USING MACRO-LEVEL COLLISION PREDICTION MODELS TO EVALUATE THE ROAD SAFETY EFFECTS OF MOBILITY MANAGEMENT STRATEGIES: NEW EMPIRICAL TOOLS TO PROMOTE SUSTAINABLE DEVELOPMENT

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ABSTRACT

Mobility management (also called Transportation Demand Management, or TDM) consists of various strategies that change travel behaviour to increase transportation system efficiency. Mobility management policies and programs are generally promoted as ways to reduce traffic congestion, parking problems and pollution emissions; road safety is seldom a major objective. However, research described in this paper indicates that mobility management strategies also provide significant safety benefits. This paper describes how community-based, macro-level collision prediction models (CPMs) can be used to calculate the road safety effects of specific mobility management strategies (MMS). It summarizes the results of road safety evaluations of three mobility management strategies using recently developed macro-level CPMs, and using data from 479 urban neighbourhoods in the Greater Vancouver Regional District (GVRD), in British Columbia (BC), Canada. The results suggest that a smart growth strategy of more compact, multi-modal land use development patterns can reduce per capita neighbourhood collision frequency by 20% (total) and 29% (severe); that a congestion pricing strategy has the potential to reduce neighbourhood collision frequency by 19% (total) and 21% (severe); and improving transportation options (better walking and cycling conditions, and improved ridesharing and public transit services) could reduce collision frequency by 14% (total) and 15% (severe). These model predictions are consistent with actual observed mobility management collision reductions. This study indicates that mobility management strategies can significantly increase traffic safety in addition to providing other economic and environmental benefits.

INTRODUCTION

Mobility Management includes various strategies that help solve transportation problems by changing travel behaviour and increasing transportation system efficiencies (3). Mobility management is generally implemented to reduce traffic congestion, parking problems, energy consumption and pollution emissions. Mobility Management Strategies (MMS) increase transport system efficiency by causing various types of changes in travel behaviour, such as (4): switches in travel mode (e.g. carpooling instead of driving alone), changes in travel time (e.g. earlier or later travel times, to less congested off-peak periods), and/or changes in work/home location (e.g. working closer to home). Many of the local, regional, and global benefits of these changes in travel behaviour have been extensively researched (4, 5, 6, 7, 8). However, many politicians, businesses, and residents remain reluctant to support mobility management policies and programs, apparently because they consider the overall benefits smaller than the incremental implementation costs (9, 10, 11, 12, 13).

There is still some debate among researchers as to the magnitude of mobility management benefits (5, 9), due, in part, to the lack of reliable empirical tools for predicting how MMS cause transportation system changes (14, 15). Mobility management impacts have generally been quantified using conventional four-step transportation planning or activity-based models, which have been shown to have significant errors, leading to over and/or underestimation of MMS effectiveness (15). In addition, many mobility management policies and programs take several years for full implementation, require program compromises during the approval process, and then are superimposed after unforeseen changes to the subject land use and transportation systems. Thus, it can be difficult to isolate the effects of MMS from other trends and system changes. Because some MMSs involve new investments, higher user fees or vehicle use restrictions, mobility management program implementation must overcome the uncertainty of benefits.

For these reasons, mobility management implementation is often difficult, even when such policies and programs are cost effective solutions to widely recognized problems such as traffic and parking congestion, excessive energy consumption and pollution emissions (16). Unless a clear self-interest can be perceived (i.e. it is in *my* best interest to change *my* behaviour) people are reluctant to support policies that will force them to change their behaviour.

In summary, there appear to be three basic barriers to optimal mobility management implementation:
1) a lack of reliable empirical tools to accurately predict the benefits of MMSs; leading to,
2) a lack of defendable data with which decision-makers can justify implementing mobility-reducing MMSs; leading to,
3) a lack of public support for mobility management implementation.

Recent results in sustainable road safety research (1, 2) may help solve this problem by expanding the list of mobility management benefits to include road safety.

The enormity of the social and economic burden of road collisionsis a major problem worldwide. In 2004 the World Health Organization declared injuries due to road collisions as one of the leading epidemics of our time (17). The United Nations has made a similar declaration for 2007 (18). In the United States, more productive years of life are lost due to road collisions than any other disease, more than heart disease and cancer combined (20). In Canada, approximately 60,000 road collisions were reported in 2003, resulting in over 200,000 people injured and 3,000 people killed (19). At current trends injuries due to road collisions will be the third leading cause of death worldwide by 2020 (17). In addition to the human cost, these road casualties put an enormous economic burden on society, estimated to range from 1% to 2% of gross national product worldwide, estimated to total US$518 billion in 2004 (17).

