Research article

# Assessing the knock-on effects of flooding on road transportation

Katya Pyatkova[a,*], Albert S. Chen[a], David Butler[a], Zoran Vojinović[b], Slobodan Djordjević[a]

[a] University of Exeter, Centre for Water Systems, North Park Road, Exeter, EX4 4QF, United Kingdom
[b] IHE Delft Institute for Water Education, Westvest 7, 2611 AX, Delft, Netherlands

A B S T R A C T

Flooding can affect every aspect of our lives and road transportation is not an exception. However, the interaction between floods and transportation was not investigated closely in the past. As transportation is the lifeline of any economy, it is essential to analyse potential dangers and threads that can lead to network capacity restraints. Considering the potential of flooding to affect large areas for long durations, disruptions to transportation can result in extensive knock-on effects. To examine how flooding can impact road transportation a novel methodology was developed into a software tool which integrates flood and traffic models. The flood is simulated with InfoWorks flood model and the traffic is represented by a detailed microscopic model (SUMO), which simulates individual vehicles and their interactions. Comparing normal (dry) traffic scenario with a flooded one yields the impacts of flooding on traffic (travelled distance and time, fuel consumption and $CO_2$ emissions, maps of speed changes on the roads). The results indicated that delays persist long after the perturbations of flooding have subsided and that durations of trip delays are extremely long in some cases whereas distance impacts are typically negligible. Major knock-on effects on the system indicated that even not flooded critical infrastructure should be considered in flood analysis, as their services may be indirectly impacted by the flood conditions. Although substantial, the impacts proved challenging to monetise as time delays are spread around many drivers and some trips (such as delay to a doctor's trip to the hospital) can have significant, but intangible consequences.

## 1. Introduction

The total number of flood events globally has been steadily increasing in the past century (Munich, 2017). Coping better with floods stems from an improved understanding of complex interactions between the hazard characteristics and the inherent vulnerabilities of the system. Flood conditions can result from complex interactions between different sources (coastal, pluvial, and fluvial) and causes (natural, operational, and social). In addition to the hazard complexity, floods can also lead to a variety of consequences. The impact of flooding is often classified according to the contact of a subject with the flood.

*Direct flood impacts* occur when the exposed element has physical contact with the flood water. One of the most prominent direct consequences of flooded roads is the high proportion of flood victims that lose their lives attempting to drive through the flooded waters. In the USA more than half of the flood victims perish in their vehicles with a staggering 70% in Texas (Sharif et al., 2015). Many factors play a role in the decision to drive through flooded waters but the most often reasons for risky behaviour ware not taking warnings seriously and the inability to predict vehicles' behaviour in the water (Drobot et al., 2007;

Haynes et al., 2017; Salvati et al., 2018). Such a considerable security concern should prompt drivers to avoid venturing into flooded waters and turn around to seek safe ways to reach their destinations. That behaviour though will put a strain on the transportation system.

*Indirect impacts* develop when the flood affects certain dynamics in the system although the receptors of the indirect impacts do not have physical contact with flood waters. These impacts typically evolve into a larger area and last for a longer period of time than the flood itself (Messner et al., 2007). Traffic delays due to congestion can be considered a lost opportunity, whereas the impact is distributed among many users using the transport system.

Several descriptive studies have assessed the consequences of past flood events on a road transport system. Department for Transport UK (2014) reported that one single day of flooding on the motorway network in the UK accounted for 2% of the annual delays in the whole country. Affleck and Gibbon (2015) described how a 15 min journey turned into a two-hour reroute after the collapse of several bridges in Workington. McDermott et al. (2017) assessed the cost of Storm Desmond to traffic disruption in Ireland to be € 3.8 million. These studies give confidence that flooding can be catastrophic for transportation
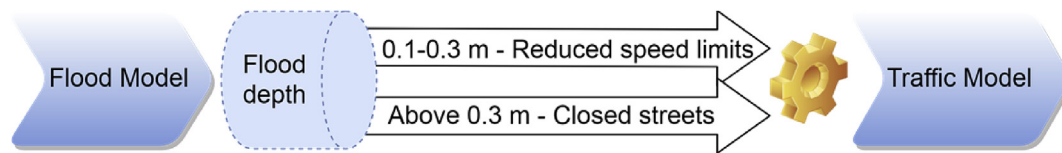
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**Fig. 1.** The general outline of the flood and traffic integration tool.



**Fig. 2.** Google Earth Pro image of Marbella.

systems and their users. However, potential flood impacts on traffic systems have not been studied in detail in the past. Suarez et al. (2005) concluded that climate change could potentially double both travel time and travel distance, whereas Chang et al. (2010) considered traffic delays to be a more significant consequence than the longer distance. It is intuitive to expect that the urban environment has many rerouting options, so the travel distance should not be increased as much as the travel delays due to congestion. Balijepalli and Oppong (2014) assessed the vulnerability and the robustness of the traffic system in York, UK. Nine roads were considered prone to flooding and were either closed for traffic or with reduced capacity. The vulnerability and robustness indices were calculated assuming each flooded street is independent. This rarely happens, because usually, flooding affects larger areas than just one street. However, the research identified the most vulnerable streets and also suggested that traffic delays are the most significant impact. All three studies employ a macroscopic traffic model, which only poorly represents congestion or diversions. Furthermore, the information about flood hazard in these studies is coarse with no representation of drainage system, which is essential for a correct spatial description of urban floods (Butler and Davies, 2011; Chen et al., 2007; Djordjevic et al., 2011).

