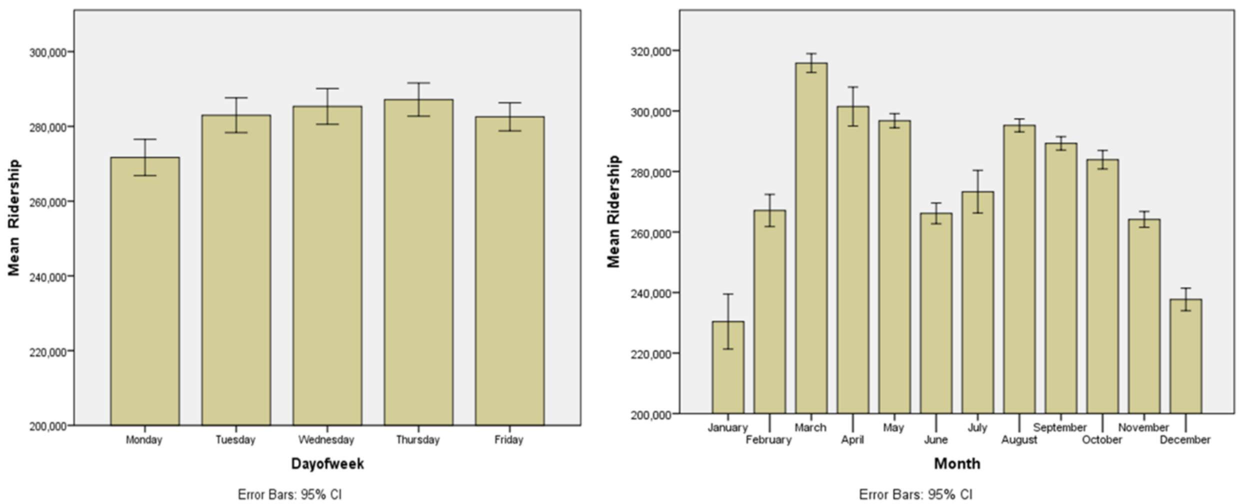
Hourly cumulative rain data was acquired from Brisbane Weather Observation Centre. It is worth mentioning that the weather station measures weather variables from 9:00 am for a 24-hour period. In this study, precipitations only between 6:00 am to 9:00 pm were considered as whole day rainfall. This is because patronage numbers are negligible in the late night (after 9:00 pm) and in early morning (before 6:00 am). The morning peak hour rainfalls were considered between 6:00 am to 10:00 am.

5. Seasonality Analysis and Adjustment

The primary intent of this study is to examine the impact of rainfall on day-to-day bus use. Since ridership and weather inherently fluctuates from hour to hour and from day to day, an important issue is how to design the analysis and adjust for seasonality effects. As the first step, the daily bus ridership was segmented into each weekday (i.e., from Monday to Friday). The results of this segmentation can be translated as the daily share of the given week’s passenger volume. Figure 2 (a) shows the mean daily share by day of week for the three-year analysis period.

Similar method was adopted for each month of Year (i.e., from January to December) as illustrated in Figure 2 (b).

Figure 2: Average bus ridership by day of week (a) & month of year (b)



The mean and standard deviation of daily ridership by day of week and by month of year are presented in Table1 and Table 2, respectively. The degree of variations shows the discrepancies among days of week are not as large as that throughout the months of the year. The only substantial variation in mean within the day of week ridership pattern is in Monday.

Table 1: Mean daily ridership by Day of Week.

Day of week	Total observation	Mean	Standard Deviation
Monday	105	271,680	25,023
Tuesday	117	282,979	25,417
Wednesday	113	285,347	25,587
Thursday	118	287,162	24,334
Friday	117	282,561	20,447

Table 2: Mean daily ridership by Month of Year.

