Report

Queensland Cycle Crash Models

Prepared for ARRB Group Ltd

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1 Introduction

1.1 Background

Cycling is a sustainable mode of travel and an alternative to motor vehicle trips, particularly for shorter trips (less than 5km). While promoting more cycling is likely to bring many benefits, the risk and consequences of having a crash while cycling is typically higher than while travelling as a driver or passenger in a motor vehicle. However, research by Turner et al (2006) demonstrates that a 'safety in numbers' effect for cyclists is commonly seen. At the traffic signals, roundabouts and mid-block sections considered in the research, the crash risk per cyclist reduced at higher cycle volumes. For several of the models, the crash risk per cyclist at high average daily traffic cycle volumes was several magnitudes lower than at low volumes.

While this is reassuring, it remains that when a motor vehicle driver or passenger chooses to switch to cycling, their crash risk will generally increase, particularly when travelling on low-volume cycle routes or high-volume motor vehicle routes.

The challenge is to create an environment for cyclists that are as safe as possible. This can be achieved through a series of measures, including, where practical, reducing traffic volumes and speeds on high cycle volume routes, building on-roadway cycle lanes and intersection facilities, and constructing off-roadway cycle paths. The safety benefit of most of these measures has not been adequately quantified.

1.2 Purpose and Objectives of Project

The purpose of this research is to start to establish the relationship between cycle versus motor-vehicle crashes with predictor variables, including traffic volume, cycle volume, site layout and for some situations operating speed for Queensland. Such relationships have already been developed for New Zealand and for traffic signals in Adelaide. To produce robust models large sample sizes of each site type (traffic signals, roundabouts and mid-block sections) are required. At this stage only limited data is available for Queensland sites so the method selected builds on the previous research by adding this data to a larger sample set. Calibration factors for Queensland can then be developed.

This research is necessary, as many road safety specialists expect that a large mode shift from motor vehicles to cycling will lead to a significant increase in crashes. The research by Turner et al (2006) shows that a 'safety in numbers' effect occurs and that the crash risk drops significantly as cycle volumes increase. However, in most cases, the crash risk still remains higher than that of motor vehicle drivers and passengers. This research helps us in understanding what the impact of increased cycling has on crash occurrence and what might be required to mitigate the increased risk.

2 Sample Size and Predictor Variables

This section discusses the site selection process; the location and types of traffic signals, roundabouts and mid-block sections included in the sample set; and the collection of motor vehicle and cyclists counts, crash data, road layout, including cycle facilities, and other variables such as operating speed.

2.1 Site Selection

The research team had access to an existing sample set of roundabouts, traffic signals and mid-block sections that was collected in three previous studies. The majority of the existing sites are from cities across New Zealand. Traffic signal data was also available from Adelaide. A number of additional sites were added from Queensland to increase the sample size and to allow a Queensland calibration factor to be added. It was anticipated that a larger sample size of Queensland sites would be available, so more robust calibration factors could be developed.

2.2 Selection Criteria

While a wide variety of operational and layout features were included in the sample set, sites that had been constructed within the last five years or had undergone significant modification during this period were excluded, as their crash history over the last five years would not be representative. The broader selection criteria were:

- at least five years since installation
- all approaches two-way
- standard layout, generally in accordance with Austroads design standards
- urban speed limits only (70km/h or less).

2.3 Sample Size

Experience in other studies of this type indicates that a sample set of at least 100 sites for each site is the minimum necessary to develop crash prediction models for the major crash types. In total, a sample set of 115 traffic signals, 119 roundabouts and 110 mid-block sections were available across Queensland, New Zealand and South Australia (Adelaide). Table1 shows a breakdown of the sites by location and site type.

Type	New Zealand	South Australia	Queensland	Total Intersections	Total Approaches
Mid-block	97		13	110	
Roundabout	104		15	119	401
Traffic Signals	56	46	13	115	430
TOTAL	257	46	41	344	

Table 1 – Sample Size by Jurisdiction and Site Type

Table 2 shows a break-down of the roundabout sites in New Zealand by city, number of legs and number of circulating arms. This shows that there is a fair amount of variability in the types of roundabouts that are included in study. As expected, the majority of roundabouts have four arms and that there are more single lane roundabouts than multi-lane roundabouts.

Type	Location			
	Christchurch	Auckland	Palmerston North	Total
Single-lane circulating				
three-arm	-	2	2	4
four-arm	35	22	8	65
Two-lane circulating				
three-arm	-	4	-	4
four-arm	4	21	3	28
five-arm	-	3	-	3
TOTAL	**39**	**52**	**13**	**104**

Table 2 New Zealand Roundabout locations and types

3 Predictor Variables

3.1.1 Motor vehicle counts

The flow variables used in the intersection models (traffic signals and roundabouts) were first defined for four-arm intersection in Turner (1995).

Each vehicle movement is numbered in a clockwise direction starting at the northernmost approach. Approaches are also numbered using the same technique and are numbered in a clockwise direction (see figure 1).

Table 3 shows the range in traffic and cycle approach (or circulating) flows for each intersection type. The cycle flow at roundabouts is circulating cyclists as they are the key cycle flow variable for entering versus circulating cycle crashes.

Type	Traffic Flow			Cycle Flow		
	Minimum	Mean	Maximum	Minimum	Mean	Maximum
Mid-blocks#	1,898	23,450	45,000	9	249	1,200
Roundabout	64	5,993	30,303	0	38	615
Traffic Signals	43	11,190	32,595	0	137	855

Two-way flows on mid-blocks

Table 3 – Traffic and cycle flow ranges for each site type

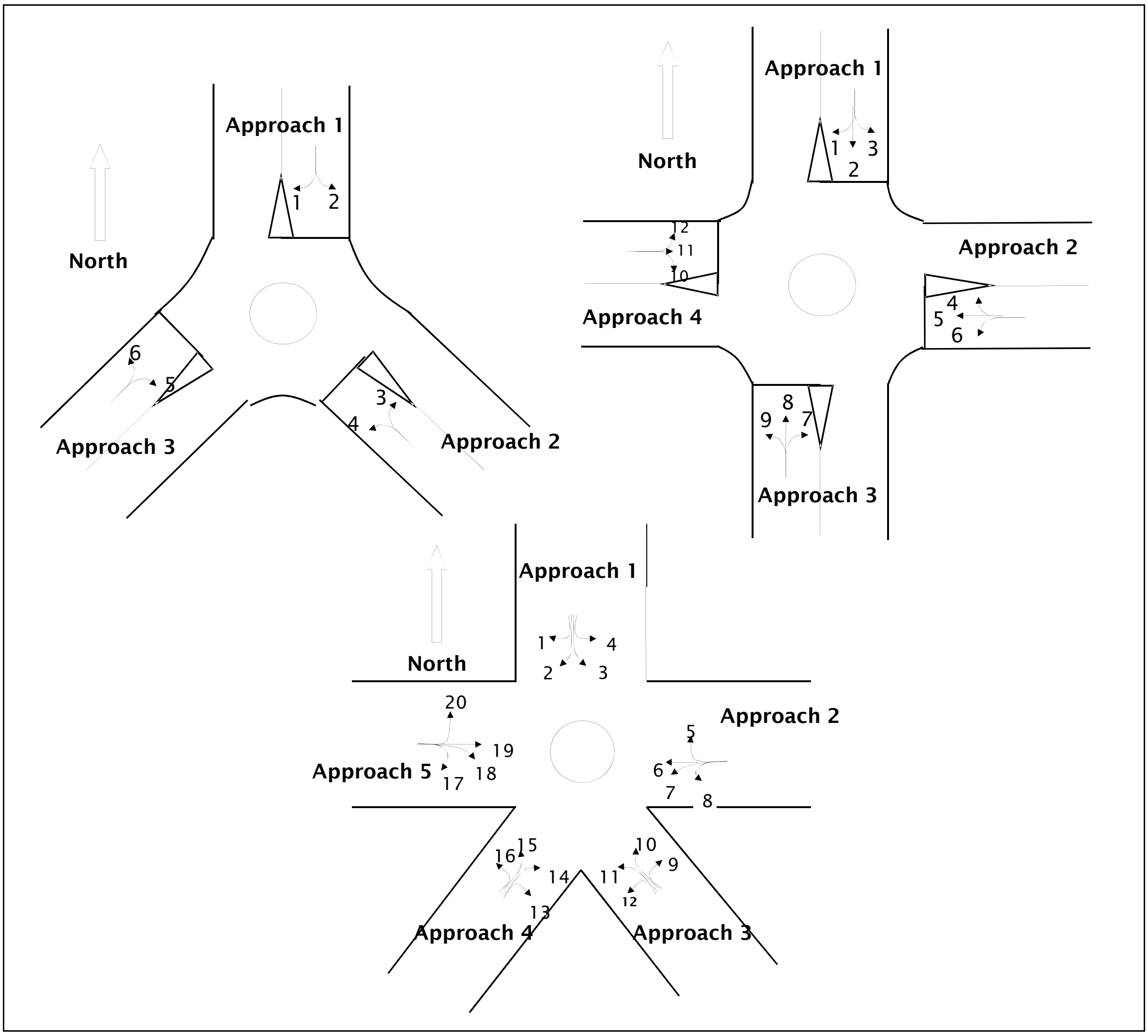


Figure 1 Numbering convention for movements and approaches

Individual movements are denoted as a lower case character for the user type (eg q_i). Totals of various movements are denoted with an upper case character (eg Q_i). Models are developed for each approach and are defined using the totals of various movements. These are:

Q_e entering volume for each approach

Q_c circulating flow perpendicular to the entering flow (for roundabouts)

Q_a approach flow (the sum of the entering and exiting flows for each approach).

All volume counts were factored up to the annual average daily traffic using the weekly, daily and hourly correction factors given in the *Guide to estimation and monitoring of traffic counting and traffic growth* (Traffic Design Group 2001). The hourly factors were calculated from flow profiles for the different road types. It is unclear how well these New Zealand profiles relate to those in Australia. The use of or development of such factors for each Australian jurisdiction would be a useful next step in developing better crash mdoels.

For midblock sections the traffic volume is the two way traffic count normally collected using automated traffic counters. These counts are normally of longer duration, often a week, and so require less factoring than the manual counts collected at intersections.

3.1.2 Cyclist counts

Manual cyclist movement counts have been collected at most intersection sites for the morning and evening peaks, and at mid-day. Like motor vehicle counts, daily and hourly correction factors were used to estimate annual averaged daily volumes. Seasonal factors were also applied. In New Zealand these took into account the secondary school terms and holidays. Three separate profiles were used. These were applied based on the location of the intersection and the vicinity of schools. The three profiles were 'commuter', 'school/off-road' and a combination of both. The commuter profile was always used for dual-lane roundabouts, as it was not expected that many school cyclists would travel through these. These factors are updated versions of those found in the *Cycle network and route planning guide* (Land Transport New Zealand 2004). In Queensland and Adelaide the cycle counts were adjusted using local scaling factors.

The cyclist flow variables are defined by movement in the same way that motor vehicle movements are defined: they are numbered in a clockwise direction at intersections, starting at the northernmost approach. Individual cyclist movements are denoted as a lower case character for the user type (eg c_i). Totals of various movements are denoted with an upper case character (eg C_i).

Midblock cycle counts have been developed from intersection counts or taken from mid-block counts, some of which are longer duration automatic counters.

3.1.3 Intersection layout and other variables

Data on the layout of each intersection was collected on site. This included such items as:

- road markings
- diameter of roundabouts
- pedestrian and cycle facilities provided
- presence and utilisation of parking (mid-block)
- presence of central painted (or flush) median (mid-block)
- surrounding land use
- features that obstruct visibility
- approach and circulating speeds at roundabouts.

Further details on the range in the intersection layout and other variables, eg. travel speed, follow.

For midblock a total of 27 routes out of 110 had a flush or painted island.

Table 4 shows the distribution in the measured approach (or entering) speed of roundabouts.

Jurisdiction	Minimum (kph)	Mean (kph)	Maximum (kph)
New Zealand	15	27	49
Queensland	20	30	45
TOTAL	15	28	49

Table 4 – Approach speed distribution at Roundabouts

Table 5 shows the proportion of traffic signal approaches for which each cycle facility or other layout variable applied for each jurisdiction.

Type of Treatment	New Zealand		South Australia		Queensland	
	Number	Proportion	Number	Proportion	Number	Proportion
Cycle Storage Box	82	38%	59	36%	15	31%
Approach cycle lane	85	39%	90	55%	18	37%
Painted cycle lane	37	17%	0	0%	6	12%
LT cycle transition treatment	87	40%	90	55%	18	37%
Shared left and through lane	121	56%	40	25%	20	41%
Shared Right Turn	61	28%	21	13%	8	16%
RT protection phase	34	16%	143	88%	26	53%
Free left turn	26	12%	96	59%	9	18%

Table 5 – Approaches with various cycle and layout features at traffic signals

Table 5 generally shows that the Queensland and New Zealand traffic signals have a similar proportion of sites/approaches with cycle facilities and the other variables that might impact on cycle safety. The major difference being the proportion of approaches with right turn protections being much lower in Christchurch. In general Christchurch has a lower use of right turn protection than other New Zealand cities, and it appears Australian cities. The characteristics of the South Australian signalised intersections are quite different than the other intersections. All of the South Australian intersections are on State or National Highways, so are typically multi-lane roads, which is reflected in the higher proportion of free left turns, low proportion of shared left turn lanes and higher proportion of approaches with left turn cycle lane transition treatments.

4 Crash Modelling Methods

4.1 Introduction

The aim of crash prediction modelling in this case is to develop relationships between crashes (by type) and flow predictor variables (traffic and cycle flows) and the non-flow predictor variables, such as road width, cycle facility provision, presence of parking and operating speed.

The models are called "generalised linear models" and typically have a negative binomial or Poisson error structure. Generalised linear models were first introduced to modern road crash studies by Maycock and Hall (1984) and extensively developed in Hauer et al (1989). These models were further developed and fitted using crash data and traffic counts in the New Zealand context for motor vehicle only crashes by Turner (1995).

Over recent years, the process has been refined to allow for incorporating non-flow variables, which allow different functional forms, improved goodness of fit statistics and the selection of 'preferred' models. This chapter outlines the current modelling process used, which is:

- selecting the correct functional form for model parameters
- fitting crash prediction models
- selecting models for goodness of fit testing
- testing goodness of fit and selecting preferred models
- interpreting crash relationships and significance.

