Assessing the Impacts of a Teleworking Policy on Crash Occurrence: The Case of Flanders, Belgium

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Total number of words: 7588 (2 Tables and 2 Figures included)
Date of 1st submission: 24/07/2012
Date of 2nd submission: 15/11/2012

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ABSTRACT

Travel demand management (TDM) consists of a variety of policy measures that affect the effectiveness of transportation systems by changing travel behavior. The primary objective of such TDM strategies is not to improve traffic safety, although their impact on traffic safety should not be neglected. The main purpose of this study is to simulate the traffic safety impact of conducting a teleworking scenario (i.e. 5% of the working population engages in teleworking) in the study area, Flanders, Belgium. Since TDM strategies are usually conducted at a geographically aggregated level, crash prediction models (CPMs) should also be developed at an aggregate level. Given that crash occurrences are often spatially heterogeneous and are affected by many spatial variables, the existence of spatial correlation in the data is also examined. The results indicate the necessity of accounting for the spatial correlation when developing crash prediction models. Therefore zonal crash prediction models (ZCPMs) within the Geographically Weighted Generalized Linear Modeling (GWGLM) framework are developed to incorporate the spatial variations in association between the number of crashes (NOCs) (including fatal, severe and slight injury crashes recorded between 2004 and 2007) and other explanatory variables. Different exposure, network and socio-demographic variables of 2200 traffic analysis zones (TAZs) are considered as predictors of crashes. An activity-based transportation model framework is adopted to produce detailed exposure metrics. This enables to conduct a more detailed and reliable assessment while TDM strategies are inherently modeled in the activity-based models. In this study, several ZCPMs with different severity levels and crash types are developed to predict the NOCs for both the null and the teleworking scenario. The models show a considerable traffic safety benefit of conducting the teleworking scenario due to its impact on the reduction of total Vehicle Kilometers Traveled (VKT) by 3.15%. Implementing the teleworking scenario is predicted to reduce the annual VKT by 1.426 billion and total NOCs to decline by 2.62%.

INTRODUCTION

Urbanization and population growth together with employment and motor vehicle growth largely and negatively affect transportation systems' performance. To diminish these negative impacts, different policy measures and strategies have been applied by authorities. These programs and strategies that promote more efficient use of transportation systems are generally called TDM strategies (*1*). TDM therefore consists of several policies and strategies which aim to overcome transportation problems by means of mode shift (e.g. using public transportation instead of cars, biking for short distance trips or carpooling), travel time shift (e.g. avoiding traffic peak-hours by leaving home/the work place earlier or later) or travel demand reduction (e.g. teleworking). In general, TDM strategies are implemented to improve transportation systems' efficiency. However, their potential secondary impacts such as traffic safety or environmental effects should not be overlooked.

"Teleworking" is a general term used when application of telecommunication systems substitutes for actual travel to the work place. Teleworking is one of the most popular and effective components of commute trip reduction programs (*2*). Teleworking can significantly reduce participating employees' commute travel and consequently the total distance traveled. As mentioned earlier, TDM strategies usually have consequential impacts (e.g. impacts of reduced travel demand after applying a teleworking strategy) such as traffic safety, which is interesting to be investigated. To the best of our knowledge, traffic safety impacts of teleworking as a TDM strategy have not been investigated before in a proactive manner. The main goal of this study is therefore to evaluate the road safety impacts of a teleworking scenario by coupling ZCPMs with an activity-based model for Flanders, Belgium. This way, the behavioral impact of the TDM scenario in terms of traffic demand is incorporated in the safety analysis. By assigning traffic demand to the road network, the impacts of responses to TDM, such as changes in trip planning, route choice and modal choice are incorporated into the analysis.

The most immediate and direct impacts of teleworking are travel demand and consequently a reduction of total distance traveled. Previous research has evaluated these impacts from individual and global points of views; i.e. some studies focused on the changes of only telecommuter's behavior and their travel pattern (individual) whereas other studies investigate the effects of a telecommuting strategy on a more global level.

Henderson and Mokhtarian (*3*) compared the differences in non-telecommuting days and telecommuting days for a telecommuting group. They showed that vehicle miles traveled (VMT) and the number of daily trips reduced by 66.5% and 31.9%, respectively. Koenig et al. (*4*) compared participants' telecommuting day travel behavior with their non-telecommuting behavior. They concluded that the number of person vehicle trips reduced by 27% while VMT decreased by 77%. Moreover, Mokhtarian and Varma (*5*) compared several travel indicators between telecommuting days and non-telecommuting days for a sample of 72 center-based telecommuters in California. An average reduction of 11.9% in person miles traveled and 11.5% in VMT was found over a five-day work week.