Month	Total observation	Mean	Standard Deviation
January	13	230,406	15,027
February	59	267,101	20,399
March	64	315,820	12,508
April	36	301,455	19,039
May	61	296,783	9,163
June	49	266,148	11,932
July	43	273,307	22,9001
August	61	295,218	8,278
September	40	289,277	6,915
October	56	283,884	11,368
November	64	264,159	10,437
December	25	237,698	9,020

In contrast, the variation of the monthly mean ridership is significant. The lowest monthly ridership is found in January and the highest ridership level is observed in March. The difference between these two months' ridership is more than 85,000 passengers per day. This is a considerable amount that accounts for approximately 37% and 27% of the monthly ridership in January and March, respectively. The variation during the summer months (i.e., December and January) is relatively small because of lower ridership levels due to holiday and vacation activities. During the winter months (i.e., June and July), the mean ridership is also low mainly because of school holidays.

Analysis of Variance (ANOVA) was used to determine the statistical significance of variability observed from the mean ridership. The mean ridership for each day of week was compared against one another. Table 3 shows that Monday ridership is statistically different $(p = 0.00 \leq 0.05)$ from other days.

More fluctuations are observed between the monthly ridership volumes, which are statistically significant as shown in Table 4. For example, the January ridership is statistically different from all other months except December $(p = 0.88 > 0.05)$. The same result was achieved for the month of March. The p value in Table 3 and Table 4 indicates the chance of similarity between two groups of data. A small p value (i.e. $p < 0.05$) shows that the two groups are statistically distinct having different statistical characteristics. The non-significant results (i.e. $p > 0.05$) are highlighted in these tables. The outcomes of the analysis confirm the existence of seasonality in both the daily and monthly ridership patterns.

Table 3: Multiple comparison results of *p*-values for day of week (with 95% confidence interval)

Weekdays	Mon	Tue	Wed	Thu	Fri
Mon	-	0.00	0.00	0.00	0.00
Tue	0.00	-	0.96	0.69	0.99
Wed	0.00	0.96	-	0.98	0.89
Thu	0.00	0.69	0.98	-	0.52
Fri	0.00	0.99	0.89	0.52	-

Table 4: Multiple comparison results of *p*-values for month of year (with 95% confidence interval)

Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Jan	-	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.88
Feb	0.00	-	0.00	0.00	0.00	0.99	0.96	0.00	0.00	0.00	0.99	0.00
Mar	0.00	0.00	-	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Apr	0.00	0.00	0.01	-	0.96	0.00	0.00	0.77	0.03	0.00	0.00	0.00
May	0.00	0.00	0.00	0.96	-	0.00	0.00	0.99	0.00	0.00	0.00	0.00
Jun	0.00	0.99	0.00	0.00	0.00	-	0.79	0.00	0.00	0.00	0.99	0.00
Jul	0.00	0.96	0.00	0.00	0.00	0.79	-	0.00	0.00	0.22	0.39	0.00
Aug	0.00	0.00	0.00	0.77	0.99	0.00	0.00	-	0.01		0.00	0.00
Sep	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.00	-	0.17	0.00	0.00
Oct	0.00	0.00	0.00	0.00	0.00	0.00	0.22	0.00	0.17	-	0.00	0.00
Nov	0.00	0.99	0.00	0.00	0.00	0.99	0.93	0.00	0.00	0.00	-	0.00
Dec	0.88	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-

As revealed from the ANOVA tests, it is essential to eliminate the seasonality from the ridership data to capture the true effect of rainfall. Following two formulas are used for seasonal decomposition for the day of week and the month by year ridership.

$$Seasonal\ decomposition\ (By\ day) = \frac{Ridership\ data\ for\ each\ day\ of\ week}{SI(Seasonal\ Index)}$$

$$Seasonal\ decomposition\ (By\ month) = \frac{Ridership\ data\ for\ each\ day\ of\ month}{SI(Seasonal\ Index)}$$

The seasonal index (SI) is a measure of the degree of seasonality. For example, a SI value above 1.0 indicates that the ridership volume of a particular day is higher than the mean of that day or month. A SI value below 1.0 indicates the opposite. Figure 3 and 4 compares the original seasonally adjusted ridership volumes by day-of-week and month-of-year, respectively.

