MobRISK: A model for assessing the exposure of road users to flash flood events

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Abstract. Recent flash flood impact studies highlight that road networks are often disrupted due to adverse weather and flash flood events. Road users are thus particularly exposed to road flooding during their daily mobility. Previous exposure studies, however, do not take into consideration population mobility. Recent advances in transportation research provide an appropriate framework for simulating individual travel-activity patterns using activity-based approach. These activity-based mobility models enable prediction of the sequence of activities performed by individuals and locating them with a high spatial-temporal resolution. This paper describes the development of MobRISK microsimulation system: a model for assessing the exposure of road users to extreme hydro-meteorological events. MobRISK aims at providing an accurate spatiotemporal exposure assessment by integrating travel-activity behaviors and mobility adaptation with respect to weather disruptions. The model is applied in a flash flood prone area in Southern France to assess motorists' exposure to September 2002 flash flood event. The results show that risk of flooding mainly occurs in principal road links with considerable traffic load. However, a lag time between the timing of the road submersion and persons crossing these roads contributes to reduce the potential vehicle-related fatal accidents. It is also found that socio-demographic variables have significant effect on individual exposure. Thus, the proposed model demonstrates the benefits of considering spatiotemporal dynamics of population exposure to flash floods and presents an important improvement in exposure assessment methods. Such improved characterization of road user exposures can present valuable information for flood risk management services.

1 Introduction

Flash flooding is considered as one of the most dangerous natural hazard in term of human losses. The rapidness and suddenness of this hydro-meteorological phenomenon makes it hardly predictable and decreases the efficiency of rescue operations and the available time for people to protect themselves and to adapt their daily activities and mobility behaviors. Therefore, several vehicle-related accidents occur during flash floods. Death circumstances investigations showed that, in post-industrial countries over half of flood victims are motorists trapped by road flooding (Ashley and Ashley, 2007; Sharif et al., 2012; Terti et al., 2016). Hence, daily mobility is pointed out as one of the primary cause of population exposure and vulnerability to flash floods (Ruin, 2010). However, mobility aspects are not systematically included in studies assessing human exposure and vulnerability to natural hazards. In order to integrate social vulnerability in risk measurement, population density data is often used assuming a static distribution, which contrasts with the fast dynamics of the flash flood phenomenon. Recently, it has progressively been acknowledged that variation of population distribution may provide a more accurate assessment of human exposure to natural hazards. Aubrecht et al. (2012) stressed the importance of including temporal variations of social vulnerability in every phase of disaster management cycle. For instance, Freire and Aubrecht (2012) considered night and daytime specific population densities for assessing population exposure to earthquake hazard in Lisbon Metropolitan Area. Results showed that people are potentially at risk in the daytime period. In the context of flash floods, Terti et al. (2015, 2017) and Spitalar et al. (2014) showed that daily and sub-daily variation of population distribution may provide an appropriate assessment of human exposure to such short-fuse weather events.

In fact, motorists' exposure to flood events is directly related to disruption and degradation of the road network. Road network studies use graph theory and more specifically directed graph (called network) where the so-called edges or arcs represent the road segments linking the nodes or vertices corresponding to the road intersections. Several studies in transportation research focused on road network vulnerability to adverse weather conditions (Koetse and Rietveld, 2009; Transportation

Research Board, 2008). Different methods were developed in order to identify critical road segments where disruptions would lead to severe consequences. Berdica (2002) defined road segments vulnerability as a function of the probability of occurrence of hazardous event and the importance of related impacts in term of serviceability of road links. Jenelius et al. (2006) quantified the road network vulnerability by introducing the concept of criticality of the network constituents (e.g. link, node, groups of links and/or nodes), which includes both the probability of the constituents failing and the consequences of that failure for the system as a whole. Links criticalities depend on their weakness and their importance for the functioning of the whole network measured by the increased generalized travel cost when these links are closed.

Recently, Versini et al. (2010a) proposed a method for assessing road susceptibility to flooding in the Gard region (France) based on an inventory of observed flooded road sections over the last 40 years. The risk of road flooding is computed by combining susceptibility to flooding on a given road with simulated stream discharge of the corresponding river segment (Versini et al., 2010b). Naulin et al. (2013) extended the road flooding forecasting tool to the entire Gard region and proposed a method for allocating probabilities of flooding to road/river intersections (called "road cuts") depending on return periods of stream discharges (Naulin, 2012). Versini and Naulin’s studies contribute to better forecast the chance of road flooding, hence providing a strong base to further analyze the impacts of those on road users exposure.

To consider the risk for mobile people during flash flood there is a need to integrate travel-activity behaviors and individual responses to weather disruptions. Recently, impacts of extreme weather events on traffic flow and travel behaviors received much attention in transportation research (Böcker et al., 2013; Al Hassan and Barker, 1999; Koetse and Rietveld, 2009; Chung et al., 2005). Böcker et al. (2013) provided an extensive literature review on the potential impacts of weather on individual daily travel behaviors such as trip generation, travel destination and mode choices. Tsapakis et al. (2013) showed that high intensity of snow and rain decreases travel speed and increases travel time in the Greater London area. They also found that the impacts of weather conditions largely depend on drivers' attitudes, socio-economic characteristics and other contextual factors. Andrey et al. (2013) investigated the effect of exposure frequency to adverse weather conditions on drivers’ adaptation behaviors and concluded that drivers do not tend to acclimatize to local weather pattern. Based on a survey on travel decisions, Khattak and De Palma (1997) showed that adverse weather has a strong impact on travel decision changes such as route choice, transport mode choice and departure time.

These decisions partly depend on individual risk perception and personal evaluation of the environmental threat, which largely vary between individuals. Ruin et al. (2007) examined the effects of socio-demographic characteristics on perceived risk related to driving under heavy rain and through flooded roads. It was found that young male drivers have a clear tendency to underestimate the corresponding risk. Other factors seem to have significant effect on mobility adaptation to flood events such as flood danger knowledge, flooding experience, and route familiarity (Drobot et al., 2007; Ruin et al., 2009). In addition to risk perception, daily constraints related to professional and family activities are strong drivers of mobility whatever the weather conditions (Ruin et al., 2007; Ruin et al., 2014). The perceived importance and flexibility of planned and scheduled activities might play an important role in mobility adaptation capacities. Cools et al. (2010) demonstrated that travel change decisions related to weather conditions depend on trip purposes, leisure and shopping activities being more susceptible to be cancelled and postponed than work/school activities.

These findings thus highlight the relevance of considering both individual socio-demographic characteristics and daily activity schedules and constraints to establish an accurate assessment of population exposure to road flooding. Recent advances in mobility modeling following an activity-based approach offer an appropriate framework to micro-simulate individual travel-activity patterns (Rasouli and Timmermans, 2014). These activity-based models consider travel behavior as derived from the demand of activity participation and aim at predicting the sequence of activities conducted by individuals (McNally, 1995). Activity-based models gain increasing interest in dynamic exposure assessment research, especially illustrated in air pollution exposure studies (Beckx et al., 2008; Beckx et al., 2009; Pebesma et al., 2013) and homeland security application (Henson et al., 2009). Flood exposure studies can also benefit of the rich information provided by this kind of mobility modeling approach. Indeed, the combination of individual travel-activity simulation with roads flooding forecast makes possible a thorough assessment of motorists' exposure and its evolution in time and space as regard as the flood hazard.

In this paper we present the so called MobRISK model, which aims at providing an assessment of motorists' exposure to flash floods by taking into account travel-activity behaviors and mobility adaptation with respect to weather disruptions and roads flooding. MobRISK is considered as a micro-simulation system since each individual of the population is represented individually similarly to agent-based models (Gilbert, 2007). It is also an activity-based mobility model in which the full individual travel-activity patterns are simulated. We illustrate the potential benefits of the proposed model through an application of MobRISK in the Gard region, which is a flash flood prone administrative area (French *département*) located in southern France. The objective of the proposed case study is to quantify motorists' exposure to the 8-9 September 2002 major flash flood event that triggered 24 victims in the Gard area.

The remainder of the paper is organized as follows. The next section describes the conceptual modeling approach used in MobRISK model. Section 3 details the required input data together with the description of the individual exposure measurement method. The case study area and results from MobRISK simulations are illustrated in section 4. Finally, section 5 discusses the results and provides insights for further research and potential improvements of the model.

2 MobRISK modelling approach

MobRISK is a model for assessing and simulating road users' exposure to road flooding due to extreme flash flood events by combining travel-activity simulation following an activity-based approach with hydro-meteorological data. MobRISK architecture includes: (i) the simulated environmental changes considered for the study such as roads' flooding; (ii) an activity based mobility model reproducing population travel-activity behaviors; (iii) a decision-making model predicting individual responses to weather disruptions. A Discrete Event Simulator (DES) rules the main temporal loop of the simulations. In addition, the user input data is stored in a spatial relational database management system (Fig.1).

2.1 Discrete event simulation

The core of the MobRISK simulator is a parallel discrete event simulator (PDES) that rules the main temporal loop of the simulation. The pending event set is organized as a priority queue, sorted by event time and so handled in chronological order (Fujimoto, 1999; Robinson, 2004). Event-driven simulations are efficient in term of computation time as they avoid unnecessary time steps. Four types of events are handled in MobRISK:

- Road flooding: records different changes in probabilities of road flooding during a simulation period,
- Environmental cue: reports the changes in environment and weather conditions that might be perceived by individuals such as precipitation intensities,
- Broadcast: contains diverse warning and alert information that can be received by individuals and may affect their travel decisions,
- Travel-activity: records changes of individual locations (at the road nodes resolution) and the travel purposes.

2.2 Mobility modelling

As explained in Section 1, to better understand and analyze mobility behaviors under environmental perturbations, we need to integrate daily travel motivations in the mobility modeling. Following an activity-based approach for mobility modeling, travel demand is considered as derived from the human need to perform different activities distributed in time and space (Recker et al., 1986). Recently, activity-based models have been gaining increasing attention due to the rich information they provide and the incorporation of behavioral and psychological components and decision-making processes.

Activity-based approach in travel modeling emerged in the 1970s as complementary of the concept of Time-geography of Hägerstrand (1970) and Chapin (1974), which introduced the importance of various spatial and temporal constraints on individuals' mobility behavior. While classical trip-based models, commonly referred to as “four steps models”, are focusing essentially on the quantification of trips generated by population mobility without considering the sequential characteristics and the behavioral dimension, activity-based models aim at predicting how, why, when, how often, where and with whom the different activities are conducted by the individuals (Bhat et al., 1999). McNally (1995) identified the most important specificities of activity-based modeling: (i) Travel is derived from the demand for activity participation; (ii) Sequences and patterns of travel behavior are the units of analysis instead of individual trips in trip-based models; (iii) Household and socio-demographic characteristics affect travel-activity behavior; (iv) Spatial, temporal and interpersonal factors that constrain travel-activity patterns are taken into account.