In a study conducted by Nilles (*6*), it was estimated that if 10% of the workforce telecommutes on any given day, total vehicle travel would decline by 4%. Results of another study (*7*) indicated that estimated VMT without telecommuting would have been 1.78% to 3.31% higher compared to the observed VMT, with a mean impact of 2.12%. in another study, Choo and Mokhtarian (*8*) found that teleworking appears to reduce VMT as little as 0.34%. In contrast to the above mentioned studies which report a relatively modest impact of teleworking on distance traveled, other studies report quite higher numbers. For instance, Vu and Vandebona (*9*) estimated a reduction of 10.8% to 15.46% in VKT after evaluating different teleworking scenarios in Australia. Dissanayake and Morikawa (*10*) investigated the reductions of VKT for car and motorcycle travel after a telecommuting policy implementation. The results revealed that the telecommuting policy proposed in their study significantly reduces congestion and vehicle usage reduces by 18–20%.

Based on the literature, it can be concluded that although teleworking seems to decrease significantly the amount of VKT, individual estimations by different studies tend to vary strongly. This uncertainty was also reported by Choo et al. (*7*) who claimed that a wide range of answers to the question of "what impact on travel?" can be obtained. They concluded that although teleworking has a statistically significant impact on reducing travel demand, the magnitude of this impact would not be very extraordinary. The main focus of this paper is not to assess the magnitude of the impact of teleworking on distance traveled, however, it is important to assure that the estimates of our study are reasonable and in line with the findings of other studies.

Kochan et al. (*11*) studied the effects of teleworking on total distance traveled in Flanders, Belgium. It was reported that in 2002, in Flanders, the total distance traveled decreased by 1.6% where the proportion of teleworkers that telework on a working day was 3.8% (*11*). These results are in line with the findings of literature. Therefore, our study will be based on the framework presented in Kochan et al. (*11*), although we simulate a 5% of the working population engages in teleworking instead of 3.8% (detailed information about implementation of this teleworking scenario is provided in the next section of the paper).

It can be concluded that the cause-effect relationship between teleworking and a reduction in VKT is well-established. Moreover, the relation between different types of exposure metrics (e.g. number of trips or VKT) and crashes has also been reported and well documented in literature (*12–17*) and although exposure might not be the direct cause of crash occurrence, but is a major predictive variable to estimate the number of crashes. Therefore, it is plausible to utilize the association between the teleworking scenario and the number of crashes so as to evaluating the traffic safety impacts of such TDM strategy.

The structure of this paper is as follows. Initially, the activity-based model and the procedure of implementing the teleworking scenario will be briefly introduced. In the next sections the data preparation, model construction and the teleworking scenario evaluation process will be demonstrated. Finally, the results of this evaluation will be shown followed by the final conclusions and discussion.

IMPACT OF TELEWORKING ON TRAVEL DEMAND

Traditionally, travel was assumed to be the result of four subsequent decisions which were modeled separately, also referred to as four-step models. More recently, several studies claim that travel plays a rather isolated role in these models and the reason why people undertake trips is neglected completely. This gave rise to a new framework of models, called activity-based transportation models. The main difference between four-step models and activity-based transportation models is that the latter try to predict interdependencies between several facets of activity profiles (*18*). The major advantages of activity-based models are that they deal with participation of various types of activities during a day. Moreover, a microsimulation approach which considers a high behavioral realism of individual agents is often adopted in these type of models (*11*). Interactions between family members like using the household vehicles, sharing household responsibilities or performing joint activities affect people's travel behavior. Four-step models that ignore such linkages, misstate people's responses to TDM strategies. As a result, activity-based models are capable of treating TDM strategies and policy issues more effectively compared to four-step models (*19*).

FEATHERS Framework

The FEATHERS (Forecasting Evolutionary Activity-Travel of Households and their Environmental RepercussionS) framework (*20*) was developed to facilitate the development of activity-based models for transportation demand in Flanders, Belgium. The real-life representation of Flanders is embedded in an agent-based simulation model which consists of over six million agents, each agent representing one member of the Flemish population. A sequence of 26 decision trees are used in the scheduling process and decisions are based on a number of attributes of the individuals (e.g. age, gender), the households (e.g. number of cars) and the geographical zones (e.g. population density, number of shops). For each agent with its specific attributes, the model simulates whether an activity (e.g. shopping, working, leisure activity, etc.) is going to be carried out or not. Subsequently, amongst others, the location, transport mode and duration of the activity are determined, taking into account the attributes of the individual (*21*). Traffic demand is subsequently assigned to the road network in such a way that an equilibrium is established between transportation demand and supply (*22*), which results in a time-dependent traffic state on the road network. In order to run, calibrate and validate the activity-based model, three major types of data are required (*23*); data describing the environment (e.g. population density, level of service of the transportation networks), a synthetic population which is simulated and finally activity-travel data originating from a representative sample of the population from which the human behavior is derived.