Pregnolato et al. (2017) had a different approach to assessing impacts – they proposed a flood depth – speed reduction function after carrying out video analysis. They also compared traffic counter data between dry conditions and flood conditions in several locations in Newcastle. The traffic counts registered less traffic on the flooded roads although it was unclear whether the roads were blocked, or drivers chose to delay their journeys. The actual flood depth from the event was not recorded, therefore the study could not validate the proposed function with real data.

To avoid fatalities and financial loss, it is necessary to examine the flood conditions under which vehicles become uncontrollable. Vehicles' stability in flooded waters is becoming an increasingly relevant topic in the context of growing urbanisation and climate change. Smith et al. (2017) were tested full-scale vehicles' traction in varying static water. They used a small vehicle (Toyota Yaris) and a typical large 4WD

(Nissan Patrol). The use of a 4WD was justified by the increase of 4WD related fatalities in Australia (Haynes et al., 2017). The experiments confirmed the reduction of traction with deeper standing depths of water (Smith et al., 2017). The experiments showed that the Toyota Yaris completely floated at 0.6 m standing water depth, and the Nissan Patrol floated at 0.95 m. There is a consensus between most authors that the stability threshold for still water depth should be 0.3 m for small passenger and 0.5 m for 4WD (Martínez-Gomariz et al., 2017; Shand et al., 2011; Smith et al., 2017).

Previous research has outlined the potential problems of transport networks during flood events but has provided little on the issue of congestions and knock-on effects. By integrating a detailed flood model and a microscopic traffic model (SUMO; Krajzewicz et al., 2012), the research presented in this paper aims to develop a novel approach to simulate the phenomena of queueing due to flooding. This can give an insight into the behaviour of the traffic system under time-varying flood conditions/traffic supply reductions.

## 2. Materials and methods

### 2.1. Methodology

To capture the complex dynamics between floods and road transportation systems, full integration of flood and traffic models is carried out. The flood maps obtained from hydraulic modelling results are translated into timely traffic model inputs. The rationale is that flood severity (extent and depth) and its propagation over time govern the situation on the road (Pyatkova et al., 2019). To ensure a dynamic and comprehensive communication between both models, we have developed a consistent and homogeneous approach to combine the temporal variation of both flooding and network capacity. Fig. 1 describes the workflow of the integration tool – it performs one-way communication between the flood and the traffic models. Depending on flood depth, some roads will endure slower traffic and others must be closed for traffic. The criteria to distinguish shallow from deep waters is based on previously discussed research about stability thresholds of flooded

vehicles. To ensure consistency for all simulated vehicles in the network, 0.3 m is the minimum safety requirement that is applied as a criterion for street closures. Once a street is closed for traffic, the vehicles originally passing through the street are rerouted just before reaching the closure location by choosing the shortest path from their current location to their destinations. The rerouting process assumes that drivers have no initial information that a part of their route has been flooded. Their route diversion is made as they approach the link closure and then a new route is assigned based on the shortest path to their specific destination. Streets with shallow flood depth (less than 0.3 m) suffer a speed reduction of 20 km/h.

The interoperability of the previously described actions is ensured by a specifically designed Python tool[1] translating the spatially varying flood information into a transport model output. There are two ways of applying this framework – static and dynamic. The *static* integration uses one flood map with a global duration of flooding for all flooded roads. This method is rapid and straightforward, but unable to describe flood propagation. This type of integration could be sufficient for groundwater flood event that usually is prolonged and does not vary significantly over time, assuming that if a long-term event lasts several days, the spatial differences in duration may be insignificant and neglectable. The *dynamic* integration of flood and traffic models follows the same methodology as the static integration, but it is run in a loop multiple times using flood maps at different during an event. In that manner, the temporal variation of flood development is translated directly into road closures or speed reductions in the traffic model. This paper compares the results of static and dynamic integration for the same flood event.

Once the traffic model is run with the flooding information, the differences between the traffic model results under normal conditions and flooded conditions yield the actual flood impacts induced to a road network. The impacts on the transport system are expressed in speed maps, travel delays, additional travelled distance, additional fuel consumption and additional greenhouse gas emissions.

Accomplishing the integration of flood and transport models was the fundamental cornerstone of this research and it enabled interoperability between two models that have not been previously integrated. Consequently, it allows for a straightforward implementation of the methodology into different case studies or different transport scenarios. Although the tool is an achievement on its own, it does not answer research questions, but instead makes answers possible. It is important to note that the considered flood scenarios do not necessitate any evacuations and the paper focuses on how ordinary trips would be impacted by the flooded conditions.

