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The association of rainfall and other weather variables with road traffic volume in Melbourne, Australia

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Abstract

An investigation into the effect of weather variables on traffic flow at a site in Melbourne, Australia, for the period 1989–1996 was performed. Rainfall was the strongest correlated weather parameter and it had the greatest impact in winter and spring, when traffic volume is reduced on wet days. There are statistically significant decreases of 1.35 and 2.11% in traffic volume on wet days in winter and spring. The reduction increases to 2–3% over the 2–10 mm range, the largest being 3.43% for the 2–5 mm class in spring.

For the first time, our study considers separately daytime and nighttime periods. We found a reduction of 1.86% in winter and 2.16% in spring during daytime rainfall. The reduction at nighttime is significant over all seasons, ranging from 0.87% in winter to 2.91% in spring.

We have explored an application where the traffic volume was used to normalise the road accident count and found the rain effect to increase by 2.4, 1.9 and 5.2% relative to the daily, daytime and nighttime dry mean accident count. Generally, the normalised count is greater than the raw count, with a larger increase for the higher rainfall classes.

Keywords: Road traffic; Rainfall; Weather; Road accidents

1. Introduction

There is an appreciation that inclement weather is associated with more hazardous driving conditions. Various studies show that precipitation in the form of rainfall and snowfall generally results in more accidents (Codling, 1974; Satterthwaite, 1976; Sherretz and Farhar, 1978; Brodsky and Hakkert, 1988; Fridstrøm et al., 1995; Levine et al., 1995; Edwards, 1999; Eisenberg, 2004). Furthermore, there is some evidence that wet or snowy weather, particularly if coupled with severe storms, can deter motorists from venturing onto the road, i.e. there is a reduction in traffic volume (Knapp and Smithson, 2000). This avoidance of the prevailing weather may be due to a self-assessment by the road user or based on road weather information systems that convey road weather alerts via the media or telephone services (Khattak and DePalma, 1997; Hansen et al., 2001).

In order to assess the risk of an accident in wet conditions, one would ideally like to know the exposure of a given vehicle to other traffic during these conditions compared with dry periods. The most useful measure of this is traffic volume, which tends to be recorded as 'snapshots' on major roads in urban areas or more continuously only at a small number of locations. Hence, in many studies where volume is not available, techniques such as the matched-pair method (Codling, 1974; Changnon, 1996; Andrey et al., 2003) are used to control for differences in traffic volume during wet and dry periods. Gasoline sales are sometimes used as a proxy for traffic volume (Fridstrøm et al., 1995).

Therefore, we have the situation where the risk of an accident in wet or snowy conditions is dependent on the traffic volume, which *itself* is dependent on those same conditions. However, there are few references on the effect of rainfall and other weather variables on volume (Codling, 1974; Changnon, 1996; Hassan and Barker, 1999). In this study, we will establish the associations between rainfall and traffic volume since it is of interest in its own right as well as for accident research. The relationships between traffic volume and other weather variables will also be explored. We will also present a short application where the traffic volume is used to normalise the accident count, which is then analysed for rainfall effects.

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The study pertains to the city of Melbourne, Australia and its metropolitan area, with a population of 3.5 million (June 2002) and covering an area of 8800 km^2. The city is located at 37.8°S, 145.0°E on Port Phillip Bay and enjoys a temperate climate with mild winters (the average July maximum temperature is 13.4 °C) and moderately hot summers (the average January maximum is 25.8 °C). We use traffic volume data for the period 1989–1996. A preliminary investigation revealed that standard linear regression was an appropriate method of analysis. Levine et al. (1995) also found this to be true for their analysis of daily road accidents in Honolulu.

In Section 2, we describe the data available for this study, followed by an outline of the method of analysis in Section 3. The main results and an application are presented in Section 4, and these are discussed in Section 5. Finally, our main conclusions are given in Section 6.

2. Data

This study is based on data of traffic volume, weather variables, holiday information and accident counts. Ideally, we would like information on the traffic volume over the Melbourne metropolitan area (MMA) for each day of our study period 1989–1996. However, the only data available are intermittent counts of the volume on a small number of major roads. VicRoads, a state government authority responsible for managing Victoria's major road network, recorded the volume used in this study at two sites: one on the Southeastern Freeway (now renamed as the Monash Freeway) (VSE), and the other on the Westgate Freeway (VWG). The former is a major southeastern arterial road, the latter is the major link to the western side of the city. The data were provided as 1-h volume counts for each direction of travel. These sites had the best overall coverage over time but the data are not sampled uniformly, often only as 'snapshots'. Thus, we have an uneven spread of data over the period 1989–1996. Owing to the high correlation between the two volume datasets (a correlation coefficient of 0.96 for the daily series), it was decided to exploit this and augment the VSE dataset using the VWG data. The best technique was to fit a regression model incorporating a linear time trend, day of the week (DOW) effects and holidays to each of the two datasets to get two residual series RVSE and RVWG. The series RVSE was regressed on RVWG:

$$\mathrm{RVSE} = a_0 + a_1\,\mathrm{RVWG} \qquad (1)$$

to get a series of fitted values $\widehat{\mathrm{RVSE}}$. This series was then considered to be a pseudo-residual series from the model for VSE. Using $\widehat{\mathrm{RVSE}}$ at times in VWG that were *not* present in VSE, the regression model for VSE then gave pseudo-observations in VSE at these times. There were 360 points in VWG that were not present in VSE, increasing the number of volume points in VSE from 542 to 802. This final series is called the *augmented* volume series (VSEA) and is shown in Fig. 1(a). In particular, augmentation improved the coverage over 1993. For the traffic volume period, there are 802 days in all with 171 days in summer, 208 days in autumn, 264 days in winter and 159 days in spring.

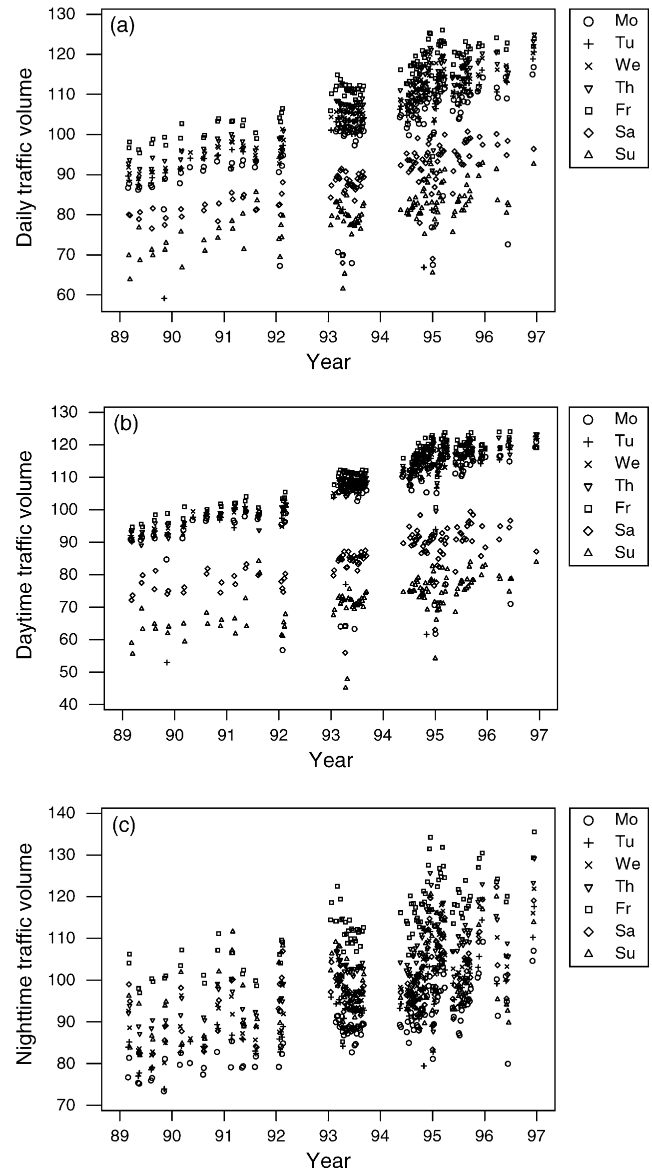

Fig. 1. Traffic volume at the Southeastern Freeway recording site. Each series is normalised to a mean of 100. Data over 1993 is infilled using the Westgate Freeway traffic volume. The series are: (a) daily traffic volume, (b) daytime traffic volume, and (c) nighttime traffic volume.

Since we do not know the total number of vehicles on the road in the MMA on a given day, we will normalise VSEA to have a mean daily volume of 100. In our volume regression models, this means that many effects (coefficients) are expressed as percentage changes relative to the mean of the VSEA series.

At a late stage in the study, some additional volume data at the two sites for the period 1997–2003 were made available. However, there are major changes to the freeway system that occurred over this period, especially in April 2000 with the opening of City Link, which includes a freeway–tunnel connection between the Westgate and Monash Freeways. An initial analysis suggested that the character of the two volume series might have changed. Amundsen and Elvik (2004) investigated the effects of road safety of new urban arterial roads in Oslo and found that such projects can lead to induced traffic (in their case 16%). Since we desire VSEA to represent the traffic patterns (and trend) of the MMA, we will not use the extra data in this study.

