Investigating the impact of river floods on travel demand based on an agent-based modeling approach: The case of Liège, Belgium

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Abstract

In Belgium, river floods are among the most frequent natural disasters and they may have important consequences on travel demand. In order to better understand how the travel patterns vary, we propose to set up a large scale scenario based on MATSim for guarantying an accurate assessment of the impact of river floods on the transportation system. As inputs, the current agent-based model requires a base year population. A synthetic population with respective set of attributes is generated as a key input. Afterwards, agents are assigned activity chains through an activity-based generation process. Finally, the synthetic population and the transportation network are integrated into MATSim. Regarding data, households travel surveys, OD matrix of Belgium have been used to set up the demand. For simulating river floods effects, a steady-state inundation map has been integrated within MATSim. In the current study, five scenarios have been tested where critical links are associated various levels of service, i.e. 10%, 25%, 50%, 75% and 100% (base case scenario). They are systematically compared to the standard scenario to estimate the deviations in terms of traffic patterns and travel times. The results suggest that compared to the standard scenario, the average trip travel time increased by 16.36%, 44.44%, 126.77% and 144.44% with respect to scenarios 75%, 50%, 25% and 10% respectively. Also, the traffic flows have been re-distributed more uniformly accross the transportation network. Roads with important traffic volumes are subjected to a decrease of activity on the contrary of roads with low traffic volumes. A very few studies have focused on how river floods affect transportation systems, this paper provided new insights in term of methodology and traffic patterns analysis under disruptions.

Keywords: Agent-based modeling, river floods, travel demand, MATSim

1. Introduction

The assessment of the impact of river floods on the transportation system with an emphasis on the travel demand, is of great importance in the Meuse river basin (Belgium) for mitigating future flood risk. According to Saadi et al. (In press), flood risk is expected to increase in the coming decades along with higher intensities and flood damages. Furthermore, Saadi et al. (In press) have demonstrated that the changes in land-use patterns at catchment scale also influence the overall river flood risk. In this context, the transportation sector is also an amplifying vector of future flood risk in the Meuse river basin. According to the predictions operated by Statistic Belgium, the population is expected to increase by 17% between 2013 and 2060. As a result of the population growth and the increase in travel demand, the traffic flows will inevitably increase in the future.

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Modeling the decision-making process of individuals under natural disasters, e.g. floodings, earthquakes, hurricanes, is of great importance for policy recommendations and for developing efficient prevention strategies. In this regard, a large part of the literature is dedicated to network vulnerability. Accessibility indicators are generally used to characterize the performances of road networks after disruptions or road segments failures. Also, to a lesser extent, impacts of natural disaster on travel demand have been investigated. The key idea is to anticipate the potential decision-making reactions that individuals can adopt under extreme natural events. Pregnolato et al. (2016) developed an integrated framework for assessing disruptions occurring in transportation systems under flood events. High-resolution flood models have been merged with transport models in order to determine the resilience values of different adaptations. In doing so, the most critical zones of the network can be quickly identified and prioritized in the context of flood risk management (Pregnolato et al., 2016). Limited available financial resources can be optimally allocated to the most critical infrastructure zones.

In order to enable policy sensitive effects within the modeling framework, we opt, in the current study, for an agent-based micro-simulation approach. In doing so, the complex underlying interactions in the travel behavior of the travelers can be captured. In the literature, various studies based on the agent-based paradigm have been proposed to investigate, e.g. the emissions of air pollutant (Hülsmann et al., 2014) using a fully integrated approach or the behavior of individuals in the context of a large scale evacuation scenario (Lämmel et al., 2010).

In the literature, a significant part of the research has been dedicated to the study of disruption effects on the transportation networks, i.e. road network vulnerability, due to extreme events. In this regard, Chen et al. (2015) developed a methodological framework to represent the accessibility under flooding disasters. The accessibility-based indexes have been estimated for different extreme flooding scenarios including a systematic implementation of the shortest travel times.

Similarly, Du et al. (2015) have investigated the vulnerability of transportation networks under seismic disasters for logistics. In addition to vulnerability assessment of the road segments, they have also included the probability of occurrence of the degradations.

Erath et al. (2009) proposed a methodology that integrates transportation vulnerability to natural hazards. The feature has been incorporated into the infrastructure management systems of the Swiss road network. The model aims at estimating the impact caused by the failure of road segments on the distribution of congestion within the entire road network. In their study, four demand shifts have been introduced: shifts in mode choice, destination choice, detours and activity-travel suppression. The results revealed that the "detours" are, by far, the most significant demand reaction towards potential disruption.

Besides, lots of studies have been dedicated to evacuation modeling using different approaches. Based on the network fundamental diagram (NFD), Zockaie et al. (2014) studied the urban network traffic flow under demand uncertainty and capacity constraints for large scale evacuation. In contrast, Yin et al. (2014) opted for an agent-based modeling approach to simulate households behavior in the context of hurricane evacuation. In their study, econometric and statistical models have been merged to better capture the underlying decision-making process of individuals during the evacuation.

Based on the framework of Saadi et al. (2014), MATSim has been used for modeling the mobility of the travelers through the transportation network taking into account traffic congestion. MATSim has widely been used in different fields, and often integrated within other sub-modules to merge external phenomenon and examine the effects on the travel demand and the related traffic flows. MATSim can estimate, in details, time dependent traffic flows for each road segment of the network. Regarding its algorithmic structure, the MATSim framework includes a feedback loop, i.e. re-planning, such that every single traveler is capable of optimizing its daily activity-travel patterns based on a scoring function calibrated according to Charypar & Nagel (2005).

The agent-based micro-simulation approach is particularly interesting to assess the changes in traffic flows of the road segments which are directly situated in the vulnerable areas. In addition, the driver's dynamics can be captured more efficiently for each vehicle as well as rerouting.

The main contribution of this paper is the calibration of MATSim in the context of natural hazards, i.e. river floods. To our knowledge, no studies really investigated the effects induced by river floods in urban areas. We will show that it is important to use highly disaggregate data to capture as much as possible the changes in travel behavior of the agents subjected to flood risk.