Figure 3: Average ridership by day of week before and after seasonal decomposition

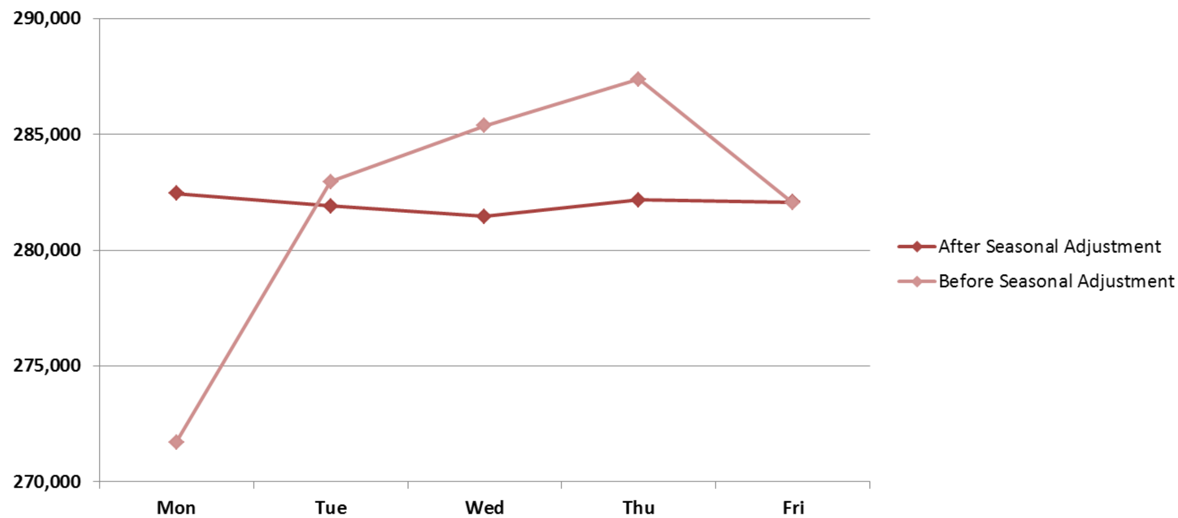
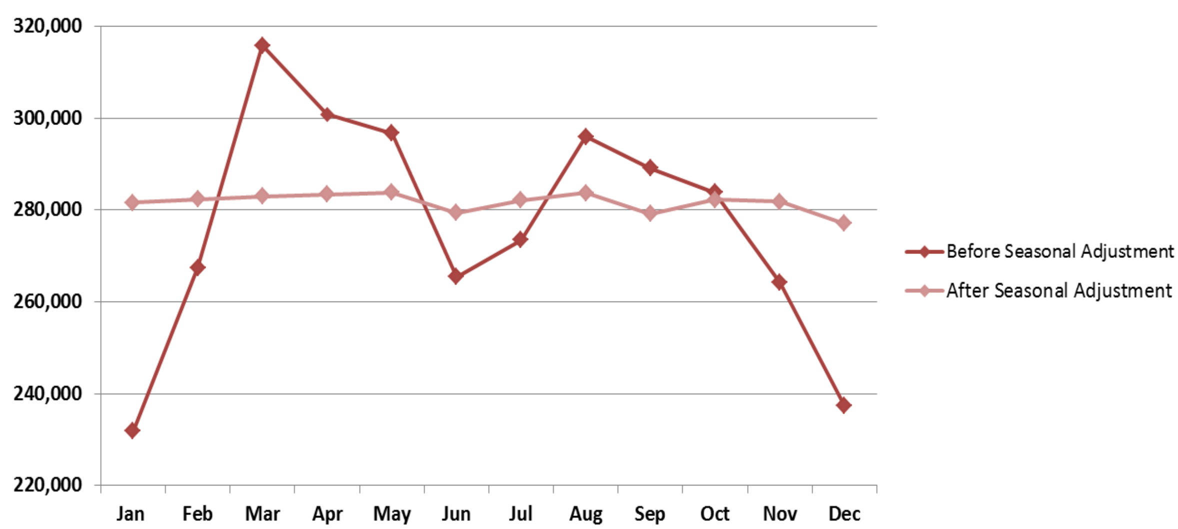


Figure 4: Average ridership by month of year before and after seasonal decomposition



