

Crash Modification Functions for Passing Relief Lanes on Two-Lane Rural Roads

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ABSTRACT Passing relief lanes on two-lane rural roads provide passing opportunities that would otherwise be scarce where there are extensive no passing zones and/or high opposing traffic volumes. The paper addresses the safety effects of installing a passing lane or lengthening an existing one. It stands to reason that the effect of installing a passing lane will depend on the actual length of that lane. By extension, it is also reasonable to expect that the safety effects of lengthening an existing one will depend not only on the amount of the lengthening, but also on the original length. Yet, knowledge that can be applied to estimate these two sets of effects in a design process is lacking. The crash modification factors (CMFs) in the Highway Safety Manual (HSM) and in the CMF Clearinghouse for installing a passing lane are all single valued, of the order of 0.75. And neither source provides CMFs for lengthening an existing passing lane. This paper seeks to address these voids by developing continuous crash modification functions (CMFunctions) for both sets of design decisions using Michigan and Ontario crash, geometric, and traffic data for passing lane and reference sections. Generalized linear modeling and full Bayes Markov Chain Monte Carlo (MCMC) simulation are used to develop cross-section regression models from which crash modification functions are derived and compared. The results are consistent with those from credible before-after studies, so are recommended for implementation in practice, in particular for HSM applications.

Keywords: passing lanes; crash modification factors; full Bayes; generalized linear modeling; Markov Chain Monte Carlo

INTRODUCTION

Passing lanes are intermittently placed as auxillary lanes on two-lane rural roads that provide drivers passing opportunities that would otherwise be scarce where there are extensive no passing zones and/or high opposing traffic volumes. The operational benefits are well known, with benefits to traffic operations 3 to 8 mi (5 to 13 km) downstream of the passing lane, according to Neuman et al., (1) who suggest that these operational effects can translate into safety benefits. Credible knowledge on both operational and safety benefits can greatly assist in making decisions on where passing lanes are justified.

The Highway Safety Manual (2) provides procedures for evaluating the safety effects of a design decision for a road being designed or a treatment that is being considered for an existing road due to a safety concern. For estimating these safety effects, crash modification factors (CMFs) are required, desirable for the specific circumstance. For installing a passing lane, the HSM recommends a single CMF of 0.75 for total crashes, regardless of the length of the lane. This CMF was based on a rather dated Midwest Research Institute (MRI) study (3). However, it seems reasonable to expect that the CMF for installing a passing lane should not be single valued and should at least depend on the length of that lane. A later MRI study (4) did find that crash frequency per mile per year within passing lane sections ranges from 12 to 24 percent lower than for conventional sections, with larger differences in crash rate at increasing levels of average daily traffic. However, a continuous function was not developed. More recent studies (5-8) also developed single valued CMFs typically of the order of the HSM CMF. And no study to date has developed CMFs for extending an existing passing lane.

The present study builds on an earlier one (5) that developed and recommended single valued crash modification factors (CMFs) for various crash types based on a cross-sectional analysis of Michigan two-lane rural roads with and without passing lanes. An empirical Bayes before-after study was also performed, but definitive results based on only 7 locations could not to be obtained, although they did provide some corroboration for the CMFs from the cross-sectional analysis. That analysis suggested that the cross-sectional approach could also be used to potentially develop crash modification functions (CMFunctions) that would model the variability of the crash modification factor. However, these were not developed in that research. The present study seeks to develop those functions by expanding the database to include sites from Ontario, Canada. This expanded dataset was intended to improve statistical rigour of any CMFunctions developed and in so doing to assess their transferability. It was also of interest to investigate the possibility of developing CMFs for extending passing lanes to fill that research need.

The lack of progress in developing CMFunctions, even from cross-sectional data that are more suitable for this task, is likely because of limitations imposed by the generalized linear modeling (GLM) functional form typically used to represent the safety effects of influential variables that affect the CMF. This issue is resolved in the paper by performing the modeling using the WinBUGS software to apply full Bayes-Markov Chain Monte Carlo (MCMC) estimation techniques (9), one of the tools that can be used for model forms that cannot be linearized for applying GLM.