Most Road Safety Improvement Programs (RSIPs) focus on engineering, enforcement, and/or education to reduce collisions and casualty rates per vehicle mile or kilometre. The most effective, long-lasting road safety strategies tend to be those that focus on engineering safer road environments that lead to a reduction in exposure and risk of collision for drivers and their passengers (21). Traditionally, the engineering of safer roads has taken a *reactive* approach, including the identification, diagnosis and remedy ("improvement") of hazardous or collision-prone locations (called "black spots"), implementing remedial treatments *after* safety problems were identified (21). Unfortunately, this reactive approach requires several years of collision records, along with the associated toll in human casualties, before a safety problem is identified and fixed, often at a high cost in existing communities.

Given the continuing burden of injuries due to road collisions, practitioners have been pursuing a more *proactive* approach, to evaluate road safety *before* problems occur, as part of the land use and/or transportation planning process (19, 21). However, until recently practitioners lacked the necessary empirical tools to evaluate road safety proactively. Recent research on Sustainable Road Safety (SRS) (1, 2), has resulted in the development of improved empirical tools to do pursue proactive road safety, including community-based, macro-level collision prediction models (CPMs). In several case studies to date, these CPMs and model-use guidelines has demonstrated their potential for use to improve road safety in communities across Canada and the world (1). These new empirical tools present an opportunity to verify earlier research on, and refine estimates of, the road safety effects of MMSs.

Traffic monitoring after the implementation of certain mobility management strategies indicates that they can provide significant road safety benefits (1, 4). If true, this is good news, because it identifies a new set of potential road safety strategies that provide a variety of sustainable development planning benefits to society, as indicated in Table 1.

This paper has two main objectives:

(1) To demonstrate the use of previously developed macro-level collision prediction models (CPMs) to provide empirical road safety estimates in a case study; and,

(2) To empirically verify earlier road safety estimates for three mobility management strategies (MMSs).

PREVIOUS WORK

Due to a lack of reliable empirical tools, limited research exists on the road safety effects of mobility management strategies (1, 2, 4). A comprehensive literature review (4) of various mobility management strategies found that much of the data were improperly aggregated, and models failed to correct for potentially confounding factors. For example, we generally know that a reduction in one person's vehicle mileage should provide a reduction in their individual collision risk (1, 2). And, we also know that in the range of 70% of all severe collisions involve multiple vehicles; therefore, we can hypothesize that some further reduction in the collision risk of other motorists (regardless of whether or not they reduce mileage) should occur also, since their vehicles are exposed less to this drivers' errors (1, 2, 4). However, limited research has produced limited findings, particularly at a fine-grained scale, thus precluding the ability to confirm this hypothesis until recently. With the advent of community-based, macro-level collision prediction models, reliable empirical evaluations of mobility management strategies appear possible.

By definition, *macro*-level CPMs evaluate the safety of a neighbourhood, a city, or a region using neighbourhood traits as inputs (e.g. population density, intersection density, mode split, traffic density). Based on Dutch research from the mid-1990's, two North American researchers developed early version (22, 23), but neither attempted to use CPMs in road safety evaluations. In 2006, using a refined methodology, researchers (2) developed forty-seven community-based, macro-level collision prediction models, each significantly associated with one or more of twenty-two input variables. For each neighbourhood, which were typically defined to coincide with traffic analysis zones (TAZs) used in regional transportation planning models (e.g. Emme/2 in the GVRD), input variable values were obtained using aggregated data off of geo-referenced travel demand, demographic, and road network mapping (e.g. ArcGIS) provided by regional road, land use, census, and auto insurance authorities (1). The CPMs output a prediction of the number of collisions that can be reasonably expected to occur in that same neighbourhood (or TAZ) per unit time (e.g. every three years). Samples of the models developed and used in this case study are given in Table 2, with descriptive statistics and input data in Table 5 (2).

Contrary to traditional linear collision prediction models that had been assumed until recently by Dutch and other researchers, the non-linear form of these empirically derived macro-level CPMs in Table 2 (1, 2) confirmed that collision frequency was non-linearly related to Vehicle Kilometres Traveled (VKT). In other words, whereas traditional linear CPMs associated collisions linearly with VKT (e.g. Collision frequency = collision rate x $\text{VKT}^{\text{Power = 1.0}}$), these newly developed CPMs associated collisions non-linearly with VKT (e.g. Collision frequency =

proportionality constant x $VKT^{Power < 1.0}$), with the power of the VKT exponent ranging from 0.55 to 0.85. Generalized linear regression modelling (GLIM) techniques were used to develop and calibrate these CPMs, including an assumed negative binomial residual statistical pattern distribution, a 95% level of confidence statistical test, and the Pearson and Chi-square model goodness-of-fit statistical tests. All developed models met these tests, and were categorized for use into one of sixteen groups shown in Table 3 (2), based on the following factors:

- Four themes of neighbourhood traits (exposure or traffic density, road network, socio-demographics, and TDM).
- Two classes of predominant land use (rural or urban). Urban includes urban and suburban.
- Two sources of exposure variable data derivations (modelled or measured). Modelled exposure variables were outputted from transportation planning models, such as Emme/2 (e.g. VKT). Measured exposure variables (e.g. Total Lane Kilometres = TLKM) were derived from geo-coded mapping.