The weather variables recorded at the central Melbourne weather station were obtained from the Australian Bureau of Meteorology and comprise rainfall, cloud amount, maximum and minimum temperature, surface pressure and wind speed. Most of the weather variables are daily. Many studies use daily rainfall that in Australia is recorded at 9:00 a.m. for the previous 24 h. Our data includes 3-h rainfall totals and thus we can construct 24 h, daytime and nighttime rainfall totals to match our volume data.

Much of the school and public holiday information was obtained from the Department of Education, Employment and Training (Catherine Herrick, personal communication).

The database of road traffic accidents for the MMA was provided to us by VicRoads. It consists of individual accident events with information such as the number of vehicles involved in the accident, the date and time of the accident, the severity of the accident, weather condition (e.g. rain or clear), road condition (e.g. wet road), and light condition (e.g. daylight). The database is restricted to accidents that involved some sort of injury that required medical attention, i.e. it does *not* cover damage-only accidents. The severity data is categorised as fatal, serious and other injury. In this study, we will mainly look at all categories of severity combined together, i.e. our ‘accident count’ is the number of accidents per day involving injury. The database covers the period 1 January 1987 to 31 December 1996 (10 years or 3653 days). However, in this study, we will only consider the period that corresponds to the 802 days of traffic volume spread over 1989–1996.

3. Methods

In order to quantify the effects of rainfall and other weather variables on the traffic volume, we design regression models incorporating terms to represent the trend, day of the week variation, holidays and weather effects. Some initial investigations showed that standard regression analysis was appropriate since the model residuals appeared to be approximately normally distributed. See Myers (1986) and Chatterjee et al. (2000) for a discussion of regression analysis and Levine et al. (1995) for an application to daily traffic accidents in Honolulu. For our purposes, a typical model form for a daily volume series is:

$$V = a_0 + a_1 t + d_1\,\mathrm{Mo} + d_2\,\mathrm{Tu} + d_3\,\mathrm{We} + d_4\,\mathrm{Th} + d_5\,\mathrm{Fr} + d_6\,\mathrm{Sa} + s_1 S + p_1 P + x_1 X + b_1 W_1 + b_2 W_2 + \cdots \quad (2)$$

where V is volume, t is a daily time index (t = 1 is 1 January 1987), Mo–Sa are day of the week *dummy* (or indicator) variables, S and P are dummy variables for school and public holidays, X is a dummy variable for the Christmas ‘shutdown’ period and W_1, W_2, . . . are weather variables (dummy or quantitative), e.g. rainfall. See Hardy (1993) for a treatment of dummy variables in a regression context.

The dummy variable ‘Mo’ is equal to 1 if the day is a Monday and 0 otherwise. The variables ‘Tu–Sa’ are defined in the same way. There is no Sunday variable because of the linear constraint imposed on the seventh day of the week variable, i.e. if there was a variable called ‘Su’ it would consist only of zeros—the *reference* class. In this sense, the constant term a_0 contains the Sunday effect. Hence, for example, the coefficient d_1 represent the difference of the Monday and Sunday means.

The same applies to any set of dummy variables representing some effect that falls into categories or *classes*. We will be using a wet versus dry day effect to compare wet days with dry days. If we introduce a dummy variable W_1 to be equal to 1 on wet days and 0 on dry days, the coefficient b_1 will be the difference of the mean of wet days and the mean of dry days. Of course, when we have a multiple regression model as given above, b_1 is the effect of wet days allowing for the effect of the other variables (or more precisely, given the other variables are held at fixed levels). We will also make use of rain classes, an extension of the wet versus dry effect, where we take our reference class to be 0 mm and have dummy variables for each of our chosen classes: 0–1, 1–2, 2–5, 5–10, 10–20 and >20 mm, e.g. the coefficient of the class 2–5 mm represents the difference in the mean of this class from the mean of the reference (dry) class. We also used stepwise regression (Myers, 1986) to fit the set of 3-h rainfall variables, i.e. the rainfall for 00:00–03:00, 03:00–06:00, . . ., 21:00–24:00 local time, to the volume series otherwise correlations between the separate 3-h variables can lead to misleading coefficients. The constant term will not usually be listed since our interpretation is mainly concerned with *differences* from the reference class (Sunday, dry days). Owing to our normalisation of the volume series (mean of 100), the coefficients for dummy variables may be interpreted as *percentage* changes relative to the mean daily volume. For instance, a wet versus dry day effect of −2.0 corresponds to a decrease in volume by 2% of the mean daily volume on wet days.

In our initial exploratory models, we used a complex representation of public and school holidays. For instance, we had dummy variables for Australia Day and the school holidays after Term 1. A simpler description was made using the variable P (S) with 1 if the day was a public (school) holiday and 0 otherwise. It was found that there was only a small difference between the complex and simple cases, so we will use the simple representation in this study. The variable X is set to 1 if the day falls in the Christmas period and 0 otherwise.

Generally, we will design a *baseline* model that has trend, day of the week and holiday effects. Next, we present models incorporating the rainfall effects. In some of our earlier investigations, we looked at other weather variables and these will be tabulated as well. The percentage of variance accounted or 'explained' by the model (R^2) and the residual standard deviation (s) are tabulated. Either is useful to gauge the overall 'fit' of the model and to observe any improvement to the fit when rainfall and other weather variables are added to the baseline model. The difference in R^2 between a given model and the baseline model may be taken as a *reasonable* indication of the contribution of the additional variables. For instance, the baseline model might have an R^2 value of 50% and a model including rainfall improves R^2 to 65%. Thus, rainfall explains about 15% of the variance of the model. Strictly, this is not correct because adding rainfall will affect the other coefficients but tests indicate that the change is typically small. Model coefficients are deemed significant if they differ from zero at the 5% level. Depending on the context, coefficients that are not significant will be either omitted or printed in italics in tables. The case of no data is denoted by n.d. Sometimes a p-value will be noted if the result is nearly significant. Also, if a result is obtained from a small number of observations or cases then this will be noted.

We will consider the three volume series—daily, daytime and nighttime—separately. In this study, *day* (or daily) will refer to a 24-h day while *daytime* and *nighttime* will refer to the 12-h periods, 6:00 a.m.–6:00 p.m. and 12:00–6:00 a.m., 6:00–12:00 p.m. These periods are regarded as the times of nominal daylight and darkness, respectively. This temporal division has been performed as it could be argued that the nature of the volume–weather relationship would change with time of day. For example, nighttime driving is more likely to be discretionary and more closely linked to weather conditions. We will design models for all days and the four seasons—summer (December–February), autumn (March–May), winter (June–August) and spring (September–November). For the traffic volume period, there are 802 days with 171 days in summer, 208 days in autumn, 264 days in winter and 159 days in spring.

Finally, we present an application highlighting the effect of rainfall on road accidents in regression models that include the rain-affected traffic volume. These models are similar to those given by Eq. (2) for traffic volume except the non-linear trend and day of the week variation are estimated by singular spectrum analysis (SSA) (Ghil et al., 2002), a technique related to principal component analysis. SSA is useful for extracting important modes of variability in a time series such as a non-linear trend or a periodic signal with an amplitude modulation, i.e. a time-varying envelope. In the application, we compare the accident count with the volume normalised count (VNC) defined as:

$$\mathrm{VNC} = \frac{C}{V} \tag{3}$$

where C is the accident count and V is the traffic volume normalised to mean of unity rather than 100 as in most of the analysis. Normalising V in this way gives VNC in comparable units to C. In this application, we define the *rain effect* to be the number of additional accidents on a wet day expressed as a percentage of the dry day mean. The 'number' is given by the wet versus dry effect when comparing wet and dry days or the rain class effect when comparing the amount of rain on a wet day and dry days. These effects are regression coefficients estimated in a model that includes trend, DOW variation, school and public holidays and the Christmas period. For the wet versus dry effect, if there are no other terms in the model then this is simply the difference between the wet day and dry day means.

4. Analysis and results

In Section 4.1, we present the general features of the traffic volume series. In Sections 4.2–4.4, we consider the daily, daytime and nighttime volume model cases. Finally, in Section 4.5, we give an application of the effect of rain on accidents where the volume is included in the model.

4.1. General features of the traffic volume series

We first consider the general features of the three traffic volume series. The most obvious feature of the daily series in Fig. 1(a) is that there are two bands, the upper one being for most weekday volumes (Monday–Friday) and the lower one containing the weekend volumes (Saturday and Sunday). Furthermore, Friday tends to have the highest volume and Sunday the lowest with a linear increase from Sunday to Friday. Public holidays tend to be similar to Sundays. The volume series displays a distinct upward trend. Fig. 2(a) shows the mean traffic volume versus DOW showing the features described earlier. The increase from Monday to Friday is 12%. There is a decrease of 23% of the mean daily volume from Friday to Saturday and a further 9% to Sunday. We will also be considering the 12-h volumes for daytime and nighttime defined earlier. In our analyses, we will also *individually* normalise the series to a mean of 100. This has been done in Fig. 2 but for display purposes, we have assigned a mean of 70.7 to the daytime series and 29.3 to the nighttime series so the three cases may be displayed in their true relativity (the actual means in number of vehicles per day, daytime and nighttime are 95,888, 67,757 and 28,104, respectively).