DATA SUMMARY

Crash, geometric and traffic data for sections with passing lanes and reference segments without passing lanes were obtained from the Ministry of Transportation, Ontario and the Michigan DOT. All animal related crashes were removed from the data. The Michigan data were the same data used by the earlier study (5). Data for passing lane sites and reference segments are summarized in Table 1.

1 **TABLE 1: Summary of Data for Passing Lane and Reference Sites**

Item		Michigan PL Sites	Michigan Reference Sites	Ontario PL Sites	Ontario Reference Sites
No. of Sites		237	100	44	122
Years	Min	3	10	4	4
	Max	11	10	4	4
	Mean	10.69	10	4	4
Average AADT	Min	1,016	1,019	2,000	2,060
	Max	16,688	29,334	11,300	12,400
	Mean	4,964.6	5,111.4	5,513.6	4,259.9
Segment Length (km)	Min	0.60	1.61	1.2	1.2
	Max	7.16	1.61	3.2	3.8
	Mean	2.49	1.61	1.99	1.87
	Sum	321.85	161	87.7	227.9
Total Crashes/km-year	Min	0	0	0.10	0
	Max	4.41	13.48	1.36	2.2
	Mean	0.63	1.36	0.57	0.61
	Sum	2128	2191	251	696
Fatal/Injury Crashes/km-year	Min	0	0	0	0
	Max	1.71	3.54	0.40	0.92
	Mean	0.19	0.38	0.13	0.16
	Sum	657	613	56	182

4 METHODOLOGY OVERVIEW

As noted in the introduction, the research was primarily accomplished using full Bayes-Markov Chain Monte Carlo (MCMC) estimation techniques. The two main advantages are the ability to consider prior information about parameter coefficients and the flexibility of functional form that can be used in the process (9). By contrast, the model form estimated using conventional generalized linear models (GLM) is log-linear, thereby restricting the estimated CMF to be only dependent on the difference in the variable of interest, not the actual values. To estimate complex functional forms, e.g., those that cannot be linearized for a GLM approach, the full Bayes (FB) approach takes advantage of Markov Chain Monte Carlo (MCMC) sampling techniques.

WinBUGS software was employed to apply the full Bayes MCMC estimation technique. In this, each parameter is assigned a distribution with a mean and a variance. For this research, all parameters were assumed to follow a normal distribution. The way that prior distributions were chosen is mainly based on a suggestion in (10) that “after the model has been fit, one should look at the posterior distribution and see if it makes sense” and then revise the prior distribution if necessary. With this in mind, diffuse prior distributions for all the parameters (i.e. normal distribution with mean of 0 and variance of 10) were initially used to let the model potentially include wide ranges of parameter values. Then, the same GLM function in WinBUGS was written to compare the estimates of MCMC with the

conventional GLM. The results showed that the posterior distribution did not make sense, implying that “additional prior knowledge is available that has not been included in the model” (10).

Based on the significance of the variables in the conventional GLM model, the variance of the parameters for the prior distribution was decreased. It was found that the results of MCMC agree with the conventional GLM estimates when using less diffuse priors. Several reasonable mean values for the prior distributions were used to see how much the parameter estimation depends on the chosen priors. In the end, it was concluded that the parameter estimates mostly depend on the data used and that the prior has little impact. Therefore, the final prior distributions were chosen to be normal distributions with a mean value of zero and a variance of 0.01 for the parameters that are found significant in the conventional GLM estimates. Different functional forms were considered and a power function was finally selected as the best one for the CMFunction. For comparison purposes, conventional GLMs were also estimated for developing CMFunctions.

ANALYSIS, RESULTS AND DISCUSSION

As noted above, CMFs were derived from conventional GLMs and from full Bayes-Markov Chain Monte Carlo (MCMC) models. The analysis is presented separately before the results are compared.

CMFs from GLMs

As noted, conventional GLMs were also estimated for comparison purposes. These do allow the CMF for installing a passing lane to depend on its length but the implied CMFs for extending a passing lane by a given amount do not depend on the original length. The estimated models based on the combined Michigan and Ontario data for total and fatal-injury crashes were of the form:

$$\frac{\text{Crashes}}{\text{Year} * \text{km}} = e^{(\alpha + \beta_3)} AADT^{\beta_1} e^{\beta_2 (LenPL)} \quad ..1$$

where,

$AADT$ = annual average daily traffic

$LenPL$ = passing lane length (km) = 0 for segments without passing lanes

$\alpha, \beta_1, \beta_2, \beta_3$ = model parameters to be estimated, with β_3 being a Michigan-specific constant.