Generally, these newly developed macro-level collision prediction models have found observed effects consistent with intuition. Specifically, *increased* collisions are non-linearly associated with *increases* in the following explanatory variables:

- Exposure - vehicle kilometres travelled (VKT), total road lane kilometres (TLKM), and average congestion (VC).
- Socio-Demographic - job density (WKGD), population density (POPD), unemployment (UNEMP), residential unit density (NHD).
- TDM – shortcut capacity/attractiveness (SCC, SCVC), number of drivers (DRIVE), total commuters (TCM), total commuter density (TCD). SCC measures the ability of vehicles to shortcut on local roads through a particular zone, in vehicles per hour. SCVC is simply SCC multiplied by congestion level VC.
- Network - signal density (SIGD), intersection density per unit area (INTD), intersection density per lane-km (INTKD), arterial-local intersection percent (IALP), arterial lane kilometre percent (ALKP).

Also, the models revealed that *decreased* collisions were associated with *increases* in several other explanatory variables:

- Socio-Demographic - family size (FS).
- TDM - core size and percentage (CORE, CRP).
- Network - 3-way intersection percent (I3WP), local road lane-kilometre percent (LLKP), and Core area (CORE).

While most of these input variables are self-explanatory, there are two new neighbourhood descriptor variables, shortcut capacity/attractiveness (SCC/SCVC) and CORE (2). A key component of SCC and SCVC is to determine the degree of traffic calming present in the neighbourhood. Their formulations are given in equations 1 and 2 as:

$$SCC = \frac{L \cdot W \cdot C_f \cdot (R_{NS} + R_{EW}) \cdot C_{TC}}{A_r} \quad (1)$$

$$SCVC = SCC \cdot VC \quad (2)$$

where L = average number of local road 'lanes' in each direction (default = 1); W = one-way (= 1) or two-way (= 2) traffic flow; C_f = typical local road free-flow capacity = 150 veh/lane/hr; R_{NS}, R_{EW} = number of local roads running completely across the zone, sum of north-south and east-west 'roads', respectively (default = 0); C_{TC} = degree of zonal traffic calming (traffic calmed = 0; no calming = 1; , some = 0.5); A_r = zonal area; and, VC = Average zonal congestion level (2).

These models have been used in three road safety planning applications to date (1, 24, 26). The first involved a traditional road safety application evaluating the road safety level of existing neighbourhoods, to identify collision-prone neighbourhoods, and to recommend possible remedial treatments to reduce collisions (24). This application demonstrated that macro-level models can be used to complement traditional road safety methods, and to provide an enhanced *early-warning* capability for road safety engineers. The second case study focused more on road safety planning applications, including evaluations of four neighbourhood road patterns (existing grid and cul-de-sac patterns, and two other theoretical patterns), and of area-wide traffic calming (repeating a 10 year old conventional study, but using only the *before* data with the new models to predict the *after* results). The third case study used the models to evaluate the road safety effects of a regional transportation plan. These studies were used to demonstrate that macro-level CPM predictions are practical to use in local and regional planning processes, and to predict the road safety levels for both existing and planned neighbourhoods. In effect, this also demonstrated a method of using these new models to do a sensitivity analysis of the road safety impacts of varying certain neighbourhood design features, within certain guidelines. Based on the results of these case studies, model-use guidelines for using macro-level CPMs have been prepared (1).

The macro-level CPM use guidelines pertain to the selection of which of the forty-seven models to use, techniques to conduct the actual analysis, and proper statistical tests and interpretation of results. As not every macro-level CPM was appropriate for each safety application, a six-step selection process has been recommended, and was followed in this case study. The first step involved choosing the CPM *type* (i.e. *micro*- or *macro*-level) based on the scope of the safety evaluation. MMSs usually affect entire neighbourhoods (i.e. traffic zones), a municipality, or part of a region (as opposed to a single intersection, for which *micro*-level CPMs are used); therefore, macro-level CPMs were used. The second step narrowed the model focus by considering the safety application *task*, which in this application was *proactive* (i.e. MMS plan). Therefore, only some of the sixteen groups were appropriate. The third step looked at the predominant type of land use in each neighbourhood under evaluation, which in this case was urban, suggesting that only urban CPMs be used. The fourth step looked at the specifics of the analysis to identify which input variables would be changing with each MMS. These changing variables were termed *trigger* variables, and depend on planning scope (e.g. present situation to future conditions, future vs future scenario comparisons), and the specifics of the planning schemes involved. For example in this case, MMSs would be expected to reduce driving, exposure, and congestion levels, suggesting that VKT, VC, and DRIVE would be trigger variables. These trigger variables are found in the urban TDM models (i.e. groups 9 and 10 in Table 3). Other triggers variables and models used to evaluate MMS are detailed below in the *approach* to the case study.