4.2 Selecting Correct Functional Form

When crash prediction models were developed for conflicting flow-only variables, only one model was generally developed for each crash type. The form of the functional form of the crash model was assumed to be a power function as shown in equation 3.1.

$$A = b_0 x_1^{b_1} x_2^{b_2} \qquad \text{(Equation 3.1)}$$

However, with the inclusion of non-flow variables and the realisation that a power function may not always be appropriate, a tool was needed to determine potential functional forms for all predictor variables being included in the model. Also, if the functional form does not match the relationship between the predictor variable and crashes then the fit of the model is likely to be poor and the model may be misleading, particularly over certain ranges of the variable. Hauer and Bamfo's (1997) integrate-differentiate method is such a tool that assists in identifying possible functional forms.

The integrate-differentiate method has been used in this study with three different functional forms; these were: power functions (equation 3.2), exponential functions (equation 3.3) and Hoerl's functions (equation 3.4).

$$A = b_0 x_1^{b_1} \qquad \text{(Equation 3.2)}$$

$$A = b_0 e^{x_1 b_1} \qquad \text{(Equation 3.3)}$$

$$A = b_0 x_1^{b_1} e^{x_1 b_2} \qquad \text{(Equation 3.4)}$$

where:

A = annual mean number of crashes

x_1 = continuous flow or non-flow variable

b_0, b_1 and b_2 = model parameters.

4.3 Fitting Crash Prediction Model Parameters

Once the functional form for each variable has been determined, generalised linear models can then be developed using either a negative binomial or Poisson distribution error structure. Software has been developed in Minitab in order to fit such models (ie to estimate the model coefficients). This can be readily done, however, in many commercial packages, eg GENSTAT, LIMDEP or SAS.

4.4 Adding Variables To The Models

Given the large number of possible variables for inclusion in the models for a particular crash type, a criterion is needed to decide when the addition of a new variable is worthwhile. This balances the inevitable increase in the maximum likelihood (*ML*) of the data against the addition of a new variable (where *p* is the number of variables included in the model and *n* is the total number of observations in the sample set). We chose to use the popular Bayesian Information Criterion (BIC). We stop adding variables when the BIC reaches its lowest point. The BIC is given by equation 3.5.

$$BIC = (-2\ln(ML) + p\ln(n))/n \qquad \text{(Equation 3.5)}$$

The model with the lowest BIC is typically the preferred model. Addition of a new variable to a model generally provides an improved fit, though this may be slight and may therefore not reduce the BIC. In figure 2, the BIC values indicate that the parsimonious number of parameters is two. However, if the analyst considers that a model with three parameters includes an important variable that the model with two parameters does not, then he/she could justifiably select the model with three parameters, depending on the outcome of goodness of fit testing (see section 3.5).

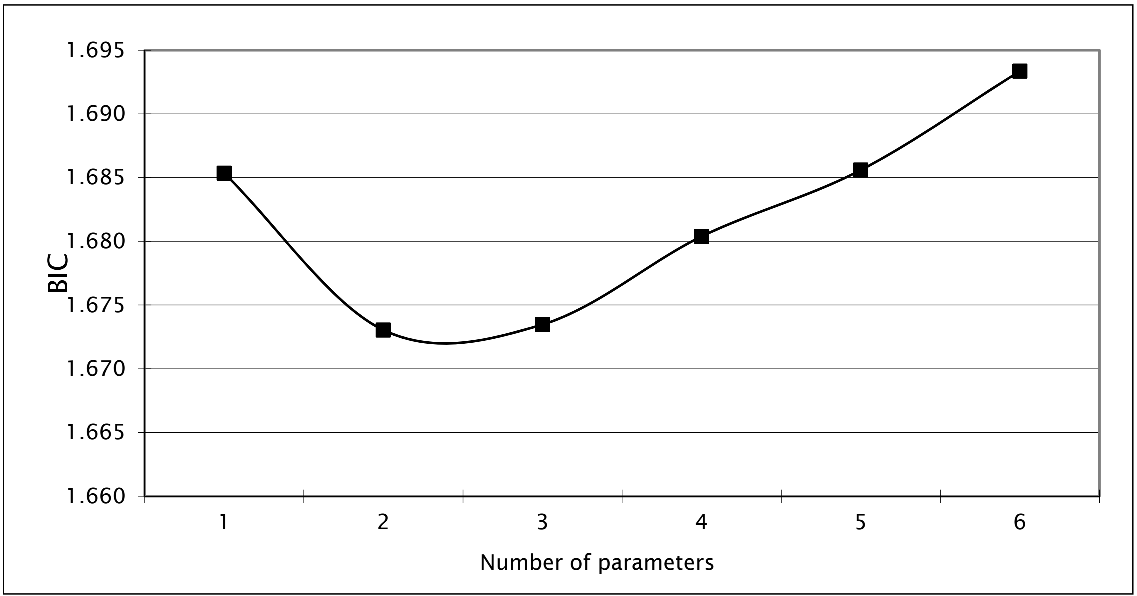


Figure 2 Graph used to determine the number of parameters yielding the optimal BIC

Modelling every possible combination of variables to determine which has the lowest BIC would be time-consuming and inefficient. The process used in this study is to introduce each non-flow variable to a model with the main flow variables. Many studies have shown that flow variables are generally more important predictor variables than non-flow variables. The variables that maximise the log-likelihood (and therefore minimise the BIC) are then added to the flow-only model in a forward substitution process and the BIC is calculated. This process is repeated for a number of variable combinations (but not all combinations), taking into account that some variables may be correlated, as this is fairly common, particularly for layout/design variables.

Where variables are correlated, the 'best' two variables may not result in a better model. The correlation between different variables can be determined by examining the correlation matrix. The correlation matrix is a matrix of correlation coefficients between the variables used for modelling. Correlation coefficients indicate the strength and direction of a linear relationship between two random variables, where a value of one indicates a perfect positive correlation between two variables and a value of zero indicates statistical independence. Figure 3 illustrates an example of different values of linear correlation. The more scattered the data the lower the correlation value (compare the bottom left scatterplots with the corresponding value on the top right on the diagonal – for example the 0.025 value is the most scattered of the data plots (bottom left)).

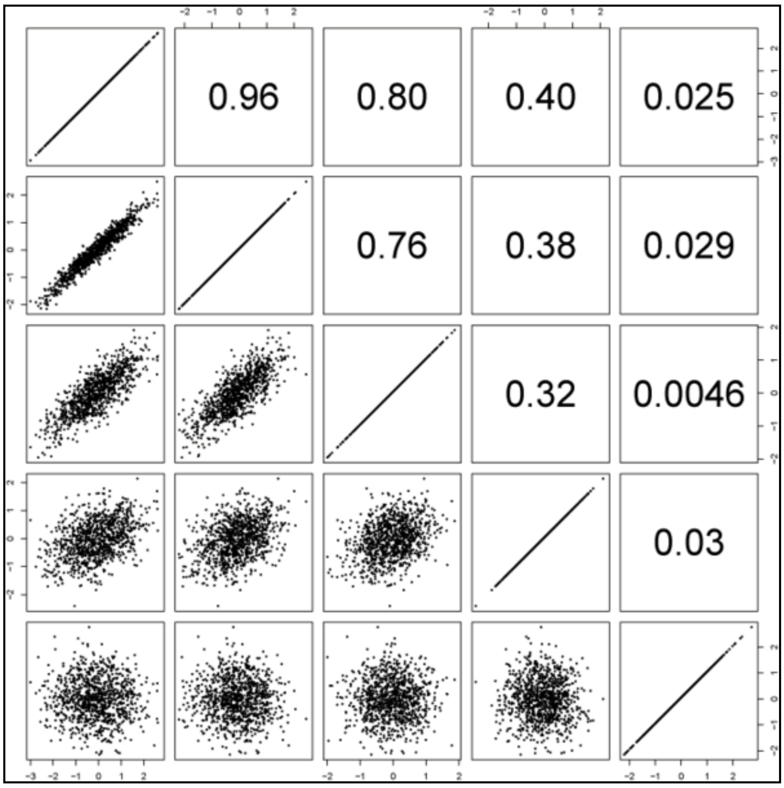


Figure 3 Examples of linear correlation

4.5 Testing Goodness of Fit and Preferred Models

After the model with the lowest BIC has been obtained, the models are ranked in order of lowest (best) to highest (worst) BIC. A number of models are then selected for goodness of fit testing, because although the BIC provides us with models based on a parsimonious variable set and maximum likelihood, the models may still not fit the data well. Additionally, likelihood and goodness of fit are not directly related, meaning that the model with the best likelihood or BIC may not be the model with the best goodness of fit.

The models that are selected for goodness of fit testing are those that have a low BIC and have the variables that professional knowledge deems necessary. These 'necessary' variables are usually limited to the conflicting flow variables, such as entering and circulating flows in predicting entering versus circulating crashes.

The usual methods for testing goodness of fit for generalised linear models involve using the test statistics: scaled deviance G^2 (twice the logarithm of the ratio of the likelihood of the data under the larger model to that of the data under the smaller model) or Pearson's χ^2 (the sum of squares of the standardised observations). These statistical tests are not accurate for testing goodness of fit for crash prediction models, except at an aggregate level (total crashes) at higher flow intersections where crash rates are relatively light. In most cases, the models are fitted to data with very low crash means, and the result is the 'low mean value' problem. This problem was first pointed out by Maycock and Hall (1984).

In Wood (2002), a grouping method has been developed that overcomes the 'low mean value' problem. The central idea is that sites are clustered and then aggregate data from the clusters is used to ensure that a grouped scaled deviance follows a χ^2 distribution if the model fits well. Evidence of goodness of fit is provided by a p-value. If this value is less than 0.05, say, this is evidence at the 5% level that the model does not fit well (i.e. 95% confident). Software has been written in the form of Minitab macros in order to run this procedure.

Once the goodness of fit has been calculated for the models selected for testing, the 'preferred' model is identified. This is the model that maximises the goodness of fit.

If the model fits poorly over a certain range of predictor variables (for example high or low volumes), this can be identified using the grouping technique by plotting predicted crashes against reported crashes. A poor fit is illustrated by a group that has a different predicted and reported number of crashes (where the plotted point is furthest from the 45 degree line). The site features of approaches in any outlier groups can then be examined to determine where the model relationship may not apply.

4.6 Model Interpretation

4.6.1 Determining significance

Once models have been developed, the relationship between crashes and predictor variables can be interpreted from the parameter values in most cases. However, caution should always be exercised when interpreting such relationships when multiple predictor variables are used because two or more variables can be correlated. Where variables are correlated or where a variable appears twice in the model (Hoerl's function), it is advisable to plot the model to understand the relationship between the predictor variables and crashes.

When examining the relationships with non-flow variables, it is important to determine whether they are significant. The significance of the model parameters is determined by examining the 95% confidence interval for the model parameter to identify if the relationship changes in trend over the range of the confidence interval. For example, a relationship may be significant if the both the upper and lower limits of the confidence interval indicate crashes increase with increases in the value of the predictor variable.

In the following sections, guidance is given on interpreting crash relationships for:

- power functions
- exponential functions
- covariates.

4.6.2 Power functions

Equation 3.6 presents a model with a single variable (such as a flow or speed) with a power function form. This section examines interpretation of the relationship between crashes and a predictor variable in a model of this type. The method can also be used to examine a single variable with a power function form in a multiple variable model.

$$A = b_0 x_1^{b_1} \qquad \text{(Equation 3.6)}$$

where:

A	=	annual mean number of crashes
x_1	=	continuous flow or non-flow variable
b_0 and b_1	=	model parameters.

In this model form, the parameter b_0 acts as a constant multiplicative value. If the number of reported injury crashes is not dependent on the value of predictor variable (x_1), then the model parameter b_1 would be zero. In this situation, the value of b_0 is equal to the mean number of crashes. The value of the parameter b_1 indicates the relationship that the predictor variable has (over its range) with crash occurrence. Five types of relationship exist for this model form, as presented in figure 4 and discussed in table 3.

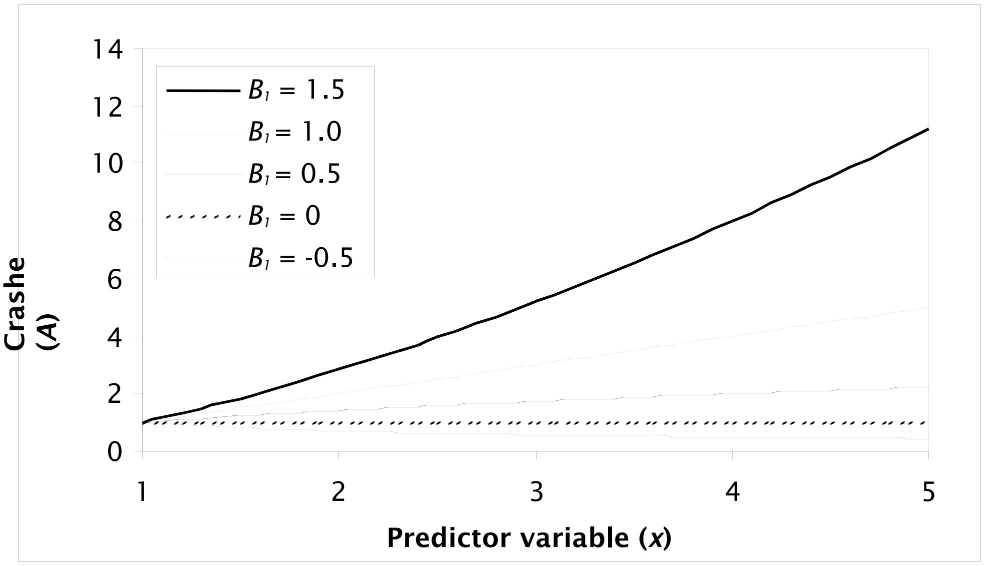


Figure 4 Relationship between crashes (*A*) and predictor variable *x* for different values of model exponents (b_1)

Table 3 Relationship between predictor variable and crash rate

Value of exponent	Relationship with crash rate
$b_i > 1$	For increasing values of the variable, the number of crashes will increase at an increasing rate
$b_i = 1$	For increasing values of the variable, the number of crashes will increase at a constant (or linear) rate
$0 < b_i < 1$	For increasing values of the variable, the number of crashes will increase at a decreasing rate

Value of exponent	Relationship with crash rate
$b_i = 0$	The number of crashes will not change with changes in the predictor variable
$b_i < 0$	For increasing values of the variable, the number of crashes will decrease

Generally, models of this form have exponents between $b_i = 0$ and $b_i = 1$, with most flow variables having an exponent close to 0.5, ie the square root of flow. In some situations, however, parameters have a value outside this range. For cycle flows the variable is often well below 0.5 which indicate a strong 'safety-in-numbers' effects; ie as cycle flows increase the individual risk of a cyclists having a crash reduces.