Furthermore, a key challenge is also to maintain a highly spatial resolution when it comes to integrate the agent-based micro-simulation with a detailed river flood map. In this regard, the scenario is based on the results of a steady-state river flood map derived from (Beckers et al., 2013) to identify which road segments are subjected to capacity mitigation.

An accurate analysis of the aspects that may influence the intensity of eventual flood risk in the future is absolutely necessary. In this context, the integrated agent-based micro-simulation model can be an efficient tool for urban and transport planners to prevent urban areas from eventual direct or higher order damages due to river floods. For example, such detailed models are particularly suitable to establish some policy recommendations in terms of extension of the transportation network, reorganization of the traffic flows within the vulnerable areas (catchment scale), land-use change, identification of the bottlenecks, etc.

2. Data

In the current study, four data sources are used for calibrating the agent-based model. (1) A detailed dataset describing the socio-demographics of 15,822 individuals is extracted from the Belgian National Household Travel Survey of 2010 (BELDAM). As described in Section 3.2, this dataset will be used to generate a synthetic population. Then, (2) a dataset including a list of 37,680 trips performed by the individuals is also extracted from the BELDAM survey. Each single trip is characterized by information related to departure times, locations, trip purpose and trip mode. Also, (3) a partial work-school O-D matrix corresponding to Liège area has been derived from the full O-D matrix of Belgium. The latter one will be used to draw work-school locations at the municipality level as it is the finest available level of aggregation allowed by the data. In addition, the work-school OD matrix is more stable and reliable as it comes directly from the Census. An additional OD matrix has been extracted from the trip dataset of BELDAM to draw the rest of the activity locations. Finally, (4) an inundation map in the form of a shape-file is used for modeling river floods that can potentially occur along the river Meuse according to Beckers et al. (2013).

3. Modeling approach

3.1. Problem statement

Flood risk management within the European context is of great importance as flood hazard is expected to increase in several countries due to climate change. In addition to climate change, land-use change is also supposed to influence future flood risk. In Belgium, the Meuse is a 905 km long river that crosses three different European countries (France, Belgium and the Netherlands). A 185 km segment out of 905 of the river Meuse is located in Belgium (Beckers et al., 2013). As presented in Figure 1, the impact assessment of river floods on travel demand is conducted for the Meuse river basin which crosses the Walloon region. In the current study, we will mainly focus on the city of Liège as it includes the most important human activity.

Figure 1: Inundation extent in Liège Area

3.2. Population

Population synthesis is performed by using a Hidden Markov Model (HMM)-based approach as presented in Saadi et al. (2016b). A set of four attributes (age, residential location, socio-professional status and gender) has been selected from the BELDAM survey to obtain a micro-sample. As the sample size of that survey is lower than 1%, the HMM-based approach is more suitable than IPF, as highlighted in Saadi et al. (2016b). Indeed, the micro-sample, may not cover all the combination of attributes. Thus, the HMM is capable of incorporating more heterogeneity into the micro-sample such that new combination of attributes are present within the synthetic population (Saadi et al., 2016b).

To ensure that the HMM has been calibrated correctly, two independent datasets, i.e. training and test datasets, have been generated from the original one. Comparing the simulated population synthesis with the observed one is of great importance to ensure that the transition and emission probabilities have been optimally determined. In this regard, Figure 2 presents the fit between the simulated and observed marginal distributions with respect to each attribute. One could depict from that figure that the matching is quite accurate. Minor deviations can be attributed to randomness involved within the HMM. In addition to the marginal distributions, Figure 3 presents the fit between the simulated and observed joint distributions. Indeed, to ensure that the transition distributions have been estimated properly, the attributes are jointly compared to those of the validation dataset. The results reveal that the R-squares are higher than 90% for each single fit. Also, all the slopes are close to 1 except for the full attributes fit which presents a slope of 0.87. Based on the fitted distributions presented in Figures 2 and 3, one can conclude that the current population synthesis of four attributes has been performed correctly. A brief description of the socio-professional categories is provided in Table A.2.