The procedure of augmentation was carried out for the daytime and nighttime cases with the expanded volume data shown in Fig. 1(b) and (c). Both series also show an increasing trend over the study period. Like the daily case in Fig. 1(a), the daytime volume has two major bands, the upper corresponding to Monday–Friday, the lower to Saturday and Sunday. However, the upper band is much tighter than the daily case and the lower band is split into a Saturday (higher) and Sunday part (lower). Fig. 2(a) shows the increase from Monday to Friday is 7%, with a fall of 26% to Saturday and another 13% to Sunday. The upper band is strongly influenced by the weekday work pattern. The nighttime volume shown in Fig. 1(c) is quite different to the other two cases. It has a less

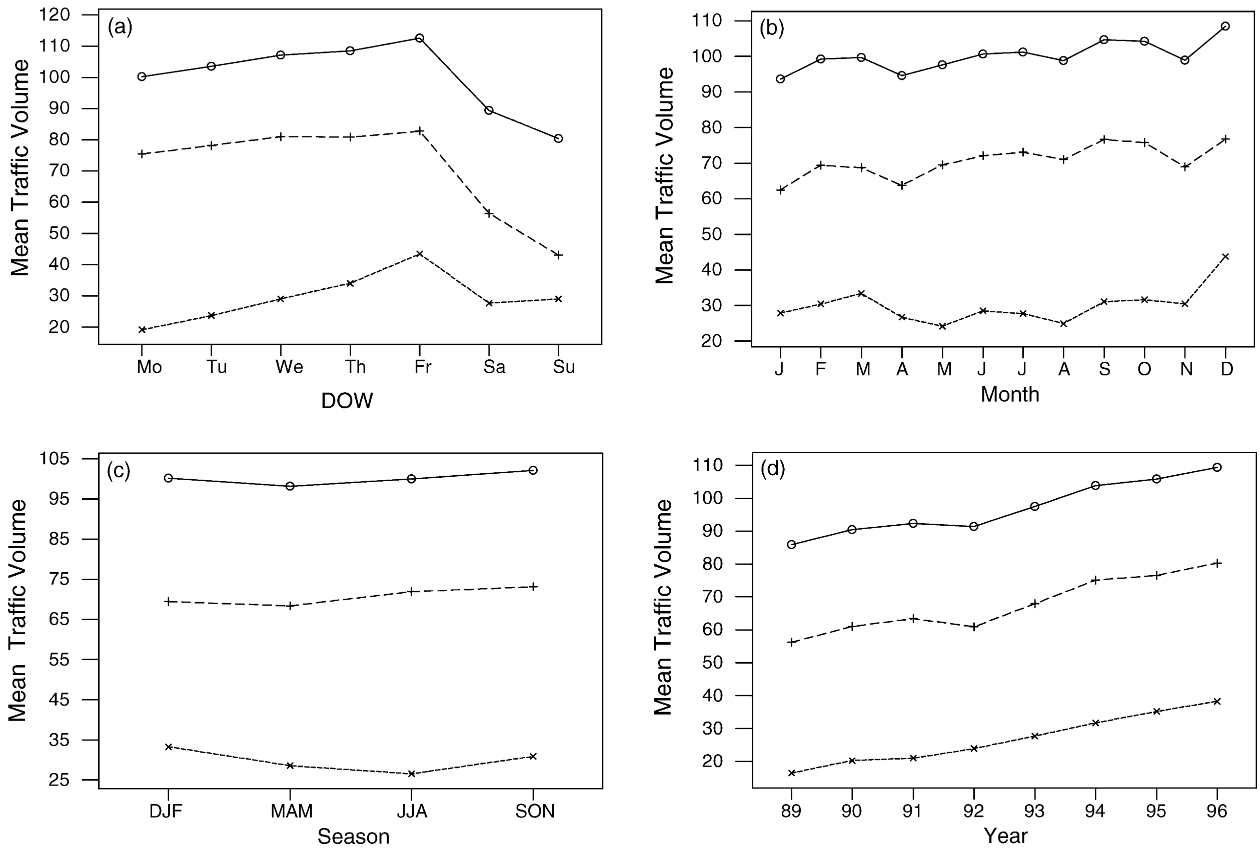

Fig. 2. Mean daily traffic volume profiles by: (a) day of the week, (b) month, (c) season, and (d) year. For this figure, the daily series (circles) is normalised to 100, the daytime series (pluses) to 70.7 and the nighttime series (crosses) to 29.3 in order to show their mutual relationship.

obvious differentiation between days of the week. Despite the lower volume level at night, Fig. 2(a) shows a linear increase of 24% from Monday to Friday, followed by a decrease of 16% to Saturday and Sunday. Daytime and nighttime volumes are about 70 and 30% of the daily volume.

It is of interest to observe the monthly, seasonal and annual behaviour of these volume series. For each timescale, we show the mean daily, daytime and nighttime volume. Fig. 2(b) shows the mean monthly pattern over the year for the daily, daytime and nighttime series. The variation is quite modest at about 11% for the daily and daytime series, which behave similarly, with a slight upward trend over the 12 months to a maximum in December. The nighttime series has a smaller variation of 8%, with a weak annual cycle (minimum in August and maximum in December). Fig. 2(c) shows the seasonal variation of the three volume series. The daily series has slightly lower values in autumn and winter compared with spring and summer. The daytime series shows a slight fall from summer to autumn and a small rise through winter to spring. The nighttime series has a slight fall from summer to winter and a small rise to spring, i.e. the weak annual cycle described earlier. Finally, we consider the annual mean daily, daytime and nighttime volumes shown in Fig. 2(d). All three series show an increase over the study period of 24, 24 and 22%, respectively. There is a slight dip around 1992 due to reduced data coverage in that year.

4.2. *Daily traffic volume models*

Table 1 gives the baseline models for the daily volume series for all days and also for the four seasons. For all days, we see that this model incorporating trend, day of the week and holidays explains a high fraction of the variance of the series (94.3%). There is an upward trend of 0.010% per day or 3.6% per annum. The mean volume on Friday is 32% (of the mean daily volume) higher than the mean volume on Sunday (reference class). There is an increase of 10.9% from Monday to Friday with a decrease of 22.8% from Friday to Saturday. School holidays show a reduction in volume of 3.4% (of the mean daily volume) compared with school days. Public holidays show a large reduction in volume of 28.7% (of the mean daily volume) compared with non-public holidays while the Christmas ‘shutdown’ period experiences volumes that are down by 19.1% (of the mean daily volume) compared with other days. For brevity, we will omit ‘of the mean daily volume’ in future discussions. The seasons display a similar profile to the all-days case. The percentage of variance explained is about 95% in summer and autumn, increasing to 97% in winter and falling to 94% in spring. The decrease from Friday to Saturday is about 23, 22, 22 and 25% for summer, autumn, winter and spring, respectively.

The effect of single rainfall variables is shown in Table 2. For the all-days case on wet days, the volume is decreased

Table 1
Baseline models for daily traffic volume[a]

	Season				
	All	DJF	MAM	JJA	SON
Trend	0.010	0.011	0.010	0.009	0.010
Monday	21.1	20.5	20.4	22.0	22.1
Tuesday	23.8	23.7	22.6	24.7	23.8
Wednesday	26.1	25.5	25.3	26.9	26.9
Thursday	27.8	26.7	26.5	28.4	30.2
Friday	32.0	31.4	30.5	32.7	33.6
Saturday	9.2	8.4	8.8	10.3	8.7
School holidays	−3.4	−5.0	−3.3	−2.3	−2.9
Public holidays	−28.7	−34.3	−25.8	−35.5	−26.1
Christmas period	−19.1	−20.8			
Residual standard deviation	3.32	3.42	3.30	2.42	3.57
Variance explained (R^2, %)	94.3	94.9	94.8	96.6	93.9

[a] Coefficients are deemed significant at the 5% level. Depending on the context, coefficients that are not significant will be either omitted or printed in italics in tables. The case of no data is denoted by n.d.

by 1.29% compared with dry days. Using 24-h rainfall, we see that the volume decreases by 0.08% per mm of rainfall. Fig. 3(a) shows the residuals from the baseline model versus 24-h rainfall. The regression line has a slope that approximates the wet versus dry coefficient when this variable is added to the baseline model. The R^2 values are only 0.1–0.3% higher than the baseline model. For the seasons, there is a decrease in volume on wet days of about 1% in winter and 2% in spring. The decrease of 0.8% in summer and autumn is not significant (although the latter is significant at the 10% level). Similarly for 24-h rainfall, the volume decreases by 0.33% per mm in winter and 0.18% in spring (the latter has a p-value of 0.06). The volume decreases of 0.022 and 0.026 for summer and autumn are not significant.

Table 3 shows the combinations of 3-h rainfall variables that are significant in a stepwise regression. For the all-days case, we see that the rainfall for 12:00–15:00 local time is associated with a volume reduction of 0.57% per mm and the rainfall for 21:00–24:00 is associated with a volume reduction of 0.40% per mm—these effects depend on the presence of both variables in the model. This sort of model is not significant for the seasons except in winter where rainfall occurring at 12:00–15:00, 15:00–18:00 and 21:00–24:00 is associated with a decrease in the volume. The rainfall during 12:00–15:00 has the largest effect with a 0.73% decrease per mm of rainfall in this period.

