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# Applying a joint model of crash count and crash severity to identify road segments with high risk of fatal and serious injury crashes<sup>\*</sup>

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## ABSTRACT

Both crash count and severity are thought to quantify crash risk at defined transport network locations (e.g. intersections, a particulate section of highway, etc.). Crash count is a measure of the likelihood of occurring a potential harmful event, whereas crash severity is a measure of the societal impact and harm to the society. As the majority of safety improvement programs are focused on preventing fatal and serious injury crashes, identification of high-risk sites—or blackspots—should ideally account for both severity and frequency of crashes. Past research efforts to incorporate crash severity into the identification of high-risk sites include multivariate crash count models, equivalent property damage only models and two-stage mixed models. These models, however, often require suitable distributional assumptions for computational efficiency, neglect the ordinal nature of crash severity, and are inadequate for capturing unobserved heterogeneity arising from possible correlations between crash counts of different severity levels. These limitations can ultimately lead to inefficient allocation of resources and misidentification of sites with high risk of fatal and serious injury crashes. Moreover, the implication of these models in blackspot identification is an important, unanswered question.

While a joint econometric model of crash count and crash severity has the flexibility to account for the limitations mentioned previously, its ability to identify high-risk sites also needs to be examined. This study aims to fill this research gap by employing the joint model for blackspot identification. Using data from state-controlled roads in Queensland, Australia, a new *risk score* is developed based on predicted crash counts by severity, weighted by the cost ratio of severity levels. This weighted risk score is then used for identifying road segments with high risk of fatal and injury crashes. Results show that the joint model of crash count and crash severity has substantially improved prediction accuracy compared to the traditional count models. The correlation between crash counts of different severity levels captures the unobserved heterogeneity caused by the extra-variation in total crash counts and moderates the parameters in the joint model. In comparison with the traditional approaches, the proposed weighted risk score approach with the joint model of crash count and crash severity leads to the identification of a higher number of fatal and serious injury crashes in the top ranked sites flagged for safety improvements.

## 1. Introduction

Crash count and crash severity have been widely used in transport safety as two indicators of crash risk along road segments (Washington et al., 2018). Crash count is a measure of the likelihood of crash occurrence, whereas crash severity is a measure of the societal impact of crashes and their harm to the society. Although federal road agencies and departments of transport aim to reduce crash counts across their

road networks, safety improvement programs are primarily focused on preventing fatal and serious injury crashes, as the cost per person of fatal and serious injury crashes are substantially higher than minor injury and non-injury crashes (Harmon et al., 2018). In addition, the collective social cost of crashes in the society is substantially higher than the individual social costs (Tay, 2002). As a result, considering crash severity in conjunction with crash count is paramount for identification of high-risk sites (also referred to as *blackspots* or *hotspots*).

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The several studies have incorporated crash severity into the identification of high-risk sites (which will be comprehensively reviewed in the next section) can be divided into three groups based on their methodological approaches: multivariate crash count models, equivalent property damage only (EPDO) models, and two-stage mixed models of crash count and crash severity (Washington et al., 2018). All of these approaches, perhaps not surprisingly, have some methodological/empirical limitations. The multivariate modelling of crash counts has been mostly achieved by assuming a Poisson lognormal distribution for crashes of different severity levels because the resulting count model has a hierarchical representation in the Bayesian platform (Shaon et al., 2019). Other distributions such as Poisson-Gamma (or Negative Binomial) make the multivariate crash count models computationally burdensome. More importantly, multivariate crash count models neglect the ordered nature of crash severity. The EPDO approach requires non-parametric models (such as quantile regression) because EPDO data are not distributed according to well-known statistical distributions. As such, additional complexity in crash severity data, for example unobserved heterogeneity, is not easily accounted for in this approach. The two-stage mixed modelling of crash count and crash severity again fails to account for the possible correlation between crash counts of different severity levels. These shortcomings render the existing approaches suitable for certain, 'well behaved' conditions only, and perhaps leave researchers to develop a rigorous methodology that can capture additional complexity combining crash frequency and injury severities.

Recently, an alternative approach was proposed by Yasmin and Eluru (2018) to explicitly incorporate the severity of crashes into crash count prediction. Unlike the two-stage mixed models, this approach is based on a joint (one-stage) modelling of crash count and crash severity, whereby a crash count model is jointly estimated with a crash severity model, and a correlation term is added to the overall model to account for the common factors between the two model components. The overall joint model has two important properties: 1) the parameters of the crash count model are influenced by the parameters of the crash severity model in a joint estimation process, and 2) the overall model parameters are moderated by the correlation between the two model components. Yasmin and Eluru (2018) showed that the joint model of crash count and crash severity is superior to traditional crash count models in terms of statistical fit. However, the performance of this model was not evaluated in identification of high-risk sites mainly because a blackspot identification criterion for this model does not exist to date, and thus, its potential for blackspot identification remains unexplored. This study aims to bridge this gap by investigating the applicability and the performance of the recently developed joint model of crash count and crash severity in identifying highway segments with high risk of fatal and injury crashes.

## 2. literature review

Multivariate modelling of crash counts is one of the most popular approaches in the literature to consider crash severity while identifying high-risk sites. Aguero-Valverde and Jovanis (2009) applied a full Bayesian multivariate Poisson lognormal regression to model crashes in Pennsylvania, United States and found a high correlation (from 0.47 to 0.97) between crash counts of different severity levels. They used the costs of different crash severity levels to convert the outcome of the multivariate model to expected crash cost and compared the expected crash cost with the observed crash cost to rank highway segments. They found that high-risk segments identified by the outcome of the multivariate model have consistently higher excess costs than those segments identified by the univariate model. The assumption of a lognormal distribution for the correlation between the crash counts of different severity levels in the multivariate setting resulted in crash counts following a Poisson lognormal distribution. This assumption, however, may not be entirely accurate as crash counts of different severity levels

(fatal crashes with excess zero counts for example) may not be Poisson-lognormally distributed (Aguero-Valverde, 2013). In addition, the multivariate model does not consider the ordinal nature of crash severity levels and thus may lead to incorrect inferences about the effects of explanatory variables and result in misidentification of blackspots and inefficient allocation of resources.

EPDO is another popular approach to incorporate crash severity into the selection of high-risk sites. Washington et al. (2014) converted the crash counts of different severity levels to an equivalent property damage only count by applying weights based on average cost ratios by severity. They applied a non-parametric quantile regression on EPDO data in order to estimate the effects of covariates on various quantiles of the population, rather than the population mean. Finally, they compared the outcome of the quantile regression model with the observed EPDO and ranked sites accordingly. They found that the high-risk sites identified by the EPDO approach places more emphasis on more harmful crashes than does the conventional count approach. As EPDO data are not distributed like any well-known distributions, non-parametric quantile regression models must be used in this approach. This requirement is a limitation of this EPDO approach as there is no likelihood function to be maximized in this approach and thus the complexity of crash data (e.g. unobserved heterogeneity) cannot be readily incorporated into the modelling process. Recently, some studies have used parametric regression models (e.g. lognormal hurdle and Tobit regression) to model EPDO rate as a function of exogenous covariates (Ma et al., 2016); however, the appropriateness of these distributional assumptions has not been tested.