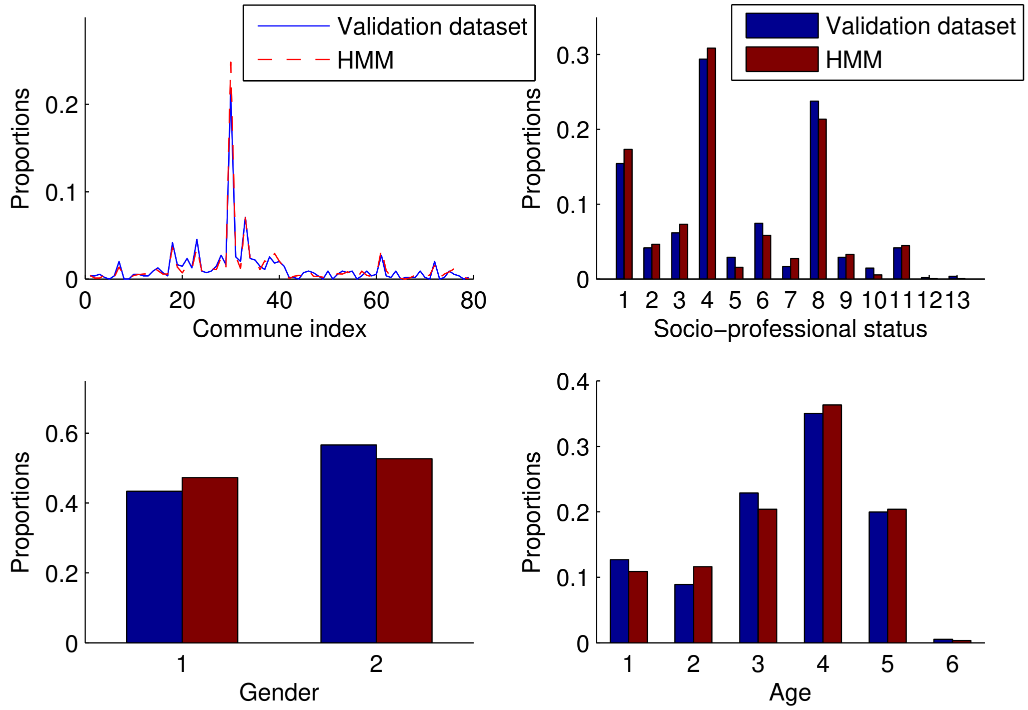


Figure 2: Fit between the simulated and observed marginal distributions

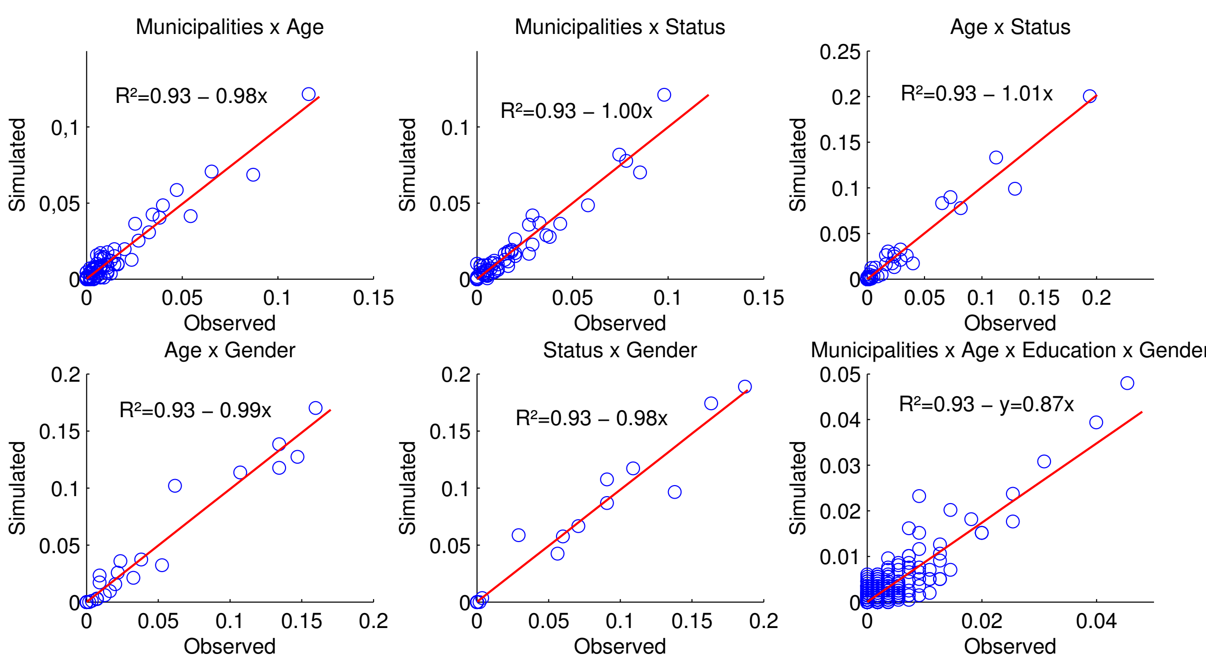


Figure 3: Fit between the simulated and observed joint distributions

3.3. Activity-travel patterns assignment

Based on the socio-demographics, each individual has been assigned activity-travel patterns, i.e. succession of activities and trips (Saadi et al., 2016a). In this way, the built travel demand reached a set of

15,000 individuals including detailed information about activity locations (at municipality level) and activity end times. The sample represents 4.5% of the population that effectively perform trips during a typical weekday.

With respect to the activity locations, the residential locations that have been previously synthesized are used to generate the rest of the activity locations. As outlined by Cools et al. (2010), OD matrices derived from activity-travel surveys do not present enough accuracy. Ideally, an OD matrix from a census is the best option. Therefore, based on the full independent work-school OD matrix of Belgium, an OD matrix describing the trip patterns of Liège area has been extracted. Thus, when home, work or school trip purposes are detected in the trip file of BELDAM, non-home activity locations are drawn from the distributions associated to that full OD matrix. However, for other trip purposes, the only way is to use the OD matrix derived from BELDAM. However, since home, work and school trip purposes form the most important proportion of the whole number of trips, the "bias" in the OD matrix extracted from the travel survey is quite limited. Besides, the in-coming and out-going flows have been ignored in the current study. In doing so, one can study the impact with an emphasis on the critical portion of the travel demand.

In 2015, the population of Liège accounts for exactly 1,094,791 individuals. The real population size is never incorporated as input in MATSim, otherwise the computer run-time would be too high, but samples. In thus study, 4.5% of the individuals who are effectively traveling is considered. Thus, 15,000 agents have been generated from the HMM for creating the synthetic baseline population. As a result, the scaling parameters have been set up to 0.045 such that MATSim is capable of re-scaling traffic flows as it is simulating traffic for 100% conditions.

Also, to preserve a sufficient daily activity-travel patterns characterization level, we assume that population of Liège has the same travel patterns than whole Belgium. This assumption is necessary to use all the dataset dedicated to trips.

3.4. Network and flooding scenario

The transportation network is derived from the OpenStreetMap online platform. After cleaning and adapting the network to the format adapted to MATSim, two key inputs, i.e. population and network, have been integrated into the modeling framework for performing the simulations. In particular, each road segment is represented by a link characterized by three main parameters: (1) the free flow speed, (2) the length and (3) the capacity. In MATSim, the routing module determines the shortest path based on the link travel times. In this context, the router module can find the path from one node to another on the basis of a weighted graph. Regarding the model settings, the scaling parameters have been adapted to a scenario for a sampled population of 4.5%. In order to converge towards the best solution, results are estimated for iterations between 100 and 250. Figure 4 presents the adopted approach for updating the link capacities of the transportation network based on the considered scenario. The flowchart shows that various file formats are handled using different programs and scripts to obtain the final network file which can be read by MATSim.