The parameter estimates, which were obtained using the SAS software package, are shown in Table 2, and all are statistically significant at the 5% level ($P < 0.05$), except for the Michigan-specific constant. That constant was included in the final models nevertheless since it improved the precision of the estimate of β_2 , the parameter that is essential for the estimation of the CMFunctions, as will be seen later. The cumulative residual plots, shown in Figures 1 and 2, indicated that the model fit is reasonable over the range of passing lane lengths.

TABLE 2: GLM Parameter Estimates - Combined Ontario and Michigan (MI) Data

	Total crashes		Fatal-Injury crashes	
<i>Coefficient</i>	<i>Estimate</i>	<i>P-Value</i>	<i>Estimate</i>	<i>P-Value</i>
α	-7.0024	<.0001	-8.153	<.0001
β_1	0.783	<.0001	0.7539	<.0001
β_2	-0.1762	<.0001	-0.1863	0.0001
β_3	0.0031	0.9761	0.1752	0.1708

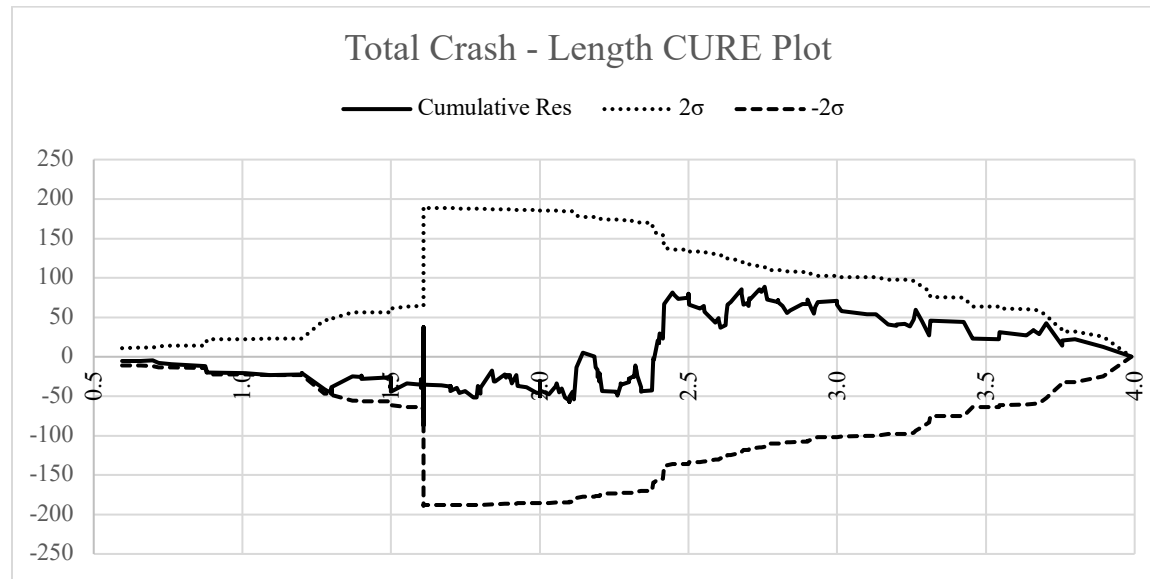


Figure 1 Total Crash – Length (km) CURE Plot for the GLM

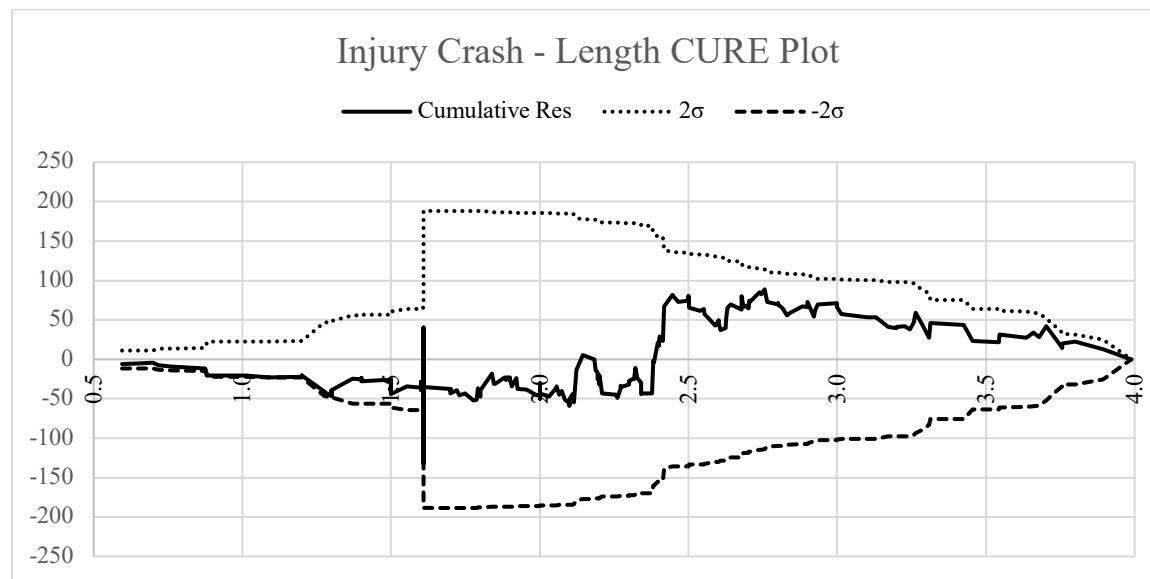


Figure 2 Injury Crash – Length (km) CURE Plot for the GLM

CMFs from Full Bayes-Markov Chain Monte Carlo (MCMC) Models

The estimated models for total and fatal-injury crashes were of the form:

$$\frac{\text{Crashes}}{\text{year.km}} = \exp(a) * \exp(b * (\text{if in Michigan})) * AADT^c * \exp(\exp(e * \text{LngPL})) \quad ..2)$$

where,

$AADT$ = annual average daily traffic

LngPL = passing lane length (km)

if in Michigan = 1 for Michigan data and 0 for Ontario sites

a, b, c, d, e = model parameters to be estimated