Finally, two-stage mixed modelling of crash count and crash severity is another approach to consider crash severity for identifying high-risk sites. Miranda-Moreno et al. (2009) first introduced this approach and defined a total risk index as a multiplicative factor of crash count at a site and its expected consequences including expected number of fatal, serious, and minor injuries. They employed Bayesian framework to estimate a hierarchical Poisson model of crash count and a multinomial model of crash severity, independently. They constructed a total risk score per segment and compared it with a standard value established by decision makers and ranked highway segments accordingly. They found that the two-stage mixed model were able to identify high-risk highway segments based on crash count and crash severity and thus improved the effectiveness of allocating resources for safety improvements. In more recent studies, Wang et al. (2011) and Stipanovic et al. (2019) used a similar two-stage mixed modelling approach to identify high-risk sites based on crash count and crash severity and found that this approach is superior to the traditional count based approaches. However, the two-stage (independent) modelling of crash count and crash severity in all of these studies crucially ignores the possible correlation between crash counts of different severity levels. This ignorance may result in biased parameters and in turn may lead to incorrect predictions of crash count and crash severity.

Recently, a joint model of crash count and crash severity has been proposed by Yasmin and Eluru (2018) which is more flexible than the existing approaches in that it does not require the methodological/empirical assumptions of the above approaches. In particular, this approach is not constrained to any distributional assumptions for the extra-variation in crash counts over and above that accounted for by the Poisson density. The joint model is estimated using maximum likelihood estimation methods and so it can accommodate the complexities associated with crash data, e.g., unobserved heterogeneities. The crash count and crash severity model components are jointly estimated (in one stage) and the parameters of the joint model are moderated by the correlation between crash count and crash severity. As such, the joint model of crash count and crash severity represents a promising alternative to the existing approaches, but importantly, requires further exploration regarding its ability for blackspot identification.

### 3. Methodology

This section presents the structure of the joint model of crash count and crash severity which was first introduced by [Yasmin and Eluru \(2018\)](#). To describe the model structure more elaborately, the crash count and crash severity model components are presented separately. The joint model of crash count and crash severity is then presented, followed by the selection criteria for identifying highway segments with high risk of fatal and injury crashes. Let  $Y_{it}$  represent the total observed crash count on the  $i$ th highway segment ( $i = 1, 2, 3, \dots, N$ ) and in the  $t$ th year ( $t = 1, 2, 3, \dots, T$ ).

#### 3.1. Crash count model

The transport safety literature has shown that  $Y_{it}$  follows a negative binomial (NB) distribution with mean  $\mu_{it}$  and inverse dispersion parameter  $\varphi$ :

$$Y_{it} \sim NB(\mu_{it}, \varphi)$$

Assuming an exponential function for the mean of the negative binomial distribution, the total predicted crash count ( $\mu_{it}$ ) on the  $i$ th segment and in the  $t$ th year can be expressed as a function of exogenous explanatory variables ([Afghari et al., 2018a](#)):

$$\mu_{it} = \exp\left(\sum \beta_i X_{it} + \varepsilon_{it}\right) \quad (1)$$

where  $X_{it}$  are other explanatory variables and  $\beta_i$  are estimated regression parameters (including the intercept) and  $\exp(\varepsilon_{it})$  is a random error term, which follows a Gamma distribution with mean 1 and variance  $1/\varphi$ . To account for unobserved heterogeneity, model parameters ( $\beta_i$ ) are allowed to vary across highway segments ([Anastasopoulos and Mannering, 2009](#)). Note that parameters are fixed across time to account for multiple observations on a segment during different time periods (i.e. panel data setting). Such a model specification is referred to as *grouped random parameters* ([Sarwar et al., 2017](#)) in which model parameters are assumed to follow probabilistic distributions (e.g. Normal, Uniform, Triangular, etc.) across the observations within each group (or panel). The probability density function of the RPNB model is:

$$P(Y_{it} = y_{it} | \beta, \varphi) = \frac{\Gamma(y_{it} + \varphi)}{y_{it}! \Gamma(\varphi)} \left(\frac{\varphi}{\varphi + \mu_{it}}\right)^\varphi \left(\frac{\mu_{it}}{\varphi + \mu_{it}}\right)^{y_{it}} f(\beta) \quad (2)$$

where  $\Gamma(\cdot)$  is the gamma function and  $f(\beta)$  is the density function of the model parameters. The log-likelihood function ( $LL$ ) of the model is obtained by integrating the probability density function of the model over the entire set of random parameters, applying the logarithm transformation and summing it over observations to yield:

$$LL = \sum_{i=1}^N \text{Log} \left( \int_{\beta} P(Y_{it} = y_{it} | \beta, \varphi) d\beta \right) \quad (3)$$

To estimate this complex log-likelihood function, Maximum Simulated Likelihood Estimation is used where quasi random draws from Halton sequences are employed to simulate the densities of the random parameters ([Bhat, 2001](#)). It has been shown that this simulated maximum likelihood estimator is unbiased and consistent for a large number of draws ([Munkin and Trivedi, 1999](#)).

#### 3.2. Crash severity model

To incorporate crash severity into the models, let  $s$  ( $s = 1, 2, 3, \dots, S$ ) represent crash severity categories (e.g. property damage only crashes, minor injury crashes, serious injury crashes, fatal crashes, etc.) on highway segments. In ordered models, the actual proportion of total crashes by severity levels ( $Y_{sit}$ ) is associated with an underlying latent variable ( $Y_{it}^*$ ). This latent variable is then mapped to the actual severity proportions by thresholds ( $\tau$ ) and using the following linear function:

$$Y_{it}^* = \kappa X_{it} + \delta_i \text{ and } Y_{sit} = S \text{ if } \tau_{s-1} < Y_{it}^* < \tau_s \quad (4)$$

where  $\kappa$  is the vector of parameters,  $X_{it}$  is the vector of covariates and  $\delta_i$  is the random error term.

To estimate the latent propensity of crash severities, it is assumed that:

$$E(Y_{sit} | X_{it}) = H_{sit}(\cdot), \quad 0 \leq H_{sit}(\cdot) \leq 1, \quad \sum_{s=1}^S H_{sit} = 1 \quad (5)$$

where  $H_{sit}(\cdot)$  is the probability density function for the severity category  $s$ . Depending on the distributional assumption for the probability of error terms,  $H_{sit}(\cdot)$  can take standard normal or standard logistic probability density functions for the ordered probit or ordered logit models, respectively. The latter functional form is used in this study to construct an ordered logit model for crash severity. The probability of each crash severity category is then presented as:

$$P(Y_{sit} = s) = \varphi\{\tau_s - (\kappa X_{it})\} - \varphi\{\tau_{s-1} - (\kappa X_{it})\} \quad (6)$$

where  $\varphi(\cdot)$  is the standard logistic cumulative probability density function. The corresponding quasi log-likelihood function is then expressed as:

$$LL = \sum_{i=1}^N \text{Log} \left( \int_{\kappa} \prod_{s=1}^S P(Y_{sit} = s)^{w_{sit}} d\kappa \right) \quad (7)$$

where  $w_{sit}$  is the fraction (proportion between 0 and 1) of crashes in severity category  $s$  at road segment  $i$  and time period  $t$ , and the rest of notations are as previously stated. These fractions sum to unity over the categories ( $\sum_{s=1}^S w_{sit} = 1$ ). This model is referred to as *fractional split* ([Afghari et al., 2018b](#)). Note that  $w_{sit}$  takes binary values (0 or 1) in conventional logit models; one for the chosen alternative and zero for the non-chosen alternative. Maximum simulated likelihood approach is used to estimate this log-likelihood function.