Over the last years, several activity-based models have been developed: TRANSIMS (Smith et al., 1995), ALBATROSS (Arentze and Timmermans, 2000), CEMDAP (Bhat et al., 2004), MATSIM (Balmer et al., 2006), and ADAPTS (Auld and Mohammadian, 2009). Although the mentioned models follow the same activity-based paradigm and provide useful frameworks for modeling individual motilities, they have some differences regarding the activity scheduling approach used, decision-making process integration and required input data structure. These differences depend essentially on research purposes and data availability.

Whereas the mentioned models are essentially applied for transport forecasting and urban planning, the main objective of MobRISK is to assess population mobility exposure to road flooding, which requires essentially the combination of travel-activity simulation with hydro-meteorological data and road flooding impact. Census data and travel-activity survey data are needed in order to assign daily activity programs to the population. Then, by locating the different activity areas, population mobility is generated when individuals attempt to implement their activity programs. Finally, individual exposure over the flash flood event is defined by the chance (given the location and timing) of crossing flooded roads along each individual's route.

3 Data and method

MobRISK microsimulator was developed to measure the exposure of inhabitants and people working in the Gard administrative area, a region of Southern France that has a long flash flooding history. This region is characterized by a typical Mediterranean climate with heavy rainfall events during the autumn season (Delrieu et al., 2005; Gaume et al., 2009). In fact, since 1225, the Gard region suffered 506 floods. Sixty six percent of the 353 municipalities cumulates at least 10 referenced flood events and some of them were affected more than hundreds times (CG30, 2015). Between 1316 and 1999, Antoine et al. (2001) recorded 27 fatal flood episodes and 277 deaths in the Gard. Since 1999, five fatal events added about 30 casualties to the toll. In 2015, nearly 65% of the businesses and 35% of the population of the Gard area were located in flood prone zone.

In 2010, 726 783 inhabitants were living in the Gard administrative area which has a surface of 5 852km2. Among the 353 municipalities, 267 are essentially rural. Urban areas are mostly located next to Nimes, the capital of the department cumulating 145 501 inhabitants, and Alès (41 118 inhab.) (Fig. 2). The road network of the Gard region counts 12 322km of roads likely taken by commuters (paved roads) distributed between local roads (83,8%), principal roads (4,8%), regional roads (10,3%) and highways (1,1%). The river network is described by 6 443 river sections cumulating 7 087km of length. Based on the work of Versini et al. (2010), a total of 1970 potential road cuts, which would be called "low water crossing" in the USA, have been identified based on road-river intersections[1] that are sensitive to flooding (see the detailed description in section 3.2) (Debionne et al., 2016).

This section provides an overview of the required input data used in MobRISK model. MobRISK makes maximum use of existing national databases, both geographical and social. SpatiaLiTE, the spatial extension of SQLiTe[2] is used extensively for input database building and pre-processing. The goal of input data pre-processing is to i) identify the socio-demographic characteristics of individuals and households corresponding to the study area, ii) attribute daily schedules to every individual, and iii) localize the areas where they are susceptible to conduct their activities. Concerning the geographical data, road and river networks data are used for identifying the vulnerability of road sections to flooding.

[1] Even though the points exposed to flooding may be of 3 distincts types: river crossings, low accumulation points and river adjacent points. Low points and river bordering points are much more difficult to identify as they are mostly due to very local settings that are not detectable on the DTM (Versini et al., 2010). Therefore those 2 types were not considered in Versini's work, hence in the study presented in this paper.

2 SQLite is a free relational database management system contained in a C programming Library. SpatiaLite is its spatial extension, providing vector geodatabase functionality (Wikipedia)

3.1 Population data

Socio-demographic description of the population is based on census data provided by the INSEE in 2010 (French National Institute of Statistics and Economic Studies). We use especially the INDCVI dataset, which contains the description of socio-demographic characteristics of the individuals, their household composition and household geographical localization at the municipality resolution. In addition, we combine MOBPRO (Professional Mobility) and MOBSCO (Student Mobility) datasets issued from the INSEE complementary exploration of census data. These datasets describe individuals' commuting patterns (i.e. municipalities of work and school activities, usual commuting modes of professionals[3], and traveled distances), socio-demographic characteristics and household characteristics. These data are stored into "individual" and "household" tables in a way that every individual is attached to one household (Fig. 3a).

The description of individual activity schedules is based on travel activity data, provided by the French National Transport and Travel Survey (ENTD) carried out by the INSEE from 2007 to 2008. In this survey, the responders were requested to indicate their socio-demographic characteristics (age, gender, professional status...), their household composition and their mobility description during one weekday and one weekend. They were instructed to mention the different trips they made during the days of the survey, transport modes, trips' purposes, and time of departure and arrival. Based on these information, individuals' schedules are thus retrieved, representing a sequence of activities mentioned by responders as trip purposes. Ten main activities are proposed in the survey: home, school, working, shopping, medical appointment, administrative procedure, visiting, accompanying persons, leisure, and holidays activities.

The main objective of using the ENTD data is to assign daily schedules to the individuals described by the census data based on the effects of socio-demographic variables on schedules dissimilarities. The dissimilarities between schedules or pairs of sequences are measured by counting the number and type of operations needed to transform one sequence into the other (to match them). The operations considered are insertions/deletions or substitutions of activities. Figure 4 illustrates the

3 The usual commuting mode is one of the variable of MOBPRO datasets. It includes 5 modalities of response: 1) no transport, 2) on foot, 3) two-wheel vehicle, 4) car, truck and van, 5) public transport.

matching of a pair of sequences in two different ways regarding the type of operation: (i) using only substitutions by replacing the different elements of one sequence by those in the second one; (ii) using a combination of insertions and deletions operations. The Optimal Matching (OM) distance metric - allowing both substitutions and insertion/deletion of activities (Lesnard et al., 2011) is used in this study. Then a method proposed by Studer et al. (2011) called "discrepancy analysis" allows measuring the relationships between categorical variables (e.g. gender, age, education level, professional status…) and a set of sequences described by the matrix of dissimilarities (measured with the OM method). It consists in measuring the pairwise dissimilarities between different activity sequences and implementing an ANOVA test to identify socio-demographic variables that explain the discrepancy of the sequences.

Additionally to measuring the effect of socio-demographic variables on sequence dissimilarities, Studer et al. (2010, 2011) proposed a complementary regression tree analysis, which consists on a recursive partitioning of the sequences based on splitting criterion derived from the dissimilarity analysis. All individual activity sequences are grouped in the first node of the tree (root node). A discrepancy analysis is displayed to identify the variable explaining the greatest part of sequences discrepancy. The sequences are then partitioned based on this variable in such a way that the resulting child[4] nodes are as much as possible homogeneous (with low within dissimilarity). This operation is repeated recursively until no significant effect of socio-demographic variables is registered in nodes' sequences. Hence, schedule attribution rules can be extracted from the obtained tree with respect to strength of relationships between socio-demographic characteristics and activity sequences. Then, every individual in the study area is connected to an average week schedule and an average weekend schedule based on these attribution rules (Fig. 3a). The proposed framework is implemented into a free package in R software called TraMineR (Gabadinho et al., 2011). Sequences discrepancy analysis methods have been especially used for exploring individual life trajectories (Studer et al., 2010; Widmer and Ritscard, 2009). Recent applications of sequences analysis methods on activity schedules and diary data have

[4] A child node is a node directly connected to another node when moving away from the Root node of the tree

revealed the advantages of these approaches for capturing the complex structures of activity patterns and providing more accurate schedules classifications (Lesnard and Kan, 2011; Kim, 2014).

3.2 Geographical data

The next step in pre-processing the data for activity-based mobility modeling consists in locating the different areas where individuals might conduct their activities. Concerning housing activities, census data provide municipality of residency of every household. In order to have more precise spatial resolution, we use the RFL data (Household Localized Taxes) published by the INSEE in 2010. RFL data concerns the number of households and individual living and their socio-demographic description provided at 200mx200m resolution for the whole France territory. Then, each household is located in the grid with respect to household densities by pixel. Concerning work and school activities, MOBPRO and MOBSCO datasets provide the municipalities' codes of both work and school places for workers and students. In order to enhance the spatial resolution, work and school places are assumed to be mostly located close to municipalities' administrative centers. Therefore, we assign a road node inside a buffer with a radius of 200 m around administrative centers of work and school municipalities to every worker and student. Finally, since we do not have reliable data for the locations of other activities (shopping, leisure, visiting...) we randomly assign to every individual a road node inside a buffer of 500 m around the administrative center of his/her municipality of residency.

The road network sensitivity to flooding is based on the connection of three datasets providing the description of the road and river networks and a list of the road sections susceptible to flooding called "road cuts". Road network data is provided in *BD-CARTO®* database by the *IGN* (French National Mapping Agency) describing the road segments that compose the whole French road network by specifying their characteristics (regional, principal or local roads) and their locations in 2010. The second geographic information layer used refers to the river network provided by the *BD-CARTHAGE®* database. It contains the different hydrographic segments and their attributes. The road cuts (low water crossings) dataset is derived from the intersection of river and road networks and calibrated by using an inventory of road flooding during the last 40 years provided by the Gard road management services. Based on this dataset, Versini et al. (2010a) identified 1 970 road cuts in the Gard road network and produced a classification of these road sections according to their susceptibility to flooding (Fig. 5). The four susceptibility classes range from s_0 to s_3 counting respectively 1 093, 359, 297 and 221 points. The "very-low" susceptibility to flooding class s_0 corresponds to road-river intersections that have empirical return periods of flooding exceeding 40 years. The "weak" s_1, "medium" s_2 and "high" s_3 susceptibility classes have an empirical flooding return period smaller than one year in respectively 20%, 35% and 65% of their points. Based on road cuts classification, Naulin et al. (2013) developed a method to compute a probability of submersion for each road cut by combining the susceptibility classes and simulated stream discharges at the section of river responsible of the road cut. Therefore, an interval of probability of submersion is assigned to every road cut for each combination susceptibility class/return period of stream discharge. In order to have one value of probability of submersion, the probability intervals are simplified in this study by considering the average value within interval probabilities limits (Table 1).

3.3 Route choice and exposure measurement methods

Once the different activities of each individual schedules are located and road section attributes are specified, route selection criteria needs to be defined. Although various factors are involved in route choice process, several studies indicated that minimizing travel time is the principal criterion for selecting routes (Papinski et al., 2009; Ramming, 2002, Bekhor et al., 2006). Therefore we chose to use the classical Dijkstra's algorithm, a single source shortest path algorithm that provides trees of minimal total length/time in a connected set of nodes (Dijkstra, 1959). The activity patterns attribution concerns only the starting times and durations of the activities' sequences, which means that travel duration is computed based on the distance between the different activity locations for each individual. Therefore, the implemented schedules may be distorted compared to the assigned ones in term of travel durations. Finally, motorists' exposure to road submersion can be measured based on the probability to encounter one or several flooded road cuts on their route during the simulated event period. The more important the probability of crossing submerged road cut is, the higher is the individual exposure. Since individuals are susceptible to cross several road cuts with different probabilities of submersion, total exposure is computed by calculating the joint probability of submersion of all the crossed road cuts. The individual exposure index is calculated with the following Eq. (1):

$$E(ind) = 1 - \prod_k (1 - P(Sub_k)) \quad (1)$$

where *E(ind)* refers to the computed individual exposure and $P(Sub_k)$ is the probability of submersion in the k^{th} road cut crossed. An example of exposure measurement is illustrated and explained in Fig. 6.