### 2.2. Advantages of employing microsimulation technique

The most commonly used type of transport model is a macroscopic model that establishes a relationship between flow and concentration of vehicles on the road (Lighthill and Whitham, 1955). Compared to micro-simulation, a micro-simulation technique facilitates a more detailed representation of the traffic processes. Microscopic transport modelling simulates every single vehicle in the transport system. It is capable of modelling pedestrians, different transport modes and their driving behaviour. There are several reasons to adopt a micro-simulation technique for the assessment of flood impacts:

1) Rerouting
   - When a street is closed due to flooding, each vehicle will be rerouted individually, according to its destination. Hence, the rerouting algorithm ensures a detailed representation of the traffic condition during flooded conditions;
   - Microscopic traffic models can simulate the dynamics of the flood

propagation both spatially and temporally. For instance, depending on the flood severity, it can allow closure of only one lane, while keeping the traffic active in other lanes;
2) Congestion
   - Provides a comprehensive representation of congestions, because it models the interactions among vehicles rather than their concentration.
3) General traffic
   - The intermodal description of different vehicle types is essential for the overall consumption of fuel and greenhouse gas emissions. Different modes of transportation also indicate varying costs of travel delays and thus contributes to a realistic representation of fuel consumption and
   - As results are produced for individual vehicles, impacts on individual trips can be investigated.

This is essential for the computation of traffic delays because it enables the assessment of individual delays and the number of delayed vehicles.

The specific transport model used in this paper is SUMO (Simulation of Urban MObility) developed in the Institute of Transportation Systems at the German Aerospace Center (Krajzewicz et al., 2012). It is an open source model, which enabled access to scripts and various schemes. This facilitated the development of the flood-transport integration tool.

## 3. Application

The framework is applied in the Spanish city of Marbella. It is located on the Mediterranean coast to the south and Sierra Blanca piedmont to the north. Sierra Blanca piedmont reaches 1200 m, needing only 5 km stretch to the sea coast (Fig. 2). The mountain has vegetation, but rather than having dense forests, it is mainly covered by bushes and scattered trees (observation from Google Earth Pro). The steep slopes and the lack of thick forestation decrease the retention capacity of the region and are prerequisites for flash floods.

### 3.1. Flood model

The flood model results were provided by CetAqua (Spain) as a part of PEARL project collaboration, and the set-up of the flood model is described in PEARL (2017). InfoWorks 1D-2D model (Innovyze, 2016) was run with a design rainfall event of 1 in 100 year return period. The model was run on a territory, covering central Marbella and the upstream reaching the drainage divide in the mountain of Sierra Blanca piedmont. Thus, a significant amount of runoff in the city originated in the mountains. The analysis was based on one rain gauge and three water level sensors. The simulation was calibrated with the information of the flood event in 2016 – measurements and photos form flooded roads (PEARL, 2017). The model assumed that massive infrastructure like railway and motorways have independent drainage and thus are protected by vertical walls. This practically means that the motorway cannot be flooded. The produced flood maps were fed into the integration tool, which identified the streets with speed reduction or closure and wrote the input files for the traffic model. Fig. 3 depicts the variation of the number of flooded streets over time. A rather short rainfall event results in the quick development of a flood event – the peak of the rainfall event is almost immediately followed by a peak in the number of streets with deep flooding. It can be observed that after the peak of the rainfall, the number of streets with deep flooding is greater than the number of streets with shallow flood depth. That phenomenon can be explained by the hilly terrain in Marbella which contributes to fast accumulation of water in low-lying areas.

### 3.2. Traffic model

All traffic models consist of two main components – traffic supply and traffic demand. The traffic supply describes the capacity of the

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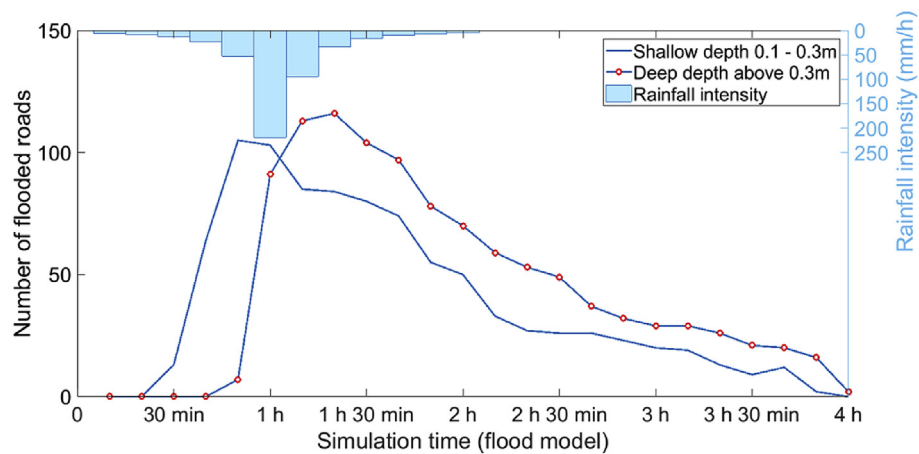[1] The developed Python tool is open-source and can be shared upon request.