#### 3.3. Joint model of crash count and crash severity

To generate the correlation between the above mentioned ordered severity model and the previously described count model, a correlation term ( $v_{it}$ ) is now defined as:

$$v_{it} = \gamma_i m_i \quad (8)$$

where  $\gamma_i$  is the vector of parameters and  $m_i$  is the vector of covariates capturing the observed correlation between crash count and crash severity components. This correlation term is then added to the propensity function of the severity model and the predicted mean of the count model:

$$Y_{it}^* = \kappa X_{it} + \delta_i + v_{it} \quad (9)$$

$$\mu_{it} = \exp\left(\sum \beta_i X_{it} + \varepsilon_{it} + v_{it}\right) \quad (10)$$

The log-likelihood function of the overall joint model of crash count and severity is then expressed as:

$$LL = \sum_{i=1}^N \text{Log} \left( \int_{\Omega} P(Y_{it} = y_{it} | \beta, \varphi, \lambda, \eta, \gamma) \times \prod_{s=1}^S P(Y_{sit} = s)^{w_{sit}} d\Omega \right) \quad (11)$$

where  $\Omega$  represents the vector of random parameters in the joint model ( $\beta$  and  $\kappa$ ) and the rest of the notations are as previously stated. Maximum simulated likelihood approach is used to estimate the joint econometric model.

#### 3.4. Weighted risk score to combine crash count and crash severity

The estimated crash count and crash severity models can be used to derive the crash count predictions of different severity levels on road segments by multiplying the total crash count and the proportions of

each severity level:

$$\mu_{sit} = \mu_{it} \times P(Y_{sit} = s) \tag{12}$$

A new weighted risk score (WRS) is now developed based on the cost ratio of crash severity levels:

$$WRS_i = \sum_{s=1}^S cr_s \mu_{sit} \tag{13}$$

where  $WRS_i$  is the predicted weighted risk score for segment  $i$  and  $cr_s$  is the ratio of the cost of a crash in severity level  $s$  to the cost of a reference crash severity level. This weighted risk score is analogous to the property damage only equivalency factor in the EPDO approach (Washington et al., 2014) but the weights are applied to the predicted crash counts post estimation and thus the distribution of observed crash counts are intact. This weighted risk score can now be used in ranking highway segments based on their crash count and crash severity.

### 3.5. Selection criteria: potential for improvement and excess weighted risk score

Two selection criteria are used in this study for identifying high-risk sites: potential for improvement (PFI) following the Empirical Bayesian (EB) method with the independent crash count model and excess weighted risk score for the joint model of crash count and crash severity. The EB approach has widely been used in the literature to identify high-risk sites (Afghari, 2019). The EB approach combines the predicted and observed number of crashes and accounts for the regression to the mean effect (Cheng and Washington, 2005; Washington et al., 2018). Many studies have shown that the EB approach is superior to alternative approaches in identifying high-risk sites (Montella, 2010). The EB estimator is a weighted sum of the predicted and the observed crash counts such that:

$$EB_{it} = \omega_1 Y_{it} + \omega_2 \mu_{it} \tag{14}$$

$$\omega_1 = \frac{\mu_{it}}{(\mu_{it} + \frac{1}{k})} \text{ and } \omega_2 = \frac{1}{k(\mu_{it} + \frac{1}{k})}$$

where  $k$  is the over-dispersion parameter estimated during the SPF calibration process, and  $w_1$  and  $w_2$  are weights calculated based on the mean and variance of the SPF estimate (Persaud et al., 2010). Potential for improvement (PFI) has been used as the selection criteria for identifying high-risk sites based on their EB estimate (Washington et al., 2018). PFI is defined as the difference between the EB estimate and the predicted mean of crash count at a site:

$$PFI_{it} = EB_{it} - \mu_{it} \tag{15}$$

Highway segments are ranked according to decreasing PFI and segments with higher PFI are identified as high-risk sites.

Despite its appealing properties, the EB approach rests on distributional assumptions about crash occurrence (Poisson-Gamma or negative Binomial) which do not hold for the weighted risk score approach in this study. As such, *excess weighted risk score* is used as the selection criteria for ranking highway segments based on crash count and crash severity. The excess weighted risk score (EWRS) is defined as:

$$EWRS_{it} = WRS_{it} - \overline{WRS_{it}} \tag{16}$$

where  $WRS_{it}$  and  $\overline{WRS_{it}}$  are observed and predicted weighted risk scores. Segments are ranked according to the decreasing  $EWRS_{it}$  and segments with higher  $EWRS_{it}$  are identified as high-risk sites.

## 4. Empirical data

The data used to compare the performance of candidate models were collected for a random sample of highway segments and major arterial road sections (rural and urban) along the state-controlled roads in Queensland, Australia. The extent of the studied network is 1,477 km

**Table 1**

Descriptive statistics of crash data used in this study.

Variable	Sum	Mean	St. D.	Minimum	Maximum
Fatal crashes	84	0.040	0.202	0.000	2.000
Fatal crashes in 2010	20	0.038	0.192	0.000	1.000
Fatal crashes in 2011	16	0.031	0.173	0.000	1.000
Fatal crashes in 2012	28	0.054	0.234	0.000	2.000
Fatal crashes in 2013	20	0.038	0.202	0.000	2.000
Serious injury crashes	5057	2.427	3.822	0.000	43.000
Serious injury crashes in 2010	1245	2.390	3.713	0.000	35.000
Serious injury crashes in 2011	1210	2.322	3.704	0.000	38.000
Serious injury crashes in 2012	1227	2.355	3.636	0.000	35.000
Serious injury crashes in 2013	1375	2.639	4.209	0.000	43.000
Minor injury crashes	991	0.476	0.996	0.000	12.000
Minor injury crashes in 2010	313	0.601	1.138	0.000	8.000
Minor injury crashes in 2011	277	0.532	1.099	0.000	12.000
Minor injury crashes in 2012	221	0.424	0.909	0.000	9.000
Minor injury crashes in 2013	180	0.345	0.779	0.000	6.000
Total crashes	7252	2.942	4.573	0.000	51.000
Total crashes in 2010	1578	3.029	4.619	0.000	42.000
Total crashes in 2011	1503	2.885	4.566	0.000	51.000
Total crashes in 2012	1476	2.833	4.294	0.000	40.000
Total crashes in 2013	1575	3.023	4.810	0.000	48.000

consisting of 521 road segments. The dataset includes crash data as well as roadway geometric and traffic characteristics data. Four years of crashes (from 2010 to 2013) were collected in three severity categories: fatal, serious injury and minor injury. The Queensland Department of Transport and Main Roads stopped collecting property damage only crash data in 2010 and so crashes in this category are not included in this study. Descriptive statistics of the crash data are presented in Table 1.