6. Ridership Analysis

6.1. Effects of rain on daily bus ridership

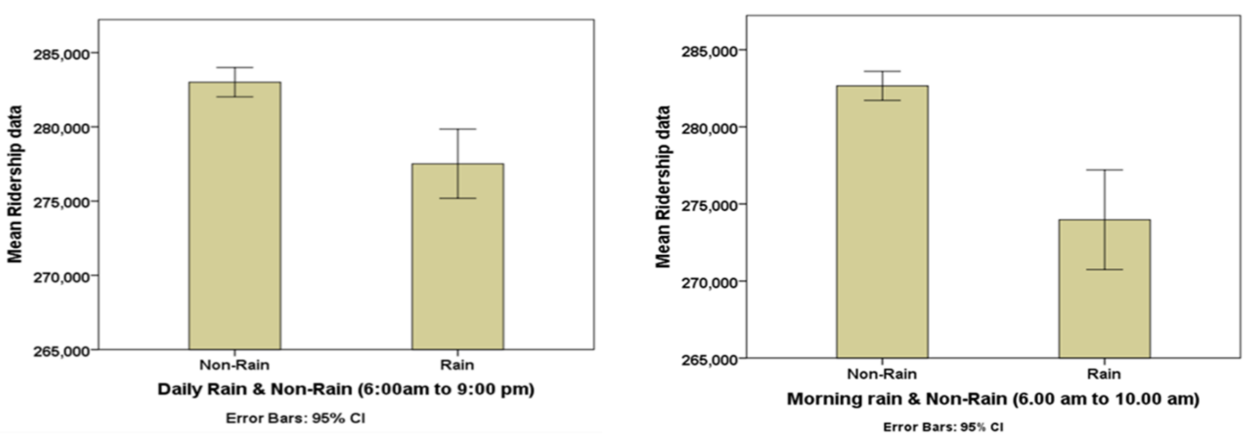
Commuting trips to work or school compose the majority of all trips. Since most commuting trips are made in the morning, it is a reasonable assumption that the mode choice is highly affected by the rainfall during the morning peak-hours. This study examines the ridership volume with respect to the rainfall in two analysis periods: morning peak-hours (from 6:00 am to 10:00 am) and whole day (from 6:00 am to 9:00 pm). To portray an accurate image of wet weather impact on bus ridership, the rainy day is defined when study area receives at least 1 mm of rainfall during the analysis period. Similarly, the non-rainy day is defined when the study area receives less than 1 mm of rainfall.

The analysis excludes public holidays and school holidays when ridership is heavily influenced by random events and vacation activities. This paper also excludes the major Brisbane flood event of 2011. The average weekday bus ridership during the school holidays was found 5.8% lower than the average ridership in regular weekdays. Additionally, the ridership in weekends is separately analysed from weekdays. Weekend bus ridership is relatively lower than weekdays and the dominant types of trip are non-commuting such as recreational and shopping. Table 5 shows the analysis result comparing the seasonally adjusted ridership values in rainy days and non-rainy days.

Table 5: Average daily ridership in rainy days and non-rainy day

Period of rain	Year	Rainy days	Ridership mean		Ridership change	t-test Significance
			No-Rain	Rain		
Whole day rain (6.00 am to 9.00 pm)	2010 2011 2012	67 45 53	283,357	276,056	- 2.58%	0.00 (Sig)
Morning rain (6.00am to 10.00 am)	2010 2011 2012	34 25 31	282,695	272,720	- 3.50%	0.00 (Sig)

Figure 5: Impact of whole day rain and morning peak hour's rain on daily ridership