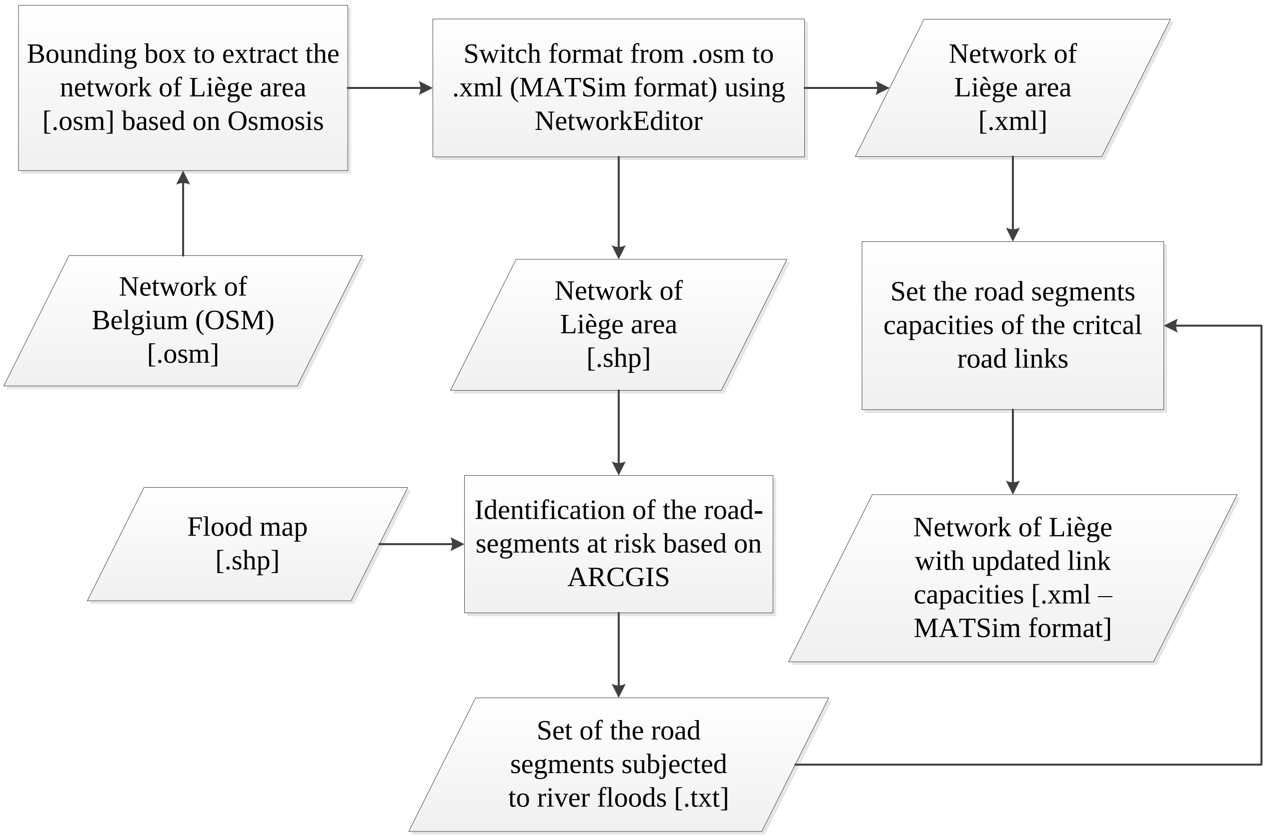


Figure 4: Network updating

3.5. MATSim

In the current section, we present the main features of MATSim as well as the key parameters associated with the various modules, i.e. qsim, strategy, controller. The simulations performed in the current study are based on an agent-based framework (Horni et al., 2016). Daily life of individuals is simulated as well as their underlying interactions. Indeed, each single individual derived from the synthetic population is assigned a combination of trips and activities with detailed activity locations, expected activity end times or travel times and activity type. As MATSim consists of an evolutionary process, then to converge towards a stable solution with the best overall scoring, information about activity times can be reasonably modified. MATSim is capable of taking into account traffic congestion to enable more realistic scenarios. The initial inputs that need to be provided are the demand and the network. At the end of the micro-simulation procedure, traffic flows associated to each single road segment of the network is estimated.

With respect to the choice set generation, a specified portion of agents can modify their daily plans to incorporate additional daily plans in each iteration. In this way, instead of a single initial plan, each agent will generate other combinations of activity-travel patterns, i.e. plans, in order to select the best one among a choice set. Also, each agent keeps in memory the predefined number of daily plans to enable more options. Generally, daily plans with best scores are selected; however, lower-score plans are allowed to be re-selected. The addition of new plans is generally associated to strategy options. In order to explore other solutions, agents are allowed to change the routes according to a probability of execution of 10% in each iteration. This is a route choice option that can be included within the strategy module of MATSim. Indeed, including a strategy is interesting for achieving a faster convergence and a better stability.

At this step, each single agent has built a set of plans from which a selection can be made based on a utility-based choice model. Basically, the components of the plan are scored in order to establish a ranking.

$$U_{plan} = \sum_{i=1}^{m} (U_{act,i} + U_{travel,i}) \tag{1}$$

where m designates the number of activities. U_{plan} is the utility/score of a single plan. $U_{act,i}$ is the utility of performing activity i, generally it is positive. However, traveling, represented by $U_{travel,i}$, generates a negative utility such that the score is decreased. The probability of selecting a plan is given by $P_i = \exp(\mu U_{plan})$ where μ controls the weight given to higher scores (μ=1). In particular, the utility of an activity i is defined by $U_{act,i} = U_{dur,i} + U_{wait,i} + U_{late-ar,i} + U_{early-dep,i} + U_{short-dur,i}$ where $U_{dur,i}$ is the core component of the utility of performing an activity. $U_{dur,i}$ is defined as follows $U_{dur,i} = \beta_{perf,i}.t_{typ,i}.\ln(t_{perf,i})$. It can be noticed that typical $t_{typ,i}$ and performed $t_{perf,i}$ durations are involved in the formulation. Also, $\beta_{perf,i}$ is the marginal utility of activity i at the typical duration. Typical durations are estimated from distributions derived from surveys. $U_{wait,i}$ is the negative utility of waiting the beginning of an activity i, $U_{late-ar,i}$ is the negative utility of arriving an activity i after its supposed beginning time, $U_{early-dep,i}$ is the negative utility of leaving an activity i before its supposed end time and $U_{short-dur,i}$ is the negative utility for performing an activity i shorter than its supposed reasonable duration.