The MCMC sampling procedure was run in WinBUGS software for 100,000 iterations to calculate the posterior estimates of parameters. The first 10,000 iterations were not considered for the parameter estimation and were discarded as burn-in. Tables 3 and 4 present the parameter estimates and their associated statistics at 95% credible intervals for the total crash and fatal-injury crash models, respectively. The results show that all parameters used are effectively significant at 95% credible interval in both total and fatal-injury crash models. That the Michigan specific constant is now significant, in contrast to the GLM estimate, an outcome that is likely a result of the use of a more appropriate model form.

TABLE 3: Parameter Estimates and MCMC Statistics for the Total Crash Model

Parameter	Mean	Standard deviation	MC error	2.50%	median	97.50%
a	-8.458	0.794	0.043	-10.080	-8.422	-7.015
b	0.216	0.111	0.002	-0.005	0.217	0.434
c	0.836	0.095	0.005	0.666	0.833	1.031
e	-0.193	0.076	0.001	-0.363	-0.185	-0.063
Dispersion Parameter	1.103	0.092	0.001	0.933	1.100	1.294

TABLE 4: Parameter Estimates and MCMC Statistics for The Fatal-Injury Crash Model

Parameter	Mean	Standard deviation	MC error	2.50%	median	97.50%
a	-9.765	0.804	0.043	-11.320	-9.775	-8.176
b	0.399	0.133	0.002	0.135	0.400	0.655
c	0.824	0.095	0.005	0.636	0.825	1.008
e	-0.185	0.084	0.001	-0.373	-0.176	-0.048
Dispersion Parameter	1.022	0.113	0.001	0.819	1.016	1.264

CMFunction Estimation and Comparison

For the GLM approach, based on Equation 1, the CMF for installing a passing lane of length LngPL is given by the following CMFunction:

$$\text{CMF} = e^{(\beta_2 \times \text{LngPL})} \quad .. 3)$$

For the FB MCMC modeling approach, based on Equation 2, the CMF for increasing a passing lane from LngPL1 to LngPL2 is given by CMFunction shown in Equation 4. In using this equation for installing a passing lane of length PL2 , a value of 0 is substituted for PL1 .