The effect of rain classes is shown in Table 4 where the reference class is 0 mm, i.e. dry days. For the all-days case, there are volume reductions with the varying amount of 24-h rain. For the 0–1 mm class, there is a volume reduction of 0.85%, increasing to 2.33% for the 5–10 mm class. The effects for classes 10–20 and >20 mm are not significantly different from dry days. As in Table 3, the cases for summer and autumn are not significant. Like the all-days case, winter and spring show generally greater volume reductions for the wetter days. For winter, there are reductions of 0.73, 2.90 and 2.41% for the 0–1, 5–10 and 10–20 mm classes. For spring, there are larger effects of 3.43 and 2.78% for the 2–5 and

Table 2
Daily traffic volume models: Single rainfall variables[a]

	Season				
	All	DJF	MAM	JJA	SON
Wet vs. dry days	−1.29	*−0.77*	*−0.81*	−1.35	−2.11
Residual standard deviation	3.26			2.33	3.44
Variance explained (R^2, %)	94.6			96.8	94.4
24-h rainfall	−0.080	*−0.022*	*−0.026*	−0.33	*−0.18*
Residual standard deviation	3.31			2.31	
Variance explained (R^2, %)	94.4			96.9	

[a] Coefficients are deemed significant at the 5% level. Depending on the context, coefficients that are not significant will be either omitted or printed in italics in tables. The case of no data is denoted by n.d.

Table 3
Daily traffic volume models: multiple rainfall variables (3-h rainfall)[a]

Time period	Season				
	All	DJF	MAM	JJA	SON
00:00–03:00					
03:00–06:00					
06:00–09:00					
09:00–12:00					
12:00–15:00	−0.57			−0.73	
15:00–18:00				−0.36	
18:00–21:00					
21:00–24:00	−0.40			−0.53	
Residual standard deviation	3.28			2.31	
Variance explained (R^2, %)	94.5			96.9	

[a] Coefficients are deemed significant at the 5% level. Depending on the context, coefficients that are not significant will be either omitted or printed in italics in tables. The case of no data is denoted by n.d.

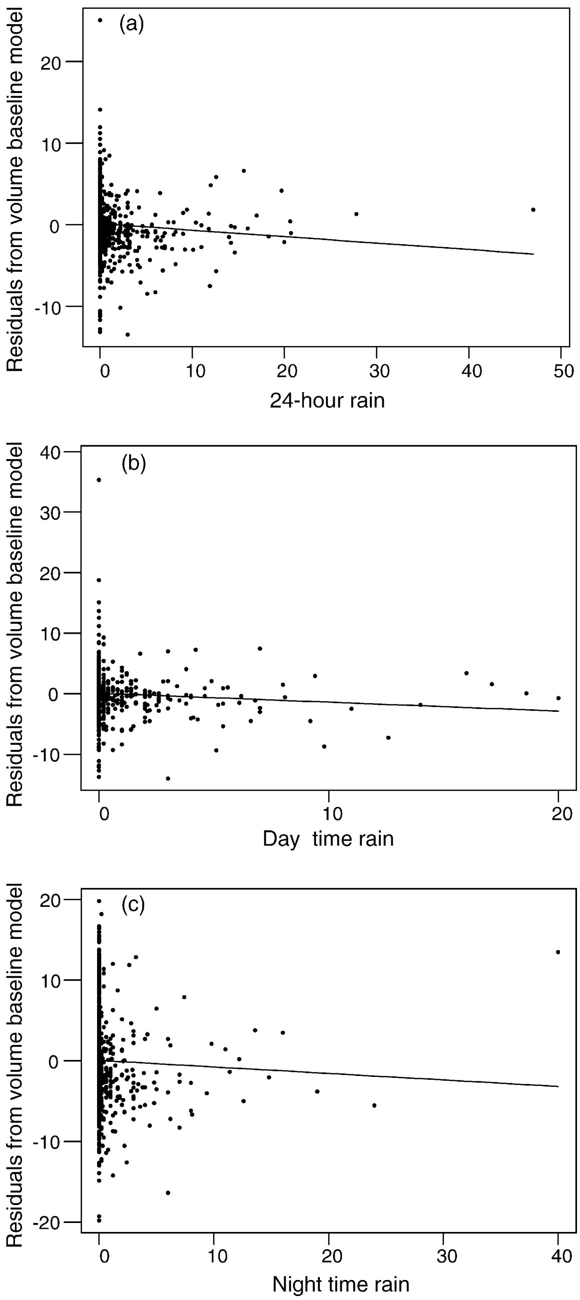

Fig. 3. Residuals from the baseline model regressed against: (a) 24-h rainfall, (b) daytime rainfall, and (c) nighttime rainfall. The slope of the line is approximately equal to the rainfall coefficient if the rainfall is added to the baseline model.

5–10 mm classes. The effect for the 1–2 mm class (−1.91%) has a *p*-value of 0.07.

Table 5 gives single variable regression models for other weather variables although our main focus is on rain-related variables. The impact of all of them, like rainfall, is small as seen by the R^2 values, however, they seem to have physically sensible signs. For the all-days case, there is a 0.28% decrease in volume as cloud amount increases (and presumably the occurrence of rain). The effect is larger for heavy cloud amount in the 6–8 oktas class with a reduction of 1.25% that

Table 4
Daily traffic volume models: multiple rainfall variables (rain classes)[a]

Rain class (mm)	Season				
	All	DJF	MAM	JJA	SON
0–1	−0.85			−0.73	*−1.21*
1–2	−1.04			−1.43	*−1.91*
2–5	−2.14			−1.77	−3.43
5–10	−2.33			−2.90	−2.78
10–20	*−0.86*			−2.41	*−1.22*
>20	*0.11*			n.d.	n.d.
Residual standard deviation	3.25			2.29	3.44
Variance explained (R^2, %)	94.6			97.0	94.6

[a] Coefficients are deemed significant at the 5% level. Depending on the context, coefficients that are not significant will be either omitted or printed in italics in tables. The case of no data is denoted by n.d.

is similar to the wet–dry case of 1.29% (Table 1). The coefficient of 0.038% for surface pressure anomaly (from long-term monthly mean pressure) indicates that a fall in pressure of 1 hPa results in a volume reduction of 0.038%. Higher average wind speed leads to a volume reduction. The coefficients for maximum temperature and maximum temperature anomaly (from long-term monthly mean) indicate that higher temperatures lead to volume increases of 0.12 and 0.08% per °C. The seasons show considerable variation in significant effects with summer having the least. We see that increasing cloud amount is associated with reduced volume, typically around 0.2% increasing to 0.3% in spring, with the effects for summer and autumn being significant at the 10% level. The effect of surface pressure (and anomaly) is present in winter and spring. Decreasing pressure associated with a volume reduction of 0.11% per hPa in spring.

Fig. 4(a) shows the residuals from the baseline model versus maximum temperature. The regression line has a slope that approximates the temperature coefficient (0.12% per °C) when this variable is added to the baseline model. This temperature effect on volume has some correspondence with the seasonal behaviour of the daily series in Fig. 2(c), with higher volumes in summer and autumn (higher temperatures) and lower volumes in winter and spring (lower temperatures). Minimum temperature has a similar effect to maximum temperature with a 0.12% per °C increase in volume.

4.3. *Daytime traffic volume models*

The daytime traffic volume refers to the time period 06:00–18:00, i.e. 6:00 a.m.–6:00 p.m., which we regard as the nominal daylight period. Owing to our normalisation of the daytime volume series (mean of 100) the coefficients for dummy variables may be interpreted as percentage changes relative to the mean daytime volume.

Table 6 gives the baseline models for the daytime volume series for all days and the four seasons, respectively. For all days, we see that the baseline model incorporating trend,

Table 5
Daily traffic volume models: other single variables[a]

	Season				
	All	DJF	MAM	JJA	SON
Cloud amount	−0.28	*−0.22*	*−0.24*	−0.23	−0.30
Residual standard deviation	3.29			2.28	3.53
Variance explained (R^2, %)	94.5			96.7	94.1
Heavy cloud amount (6–8 oktas)	−1.25			−1.25	
Residual standard deviation	3.29			2.40	
Variance explained (R^2, %)	94.5			96.6	
Surface pressure				0.055	0.11
Residual standard deviation				2.37	3.49
Variance explained (R^2, %)				96.7	94.2
Surface pressure anomaly	0.038			0.060	0.12
Residual standard deviation	3.31			2.36	3.49
Variance explained (R^2, %)	94.4			96.7	94.3
Average wind speed	−0.23			*−0.20*	
Residual standard deviation	3.31				
Variance explained (R^2, %)	94.4				
Maximum wind speed	*−0.14*				
Residual standard deviation					
Variance explained (R^2, %)					
Maximum temperature	0.12		0.16	0.17	
Residual standard deviation	3.24		3.19	2.37	
Variance explained (R^2, %)	94.6		95.2	96.7	
Maximum temperature anomaly	0.08			0.17	
Residual standard deviation	3.31			2.38	
Variance explained (R^2, %)	94.4			96.7	
Minimum temperature	0.12		0.16	*−0.10*	
Residual standard deviation	3.28		3.25		
Variance explained (R^2, %)	94.5		95.0		

[a] Coefficients are deemed significant at the 5% level. Depending on the context, coefficients that are not significant will be either omitted or printed in italics in tables. The case of no data is denoted by n.d.