4 Results

Even though MobRISK model development is at the scale of the Gard department, we present in this section a first application of the model in the sub-region of Ales located in the north of the Gard administrative area (Fig. 2).

4.1 Case study

The objective of this case study is to assess road users exposure to road flooding during the 8-9 September 2002 event, considered as one of the most catastrophic flash flood in the area since the one of 1958. In this first application, adaptation decisions generated by the decision making model are not considered and we assume that individuals' travel plans do not change with the weather conditions and encountered flooded roads. The selected domain of this case study is composed of 61 municipalities around Ales, which is the second largest municipality of the Gard region in term of demography (Fig. 2). This first simulation provides an estimation of motorists' exposure to submersion based on their daily mobility for the Sunday and Monday of this past flash flood event. During this event, the rainfall accumulation exceeded 600 mm in 12 hours causing 24 deaths and economic damages estimated to 1.2 billion €. A more detailed hydro-meteorological description of this event is provided in Delrieu et al. (2005). In terms of human impacts and death circumstances, more than half of the victims were outside buildings and five of them are vehicle-related fatalities (Ruin et al., 2008). The flash flood event started a Sunday evening, which might have limited the number of victims related to car driving accidents.

In order to evaluate daily mobility exposure to flash flood risk, MobRISK output contains a record of the different road nodes crossed by the individuals on their route (including the road cuts), the time at which they passed these nodes and the individual exposure index (Eq.1). The results are presented into three main sections: (i) results of population mobility simulation, (ii) analysis of road submersion risk, (iii) and analysis of population exposure to road submersion.

4.2 Population mobility

The study area resident population is of 111 511 individuals. An overview of the population socio-demographic characteristics is displayed in Table 2. As explained in Section 3.1, we used travel-activity data from the National Travel and Transport Survey to attribute programs of activities to the population in our study area. In order to respect the regional statistical representativeness of the survey sample and benefit of a rich schedule library with satisfactory variability, we select travel activity data corresponding to survey responders living in the Languedoc Roussillon *Region*[5]. Since we are interested in motorists' exposure, only individuals using principally motorized transport modes are selected: representing 1 240 week day schedules and 1 087 weekend schedules.

We conducted a multi-factor discrepancy analysis on the different schedules in order to assess the effect of socio-demographic variables on the activity sequences dissimilarity. We analyzed the effects of six variables: gender, age, education level, professional status, profession and household composition. The choice of these variables is based on previous studies on the effect of socio-demographic characteristics on daily travel-activity behavior (Pas, 1984). These variables are considered as independent variables and the matrix of dissimilarities *(d_{ij})* between sequences is the dependent variable. Similar to ANOVA test, individuals are grouped based on the selected factors and we attempt to compare the inter-group and intra-group variance to measure how much the chosen factors explain the total variance. The variance is then calculated based on the Eq. (2) where the Sum of Squares (*SS*) is expressed using the average pairwise squared dissimilarities (Anderson, 2001):

$$SS = \sum_{i=1}^{n}(y_i - \bar{y})^2 = \frac{1}{2n}\sum_{i=1}^{n}\ \sum_{j=1}^{n}(y_i - y_j)^2 = \frac{1}{n}\sum_{i=1}^{n}\ \sum_{j=i+1}^{n} d_{ij}^2 \qquad (2)$$

[5] Before 2015, France was divided into 22 French administrative "*Regions*" each further divided into "*départements*". The Languedoc Roussillon *Region* contained 5 "*départements*" including the Gard.

We observed that these selected variables explain 20 % ($R^2 = 0.20$) of the total discrepancy for week schedules and only 3 % ($R^2 = 0.03$) for weekend schedules (Table 3). Globally, there is a statistical significant effect of the selected variables on schedule discrepancy (p-value < 0.05). For an average weekday, the most significant variable is the professional status ($F = 157\ 530$ and $p < 0.05$). For the weekend, results indicate that the majority of variables have moderate but significant contributions to explain the total discrepancy except the gender which is not significant ($F= 4\ 060$, $p > 0.05$).

We displayed a regression tree analysis generating 12 clusters for weekday schedules representing essentially 3 classes of working men schedules (clusters 1, 2 and 3), 3 classes of working women schedules (clusters 4, 5 and 6), two classes of students (clusters 7 and 8) and 4 classes of non working persons dependant on their age and gender (clusters 9, 10, 11 and 12) (Fig. 7a). For weekend schedules, the regression tree generated 10 clusters composed of a class of student (cluster 3), 5 classes of working persons dependant on their household type and age (clusters 1, 2, 4, 5 and 6), and 4 classes of non-working persons dependant on their age and household size (clusters 7, 8, 9 and 10) (Fig. 7b). These results are used to produce "if - then" rules for assigning one weekday schedule and one weekend schedule to the individuals living in the study area. Each individual, according to his socio-demographic profile, is randomly assigned with one of the list of schedules corresponding to the appropriate cluster. MobRISK mobility model is implemented to simulate population mobility during one average weekend followed by an average weekday in order to have mobility patterns similar to the 8-9 September 2002, which happen to be a Sunday and a Monday. MobRISK generated in total 737 135 trips: 333 453 trips on Sunday and 403 682 on Monday. The average number of trips per individual is of 3.06 on Sunday and 3.64 travels on Monday. When we examine the trip goals, we observe that more than 40% of individuals' trips are made to reach home destination. Obviously, the main difference between weekdays and weekend in term of trip goals consists in commuting trips, which are more important during weekdays. Whereas, visiting and leisure travels are more important during the weekend (Fig. 8).

4.3 Road network sensitivity to flooding

As mentioned in Section 3.2, a probability of submersion is assigned to every road cut by combining the flooding susceptibility level of road section and the return period of stream discharge in river section.

The CVN distributed hydrological model (Vannier et al., 2016; Branger et al., 2010; Viallet et al., 2006) is used to compute the discharge at the 738 road cuts identified in the Ales case study in hourly time steps for the 2002 flash flood. The CVN model is especially developed for simulating hydrological responses in flash flood events in Cévennes region (south of France). Moreover, the implementation of CVN model for reconstructing the 8th and 9th September 2002 event in the Gard region has provided satisfactory results (Braud et al., 2010; Anquetin et al., 2010). Discharge return periods are then computed at each road cut for hourly time steps and translated to submersion probabilities thanks to the relationship proposed by Naulin (2012, p93-94). Fig. 9 shows that the period with the highest probability of road submersion takes place during the night of Sunday 8th to Monday 9th, leading to "weak" population exposure since less people are on the roads in the middle of a Sunday night. The spatial distribution of the simulated road submersion hazard for the whole flash flood event period, computed by summing up the hourly probabilities of flooding, shows a concentration of high flooding hazard in the south of the Ales municipality (Fig. 10).

4.4 Exposure analysis

A first method for assessing road users exposure to road flooding consists in quantifying the simulated traffic load in the potential road cuts identified in the study area during the two selected days. The computed exposure corresponds to the maximal exposure since the whole daily trips are assumed to be motorized. The results reveal that motorists were essentially exposed to road cuts corresponding to the two lowest levels of susceptibility (Table 4).

The spatial distribution of traffic load on potential road cuts shows a high motorists' exposure on the main roads connecting Ales to the other major cities of the area: Road *D6110*, Road *N106*, Road *D981*, Road *D904* (Fig. 11). Fig. 12 shows the dynamic of road users' exposure to potential road cuts presenting two peaks on Sunday, one at 10 a.m. and the other one at 4 p.m. indicating, for the first peak, more than 25 000 motorists crossing potential road cuts per hour. On Monday September 9, three peaks are detected at 7 a.m., 12 a.m., and 5 p.m. corresponding essentially to commuting trips and reaching 40 000 people crossing potential road cuts per hour. The comparison between temporal dynamics of roads submersion probabilities and traffic load in potential road cuts indicates a clear lag time between the period corresponding to high road submersion probabilities and the one with a larger number of exposed road users (Fig.13). Indeed, this lag time is considered as an important factor contributing in reducing vehicle related accidents and fatalities for the 2002 flash flood event in this area.

This exposure measurement provides an estimation of traffic load on potential road cuts. Hence, by combining the flood hazard, represented by the hourly probabilities of submersion at road cuts, with human exposure, given by maximal traffic load passing these road cuts, it is thus possible to identify the number of persons who might have been endangered by crossing road cuts at the time they were submerged. The proposed risk index (Eq. 3) characterizes the number of motorists who could be in effective danger by multiplying for every hour time step the probability of submersion in road cuts with the number of motorists crossing them.

$$N(Ind_{danger})_{rc,t} = \sum_{i}^{n_{rc}} P(submersion)_{rc,t} * N(ind_{exposed})_{rc,t} \qquad (3)$$

where *(rc)* refers to the crossed road cut and *(t)* is the time period.

In Fig. 13, the time evolution of the risk index reveals a different pattern than those associated with flooding hazard or with the traffic load at road cuts. It clearly illustrates that the period corresponding to the highest risk of flooding for road users occurred on September 9th from 5 a.m. to 11a.m. with a peak at 7 a.m. representing more than 1 500 motorists/hour in significant danger of flooding. The spatial distribution of the risk index cumulated for the whole event shows that the majority of road cuts presenting a considerable danger in term of potential victims are located around Ales municipality (Fig. 14). The results of the simulation for the entire event show that in average, 15 individuals might have crossed dangerous road cuts. Geo-located vehicle-related fatal accidents data provided by Ruin et al., (2008) are used as a first evaluation of this result. One vehicle-related victim (Fig. 14) was identified in our study area at a location that effectively corresponds to a road cut with high risk level (the 16th most dangerous road cut, $N(Ind_{danger})$ = 162). The proposed risk index mapping might thus provide an efficient indicator of flood risk magnitude in road network since it combines both environmental and social parameters.

Finally, we investigate the effect of socio-demographic variables on individual exposure to road submersion. The MobRISK simulation of the probability, for each individual, of crossing submerged road sections on his daily route, indicates that the average individual exposure (Eq. 1) is 0.17 (a probability of 17% to cross submerged roads during the event period) with a variance of 0.10. 75% of the road users have a zero-risk of crossing submerged road cuts. Individual exposure varies with socio-demographic characteristics such as: age, gender, professional status and profession. For instance, men are more exposed than women ($Exposure_{men}$= 0.18; $Exposure_{women}$= 0.15). Not surprisingly, workers are the most exposed with an average risk of 0.28 while retired and unemployed have an average risk of 0.10. Managers, laborers and professors seem to be the most exposed professionals with an average exposure of 0.27 (Table 5). An analysis of variance (one way ANOVA test) showed that the effects of the 4 selected variables are statistically significant (Table 6). The most exposed individuals are mainly young working males who are generally more motorized and commute daily longer distances (Debionne et al., 2016). These results confirm the benefit of integrating mobility behaviors into social vulnerability assessment. This integration points out different socio-economic vulnerability profiles that are usually not considered when dealing with static (resident) vulnerability. Classic static social vulnerability index usually attributes high vulnerability level to women, elders and persons with low professional status (Cutter et al., 2000). These social profiles seem to be less exposed to road flash flooding.