4.6.3 Exponential functions

Equation 3.7 presents a model with a single variable (such as a flow or speed) with an exponential function form. As with power functions, the interpretation can also be used to examine a single variable in a multiple variable model.

$$A = b_0 e^{x_1 b_1} \qquad \text{(Equation 3.7)}$$

where:

A = annual mean number of crashes;

x_1 = continuous flow or non-flow variable; and

b_0 and b_1 = model parameters.

The value of the parameter b_1 indicates the relationship that the predictor variable has (over its range) with crash occurrence. Three types of relationship can be seen for this model form, as presented in figure 5 and discussed in table 4.

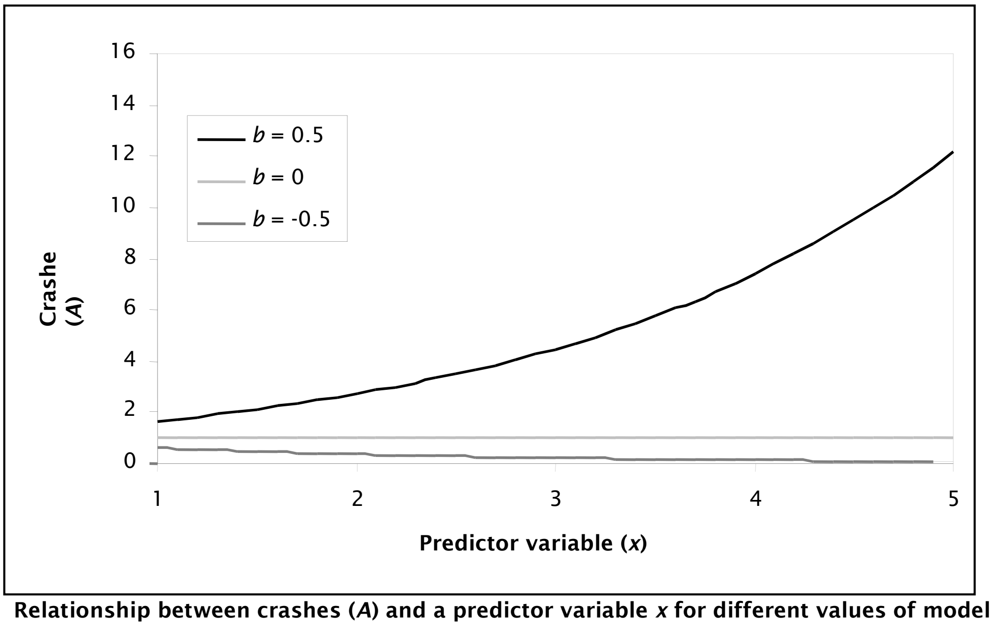


Figure 5 Relationship between crashes (*A*) and a predictor variable *x* for different values of model parameter (b_1)

Table 4 Relationship between predictor variable and crash rate

Value of parameter	Relationship with crash rate
$b_i > 0$	For increasing values of the variable, the number of crashes will increase at a increasing rate

Value of parameter	Relationship with crash rate
$b_i = 0$	The number of crashes will not change with changes in the predictor variable
$b_i < 0$	For increasing values of the variable, the number of crashes will decrease at a decreasing rate

4.6.4 Covariates

In the modeling exercise, covariates are different b_0 parameters for different cities or jurisdictions. As all crash prediction models include multiplicative b_0 parameters regardless of the functional form of the predictor variables, covariates can be applied to all models.

An alternative to having multiple b_0 values, is to present the b_0 value for one jurisdiction (Auckland) and a multiplier for the other cities. This multiplier factor indicates how much higher (or lower) the number of crashes is for similar sites in different cities/jurisdictions. In this case different b_0 values are provided for New Zealand, Queensland and South Australia (Adelaide).

4.7 Queensland Modeling

The methods outlined in this section show the full process used to develop the New Zealand crash prediction models. Given the small sample size of the Queensland data and the tight timeframes for this stage of the study, the model forms and key predictor variables have generally not been changed with the addition of the Queensland data. Rather the data has been added to the modeling database and the models re-run. The only exception is the traffic signal models where we have taken the opportunity to reduce the number of predictor variables.

At this stage goodness-of-fit testing has also not been undertaken for the new models, given the number of additional sites from Queensland is fairly small compared with the overall sample set. It is unlikely that these additional sites would have a major impact on the overall goodness of fit of the models, at least in a positive way.

Given the availability of suitable data it would be worthwhile looking at models with other prediction variables. The analysis sections that follow make some recommendations on where further refinements of the models for Queensland would be desirable. Ideally before doing this, more Queensland sites would be added to the sample set and validation of the new models at groups of sites in Queensland would be undertaken.

5 Mid-block cycle crash prediction models

The following section presents the crash prediction models developed for the following cyclist crash types:

- total mid-block cycle crashes
- mid-block turning cycle crashes (into and out of drive-ways and low volume side-roads)
- mid-block non-turning cycle crashes

The models have been developed for undivided arterial roads only.

To apply the models an analyst either uses the total mid-block crash prediction model or uses the sum of the turning and non-turning cycle crash prediction models. The latter method is likely to be more accurate when there are more or less side-roads and accesses than a typical route.

The models were developed in accordance with the process outlined in chapter 3. Each model is presented in the following sections. The original models from New Zealand are presented first (from extracts from the original research reports) and then the models with the Queensland data, along with the Queensland covariate, are presented next.

5.1 Total Cyclist versus Motor Vehicle Crashes

In the New Zealand study (Turner et al.2009) ten models were developed for this crash type before settling on a preferred model (see appendix A for the models calculated for this and all other crash types). Appendix B outlines the full set of predictor variables and model parameters that were calculated for each of the ten models. Equation 4.1 presents the preferred model form, which includes the total two-way flow for both motor vehicles and cyclists, the length of the mid-block section and a covariate for the presence of a flush (painted) median.

$$A_{UCMN\,0} = 1.05 \times 10^{-2} \times Q^{0.25} \times C^{0.16} \times L^{0.45} \times \phi_{FLUSH\ MEDIAN} \qquad \text{(Equation 4.1)}$$

where:

A_{UCMN0}	= annual number of mid-block crashes involving cyclists only (subscript denotes model type – see Appendix C);
Q	= total two-way motor vehicle flow for the link (AADT)
C	= total two-way cycle flow for the link
L	= length of mid-block in kilometres (measured from aerial photos)
$\Phi_{FLUSHMEDIAN}$	= factor to multiply the crash prediction by if a flush (painted) median is present. This factor is $\Phi_{FLUSHMEDIAN}$ = 0.63.

The length for each mid-block starts 5Om from the yield line of a major intersection and ends 50m prior to the yield line of the next major intersection. A major intersection is in most cases a set of traffic signals or a roundabout. It may also be a higher volume priority controlled intersection if there is a large change in the mid-block traffic flow at a location or the road is terminating.

Equation 4.1 implies that the presence of a flush (painted) median mid-block can reduce cyclist crashes by 37%. All of the flush medians were at least 2m wide, but some were up to 4m wide (typically they were 2.5 to 3m wide). The safety benefit provided by flush medians to cyclists is likely to result from the extra usable road width that flush medians provide to motorists to avoid cyclists travelling on the side of the carriageway. In the absence of a flush median, drivers would need to cross the centre-line into the opposing traffic lane, which they would generally not feel comfortable doing even if at the time there is no opposing traffic.

Equation 4.1 has a *p*-value of 0.05, indicating a model with good fit (values below 0.05 indicate a poor model). The goodness of fit can be illustrated by comparing the predicted mean number of crashes and the reported number of crashes for 'grouped' (approach) data (as outlined in Wood (2002)). Figure 4.1 presents this comparison between 'grouped' reported and predicted crashes for the preferred model. A poor fit is illustrated by a group that has different predicted and reported numbers of crashes (where the plotted point is furthest from the 45 degree line). If we have no evidence of poor fit, this gives us valid grounds for increased confidence in the model. Figure 4.1 indicates a generally good fit for most approach groups. However, the New Zealand model appears to underestimate crashes at sites with higher traffic volumes.

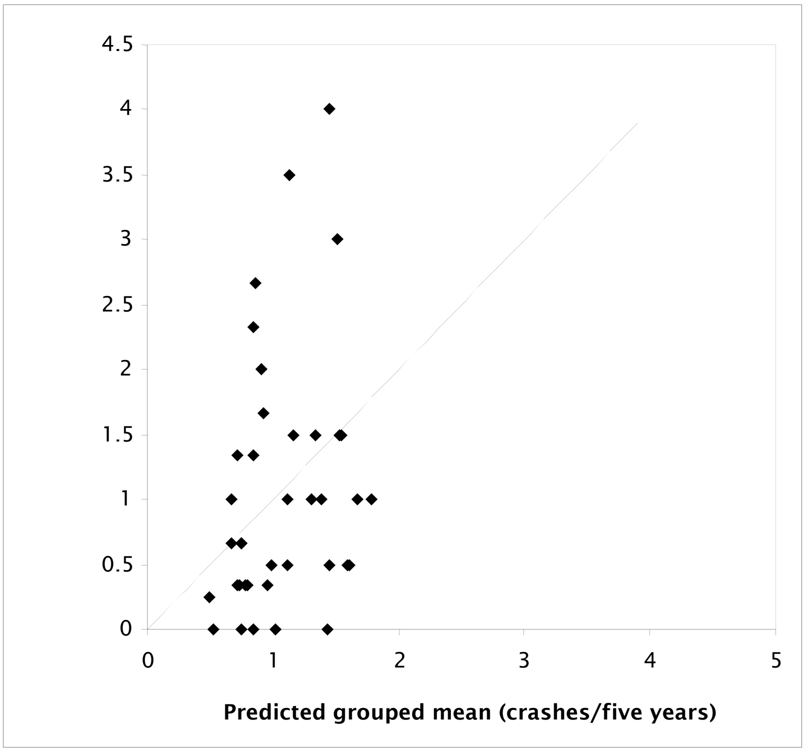


Figure 4.1 **Relationship between predicted and reported crashes for A_{UCMN0}**

A number of other models were developed, but did not have as good a fit as the preferred model presented. These included non-flow variables with significant relationships, such as:

- effective width of the kerbside lane, including the vehicle lane and cycle lane, where present
- the presence of a cycle lane
- mean motor vehicle speed along each mid-block section.

5.1.1 Discussion

The models show that crashes increase with increasing traffic volume, mid-block length, effective width and mean motor vehicle speed. The impact of increasing traffic flows and speed on cycle safety reinforces the strategy to move cyclists off busy and high speed roads where this is feasible. The models indicate there is a strong safety-in-numbers effect for cyclists (given low exponent on cycle flows), with the individual risk per cyclists reducing considerably as the volume of cyclists increases. This supports strategies to develop well connected cycle corridors, with few pinch-points, that can attract suitable numbers of cyclists, rather than strategies to provide facilities on all roads in a piecemeal fashion.

One of the New Zealand models (Turner et al. 2009) suggests that the presence of a cycle lane increases crashes by 21%. However further analysis using before and after data, and from a review of studies undertaken elsewhere, showed that cycle lanes do reduce crashes by between 10% and 20%. The increase in crash in the model may be as a result of bias in sites where cycle facilities have been installed. They may have been installed at sites which already had a cycle crash problem.

5.1.2 Queensland Modelling

Table 4.1 shows the model parameters for the original models (as above) and the new model with the Queensland data. The original research data-set included 97 sites. A further 13 sites have been added from Queensland. Covariates have been developed for both New Zealand and Queensland.

	Constant (b0)	Traffic Flow exponent	Cycle Flow Exponent	Length Exponent	Flush Median Factor
Original Model	1.05E-2	0.25	0.16	0.45	0.63
NZ Covariate	3.71E-3	0.29	0.24	0.52	0.77
Qln Covariate	1.82E-2	0.30	0.24	0.51	0.77

Table 4.1 All Cycle versus Motor-vehicle crashes on mid-blocks Model Parameters

The addition of the Queensland data (from 13 sites) has been to increase the importance of the predictor variables over the constant value. This means that variations in the values of the predictor variables will have more effect on the crash predictions than with the original (NZ) model. The importance of the flush median is also reduced, at only 23% reduction in crashes compared with 37% previously. This may be as a result of there being few flush (painted) medians in the Queensland data-set. This needs further investigation.

A comparison between the constant covariate values in the new model shows that the rate of cycle crashes in Queensland is five times that of New Zealand for a given combination of flows and length. This may be due to higher reporting rate of crashes in Queensland or due to a number of other factors that are not currently in the model, such as different lane widths and parking utilisation and turn-over. Further analysis is required to understand this difference.

5.2 Mid-Block Turning Cycle Crashes

This model considers only the crashes that involve cyclists that are turning into or out of the mid-block sections from drive-ways and minor side-roads. For this crash type, 18 models were developed. Appendix B outlines the full set of predictor variables and model parameters that were calculated. Equation 4.2 presents the preferred model form, which includes the total two-way flow for motor vehicles, the length of the mid-block section and a covariate for the presence of a flush median.

$$A_{UCMN\,1} = 3.50 \times 10^{-2} \times Q^{0.19} \times L^{0.54} \times \phi_{FLUSH\ MEDIAN} \qquad \text{(Equation 4.2)}$$

where:

A_{UCMN1} = annual number of mid-block turning crashes involving cyclists v motor vehicles (subscript denotes model type – see appendix C)

Q = total two-way motor vehicle flow for the link

L = length of mid-block in kilometres (measured from aerial photos)

$\Phi_{FLUSHMEDIAN}$ = factor to multiply the crash prediction by if a flush median is present. This factor is: $\Phi_{FLUSHMEDIAN} = 0.48$.

Equation 5.2 suggests that the presence of a flush median mid-block can reduce interactions between turning cyclists and motor vehicles by more than 50%. Again, this reduction may be a result of the extra width that flush medians afford to motorists to avoid cyclists travelling on the side of the carriageway. The flush median also allows right-turning traffic, both cycles and motor vehicles, to be separated from through-traffic, further reducing the likelihood of interactions. This appears to be a good option where there are a lot of turning movements. It appears to be less important when most of the cyclists are travelling straight through as evident in the next model where flush median is not one of the key variables in the preferred model.

5.2.1 Queensland Modelling

Table 4.2 shows the model parameters for the original models, as above, and the new model with the Queensland data. Covariates have been developed for both New Zealand and Queensland.