Implementation of Teleworking Scenario in FEATHERS

It is known from literature that one of the major advantages of the activity-based modeling approach is its sensitivity to scenarios that are generally important in transport planning and policy making (*24*). In contrast to trip-based and tour-based models, activity-based models are sensitive to institutional changes in society in addition to land-use and transportation-system related factors. Such changes are related to work times and work durations of individuals and opening hours of stores or other facilities for "out-of-home" activities. More information about this procedure can be found in (*11*).

MACRO-LEVEL CRASH PREDICTION APPROACH

CPMs can be developed at different levels of aggregation, for instance at the local level (road and intersection) or at the regional level (e.g. TAZ). Recently, crash analyses at a regional level receives more and more attention. Several studies examined the association of a collection of zone-level factors such as traffic patterns, socio-demographic and socio-economic variables, land use patterns and weather conditions with crashes, aggregated by a specific spatial scale (*13*), (*16*), (*17*), (*25–36*). Macro-level crash analyses can provide important information enabling for instance in cross-sectional comparisons between different zones, or to identify safety problems in specific zones and therefore, safety interventions could be implemented to improve the traffic safety situation (*35*). Furthermore, it is indispensable to take traffic safety into account already during the planning stage of transportation projects. To do so, traffic safety impacts of different transportation project alternatives should be compared and assessed by a number of factors which have zone-level characteristics (*35*).

Moreover, TDM strategies are usually performed and evaluated at geographically aggregated levels rather than merely at the level of individual intersections or road sections. Therefore the impact of adopting a TDM strategy on transportation or traffic safety should also be evaluated at a level higher than the local consequences. indeed, local level CPMs mostly aim to predict the safety effects of infrastructural improvements. However, these models are not typically designed to evaluate traffic safety impacts of TDM strategies; thus, the application of CPMs at a higher aggregation level will be more practical (*37*).

METHODOLOGY

Data Preparation

The study area in this research is the Dutch-speaking region in northern Belgium, Flanders. Flanders has over 6 million inhabitants, or about 60% of the population of Belgium. As already mentioned before, an activity-based model within the FEATHERS framework is applied on the Flemish population to derive the in-depth information of Flemish peoples' travel behavior and travel demand for a null-scenario (current situation) and some TDM scenarios like teleworking, increasing fuel price, etc. FEATHERS produces traffic demand by means of origin-destination (OD) matrices. These OD matrices include the number of trips for each traffic mode at different disaggregation levels (i.e. age, gender, day of the week, time of day and motive). This traffic demand is then assigned to the Flemish road network to obtain detailed exposure metrics at the network level. To carry out the assignment of vehicle trips to the road network, the user equilibrium method was selected. The fundamental nature of equilibrium assignment is that travelers will strive to find the shortest path (e.g. minimum travel time) from origin to destination, and network equilibrium occurs when no traveler can decrease his travel effort by shifting to a new path. This is an optimal condition, in which no user will gain from changing travel paths once the system is in equilibrium. Exposure metrics are then geographically aggregated to the TAZ level. This has been carried out at the zonal level, comprising 2,200 TAZs in Flanders. The average size of TAZs is 6.09 square kilometers with a standard deviation of 4.78 square kilometers. In addition, a set of socio-demographic and road network variables were collected for each TAZ (see Table 1).

According to the literature, "exposure" (i.e. number of trips (NOTs) and VKT) (*12–16*), (*36*), (*38*), "number of intersections" (*16*), (*26*), (*39*), (*40*), "income level" (*16*), (*29*), (*32*), (*34*), (*35*), "degree of urbanization" (*16*), (*39*), "speed" (*26*), "number of inhabitants" (*34*), (*39*), etc., are found to be important predictors of crashes. The crash data used in this study consist of a geo-coded set of fatal and injury crashes that occurred during the period 2004 to 2007. Table 1 shows a list of selected variables, together with their definition and descriptive statistics, which have been used in developing the ZCPMs presented in this paper.