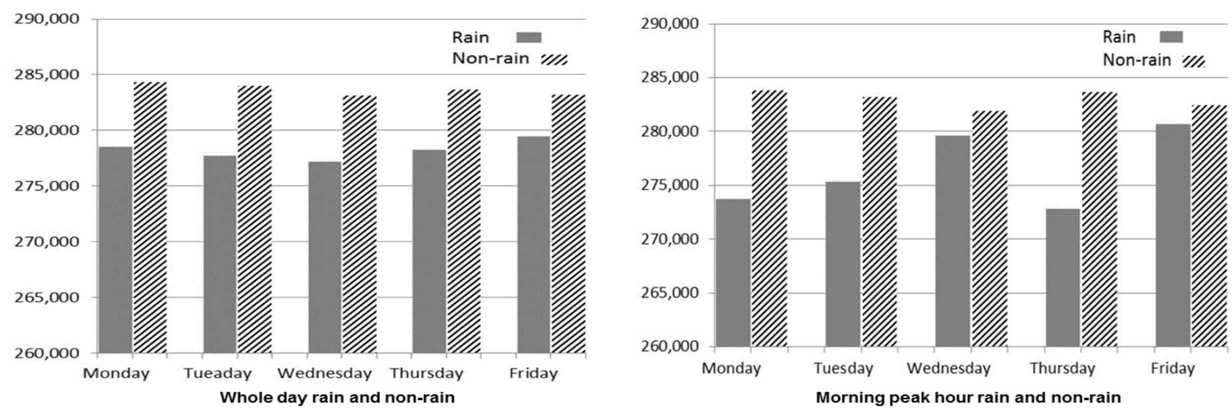
It is observed from the analysis results that rain has a clear impact on Brisbane's daily bus ridership. The occurrence of whole day rainfall and morning rainfall resulted in 2.58% and

3.50% reduction in the bus ridership, respectively. This result indicates that rain in the morning has a greater influence on people's mode choice and thus the transit ridership. Apparently, this is because commuters tend to choose their transport mode in the morning period. An independent t-test was conducted to determine whether the mean differences between two groups are statistically significant. The variance of mean in rain and non-rain day ridership for the whole day is 5,495 ± 1,200 and for morning is 8,679 ± 1,828. Both of the mean differences are statistically significant with 95% confidence interval. Likewise, the ridership pattern in rainy days fluctuates more compared with non-rainy days within each group, as shown in figure 5.

6.2. Effect of rain on ridership by day of week

It is conceivable that the degree of rain effects may vary by different days of the week. Figure 6 (a) and Figure 6 (b) compares the bus ridership by day of week in whole day and morning peak hour rain and non-rain conditions. The two graphs show significant and consistent ridership reductions in rainy days. Observed ridership reductions are more significant with the morning rain. The most significant reduction is 3.80% and 2.22% with the morning rain and the whole day rain, respectively.

Figure 6: Impact of whole day rain (a) and morning rain (b) on day of week ridership



For a statistical confirmation of the test significance, 10 individual independent t-tests (5 for daily rain/non-rain and 5 for morning rain/non-rain) were conducted. For both scenarios, the t-test results confirmed that the ridership changes are statistically significant. The reductions in ridership and the t-test significance levels vary substantially between the whole day rain and morning rain scenarios (See table 6). Consistent with the previous analysis results, rain in the morning had a greater effect on ridership than the whole day rain scenario. Similarly, the t-test significance level was also superior for morning rain. For example, Monday ridership decreased by 3.6% (with $p = 0.001 < 0.005$) for morning rain compared to 2.05% for daily rain (with $p = 0.031 < 0.05$).

Table 6: Effect of daily and morning rain on day of week's ridership and their significance

Day of week	Whole day rain (6:00 am to 9:00 pm)		Morning rain (6:00 am to 10:00 am)	
	Ridership change	t-test Significance	Ridership change	t-test Significance
Monday	-2.05%	0.031 (sig)	-3.6%	0.001 (sig)
Tuesday	-2.22%	0.037 (sig)	-2.8%	0.006 (sig)
Wednesday	-2.09%	0.044 (sig)	-0.8%	0.407 (non-sig)
Thursday	-1.90%	0.143 (non-sig)	-3.8%	0.006 (sig)
Friday	-1.30%	0.504 (non-sig)	-0.6%	0.504 (non-sig)

6.3. Effects of rain on Weekends

Coinciding with the previous studies, this analysis confirmed that variation in ridership due to rain is stronger on weekends rather than weekdays. Rainfall causes the passenger number to decrease by 4.3%, on weekends compared to 2.6% on weekdays. Higher number of discretionary and recreational passengers on weekends (Guo, 2007; Kalkstein, 2009), who are more likely to avoid public transport on rainy days are considered to be responsible for this outcome. While the difference looks substantial, it is statistically insignificant due to great difference in Saturday's and Sunday's ridership (32% less ridership on Sundays). Additionally, the effect of morning rain on weekend ridership was not analysed because of the greater number of occasional passengers on weekends.