	Constant (b0)	Traffic Flow exponent	Length Exponent	Flush Median Factor
Original Model	3.50E-2	0.19	0.54	0.48
NZ Covariate	6.39E-3	0.33	0.58	0.67
Qln Covariate	1.52E-2	0.33	0.58	0.67

Table 4.2 Turning Cycle versus Motor-vehicle crashes on mid-blocks Model Parameters

Again, the addition of the Queensland data has been to increase the importance of the predictor variables over the constant value. This means that variations in the values of the predictor variables will have more effect on the crash predictions than with the original (NZ) model. So as traffic volumes increase there will a greater effect on the crash rate than in the New Zealand-only models. The importance of the flush median is also reduced, at 33% reduction in crashes compared with 52% previously.

A comparison between the constant covariate values in the new model shows that the rate of cycle crashes in Queensland is approximately two and half times that of New Zealand for a given combination of flows and length. This is lower than the difference in overall cycle crashes (of five times). Further analysis is required to understand this difference.

5.3 Mid-Block Non-Turning Crashes

5.3.1 Cyclist v motor vehicle crashes

This model includes all crashes where the cyclist was travelling straight through on the link and is hit by a vehicle; either as a sideswipe or while the vehicle is turning. For this crash type, ten models were developed. Appendix B outlines the full set of predictor variables and model parameters that were calculated. Equation 4.3 presents the preferred model form, which includes the total two-way flow for motor vehicles, cyclists, and the length of the mid-block section.

$$A_{UCMN\,2} = 2.28 \times 10^{-4} \times Q^{0.31} \times C^{0.50} \times L^{0.27} \qquad \text{(Equation 4.3)}$$

where:

A_{UCMN2} = annual number of mid-block non-turning cyclists v motor vehicle crashes (subscript denotes model type – see appendix C)

Q = total two-way motor vehicle flow for the link

C = total two-way cycle flow for the link

L = length of mid-block in kilometres

Equation 4.3 indicates that crashes increase with increasing motor vehicle flow, cycle flow and mid-block length. Equation 4.3 has a *p*-value of 0.31, indicating a model with good fit.

Figure 4.3 presents the comparison between the predicted and reported number of crashes for the preferred model and indicates a generally good fit.

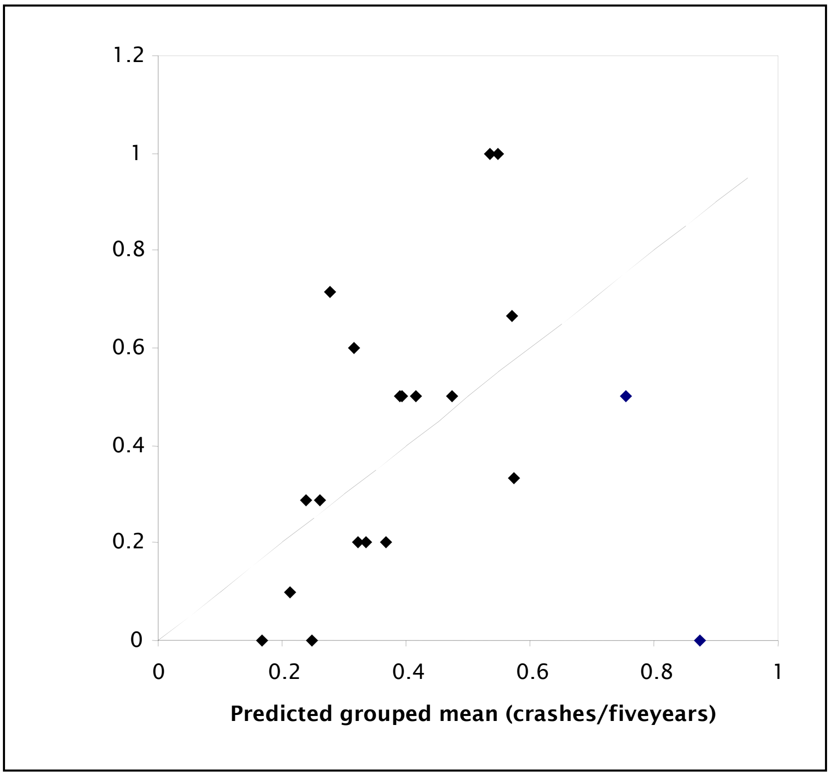


Figure 4.3 Relationship between predicted and reported crashes for A_{UCMN2}

Report years)

5.3.2 Queensland Modelling

Table 4.3 shows the model parameters for the original non-turning cycle crash models, as above, and the new model with the Queensland data. Covariates have been developed for both New Zealand and Queensland.

	Constant (b0)	Traffic Flow exponent	Cycle Flow Exponent	Length Exponent
Original Model	2.28E-4	0.31	0.50	0.27
NZ Covariate	1.96E-2	0.18	0.47	0.46
Qln Covariate	1.17E-2	0.18	0.47	0.46

Table 4.3 Non-turning Cycle versus Motor-vehicle crashes on mid-blocks Model Parameters

The addition of the Queensland data (13 sites) has been to reduce the importance of the traffic volume variable; as traffic volumes go up the crash rate does not increase at the same rate as it does for the New Zealand data alone. The relationship with cycle flow is similar, with a reduced safety-in-numbers effect as the cycle volumes increase. It appears that the safety-in-numbers affect has a much bigger impact on turning related crashes (refer to models in Appendix B). This may-be due to the surprise factor of cyclists pulling out from side-roads and accesses when they are not expected. The absence of the flush median variable in the preferred model indicates this is less important for crashes not involving turning (it leads to approximately a 5% reduction in crashes).

A comparison between the constant covariate values in the new model shows that the rate of cycle crashes in Queensland is less than that of New Zealand (around 60%) for a given combination of flows and length.

6 Roundabout Crash Models

6.1 Introduction

The following sections present the cycle versus motor-vehicle crash models developed for entering versus circulating (cyclists circulating) and 'other' cyclists crash types at urban roundabouts. The New Zealand crash prediction models for roundabouts were developed in Turner et al. (2009b)

6.2 Entering versus Circulating Cyclist Crash Models

Models were developed for entering versus circulating crashes involving motor vehicles (entering) and cyclists (circulating). A much smaller percentage of crashes involve cyclists entering and motorists circulating. Therefore these crashes are included in the 'other cyclists' crash type. The NZ Transport Agency crash types that are included in this dataset are crash codes H, J, K and L (see Appendix B). The Queensland crash coding was converted to the equivalent NZ Transport Agency coding.

Twenty-two models were developed in total. Appendix A outlines the predictor variables and Appendix B the parameters of the models developed. Equation 5.1 presents the preferred model form, which includes entering motor vehicle volumes, circulating cyclist volumes and the mean speed of the entering motor vehicles.

$$A_{UCAR\,1} = 3.88 \times 10^{-5} \times Q_e^{0.43} \times C_c^{0.38} \times S_E^{0.49} \qquad \text{(Equation 5.1)}$$

where:

A_{UCAR1} = annual number of entering v circulating cyclist crashes

Q_e = entering flow on the approach

C_c = circulating cyclist flow perpendicular to the entering motor vehicle flow

S_E = free mean speed of vehicles as they enter the roundabout.

Equation 5.1 has a *p*-value of 0.61, indicating a good fit for the model. Figure 5.1 presents the comparison between reported and predicted crashes of the preferred model. Figure 5.1 indicates a generally good fit, except for an outlier with a reported grouped mean of 2.0 and a predicted grouped mean of 0.73. This outlier comprises of a group of three approaches with high entering motor vehicle volumes and high cyclist circulating volumes.

The entering speed is an important variable in the model. Crashes increase as the mean speed increases, but at a reducing rate. As entry speeds increase drivers often have less time to react to road users on the roundabout and may miss the circulating cyclist who is off to the right of other traffic, in the shoulder of the circulating lanes. Apart from entering vehicle speed, other significant relationships between non-flow variables and crashes are:

- presence of a downhill gradient on the approach to the roundabout
- circulating vehicle speed.

The models showed that the number of crashes increases with increasing circulating and entering vehicle speeds, and with the presence of a downhill gradient (see Appendix B). There was no increase observed for multiple circulating lanes, although this factor may well be taken into account in the entering and circulating speed variable, as larger roundabouts often have higher travel speeds. In other research (Turner and Roozenberg, 2007) on higher (rural) speed limit roundabouts, it was found that motor-vehicle crash rates were 35% higher than for lower speed roundabouts. It is reasonable to assume that at least a 35% increase would be expected for cycle related crashes.

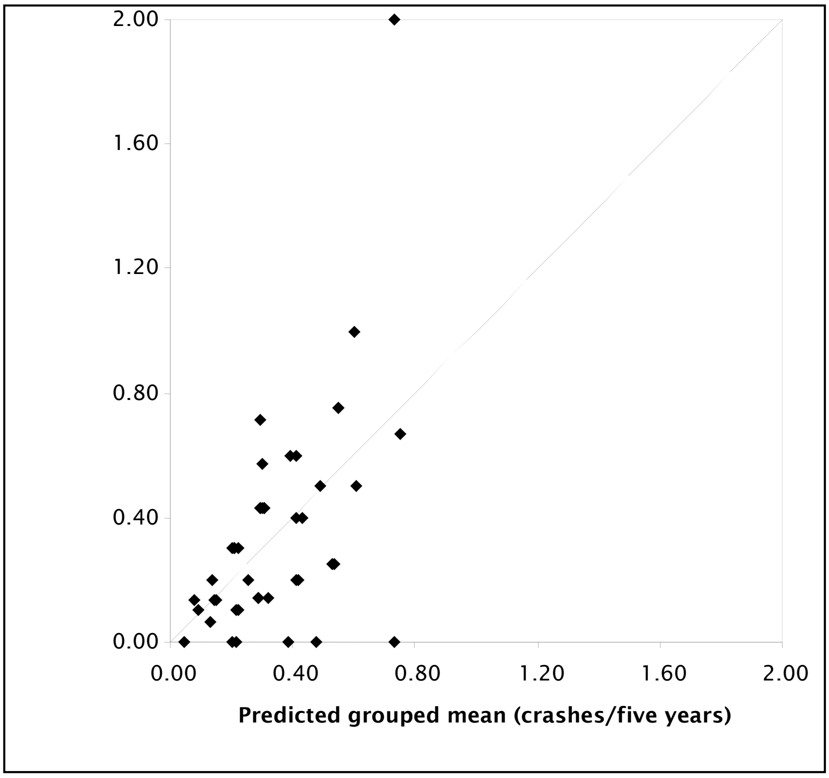


Figure 5.1 Relationship between predicted and reported crashes for the A_{UCAR1} model

Report years)

6.2.1 Queensland Modelling

Table 5.1 shows the model parameters for the entering versus circulating cycle crash models (cyclists circulating), as above, and the new model with the Queensland data. Covariates have been developed for both New Zealand and Queensland.

	Constant (b0)	Traffic Entry Flow exponent	Cycle Circulating Flow Exponent	Entry Speed Exponent
Original Model	8.20E-5	0.43	0.38	0.46
NZ Covariate	1.55E-4	0.39	0.37	0.34
Qln Covariate	6.76E-5	0.39	0.37	0.34

Table 5.1 Entering versus Circulating Cycle Crash Model Parameters

The addition of the Queensland data has had very little impact on the traffic and cycling flow exponents, but has reduced the impact of the increase in entry speed. This indicates that increase in entry speed is less of a factor in the variability in such crashes in Queensland. There is still a safety-in-numbers effect for cyclists (with exponents around 0.37 on the cycle flow), although not as high as observed on mid-block sections.

A comparison between the constant covariate values in the new model shows that the rate of entering versus circulating cycle crashes in Queensland is under half that observed at New Zealand roundabouts for a given combination of flows and speed. This may be due to different design standards for roundabouts. The New Zealand data-set includes a lot of older roundabout designs (based on older design requirements) and some unusual roundabout layouts. Further analysis is required to understand this significant difference.

6.3 'Other' Cyclist Crash Models

Twelve models were developed for 'other' crashes involving cyclists entering and exiting the roundabout. The crash types that are included in the dataset are those involving both cyclists and motor vehicle but exclude crashes where the cyclist is circulating and the motor vehicle is entering, as this is covered by the previous model. Further disaggregation of cycle crashes was not possible given the low numbers of some cycle crash types.

Appendix A outlines the predictor variables and the parameters of all the models. Equation 5.2 presents the preferred model, which includes both the motor vehicle and cyclist approach flows.

$$A_{UCAR2} = 2.07 \times 10^{-7} \times Q_a^{1.04} \times C_a^{0.23} \qquad \text{(Equation 5.2)}$$

where:

A_{UCAR1}	=	annual number of 'other' crashes involving cyclists
Q_a	=	approach flow (sum of entering and exiting motor vehicle flows)
C_a	=	cyclist approach flow (sum of entering and exiting cyclist flows).

The model indicates that as traffic volumes or cyclist volumes increase, the number of crashes also increases in almost a linear manner. The number of crashes is influenced more by an increase in the motor vehicle volume than an increase in the cyclist volume. Increasing the cyclist volume has a 'safety in numbers' effect, where the per-cyclist crash risk drops as the number of cyclists increase. More evidence of this effect can be found in Turner et al (2006).

The preferred model has a *p*-value of 0.50, indicating a good fit. Figure 5.2 presents the comparison between the predicted and reported number of crashes for the preferred model.

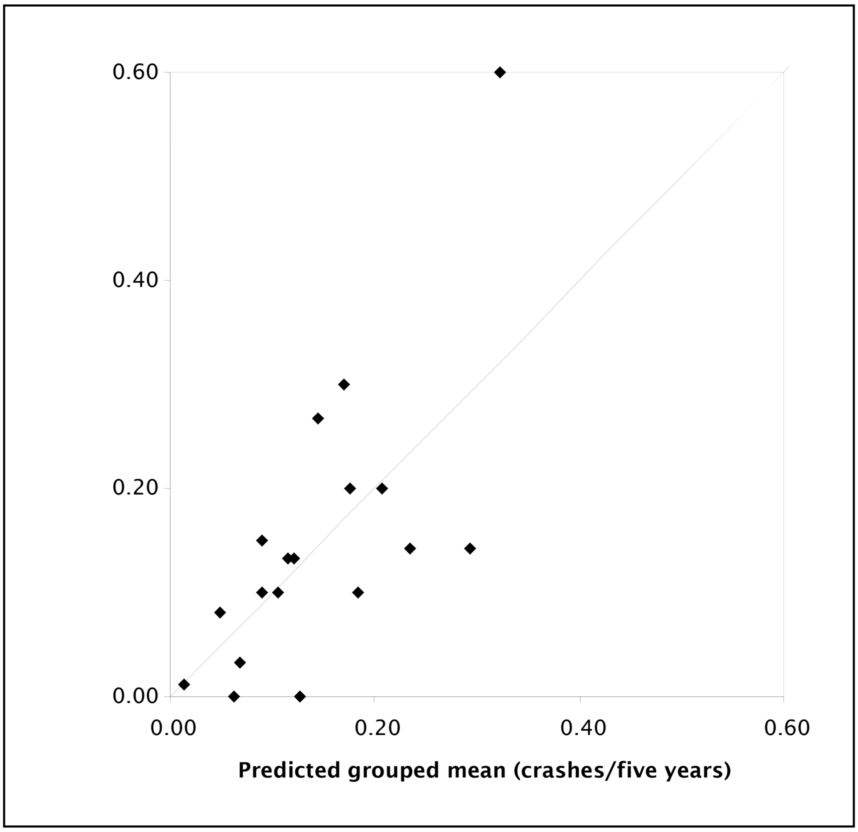


Figure 5.2 Relationship between predicted and reported crashes for the A_{UCAR2} model

Report years)

There were few strong relationships found with non-flow predictor variables, which may in part be due to so many crash types being aggregated together. Interestingly as the visibility increases, the number of crashes decreases, which is the opposite to that found for the main motor-vehicle only crash types. This matter needs further investigation.