The fifth step identifies which of the six collision types (i.e. total, severe, AM, AM/PM, non-rush, and/or pedestrian) are of interest in the safety evaluation. Unless the specifics of the application suggest otherwise, for most evaluations including this study, total and severe collision type CPMs can be used, because they generally are reflective of the data and the most commonly used in safety analyses. The sixth and final step in model selection is to check that datasets can be assembled to use the selected models. Adequate data ensures that the selected models will provide accurate and credible results. A detailed discussion on extraction methods and typical values for the data used for this study has been described previously (1), and is summarized below. The six step model *selection* process is summarized in Table 4 as a decision aid. An urban traffic calming example has been highlighted. Other guidelines, on model *use,* and on *interpretation* of results, are described below.

CASE STUDY

Background

Three MMSs have been evaluated using macro-level CPMs, related to smart growth, congestion pricing, and improved transport options. *Smart growth* involves more compact, mixed, multi-modal land use patterns. *Congestion pricing* refers to peak period road tolls, parking charges, distance-based insurance, and/or fuel taxes. *Improving transport options* refers to various policies and programs that improve walking and cycling conditions, ridesharing and public transit service quality, and increase support for carsharing, telework and flex-time. These three MMSs were chosen to study because they represent a broad cross section of strategies, and are being debated for implementation in many communities. Most importantly, input data was available to evaluate them with empirical, community-based, macro-level CPM predictions (2). Details of each MMS, and specific input values for related trigger variables are described below.

Input data for each of these three strategies is given in Table 5, and came from one or more of four sources. First, a regional database used to develop the CPMs was available, and provided base case data (control input values), based on 479 urban neighbourhoods in the GVRD (1). The database had previously been extracted and compiled from geo-coded collision records, TAZs, modelled outputs, road networks, and land use maps, and, from national census databases. The second data source used for this case study consisted of two comprehensive literature reviews on observed transportation changes due to various MMSs (3, 4, 25). Third, data from recent road safety research (1) on the observed traffic impacts of traffic calming was used to augment smart growth impacts. Fourth, because data for these three MMSs was not yet available via the GVRD regional four-step transportation planning model, data for the modeled variables VKT and VC were based on values found in the literature. Although this introduced an obvious source of uncertainty into the study input values, using values from the literature was considered a reasonable proxy, and at least provided the general domain of inputs. Moreover, the focus of this study was on demonstrating the use of collision prediction models in evaluating MMSs assuming that the modeled data had already been generated, not on demonstrating the use of four-step models. A road safety planning case study combining a regional transportation planning (i.e. four-step) model process with a community-based, macro-level CPM to conduct an MMS evaluation on a regional scale is the subject of a forthcoming technical journal article (26).

Approach

The general approach - selection, analysis, and interpretation - followed the recommended guidelines (1). First, the urban planning MMS nature of the application, the availability of datasets, and the input variables triggered by each MMS prompted use of urban measured and modelled CPMs for total and severe collisions from the socio-demographic, TDM, and network models (model groups 5, 6, 9, 10, 13, and 14). Trigger variables were identified for each MMS according to what impacts have been observed in other research (3, 4, 25). Impacts of a smart growth MMS were expected to trigger changes in fourteen input (trigger) variables - Exposure: VKT (decrease), TLKM (decrease), VC (decrease); Socio-demographic: POPD (increase), WKGD (increase), NHD (increase); TDM: SCC (decrease), CORE (increase), DRIVE (decrease); and, Network: SIGD (decrease), I3WP (increase), INTD (increase), ALKP (decrease), and LLKP (increase). The transport improvement MMS triggered changes in four variables - Exposure: VKT (decrease), VC (decrease); and, TDM: DRIVE (decrease), and TCM (decrease). The Pricing MMS triggered changes in only three variables - Exposure: VKT (decrease), VC (decrease); and, TDM: DRIVE (decrease). After identifying the trigger variables, the macro-level CPMs were run.