When analysed separately, Saturday ridership was found to be more sensitive to rain than Sunday ridership. Rainfall resulted in an average decrease in ridership by 8.15% in Saturdays compared to 5.7% on Sundays. T-test verified both of these weekend values to be statistically significant with 95% confidence with $p = 0.000$. The result reflects that, if it rains on Saturdays, people may postpone their weekly shopping or other weekend activities, for Sundays. This forces people to make that trip on Sundays, even if it rains.

Table 7: Rain effect on weekend ridership

Day of week	Ridership change	t-test Significance
Weekend (Saturday & Sunday)	- 4.3%	0.10 (non-sig)
Saturday	- 8.2%	0.00 (sig)
Sunday	- 5.7%	0.00 (sig)

6.4. Effects of rain and non-rain condition by season

Since the precipitation amount changes through the year, it is expected that the effect of rain will have a different level of influence on ridership by season. The ridership analysis in the previous sections has shown the rain negatively affects the bus ridership. Then it is a conceivable assumption that the wet season associated with the summer months are expected to have ridership below the average. In order to test the ridership difference between wet and dry seasons, an independent sample t-test was conducted for each season. Table 8 shows that among all four seasons only the rain during the summer months has a significant effect on daily bus ridership with 95% confidence interval. Ridership reduces by 4.7% compared to non-rain situation in summer. Brisbane receives the highest amount of precipitation during the summer months along with above average temperature. Hence, combinations of these high precipitation and temperature may have resulted in uncomfortable conditions for transit use. Table 9 shows average rainfall and temperature by month in Brisbane.

Table 8: Impact of seasonal rainfall on ridership

Season	Mean ridership		Ridership Change	t- test Significance
	Rainy day	Non-rainy day		
Summer (Dec to Feb)	274,453	288,053	- 4.70%	0.00 (sig)
Autumn (Mar to May)	281,212	285,082	- 1.36%	0.20 (non-sig)
Winter (Jun to Aug)	275,020	283,157	- 2.87%	0.15 (non-sig)
Spring (Sep to Nov)	279,121	282,022	- 1.03%	0.06 (non-sig)

Table 9: Average rainfall (mm) and average temperature (ºC) in Brisbane by month (2010-2012)

Weather Variables	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Rainfall (mm)	233.1	197.2	143.2	95.2	55.6	46.3	30.5	60.5	42.6	148.5	63.4	221.0
Temperature (^{0}C)	29.8	30.2	28.4	26.7	23.7	21.2	21.5	22.6	25.1	25.9	27.9	27.7

The occurrence of rain results in a small decrease of passengers in autumn (1.36%) and spring (1.03%) and these are not statistically significant differences at the 95% confidence level. A popular assumption has been that rainfall reduces ridership in winter. Although, the passenger reduction in the winter months at 2.87% looks substantial coinciding with the assumption, this change is not statistically significant with 95% confidence. Again, this result may be explained with the relatively low amount of precipitation in the Brisbane region during winter. The effect of precipitation amount of bus ridership is discussed in the next section.

6.5. Effects of the precipitation amount on bus ridership

This study develops two linear regression models to correlate the two continuous variables; amount of rain and daily bus ridership. One model uses the whole day rainfall while the other model uses only the morning peak-hours rainfall. The daily bus ridership data used in these models are seasonally adjusted. These two models are used to estimate daily bus ridership given the value of rainfall amount. Figure 7 shows the association between daily ridership and volume of daily rainfall, with a best-fit regression line. Visible inspection illustrates that most of the rain amount skewed to the left side of the graph. This pattern does not generally yield a strong correlation between variables.