5 Discussion and perspectives

MobRISK microsimulator is to our knowledge the first of its kind combining social and hydro-meteorological state of the art knowledge to understand the dynamic of human exposure and behavioral response[6] to short fuse weather event. This first implementation of MobRISK shows the potential of this tool for emergency planning and road management in crisis situation. Other examples of microsimulations often use a multi-agent platform to simulate such dynamic interactions (see for instance, Dawson et al., 2011) nevertheless those models do not allow to address the scale of a French department (c.a. about 6000km2) involving about 700 000 agents. Because MobRISK is newly developed, several improvements are planned for improving its reliability, optimizing its functioning and moving toward a more operational tool.

[6] The case study presented in this paper do not include the output of the behavioral model that was not yet fully operational at the time of the writing of this paper.

The next step of its development is to better reproduce the travel durations observed in the ENTD dataset. In fact, activity-based mobility modeling approach requires data describing the location of different activities conducted by the individuals. Whereas work and school activities locations are identified based on census data, it is more complicated to locate secondary activities such as shopping and leisure activities. We assume for this first application that secondary activities are located within a buffer of 500m around the place of residency. However, future efforts are needed to improve the secondary activities location rules by taking into consideration travel cost and places knowledge (Marchal and Nagel, 2005). The buffer size used for secondary activities locations may affect the simulated travel durations. A comparison between simulated trip duration in MobRISK and observed trip duration retrieved in the ENTD data indicates an under estimation of simulated travel durations corresponding especially to secondary activities travels (Fig. 15). This underestimation may be explained by the buffer size selected for secondary activities location, which seems to be too small compared to the real size of activities space and the shortest path criteria used for route choice. As a consequence, our model currently underestimates the computed motorists' exposure.

Another important issue is to investigate the link between exposure and human impact. Individual exposure measurement is merely defined as the probability of encountering flooded roads without taking into account the water height and flow level. This limitation is due to the difficulty to provide the necessary information because of the large number of parameters to integrate regarding roads infrastructures and geomorphologic specificities of road cuts. On the social side, understanding behavioral responses is key to the estimation of human impacts. Since recently, this aspect is taken into account in MobRISK that now incorporates a decision making module to consider possible activity rescheduling decisions and mobility adaptation to weather disruptions. The integration of individual decisions and coping capacities enables us to shift from exposure measurement to social vulnerability quantification (Terti et al., 2015). To advance in this direction the use of well-described, geolocalised, time-stamped and reliable human impact datasets is needed for model verification (Terti et al., 2017).

While activity-based mobility models are using classically travel-activity patterns simulation we opted for a schedule assignment method based on the effect of socio-demographics on activity sequences discrepancy. This choice is consistent with the main purpose of MobiCLIMeX project, which aimed at understanding the driving forces of dynamic exposure over past flash flooding events. Nevertheless, this tool could also be used to evaluate the longer-term evolution of human exposure related to climate change and its consequences in terms of extreme weather patterns. To move toward this direction, the module reproducing travel-activity patterns by schedule assignment would need to evolve toward the simulation of mobility scenarios.

In terms of implementations of MobRISK, the next step is to extend the simulation of the 8-9 September 2002 flash flooding event to the whole Gard area, as nearly all the municipalities of the Gard were impacted by this event. Other lesser severe events with a different space-time distribution of the rainfall may also be implemented to investigate the influence of the timing of the event on motorists' exposure.

6 Conclusion

This paper describes the MobRISK model, developed to capture the spatial temporal dynamics of motorists' exposure to road submersion, in particular associated with flash-flood hazard, for which fatalities are often vehicle-related when water level and velocity would cause a vehicle to be washed away. MobRISK is one of the first of it kind as it allows simulating the coupled dynamics of social and hydro-meteorological processes at the scale of a French department of several thousands square kilometres. The small temporal and space resolutions (of the order of magnitude of the minute and the meter) address the specific need of short-fuse weather events as flash floods that perturb and affect daily and sub-daily social practices. Its current application allows reproducing past flooding events in order to evaluate the variability of human exposure according to the distribution of rainfall and the timing of occurrence of the road flooding. MobRISK simulates individual mobility using an activity-based approach and individual exposure to road submersion benefiting from previous works and existing datasets characterizing road network sensitivity to flash flood in the Gard area. The first application of MobRISK simulation over the Ales area for the period of the 8-9 September 2002 flash flood event offers the possibility to identify in time and space the road sections bearing a higher risk for population both in term of submersion probability and traffic load.

The results show that road submersion hazard was mainly located on principal roads connecting Ales municipality to other major cities of the Gard area. The temporal analysis indicates that the highest road submersion hazard occurred at night, at the end of a weekend, when traffic load is supposed to be lower. The simulation combining road submersion and individual mobility dynamics confirm this hypothesis and show a clear lag time between traffic load patterns and road flooding. In order to take into account both hydro-meteorological hazard and social exposure, a risk index is proposed by multiplying roads submersion probability with the maximal number of motorists passing these roads.

The risk index helps to better characterize spatio-temporal dynamics of population exposure to road submersion. Its output seems coherent with the location of the fatal vehicle-related accident that happened on Monday September 9th at 6am within our study area. In fact the road section where the accident occurred effectively shows one of the highest risk levels of the area. To further assess the performance of this model a diversity and large amount of ground truth data would be needed. Fortunately, fatal accidents are extremes and exceptional events. During flash flooding many dangerous situations actually emerge and hopefully end up happily with no casualty (Ruin et al., 2014). Geolocated and time-stamped data on traffic accidents, 911 calls, emergency safety operations, or even social media observations would be vary valuable for the assessment of such model.

This methodology also allows investigating the socio-demographic profiles of the most exposed people. The results highlight significant effects of some socio-demographic variables such as age, gender and professional activity. We show that young working males are clearly the most exposed to road flooding which is coherent with analyses based on vehicle-related accidents in the USA (see for instance Terti et al., 2017).

The presentation of the model development and results to emergency and risk managers shed light on their interest for such dynamic approach and on the potential of this model for operational purpose. Identifying the hot spots of the road network associated with various hydro-meteorological and vulnerability scenario would indeed help, for instance, to prepare for flood crisis road management or to pre-position emergency response teams. Another interest of such tool is its potential ability to also address the exposure of people when they are not traveling. In fact, knowing about people's usual space-time mobility means that the model can also provides information about the exposure of people when they are not moving and spend time in flood prone zones. Moving toward an operational tool that could eventually be used on near real-time is one of our goal. We are planning to address it by enhancing our collaboration with scientists experts in the various domains of the model (meteorologists, hydrologists, psychologists and transport modelers) and operational stakeholders experts of warning response systems.

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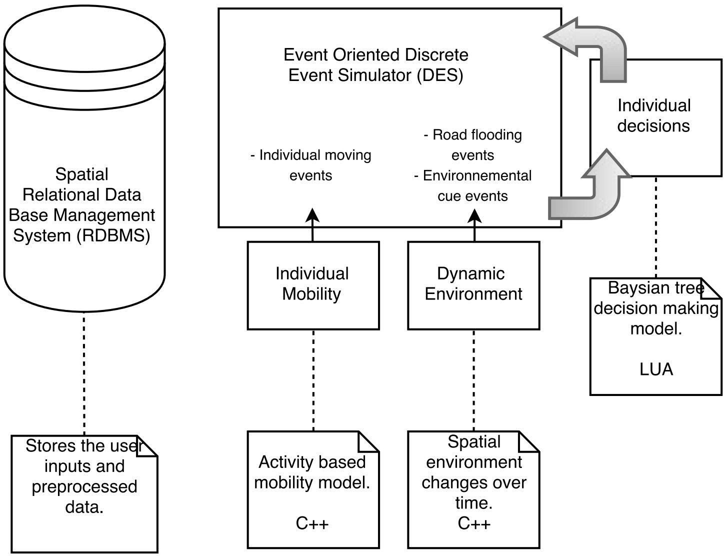

Figure 1: MobRISK model architecture.

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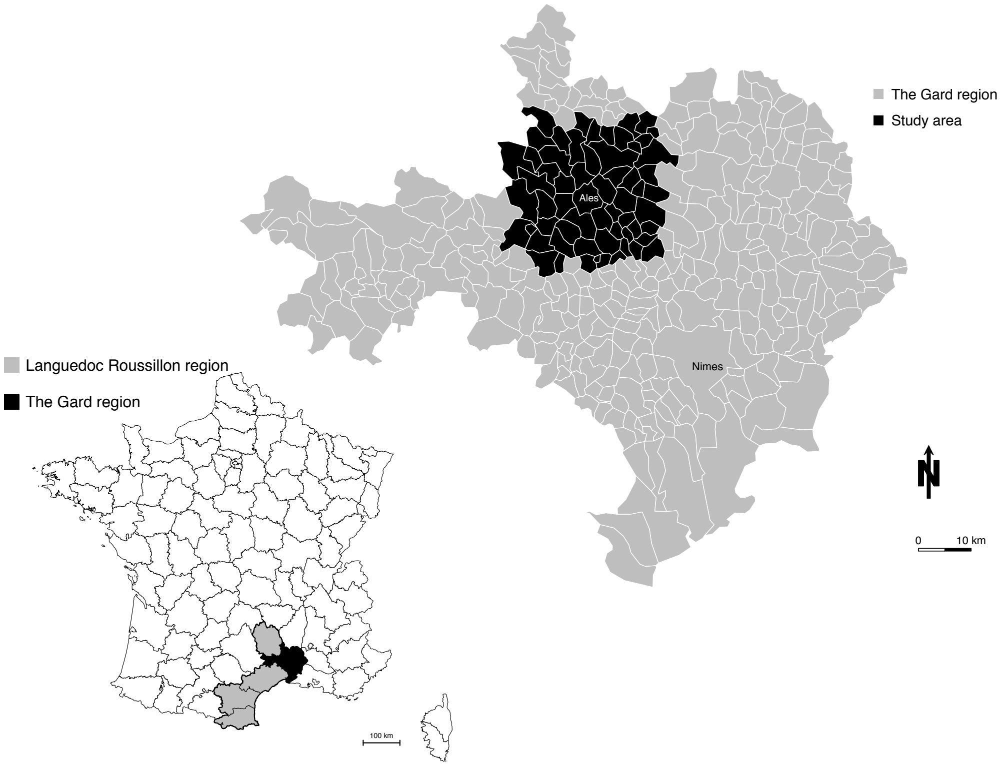

Figure 2: Map of study area municipalities. Source: Compiled by author from BD-TOPO for regions' and municipalities' boundaries (http://professionnels.ign.fr/bdtopo).