TABLE 1 Selected Variables to Develop ZCPMs

	Variable	**Definition**	**Average**	**Min**	**Max**	**SD**
Dependent variables	CCFS	total Car-Car/Fatal and Severe injury crashes observed in a TAZ (2004-2007)	2.82	0	21	3.04
	CCSL	total Car-Car/Slight injury crashes observed in a TAZ (2004-2007)	19.17	0	226	20.73
	CSFS	total Car-Slow mode/Fatal and Severe injury crashes observed in a TAZ (2004-2007)	1.32	0	15	2.04
	CSSL	total Car-Slow mode/Slight injury crashes observed in a TAZ (2004-2007)	10.09	0	192	17.94
Exposure variables	NOTs Car	average daily number of car trips originating/arriving from/at a TAZ	2765.8	0	18111.4	2869.8
	NOTs Slow	average daily number of slow-mode trips originating/arriving from/at a TAZ	1018.2	0	11587	1321.6
	Motorway VKT	average daily vehicle kilometers traveled on motorways in a TAZ	27471.82	0	946152.8	84669.53
	Other Roads VKT	average daily vehicle kilometers traveled on other roads in a TAZ	26662.85	0	303237.6	28133.04
Network variables	Capacity	hourly average capacity of links in a TAZ	1790.1	1200	7348.1	554.6
	Intersection	total number of intersections in a TAZ	5.8	0	40	5.9
	Urban	Is the TAZ in an urban area? "No" represented by 0 "Yes" represented by 1	0	0	1	-[a]
	Suburban	Is the TAZ in a suburban area? "No" represented by 0 "Yes" represented by 1	0	0	1	-
Socio-demographic variables	Income Level	average income of residents in a TAZ described as below: "Monthly salary less than 2249 Euro" represented by 0 "Monthly salary more than 2250 Euro" represented by 1	1	0	1	-

a: Data not applicable.

Motivation for Conducting Spatial Analysis

The most common modeling framework for ZCPMs is the Generalized Linear Modeling (GLM) framework (*12*), (*14*), (*16*), (*17*), (*25–27*), (*29–31*), (*38–45*). Within a GLM framework, fixed coefficient estimates explain the association between the dependent variable and a set of explanatory variables. In other words, a single model is fitted on the observed data for all locations (TAZs). However, not surprisingly different spatial variation, which is often referred to as "spatial non-stationarity", may be observed for different explanatory variables especially where the study area is relatively large. Neglecting this spatial variation may deteriorate the predictive power of ZCPMs and also has impacts on significance of explanatory variables. Checking for the existence of spatial correlation of dependent and explanatory variables can be carried out by means of different statistical tests such as "Moran's autocorrelation coefficient" commonly referred to as Moran's *I*. The results of the analysis indicate the necessity of considering this spatial correlation since the spatial status of all variables are found to be non-stationary.

Model Construction

Inclusion of spatial variation in traffic safety studies has been considered by several researchers. However, there are different spatial modeling techniques that can be applied. Auto-logistic models, Conditional Auto-regression (CAR) models, Simultaneous Auto-regression (SAR) models, Spatial Error Models (SEM), Generalized Estimating Equation (GEE) models, Full-Bayesian Spatial models, Bayesian Poisson-lognormal models are some of the most employed techniques to conduct spatial modeling in traffic safety (*29*), (*32*), (*35*), (*46–53*). The output of these models are still fixed variable estimates for all locations, however spatial variation is taken into account.

Another solution for taking spatial variation into account is developing a set of local models, so called Geographically Weighted Regression (GWR) models (*54*). These models rely on the calibration of multiple regression models for different geographical entities. The GWR technique can be adapted to GLM models and form Geographically Weighted Generalized Linear Models (GWGLMs) (*54*). GWGLMs are able to model count data (such as number of crashes) while simultaneously accounting for spatial non-stationarity. Hadayeghi et al. (*36*) used the GWR technique in conjunction with the GLM framework using the Poisson error distribution.

They developed different Geographically Weighted Poisson Regression (GWPR) models to associate the relationship between crashes and a set of predictors. The comparison between GLMs and GWPR models revealed that the GWPR models clearly outperform the GLMs since they are capable of capturing spatially dependent relationships.

Reviewing the literature for different model forms showed that the following GLM model has been widely used in different studies (*12*), (*16*), (*38*), (*40*), (*44*):

$$E(C) = \beta_0 \times (Exposure)^{\beta_1} \times e^{\sum_{i=2}^{n} \beta_i x_i} \qquad (1)$$

Where;

$E(C)$ is the expected crash frequency, β_0 and β_i are model parameters, $Exposure$ is the exposure variable (e.g. VKT or NOTs) and x_i's are the other explanatory variables.

Logarithmic transformation of equation (1) when considering only one exposure variable yields:

$$ln[E(C)] = ln(\beta_0) + \beta_1 ln(Exposure) + \beta_2 x_2 + \beta_3 x_3 + \ ... + \beta_n x_n \qquad (2)$$

The Geographically Weighted form of Equation (2) would be:

$$ln[E(C)(\boldsymbol{l}_i)] = ln(\beta_0(\boldsymbol{l}_i)) + \beta_1(\boldsymbol{l}_i)ln(Exposure) + \beta_2(\boldsymbol{l}_i)x_2 + \cdots + \beta_n(\boldsymbol{l}_i)x_n \quad (3)$$

The output of these models will be different location-specific estimates for each case (here each TAZ). All variable estimates are functions of each location (here the centroid of each TAZ), $\boldsymbol{l}_\mathrm{i} = (x_\mathrm{i}, y_\mathrm{i})$ representing the x and y coordinates of the i^{th} TAZ.