Roadway geometric and traffic operational characteristics include Annual Average Daily Traffic (AADT), percentage of heavy vehicle traffic, segment length, number of lanes, lane width, functional classification of the road (urban\rural), radius of horizontal curves, degree of horizontal curves, general terrain (vertical alignment), pavement seal conditions, speed limit, level of service, pavement roughness and rutting conditions. Furthermore, presence of shoulder, shoulder type (paved\unpaved), shoulder width, presence of shoulder marking, presence of median, median type (paved\unpaved), median width, and presence of median marking were extracted manually for these 521 segments and added to the dataset. Dummy values were assigned to the categorical variables for the functional classification of the road, presence of shoulder, shoulder type, presence of shoulder marking, presence of median, median type, presence of median marking, general terrain, speed limit, level of service and pavement seal conditions of road segments. The roadway geometric and traffic characteristics data were merged with crash data based on spatial coordinates of crashes and road segments. Table 2 presents descriptive statistics of explanatory variables used in this study.

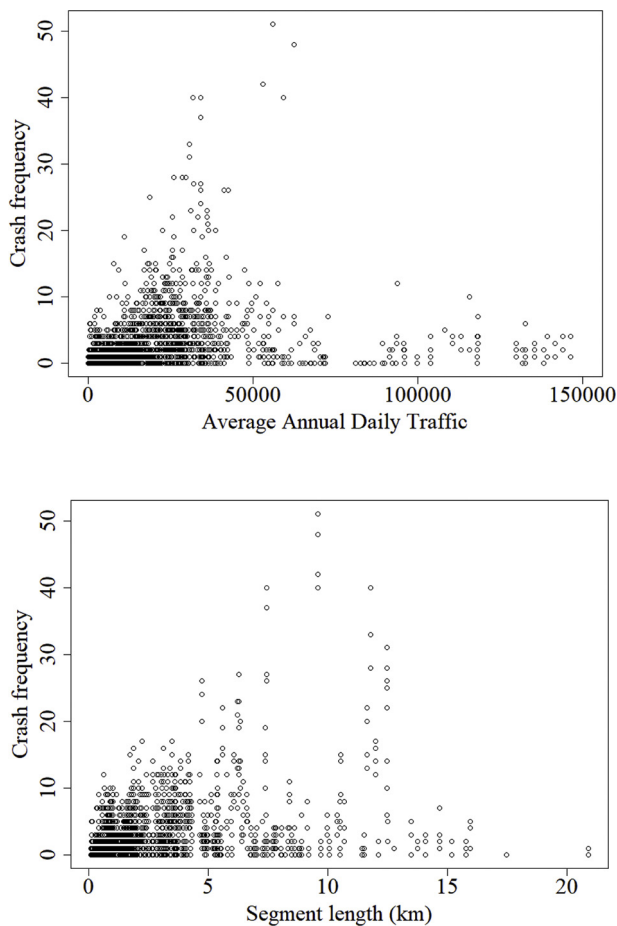
## 5. Results and discussion

The crash count model (Eq. 3) and the crash severity model (Eq. 7) were first estimated to be used as the baseline for comparison purposes. The joint model of crash count and crash severity (Eq. 11) was then estimated and compared with the independent crash count and crash severity models. In all models, explanatory variables were tested for multicollinearity by computing the Pearson correlation coefficients, and the variables with unacceptably high (> 0.7) correlation coefficients were excluded from the models. In addition, AADT and segment length were used as the measures of exposure for both models. The relationship between these two variables and crash counts has been extensively studied in the road safety literature. While some research findings indicate that AADT and segment length have linear relationship with crash counts (Geedipally et al., 2009; Qin et al., 2005) and thus may be

**Table 2**  
Descriptive statistics of explanatory variables used in this study.

Variable	Mean	St. D.	Minimum	Maximum
Average annual daily traffic (vehicles per day)	23482.960	28038.900	34.000	146357.000
Fraction of heavy vehicle traffic	0.098	0.086	0.000	0.965
Length (km)	2.834	3.195	0.080	20.903
Number of lanes	3.070	1.710	1.000	8.000
Lane width (m)	3.070	0.420	2.000	5.000
Shoulder width (m)	0.910	1.470	0.000	15.000
Median width (m)	4.000	4.950	0.000	38.000
Radius of horizontal curve (m)	12096.480	5880.050	127.800	41218.000
Degree of horizontal curve	0.817	1.047	0.053	10.517
Roughness (mm/km)	50.490	33.960	0.000	150.000
Rutting	2.810	2.010	0.000	9.600
<b>Categorical Variables</b>	<b>Observation Frequency</b>		<b>Sample Share</b>	
Functional classification of road – rural	172		33 %	
Presence of shoulder	318		61%	
Shoulder type – paved	500		96%	
Presence of shoulder marking	77		15%	
Presence of divided median	232		44%	
Presence of median marking	97		19%	
High speed limit (> 100 km/h)	103		20%	
Medium speed limit (> 50 and < 100 km/h)	292		56%	
Low speed limit (< 50 km/h)	126		24%	
Terrain – rolling and/or mountainous	57		11%	
Pavement seal conditions – sealed	396		76%	
LOS – E or F	79		15%	

NOTE: MJ = megajoules.



**Fig. 1.** Scatterplots of Average Annual Daily Traffic (AADT) and segment length versus crash counts in the dataset used for this study.

included in models as offset variables, other findings indicate that there is a non-linear relationship between these two variables and crash counts (Geedipally et al., 2009; Qin et al., 2004; Caliendo et al., 2007)

and that the non-linear relationship is warranted by estimating parameters for these two variables. In the dataset used for this study, the scatterplots of ‘Crash counts versus AADT’ and ‘Crash counts versus segment length’, as presented in Fig. 1, confirm the possible non-linear relationships between these two variables and crash counts.

In addition, Anastasopoulos and Mannering (2009) have shown that estimating a parameter for segment length may reflect the boundary effect of road segmentation—crash counts may be clustered at the boundary of road segments because of a sudden change of roadway geometry. In accordance with the latter rationale, the logarithm of AADT and segment length are used as explanatory variables with estimable parameters (coefficient) in the models in this study to account for possible non-linear relationship between these two measures of exposure and crash count, and to account for potential boundary effects of road segmentation.

**5.1. Baseline: independent models of crash count and crash severity**

The grouped random parameters negative binomial crash count model and the fractional split ordered logit crash severity model were estimated separately using maximum simulated likelihood approach with 800 Halton draws. The required number of Halton draws was selected so that further increasing the number of draws does not change the estimates significantly. The estimated parameters of these models are presented in Table 3 and Table 4.