Table 6
Baseline models for daytime traffic volume[a]

	Season				
	All	DJF	MAM	JJA	SON
Trend	0.010	0.011	0.010	0.010	0.011
Monday	34.1	35.4	33.6	33.5	35.4
Tuesday	35.9	37.9	35.2	35.4	35.7
Wednesday	37.2	38.5	36.2	36.8	38.5
Thursday	37.6	38.5	36.5	36.5	40.4
Friday	39.5	40.8	38.2	38.7	41.4
Saturday	13.5	13.1	13.2	14.1	13.2
School holidays	−3.4	−4.4	−3.0	−2.5	
Public holidays	−37.8	−43.6	−34.9	−44.5	−31.6
Christmas period	−20.4	−19.9			
Residual standard deviation	3.44	3.36	3.08	2.68	4.24
Variance explained (R^2, %)	96.1	96.8	97.2	97.2	94.5

[a] Coefficients are deemed significant at the 5% level. Depending on the context, coefficients that are not significant will be either omitted or printed in italics in tables. The case of no data is denoted by n.d.

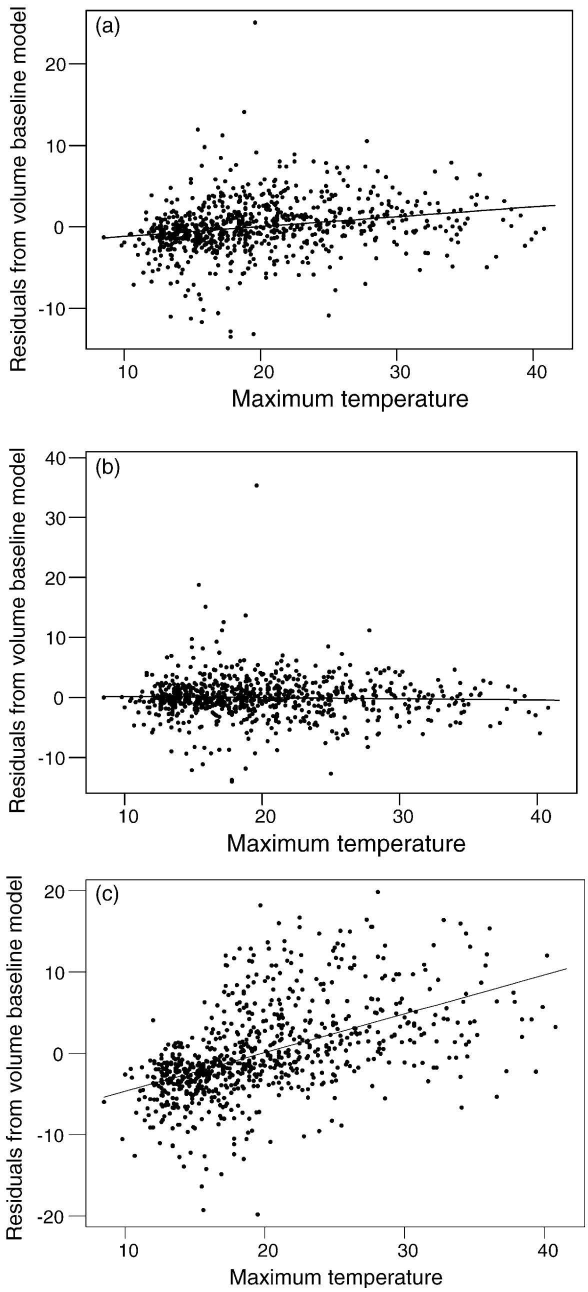

Fig. 4. Residuals from the baseline model regressed against maximum temperature for: (a) daily traffic volume, (b) daytime traffic volume, and (c) nighttime traffic volume. The slope of the line is approximately equal to the maximum temperature coefficient if the temperature is added to the baseline model.

day of the week and holidays explains a high fraction of the variance of the series (96.1%). There is an upward trend of 0.010% per day or 3.6% per annum as for the daily case. There is a smaller variation in volume over from Monday to Friday for daytime traffic compared with the daily case. Friday is about 5% higher than Monday with a 26% fall to Saturday that is 13% higher than Sunday (lowest volume of the week). School holidays are 3.4% lower than school days, public holidays show a 38% reduction and the Christmas period has volumes about 20% lower than normal. The seasons display a similar profile to the all-days case. The percentage of variance explained is about 97% in summer, autumn and winter, decreasing to 94.5% in spring. The decrease from Friday to Saturday is 28, 25, 25 and 28% for summer, autumn, winter and spring, respectively.

The effect of single rainfall variables is shown in Table 7. For the all-days case on wet days, the volume is decreased by 1.04% compared with dry days. Using daytime rainfall, we see that the volume decreases by 0.149% per mm of rainfall. Fig. 3(b) shows the residuals from the baseline model versus daytime rainfall. For the seasons, there is a decrease in volume on wet days of about 2% in winter and spring. The decreases of 0.54 and 0.14% in summer and autumn are not significant. Similarly for daytime rainfall, the volume decreases by 0.41% per mm in winter and 0.41% in spring (the latter has a p-value of 0.08). The volume decreases of 0.010 and 0.082 for winter and autumn are not significant.

The combinations of 3-h rainfall variables that are significant in a stepwise regression are given in Table 8. For the all-days case and autumn, we see that the rainfall for 12:00–15:00 local time is associated with a volume reduction of 0.50% per mm. This sort of model is not significant for summer and spring. In winter rainfall occurring at 12:00–15:00 and

Table 7
Daytime traffic volume models: single rainfall variables[a]

	Season				
	All	DJF	MAM	JJA	SON
Wet vs. dry days	−1.04	*−0.54*	*−0.14*	−1.86	−2.16
Residual standard deviation	3.41			2.54	4.14
Variance explained (R^2, %)	96.2			97.4	94.8
Daytime rainfall	−0.149	*−0.010*	*−0.082*	−0.41	*−0.41*
Residual standard deviation	3.43			2.60	
Variance explained (R^2, %)	96.1			97.4	

[a] Coefficients are deemed significant at the 5% level. Depending on the context, coefficients that are not significant will be either omitted or printed in italics in tables. The case of no data is denoted by n.d.

Table 8
Daytime traffic volume models: multiple rainfall variables (3-h rainfall)[a]

Time period	Season				
	All	DJF	MAM	JJA	SON
06:00–09:00					
09:00–12:00					
12:00–15:00	−0.50		−0.50	−0.70	
15:00–18:00				−0.45	
Residual standard deviation	3.42		3.06	2.60	
Variance explained (R^2, %)	96.2		97.2	97.4	

[a] Coefficients are deemed significant at the 5% level. Depending on the context, coefficients that are not significant will be either omitted or printed in italics in tables. The case of no data is denoted by n.d.

Table 9
Daytime traffic volume models: multiple rainfall variables (rain classes)[a]

Rain class (mm)	Season				
	All	DJF	MAM	JJA	SON
0–1	−0.95			−1.50	−2.58
1–2	*−0.82*			−1.72	*−0.83*
2–5	*−1.00*			−2.25	−3.63
5–10	−2.05			−3.91	*−1.62*
10–20	*−1.37*			*−2.26*	n.d.
>20	n.d.			n.d.	n.d.
Residual standard deviation	3.41			2.53	4.14
Variance explained (R^2, %)	96.2			97.6	94.9

[a] Coefficients are deemed significant at the 5% level. Depending on the context, coefficients that are not significant will be either omitted or printed in italics in tables. The case of no data is denoted by n.d.

15:00–18:00 is associated with a decrease in the volume. The rainfall during 12:00–15:00 has the largest effect with a 0.70% decrease per mm of rainfall in this period.

The effect of rain classes is shown in Table 9 where the reference class is 0 mm, i.e. dry daytime periods. For the all-days case, there are volume reductions with the varying amount of daytime rain. For the 5–10 mm class, there is a volume reduction of about 2%. The effects for the other classes are not significant although the reduction of 1% for the 2–5 mm class has a p-value of 0.08. As in Table 4, the cases for summer and autumn are not significant. Like the all-days case, winter and spring show generally greater volume reductions for the wetter days. For winter, there are reductions of about 2% for classes <5 mm and 4% for the 5–10 mm class. The 10–20 mm class did not have a significant effect on the volume. For spring, there are reductions of about 2.6 and 3.6% for the 0–1 and 2–5 mm classes. The effects for the 1–2 and 5–10 mm classes are not significant.

For comparison with the daily case, Fig. 4(b) shows the residuals from the baseline model versus maximum temperature indicating that there is no significant relationship between the daytime volume and maximum temperature. The temperature coefficient of −0.02% per °C is not significant.

4.4. Nighttime traffic volume models

The nighttime traffic volume refers to the time periods 00:00–06:00 and 18:00–24:00, i.e. 12:00–6:00 a.m. and 6:00–12:00 p.m., which we regard as the nominal darkness period. Owing to our normalisation of the nighttime volume series (mean of 100), the coefficients for dummy variables may be interpreted as percentage changes relative to the mean nighttime volume.