**Fig. 3.** Variation of the number of flooded roads with shallow and deep flooding compared to the rainfall intensity (on top).
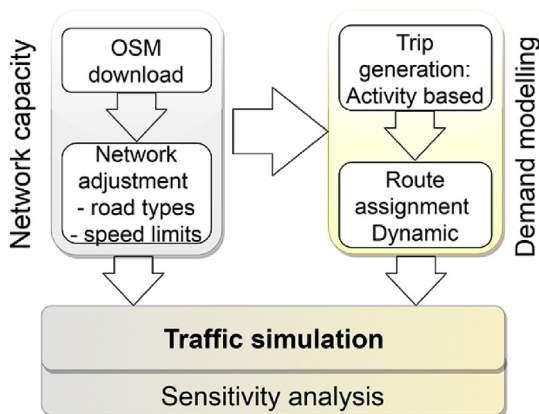


**Fig. 4.** Flowchart of the structure of the traffic model in Marbella.

infrastructure (road network and the rules to operate the traffic). The traffic demand represents the 'behaviour of consumers of transport services and facilities' (Ben-Akiva and Lerman, 1985). The road transport modelling simulates how these two components interact over time and space and Fig. 4 illustrates what the different elements of the model are and how they are integrated.

The road network was downloaded from OpenStreetMap (OSM)[2] and filtered in JOSM[3] to ensure that all streets, rules, permitted speed limits are up to date and correct. Generally, Marbella has a good transportation system, but this system is primarily affected by three factors. Firstly, the city is situated in a very hilly area such that the neighbourhoods are surrounded by hills and have very few connecting roads to the other parts of the city. Secondly, the city centre is pedestrian, and large areas of the city are not accessible by car. The city centre also floods, which complicates choosing alternative routes. Thirdly, the large number of one-directional roads limits the options of rerouting, just because drivers may not be allowed to make a U-turn before the flooded section of a road.

The trip definition is central to traffic demand modelling. A trip is defined with beginning time, starting position (origin) and end position (destination). With a microscopic modelling technique, the trips must be computed for each vehicle in the network. To compensate for the lack of traffic demand data, an activity-based traffic demand model was set to predict the attributes of trips (purpose, origin, destination and timing) based on detailed statistical and specific spatial data. A central presumption of this model was that people travel to satisfy a particular

purpose or activity, e.g. going to work, school, shopping, meeting up with friends. The model computed synthetic traffic demand according to demographic statistics for the population of a specific area. The statistical input was both general (for the whole case study domain) and specific (with information about precise locations in the city). The model populated virtual households and residents to assign them jobs depending on each person's age and employability. Automobiles were associated with adults depending on the car ownership rate. In this manner, a household can have one, two or no cars available for transportation. Some, but not all bus lines were added to the model and residents might opt to use public transportation, if there were stops in the vicinity of their residence or work positions. The drivers may need to pass via certain roads to drop off children or family members and the additional stops are also specified in the trips file.

After the trips were defined, a route assignment model computed the most likely routes to connect origins and destinations. This model was represented by a dynamic user equilibrium and was run 50 times iteratively to minimize the cost function of travel time for each trip and each vehicle. Thus, the travel times of vehicles were computed as interacting participants of the travel system, rather than assuming they were travelling in isolation. The main hypothesis in this approach was that drivers have a perfect knowledge of the traffic system, which can be expected for commuter traffic.

The air quality due to transportation was assessed after integrating a separate model into the traffic simulation. HBEFA 3 (Handbook of Emission Factors for Road Transport) models the fuel consumption and emissions per vehicle depending on the movement of vehicles and emission maps (Hausberger et al., 2009). These were computed using a database of emissions of different vehicle types in different driving situations. The applied emissions model HBEFA 3 adopted emissions data valid before the Volkswagen emissions scandal enfolded in 2015 and its emissions of $NO_x$ were not updated according to the new and more realistic expectations of diesel engine emissions.

According to EUROSTAT (2016) in Spain, the total share of diesel passenger vehicles was 57%, so it was assumed that the same proportion is valid for Marbella. Considering the tendency of wealthy people to purchase SUVs, most likely the diesel engine cars' share in Marbella can be above average. However, the traffic model was consistent with the average data in Spain. All 300 modelled busses were diesel vehicles.

Due to the lack of traffic counts data, the model could be validated with Google traffic maps of the typical traffic for different hours of the day (Fig. 5). The validation of the activity-based model is achieved by visually comparing model results with Google maps traffic data for typical traffic. Google has not disclosed officially how their traffic prediction works or what exactly the used colour coding means. It is very likely that Google Traffic is recording traffic data anonymously and averaging the results for different periods of the day for each