The results of the crash count model (Table 3) show that among all of the contributing factors to crash occurrence, ten factors are significant with at least 95 % confidence. The positive parameters of logarithm of AADT (0.286) and segment length (0.556) indicate that the likelihood of crash occurrence increases with increased exposure to crashes. However, the effect of AADT varies significantly across road segments with mean 0.286 and standard deviation 0.054. The positive parameters of number of lanes (0.283), presence of shoulder (0.063), level of service (0.087) and medium speed limit (0.598) indicate that these factors have increasing effects on total crash counts. The increasing effect of number of lanes might be due to aggregation of crashes by crash type in our study. Previous research has shown that the number of lanes have increasing effect on lane-changing related crashes along road segments (Venkataraman et al., 2014). In addition, the

**Table 3**  
Model results of the crash count model.

Variable	Estimate	Standard Error	t-stat	p-value
Constant	0.780	0.033	23.812	0.000
Log(average annual daily traffic)	0.286 (0.054)	0.031 (0.021)	9.311 (2.536)	0.000 (0.011)
Percentage of heavy vehicle traffic	-0.222 (0.395)	0.036 (0.055)	-6.088(7.237)	0.000 (0.000)
Segment length	0.556	0.025	21.813	0.000
Number of lanes	0.283	0.034	8.305	0.000
Rural road	-0.243	0.029	-8.347	0.000
Presence of shoulder	0.063	0.024	2.654	0.008
Median width	-0.095	0.025	-3.748	0.000
Level of service – E or F	0.087	0.023	3.844	0.000
Medium speed limit (> 50 and < 100 km/h)	0.598	0.039	15.173	0.000
High speed limit (> 100 km/h)				
Sealed pavement	-0.200	0.051	-3.912	0.000
Degree of horizontal curve	-0.041	0.024	-1.719	0.086
Inverse dispersion parameter ( $\varphi$ )	3.110	0.290	10.725	0.000
Measures of fit				
Log-Likelihood	-3911.462			
Mean Squared Predictive Error (MSPE)	43.230			
Mean Absolute Deviance (MAD)	1.990			

\*Numbers inside brackets are the estimates for the standard deviations of random parameters.

**Table 4**  
Model results of the crash severity model.

Variable	Estimate	Standard Error	t-stat	p-value
Threshold Parameters:				
Threshold: minor injury and serious injury	-1.722	0.076	-22.728	0.000
Threshold: serious injury and fatal	4.013	0.200	19.996	0.000
Rural road	0.202	0.077	2.622	0.009
High speed limit (> 100 km/h)	0.165	0.082	2.025	0.043
Measure of fit				
Log-Likelihood	-736.446			

increasing effect of presence of shoulder might be related to unsealed surface of the shoulder and other shoulder characteristics (e.g. edge drop). Past research has shown that unsealed shoulder is associated with increased crash counts (Cairney and McGann, 2000; Meuleners et al., 2011).

On the contrary, percentage of heavy vehicle traffic (-0.222), rural functional classification (-0.243), median width (-0.095) and sealed pavement (-0.200) have decreasing effects on total crash counts. The varying parameter for percentage of heavy vehicle traffic (mean = -0.222 and standard deviation = 0.395) shows that this factor has heterogeneous effect across road segments. Finally, the inverse dispersion parameter indicates that total number of crashes are over dispersed and are correctly modelled by negative binomial specification.

The results of the crash severity model (Table 4) show that among all factors, only functional classification as the rural road and posted speed limit more than 100 km/h are significantly associated with crash severities. The positive parameters of these two variables are intuitive, indicating that these variables have increasing effect on the severity of crashes along road segments.

5.2. Joint model of crash count and crash severity

The joint model of crash count and crash severity was also estimated using 800 Halton draws in the maximum simulated likelihood estimation. Again, the number of Halton draws was selected to guarantee stability of the estimates. The estimated parameters of this joint model are presented in Table 5.

Results show that the joint model of crash count and crash severity consists of a different combination of explanatory variables compared to the crash count and crash severity models. Among the statistically

significant explanatory variables, some are unique to each model component and some are common between the two model components (capturing their correlation).

Segment length, number of lanes, rural roads, presence of shoulder, median width and level of service are the statistically significant variables within the crash count model component with their parameter estimates slightly moderated than their counterparts in the independent count model. In addition, the terrain of the road is statistically significant with a negative parameter (-0.063) indicating that rolling and mountainous terrain is associated with less number of crashes and implying that drivers are more cautious in such circumstances. Sealed pavement, radius of horizontal curves and rural roads are the statistically significant variables within the crash severity model component. The negative parameter of sealed pavement indicates that sealed pavement is associated with decreased severity of crashes whereas the positive parameter of rural roads indicates that these roads are associated with increased severity of crashes. The positive parameter of radius of horizontal curves indicates that larger radius of curves (i.e. sharper curves) is associated with more injuries. This finding might suggest that drivers are more cautious along sharper curves. Numerous studies (e.g., Schneider et al., 2009; Anastasopoulos et al., 2012; Fitch and Hanowski, 2015; Oviedo-Trespalacios et al., 2018, 2019) have reported that the complexity of the road geometry triggers risk-compensating behaviour among drivers and reduces crash risk.

AADT, percentage of heavy vehicle traffic, medium speed limit and pavement roughness are the statistically significant explanatory variables that are common between the two model components and have plausible parameter estimates. The positive parameters of the logarithm of AADT (0.237), medium speed limit (0.393) and roughness (0.149) imply that these variables have increasing effects on crash count and crash severity. The negative parameter of the percentage of heavy vehicle traffic indicates that higher heavy vehicle traffic is associated with less number of crashes and lower severity of crashes.

An interesting finding from the joint model is that the dispersion parameter ( $1/\varphi$ ) of the count model component within the joint model is extremely small—albeit it is statistically significant—indicating that the over dispersion is very small. This finding implies that the unobserved heterogeneity resulted from the extra-variation in total number of crashes across sites mostly arises from ignoring the correlation between crash counts of different injury severity levels.

5.3. Comparison of goodness-of-Fit

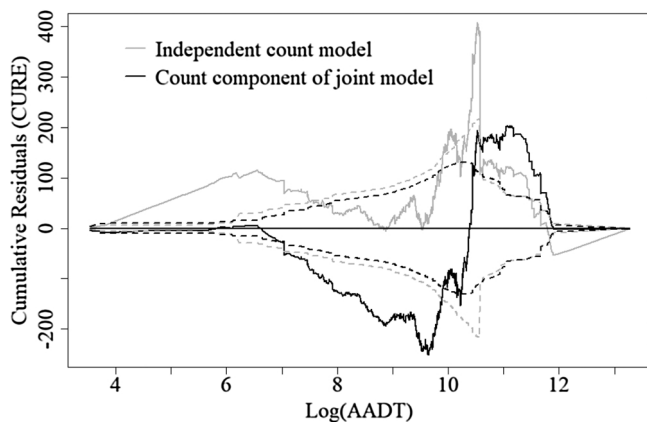
The goodness-of-fit measures associated with the count model and