Table 10 gives the baseline models for the nighttime volume series for all nights and the four seasons, respectively. For all nights, we see that the baseline model incorporating trend, day of the week and holidays explains a moderately high fraction of the variance of the series (74.1%) that is about 20% lower than the daily and daytime cases. There is an upward trend of 0.009% per day or 3.3% per annum that is slightly smaller than the daily and daytime cases. Some of the day of the week coefficients are negative because of our choice of reference day (Sunday). As shown in Fig. 2(a), Monday has the lowest volume, the highest being Friday which is 24% higher than Monday. There is a 10% rise from Thursday to Friday and a 15% fall to Saturday that has almost the same mean as Sunday. School holidays have a volume reduction of 3.6%, public holidays show a 8% reduction and the Christmas period experiences a 16% decrease in volume.

There are differences between the seasons. The summer trend is about 0.012% per day or 4.4% per annum while the other seasons have a trend of about 0.008% per day or 3.1% per annum. The percentage of variance explained is seasonal with the highest R^2 value occurring in winter (91.9%), similar values in summer and spring (83.9 and 83.5%) and the lowest in autumn (74.5%). The increase in volume from Monday to Friday is about 24% for all seasons. The decrease from Friday

Table 10
Baseline models for nighttime traffic volume[a]

	Season				
	All	DJF	MAM	JJA	SON
Trend	0.009	0.012	0.009	0.008	0.008
Monday	−9.7	−15.6	−10.6	−5.5	−9.8
Tuesday	−5.1	−10.5	−7.1	*−0.52*	−4.8
Wednesday	*−0.1*	−5.8	*−0.4*	3.5	*−0.6*
Thursday	4.8	*−1.6*	3.1	9.3	6.2
Friday	14.4	9.1	12.6	18.7	14.9
Saturday	*−1.1*	−2.9	*−1.4*	*1.2*	−2.3
School holidays	−3.6	−6.0	−4.1	−2.0	−5.7
Public holidays	−8.1	−11.6	−7.2	−10.0	−12.5
Christmas period	−15.9	−23.0			
Residual standard deviation	5.72	5.35	5.74	2.74	4.34
Variance explained (R^2, %)	74.1	83.9	74.5	91.9	83.5

[a] Coefficients are deemed significant at the 5% level. Depending on the context, coefficients that are not significant will be either omitted or printed in italics in tables. The case of no data is denoted by n.d.

Table 11
Nighttime traffic volume models: single rainfall variables[a]

	Season				
	All	DJF	MAM	JJA	SON
Wet vs. dry nights	−2.61	−2.17	−1.95	−0.87	−2.91
Residual standard deviation	5.60	5.29	5.69	2.72	4.16
Variance explained (R^2, %)	75.2	84.4	75.1	92.1	84.9
Nighttime rainfall	*−0.08*	*−0.24*	*−0.069*	−0.39	*−0.23*
Residual standard deviation				2.71	
Variance explained (R^2, %)				92.1	

[a] Coefficients are deemed significant at the 5% level. Depending on the context, coefficients that are not significant will be either omitted or printed in italics in tables. The case of no data is denoted by n.d.

to Saturday is 12, 14, 17.5 and 17% for summer, autumn, winter and spring, respectively.

The effect of single rainfall variables is shown in Table 11. For the all-nights case on wet nights, the volume is decreased by 2.61% compared with dry nights. Using nighttime rainfall, we see that the volume decreases by 0.08% per mm of rainfall but this is not significant. Fig. 3(c) shows the residuals from the baseline model versus nighttime rainfall. For the seasons, there is a decrease in volume on wet days of about 2% in summer and autumn, 1% in winter and 3% in spring. Nighttime rainfall is associated with a decrease in volume but this is only significant in winter with a decrease of 0.39% per mm.

The combinations of 3-h rainfall variables that are significant in a stepwise regression are given in Table 12. For all nights, we see that the rainfall for 21:00–24:00 local time is associated with a volume reduction of 0.72% per mm. This sort of model is not significant for autumn and spring. The same time period in summer and winter is associated with decreases in the volume of 1.51 and 0.65% per mm.

Table 13 shows the effect of rain classes where the reference class is 0 mm, i.e. dry nighttime periods. For the all-nights case, there are volume reductions with the varying amount of nighttime rain. For classes in the range 0–5 mm,

Table 12
Nighttime traffic volume models: multiple rainfall variables (3-h rainfall)[a]

Time period	Season				
	All	DJF	MAM	JJA	SON
00:00–03:00					
03:00–06:00					
18:00–21:00					
21:00–24:00	−0.72	−1.51		−0.65	
Residual standard deviation	5.70	5.30		2.71	
Variance explained (R^2, %)	74.2	84.1		92.1	

[a] Coefficients are deemed significant at the 5% level. Depending on the context, coefficients that are not significant will be either omitted or printed in italics in tables. The case of no data is denoted by n.d.

there is a 2.5% reduction, increasing to about 4% for the 5–10 mm class. The reductions for classes in the range >10 mm are not significant. The value of 3.51 is based on two observations. Rain class effects are not significant in summer. In autumn, there is a reduction of about 2% in the 0–1 mm class but the reductions for higher rainfall amounts are not significant. The value of 11.88% in autumn is based on one observation. In winter, the only significant volume reduction occurs in the 5–10 mm class (4%). The effect of rain amount was strongest in spring with volume reductions of 2% in the 0–1 mm class, and 4–5% in the 1–5 mm range.

For comparison with the daily and daytime cases, Fig. 4(c) shows the residuals from the baseline model versus maximum temperature. Unlike the daytime case, there is a distinct association of temperature and volume with a 0.49% increase in volume per °C, increasing the R^2 value by about 7% from the baseline model. There are increased volumes in summer and autumn compared with winter and spring as shown in Fig. 2(c) where we noted a weak annual cycle.

4.5. *Application: accident models including traffic volume and rainfall*

As an application, we consider some accident models that include the rain-affected traffic volume. Table 14 gives the rain effect for the daily, daytime and nighttime cases where these periods are defined in Section 3. For the daily accident count, there is an additional 5.0 accidents on wet days compared with dry days, a value close to the difference of the wet and dry means. As a percentage of the dry day mean (32.8), this is a 15.4% increase over dry days. For the daily volume normalised count (VNC), which involves volume, there is an additional 5.9 accidents on wet days or a 17.8% increase over dry days. This is 2.4% greater than the increase for the raw accident count. For the daytime count, there is a 19.8% increase on wet days compared with a 21.7% increase for VNC (1.9% greater). For the nighttime count, there is a 22.6% increase on wet days compared with a 27.8% increase for VNC (5.2% greater).

The rain class effect, which is the extension of the rain effect to wet days of different rain amount, is also shown in Table 14. For the daily accident count, there are 5.9% more accidents compared with dry days for days with 0–1 mm of rain. For days with rain amounts of 5–10 mm, there is a 25.2% increase, rising to 48.8% for amounts of 10–20 mm. Daily VNC has a similar profile but with higher percentage increases over the raw count. VNC is 2.3% greater in the 0–1 mm class (8.2 versus 5.9) and 4.3% greater in the 5–10 mm class (29.5 versus 25.2). For the daytime case, VNC is generally larger than the raw count. The 0–1 mm class is 2.4% higher (13.6 versus 11.2) and the 5–20 mm classes are about 3% higher. However, there is a decrease of 1.6% for the 1–2 mm class compared with the raw count. For the nighttime case, VNC is about 4.5–6.0% larger than the raw count with 19.2% in the 0–1 mm class and 66.2% in the 10–20 mm class compared with dry day mean.

Table 13
Nighttime traffic volume models: multiple rainfall variables (rain classes)[a]

Rain class (mm)	Season				
	All	DJF	MAM	JJA	SON
0–1	−2.67		−2.29	*−0.65*	−2.22
1–2	−2.56		*−2.35*	*−1.12*	−5.35
2–5	−2.56		*0.19*	*−0.83*	−4.30
5–10	−3.97		*−4.08*	−3.91	*−2.12*
10–20	*−1.14*		*−4.70*	n.d.	*−0.76*
>20	*3.51*		11.88	n.d.	n.d.
Residual standard deviation	5.61		5.64	2.70	4.16
Variance explained (R^2, %)	75.3		76.1	92.2	85.4

[a] Coefficients are deemed significant at the 5% level. Depending on the context, coefficients that are not significant will be either omitted or printed in italics in tables. The case of no data is denoted by n.d.

Table 14
Road accident models: rainfall effects[a]

	Daily		Daytime		Nighttime	
	Count	VNC	Count	VNC	Count	VNC
Dry mean	32.8	32.9	22.9	22.9	9.8	9.5
Wet mean	37.8	38.7	27.4	28.0	12.0	12.1
Rain effect	5.0	5.9	4.5	5.0	2.2	2.6
Rain effect as percentage of dry mean	15.4	17.8	19.8	21.7	22.6	27.8
Rain class effect as percentage of dry mean						
0.1 mm	5.9	8.2	11.2	13.6	14.7	19.2
1–2	17.8	18.2	19.7	18.1	22.1	27.3
2–5	18.8	21.9	27.6	28.7	36.0	40.4
5–10	25.2	29.5	60.0	60.8	43.3	49.5
10–20	48.8	49.7	52.7	57.8	60.2	66.2
>20	37.0	38.7	n.d.	n.d.		11.4

[a] Coefficients are deemed significant at the 5% level. Depending on the context, coefficients that are not significant will be either omitted or printed in italics in tables. The case of no data is denoted by n.d.