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[2] https://www.openstreetmap.org/.
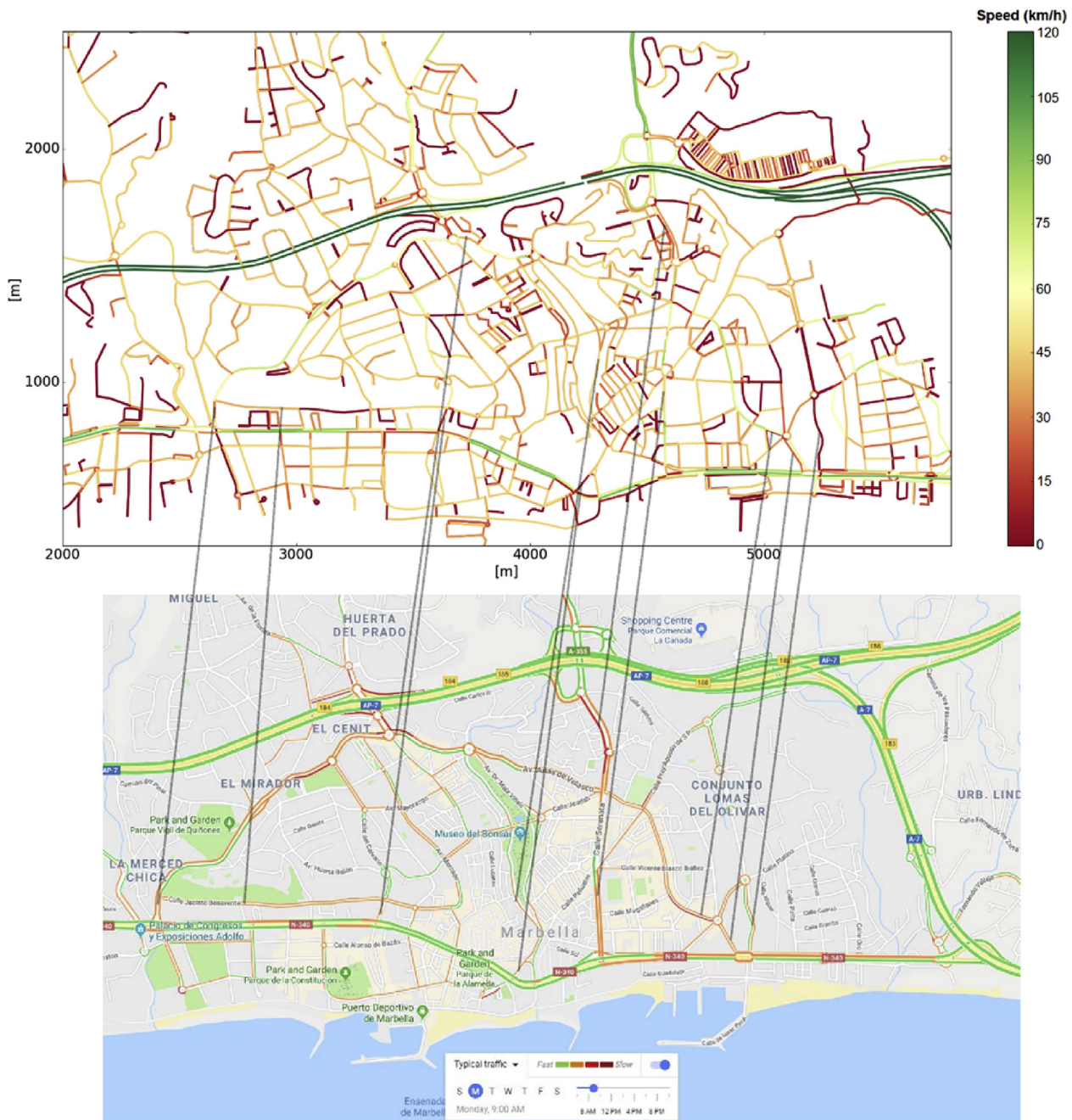[3] https://josm.openstreetmap.de/.

**Fig. 5.** Model results for average traffic speeds between 9 and 10 a.m. (top) and Google Traffic image of typical traffic intensities on a Monday morning at 9 a.m. (bottom). The lines are connecting the approximately the same locations between the maps.

section of the road. The lack of calibration brings concerns about the model accuracy and its potential inherent uncertainties in the next stages of the model integration with food locations. However, the traffic model showed high accuracy in capturing traffic trends in the transportation system (such as identifying the locations of the roads with congestion).

## 4. Results and discussion

In the past, integration of flooding and traffic models have been done statically. However, this research advances the field by integrating flooding and traffic models dynamically. In the following two sections, we use the same data and compare the more standard static approach in Section 4.1 with our novel dynamic approach in 4.2. Section 4.1 attempts to make the best possible use of static model integration while

also pointing out its weaknesses. We then move on to demonstrate in Section 4.2 the more realistic and in-depth conclusions available through the dynamic integration of flooding and traffic models.