To account for severity of crashes, different models are developed at different severity levels; i.e. "fatal + severe injury" and "slight injury" crashes. Moreover, TDM scenarios have different safety impacts on different road users. For instance, if implementing a TDM scenario results in transferring individuals out of private vehicles to non-motorized modes, safety level of car users might be improved, but injury risk for pedestrians or cyclists are increased. Therefore, to address this issue, crashes are further disaggregated into two types namely "Car-Car" and "Car-Slowmode" crashes ("Slowmode" comprises pedestrians and cyclists) and different models are fitted for these different crash types. Hence, four GWPR models are developed to associate the relationship between crash frequency and the explanatory variables. These models are constructed using a SAS macro program (*55*). The selected models are shown in Table 2 represented by the minimum, maximum, 1^{st} quartile, median and 3^{rd} quartile of the parameter estimates.

Traffic Safety Evaluation Process

OD matrices for both the null scenario and the teleworking scenario were derived from FEATHERS for scenario evaluation. After assigning the travel demand to the road network, all required variables become available to set up the evaluation task. Now, the final ZCPMs (see Table 2) are applied and crashes are predicted for each TAZ. The traffic safety evaluation can then be conducted by comparing the NOCs predicted by the final ZCPMs for the null and the teleworking scenario. Figure 1 depicts the conceptual framework of the traffic safety evaluation process in more detail.

In order to better understand the traffic safety impacts of the teleworking scenario, it is interesting to have a look at the changes in the traffic-related attributes playing a role in the whole chain due to the teleworking scenario. It turns out that the teleworking scenario reduces the average number of daily car trips by 1.465%, car passenger trips by 0.208%, public transportation trips by 1.879% and slow mode trips by 0.973%. Moreover, the analyses show that the total VKT decreases by 3.152% after implementing the teleworking scenario.

TABLE 2 Model Estimates for the Final Chosen ZCPMs

	Model #1 (CCFS)	**Model #2 (CCSL)**	**Model #3 (CSFS)**	**Model #4 (CSSL)**
Coefficients	Estimates	Estimates	Estimates	Estimates
(Intercept)	-9.763, -2.692 (-6.517, -5.569, -4.445)[a]	-7.356, -3.077 (-5.611,-4.944,-4.196)	-11.797, -5.453 (-7.889,-7.317,-6.833)	-10.897, -3.994 (-6.574,-6.075,-5.63)
ln(NOTs Car)	-0.035, 0.632 (0.093, 0.184,0.268)	0.194, 0.622 (0.352, 0.424,0.479)	-	-
ln(NOTs Slow)	-	-	0.484, 1.222 (0.616, 0.745,0.838)	0.621, 1.165 (0.794, 0.917,1.008)
ln(Motorways VKT)	-0.036, 0.047 (-0.002, 0.013,0.022)	-0.022, 0.041 (0.001, 0.011,0.018)	-0.073, 0.023 (-0.04, -0.02,-0.007)	-0.054, 0.044 (-0.019,-0.008,0.004)
ln(Other Roads VKT)	0.169, 0.669 (0.348, 0.42,0.465)	0.171, 0.632 (0.296, 0.342,0.395)	-0.05, 0.511 (0.163, 0.239,0.311)	0.0243, 0.361 (0.133,0.178,0.229)
Capacity	2.8 e-5, 1.003e-3 (3.3e-4,4.5e-4,6.3e-4)	6.5 e-6, 9.8e-4 (3.5e-4,4.8e-4,6.3e-4)	-4.2e-4, 8.2e-4 (3.3e-5,1.6e-4,3.5e-4)	-7.02e-4, 6.06e-4 (-8.4e-5,4.2e-5,1.9e-4)
Intersection	-0.0296, 0.0611 (0.007,0.019,0.029)	-0.0096, 0.0484 (0.017,0.022,0.026)	-0.063, 0.086 (0.003,0.012,0.023)	-0.0523, 0.056 (0.005,0.015,0.027)
Income level	-	-0.467, 0.637 (-0.185,-0.109,0.053)	-0.562, 1.97 (-0.25,-0.129,0.089)	-0.658, 2.525 (-0.209,-0.078,0.062)
Urban	-1.829, -0.017 (-0.89,-0.68,-0.37)	-	-	-0.193, 1.216 (0.359,0.619,0.86)
Suburban	-0.85, 0.138 (-0.4,-0.29,-0.147)	-	-	-0.219, 0.841 (0.165,0.325,0.409)
PCC[b]	0.735	0.907	0.789	0.952

a: minimum, maximum, (1st quartile, median, 3rd quartile) of the parameter estimates.
b: Pearson Correlation Coefficient (PCC) between observed and predicted crash values.