5. Discussion

5.1. Traffic volume series

The relevant results are highlighted in Section 4.1. The daily volume versus time profile in Fig. 1(a) is typical of industrialised societies with a division into work (Monday–Friday) and non-work (Saturday and Sunday) periods. The day of the week pattern is shown in Fig. 2(a) where there is an approximately linear increase from Monday to Friday, followed by a large decrease to Saturday and Sunday. Fig. 1(b) emphasises the distinction between weekday and weekend traffic. The narrowness of the daytime volume band over Monday–Friday, which is reflected by the small change over the working week in Fig. 2(a), is due to much of this traffic being obligatory, i.e. people travelling to and from the workplace, parents taking their children to school. There is a greater spread over Saturday and Sunday, which is affected to a small degree by work, e.g. the retail industry, but most of this traffic is associated with recreational and other non-work-related activities, e.g. shopping, sporting events. Fig. 1(c) shows the largely discretional nature of nighttime traffic with Friday having the highest mean volume. Although Fig. 1(b) shows no sharp separation into work and non-work periods as for the daytime, there is still a relatively large percentage increase in volume from Monday to Friday as indicated in Fig. 2(a).

An aspect of the three volume series, which may not be seen at other locations, is the approximately linear increase over 1989–1996. This upward trend of about 3.6% per annum is associated with a near linear increase in the population of the MMA from 3.09 to 3.28 million. There may be changes in other variables, e.g. a decline in public transport and a shift to motor vehicles, but population increase seems to be the most likely cause. The trend is also revealed in Fig. 2(d) where there is a slight dip around 1992 in the daily and daytime curves due to reduced data coverage in that year.

The mean daily volume by month as shown in Fig. 2(b) consists of a modest variation over the year, punctuated by small dips of about 3% in January, April, August and November that correspond to school holidays. There is also a public holiday influence in April (Easter) and a Christmas period effect in January related to the widespread shutdown in industrial activity over the last week of December and the first week of January. The mean daily volume by season as shown in Fig. 2(c) is an aggregated version of the monthly profile in Fig. 2(b). The daily and nighttime cases show a weak annual cycle with slightly lower values in autumn and winter compared with spring and summer. This cycle is also revealed in Fig. 4 where plots of the daily and nighttime residuals exhibit a positive relationship with maximum temperature (0.12 and 0.49% per °C, respectively). However, since the nighttime mean volume is 29.3% of the daily mean volume then on the daily scale the latter coefficient is 0.14%, comparable to the daily value. The daytime case shows no significant variation with maximum temperature as shown in Fig. 2(c) and Fig. 4(b). This period is dominated by obligatory travel, e.g. work. Higher maximum temperatures tend to occur in November–March and this corresponds to a higher level of nighttime traffic as shown in Fig. 4(c).

Our definitions of daytime and nighttime as fixed 12-h periods are regarded as the times of nominal daylight and darkness respectively. In summer, a part of the nighttime period will be in daylight. Nighttime traffic could be increased by more discretionary travel during warm summer evenings, e.g. al fresco dining, the beach, sporting events. During the colder months, there is less incentive for outdoor activities at night.

The effect of rainfall as shown graphically in Fig. 3 is to reduce traffic volume for all three cases. Noting that these series are all normalised to 100 then, on the same scale as the daily case, the daytime and nighttime coefficients of −0.149 and −0.080 become −0.105 and −0.023 compared with the daily value of −0.080% per mm.

5.2. Daily models

There is a significant wet versus dry effect for all days and winter and spring with wet days having a reduced volume compared with dry days (Section 4.2, Tables 2–5). This is largest in winter and spring (−1.35 and −2.11%, respectively), which includes the wettest months of the year, and is not significant during the drier summer and autumn periods, although the effect is also negative. Increasing 24-h rainfall is associated with decreasing volume for all days and seasons. The effect is largest in winter (−0.33% per mm) but not significant in the other seasons although the spring value of −0.18 is the second largest. Rainfall during the intervals 12:00–15:00 and 21:00–24:00 local time tend to be jointly significant for all days and winter, the latter including 15:00–18:00 local time. The effects are negative indicating that rainfall occurring during the afternoon and late evening is associated with reduced daily traffic volume, especially in winter. Extending the wet versus dry effect to rain classes, there are significant effects for all days, winter and spring. There is generally a larger reduction in volume for the middle rain classes (2–10 mm) of 2–3%, the largest being 3.43% for the 2–5 mm class in spring. Not all effects are significant, possibly as a result of too few samples of the higher rainfall events.

The effect of other weather variables is generally significant for all days and winter and spring. The strongest effects appear in spring, followed by winter. The months June–November correspond to the wettest period of the year on average with October being the wettest historically (a mean of 67.6 mm based on the period 1855–2001), compared with a mean of 47.2 mm for February. August has the highest number of rain days per month (15.7), compared with 7.4 in February. The effect of cloud amount is significant in winter and spring (−0.23 and −0.30% per okta). Rainfall is associated with increased cloud cover but so the negative relationship is reasonable. In addition, overcast or gloomy conditions during winter and spring may also contribute to reduce volume on a daily basis. Surface pressure is correlated with daily volume in winter and spring. Rising pressure is associated with improving weather (warmer days) and more traffic while falling pressure indicates the imminent arrival of a cold front or low-pressure system, usually coupled with rainfall, and hence less traffic. For winter, the amount of heavy cloud (6–8 oktas) has a stronger effect in reducing the volume (−1.25% per okta compared with about −0.2 for mean cloud amount), this degree of cloudiness being generally associated with rainfall. Maximum temperature has a positive effect like pressure with significant effects in autumn and winter. In winter, higher temperatures tend to be associated with fine weather while lower temperatures often correspond to wet days.

Taken together, Tables 2–5 show that rainfall significantly reduces daily traffic volume in winter and spring, with other weather variables during these seasons exhibiting effects that are associated with rainfall. In particular, surface pressure and cloud amount are related to rainfall. Afternoon and late evening rainfall in winter appears to be related to reduced daily volume, possibly due to a reduction in discretionary travel. There could be fewer vehicles on the road because of rain during these intervals.

5.3. Daytime models

As for the daily case, the daytime wet versus dry effect (Section 4.3, Tables 6–9) is significant for all days and winter and spring. On wet days in winter and spring, the volume is reduced by 1.86 and 2.16%, respectively. Daytime rain reduces volume with the strongest effect occurring in winter (−0.41% per mm). A similar value occurs in spring but is not significant. Rainfall during the interval 12:00–15:00 local time significantly affects the daytime volume for all days, autumn and winter, the latter including 15:00–18:00 local time. The effects are negative indicating that rainfall occurring during the afternoon and early evening is associated with reduced daily traffic volume, especially in winter. For the winter period, the effects for the two intervals (−0.70 and −0.45% per mm) are comparable to the daily values. Regarding daytime rain classes, there are significant effects for all days, winter and spring. There is generally a larger reduction in volume for the middle rain classes (2–10 mm) of 2–3%, the largest being 3.91% for the 5–10 mm class in winter and 3.63% for the 2–5 mm class in spring. Compared with the daily case, there is a larger reduction in the 0–1 mm class in winter and spring (1.50 and 2.58%, respectively). Not all effects are significant, possibly as a result of poor sampling of the higher rainfall events. There are also a number of classes with no data. The overall effects of rainfall on daytime traffic volume are similar to the daily case with winter and spring showing a significant reduction.

5.4. Nighttime models

Unlike the daily and daytime cases, the nighttime wet versus dry effect (Section 4.4, Tables 10–13) is significant for all days and the seasons (the former cases are significant for all days, winter and spring). There is a reduction of about 2%, with 0.87% in winter and 2.91% in spring. Nighttime rainfall, like the daily and daytime cases, acts to reduce the traffic volume. Although the effects are negative for all seasons, only the winter reduction of 0.39% per mm is significant. Rainfall during the interval 21:00–24:00 local time significantly affects the nighttime volume for all days, summer and winter. It is likely that rainfall during this interval acts to discourage travel at night, this being largely discretionary to begin with. Regarding nighttime rain classes, there are significant effects for all days, winter and spring (as for the daily and daytime cases), with some additional results for autumn. In winter, the volume reduction is not significant for the lower classes and there is a 3.91% reduction for the 5–10 mm class. In spring, there are significant decreases over the 0–5 mm range, with a reduction of about 5% in the 1–5 mm range. In autumn, there is a reduction of about 2% in the 0–1 m class. Despite a reduction of about 4% in the 5–20 mm range, these effects are not significant. There is poor sampling of nighttime rainfall events, which may be distorting the effect of the higher classes.