$$CMF = \frac{\exp(\exp(e * \text{LngPL}_2))}{\exp(\exp(e * \text{LngPL}_1))} \quad \dots 4)$$

Both Equations 3 and 4 can be used directly with Imperial units if desired. Figures 3 and 4 depict CMFs estimated from Equations 3 and 4 for installing a passing lane of various lengths, and compares these to the single valued CMF from the HSM. The recommended ranges for passing lane length in Ontario (ON) and Michigan (Mich.) are also shown for reference.

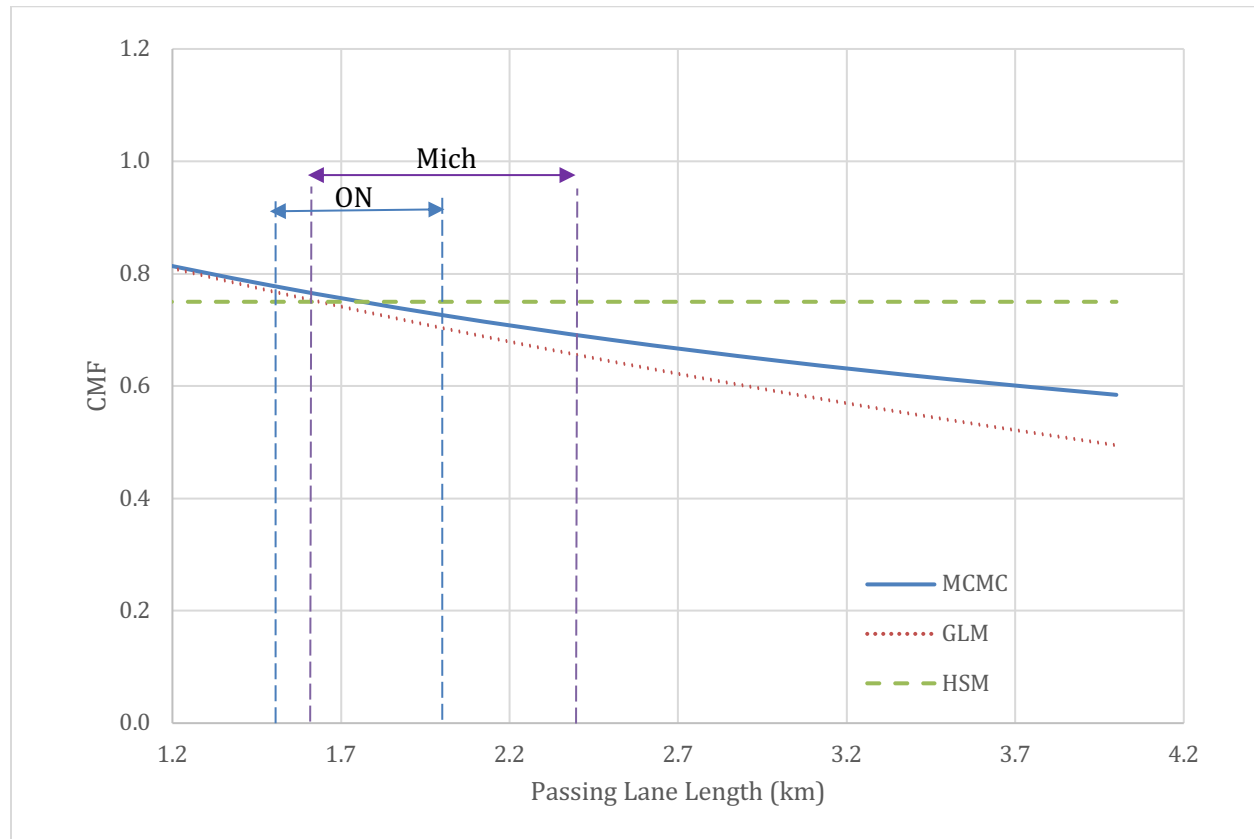


Figure 3 Total Crash CMFs for Installing a Passing Lane

Table 5 provides illustrative CMF estimates for total crashes for extending a passing lane by 500 m (0.31 miles) and 1 km (0.62 miles), based on Equations 3 and 4. It can be seen first of all that the safety benefit increases as the length of the extension increases, as might be expected. It can also be seen that, for a given increase in length the CMF based on the FB MCMC models depends on the original passing lane length and logically