### 4.1. Static integration

To address the flood impacts on transportation, first a static flood scenario is considered, and consequently, it will be compared to a dynamic flood scenario. Initially, the tool was run with static flood conditions, using a maximum flood depth map for a 1 in 100 year return period of design rainfall (hyetograph showed in Fig. 8). In other words, the flood was represented in the model by only one flood map with a fixed duration specified for the whole network. In an urban setting, the surface runoff is essential for the description of flooding on the road. The most recent integration of the two models by Chang et al. (2010)
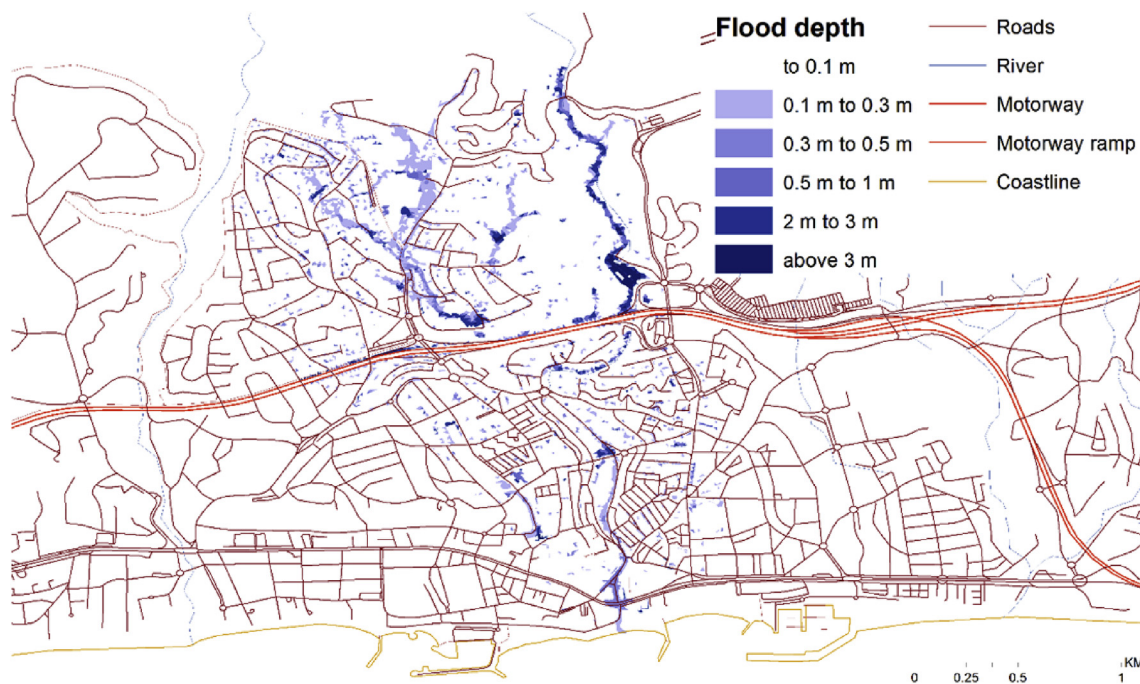
**Fig. 6.** Map of the road network in Marbella and the location of the maximum flood depth for the event with 100 years return period.
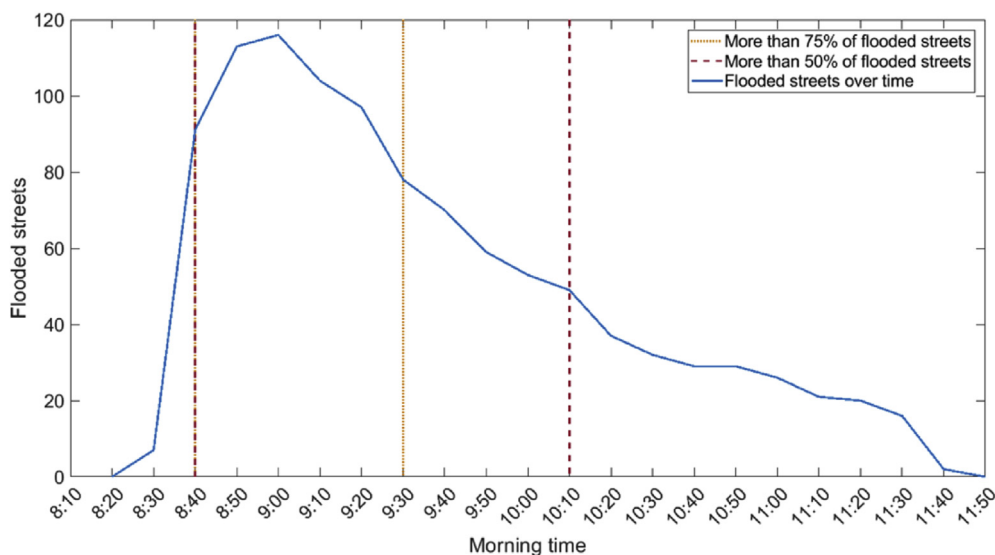


**Fig. 7.** Number of flooded streets with a flood depth deeper than 0.3 m and the duration and intensity of the rainfall event, integrated into the flood model.

modelled channel flow discharge necessary to close a bridge. So, it focused on very localised flooding, rather than a whole catchment. Fig. 6 shows the road network overlaid with the maximum flood depth and illustrates the location of the flooded area in the heart of the transportation network. The flood-traffic integration tool utilised the flood map as an input to determine which roads to be closed and which will undergo speed reductions (see Fig. 7).