The traffic simulation is based on QSim (Horni et al., 2016). QSim uses a queue-based strategy where vehicles are waiting in a queue before reaching the next link. In this way, QSim is capable of capturing the underlying traffic dynamics. According to Balac et al. (2017), the QSim approach provides better computational performances especially for large-scale scenarios. However, lane change behaviors and car following interactions are not optimally modeled with QSim although it is the most commonly used module (Balac et al., 2017).

4. Application

In the current study, we have considered five different scenarios, i.e. β=10%, 25%, 50%, 75% and 100% (standard scenario), where β is the level of service of the critical links. A β-value of 100% corresponds to road segments that are fully operational, whereas lower β-values imply that the links are partially or fully inundated with specific water depths. However, the water depths are not explicitly modeled in this study, as such data is not available. Thus, we suppose that β only describes the difficulty of traveling on a particular road segment of the network. Thus lower β-values indicate lower capacities for the critical roads. Note that the β-parameter is only dedicated to the network (supply) and is not considered in the generation of the travel demand.

To converge towards the steady-state solution, at least 100 iterations are necessary for each scenario. For the extreme scenarios, additional iterations are necessary to reach an optimal solution. Indeed, as the critical road segments have low capacities, the mobility simulator of MATSim need more iterations to enable people optimizing their daily plans by considering new activity-travel combinations.

As the sampling size of the population is 4.5%, the following parameters, i.e. *countsScaleFactor*, *flowCapacityFactor*, *storageCapacityFactor*, have been set up for scaling up the traffic counts by 22.15 and scaling down the link capacities by 0.045. The lanes are also used by the mobility simulator to enable more realism.

Figure 5 presents the temporal-based comparison between the number of en-route vehicles curves according to the different scenarios. Note that in MATSim, a full day is defined from 00:00 AM of day *d* until 06:00 AM of day *d+1*. As expected, the results reveal that the traffic congestion globally increases with floods intensity. Because of the propagation of floods and the mitigation of accessibility, the vehicles need more time to travel before reaching their final destinations. They either lose time due to increased congestion or they travel larger distances (re-routing). We can also observe that the amount of vehicles which does not succeed in performing their daily plans increased significantly under the 25% and 10% scenarios. One could depict from Figure 5 that some people could not fully perform their daily plans within the allowed period of time: the number of vehicles which are still "en-route" at 30:00:00, the maximum time-slot allowed by the mobility simulator, according to the 75%, 50%, 25% and 10% scenarios are respectively 355, 949, 3250 and 7337. As the results are associated to a sample of 4.5%, scaling-up the values is necessary. Thus, we obtain around 7,863, 21,020, 71,988 and 162,515 vehicles. The later observations are directly related to the results highlighted in Figure 7, where the number of trip arrivals present more temporal spread. For example, the transition patterns from the 50% to 25% scenarios illustrates how the spread is operated; the mitigation of the number of trip arrivals within the interval 7:30:00 and 22:30:00 is associated with an increase within the interval higher than 22:30:00. As the number of trip arrivals associated to the 10% scenario is very low compared to the other scenarios, the corresponding number of en-route vehicles in Figure 5 is, as a result, the highest.

Physically, non-achieved plans can be interpreted as partial trips cancellation. Indeed, let us consider the following pattern: HWGWH, where H, W, G correspond to home, get/bring and work respectively. Four trips are necessary for shifting from an activity towards the next one. Intuitively, if a traveler loses too much time during the first two trips, he may cancel the second work activity to avoid the last remaining trip. But, in MATSim, the framework is adjusted such that the daily plans are totally applied within the simulation.

Figure 6 highlights the additional number of en-route vehicles compared to the standard scenario. The observed trends show that traffic flows are "exponentially" increasing while shifting towards more extreme scenarios. The areas are given by the sum of the differences between the number of en-route vehicles of the standard scenario at each time-slot and those of the 75%, 50%, 25% and 10% scenarios. Relative increases (in %) from one extreme scenario to the other amount to +201.7, +687.4 and +1144.2. Thus, the traffic congestion is "exponentially" sensitive to the variation of river floods intensity.

Based on the input dataset, we can find the average number of trips per person, i.e. $\frac{37{,}680}{15{,}822} \approx 2.4$. The scaled-up number of travelers is given by $15,000 \times \frac{100}{4.5} = 333,333$. As the additional average trip travel time based on the 75% scenario is 57.50-49.50 (base case scenario) = 8.00 mins/trip, the total excess average trip travel time is 8.00 [mins/trip] $\times$ 2.4 [average number of trips/person] $\times$ 333,333 [number of travelers] = 6,399,994 mins or 106,666 hours. Similarly, the excess travel times for the 50%, 25% and 10% scenarios are respectively defined as follows 293,333 hours, 836,665 hours and 953,332 hours.

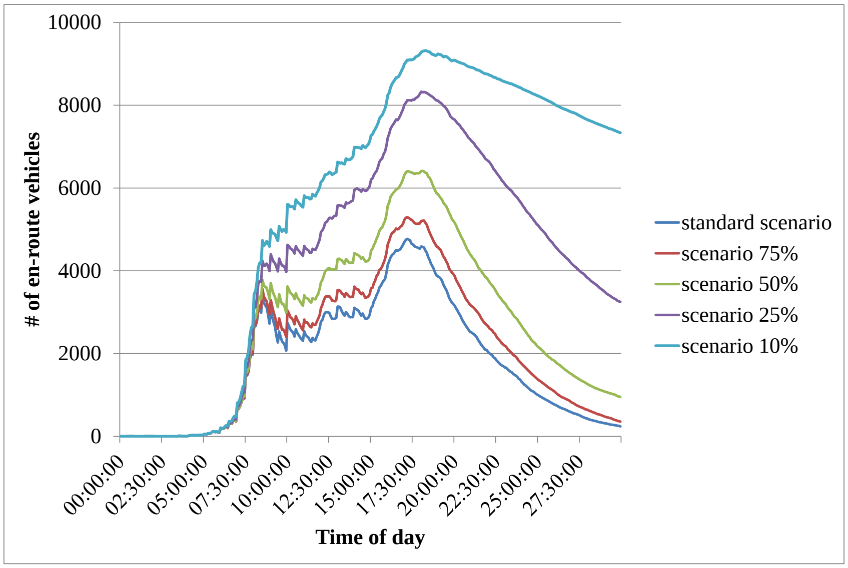


Figure 5: Scaled-up additionnal number of en-route vehicles for extreme scenarios compared to the standard scenario based on time of day (in HH:MM:SS).