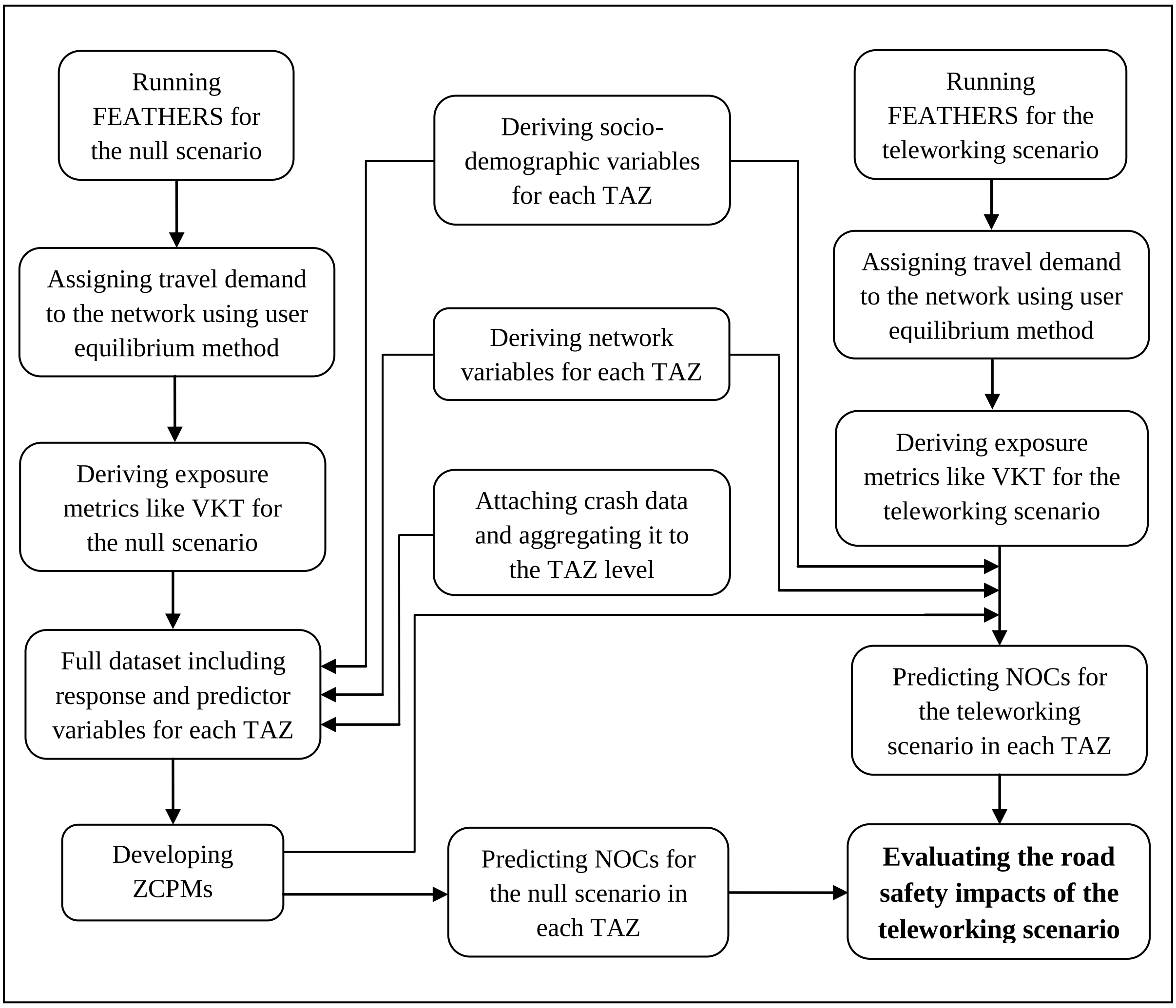

FIGURE 1 Conceptual framework of the traffic safety evaluation process.

RESULTS

Furthermore, in the teleworking scenario the total predicted number of crashes decreases compared to the null scenario as a result of this reduced exposure. The results show that the total number of CCFS and CCSL crashes is predicted to decrease by 173.4 and 1199.8 units respectively over a period of 4 years (-2.84% and -2.84%). Likewise, the total number of CSFS and CSSL crashes is predicted to decrease by 72.5 and 470.5 units respectively for the same period of 4 years (-2.46% and -2.13%). NOCs have increased in some TAZs as a result of an increase in travel demand and exposure in those specific TAZs while they are decreased in most TAZs. The reason for the increase of NOCs in a limited number of TAZs – specifically for CSFS and CSSL crashes – can be explained by a secondary effect of the teleworking scenario where the remaining trips in teleworkers daily trip schedule are switched to other modes (e.g. Slowmode) and avoided work trips by teleworkers are partially substituted by extra generated traffic (e.g. generated traffic for shopping, bringing kids to school, etc.).