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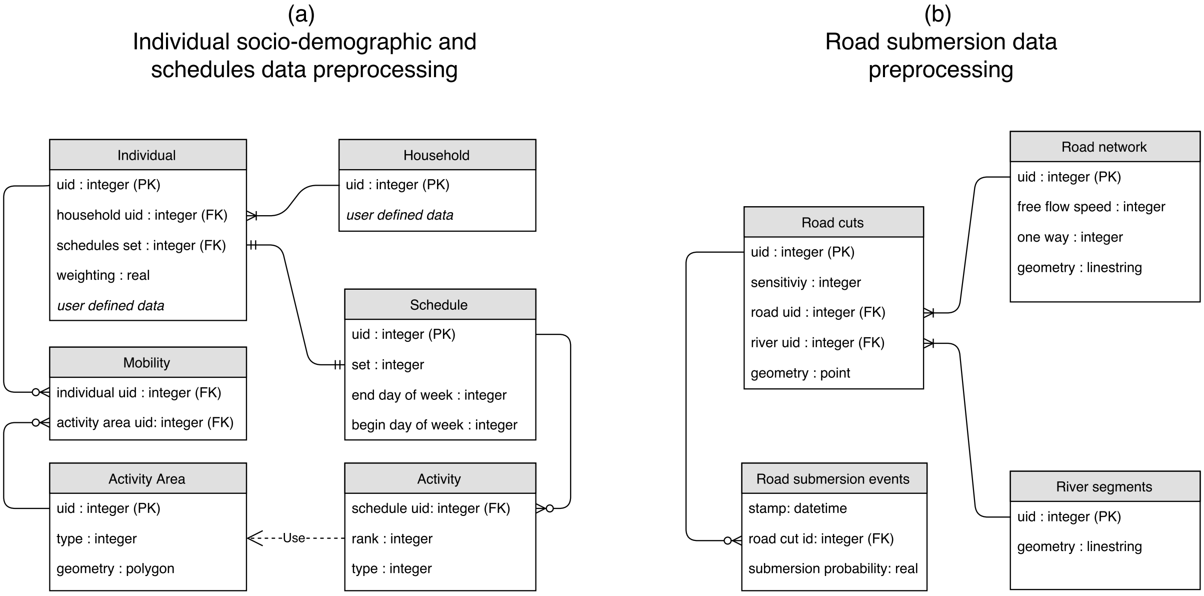

Figure 3: MobRISK relational database scheme.

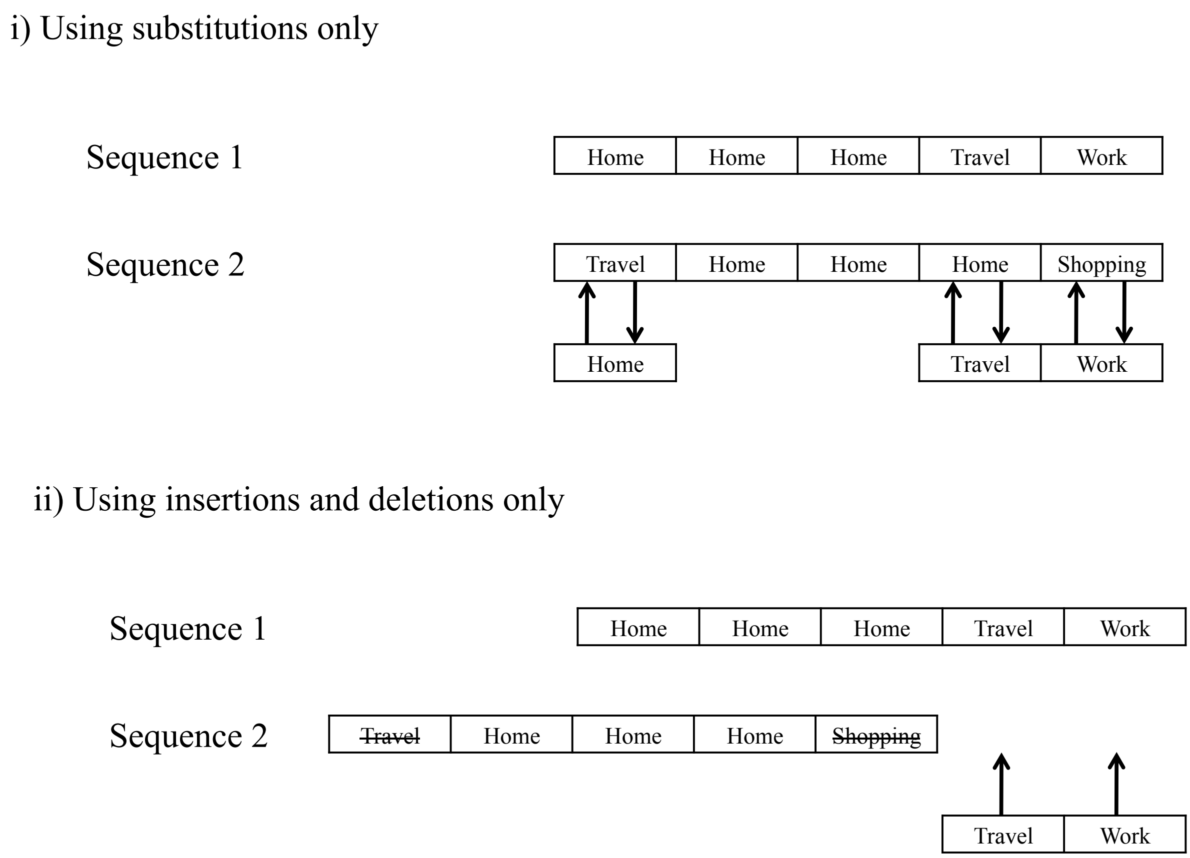

Figure 4: Schematic representation of sequence matching operations

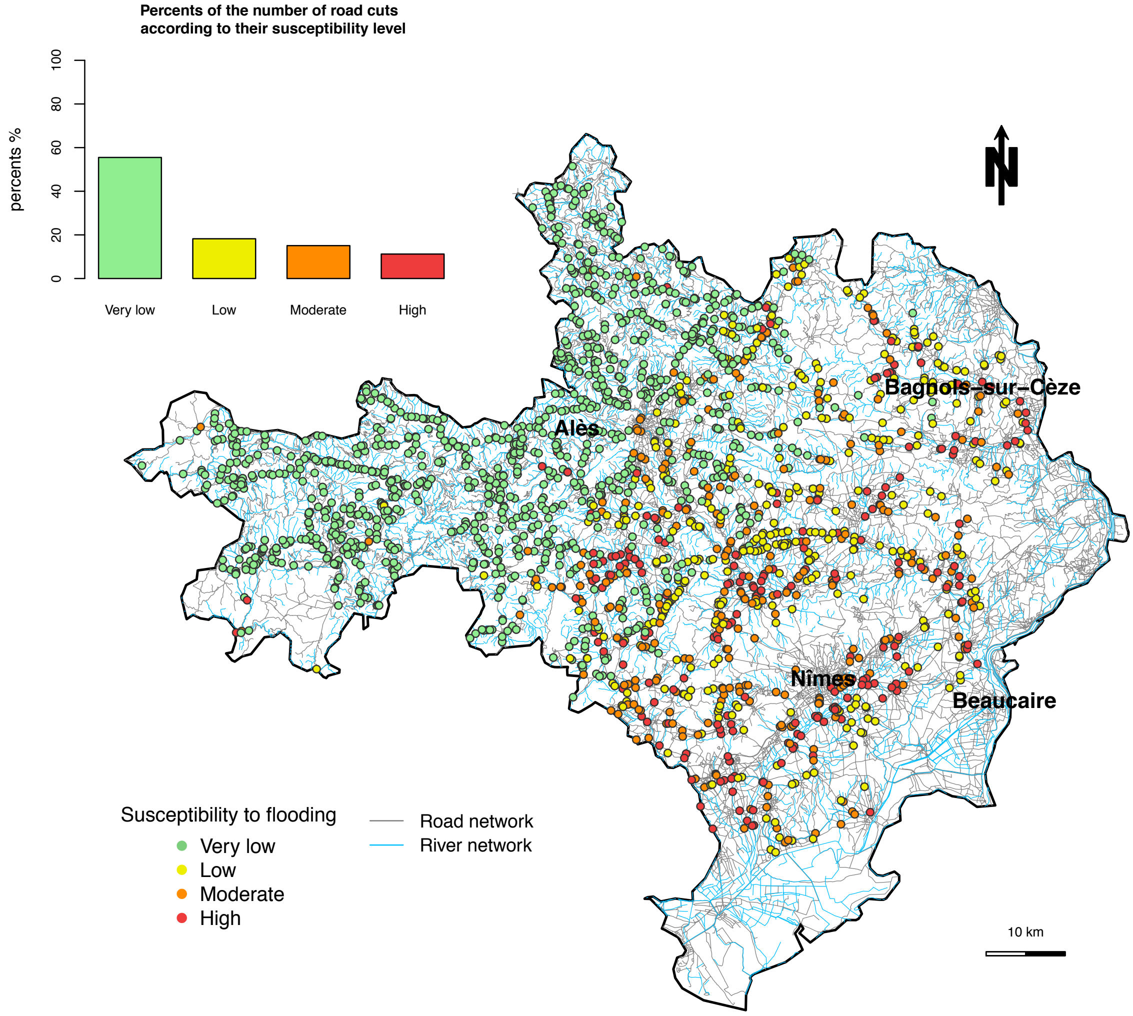

Figure 5: The spatial distribution of the 1970 road cuts identified in the Gard region with the different flooding susceptibility levels. Source: Compiled by author from BD-CARTHAGE® for hydrographic network (http://professionnels.ign.fr/bdcarthage), BD-CARTO® for road network (http://professionnels.ign.fr/bdcarto) and Versini et al (2010a) for road cuts locations and susceptibility levels.