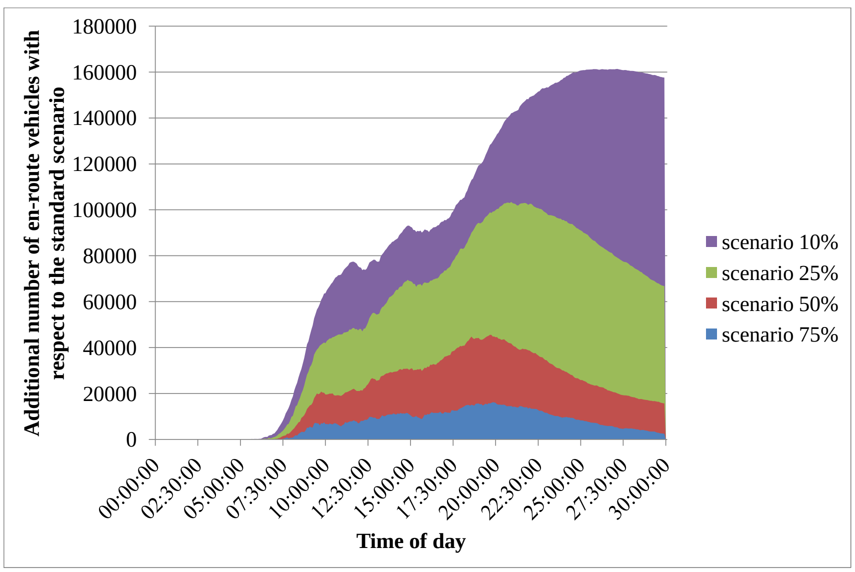


Figure 6: Comparison between the number of en-route vehicles of the standard scenario (100%) and extreme scenarios (75%, 50%, 25% and 10%) based on time of day (in HH:MM:SS).

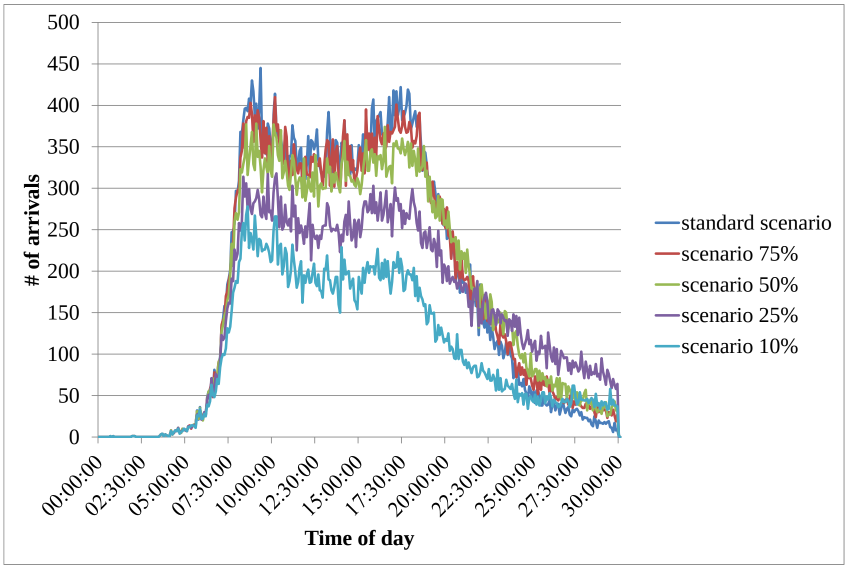


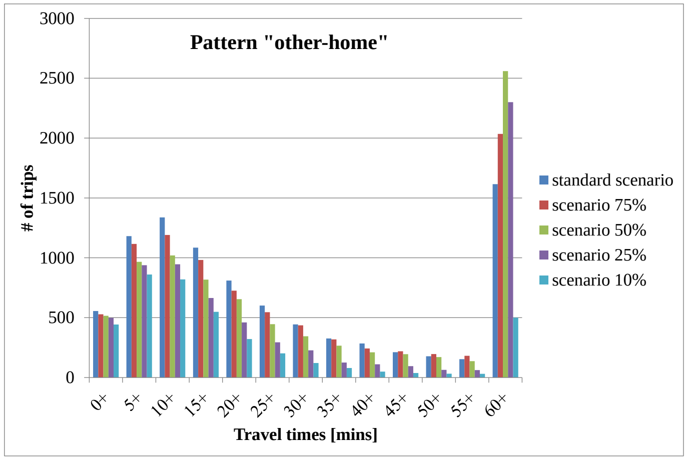
Figure 7: Comparison between the number of trip arrivals of the standard scenario (100%) and extreme scenarios (75%, 50%, 25% and 10%) based on time of day (in HH:MM:SS).

The results presented in Figure 8 represent the distribution of trip travel times for four different patterns: "other-home", "work-home", "home-other" and "home-work". We have selected those specific patterns as they present the most significant number of occurrences. A common trend can be observed with respect to the re-distribution of trip travel times. They are recategorized towards higher travel time classes when critical road capacities are decreasing. However, for the 10% scenario with trip travel times higher than 60 mins (60+), the number of trips are lower. Actually, as a significant number of travelers did not achieve their daily plans within the available period of time (Figure 6), en-route travelers have not been categorized by MATSim. Thus, the number of trips with respect to that particular category is systematically smaller. Note that the category "60+" has systematically the highest portion of trips as it is a semi-bounded bin.