In the development of CSFS and CSSL models, both car and Slowmode-related exposure variables were used. Following the implementation of the teleworking scenario, the total number of car and Slowmode trips decreased. However, these changes are not always similar in all TAZs. In fact, in more urbanized areas, the NOTs reduces more heavily and therefore, also the NOCs reduces more rapidly in these areas. An illustration of changes in the NOCs for all TAZs may present a better pattern on how different TAZs are affected by the scenario. In Figure 2, the changes in the predicted NOCs are displayed for each TAZ. Figure 2 reveals that the reductions in CCFS and CCSL crashes are greater for urban areas. As explained earlier, CSFS and CSSL crashes are also predicted to decrease more substantially in more urbanized areas; this is evident from the corresponding maps in Figure 2 where concentrations of blue dots stand for the major cities in Flanders.

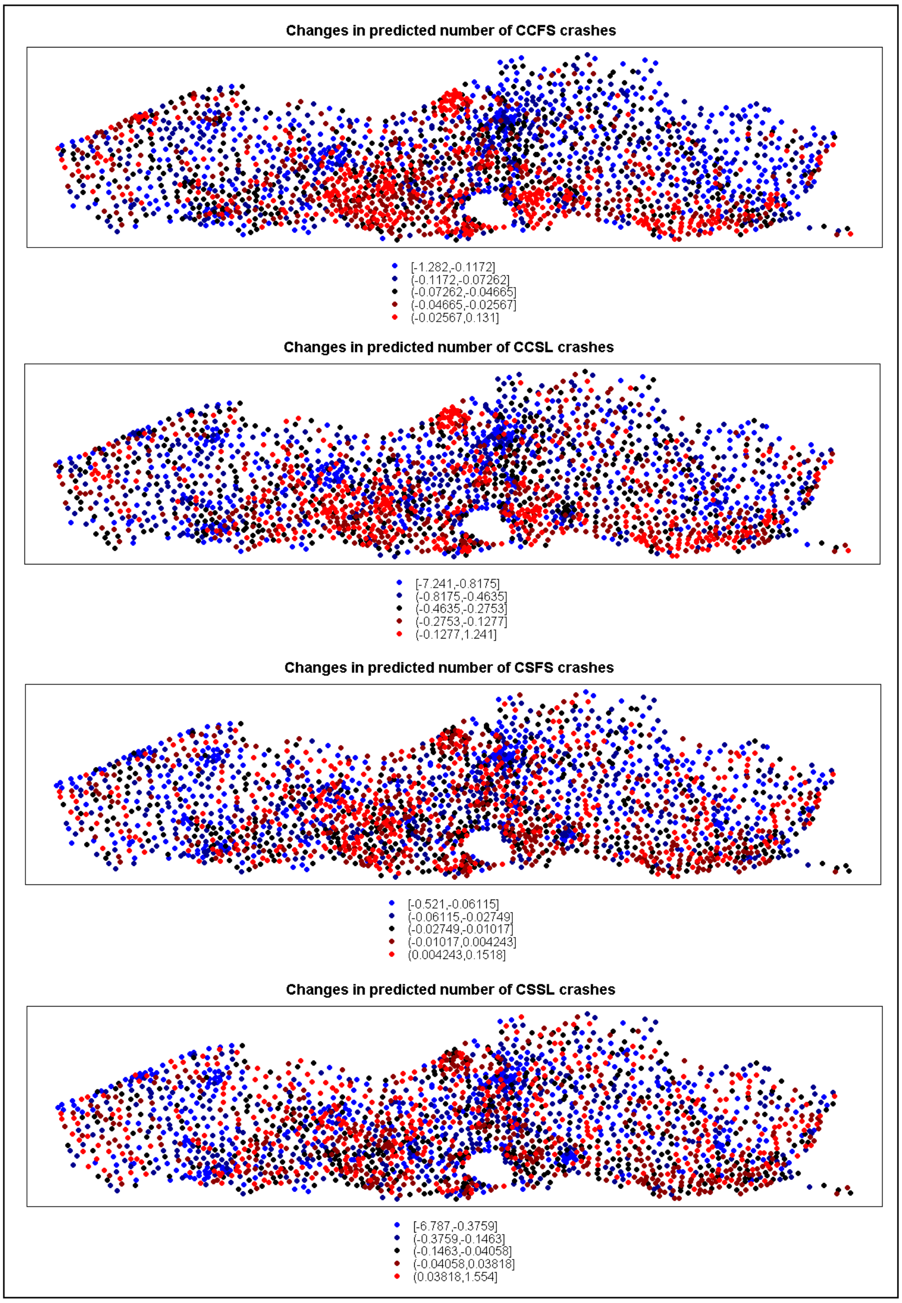

FIGURE 2 Changes in NOCs in each TAZ after the teleworking scenario implementation.