Table 1: **Probabilities of submersion of the road cuts depending on the return periods of stream discharge, Q, and the susceptibility levels as defined by Naulin (2012) with the average values used in our case study.**

	Return periods							
	$Q_2 / 2 < Q < Q_2$		$Q_2 < Q < Q_{10}$		$Q_{10} < Q < Q_{50}$		$Q > Q_{50}$	
Susceptibility levels	Probability of submersion	Utilized value	Probability of submersion	Utilized value	Probability of submersion	Utilized value	Probability of submersion	Utilized value
High	0 to 67%	33.5 %	67 to 100%	83.5 %	100 %	100 %	100%	100%
Moderate	0 to 33 %	16.5 %	33 to 57%	45 %	57 to 61%	59 %	61 to 100%	80.5 %
Low	0 to 20 %	10%	20 to 34%	27 %	34 to 35%	34.5 %	35 to 100%	67.5 %
Very low	0 %	0 %	0 %	0 %	0 %	0 %	0 to 100%	50 %

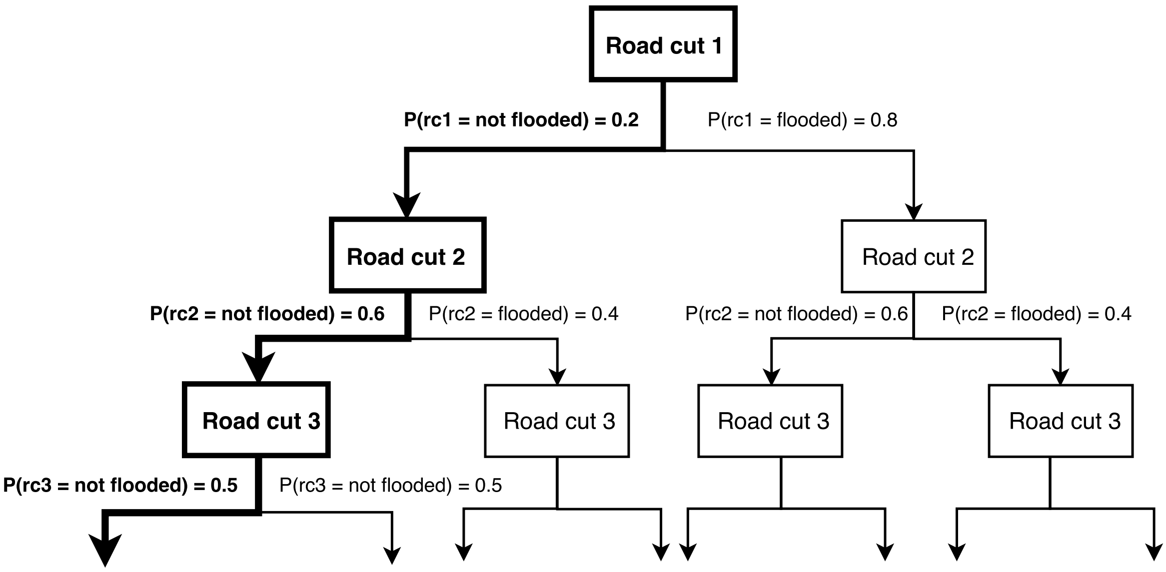

Figure 6: Probability tree diagram representing the method to measure motorists' flood risk exposure. The highlighted (bold lines) path represent the example of a motorist who crossed 3 road cuts (*rc*) with the following probabilities of submersion: *$P(rc_1 = 0.8)$, $P(rc_2 = 0.4)$* and *$P(rc_3 = 0.5)$*. His/her exposure is represented as a probability tree diagram where the nodes are the encountered road cuts and the arcs represent the probability of submersion in each road cut as shown in the Figure. First, we calculate the probability that the driver doesn't cross a flooded rod cut that corresponds to the product of probability of not submersion in the crossed road cuts: *$P(\text{not submerged road cuts}) = (1 - P(rc_1)) * (1 - P(rc_2)) * (1 - P(rc_3)) = 0.06$*. Then, final exposure corresponds to: *$1 - P(\text{not submerged road cuts}) = 0.94$*.

Table 2: **Description of socio-demographic characteristics of the population in the study area. Source: INSEE (Census data, 2010).**

Variables	Groups	Percents (%)
Gender	Male	47.76
	Female	52.23
Age	< 18 years old	19.84
	18 - 29 years old	10.62
	30 - 45 years old	20.22
	46 - 60 years old	21.78
	> 60 years old	27.52
Education level	No education	33.06
	School - College	39.1
	Bachelor	13.07
	University	14.77
Profession	Farmers	0.43
	Shop or business owners	3.92
	Managers and academics	3.72
	Manual laborers	10.29
	Administrative, Sales or Service Occupations	9.41
	Technicians	13.10
	Retired	25.29
	Unemployed	3.80
Professional status	Working	34.10
	Student	6.44
	Retired	25.29
	Unemployed	7.58
	Other situation	21.26
Size of household	1 person	15.93
	2 persons	32.82
	> 2 persons	51.23
Occupation status	Owner	60.33
	Lodger	36.81
	Other status	2.84
Number of cars by household	No car	10.58
	1 car	42.33
	>1 car	47.08

Table 3: Results of the discrepancy analysis of activities sequences for each covariate in an average weekday and an average weekend. ***(SS_T)*** **is the sum of all schedules pairwise distances divided by the number of schedules;** ***(SS_W)*** **is the sum of all schedules pairwise distances within groups divided by the number of schedules;** ***(R^2)*** **refers to the part of discrepancy explained by the variables ;** ***(a)*** **refers to the number of groups in each variables;** ***(N)*** **is equal to** ***n(n-1)/*2 where n is the sample size.**

$$R^2 = \frac{SS_B}{SS_T} \; ; \; F = \frac{SS_B/(a-1)}{SS_W/(N-a)}$$

Formulas to calculate ***F*** **and** ***R^2 for the total model*** **are provided in Studer et al. (2011) and Anderson (2001).**

Type of day	Variables		R^2	*p-value*
Average week day	Gender	29308	0.005	0.001***
	Age	184 434	0.113	0.001***
	Education level	33 868	0.034	0.001***
	Professional status	157 530	0.127	0.001***
	Profession	89 305	0.103	0.001***
	Household type	7 098	0.003	0.001***
Global		33.64	0.203	0.01**
Average weekend day	Gender	4 060	0	0.079
	Age	19 935	0.153	0.001***
	Education level	6 819	0.007	0.001***
	Professional status	15 923	0.016	0.001***
	Profession	10 508	0.015	0.001***
	Household type	7 316	0.004	0.001***
Global		3.96	0.033	0.001***

* Significance level: p < .1; ** Significance level: p < .05; *** Significance level: p < .01.

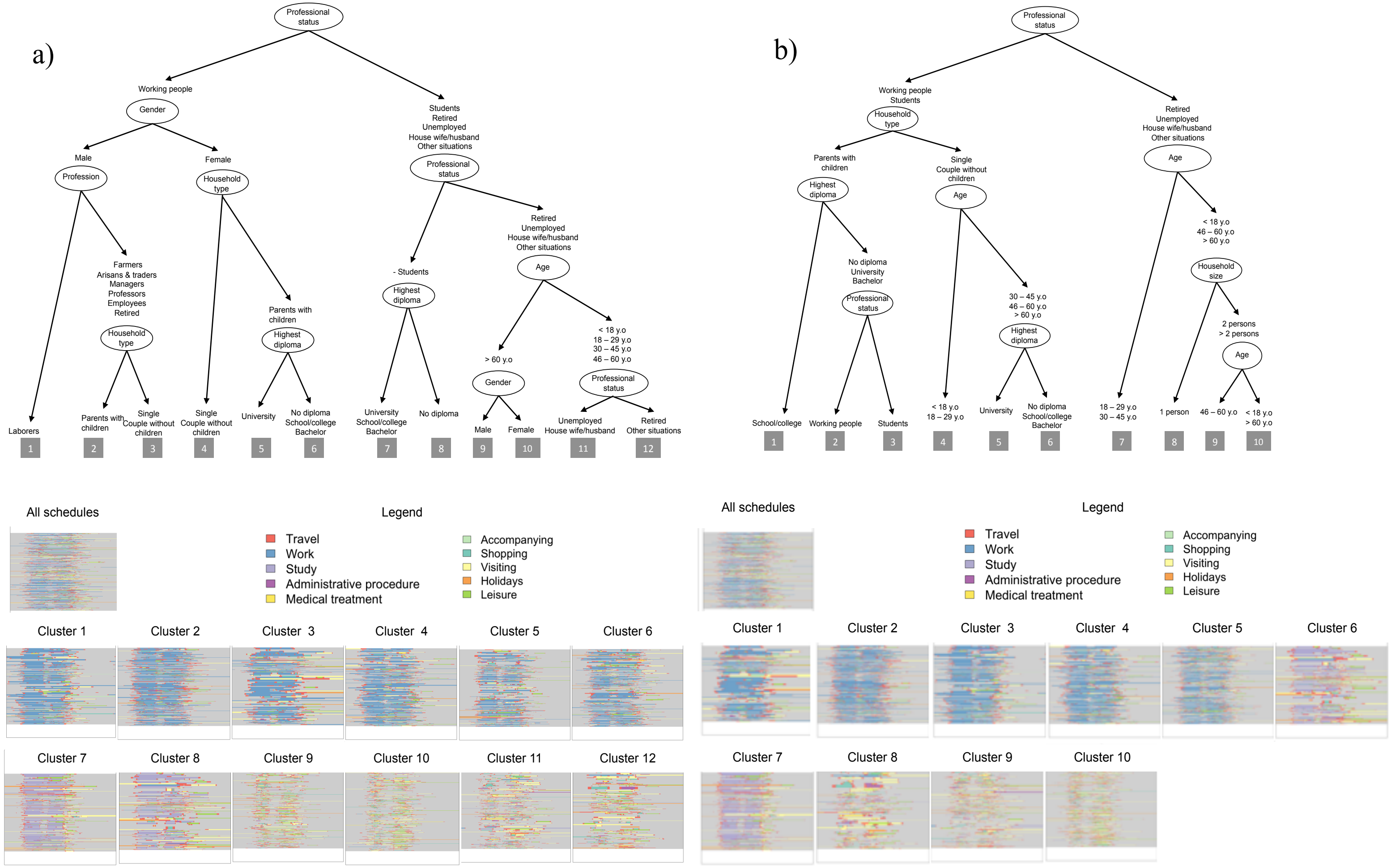

Figure 7: Regression tree results for weekday schedules (a) and weekend schedules (b) indicating 12 and 10 clusters of schedules respectively. On top, the regression tree is displayed: each node represents the variable splitting the schedules into 2 groups and each arc represents the group/category. A visual representation of the schedules corresponding to each cluster is displayed at the bottom: each activity is represented by a color and each line is representing a sequence of activities.