6.3.1 Queensland Modelling

Table 5.2 shows the model parameters for the 'other' cycle crash models, as above, and the new model with the Queensland data. Covariates have been developed for both New Zealand and Queensland.

	Constant (b0)	Approach Traffic Flow exponent	Approach Cycle Flow Exponent
Original Model	4.15E-7	1.04	0.23
NZ Covariate	2.55E-7	1.11	0.19
Qln Covariate	2.83E-7	1.11	0.19

Table 5.2 'Other' Cycle Crash Model Parameters

The addition of the Queensland data has had very little impact on the traffic and cycling flow exponents. The predictor variables do have a strong effect on the cycle crash prediction, especially the traffic flow. There is a safety-in-numbers effect for cyclists which is comparable with mid-block sections. As the cycle volumes grow the risk per cyclists reduces considerably.

A comparison between the constant covariate values in the new model shows that the rate of 'other' cycle crashes in Queensland and New Zealand at roundabouts is similar.

7 Traffic Signal Cycle Crash Prediction Models

This section presents the various crash prediction models that have been developed for the main cycle crash types at traffic signals. In addition to volume, the models attempt to look in more detail at the impact of various cycle facility types and road layout variables. A number of different models have been developed for each crash type to attempt to understand the impact of infrastructure features (see Appendix B). The previous research involved data from Christchurch in New Zealand and Adelaide in South Australia.

7.1 Right-turn against crashes (NZ type LB)

This crash type involves a cyclist riding straight through a junction colliding with a vehicle turning right from the opposite direction. This invariably involves a driver that failed to give way when turning right, having failed to see the cyclist. The preferred model form is as follows:

$$A_{UXLB} = B_0 \text{ X } C_2^{b1} \text{ X } Q_7^{\,b2} \text{ X exp (b3 X No. of through traffic lanes) X (Intersection depth)}^{B4} \text{ X } F_{Painted} \text{ X } F_{Approach\ facility} \text{ X } F_{SharedRT} \text{ X } F_{RTphasing}$$

Factor	Value	Description
$B_{0\ (Adelaide)}$	2.45E-03	Constant for Adelaide
$B_{0\ (Christchurch)}$	1.28E-03	Constant for Christchurch
B1	0.52	Exponent on through cycle flow
B2	0.19	Exponent on right turning traffic flow
B3	-0.54	Parameter on number of through lanes
B4	-0.25	Exponent on intersection depth
$F_{Approach\ facility}$	0.58	Presence of approach cycle facility
$F_{Painted}$	0.59	Coloured treatments
$F_{SharedRT}$	0.71	Shared right-turn / through traffic lane on motor vehicle movement approach (RT motor vehicles)
$F_{RTphasing}$	1.05	Fully / partially protected phasing arrangement at intersection

Table 6.1 Model Parameters for NZ and South Australia Model

This model suggests that approaches with a coloured approach cycle facility are expected to have fewer cycle injury crashes. The use of exclusive right turn phasing has very little effect on crashes.

An unexpected finding of this model is that the presence of shared lanes for right turning cars in the conflicts seems to improve safety. This is highly correlated with other factors for which it may be a surrogate.

Figure 6.1 presents the comparison between the predicted and reported number of crashes for the preferred model.

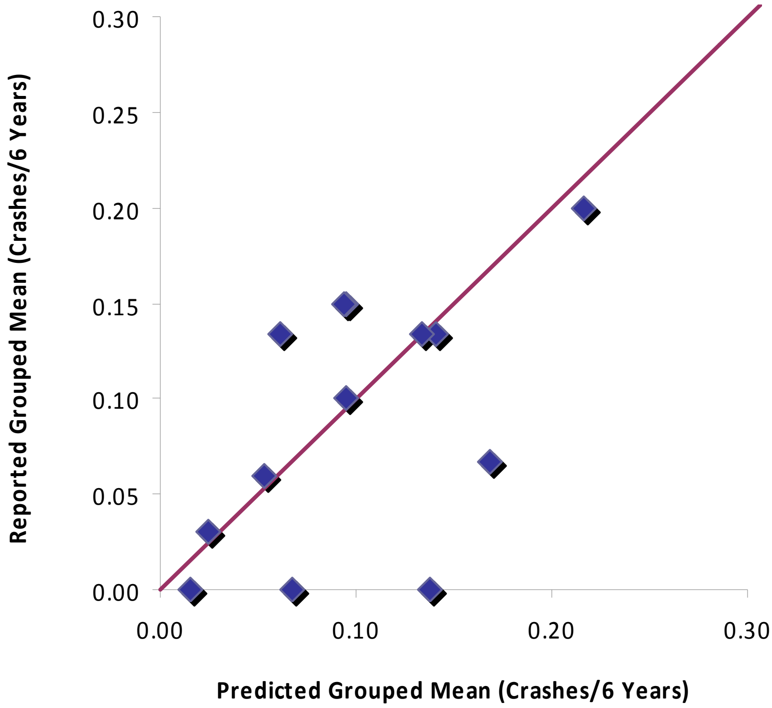


Figure 6.1 – Relationship between predicted and reported LB crashes

7.1.1 Queensland Modelling

Table 6.2 shows the model parameters for the new model with the Queensland data. Covariates have been developed for New Zealand (Christchurch), South Australia (Adelaide) and Queensland.

Factor	Value	Description
B_0 (Adelaide)	1.73E-03	Constant for Adelaide, South Australia
B_0 (Queensland)	1.26E-03	Constant for Queensland
B_0 (Christchurch)	1.26E-03	Constant for Christchurch, New Zealand
B1	0.44	Exponent on through cycle flow
B2	0.21	Exponent on right turning traffic flow
B3	-0.48	Parameter on number of through lanes
B4	-0.11	Exponent on intersection depth
$F_{\text{Approach facility}}$	0.69	Presence of approach cycle facility
F_{Painted}	0.73	Coloured treatments
F_{SharedRT}	0.89	Shared right-turn / through traffic lane on motor vehicle movement approach (RT motor vehicles)
$F_{\text{RTphasing}}$	1.22	Fully / partially protected phasing arrangement at intersection

Table 6.2 Model Parameters for New Model

The addition of the Queensland data has had some impact on the model parameters, with a shift to more weight on the constant value, rather than the predictor variables. The new model shows that approach cycle lanes (stand-up lanes) and coloured surfacing (which is only present at four sites in Queensland) do improve safety.

A comparison between the constant covariate values in the new model shows that the right turn against cycle crash rate for a given set of parameters is very similar in Queensland and New Zealand, but higher for Adelaide. Given the large change in the constant values with the addition of the Queensland data further investigation of the model would be useful to determine if some of the other model parameters need to be adjusted.

7.2 Right angle crashes (NZ type HA)

This model involves a cyclist being hit at right angles from the left or right side by a driver on an adjoining approach. This is often the result of the cyclist or driver running a red light. In some instances the cyclists may have entered on a green or amber signal and was not able to get to the safety of the other side of the intersection prior to the green signal coming up on the adjoining approach.

$$A_{UXHA} = B_0 \text{ X } C_2^{b1} \text{ X } (Q_5 + Q_{11})^{b2} \text{ X } (\text{Total Approach Width})^{b3} \text{ X } (\text{Intersection Depth})^{b4}$$

Factor	Value	Description
B_0 (Adelaide)	1.24E-04	Constant for Adelaide
B_0 (Christchurch)	2.34E-05	Constant for Christchurch
B1	0.48	Exponent on through cycle flow
B2	0.63	Exponent on through volumes traffic flows – to left and right
B3	-0.09	Exponent on total approach width
B4	-0.53	Exponent on intersection depth

Table 6.3 Model Parameters for NZ and South Australian Model

Figure 6.2 presents the comparison between the predicted and reported number of crashes for the preferred model. It shows a group of intersections with a predicted average crash rate that have no observed crashes. This outlier group has impacted on the fit of the model and so care needs to be taken with interpreting the model outputs. Further research is required to understand the reasons for the outlier group.

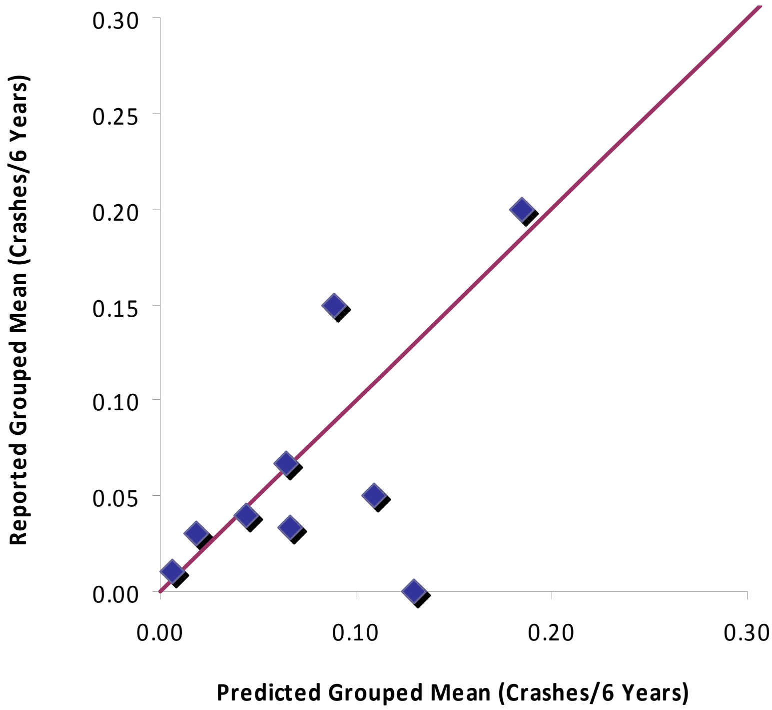


Figure 6.2 – Relationship between predicted and reported crashes

7.2.1 Queensland Modelling

Table 6.4 shows the model parameters for the new model with the Queensland data. Covariates have been developed for New Zealand (Christchurch), South Australia (Adelaide) and Queensland.

Factor	Value	Description
B_0 (Adelaide)	8.06E-05	Constant for Adelaide
B_0 (Queensland)	1.09E-04	Constant for Queensland
B_0 (Christchurch)	1.63E-05	Constant for Christchurch
B1	0.48	Exponent on through cycle flow
B2	0.62	Exponent on through volumes traffic flows – to left and right
B3	-0.09	Exponent on total approach width
B4	-0.53	Exponent on intersection depth

Table 6.4 Model Parameters for New Model

The addition of the Queensland data has had some impact on the model parameters, with a shift to more weight on the constant value. The model indicates that larger intersections are safer than smaller intersections. This could be due to longer inter-green times (amber and all red) at large intersections or that cyclists are less likely to enter the intersection in the amber when there is a large intersection due to the perception they won't be able to get right across the intersection safely. Further investigation of the crash data is required.

A comparison between the constant covariate values in the new model shows that the right angle cycle crash rate for a given set of parameters is much higher in Queensland and South Australia than for Christchurch. This may be due to cyclists being able to use the footpath in Queensland and

Adelaide, which is not allowed in Christchurch, and crossing on the pedestrian crossing illegally. This requires further investigation.

7.3 Same direction crashes (NZ types A, F, G)

This model includes all cycle crashes that occur on the intersection approach, except left turn side-swipe. The New Zealand and South Australian model is as follows:

$$A_{UXA^*FG^*} = B_0 \times C^{B1} \times Q^{B2} \times \text{Total Approach Width}^{B3} \times (\text{kerbside lane width})^{B4} \times F_{\text{Transition facility}} \times F_{\text{Painted}} \times F_{\text{shared lanes}}$$

Factor	Value	Description
B_0 (Adelaide)	9.98E-05	Constant for Adelaide
B_0 (Christchurch)	2.74E-05	Constant for Christchurch
B1	0.37	Exponent on entry cycle flow
B2	0.38	Exponent on entry traffic flow
B3	0.51	Exponent on total approach width (including B4 width)
B4	-0.16	Exponent on kerb-side lane width
$F_{\text{Transition facility}}$	0.90	Presence of transition cycle facility on approach
F_{Painted}	1.49	Coloured treatments
$F_{\text{shared lanes}}$	1.06	Presence of shared through/ left turn lanes on approach

Table 6.5 Model Parameter for New Zealand and South Australian Model

7.3.1 Queensland Modelling

Table 6.6 shows the model parameters for the new model with the Queensland data. Covariates have been developed for New Zealand (Christchurch), South Australia (Adelaide) and Queensland.

Factor	Value	Description
B_0 (Adelaide)	2.44E-05	Constant for Adelaide
B_0 (Queensland)	3.05E-05	Constant for Queensland
B_0 (Christchurch)	8.02E-06	Constant for Christchurch
B1	0.30	Exponent on entry cycle flow
B2	0.55	Exponent on entry traffic flow
B3	0.64	Exponent on total approach width
B4	-0.38	Exponent on kerb-side lane width
$F_{\text{Transition facility}}$	1.06	Presence of transition cycle facility on approach
F_{Painted}	1.53	Coloured treatments
$F_{\text{shared lanes}}$	1.22	Presence of shared through/ left turn lanes on approach

Table 6.6 Model Parameters for New Model

The addition of the Queensland data has had some impact on the model parameters, with a shift to more weight on the predictor variables. As expected shared through and left lanes are not as safe as exclusive left and through lanes. However the model also shows that the presence of a transition facility and painted cycle facilities appear to have a negative effect on safety, which is not what is expected. The overall width of the kerb-side lane or kerb-side lane plus cycle lane seems to be a lot more important in addressing crashes. The model also indicates that larger intersections, with wider approaches are less safe.