The analysis stage involved a three-step road safety evaluation. First, the eleven selected models were run using the base data for all 479 neighbourhoods to produce GVRD collision frequency averages for each model. Second, the values of previously identified trigger variables were adjusted to reflect the literature on MMS effects. Third, these new values for trigger variables were inputted into the same macro-level CPMs, which were re-run. Table 5 shows the averages for GVRD input variable values, together with the adjustments to trigger variable values for each mobility management strategy.

The resulting macro-level CPM predictions were compared to the GVRD averages for each model group, and differences noted. The differences were reviewed for reasonableness, and statistical significance using a t-test at 95% confidence interval. It is important to note that, in accord with model use guidelines, the macro-level CPM predictions were used for relative comparisons only, pending further research and model refinements. Using the absolute model predictions, except to analyze individual or small groups of neighbourhoods, is not recommended, as the community-baesd, macro-level CPMs by definition exclude major highways (i.e. freeways) from their predictive capabilities.

RESULTS

The results of this analysis are presented in Table 6. They appear to be in general agreement with intuitive expectations, and with safety impacts observed in the literature (1, 4). In accordance with model use guidelines on interpretation of results, these model predictions were tested for statistical significance, recognizing that macro-level CPM predictions are only *expected* values. That is, their predictions are estimates of the true mean frequency of collisions, which is a random variable. Given this randomness, standard statistical testing was used to verify whether the GVRD base case averages were significantly different from the MMS-adjusted predictions. A difference of means hypothesis test was used, which relies on a normally distributed test statistic, *T*, calculated according to a 95% confidence interval. The difference was significant if the calculated T-test statistic met the criterion in equation 3, as follows (27):

$$\left| \frac{[(MMS\ Avg - GVRD\ Avg) - Avg\ of\ Differences]}{Std\ Dev[Differences] \big/ \sqrt{n}} \right| \geq T_{[\frac{(1-\alpha)}{2}, n-1]} \tag{3}$$

where:

n = the number of model predictions used in deriving the comparison

α = the desired confidence interval, in this case 95%

T = 1.96 @ 95% for large n, derived from standard T-distribution tables

$Std\ \ Dev[Difference\ s]$ = the standard deviation of the differences predicted across all models.

For the urban smart growth MMS, improvements in road safety were estimated for total and severe collisions to be in the range of 20% and 29%, respectively, when compared with GVRD urban neighbourhood averages. This result is considered statistically significant using a 95% confidence interval. It is also in general agreement with the 20% road safety improvements of MMSs observed by other researchers (4, 28, 29). For the congestion pricing MMS, improvements in road safety were estimated for total and severe collisions to be in the range of 19% and 21%, respectively, when compared with GVRD urban neighbourhood averages. This result is considered statistically significant using a 95% confidence interval. It is also in general agreement with the 25% road safety improvement of road pricing MMSs observed by other researchers. The transit improvement were estimated to reduce total and severe collisions in the range of 14 and 15%, respectively, when compared with GVRD urban neighbourhood averages. This result is considered statistically significant using a 95% confidence interval. It is also in general agreement with the road safety impacts of MMSs observed by other researchers.

Overall, the observed 1:1 to 2:1 relationship between road safety improvement and *modeled* variable (i.e. VKT, VC) input values suggests that *any* reduction in VKT due to MMSs will result in a road safety benefit. Although a full four-step transportation planning model was not part of this study and thereby necessitated making assumptions for VKT and VC input values, which therefore precludes definitive empirical MMS estimates, the results in general suggest that effective MMSs could significantly augment urban road safety strategies. Comparing the input exposure variable values from Table 5 with the output safety improvements in Table 6 of all three strategies, the Smart Growth strategy yielded the highest predicted total (20%) and severe (29%) collision reductions, despite having the lowest inputted reduction in VKT (-15%). Thus, it would appear that integrated MMSs that combine land use with transportation management strategies appeared to provide greater reductions in collisions per unit of reduced VKT compared with less integrated, single-focused MMSs.

It is also noteworthy that although increased land use intensity (i.e. housing and population densities), were generally associated with *increased* collision frequency (1), Smart Growth policies were predicted to *reduce* collision frequency. This counter-intuitive result occurred in this case, however, because Smart Growth strategies reduce VKT as well as increasing population and housing density. Moreover, the overall *reduction* in VKT, which is the dominant variable associated with collision predictions, more than compensated for the population and housing density increases, and lends additional support to a conclusion supporting integrated, multi-faceted MMSs as yielding greater road safety benefits than narrower, single-focus MMSs.

OTHER IMPACTS TO CONSIDER

Mobility management strategies (MMS) can have diverse economic, social and environmental impacts (benefits and costs) which should be considered in their evaluation (3, 30, 31). Most MMSs reduce traffic congestion, road and parking facility costs, consumer transportation expenses, energy consumption and pollution emissions, as well as improving mobility options for non-drivers, and supporting strategic land use objectives (such as redeveloping existing communities and reducing sprawl). Strategies that increase walking and cycling activity tend to increase public fitness and health.