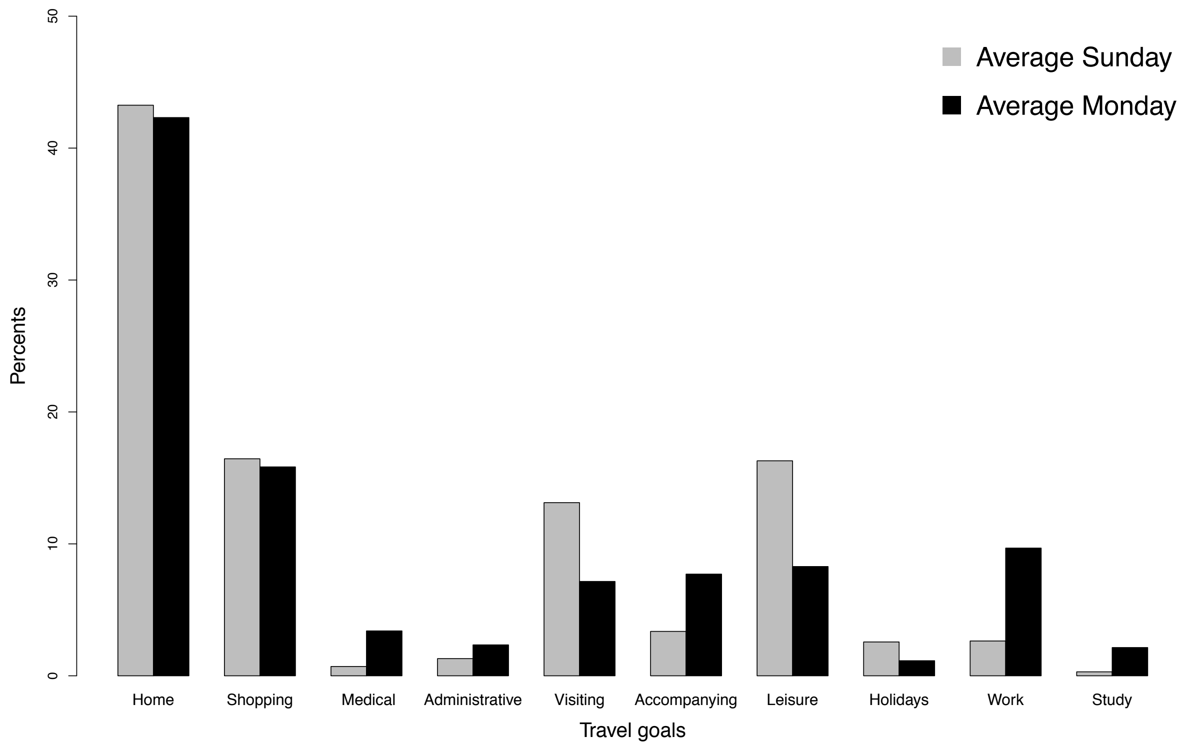

Figure 8: Differences in travel percents by travel purposes between an average Sunday and an average Monday.

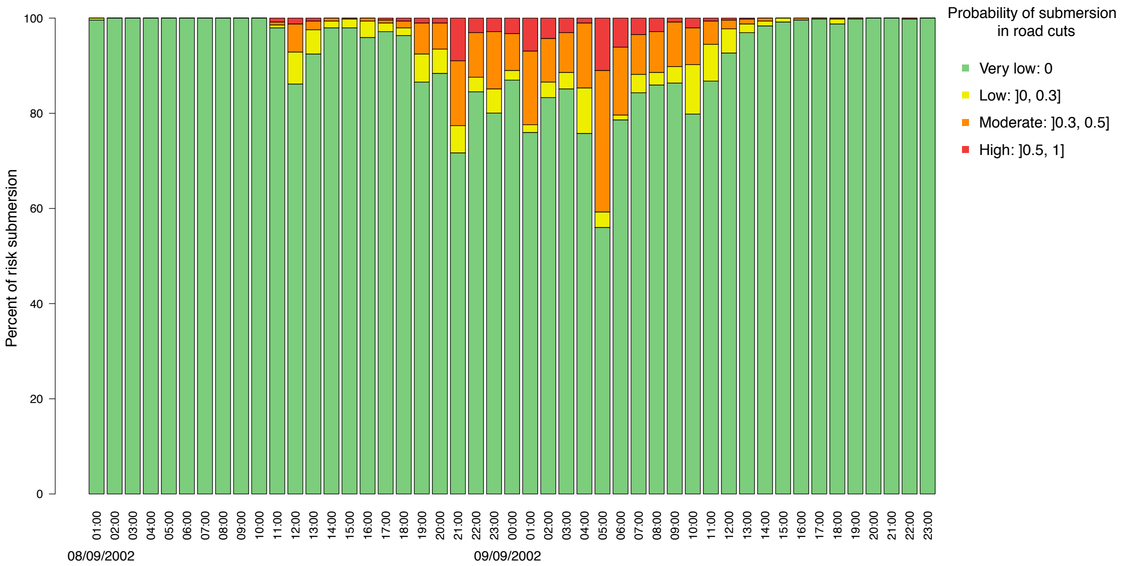

Figure 9: Temporal distribution of the simulated submersion risk in road cuts during 8th and 9th September 2002.

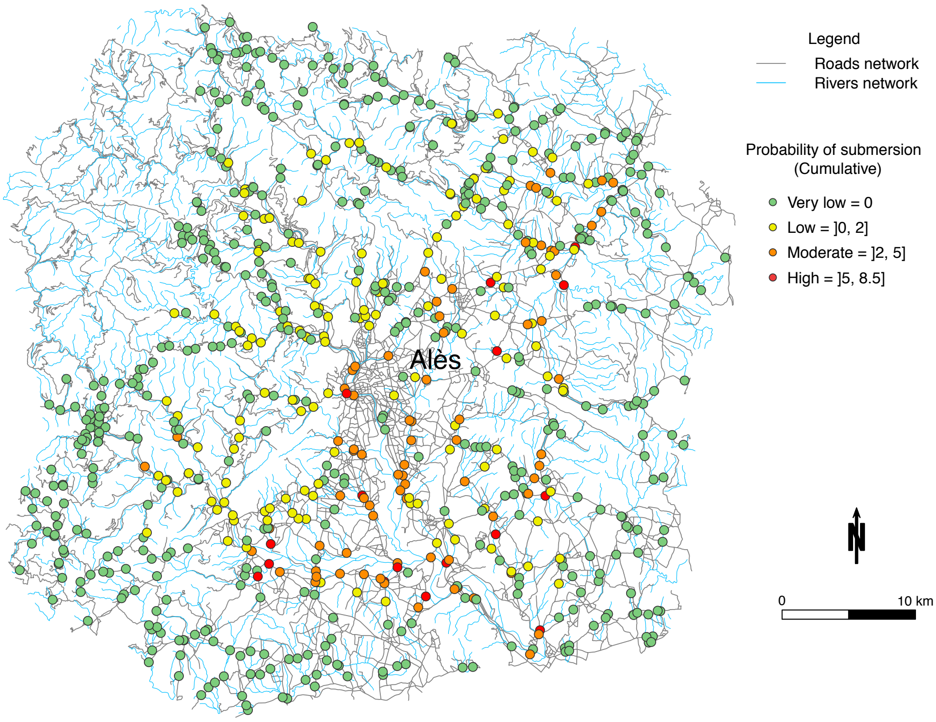

Figure 10: Spatial distribution of cumulative simulated flooding risk in road cuts in study area for the 8th and 9th September 2002 flash flood event. The value represented in the map is computed by summing up the hourly probabilities of submersion in every road cut during the event period in order to take into account both the frequency and intensities of submersions.

Table 4: Maximal number of motorists crossing potential road cuts during the event period (individuals can be counted several times if they crossed many road cuts in their itineraries).

Sensitivity levels of road cuts	Number of road cuts	Percent of road cuts by sensitivity level (%)	Number of motorists crossing road cuts (pers)	Percent of motorists crossing road cuts (%)
Very low	523	70.87	327 603	63.88
Low	103	13.96	81 488	15.89
Moderate	75	10.16	98 021	19.11
High	37	5.01	5 742	1.12
Total	738	100	512 854	100

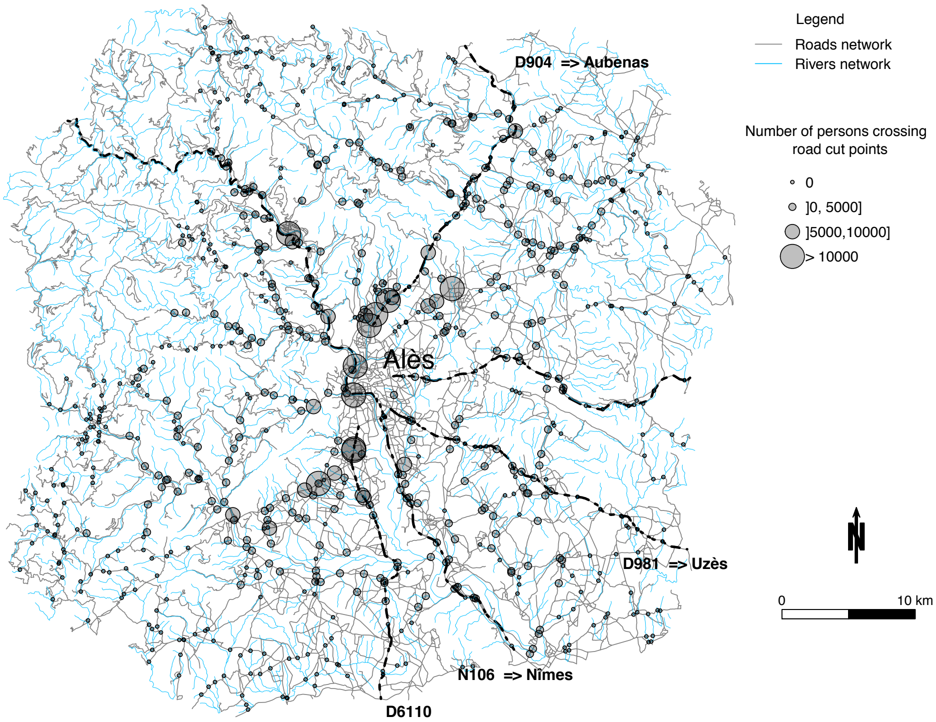

Figure 11: Spatial distribution of simulated traffic load in road cuts during the flash flood event period.

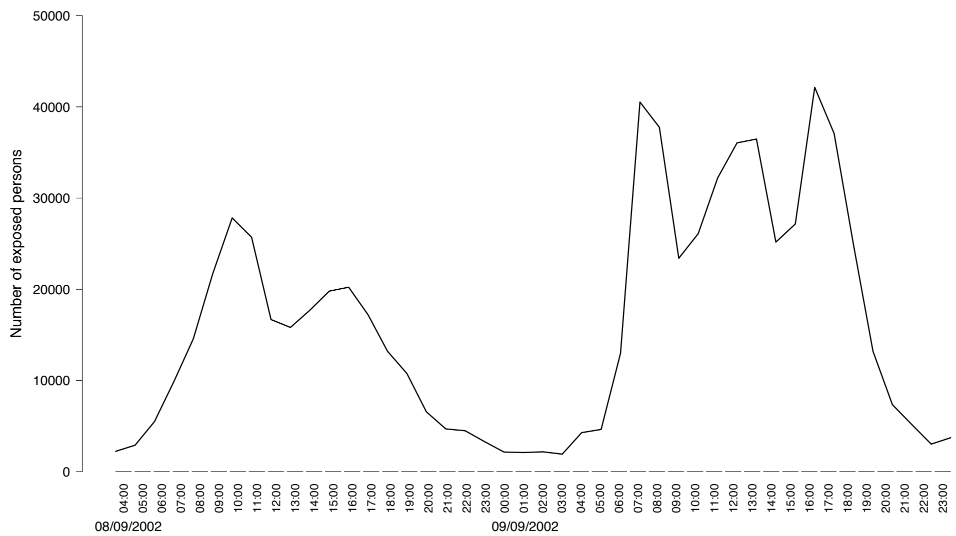

Figure 12: Temporal distribution of simulated traffic load at road cuts, which represent the hourly number of exposed persons.