A comparison between the constant covariate values in the new model shows that the same direction cycle crash rate/prediction for a given set of parameters is very similar in Queensland and South Australia, but much lower for Christchurch. It is unclear whether this is due to safer intersection design, better driver and cyclist behaviour or different crash reporting rates. It most likely takes into account all these factors.

7.4 Left turn side-swipe crashes – cyclists straight through (NZ type GB)

The model covers crashes between left turning motor-vehicles and through cyclists. They generally occur when there are shared left and through lanes where the cyclists is travelling straight along the kerb-line and the driver of the motor-vehicle turns across them.

$$A_{UXGBAC} = B_0 \text{ X } C_2{}^{b1} \text{ X } Q_3{}^{b2} \text{ X } F_{shared\ LT} \text{ X } F_{Painted} \text{ X } F_{Storage} \text{ X } F_{Transition\ facility}$$

Factor	Value	Description
B_0 (Adelaide)	2.58E-03	Constant for Adelaide
B_0 (Christchurch)	1.06E-03	Constant for Christchurch
B1	0.223	Exponent for through cycle flow
B2	0.369	Exponent for left turning traffic flow
$F_{shared\ LT}$	2.410	Presence of shared through / left turn traffic lane on approach
$F_{Painted}$	0.375	Coloured treatments
$F_{Storage}$	2.353	Bicycle storage area present on approach
$F_{Transition\ facility}$	0.739	Presence of transition cycle facility on approach

Table 6.7 Model Parameters for New Zealand and South Australian Model

Figure 6.3 presents the comparison between the predicted and reported number of crashes for the preferred model.

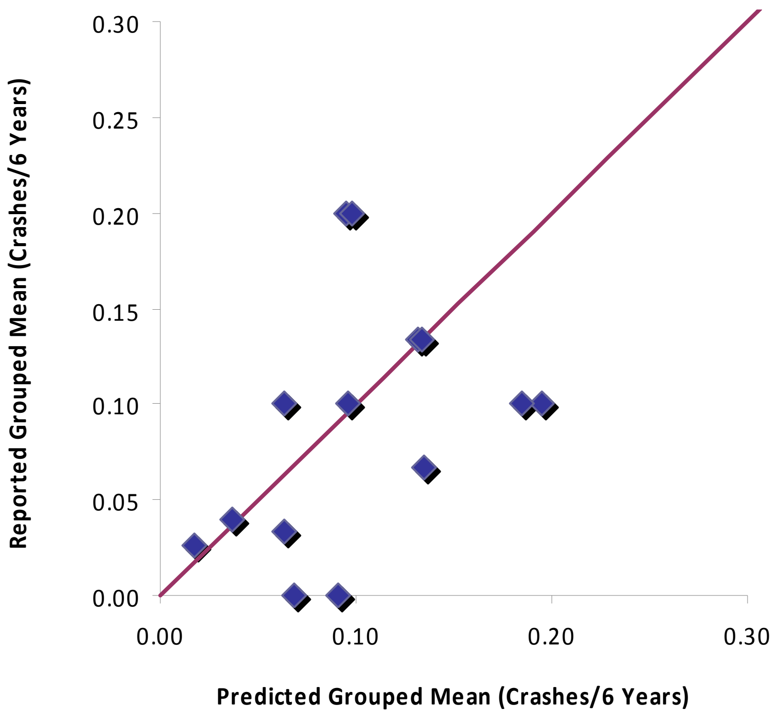


Figure 6.3 – Relationship between predicted and reported crashes

7.4.1 Queensland Modelling

Table 6.6 shows the model parameters for the new model with the Queensland data. Covariates have been developed for New Zealand (Christchurch), South Australia (Adelaide) and Queensland.

Factor	Value	Description
B_0 (Adelaide)	1.92E-03	Constant for Adelaide
B_0 (Queensland)	4.40E-03	Constant for Queensland
B_0 (Christchurch)	8.78E-04	Constant for Christchurch
B1	0.14	Exponent for through cycle flow
B2	0.13	Exponent for left turning traffic flow
$F_{\text{shared LT}}$	2.81	Presence of shared through / left turn traffic lane on approach
F_{Painted}	0.56	Coloured treatments
$F_{\text{Transition facility}}$	0.72	Presence of transition cycle facility on approach (eg. cycle lane provided between through and auxiliary left turn lane)

Table 6.8 Model Parameters for New Model

The addition of the Queensland data has had some impact on the model parameters, with a shift to more weight on the jurisdiction constant. The new model shows that the presence of a transition facility between the left and through lanes for cyclists and painted facilities reduces left-turn side-swipe crashes. A shared left and through lane significantly increases the crash rate, which is expected.

A comparison between the constant covariate values in the new model shows that the Christchurch Queensland intersections have a lower occurrence of left-turn side-swipe crashes than both Brisbane and Adelaide for given predictor variable values.

8 Conclusions and Recommendations

8.1 Conclusions

The New Zealand (and Adelaide) cycle crash prediction models developed for roundabouts, traffic signals and mid-block sections have been used as a basis for developing Queensland models for each of these sites types. At this stage the number of Queensland sites in each category is fairly small, so there is still uncertainty in how well the prediction models can explain cycle crash risk in Queensland. This can be improved by the collection of further data at the three site types across the State. At this stage the conclusions need to be treated with caution. In some cases the Queensland crash relationships with various predictor variables are very similar to that observed in New Zealand while in others it was not.

8.1.1 Mid-block Crash Models

Traffic volume (*Q*) was found to be an important variable in all models and cycle volume (*C*) was an important variable in all 'cycle v motor vehicle' crash types. Length (*L*) is also an important variable in mid-block crashes. The crash risk per cyclist per 100m tends to be higher for shorter mid-block lengthens than for longer lengthens.

The presence of a flush (or painted) median (indicated by the subscript FLUSHMEDIAN) reduces cycle-related crashes for mid-blocks, particularly crashes involving turning cyclists. This is likely to be a result of the extra space that cyclists and motor vehicles have to take evasive action if potential for a collision arises; ie. when the actions of a cyclists surprise a driver. The availability of space is a key issue for cyclists, which is reflected in this result. This, of course, is difficult to achieve on busy arterial roads, and providing (more) room for cyclists is a trade-off that needs to be made in balance with the needs of other road users. Where cycle volumes are high and carriageways are typically wide, as occurs in Christchurch, this is not as difficult to justify as it is in cities like Auckland and Brisbane, where carriageways and lane widths are typically narrower.

The presence of a cycle lane does not feature as a key discrete variable for the mid-block sections, where the presence of a flush median and/or 'no parking' appear to be more important variables. However, a before-and-after study of cycle lanes in New Zealand found that there is a benefit of around a 10% reduction in all cycle crashes.

8.1.2 Roundabout Crash Models

At roundabouts the entry speed was a key factor in entering versus circulating cycle crashes (where cyclists circulating). This is thought to be due to the reduced time that drivers have to scan the roundabout before entering, when there are higher speeds, and the higher likelihood they will miss the cyclists, especially when there are a lot of motor-vehicles using the roundabout. A combination of reduced approach visibility and suitable geometry can be used to reduce approach speeds at roundabouts.

8.1.3 Traffic Signals Crash Models

At traffic signals the size of the intersection does impact on safety. A wide kerbside lane or combined kerb-side lane and cycle lane improves safety for cyclists as they approach an intersection. Various cycle facilities do have an impact on safety. Coloured, or painted cycle facilities, does generally improve safety. A combined through and left turn lane was found to be less safe than an exclusive left and through lane.

8.1.4 Jurisdiction Covariates Approach

This research has shown how covariate cycle crash models can be developed for Queensland using a wider sample set across New Zealand and for traffic signals in Adelaide. However, some care does need to be taken in using the current models based on the small number of sites that are available for Queensland. Ideally data needs to be collected for a larger sample set of sites so that the Queensland crash models are more reflective of local conditions. Some further refinement of the research would help to identify how the Queensland cycle crash rates differ from other jurisdictions.

8.2 Recommendations

This study has demonstrated how crash prediction models for cyclists at various site types can be developed using data from a combination of different jurisdictions (or States). This is important in order to have a large enough sample of sites to have confidence in the model predictions, and to include sufficient predictor variables. With sufficient data from a jurisdiction it is possible to produce a calibrated model for use in that State. Unfortunately there are currently not enough sites from Queensland for there to be confidence in the Queensland calibration factors. A high priority for this work going forward is for a larger sample set of each site type to be pulled together. Once this data is collected and new models produced it would also be important to validate the models, by using them to predict cycle crashes at sites which were not used to build the models. This provides confidence that they are suitable, or not, for widespread application across the State.

There are a variety of benefits of developing cycle crash prediction models for Queensland, including.

1. Estimating the crash benefits (social costs) of installing cycling facilities and making improvements that enhance cycle safety (eg. reducing traffic volumes, reducing travel speeds and providing more space for cyclists, possibly through reallocation of road space)
2. Developing robust urban AusRAP/ANRAM ratings for cyclists based on the features of a road and the cycle facilities that have been installed. To make these State specific rather than rely on national or international risk rating factors (from iRAP).
3. To contribute evidence to the development of policies and guidelines on infrastructure measures that can be made to improve cycle safety
4. To evaluate the safety performance (level of safety service) of routes and series of intersections. This is achieved by comparing the cycle crash predictions with the actual number of cycle crashes observed. Is the crash rate typical or higher or lower than would be expected for the road features and operating conditions? The models can also be used to assess the benefits of various improve schemes that could be applied, including changes to the traffic flow, road width and traffic speed along a corridor.

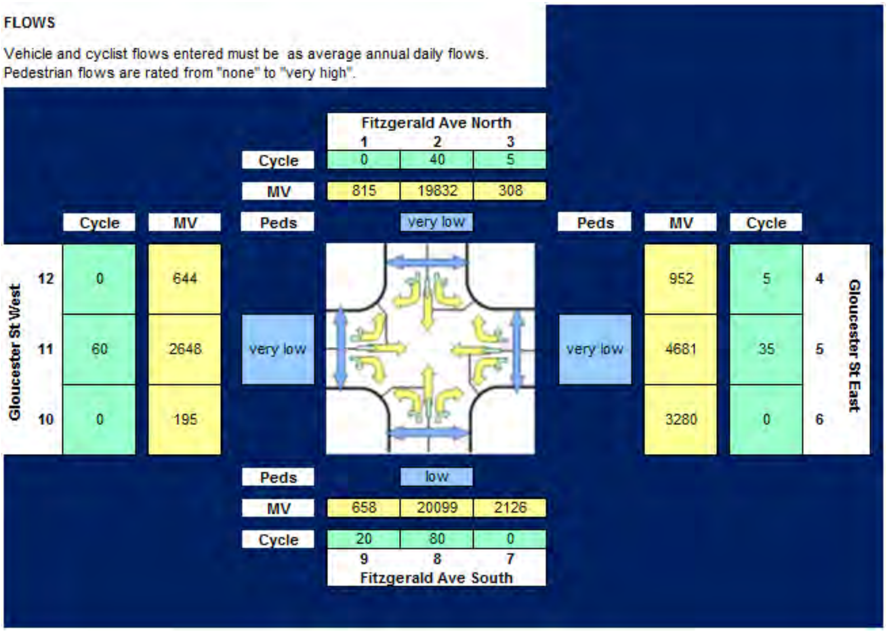
Experience indicates that for stand-alone crash prediction models the minimum sample set is around 100 sites. When the data is combined with a larger sample set and it is being used for calibration purposes (as is the case here) then around 50 sites is considered sufficient. I would recommend the following next steps (likely cost of study is $200,000 to $500,000 depending on how many sites types and what quality of models TMR want):

1) Agree the full list of site types and sub-site types for which models needs to be developed for Queensland. For example TMR may wish to add priority intersections (new site type) and divided mid-blocks (sub-site type) to the list of sites of interest.
2) Agree the key variables that are considered important for inclusion in the crash prediction models. This may or may not be different for the variables looked at in the previous models developed.

3) Collect additional data for each site type so that there is a minimum of 50 sites available for the crash modelling exercise. For priority intersections data for 100 sites would need to be collected as there is no current data-set for this site type. Ideally 100x 3-arm and 100x 4-arm intersections. For divided routes a smaller sample set would be sufficient (say 25 to 30 sites), as part of a larger sample set of Queensland mid-blocks.
4) Undertake a full model exercise for each site type. This would not only look to include the same variables used in the previous models, but test whether other variables collected need to be included within the Queensland models.
5) Assess whether there are any regional variations across the State by looking at a city/district calibration factor/dummy variable.
6) Validate the models on road sections and intersections that where not used to build the models. Consider say a further ten sites of each site type for validation.

Other pieces of work that would be beneficial include:

- Development of crash severity factors for each site type for motor-vehicle only and cycle crashes. This can be undertaken through an analysis of the State crash database. A similar exercise was recently completed in New Zealand as part of the development of the High Risk Intersection Guide, for motor-vehicle crashes. This would enable severity to be considered when evaluating the safety of various sites for cyclists.
- The development of reporting rates both for motor-vehicles and cycle crashes. This can then be compared with reporting rates from other jurisdictions, to better understand the jurisdiction specific calibration factors.
- Development of a crash prediction toolkit, in at least excel and ideally with a GIS capability to make the models more accessible and enable outputs to be presented graphically. Examples of the Beca intersection crash toolkit follow:



Geometric Variables (by approach)	Fitzgerald A	Gloucester	Fitzgerald A	Gloucester
Intersection depth (m)	21	38	21	38
Approach width (m)	16	6.5	15.4	6.2
Total number of approach lanes	5	2	5	2
Number of through lanes on approach	3	1	3	1
Length of Right-turn bay or lane on approach (m)	21	101	21	101
Shared use lane/s on approach	No	Yes	No	Yes
Shared Right-turn lane on approach	No	Yes	No	Yes
Free left turn for motor vehicles on approach	No	No	No	No
Raised median or central island on approach	Yes	No	Yes	No
Cycle facility on approach	No	No	No	No
Merge present on exit side	No	No	No	No
Signal related Variables (by approach)				
Green time on through movements per cycle (s)	59	27	59	27
Degree of saturation	26%	41%	27%	23%
Fully protected Right-turn phasing	Yes	Yes	Yes	Yes
Coordinated with upstream intersection	Yes	Yes	Yes	Yes
Overhead mast arm on approach	No	No	No	No
Other Variables (by approach)				
Speed limit 80km/hour or greater on apporach	No	No	No	No
Bus bay within 100m upstream of approach	Yes	No	No	No
Parking within 100m upstream of approach	Yes	Yes	Yes	Yes
Dominant land use on approach	Res	Res	Res	Res

CRASHES BY TYPE AND APPROACH

Crash Type	Crash Code	Fitzgerald Ave North	Gloucester St East	Fitzgerald Ave South	Gloucester St West	Total
Motor vehicle Crashes						
Right angle	HA	0.260	0.267	0.261	0.224	1.011
Right turn Against	LB	0.128	0.025	0.111	0.026	0.290
Rear end	F	0.085	0.030	0.098	0.019	0.231
Loss of Control	C and D	0.126	0.039	0.083	0.018	0.266
Other	Other	0.022	0.017	0.017	0.013	0.069
Total		**0.620**	**0.378**	**0.570**	**0.299**	**1.867**
Cycle Crashes						
Same Direction	A, E, F, G	0.018	0.014	0.020	0.011	0.064
Right turn Against	LB	0.003	0.002	0.003	0.002	0.010
Other	Other	0.016	0.012	0.017	0.010	0.055
Total		**0.037**	**0.028**	**0.041**	**0.022**	**0.129**
Pedestrian Crashes						
Intersecting	NA and NB	0.017	0.014	0.022	0.010	0.062
Right Turning	ND and NF	0.004	0.004	0.005	0.004	0.017
Total		**0.021**	**0.018**	**0.027**	**0.014**	**0.079**

	INJURY CRASHES		SERIOUS & FATAL CRASHES	
Motor vehicle crashes	**1.87**	per year	**0.22**	per year
Cycle crashes	**0.13**	per year	**0.02**	per year
Pedestrian crashes	**0.08**	per year	**0.02**	per year
All crashes	**2.07**	per year	**0.25**	per year
Return period (all crashes)	**6**	months	**4**	years

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Appendix A

Models Developed for Each Crash Type

Mid-Block Cycle Crash Prediction Models

The following section outlines the model parameters for the eight crash categories.