**Table 5**  
Model results of the joint model of crash count and crash severity.

Variable	Crash Count Model Component				Crash Severity Model Component			
	Estimate	Standard Error	t-stat	p-value	Estimate	Standard Error	t-stat	p-value
<b>Unique Parameters</b>								
Constant	0.588	0.034	17.474	0.000	-	-	-	-
<b>Threshold Parameters:</b>								
Threshold: minor injury and serious injury	-	-	-	-	-1.925	0.084	-22.946	0.000
Threshold: serious injury and fatal	-	-	-	-	4.210	0.200	21.007	0.000
Segment length	0.535	0.025	21.468	0.000	-	-	-	-
Number of lanes	0.230	0.030	7.566	0.000	-	-	-	-
Rural road	-0.354	0.030	-11.990	0.000	-	-	-	-
Presence of shoulder	0.073	0.024	3.012	0.003	-	-	-	-
Median width	-0.076	0.026	-2.891	0.004	-	-	-	-
Level of service – E or F	0.048	0.023	2.131	0.033	-	-	-	-
Terrain: mountainous and rolling	-0.063	0.022	-2.861	0.004	-	-	-	-
Sealed pavement	-	-	-	-	-0.418	0.094	-4.436	0.000
Radius of horizontal curve	-	-	-	-	0.324	0.084	3.870	0.000
Inverse dispersion parameter ( $\phi$ )	4491.761	104.043	43.172	0.000	-	-	-	-
<b>Common Parameters</b>								
	Estimate	Standard Error	t-stat	p-value				
Log(average annual daily traffic)	0.237 (0.054)	0.029 (0.020)	8.126 (2.705)	0.000 (0.007)				
Percent of heavy vehicle traffic	-0.186 (0.248)	0.032 (0.070)	-5.870 (3.565)	0.000 (0.000)				
Medium speed limit (> 60 km/hr and < 100 km/h)	0.393 (0.650)	0.036 (0.028)	10.835 (-23.209)	0.000 (0.000)				
Roughness	0.149	0.041	3.641	0.000				
<b>Measures of Fit</b>								
Log-Likelihood					-4686.048 [-3898.283**]			
Mean Squared Predictive Error (MSPE)					8.287			
Mean Absolute Deviance (MAD)					1.825			

\*Numbers inside brackets are the estimates for the standard deviations of random parameters.

\*\*Log-Likelihood of the count component within the joint model.



**Fig. 2.** Cumulative residual plots against Average Annual Daily Traffic (AADT) for the independent count model vs count component of the joint model.

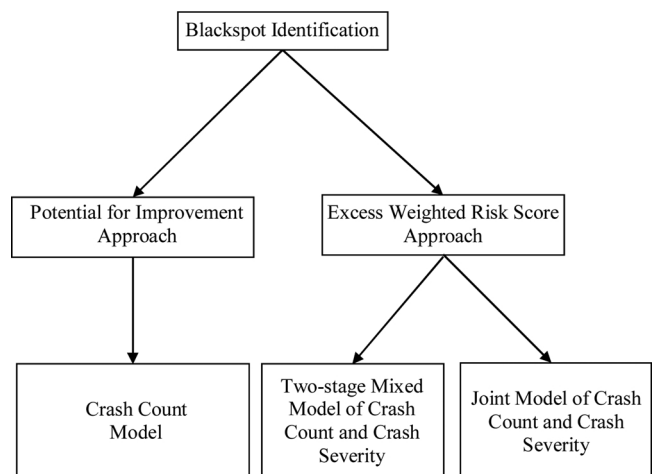
the count component of the joint model shows that the latter model has lower MSPE and MAD (8.287 and 1.825, reduced from 43.230 and 1.990 respectively) and thus has improved statistical fit. In addition to MSPE and MAD, the cumulative residual plots are also plotted against increasing order to AADT to shed more light on the statistical fit of the two models. Cumulative residual plots are helpful tools in demonstrating a model fit with respect to its covariates and identifying potential and systematic bias e.g. over/under prediction (Hauer, 2015). A superior fit occurs when the plots oscillate close to zero. Excess oscillations above/under the zero axis, on the other hand, are a sign of under/over prediction. In addition, a less biased model has an approximately equal amount of positive and negative residuals. Fig. 2 presents the cumulative residual plots (adjusted to terminate at zero) for the two models and shows that the crash count component of the joint model oscillates substantially closer to zero, maintaining more balance between the positive and negative sides and staying closer within the 95 % boundaries of cumulative residuals.

The substantially improved goodness-of-fit and cumulative residuals plot of the count component of the joint model suggests that for this sample of data, at least, the joint model is preferred for predicting crash counts for the identification of high-risk sites.

#### 5.4. Identification of high-risk sites

To identify high-risk sites across the network, the estimated models were used by three blackspot identification methods: (i) potential for improvement approach with a crash count model, (ii) excess weighted risk score approach with a two-stage mixed model of crash count and crash severity, and (iii) excess weighted risk score approach with a joint model of crash count and severity (Fig. 3).

More specifically, the crash count model was first used to determine the total predicted crash counts at individual road segments. These



**Fig. 3.** Blackspot identification methods used for identifying high-risk sites in this study.



**Table 6**  
Human capital cost of crashes by injury severity level for the state of Queensland in Australia (Australian dollars).

	Rural	Urban	Weighted average cost (33 % rural and 67 % urban)	Weights
Fatal crash	\$2,728,617	\$2,456,691	\$2,546,427	104.189
Serious injury crash	\$642,034	\$595,802	\$611,057	25.002
Minor injury crash	\$25,822	\$23,760	\$24,440	1.000

predicted crash counts were then used with the PFI approach to identify high-risk sites. The crash severity model was then used to determine the predicted probabilities of each severity level. The product of these probabilities and the previously mentioned predicted crash counts were then calculated to determine the predicted crash counts by severity (in a *two-stage mixed* model) and were used with the excess weighted risk score approach to identify high-risk sites. Finally, the joint model of crash count and crash severity were used to determine the predicted crash counts by severity while taking into account the correlation between different severity levels, and were used with the excess weighted risk score approach to identify high-risk sites. The weighted risk score for predicted crash counts of different severity levels (either from the two-stage mixed model or from the joint model) were calculated using the human capital costs (i.e. social costs) associated with Queensland crashes collected from Austroads Guide to Road Safety Part 8 (Austroads, 2015). These costs vary depending on the functional classification of the road and thus their weighted averages were used for the road network in this study. Table 6 shows the original crash costs and their weighted average across the network.

Road segments were ranked by total decreasing potential for improvement (based on the crash count model) and total decreasing excess weighted risk score (based on the two-stage mixed model and the joint model of crash count and crash severity) for the period of 2010-2013.

5.4.1. Potential for improvement vs excess weighted risk score

To illuminate the importance of incorporating crash severity into blackspot identification, the PFI approach is first compared with the EWRS approach. Table 7 shows the top 20 road segments (out of 521 road segments) identified as high-risk sites by the two approaches. The results show that 7 out of 20 road segments (shaded cells in Table 7) are

unique to the blackspot identification approach and are not commonly identified by the two approaches. The sites that are unique to the risk score approach have higher number of fatal crashes compared to the sites that are unique to the potential for improvement approach. As reported in Table 7, the ranking of sites by two approaches is different. As expected, the risk score approach puts more emphasis on fatal crashes in ranking sites, whereas the potential for improvement approach puts more emphasis on the total crashes. To obtain a more tangible understanding of the performance of these two approaches in identifying high-risk sites, the total number of crashes identified across the top 20 sites were also used for the comparison between the two approaches (Afghari et al., 2016).

The PFI approach identified 1356 crashes whereas the excess weighted risk score approach identified 1178 crashes along the top 20 sites. However, the risk score approach identified 19 fatal crashes whereas the potential for improvement approach identified 14 fatal crashes along those sites. In addition, the potential for improvement approach identified higher number of minor and serious injury crashes compared to the excess weighted risk score approach. These findings show that, in general, the independent crash count model together with the Empirical Bayesian approach leads to the identification of higher number of crashes in the top ranked sites. However, if the rationale is to identify high-risk sites with high fatal crashes, then the joint model of crash count and severity together with the risk score approach represents a better alternative. Another important consideration in blackspot identification is that excess crashes are most treatable (Cheng and Washington, 2008). To shed more light on this finding, excess crashes are calculated by subtracting predicted crashes from observed crashes along the top 20 sites (Table 8)—suggesting that installing improvements to reduce crashes in excess of ‘typical’ have much higher chance of success than expecting crash improvements beyond ‘typical’

**Table 7**  
Observed crashes along top 20 high-risk sites identified by the Potential for Improvement (PFI) versus Excess Weighted Risk Score (EWRS) approach.