increases with increasing original length. By contrast, the CMF based on the GLMs are independent of the original length, which seems illogical. To illustrate, when extending a passing lane by 500 m from 1.5 km to 2 km, there will be 6.7% reduction in crashes, while the same amount of change from 3.5 km to 4 km will decrease crashes by 4.6%. These reductions increase to 12.3% and 7.8%, respectively, for a 1 km extension.

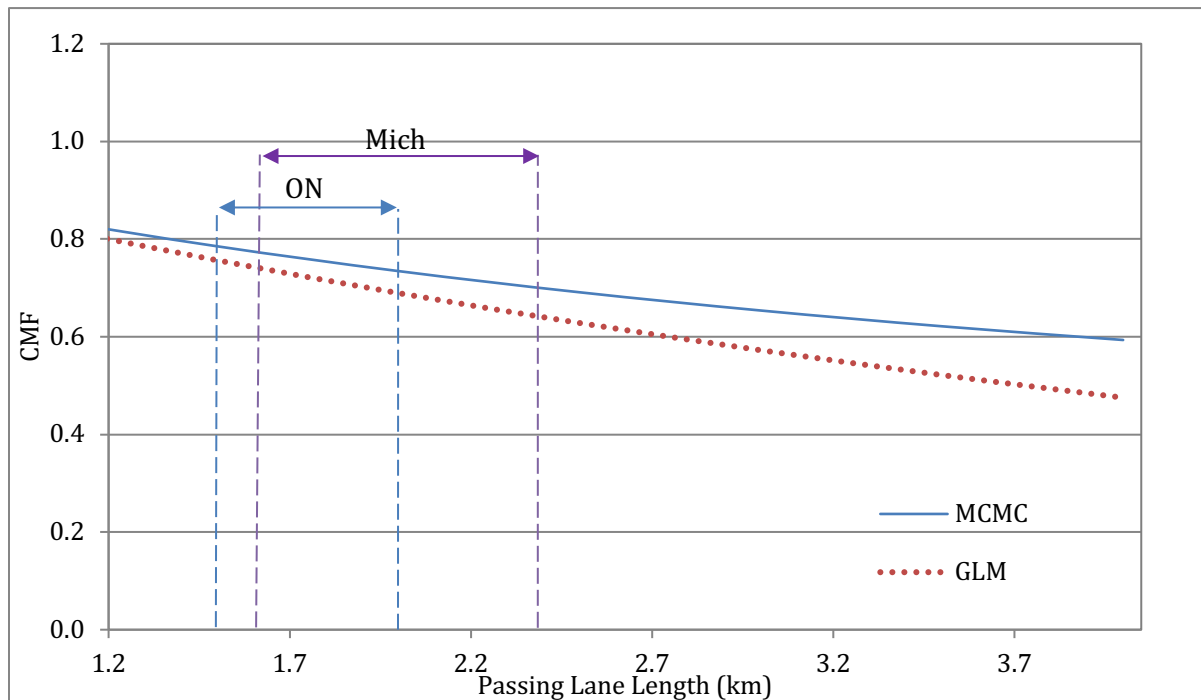


Figure 4 Injury Crash CMFs for Installing a Passing lane

Table 5: CMFs for extending an existing passing lane by 500 m (0.31 miles) and 1 km (0.62 miles)

Original passing lane length	500 m (0.31 miles) extension		1 km (0.62 miles) extension	
	CMF from FB MCMC	CMF from GLM	CMF from FB MCMC	CMF from GLM
1.5 km (0.93 miles)	0.933	0.916	0.877	0.839
2.0 km (1.24 miles)	0.939		0.888	
2.5 km (1.55 miles)	0.945		0.897	
3.0 km (1.86 miles)	0.950		0.906	
3.5 km (2.17 miles)	0.954		0.915	
4.0 km (2.49 miles)	0.958		0.922	