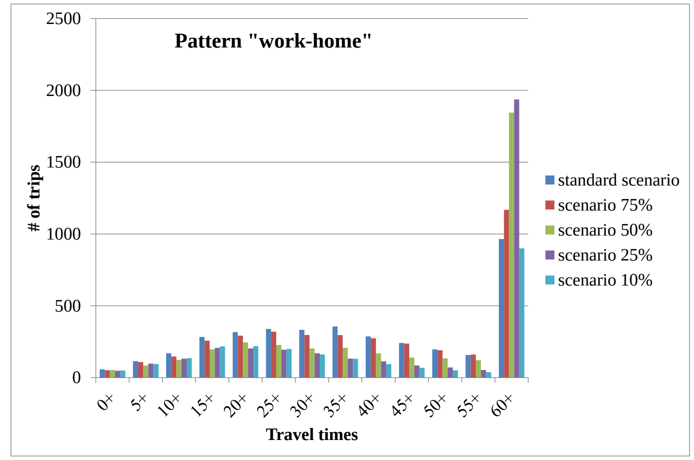
Table 1 presents the average trip durations with respect to the different scenarios. The most important increase occurs when switching towards the 25% scenario. For the rest, the relative trip duration increase is lower. Results indicate that, for the city of Liège, the overall average trip duration is around 49.50 mins when considering normal traffic conditions without disruptions. In contrast, in presence of flooded areas and depending on the intensity, the average trip time increases moderately at first with +16.36% and +44.44%, then more strongly with +126.77% and 144.44%.

Table 1: Average trip durations based on various scenarios

Scenario	Average trip duration [mins]	Relative increase [%]
100%	49.50	-
75%	57.50	+16.36 (-)
50%	71.50	+24.35 (+44.44)
25%	112.25	+57.00 (+126.77)
10%	121.00	+7.80 (+144.44)



(a)



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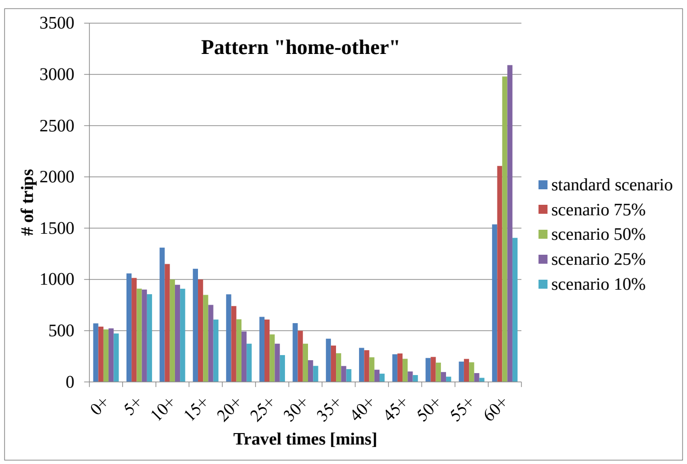

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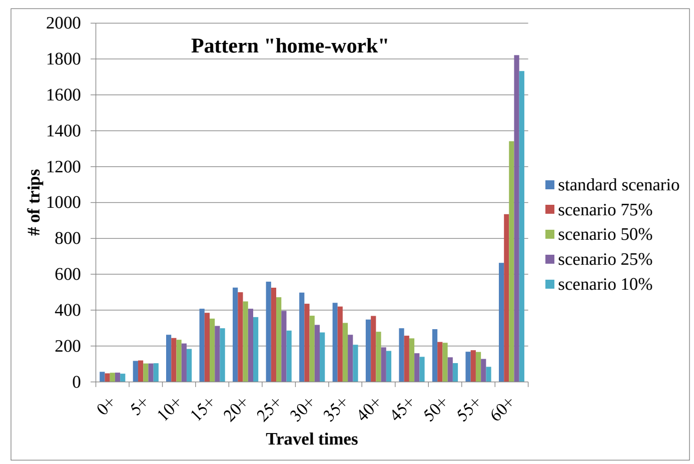

(d)

Figure 8: Comparison between the number of trip arrivals of the standard scenario with full capacity (100%) and the extreme scenarios (75%, 50%, 25% and 10%) based on time of day.

Figure 9 presents successively the relationship in terms of traffic volumes between the extreme scenario cases and the standard scenario. The data points have been overlayed to enable a better understanding of traffic volumes variability due to floods. One could depict from Figure 9 that, compared to the standard scenario, the traffic volumes tend to decrease from a global perspective, with more spread. Physically, it means that the traffic flows are being re-distributed across all the network. In particular, traffic volumes with respect to standard scenario which are higher than 2500 veh/h are decreasing when critical road capacities are decreasing. As a result, traffic volumes lower than 2500 veh/h are re-distributed towards other road segments such that more spread can be observed.

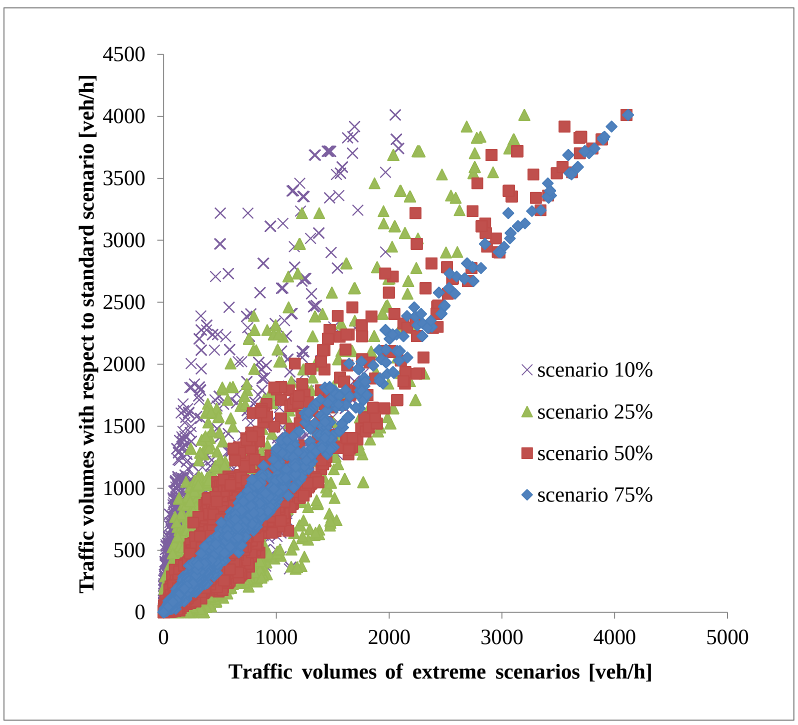

Figure 9: Comparison between the traffic volumes of the standard scenario with full capacity (100%) and the extreme scenarios (75%, 50%, 25% and 10%) based on time of day.