Top sites identified by the PFI approach						Top sites identified by the EWRS approach					
Rank	Site ID	Total excess crashes	Minor injury excess crashes	Serious injury excess crashes	Fatal excess crashes	Rank	Site ID	Total excess crashes	Minor injury excess crashes	Serious injury excess crashes	Fatal excess crashes
1	62	130	23	106	1	1	333	181	29	151	1
2	482	90	16	73	1	2	214	129	20	106	3
3	333	181	29	151	1	3	62	130	23	106	1
4	214	129	20	106	3	4	482	90	16	73	1
5	191	72	8	64	0	5	400	47	6	41	0
6	155	76	15	58	3	6	191	72	8	64	0
7	21	49	14	34	1	7	155	76	15	58	3
8	218	49	8	41	0	8	21	49	14	34	1
9	250	64	12	52	0	9	218	49	8	41	0
10	455	58	10	48	0	10	147	34	6	27	1
11	227	46	8	38	0	11	401	31	7	24	0
12	460	48	5	43	0	12	271	25	1	23	1
13	167	45	7	38	0	13	253	22	1	21	0
14	36	44	10	34	0	14	35	58	6	51	1
15	422	54	10	43	1	15	22	33	9	23	1
16	400	47	6	41	0	16	437	26	3	23	0
17	375	40	5	35	0	17	153	19	3	13	3
18	35	58	6	51	1	18	460	48	5	43	0
19	147	34	6	27	1	19	167	45	7	38	0
20	15	42	10	31	1	20	61	14	1	11	2
Sum of observed crashes across top 20 sites identified by the PFI approach						Sum of observed crashes across top 20 sites identified by the EWRS approach					
		1356	228	1114	14			1178	188	971	19

Shaded: sites that are uniquely identified by each approach.

**Table 8**  
Excess crashes along top 20 high-risk sites identified by the Potential for Improvement (PFI) versus Excess Weighted Risk Score (EWRS) approach.

Top sites identified by the PFI approach					Top sites identified by the EWRS approach						
Rank	Site ID	Total excess crashes	Minor injury excess crashes	Serious injury excess crashes	Fatal excess crashes	Rank	Site ID	Total excess crashes	Minor injury excess crashes	Serious injury excess crashes	Fatal excess crashes
1	62	53.654	-	-	-	1	333	73.111	17.489	55.622	0.000
2	482	49.628	-	-	-	2	214	49.795	8.377	39.707	1.712
3	333	40.947	-	-	-	3	62	56.909	14.550	42.358	0.000
4	214	42.306	-	-	-	4	482	50.604	11.390	39.073	0.140
5	191	39.781	-	-	-	5	400	42.286	5.095	37.190	0.000
6	155	33.418	-	-	-	6	191	38.597	3.380	35.217	0.000
7	21	35.831	-	-	-	7	155	33.580	10.753	20.925	1.902
8	218	27.986	-	-	-	8	21	37.627	12.706	24.177	0.744
9	250	21.067	-	-	-	9	218	28.986	4.749	24.237	0.000
10	455	20.575	-	-	-	10	147	23.059	4.599	17.675	0.785
11	227	22.887	-	-	-	11	401	26.358	6.352	20.006	0.000
12	460	21.180	-	-	-	12	271	16.834	0.049	16.002	0.782
13	167	21.216	-	-	-	13	253	17.898	0.204	17.694	0.000
14	36	20.781	-	-	-	14	35	18.405	1.622	16.703	0.080
15	422	18.022	-	-	-	15	22	21.569	7.607	13.199	0.763
16	400	41.609	-	-	-	16	437	18.957	2.055	16.902	0.000
17	375	18.561	-	-	-	17	153	7.776	0.593	4.315	2.867
18	35	14.813	-	-	-	18	460	23.834	3.340	20.494	0.000
19	147	21.500	-	-	-	19	167	22.285	4.608	17.678	0.000
20	15	14.944	-	-	-	20	61	9.078	0.000	7.129	1.950
Sum of observed crashes across top 20 sites identified by the PFI approach					Sum of observed crashes across top 20 sites identified by the EWRS approach						
408					618						
					120						
					486						
					12						

Shaded: sites that are uniquely identified by each approach.

at a site.

The results show that out of 1356 crashes identified by the potential for improvement approach, only 408 crashes are excess (30.0 %) whereas out of 1178 crashes identified by the excess weighted risk score approach, 618 are excess (52.4 %). This finding shows that the excess weighted risk score approach leads to the identification of more treatable crashes along the top ranked sites. The ranking of sites also paints a similar picture of model performance. The top ranked sites identified by the risk score approach have substantially higher excess crashes than the top ranked sites identified by the potential for improvement approach (for example, see sites of rank 1, rank 3, rank 4 and rank 5 in Table 8). Moreover, the excess weighted risk score approach provides additional information about excess crashes by severity levels which cannot be obtained by the other approach. This additional information indicate that the majority of the excess crashes (498 out of 618) are fatal and serious injury crashes.

#### 5.4.2. Two-stage mixed model vs joint model

As illustrated previously, the PFI approach identifies higher total crashes in high rank sites while the EWRS approach identifies crashes with higher severities. However, this comparison may not provide a thorough understanding of the blackspot identification performance of the joint model within the EWRS approach because an approach that only looks into total crashes is not going to identify as many fatal and severe injury crashes compared to an approach that emphasizes severe crashes, regardless of model specification. As a result, the EWRS approach is selected as the blackspot identification approach and the performance of the joint model is now compared with that of a two-stage (independent) mixed model of crash count and crash severity. Table 9 and Table 10 show the top 20 road segments identified by the EWRS approach using these two model specifications.

The results show that 4 out of 20 road segments (shaded cells in Table 9 and Table 10) are unique to the model specification and are not commonly identified by the two models. The sites that are unique to the joint model have higher number of fatal crashes compared to the sites that are unique to the two-stage mixed model. In addition, the ranking of sites by these two models is different. The two-stage mixed model identified 1257 crashes whereas the joint model identified 1178 crashes along the top 20 sites. The joint model identified 19 fatal crashes

whereas the two-stage mixed model identified 14 fatal crashes along those sites. Similar to the PFI approach with the crash count model, the EWRS approach with the two-stage mixed model identified higher number of minor and serious injury crashes compared to the EWRS approach with the joint model. However, a closer look at 'excess crashes' revealed the true benefit of the joint model (Table 10). Out of 1257 crashes identified by the two-stage mixed model, only 586 crashes are excess (46.6 %), whereas out of 1178 crashes identified by the joint model, 618 are excess (52.4 %). This finding shows that the joint model leads to the identification of more treatable crashes along the top ranked sites. The ranking of sites also paints a similar picture of model performance.