SUMMARY

The paper addressed the development of crash modification functions for passing relief lanes on two-lane rural roads. Advancements in vehicle technology related to features such as braking and acceleration capabilities indicate a need to revisit the rather dated, single valued, crash modification factor currently in the Highway Safety Manual (HSM). Generalized linear modeling and full Bayes Markov Chain Monte Carlo (MCMC) simulation were used with data from Michigan, U.S.A., and Ontario,

Canada to develop cross-section regression models from which crash modification functions (CMFunctions) were derived. The resulting CMFs were compared to those derived from conventional Generalized Linear Models (GLMs) and the CMF available in the Highway Safety Manual (HSM). The CMFunctions developed from MCMC simulation and from GLMs are such that safety effects of installing a passing lane on two-lane rural roads will logically depend on the actual length of that lane, which is not the case for the single valued CMF in the HSM. The MCMC models provide CMFs for lengthening an existing passing lane that depend not only on the amount of the extension, but also on the original length, unlike the GLM CMFs which provide a constant CMF for a given extension, regardless of the original length. The results are logical and are reasonably consistent with those from credible before-after studies, so are recommended for implementation in practice, in particular for HSM applications. Specifically, they can be applied in procedures for evaluating the potential safety effects of installing a passing lane on a road being designed or on existing road due to a safety concern. This information can be considered, in turn, along with the operational benefits, in prioritizing locations for this treatment.

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AUTHOR CONTRIBUTIONS

The research was supervised by Bhagwant Persaud, who led the writing of the paper. Alireza Jafari Anarkooli performed the MCMC modeling while Shahram Almasi developed the GLMs. Craig Lyon provided high level statistical oversight for the modeling exercises. All co-authors reviewed the paper.

REFERENCES

1. Neuman, T. R., R. Pfefer, K. L. Slack, K. K. Hardy, H. McGee, L. Prothe, K. Eccles, and F. Council. *NCHRP Report 500: Guidance for Implementation of the AASHTO Strategic Highway Safety Plan. Volume 4: A Guide for Addressing Head-On Collisions*. Transportation Research Board of the National Academies, Washington, D.C., 2003.
2. Highway Safety Manual (HSM), First Edition. FHWA American Association of State Highway and Transportation Officials, U.S.A, 2010.
3. Harwood, D. W., and A. D. St. John. *Passing Lanes and Other Operational Improvements on Two-Lane Highways*. Report No. FHWA/RD-85/028, Federal Highway Administration, 1984.
4. Potts, I., and D.W. Harwood. *Benefits and Design/Location Criteria for Passing Lanes*. Missouri Department of Transportation, 2004.
5. Persaud B., Lyon C., Bagdade J., and A. Ceifetz. Evaluation of Safety Performance of Passing Relief Lanes. *Transportation Research Record: Journal of the Transportation Research Board*, No. 2348, pp. 58–63, 2013.
6. Espada I., Christopher Stokes C., Cairney P. Long Truong L., Bennett P. and M. Tziotis. *Passing Lanes: Safety and Performance*. Austroads Publication No. AP-R596-19, 2019.

- 1 7. Schumaker, L, Ahmed, M & Ksaibati, K. Policy considerations for evaluating the safety effectiveness
2 of passing lanes on rural two-lane highways with lower traffic volumes: Wyoming 59 case study, *Journal*
3 *of Transportation Safety and Security*, vol. 9, no. 1, pp. 1-19, 2017.
- 4 8. Cafiso, S, D'Agostino, C & M. Kiec. Investigating the influence of passing relief lane sections on
5 safety and traffic performance, *Journal of Transport and Health*, vol. 7, part A, pp. 38-47, 2017.
- 6 9. Qin X., Ivan J., Ravishanker N., and J. Liu. Hierarchical Bayesian Estimation of Safety Performance
7 Functions for Two-Lane Highways Using Markov Chain Monte Carlo Modeling. *Journal of*
8 *Transportation Engineering*, Vol. 131, No. 5, pp. 345-351, 2005.
- 9 10. Gelman A. Prior distributions for variance parameters in hierarchical models (comment on article by
10 Browne and Draper). *Bayesian analysis*. 2006;1(3):515-34.