5. Discussion

In terms of policy recommendations, the results presented in Section 4 show that depending on the intensity of river floods, different flood risk management need to be taken. Although the 75% and 50% scenarios show a rather slight impact, we can observe that the shifts towards the 25% and 10% scenarios affect the transportation system in a much more pronounced way. Thus, two management policies can be defined: low impact and high impact. A particular transport geographic problem with these policies is that in case of intense floods, the city is divided into two areas: northwestern and southeastern with housing-job locations located on both sides of the river. Effective measures must be taken to prevent commuting patterns from being isolated from the other side.

With respect to the transportation network, there is a need to highlight the improvements that can be achieved for updating the critical link capacities. In the current study, the inundation map corresponds to a shape file which consists in a set of polygons. Thus, the critical road segments can be intersected based on the inundation map using ArcGis. Although the critical links can be identified, it is more difficult to evaluate to which extent the link capacities should be reduced. Therefore, because of data limitations, we had to assume that all the critical road segments are mitigated according to the same proportions. In practice, this assumption could potentially lead to a slight under or over-estimation of the final outcomes. Indeed, the critical road segments are not necessarily impacted in the same way in terms of intensity. In further research, more elaborated inundation map format could be adopted such as raster file. In doing so, a discretized inundation map would give detailed information about flow velocity and water depth based on geographical coordinates. Also, to know whether a road segment is impacted or not, the transportation network can be coupled with a digital elevation model (DEM) in order to allow a better comparison with water depth. Another aspect associated to the physical meaning of the mitigated critical road segment capacities should also be extended in further research. For example, a critical road segment could be fully covered by floods while water depth is very low. In this context, vehicles can still travel through this link with a slower velocity. In this context, one can intuitively notice that a categorization of the critical road segments is more appropriate for including physical meanings. Normal road conditions are associated to a capacity of 100 % while a closed road is synonym of 0 % capacity. The difficulty lies in explaining the values in-between 0 and 100.

Regarding the demand, we have only considered intra-urban trips in the current study. This assumption need to be made because of different reasons. First, external flows coming from Luxembourg, Germany and the Netherlands, i.e. the neighboring countries, cannot be modeled because of the lack of data. Indeed, the OD matrix is limited to Belgium. Then, to enable a better assessment of the impact on trip travel times, it is necessary to focus as much as possible on the target population, the most vulnerable to floods. The commune scale is the most disaggregated spatial resolution that can be considered given the data. Of course, the generation of activity locations based on the communes can be accompanied by some estimation errors in terms of trip distances as each single activity location is randomly selected based on the considered commune. However, this approximation is limited from an average trip travel time perspective as over-estimated trip lengths are probably mitigated by under-estimated trips lengths.

6. Conclusions

In the current study, a large scale scenario has been calibrated for assessing river floods impact on intra-urban travel demand using an agent-based micro-simulation approach for the city of Liège, in Belgium. After synthesizing the population for specific socio-demographics and residential location using HMM, resulting activity-travel patterns, drawn from distributions derived from the BELDAM survey, have been assigned to each single individual. In doing so, the travel demand can be integrated as input within the

MATSim framework. In parallel, the transportation network of Liège area, i.e. southeastern region of Belgium, has been extracted from OpenStreetMap (OSM). The two inputs are simultaneously used for simulating the mobility of the individuals living in Liège area. To maintain a good trade-off between run-time and simulation realism, a population of 4.5% has been sampled as proceeded in other studies (Hülsmann et al., 2014; Lämmel et al., 2010; Novosel et al., 2015). This suggested procedure presents also the advantage to mitigate the run-time as a lower amount of agents is processed during the simulations.

- As outlined in Section 4, the impact on the demand associated to the 10% and 25% scenarios is significant, whereas the impact of the 50% and 75% scenarios is more moderate.

- The spatial resolution adopted in the current study is acceptable to capture the changes in trip travel times due to river floods. One can clearly distinguish the traffic flows changes based on the considered the different scenarios.

Besides, based on the monetary value of time, results stemming from MATSim can be used for assessing the overall economic loss due to flood risk based on any scenario. A detailed impact economic assessment can be considered in further analysis in order to provide policy makers with new insights in terms of flood risk management decision tools.

Regarding the transport mode, we have considered only car mode while public transport, i.e. bus, might be impacted by flood risk. Indeed, various bus lines are situated within the inundated areas. Additional attributes can be added to the synthetic individuals for a further disaggregated representation of the population.

In order to improve the predictive capabilities of the model, the trips performed by commuters coming from or going to the surroundings should be taken into account. Also, the traffic patterns associated to freight are of great importance in terms of impact on time losses. The latter aspects should be handled in further studies.

In order to make the time losses more plausible, additional research can be oriented towards the comparison between the base case scenario and the observed traffic counts. In addition, the predicted traffic flows can be compared with those stemming from online platforms such as Google traffic or TomTom. In the context of an in-depth analysis, the overall population can be disaggregated based on socio-demographics or transport-related characteristics in order to assess the influence on the travel behavior.

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Appendix A. Data labels

Table A.2: Socio-professional status categories

ID	Description
1	Student
2	Housewife (husband)
3	Job seeker
4	Pensioner
5	Disabled person
6	Blue-collar worker
7	White-collar worker (executive)
8	White-collar worker (non-executive)
9	Self-employed person
10	Liberal profession
11	Teacher
12	Farmer
13	Other