5.5. Accident models including traffic volume

The main purpose of this application (Section 4.5, Table 14) is to show how variations in traffic volume affect the road accident count. We compare the (raw) accident count with the volume normalised count (VNC). For the daily case using the accident count, there are 15.4% more accidents on wet days as a percentage of the dry day mean compared with 17.8% using VNC, i.e. the rain effect is 2.4% larger when the volume is incorporated. For the daytime case, the rain effect is 1.9% larger using VNC and for the nighttime case it is 5.2% larger than the accident count. The rain class effect is generally larger using VNC for the three cases too. Daily VNC is 2.3% larger in the 0–1 mm class and 4.3% larger in the 5–10 mm class. Daytime VNC is 2.4% larger in the 0–1 mm class and about 3% larger over the 5–20 mm range. Nighttime VNC is 4.5% larger in the 0–1 mm class and about 6% larger over the 5–20 mm range. Hence, the rain class variation reflects the simpler rain effect based on wet versus dry periods. In a basic way, VNC is compensating for volume changes, especially the observed reduction due to rainfall, which influence the accident count. We note that there are more accidents on wet days and with increasing rain amount. The daily VNC ranges from about 10 to 40%, the daytime VNC from 15 to 60% and the nighttime VNC from 20 to 65% as the rain amount increases from 0–1 to 10–20 mm.

For the purposes of this application, we will highlight the literature discussing the relationship between road accidents and rainfall, some including the effect of traffic volume. Levine et al. (1995) found the daily accident count (including damage-only cases) for Honolulu in 1990 fluctuated according to an interaction between traffic volume, weekday travel patterns and weather. They included volume as a regression variable but did not investigate direct effects of rainfall or other weather variables on the traffic level. For every inch (2.54 cm) of rainfall, there were 13.4 more accidents per day. Andreescu and Frost (1998) found that there were about 20 additional accidents on days with rainfall in Montreal during 1990–1992 (damage-only accidents exceeding a cost threshold of US$ 500 are included). Golob and Recker (2003) in a study of freeway road accidents in Southern California during 1998 found more adverse conditions were associated with the lowest volumes and variations in flow. We also note that many accident versus volume studies do not include weather variables. For instance, Dickerson et al. (2000) modelled the relationship between road accidents and traffic flows in London during 1993–1995, Martin (2002) looked at the connection between accidents and volume on interurban motorways in France during 1997–1998, while Amundsen and Elvik (2004) investigated the effects of road safety of new urban arterial roads in Oslo during 1986–1999. None of these studies considered any weather effects on accidents or volume.

5.6. General remarks

We have found that the reduction in traffic volume is linked to the cool-wet period of the year, i.e. winter and spring. This is the period that results in a significant reduction in volume. In addition, a number of other weather variables for the daily case are significant at this time. Many of these, like cloud amount and surface pressure, are associated with rainfall and their model coefficients are consistent with this relationship.

The majority of the relatively few studies on the effect of weather on traffic volume concentrate on the northern hemisphere winter, especially in countries affected by snow. An early work on this is by Codling (1974) who considers traffic flow changes across Great Britain during 1969–1970 based on 50 census sites. He defined a ‘rainy’ day to be one on which at least 50% of casualties (injured persons) were reported in rain. A ‘dry’ day was one on which less than 10% of casualties occurred in rain. Rainy days without two corresponding dry days exactly a week or fortnight before and after the rainy day were rejected, leaving 16 rainy days for study. On weekdays, the average volume reduction on wet days was just over 1%, with Sunday having a large reduction of 17.8% in January and 7.6% in September. The sampling across days of the week and months is not uniform. In addition, Codling looked at traffic volume in London for 1969 and found that on wet days there was a 2% reduction (this was based on seven events, five in winter and all weekdays).

Although predominantly an accident study, Andreescu and Frost (1998) show the mean daily traffic volume at a Montreal site for the 12 months of 1992 (see their Fig. 1), revealing a large volume reduction during winter that is associated with a sharp increase in the number of accidents. Hassan and Barker (1999) in a study covering the Lothian region of Scotland (including Edinburgh) during 1987–1991, found a reduction in the average weekday traffic activity, although significant, of less than 3% for unseasonable sunshine hours, maximum temperature, minimum temperature and rainfall. However, at weekends, there were reductions of more than 4% in the average traffic activity on both the days with the highest rainfalls and the days with lower than expected minimum temperatures. There was an average reduction of 10% in weekday traffic activity when snow was lying. At weekends, there was an average reduction of 4% in traffic activity on the days with the highest rainfall and an average reduction of 15% on the days when snow was lying. Knapp and Smithson (2000) found that winter storms in Iowa generally decreased traffic volumes, although the impact varied greatly with an average reduction of 29%. Changnon (1996) in a study dealing with the effects of summer precipitation on urban transportation in Chicago during 1977–1979 found there was a reduction of about 1% in the traffic volume on wet weekdays and 9% on wet weekends. The larger weekend decrease was attributed to the greater number of discretionary trips normally associated with these days of the week.

We note that the reduction in traffic volume during the cool-wet season may not be due to just rainfall directly. It could be that cold or gloomy conditions associated with rain days in winter and spring may be a deterrent for discretionary travel. We have seen that winter daytime rainfall during 12:00–18:00 local time, i.e. the afternoon and early evening, is associated with a traffic reduction, most likely non-essential travel. Similarly at night, winter rainfall during the late evening (21:00–24:00 local time) lead to a reduction in traffic. The effect also occurred in summer. It may be that regardless of the season, travel on wet nights is considered more hazardous and hence not undertaken.

While our study would have produced more robust results with additional data, we are confident that the relatively short number of traffic volume measurements available (802 days) is sufficient. For the purpose of computing the general properties of the volume series, this is reasonable since it has a highly regular form that reflects the important contribution of obligatory daily travel. However, in terms of sampling rainfall this set of days is somewhat deficient in representing the less frequent higher rainfall events, i.e. >10 mm. Hence, in many cases, our results for >10 mm are possibly not showing significance due to small sampling of these events. In addition, it is possible that the effects on the traffic volume for higher rainfall are either ambiguous or require a study at a finer resolution in time to capture the effects of short-lived events, e.g. thunderstorms. In this study, we assume that the volume recorded at the two sites is representative of the MMA. Since much of the volume on these freeways consists of work-related traffic travelling to and from the suburbs then we expect this to be a reasonable indicator of traffic patterns throughout the MMA. In addition, the recording site is close to residential areas and a major shopping centre (Chadstone), which will contribute to the daily profile.

We have represented daytime and nighttime by fixed 12-h periods corresponding to nominal daylight and darkness. For instance, daylight extends into the nominal darkness period in summer. However, since working hours tend to be approximately fixed in the daytime period and other daytime activities, e.g. shopping, tend to occur within this period, we do not anticipate any significant bias using this definition. The majority of trips in the nighttime period are likely to be discretionary. Furthermore, the mid-latitude location of Melbourne means that the variation in the length of the day is not huge. We note that is some accident studies this variation is important particularly at high latitudes, e.g. Fridstrøm et al. (1995) in their Nordic study.

Finally, we recognise that our results may be rather specific to the city or region chosen for study and may reflect such factors as climate, traffic density, public transportation systems, the nature of the road network and road safety campaigns.

6. Conclusions

We have shown that rainfall in winter and spring had the greatest impact on traffic volume, i.e. there appears to be a cool-wet period effect. In general, traffic volume is reduced on wet days. There is a negative relationship between volume and rainfall amount. When considering the amount of rainfall there tended to be a larger reduction for the higher rain amounts. This applies to the daily, daytime and nighttime cases. However, the effects are statistically significant only for winter and spring, as well as for all days considered together. Our reductions in winter and spring of 1.35 and 2.11%, respectively, are comparable to those of Codling (1974) for London and Hassan and Barker (1999) for the Lothian region of Scotland. For the daily case, there is generally a reduction of 2–3% over the 2–10 mm range, the largest being 3.43% for the 2–5 mm class in spring.

None of the previous studies considered daytime and nighttime periods. We found a reduction of 1.86% in winter and 2.16% in spring during daytime rainfall. As with the daily case, there is generally a larger reduction of 2–3% over the 2–10 mm range, the largest being 3.91% for the 5–10 mm class in winter and 3.63% for the 2–5 mm class in spring. Compared with the daily case, there is a larger reduction in the 0–1 mm class in winter and spring (1.50 and 2.58%, respectively). The reduction at nighttime is significant over all seasons, ranging from 0.87% in winter to 2.91% in spring. In winter, the volume reduction is not significant for lower rainfall amounts and there is a 3.91% reduction for the 5–10 mm class. In spring, there are significant decreases in volume for amounts less than 5 mm, with a reduction of about 5% over the 1–5 mm range. We also found that rainfall during the interval 12:00–18:00 local time significantly affects the daytime volume in winter. At night, rainfall during the interval 21:00–24:00 local time significantly affects the nighttime volume during winter and summer. Given a choice, people are less likely to venture out on a wet night and road safety may play some part in that decision. For some, discretionary travel on wet nights is considered more hazardous and hence not undertaken.

For the daily case, we considered some other weather variables and found that a number of these were significant winter and spring, as well as all days. Furthermore, these variables tended to be those that are associated with rainfall, such as cloud amount and surface pressure. For winter, the amount of heavy cloud (6–8 oktas) has a stronger effect in reducing the volume (−1.25% per okta compared with about −0.2 for mean cloud amount), this degree of cloudiness being generally associated with rainfall. Maximum temperature is uncorrelated with daytime volume but shows a positive relationship with daily and nighttime volume. We looked at an application where the traffic volume was used to normalise the road accident count. In this way, the rain effect was increased by 2.4, 1.9 and 5.2% relative to the daily, daytime and nighttime dry mean accident count. Generally, the normalised count is greater than the raw count, with a larger increase for the higher rainfall classes.

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