CONCLUSIONS AND DISCUSSION

In this study, the traffic safety impacts of a teleworking scenario are evaluated. To this end, ZCPMs are coupled with the activity-based model, FEATHERS. Based on the results of the analyses, the following conclusions can be drawn:

Activity-based transportation models provide an adequate range of in-depth information about individuals' travel behavior to realistically simulate and evaluate TDM strategies. The main advantage of these models is that the impact of applying a TDM strategy will be accounted for, for each individual, throughout a decision making process instead of applying the scenario on a general population level. Activity-based models, therefore, provide more reliable travel information since, unlike traditional models, TDM strategies are inherently accounted for in these models. Activity-based models follow a disaggregate modeling approach and as such, allow for a more detailed analysis of the reduction of travel demand due to the implementation of the teleworking scenario.

Analyzing crashes at a zonal level provides important information that enables us to compare traffic safety of different zones. This information is used to identify safety problems in specific zones and consequently, implementing safety interventions to improve the traffic safety situation. Furthermore, traffic safety should be taken into account during the planning stage of transportation projects. This can be carried out by associating the NOCs with a number of factors which have macro-level characteristics, such as socio-demographic, network level exposure, etc. Moreover, TDM strategies are usually performed at geographically aggregated levels. Therefore, it seems more appropriate to also evaluate the traffic safety impacts of TDM strategies at a zonal level.

In crash analysis, predictor variables are often found to be spatially heterogeneous especially when the study area is large enough to cover different traffic volume, urbanization and socio-demographic patterns. The results of the analysis confirm the presence of spatial variation of dependent and different explanatory variables which are used in developing crash prediction models. This was examined by computing Moran's *I* statistics for the dependent and selected explanatory variables. The results reveal the necessity of considering spatial correlation when developing crash prediction models. Therefore, different zonal GWPR models were developed, using different exposure, network and socio-demographic variables.

The results of the comparison analysis confirm that the teleworking scenario has many impacts such as the reduction of total travel demand, VKT and total crash occurrence. On the whole, there is an average reduction of 166,756 daily trips (all types of modes) as a result of the teleworking scenario. This scenario also causes a reduction of 1.426 billion VKT per year, almost 3.152% of the total annual VKT by cars in Flanders.

The total NOCs is predicted to decrease by 1916 over a period of 4 years. As a result of the teleworking scenario and the average reduction in travel demand, CCFS, CCSL, CSFS and CSSL crashes are predicted to decrease by 2.84%, 2.84%, 2.46% and 2.13% respectively. This illustrates that teleworking can positively affect traffic safety of different road users and that noticeable safety benefits can be achieved. However, these positive impacts are slightly lower for "Car-Slowmode" crashes.

When considering the changes in the NOCs at the TAZ level, it turns out that especially urbanized areas (cities) benefit most from a general reduction of “Car-Car” and “Car-Slowmode” crashes. It can be concluded that in cities, in contrast to other areas, there is a higher likelihood of finding people who telework.

Finally, this paper presents an extension to the application of ZCPMs incorporated into TDM strategies. The results show the ability of ZCPMs as a reliable predictive tool which can be used during the planning stage of transportation projects. Nevertheless, also some limitations of this study should be mentioned.

A constraint in application of GWPR models is that these models are not spatially transferable. This is due to the fact that GWPR models produce local parameter estimates (local models) for each TAZ which are influenced by their adjacent TAZs. Therefore, different models need to be developed for different study areas.

The teleworking scenario studied in this research investigated the relatively short-term effects of simulating 5% of the working population as teleworkers. In other words, the model is a short-term model in the sense that neither a shift in the composition of the vehicle fleet or car ownership, nor changes in the location of businesses and/or the location choice for living as a result of the teleworking scenario are assumed. Indeed in the longer run, it can be expected that teleworkers tend to change their living location and live closer to their working place and, therefore, the magnitude of trip reduction can be diminished.

Moreover, the real power of activity-based models has not yet been fully incorporated. In this study, the methodology relied on the aggregate daily traffic information. Activity-based models are however capable of providing disaggregate travel characteristics by differentiating between many household and person characteristics like gender, age, number of cars, etc. Hence, different types of disaggregation based on time of day, age, gender and motive are on the list of potential future research in order to take full advantage of the output of activity-based models.

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