On the other hand, some MMSs impose additional external costs, such as increased noise from buses, and increased sprawl if telecommuting stimulates more dispersed land use development patterns. MMSs that apply negative incentives, such as increased fuel taxes, road tolls and parking fees, reduce user mobility benefits although the incremental losses are marginal, since, with efficient pricing, the travel foregone consists of consumers' least valued vehicle-kilometres. Many MMSs provide positive incentives, such as improved travel options (better walking and cycling conditions, improved rideshare and public transit services, more support for flex-time and telework) or financial rewards for reduced driving (for example, pay-as-you-drive vehicle insurance pricing and parking cash-out offer motorists a new opportunity to save money if they reduce their mileage – motorists who continue their current mileage are no worse off on average, and those who reduce their mileage save more money than under current pricing). Vehicle travel reductions that result from these optional, positive incentives reflect net user benefits (consumers who choose them must be directly better off overall or they would not choose the option, even if they choose slower modes or alternative destinations).

In some cases, shifts from driving to walking and/or cycling increase crash risk per passenger-kilometre, although this is often offset by reductions in travel distance (a short walking or cycling trip often substitutes for a longer automobile trip; although drivers and non-drivers tend to make similar numbers of trips, drivers trend to travel about three times as many annual passenger-kilometres as non-drivers). As non-motorized travel increases in a community, collisions per passenger-kilometre of these modes has been observed to decline (4). All of these factors should be considered when evaluating the overall value of MMSs.

CONCLUSIONS

This case study has demonstrated the use of previously developed community-based, macro-level collision prediction models (CPMs) to provide empirical road safety estimates, and to verify earlier road safety estimates for three mobility management strategies (MMSs). It is the first empirical road safety evaluation of MMSs using CPMs. Based on a review of the results of this case study, the following conclusions can be drawn:

1. There is relatively close agreement between the observed (and intuitive expectations) and predicted mobility management road safety benefits. Transportation and land use factors that tend to reduce vehicle travel appear to reduce collision frequency.
2. In comparing the inputs and results in Tables 5 and 6, it would appear that integrated MMSs that combine land use with transportation management strategies appear to provide greater reductions in collisions per unit of reduced vehicle travel compared with less integrated, single-focused MMSs.
3. Although the dominant influence of VKT on collision prediction has been noted by other researchers, these case studies suggest that it may also hold potential when estimating the road safety impacts of MMSs. This may be used as a convenient proxy by engineers,

planners, and decision-makers for predicting safety impacts of specific policies and programs.

4. Although increased land use intensity has been generally associated with increased collision frequency (2), Smart Growth policies are predicted to reduce collision frequency, because they reduce vehicle-kilometres-travelled (VKT) as well. This result lends additional support to the second conclusion that integrated, multi-faceted MMSs appear to yield greater road safety benefits than single-focused MMSs.

When evaluating road safety impacts it is important to clearly define the reference units used. The traditional practice of predicting collisions per unit of VKT (e.g., per 100 million vehicle-miles or billion vehicle-kilometres travelled) ignores increases in per capita vehicle travel as a risk factor and the possible safety benefits of mileage reductions. Similarly, the Smart Growth MMS is associated with reduced collision frequency and casualties, likely due to reduced per capita vehicle travel and traffic speeds. Since road safety, and MMSs are ultimately concerned with *people*, future research on macro-level CPMs for evaluating the road safety risk of MMSs should also explore other forms of exposure variables, perhaps those explicitly focused on some form of per capita travel consumption (e.g. VKT per capita), as is done with health risks for example, so that road safety risk could be compared with other health risks.

In summary, the results of this empirical road safety evaluation suggest that MMSs have the potential to increase road safety in addition to providing other significant economic, social and environmental benefits. It is hoped that the introduction of community-based, macro-level CPM use by practitioners will facilitate improved road safety analyses by community planners and engineers. If so, these improved decisions will facilitate improved neighbourhood road safety, quality of life, and other benefits for residents and road users. Future research will focus on refining estimates of the modeled inputs (i.e. VKT, VC) associated with each MMS. Subsequently, case studies are being pursued to develop and transfer macro-level CPMs for use in other regions on MMS and other road safety evaluations.

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Table 1. Comparing Strategies (3)

Sustainability Objectives	Mobility Management	Road Strategies
Collision Reductions	✓	✓
Congestion Reductions	✓	
Roadway and Parking Cost Savings	✓	
Consumer Costs Savings	✓	✓
Improved Mobility Options	✓	
Energy Conservation	✓	
Pollution Reduction	✓	
Physical Fitness & Health	✓	
Land Use Objectives	✓	
Community Liveability	✓	✓

Mobility management can help achieve a variety of planning objectives (✓). Traditional road safety strategies typically provide fewer total benefits.