The flood-traffic integration tool identified 142 roads (5.9% of the total number of roads in the traffic network), as listed in Table 1, to be closed for traffic and further 90 roads (3.7% of the total traffic network) to suffer slower traffic. Considering that the area of the flood model in less than a third of the area of the traffic model, 10% of affected roads is a noticeable figure. However, in traffic, the proportions of flooded streets are not that crucial as the locations and the capacities of these

**Table 1**
Number and length of streets with deep and shallow flooding. The deep flooding (above 0.3 m) will lead to a street closure, and the shallow flooding (0.1–0.3 m) will lead to slower movement of the traffic.

| | Number of streets (−) | Proportion to the whole network | Length of streets (m) | Proportion to the overall length of the network |
|---|---|---|---|---|
| Streets with deep flooding | 142 | 5.9% | 19,436 | 8.7% |
| Streets with shallow flood | 90 | 3.7% | 8509 | 3.8% |

The duration of the flood event was derived from information about flood propagation.

roads. As illustrated in Fig. 6, the city centre of Marbella is profoundly affected by the flood. Due to the nature of a coastal city, Marbella's traffic network has an oval shape that is additionally pressed by the hilly areas on the North. Therefore, a flood in the city centre may divide the city into two isolated islands and make the whole system fragmented and inflexible.

Employing static integration means simultaneous closures of all of the flooded streets. Determining the duration of the flood-induced closures in the traffic model is essential on this stage. As a matter of fact, the maximum flood depth map may not co-occur during the flood propagation, and therefore it is challenging to select a representative duration of the event. Moreover, if the selected interval of time is too long, it would overrepresent the maximum flood depth map. On the other hand, there is a risk of underrepresenting the flood event.

Fig. 7 shows that the number of flooded streets increased very rapidly from 8:20 a.m., and it peaks between 8:50 and 9:00 a.m. and then gradually decreased. The maximum number of simultaneously flooded streets was 116, and the duration of the event was derived based on that value. The maximum flood depth represented the worst condition that could be described only by the peak. However, the total duration of the flooding is 3 h and 10 min, and it must not be misrepresented. A simple approach was applied to determine the event duration. If the number of flooded streets is more than a certain threshold, that time segment qualifies to represent the flood duration. Two thresholds were applied in the flood model – 50% and 75% of the maximum simultaneously flooded streets. With a 50% threshold of flooded streets, the flood duration was 90 min, whereas if the 75% threshold is selected the period of the flood was just 50 min (Fig. 7). After the end of the flood, the roads that were previously flooded have speed reductions in the traffic model for 30 min. This is a way to overcome the binary conditions of flood/no-flood situation in the static integration.

The traffic conditions were simulated with flood duration of 50 min and 1 h 30 min. Fig. 8 depicts the differences between the two simulation results, compared to the dry weather traffic scenario. Until 9:20 a.m. the results of both flooded simulations overlapped. They registered a considerable increase in the number of vehicles before 9:00 a.m. and remained relatively constant instead of decreasing. The constant number of vehicles in the network corresponds to the drop in traffic demand after 9:00 a.m., and it means that the system was still assimilating the previous surge in vehicles. Both simulations did not recover between the two demand peaks which means that many vehicles due to start work at 9:00 a.m. were still circulating by 9:30 a.m. And this is where the two simulations with different flood durations diverge significantly. The number of vehicles in the short flooding simulation remained almost constant for the next 20 min after the flooded streets were open for traffic and started decreasing gradually until it returned

to normal conditions values at around 11:20 a.m.

When the second demand peak started, the long-duration flood simulation was already severely congested, and the number of vehicles continued to increase. Consequently, at 10:00 a.m. the number of vehicles in the flooded traffic system was seven times greater than in the normal conditions. Even after the capacity constraints were removed, the number of vehicles remained almost constant for about 5 min and started decreasing steadily until it returned back to normal at 11:05 a.m. The two simulations with different flood durations exhibited one similarity – in both cases, the system took an hour to fully recover after the flooded streets were open for traffic.

Tables 2 and 3 present changes in travel distance and time delays for 90 and 50 min flood events, respectively. The additional travel distance rose with only 6–11%, whereas the overall travel time increased by 250–400%. The sharp increase in trip duration confirms previous studies' observations that transport disruptions in an urban environment are more prominent for travel delays than additional travel distance. The difference between travel time and travel distance increase is sure evidence of thorough gridlock in the whole transport system, and this is valid for both modelled durations of the flood event. The monetary expression of the travel delays follows the methodology of HEATCO (2006) and resulted in an average value of travel delays per hour per person in Spain for 2018 to be € 29.01.

Although there was high confidence in the way the transportation model simulated the flood conditions, there was ambiguity in the way the flood was represented in the system. The main concern is related to identifying the duration of flood event when using a single flood depth map. The use of maximum flood depth maps has become a norm when assessing flood impacts on build environment to determine the worst damage on a property level. When analysing the interactions between two highly dynamic systems, such as flooding and transport, it is necessary to acquire information about the development of the flood. Such information can be depicted in one map only if that flood has a very slow development and prolonged duration (for example, Somerset levels flood 2014; Thorne, 2014).