The above findings together illustrate the true benefit of the joint model of crash count and crash severity when using within the excess weighted risk score approach in that it ultimately leads to the identification of higher number of treatable fatal and serious injury crashes. This benefit is the direct consequence of applying weights to the predicted crash counts by severity, and accounting for the correlation between the predicted crash counts of different severity which is in turn the consequence of employing the joint model of crash count and crash severity.

## 6. Conclusions

Total crash counts at transport locations have widely been used to identify high-risk sites across the network. However, the societal impact of crashes and their harm to the society is not accounted for in the existing approaches because crash severity has not been well incorporated into the traditional blackspot identification method. This study aimed to fill this gap by using the joint modelling approach to incorporate crash severity into crash count prediction and identify road segments with high risk of fatal and serious injury crashes.

Findings indicate that the incorporation of crash severity into the crash count model and capturing the correlation between crash counts of different severity levels improve the accuracy (i.e. statistical fit) of crash count predictions. In addition, accounting for such correlations influences the over dispersion of crash data and the statistical significance of explanatory variables. The joint model of crash count and crash severity provides unique information about the probability of

**Table 9**

Observed crashes along top 20 high-risk sites identified by the Excess Weighted Risk Score (EWRS) approach using two-stage mixed vs joint models of crash count and crash severity.

Top sites identified by the two-stage mixed model					Top sites identified by the joint model						
Rank	Site ID	Total excess crashes	Minor injury excess crashes	Serious injury excess crashes	Fatal excess crashes	Rank	Site ID	Total excess crashes	Minor injury excess crashes	Serious injury excess crashes	Fatal excess crashes
1	62	130	23	106	1	1	333	181	29	151	1
2	214	129	20	106	3	2	214	129	20	106	3
3	482	90	16	73	1	3	62	130	23	106	1
4	400	47	6	41	0	4	482	90	16	73	1
5	191	72	8	64	0	5	400	47	6	41	0
6	155	76	15	58	3	6	191	72	8	64	0
7	333	181	29	151	1	7	155	76	15	58	3
8	21	49	14	34	1	8	21	49	14	34	1
9	218	49	8	41	0	9	218	49	8	41	0
10	460	48	5	43	0	10	147	34	6	27	1
11	401	31	7	24	0	11	401	31	7	24	0
12	147	34	6	27	1	12	271	25	1	23	1
13	227	46	8	38	0	13	253	22	1	21	0
14	271	25	1	23	1	14	35	58	6	51	1
15	35	58	6	51	1	15	22	33	9	23	1
16	167	45	7	38	0	16	437	26	3	23	0
17	253	22	1	21	0	17	153	19	3	13	3
18	340	31	4	27	0	18	460	48	5	43	0
19	375	40	5	35	0	19	167	45	7	38	0
20	422	54	10	43	1	20	61	14	1	11	2
Sum of observed crashes across top 20 sites identified by the two-stage mixed model					Sum of observed crashes across top 20 sites identified by the joint model						
		1257	199	1044	14			1178	188	971	19

Shaded: sites that are uniquely identified by each approach.

each severity level on road segments.

From the pragmatic point of view and in terms of identifying high-risk sites, the joint model of crash count and crash severity enables the analyst to predict crash counts of different severity levels and provides more information about crashes compared to the traditional count model. Such information can be readily used to rank transport locations not only based on the total crashes but also based on the severe crashes such as fatal and serious injury crashes. However, it is important to note that determining which blackspot identification approach is more "useful" in practice may require additional considerations. For example, economic analysis (determining overall benefit and overall return on

investment given a fixed budget) of the final selection of high-risk sites and the required countermeasures may change the superiority of one approach over another (Gross et al., 2016). Nonetheless, the weighted risk score approach presented in this study is not a replacement but may serve as a complement to the existing approaches because it provides additional information for identifying high-risk sites.

This study is not without limitations. An implicit assumption in the specification of the joint model of crash count and crash severity is that crash counts of different severity levels have the same amount of over dispersion. Future research should test whether this assumption is valid. In addition, the performance of the joint model of crash count and crash

**Table 10**

Excess crashes along top 20 high-risk sites identified by the Excess Weighted Risk Score (EWRS) approach using two-stage mixed vs joint models of crash count and crash severity.

Top sites identified by the two-stage mixed model					Top sites identified by the joint model						
Rank	Site ID	Total excess crashes	Minor injury excess crashes	Serious injury excess crashes	Fatal excess crashes	Rank	Site ID	Total excess crashes	Minor injury excess crashes	Serious injury excess crashes	Fatal excess crashes
1	62	53.741	9.052	44.689	0.000	1	333	73.111	17.489	55.622	0.000
2	214	42.306	4.162	36.379	1.765	2	214	49.795	8.377	39.707	1.712
3	482	49.628	8.624	40.579	0.425	3	62	56.909	14.550	42.358	0.000
4	400	41.686	5.015	36.671	0.000	4	482	50.604	11.390	39.073	0.140
5	191	40.240	2.114	38.126	0.000	5	400	42.286	5.095	37.190	0.000
6	155	33.418	7.221	23.803	2.393	6	191	38.597	3.380	35.217	0.000
7	333	41.942	3.414	38.529	0.000	7	155	33.580	10.753	20.925	1.902
8	21	35.831	12.329	22.789	0.714	8	21	37.627	12.706	24.177	0.744
9	218	28.286	4.161	24.125	0.000	9	218	28.986	4.749	24.237	0.000
10	460	21.562	0.100	21.462	0.000	10	147	23.059	4.599	17.675	0.785
11	401	25.802	6.037	19.766	0.000	11	401	26.358	6.352	20.006	0.000
12	147	21.500	4.413	16.358	0.728	12	271	16.834	0.049	16.002	0.782
13	227	23.217	3.778	19.439	0.000	13	253	17.898	0.204	17.694	0.000
14	271	14.161	0.000	14.296	0.846	14	35	18.405	1.622	16.703	0.080
15	35	16.703	0.000	16.318	0.385	15	22	21.569	7.607	13.199	0.763
16	167	21.555	2.655	18.900	0.000	16	437	18.957	2.055	16.902	0.000
17	253	17.431	0.153	17.278	0.000	17	153	7.776	0.593	4.315	2.867
18	340	19.170	1.808	17.363	0.000	18	460	23.834	3.340	20.494	0.000
19	375	18.866	1.083	17.783	0.000	19	167	22.285	4.608	17.678	0.000
20	422	18.022	3.427	14.107	0.488	20	61	9.078	0.000	7.129	1.950
Sum of excess crashes across top 20 sites identified by the two-stage mixed model					Sum of excess crashes across top 20 sites identified by the joint model						
		586	80	499	8			618	120	486	12

Shaded: sites that are uniquely identified by each approach.

severity has not been compared with the other state-of-the-practice models including multivariate count models and equivalent property damage only models. Testing the performance of these models against each other is a worthy research direction.

### CRediT authorship contribution statement

**Amir Pooyan Afghari:** Conceptualization, Methodology, Software, Data curation, Writing - original draft, Visualization, Investigation, Software, Validation. **Md Mazharul Haque:** Conceptualization, Methodology, Supervision, Writing - review & editing. **Simon Washington:** Conceptualization, Methodology, Supervision, Writing - review & editing.

### Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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