Table 2. Sample of models used to evaluate the road safety level of MMSs (2)

Model Group #	Model Form	κ	DoF	Pearson χ^2	SD	$\chi^2_{0.05,\ dof}$
1	Urban, Modeled, Exposure					
	$Total\ Collisions/3yr = 1.15VKT^{0.685}e^{1.45vc}$	1.7	459	495	508	510
	$Severe\ Collisions/3yr = 0.16154VKT^{0.7265}e^{2.087vc}$	1.5	461	447	520	512
6	Urban, Measured, Socio-Demographic					
	$Total\ \ Collisions/3\,yrs = 74.2175TLKM^{0.8218}\cdot e^{(0.007462\,popd + 0.06295unemp - 0.743\,fs)}$	1.6	463	508	518	514
	$Severe\ \ Collisions/3\,yrs = 8.3645TLKM^{0.8532}\cdot e^{(0.0068\,popd + 0.07899unemp - 0.5637\,fs)}$	1.3	464	437	532	515
10	Urban, Measured, TDM					
	$Total\ \ Collisions/3\,yrs = 43.7285TLKM^{0.5762}\cdot e^{(0.02702scc - 0.0000277core + 0.000123tcm)}$	1.5	460	484	517	511
	$Severe\ \ Collisions/3\,yrs = 7.2283TLKM^{0.7205}\cdot e^{(0.01918scc - 0.0000334core + 0.0000909tcm)}$	1.2	461	433	532	512

A definition of each variable used in these models is given in Table 3.
κ is a model overdispersion parameter derived in CPM development.
DoF refers to degrees of freedom, related to the number of data points in model development
Pearson χ^2 is a standard statistical test of model goodness of fit
SD refers to scaled deviance, another model goodness of fit measure
χ^2 is the target Chi-Square statistic, against which the Pearson and SD measures are tested.

Table 3. Vancouver – Macro-Level Collision Prediction Model Categories (2)

Themes (traits) Neighbourhood input variables	**Urban /Rural**	**Modeled / Measured**	**Group #**
Exposure Variables VKT = vehicle kilometres traveled VC = neighbourhood congestion level TLKM = total lane kilometres AREA = total neighbourhood area	Urban	Modelled	1
		Measured	2
	Rural	Modelled	3
		Measured	4
Socio-Demographic POP = population WKG = jobs in the neighbourhood NHD = housing units per unit area FS = average family size EMP = employment level	Urban	Modelled	5
		Measured	6
	Rural	Modelled	7
		Measured	8
TDM CORE = largest contiguous area of the neighbourhood not bisected by major roads CRP = CORE size as a percentage of neighbourhood size TCM = total number of commuters SCC = short cut capacity through the neighbourhood on local roads DRIVE = number of commuters who drive	Urban	Modelled	9
		Measured	10
	Rural	Modelled	11
		Measured	12
Network SIGD = number of signals per unit area INT = number of intersections I3WP = percentage of 3-way intersections IALP = percentage of arterial-local road intersections ALKP = percentage of arterial lane kilometres	Urban	Modelled	13
		Measured	14
	Rural	Modelled	15
		Measured	16

Table 4. Candidate CPM Groups.