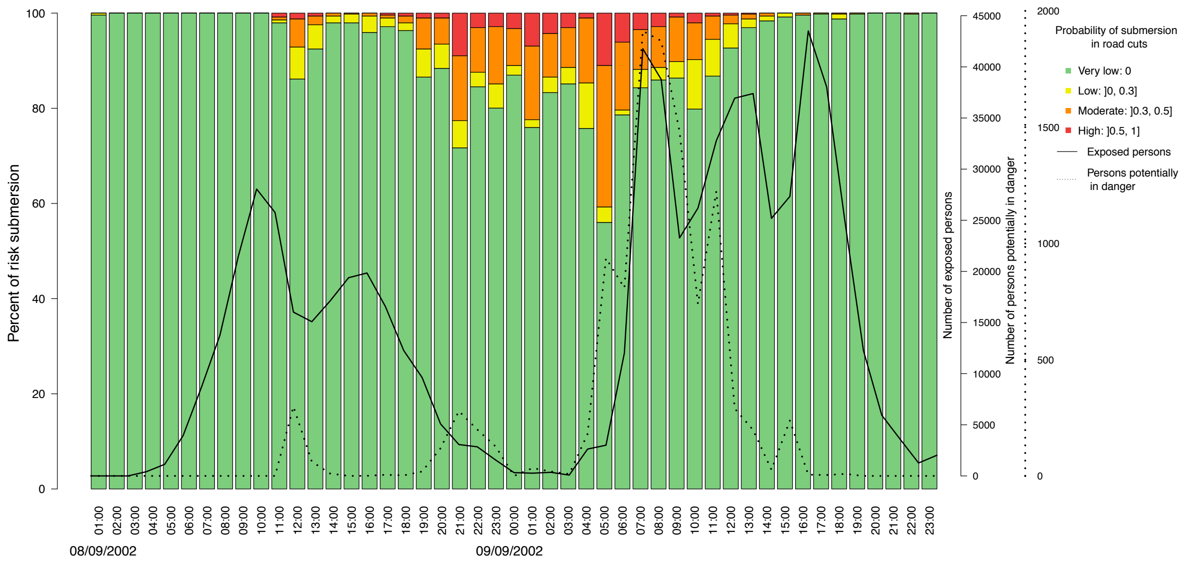

Figure 13: Time lag between temporal distribution of submersion risk (colored bars) and traffic load in road cuts (line). The risk index referring to the number of persons potentially in danger in danger (resulting from the combination of both probabilities of submersion and traffic load) is illustrated by the dotted line.

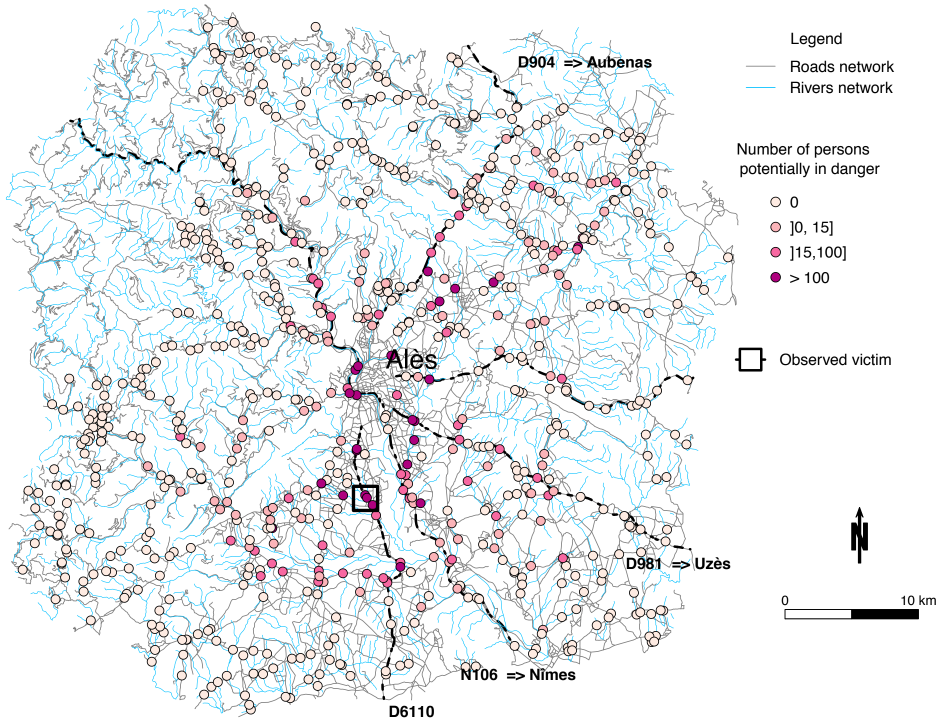

Figure 14 Spatial distribution of risk index representing the potential number of persons significantly in danger of submersion in road cuts during the event period. The location of past victim (black square) corresponds to a road cut with a high risk index.

Table 5: Motorists' exposure mean and standard deviation per socio-demographic characteristics. The bold numbers refer to the most exposed groups by variable.

Variables	Groups	Exposure (mean)	Exposure (Standard deviation)
Gender	Male	**0.18**	0.31
	Female	0.15	0.34
Age	< 18 years old	0.14	0.30
	18 - 29 years old	0.21	0.36
	30 - 45 years old	**0.23**	0.37
	46 - 60 years old	0.20	0.35
	> 60 years old	0.11	0.26
Profession	Farmers	0.16	0.32
	Shop or business owners	0.21	0.36
	Managers and academics	**0.28**	0.40
	Manual laborers	**0.27**	0.39
	Administrative, Sales or Service Occupations	**0.27**	0.39
	Technicians	0.22	0.36
	Retired	0.10	0.25
	Unemployed	0.13	0.29
Professional status	Working	**0.28**	0.39
	Student	**0.22**	0.36
	Retired	0.10	0.25
	Unemployed	0.10	0.26
	House wife/husband	0.09	0.25
	Other situation	0.12	0.26

Table 6: Results of Analysis of Variance (ANOVA) for testing the effect of socio-demographic variables on individual submersion risk. Formulas to calculate *F* and *p-value* are provided in Anderson (2001).

Variables		p-value
Gender	$F(1, 32637) = 48.03$	0.00***
Age	$F(4, 32634) = 166.5$	0.00***
Professional status	$F(5, 32633) = 366.9$	0.00***
Profession	$F(7, 32631) = 174.6$	0.00***

* Significance level: $p < .1$; ** Significance level: $p < .05$; *** Significance level: $p < .01$.

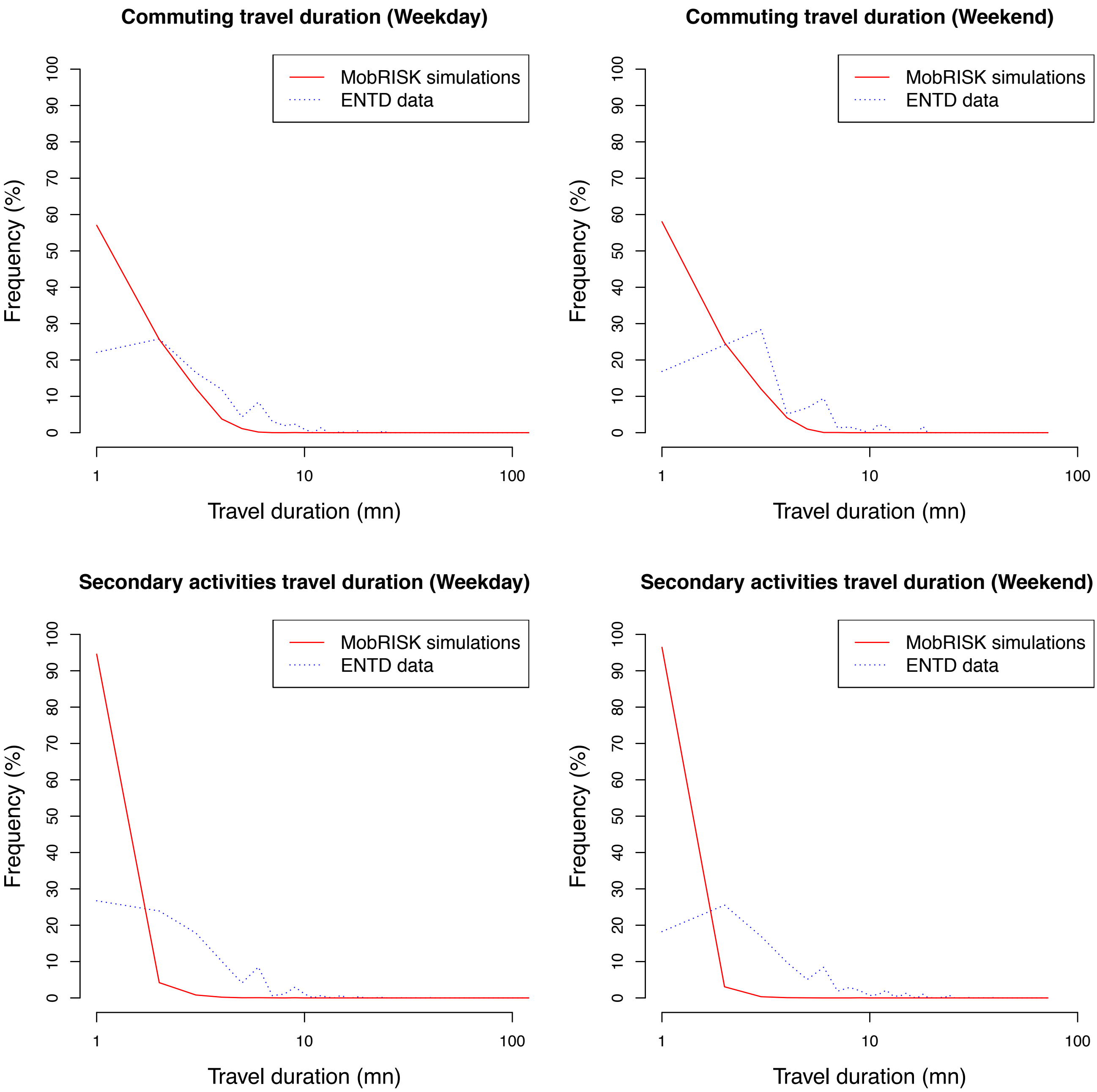

Figure 15: Comparison of travel duration distribution obtained from MobRISK simulations and ENTD data for a weekday and a weekend and corresponding to commuting and secondary activities trips (we presented only trips with duration less than 60 mn which represent more than 94% for all the cases).