Predictor variables	Parameters					Multiplier Φ	Error structure	BIC
	b_0	b_1	b_2	b_3	b_4			
Q, L	1.43×10^{-2}	0.29	0.36				*k* = 1.6	2.861
C, L	8.73×10^{-2}	0.20	0.36				*k* = 1.6	2.862
Q, C, L	8.60×10^{-3}	0.25	0.17	0.37			*k* = 1.6	2.902
Q, C, L, $\boldsymbol{\Phi_{FLUSHMEDIAN}}$	$\mathbf{1.05\times10^{-2}}$	**0.25**	**0.16**	**0.45**		**0.63**	***k* = 1.7**	**2.926**
Q, C, L, W_e	1.65×10^{-3}	0.33	0.11	0.28	0.65		*k* = 1.7	2.937
Q, C, L, $\Phi_{CYCLANE}$	7.11×10^{-3}	0.25	0.19	0.38		1.21	*k* = 1.6	2.944
Q, C, L, W	1.15×10^{-3}	0.36	0.15	0.35	0.62		*k* = 1.6	2.945
Q, C, L, S	2.04×10^{-3}	0.23	0.18	0.37	0.40		*k* = 1.6	2.949
Q, C, L, Lns	7.38×10^{-3}	0.27	0.17	0.37	-0.05		*k* = 1.6	2.949
Q, C, L, $e^{(As/100)}$, $e^{(Ar/100)}$, $e^{(Ao/100)}$*	8.26×10^{-3}	0.30	0.14	0.50	-0.03		*k* = 1.7	3.038

*For the last model, b_5 = 0.0 and b_6 = -0.01.

Table A.1 – Cyclist Mid-Block Crashes (U_{CMN0})

Predictor variables	Parameters					Multiplier Φ	Error structure	BIC
	b_0	b_1	b_2	b_3	b_4			
Q, L, $\boldsymbol{\Phi_{NOPARKING}}$	**0.84**	**0.30**				**0.25**	***k* = 1.4**	**5.120**
Q, L	0.71	0.35					*k* = 1.3	5.171
Q, L, $\Phi_{VERYLOWPARKINGUSE}$	0.76	0.21				1.64	*k* = 1.3	5.185
Q, C, L	0.66	0.29	0.35				*k* = 1.3	5.192
Q, L, $\Phi_{CYCLANE}$	0.71	0.36				1.22	*k* = 1.3	5.209
C, L, $\Phi_{NOPARKING}$	0.34	0.28				0.36	*k* = 1.3	5.211
Q, L, $e^{(Ar/100)}$	0.78	0.28	0.00				*k* = 1.3	5.211
Q, L, $\Phi_{FLUSHMEDIAN}$	0.71	0.39				0.85	*k* = 1.3	5.214
C, L	0.37	0.33					*k* = 1.2	5.218
Q, L, $e^{(As/100)}$	0.37	0.30	0.02				*k* = 1.2	5.256

Table A.2 – All mid-block crashes (U_{AMN0})

Predictor variables	Parameters					Multiplier Φ	Error structure	BIC
	b_0	b_1	b_2	b_3	b_4			
Q	2.92×10^{-2}	0.15					k = 1.0	2.304
Q, L	2.22×10^{-2}	0.21	0.42				k = 1.2	2.319
C, L	2.29×10^{-1}	-0.05	0.41				k = 1.2	2.322
Q, L, $\Phi_{FLUSHMEDIAN}$	**3.50×10^{-2}**	**0.19**	**0.54**			**0.48**	**k = 1.3**	**2.329**
Q, L, $\Phi_{VERYLOWPARKINGUSE}$	6.36×10^{-3}	0.30	0.27			1.85	k = 1.3	2.340
Q, L, $\Phi_{NOPARKING}$	1.08×10^{-2}	0.28	0.41			0.49	k = 1.2	2.353
Q, L, $e^{(As/100)}$	1.98×10^{-2}	0.19	0.38	0.03			k = 1.2	2.355
Q, L, $\Phi_{CYCLANE}$	1.90×10^{-2}	0.21	0.44			1.32	k = 1.2	2.358
Q, L, W	2.94×10^{-3}	0.31	0.40	0.63			k = 1.2	2.363
Q, L, S	8.71×10^{-4}	0.17	0.42	0.93			k = 1.2	2.364
Q, C, L	2.81×10^{-2}	0.23	-0.09	0.42			k = 1.2	2.365
Q, L, Lns	1.41×10^{-2}	0.25	0.42	-0.13			k = 1.2	2.365
Q, L, $e^{(Ar/100)}$	2.09×10^{-2}	0.21	0.42	0.00			k = 1.2	2.366
Q, C, L, $\Phi_{FLUSHMEDIAN}$	4.69×10^{-2}	0.21	-0.11	0.55		0.48	k = 1.3	2.375
Q, C, L, We	1.10×10^{-3}	0.39	-0.22	0.24	1.33		k = 1.3	2.376
Q, C, L, W	3.40×10^{-3}	0.35	-0.10	0.40	0.67		k= 1.2	2.408
Q, C, L, S	1.50×10^{-3}	0.19	-0.06	0.42	0.82		k = 1.2	2.410
Q, C, L, Lns	1.66×10^{-2}	0.29	-0.10	0.42	-0.15		k = 1.2	2.411

Table A.3 – Cyclist Mid-Block Turning Crashes (U_{CMN1})

Predictor variables	Parameters					Multiplier Φ	Error structure	BIC
	b_0	b_1	b_2	b_3	b_4			
Q, L, $\Phi_{NOPARKING}$	**1.37×10^{-3}**	**0.56**	**0.10**			**0.25**	**k = 0.8**	**3.646**
Q, L	7.26×10^{-3}	0.39	0.16				k = 0.7	3.648
C, L	$1.09E\times10^{-1}$	0.23	0.14				k = 0.8	3.653
Q, L, $\Phi_{VERYLOWPARKINGUSE}$	2.15×10^{-3}	0.48	-0.02			2.05	k = 0.8	3.655
Q, L, $\Phi_{FLUSHMEDIAN}$	8.01×10^{-3}	0.40	0.23			0.72	k = 0.7	3.687
Q, C, L	4.09×10^{-3}	0.35	0.19	0.17			k = 0.7	3.690
Q, L, $e^{(As/100)}$	7.16×10^{-3}	0.39	0.15	0.01			k = 0.7	3.694
Q, L, $\Phi_{CYCLANE}$	7.19×10^{-3}	0.39	0.17			1.06	k = 0.7	3.695
Q, L, $e^{(Ar/100)}$	5.83×10^{-3}	0.41	0.14	0.00			k = 0.7	3.695

Table A.4 – All Mid-Block Turning Crashes (U_{AMN1})

Predictor variables	Parameters					Multiplier Φ	Error structure	BIC
	b_0	b_1	b_2	b_3	b_4			
C	3.90×10^{-3}	0.53					Poisson	1.560
Q	9.95×10^{-4}	0.42					Poisson	1.589
C, L	4.52×10^{-3}	0.54	0.27				Poisson	1.595
Q, C	2.11×10^{-4}	0.30	0.51				Poisson	1.601
Q, L	8.61×10^{-4}	0.46	0.28				Poisson	1.622
Q, C, L	**2.28×10^{-4}**	**0.31**	**0.50**	**0.27**			**Poisson**	**1.635**
$C, L, \Phi_{NOPARKING}$	*	*	*			*	*	*
$C, L, \Phi_{FLUSHMEDIAN}$	4.71×10^{-3}	0.53	0.27			0.94	Poisson	1.641
$C, L, \Phi_{VERYLOWPARKINGUSE}$	4.79×10^{-3}	0.53	0.30			0.86	Poisson	1.641
$C, L, \Phi_{CYCLANE}$	4.56×10^{-3}	0.54	0.27			0.99	Poisson	1.642

Table A.5 – Cyclist Non-Turning Crashes (U_{CMN2})

Predictor variables	Parameters					Multiplier Φ	Error structure	BIC
	b_0	b_1	b_2	b_3	b_4			
$Q, L, \Phi_{NOPARKING}$	**4.39×10^{-5}**	**0.97**	**0.42**			**0.25**	**$k = 1.6$**	**4.224**
Q, L	1.25×10^{-4}	0.86	0.45				$k = 1.3$	4.261
Q, C, L	3.55×10^{-5}	0.80	0.33	0.44			$k = 1.4$	4.276
$Q, L, \Phi_{CYCLANE}$	8.34×10^{-5}	0.89	0.46			1.34	$k = 1.4$	4.290
$Q, L, e^{(Ar/100)}$	3.62×10^{-5}	0.96	0.35	0.00			$k = 1.4$	4.294
$Q, L, \Phi_{VERYLOWPARKINGUSE}$	8.37×10^{-5}	0.89	0.36			1.37	$k = 1.4$	4.297
$Q, L, e^{(As/100)}$	1.22×10^{-4}	0.85	0.42	0.02			$k = 1.4$	4.299
$Q, L, \Phi_{FLUSHMEDIAN}$	1.27×10^{-4}	0.86	0.45			0.97	$k = 1.3$	4.308
C, L	7.02×10^{-2}	0.43	0.43				$k = 1.2$	4.332

Table A.6 – All Non-Turning Crashes (U_{AMN2})

Predictor variables	Parameters					Multiplier Φ	Error structure	BIC
	b_0	b_1	b_2	b_3	b_4			
Q_{MOTOR},	1.00×10^{-2}	0.15					Poisson	0.819
Q_{CYC}	3.15×10^{-2}	0.05					Poisson	0.820
$Q_{MOTOR}, \Phi_{CYCLANE}$	6.63×10^{-3}	0.18				1.43	Poisson	0.845
Q_{CYC}, Q_{MOTOR}	8.86×10^{-3}	0.04	0.14				Poisson	0.848
$Q_{CYC}, Q_{MOTOR}, \Phi_{CYCLANE}$	**6.16×10^{-3}**	**0.03**	**0.17**			**1.41**	**Poisson**	**0.874**

Table A.7 – Cyclist Signalised Crossroad Product of Link (U_{CXT0})

Predictor variables	Parameters					Multiplier Φ	Error structure	BIC
	b_0	b_1	b_2	b_3	b_4			
Q_{MOTORr}	**3.71×10^{-4}**	**0.67**					**Poisson**	**2.125**
Q_{MOTOR}, $\Phi_{CYCLANE}$	4.41×10^{-4}	0.65				0.91	Poisson	2.153
Q_{CYC}, Q_{MOTOR}	3.39×10^{-4}	0.03	0.66				Poisson	2.153
Q_{CYC}, Q_{MOTOR}, $\Phi_{CYCLANE}$	4.07×10^{-4}	0.03	0.65			0.90	Poisson	2.181

Table A.8 – Motor Vehicle Signalised Crossroad Product of Link (U_{MXT0})

Roundabout Cycle Crash Prediction Models

Predictor variables	Parameters					Multiplier Φ	Error structure	BIC
	b_0	b_1	b_2	b_3	b_4			
Q_e, S_c	1.94×10^{-7}	0.52	2.33				k = 1.2	1.020
Q_e, $e^{(Sc)}$	4.75×10^{-5}	0.52	0.08				k = 1.2	1.020
Q_e, S_c, Φ_{MEL}	1.79×10^{-6}	0.36	2.00			1.91	k = 1.4	1.021
Q_e, Φ_{MEL}	1.20×10^{-3}	0.37				2.16	k = 1.2	1.026
Q_e, Q_c, S_c	**6.12×10^{-8}**	**0.47**	**0.26**	**2.13**			**k = 1.3**	**1.029**
Q_e, S_e	4.46×10^{-6}	0.42	1.66				k = 1.1	1.031
Q_e	3.20×10^{-4}	0.55					k = 1.0	1.031
Q_e, Q_c, S_c, Φ_{MEL}	6.73×10^{-7}	0.34	0.17	1.91		1.79	k = 1.5	1.034
Q_e, S_c, S_e, Φ_{MEL}	1.05×10^{-6}	0.32	1.68	0.58		1.87	k = 1.5	1.035
Q_e, Q_c	2.49×10^{-5}	0.48	0.37				k = 1.1	1.035
Q_e, Φ_{MCL}	6.36×10^{-4}	0.45				1.67	k = 1.1	1.037
Q_c	8.79×10^{-4}	0.44					k = 1.9	1.039
Q_e, V_{10}	1.35×10^{-4}	0.50	0.31				k = 1.0	1.040
Q_e, SSD_e	2.19×10^{-4}	0.53	0.44				k = 1.0	1.041
Q_e, SSD_c	1.64×10^{-4}	0.58	0.38				k = 1.0	1.042
Q_e, V_{LL}	1.77×10^{-4}	0.54	0.16				k = 1.0	1.044
Q_e, V_{40}	1.70×10^{-4}	0.54	0.19				k = 1.0	1.044
Q_e, Φ_{GRADD}	3.25×10^{-4}	0.55				0.85	k = 1.0	1.045
Q_e, Φ_{TJUN}	3.20×10^{-4}	0.55				1.12	k = 1.0	1.045