Table 10: Results of Linear Regression - daily average ridership vs. whole day rain amount in mm

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.246	.060	.051	11544.149

Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	Constant (Ridership)	279558.612	1399.027		199.824	.000
	Rain_Amount	-169.721	66.917	-.246	-2.536	.013

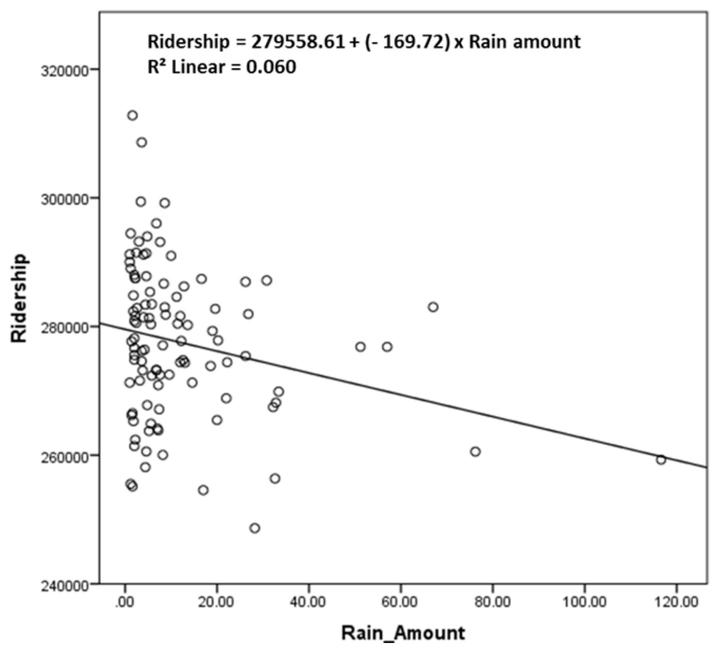
ANOVA[a]

Model		Sum of Squares	df	Mean Square	Sig.
1	Regression	857277800.4	1	857277800.4	.013[b]
	Residual	13326737387	100	133267373.9	
	Total	14184015188	101		

a. Dependent Variable: Ridership

b. Predictors: (Constant), Rain_Amount

Figure 7: Scatter plot – daily average ridership vs. whole day rain amount in mm



The regression analysis found a negative relation between two variables meaning that if the amount of rainfall increases, daily bus ridership decreases. However, this correlation is not strong with the goodness of fit (R^2) value at 0.06. This result can be interpreted as that only 6% of the variability of daily ridership is explained by the independent variable rain amount, although the coefficient table (Table 10) informs that the regression model result is statistically significant ($p=0.013<0.005$) with 95% confidence.

The association involving rainfall amounts in the morning found a much stronger correlation with the daily passenger numbers than the previous result. The following scatter plot (Figure 8) shows that the rainfall in the morning period follows a downward straight-line trend and accordingly, the regression analysis produces a negative relation between the two variables. The value of goodness of fit (R^2) is 0.183 meaning that 18.3% of the variability of daily ridership is explained by the regression model. The R^2 value of morning rain is relatively stronger than that of whole day rain. The coefficient table (Table 11) informs the regression model result is statistically significant with 95% confidence.

The results of the two regression analyses suggest that the bus ridership is more sensitive to the rainfall amount during the morning peak-hours. This is apparently because the majority of travellers (who have multiple mode options) choose their travel mode in the morning period and therefore, even a small amount of rain may convince them to change their travel mode or to postpone their journey all together.

Table 11: Results of Linear Regression - daily average ridership vs. morning rain amount in mm

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.427	.183	.160	9,010.386

Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	Constant (Ridership)	278,678.96	2209.662		126.12	.000
	Rain_amount	-969.455	341.863	-.427	-2.836	.007