START: Eligible Model Groups		Micro	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
			Exposure				Socio-Demographic				TDM				Network			
A. Scope	Single Site	R	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR
	Neighbourhood (Nbd.)	NR	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R
	Municipality (Mun.)	NR	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R
	Region (Reg.)	NR	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R
B. Task	**Reactive**																	
	Black Spots	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R
	Rd Design	R	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR
	Pro-active																	
	Nbd Rd Design	NR	?	R	?	R	NR	NR	NR	NR	?	R	?	R	?	R	?	R
	Nbd LU	NR	NR	?	NR	?	?	R	?	R	?	R	?	R	?	?	?	?
	Mun. OCP	NR	R	?	R	?	R	?	R	?	R	?	R	?	R	?	R	?
	Reg. LU	NR	?	?	?	?	R	?	R	?	?	?	?	?	?	?	?	?
	Reg. Road	NR	R	?	R	?	?	?	?	?	?	?	?	?	?	?	?	?
	Reg. TDM	NR	?	?	?	?	?	?	?	?	R	?	R	?	?	?	?	?
C. Land Us	Urban	R	R	R	NR	NR	R	R	NR	NR	R	R	NR	NR	R	R	NR	NR
	Rural	R	NR	NR	R	R	NR	NR	R	R	NR	NR	R	R	NR	NR	R	R
D. Trigger Variables																		
	Exposure	R	R	R	R	R	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR
	Socio-Demographic	?	NR	NR	NR	NR	R	R	R	R	NR	NR	NR	NR	NR	NR	NR	NR
	TDM	NR	NR	NR	NR	NR	NR	NR	NR	NR	R	R	R	R	NR	NR	NR	NR
	Network	?	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR	R	R	R	R
E. Collision Type																		
	Total Collisions	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R
	Severe Collisions	R	R	NA	R	R	R	R	R	R	R	R	R	R	R	R	R	R
	AM Collisions	R	NA	NA	NA	NA	R	R	NA	NA	NA	R	NA	NA	NA	R	NA	NA
	AM/PM Collisions	NR	NA	NA	NA	NA	NA	NA	NA	NA	R	NA	NA	NA	NA	NA	NA	NA
	Non-Rush Collisions	NR	NA	NA	NA	NA	NA	NA	NA	NA	R	NA	NA	NA	NA	NA	NA	NA
	Pedestrian Collisions	NR	NA	NA	NA	NA	NA	NA	NA	R	NA	NA	NA	NA	NA	NA	NA	R
F. Data	Measured	R	NR	R	NR	R	R	R	R	R	R	R	R	R	R	R	R	R
	Modelled	?	R	NR	R	NR	R	NR	R	NR	R	NR	R	NR	R	NR	R	NR
			Exposure				Socio-Demographic				TDM				Network			
END: Candidate Model Groups		**Micro**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**

*How to use table: Enter table at START, and work down through successive Steps A through F to END. Only the model groups chosen at each step are to continue to be carried forward as candidates for further evaluation at the next step.

An example is shown (see arrows) for a safety evalution of whether or not to implement traffic calming in an urban neighbourhood.

In this example, final selection involves modelled (9, 10) and measured (9) macro-level CPMs.

(R = Recommended; **NR =** Not Recommended; **?** = Optional, only if resources/time permit, and data relevant; **NA** = model not available.)

Table 5. Input Values* (477 Urban Greater Vancouver neighbourhoods)

	GVRD neighbourhood				Adjustments		
Variables	**Min.**	**Max.**	**Std. Dev.**	**Averages**	**Smart Growth**	**Congestion Pricing**	**Transp Imp's**
VKT	0	17,445	2,555	3,538 veh-kms	-15%	- 20%	- 15%
TKLM	4	224	32	54 lane-kms	-15%		
VC	0.01	0.90	0.15	0.32 vol./cap.	-15%	- 20%	- 15%
SCVC	0	57	4	2 (unitless)			
SCC	0	265	15.9	6.25 (unitless)	-100%		
WKGD	0	5.49	0.74	0.31 jobs/capita	100%		
POPD	0	280	36	35 persons/ha	100%		
NHD	0	122	15	12.7 units/ha	100%		
FS	2.1	3.6	0.31	3 persons/unit			
UNEMP	2	33	4	9.1 %			
AREA	5	1,614	165	171 hectares			
CORE	0	1,614	127	91 hectares	100%		
DRIVE	0	3,733	790	1,002 drivers	-15%	- 20%	- 15%
TCM	0	5,255	1,197	1,592 commuters			
SIGD	0	0.63	0.07	0.034 signals/ha	-25%		
INTD	0.02	2.12	0.28	0.46	25%		
I3WP	0	100%	24%	52%	50%		
ALKP	4%	85%	16%	32%	-20%		
LLKP	0	64%	13%	38%	25%		

* Input values for each MMS were derived by making the given adjustments to the GVRD averages.

Sample calculations for Smart Growth strategy:

$$Severe\ \ Collisions / 3\ yrs = 7.2283 TLKM^{0.7205} \cdot e^{(0.01918 scc - 0.0000334 core + 0.0000909 tcm)}$$

TLKM = 56 * (1 – 15% = 0.85) = 47.6

CORE = 91 * (1 + 100% = 2) = 180

SCC = 6.25 * (1 – 100% = 0) = 0

TCM = 1,592 * (1 + 0 = 1) = 1,592

CPM Output = 134 severe collisions in 3 yrs

Table 6. Safety Impacts of Selected GVRD TDM Strategies

GVRD Nbhd Averages*	Collision Type	Smart Growth (T - statistic)	Congestion Pricing (T - statistic)	Transport Improvements (T - statistic)
390	Total	- 20% / (2.5)	- 19% / (5.3)	- 14% / (2.7)
90	Severe	- 29% / (2.1)	- 21% / (5.3)	- 15% / (2.6)
*(Units are in Collisions per 3 years)	Observed MMS Impacts (1, 3)	- 20% / na	- 25% / na	None published

This table presents the macro-level CPM outcomes for three MMSs, relative to regional averages.