Table A.9 – Entering v Circulating (Motor Vehicle Only) Model Parameters

Predictor variables	Parameters					Multiplier Φ	Error structure	BIC
	b_0	b_1	b_2	b_3	b_4			
Q_e, $e^{(Qe/100)}$, SSD_e	3.92×10^{-2}	-0.53	0.03	1.50			k = 1.8	0.657
Q_e, $e^{(Qe/100)}$, SSD_e, S_e	2.96×10^{-4}	-0.53	0.02	1.32	1.59		k = 1.8	0.664
Q_e, SSD_e	2.86×10^{-7}	1.07	1.35				k = 1.9	0.669
Q_e, SSD_e, S_e	3.47×10^{-9}	0.89	1.13	1.92			k = 1.0	0.672
Q_e, $e^{(Qe/100)}$	**9.63×10^{-2}**	**-0.38**	**0.02**				**k = 1.7**	**0.672**
Q_e, S_e	1.73×10^{-9}	0.83	2.76				k = 1.9	0.674
Q_e, SSD_e, Φ_{MEL}	1.25×10^{-6}	0.91	1.16			1.78	k = 1.0	0.678
Q_e, $e^{(SSDe)}$	6.56×10^{-7}	1.08	0.22				k = 1.9	0.678
Q_e, Φ_{MEL}	8.99×10^{-6}	0.85				2.41	k = 1.8	0.682
Q_e	1.44×10^{-6}	1.10					k = 1.7	0.682
Q_e, V_{10}	4.87×10^{-7}	0.99	0.50				k = 1.8	0.688
Q_e, V_{40}	2.20×10^{-7}	1.03	0.60				k = 1.8	0.690
Q_e, Φ_{GRADD}	1.02×10^{-6}	1.13				2.22	k = 1.7	0.690
Q_e, V_{LL}	4.44×10^{-7}	1.05	0.38				k = 1.8	0.692
Q_e, Φ_{TJUN}	1.45×10^{-6}	1.10				1.14	k = 1.7	0.696

Table A.10 – Rear End (Motor Vehicle Only) Model Parameters

Predictor variables	Parameters					Multiplier Φ	Error structure	BIC
	b_0	b_1	b_2	b_3	b_4			
Q_a, V_{10}	**6.36×10^{-6}**	**0.59**	**0.68**				**k = 3.9**	**0.786**
Q_a, $e^{(V10)}$	3.86×10^{-5}	0.65	0.01				k = 3.4	0.786
Q_a, V_{LL}	3.31×10^{-6}	0.65	0.65				k = 3.3	0.790
Q_a, V_{40}	3.05×10^{-6}	0.60	0.81				k = 3.9	0.791
Q_a	3.41×10^{-5}	0.71					k = 2.1	0.796
Q_a, V_{10}, S_e	7.72×10^{-7}	0.51	0.58	1.00			k = 3.9	0.797
Q_e, S_e	5.08×10^{-7}	0.54	1.77				k = 2.2	0.797
Q_a, Φ_{GRADD}	3.35×10^{-5}	0.72				0.39	k = 2.4	0.805
Q_a, Φ_{TJUN}	3.52×10^{-5}	0.70				2.01	k = 2.1	0.805
Q_e	3.60×10^{-4}	0.50					k = 1.6	0.806
Q_e, SSD_e	2.63×10^{-5}	0.70	0.27				k = 2.0	0.809
Q_a, Φ_{MEL}	5.60×10^{-5}	0.65				1.24	k = 2.2	0.809

Table A.11 – Loss of Control (Motor Vehicle Only) Model Parameters

Predictor variables	Parameters					Multiplier Φ	Error structure	BIC
	b_0	b_1	b_2	b_3	b_4			
Q_a, Φ_{MEL}	**1.34×10^{-5}**	**0.71**				**2.66**	**Poisson**	**0.568**
Q_a	9.68×10^{-7}	1.04					Poisson	0.569
Q_a, V_{LL}	2.30×10^{-6}	1.10	-0.34				Poisson	0.581
Q_e, SSD_e	1.46×10^{-6}	1.05	-0.43				Poisson	0.582
Q_a, $e^{(Qa/100)}$, Φ_{MEL}	1.61×10^{-4}	0.41	0.002			2.60	Poisson	0.582
Q_a, $e^{(Qa/100)}$	1.68×10^{-4}	0.42	0.005				Poisson	0.582
Q_a, Φ_{TJUN}	9.10×10^{-7}	1.05				0.45	Poisson	0.582
Q_a, V_{40}	2.18×10^{-6}	1.08	-0.31				Poisson	0.582
Q_a, V_{10}	1.14×10^{-6}	1.06	-0.10				Poisson	0.584
Q_a, Φ_{GRADD}	9.67×10^{-7}	1.04				0.97	Poisson	0.584
Q_e, S_e	1.02×10^{-6}	1.04	-0.03				Poisson	0.584

Table A.12 – Other (Motor Vehicle Only) Model Parameters

Predictor variables	Parameters					Multiplier Φ	Error structure	BIC
	b_0	b_1	b_2	b_3	b_4			
P, Φ_{MEL}	5.60×10^{-4}	0.55				4.66	k = 1.4	0.882
P, $e^{(Qa/100)}$ Φ_{MEL}	3.84×10^{-4}	0.55	0.003			3.67	k = 1.8	0.889
Q_a, P, Φ_{MEL}	3.10×10^{-5}	0.32	0.55			3.93	k = 1.6	0.891
P, $e^{(Qa/100)}$	**3.45×10^{-4}**	**0.60**	**0.01**				**k = 1.0**	**0.919**
Q_a, P	1.58×10^{-6}	0.68	0.59				k = 1.9	0.929
P, Q_a, $e^{(Qa/100)}$	7.88×10^{-4}	0.60	-0.10	0.007			k = 1.0	0.935
P	8.41×10^{-4}	0.61					k = 1.6	0.940
P, SSD_e	2.92×10^{-4}	0.61	0.79				k = 1.6	0.945
P, V_{10}	1.38×10^{-4}	0.64	0.40				k = 1.6	0.950
P, V_{40}	1.15×10^{-4}	0.63	0.45				k = 1.6	0.950
P, S_e	3.64×10^{-3}	0.58	-0.41				k = 1.5	0.955
P, Φ_{GRADD}	8.58×10^{-4}	0.60				1.14	k = 1.6	0.955
P, Φ_{TJUN}	8.23×10^{-4}	0.61				1.17	k = 1.6	0.955
P, V_{LL}	1.05×10^{-3}	0.60	-0.05				k = 1.6	0.955
Q_a	2.46×10^{-5}	0.71					k = 1.3	1.007
Q_a, $e^{(Qa/100)}$	6.08×10^{-3}	0.02	0.01				k = 1.3	1.016

Table A.13 – Pedestrian Crossing Model Parameters

Predictor variables	Parameters					Multiplier Φ	Error structure	BIC
	b_0	b_1	b_2	b_3	b_4			
Q_e, C_c	1.51×10^{-4}	0.46	0.38				k = 1.2	1.230
C_c	7.45×10^{-3}	0.39					k = 1.0	1.236
C_c, $e^{(Qe/100)}$	5.41×10^{-3}	0.38	0.01				k = 1.1	1.243
Q_e, C_c, S_e	**3.88×10^{-5}**	**0.43**	**0.38**	**0.49**			**k = 1.2**	**1.245**
C_c, $e^{(Cc/100)}$	5.06×10^{-3}	0.58	-0.46				k = 1.1	1.245
C_c, S_e	2.59×10^{-4}	0.39	1.01				k = 1.0	1.247
C_c, Φ_{GRADD}	8.23×10^{-3}	0.37				0.50	k = 1.0	1.247
C_c, V_{40}	1.41×10^{-3}	0.40	0.39				k = 1.0	1.248
C_c, S_c	6.63×10^{-4}	0.38	0.74				k = 1.0	1.249
C_c, V_{LL}	1.69×10^{-2}	0.38	-0.19				k = 1.0	1.250
C_c, SSD_e	1.08×10^{-2}	0.37	-0.26				k = 1.0	1.250
C_c, SSD_c	5.32×10^{-3}	0.40	0.27				k = 1.0	1.250
C_c, Φ_{TJUN}	7.75×10^{-3}	0.38				0.63	k = 1.0	1.251
C_c, V_{10}	5.33×10^{-3}	0.39	0.08				k = 1.0	1.252
C_c, Φ_{MCL}	7.49×10^{-3}	0.39				0.99	k = 1.0	1.252
C_c, Φ_{MEL}	7.43×10^{-3}	0.39				1.00	k = 1.0	1.252
Q_e	3.27×10^{-4}	0.51					k = 1.8	1.262
Q_e, $e^{(Cc/100)}$	2.66×10^{-4}	0.51	0.43				k = 1.8	1.264
Q_c	4.20×10^{-4}	0.48					k = 1.8	1.264
Q_e, $e^{(Qe/100)}$	1.28×10^{-6}	1.26	-0.01				k = 1.8	1.268

Table A.14 – Motorist Entering Versus Circulating Cyclist Model Parameters

Predictor variables	Parameters					Multiplier Φ	Error structure	BIC
	b_0	b_1	b_2	b_3	b_4			
Q_a	2.33×10^{-7}	1.13					Poisson	0.611
Q_a, C_a	**2.07×10^{-7}**	**1.04**	**0.23**				**Poisson**	**0.621**
Q_a, V_{LL}	5.76×10^{-7}	1.22	-0.42				Poisson	0.622
Q_a, V_{10}	3.84×10^{-7}	1.22	-0.34				Poisson	0.624
Q_a, V_{40}	8.25×10^{-7}	1.19	-0.46				Poisson	0.625
Q_a, Φ_{TJUN}	2.13×10^{-7}	1.14				0.52	Poisson	0.626
Q_a, S_e	7.27×10^{-7}	1.17	-0.49				Poisson	0.626
Q_a, Φ_{MEL}	4.42×10^{-7}	1.05				1.24	Poisson	0.626
Q_a, SSD_e	2.75×10^{-7}	1.14	-0.22				Poisson	0.626
Q_a, Φ_{GRADD}	2.36×10^{-7}	1.13				0.89	Poisson	0.627
Q_a, C_a, V_{LL}	4.96×10^{-7}	1.12	0.21	-0.36			Poisson	0.633
C_a	2.27×10^{-3}	0.35					Poisson	0.639

Table A.15 – Other Cyclist Model Parameters

Predictor variables	Parameters					Multiplier Φ	Error structure	BIC
	b_0	b_1	b_2	b_3	b_4			
Q_a, Φ_{MEL}	**6.11×10^{-4}**	**0.58**				**1.66**	**$k = 2.2$**	**2.611**
Q_a, $e^{(Qa/100)}$, Φ_{MEL}	1.36×10^{-2}	0.19	0.004			1.55	k = 2.3	2.617
Q_a, $e^{(Qa/100)}$	1.85×10^{-2}	0.15	0.005				$k = 2.1$	2.624
Q_a	2.18×10^{-4}	0.71					$k = 1.9$	2.627
Q_a, S_e	3.70×10^{-5}	0.64	0.72				$k = 2.0$	2.632
Q_a, SSD_e	1.56×10^{-4}	0.70	0.31				$k = 2.0$	2.634
Q_a, V_{10}	1.36×10^{-4}	0.68	0.19				$k = 1.9$	2.636
Q_a, V_{40}	1.63×10^{-4}	0.70	0.09				$k = 1.9$	2.642
Q_a, Φ_{TJUN}	2.17×10^{-4}	0.71				1.17	$k = 1.9$	2.642
Q_a, V_{LL}	1.81×10^{-4}	0.70	0.05				$k = 1.9$	2.642
Q_a, Φ_{GRADD}	2.17×10^{-4}	0.71				1.08	$k = 1.9$	2.643

Table A.16 – Total Crashes Model Parameters

Traffic Signal Cycle Crash Prediction Models

For models selection for signalised intersections crash prediction models please refer to Austroads Publication AP-R380/11, Effectiveness and Selection of Treatments for Cyclists at Signalised Intersection (2011).

Appendix B

Predictor Variable Information

Mid-Block Cycle Crash Prediction Model Predictor Variables

Abbreviation	Definition
A	Annual number of crashes
C	Total two-way bicycle flow
L	Length of block in km
Lns	Number of lanes in one direction on approach
Q	Total two-way motor vehicle flow
S	Mean motor vehicle speed in km/h
W	Width of lane used by cyclists in m
e	Effective width of kerbside lane including vehicle and cycle lanes in m
$\Phi_{CYCLANE}$:	Factor for the presence of a cycle lane
$\Phi_{FLUSHMEDIAN}$:	Factor for the presense of a flush median
$\Phi_{NOPARKING}$:	Factor if parking is prohibited on a particular block
$\Phi_{VERYLOWPARKINGUSE}$:	Factor if parking is allowed but used very rarely on block
Φ_{MOTOR}:	
Φ_{CYC}:	

Table B.1 – Definition of the Predictor Variables Used in the Mid-Block Models

Roundabout Cycle Crash Prediction Model Predictor Variables

Abbreviation	Definition
Q_e	Entering volume for each approach
Q_c	Circulating flow perpendicular to the entering flow
Q_a	Approach flow (the sum of the entering and exiting flow for each approach)
Φ_{MEL}	Multiple entering lanes
Φ_{MCL}	Multiple circulating lanes
Φ_{TJUN}	Intersections with three arms
Φ_{GRADD}	Downhill gradient on approach to intersection
V_{LL}	Visibility from the limit line to vehicles turning right or travelling through the roundabout from their right
V_{10}	Visibility from 10 metres back from the limit line to vehicles turning right or travelling through the roundabout from their right
V_{40}	Visibility from 40 metres back from the limit line to vehicles turning right or travelling through the roundabout from their right
S_E	Average free mean speed of entering vehicles travelling through the roundabout at the limit line
S_C	Average free mean speed of circulating vehicles travelling through the roundabout as they pass each approach (adjacent to splitter island)
SSD_E	Standard deviation of free speeds of entering vehicles at the limit line
SSD_C	Standard deviation of free speeds of circulating vehicles as they pass the approach being modelled
P	Pedestrians crossing the approach in either direction

Table B.2 – Definitions of the predictor variables used in the models

Traffic Signal Crash Prediction Model Predictor Variables

For predictor variable explanation for signalised intersections crash prediction models please refer to Austroads Publication AP-R380/11, Effectiveness and Selection of Treatments for Cyclists at Signalised Intersection (2011).