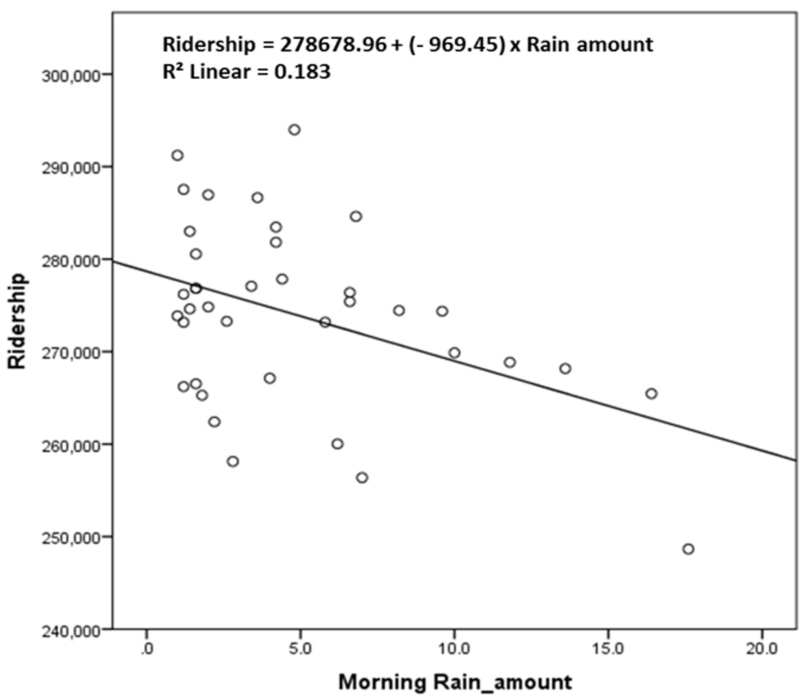
ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	652885355.7	1	652885355.7	8.042	.007[b]
	Residual	2922734227	36	81187061.86		
	Total	3575619583	37			

a. Dependent Variable: Ridership

b. Predictors: (Constant), Rain_Amount

Figure 8: Scatter plot – daily average ridership vs. morning rain amount in mm



7. Conclusion

This paper examined the influence of rainfall on the daily bus ridership using Brisbane as a case study. Daily bus passenger data from all bus stops in the Brisbane City Council area, and hourly rainfall data, provided a robust dataset to this study. Since Brisbane is increasingly turning to bus transit, particularly busway network, this analysis focuses on bus users only among other transit modes.

Bus ridership was found more sensitive to rainfall during the morning-peak hours. The passenger amount decreased by 4.3% due to morning rain, compare with 2.6% whole day rain. The analysis explored a strong negative relationship between morning peak hour's rain amount and daily passenger numbers. In other words, a small amount of morning precipitation has notable effect on entire day's ridership. This implies that most of the regular travellers make their travel decision in the morning. Thus, morning period rain has greater effect on passengers regular travel pattern and they may shift their travel mode or postpone their travel entirely. The analysis also confirmed that the effect of rain on weekends ridership is more prominent than weekdays, mostly due to the more optional and recreational trips on weekends, and this result is consistent with the previous studies (Guo et al., 2007; Kalkstein et al., 2005). In the study of the seasonal variation, it was observed that only summer rain has significant effect on travellers. The findings of this research suggest that in general, rainfall decreases ridership and the degree of impacts vary by different time of day, day of week and season.

However, it is essential to address the limitations of this study. The rain data was collected from only one site, whereas the precipitation may vary across the region. Likewise, the findings may not be readily applicable to locations with different climate and weather pattern. Moreover, the study concentrated only on one weather factor (precipitation) and combination of multiple factors may affect the ridership differently. Hence, analysing the weather-transit relationship concerning the combined effect of various weather variables (i.e. temperature, humidity, and wind speed) can be a future scope for research. Another interesting research scope may be analysing the effect of consecutive rainy days (if it rains at least or more than three days) on ridership because, the occurrence of extreme weather conditions has increased recently in this region, with more frequent heavier rains for a longer period.

Several concepts can relate the findings of this study to a more practical approach. For instance, transit facilities may be improved through re-construction or re-design of bus shelters and access infrastructure, which are more comfortable and protected during rainy days. The initial findings of this study suggest that before making any strategies or decision regarding weather- ridership association, transit authorities, policy makers and transport planners need to consider day-of-week, period of day, and seasons. Otherwise, the policy may prove to be ineffective or produce undesired outcomes.

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