The presented results were based on a relatively arbitrary principle to identify the flood duration – by selecting a time segment which had more than 50 or 75% of the maximum flooded streets. As the flood depth was a map of maximums, interpreting the condition as the duration of the peak might lead to misrepresenting the event. For a transport model, flooding should not be illustrated as a binary problem that can be addressed with a start and stop of a single flood map. And so, one can argue that the discussed results with different closure duration can be equally right or wrong. However, the maps of the speed changes did indicate a certain pattern and potentially pointed out vulnerable locations in the transport network. Previous research
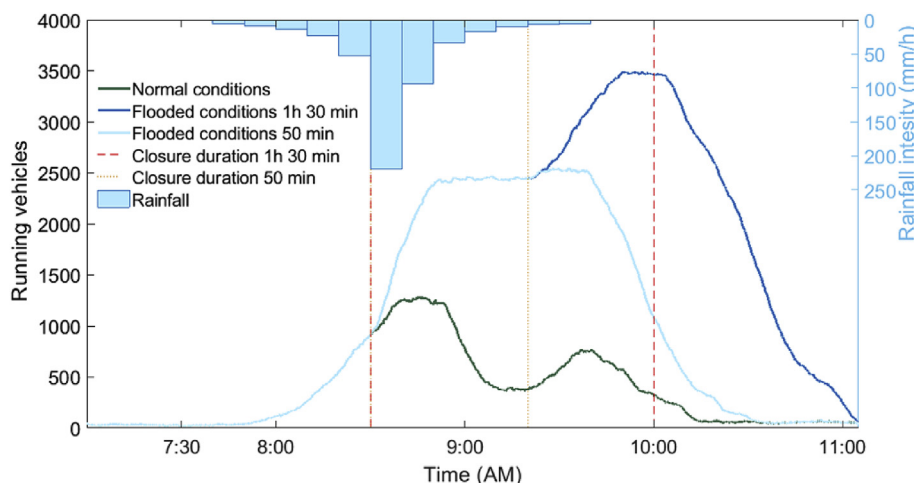


**Fig. 8.** Vehicles numbers in normal vs static flood conditions.

**Table 2**
Flood induced changes in travel distance.

| Travelled distance | Dry conditions | Flooded conditions 90 min | Flooded conditions 50 min |
|---|---|---|---|
| Sum (km) | 65,764 | 73,274 | 69,597 |
| Absolute difference (km) | | 7510 | 3833 |
| Relative increase (%) | | 111 | 106 |

**Table 3**
Flood induced changes in travel time.

| Trip duration | Dry conditions | Flooded conditions 90 min | Flooded conditions 50 min |
|---|---|---|---|
| Sum (hours) | 1527 | 5986 | 3828 |
| Absolute difference (hours) | | 4459 | 2301 |
| Relative increase (%) | | 392 | 251 |
| Cost of delays (€) | | 129,356 | 66,752 |

integrating flood results and transport models did employ a static flood map to describe the flood event (Suarez et al., 2005; Chang et al., 2010). This paper argues that this method is not sufficient to represent how does flood dynamics affect traffic because the sequence of street closures, corresponding to the flood development, is crucial for the transport model. The next section describes how flooding would impact traffic if a dynamic integration between the flood and the traffic model is implemented.

### 4.2. Dynamic integration

The dynamic integration of flood and transport models was designed to represent the flood dynamics and influence in the traffic simulations. With that intention, the traffic model was updated with flood propagation information every 10 min. The total simulated flood duration was 3 h and 20 min, and so the flood-transportation tool was run iteratively 20 times to provide a temporal and spatial variation of both street closures and speed reductions. The rerouters expressed the direct impact of flooding on the traffic network so that vehicles passing by a flood would need to choose alternative routes. Therefore, the number of cars that were rerouted can be considered as the initial perturbation in the system. Fig. 9 presents the change of rerouted vehicles over time. This change is a direct consequence of both the number of street closures and the changes in traffic demand. It should be noted, that the spatial dimension of street closures is also crucial for the number of rerouters. For example, at the beginning of the flooding, around 8:30 a.m., the demand was considerable, but the closed streets were localised only in the upper catchment and did not affect many trips. The flooding in the main road consequently led to an increase in

rerouted vehicles. The maximum street closure (at 9:00 a.m.) affected only around 200 vehicles, due to rapid changes in traffic demand in that part of the day. Therefore, the number of closed streets did not translate directly in the number of affected vehicles.

To investigate how the flood propagation impacts the transportation system, few parameters are examined – travelled distance, travel duration, waiting time, fuel consumption $CO_2$, $NO_x$, $PM_x$ emissions. The differences between the normal conditions and the flooded conditions yield the actual impacts. Average values for the whole simulation and hourly averages are considered to depict both the global consequences and their temporal variation. To assess and compare the hourly traffic, vehicles were selected based on the starting time of their trip in the normal weather conditions. The reasoning behind is that sometimes due to depart delays the same vehicles might start their journeys at different hourly intervals. The hourly statistics of vehicle journeys may not fully represent the actual traffic conditions in the particular time segment. This logic of such a comparison was to ensure all vehicles' trips were analyzed and examined from a temporal perspective.

#### 4.2.1. Travel distance

The travelled distance is the most commonly discussed impact of an interrupted transport system because it does not necessarily require a traffic model and can be assessed based on the assumptions about the road network. In a dense urban environment, the additional travel distance may not be very significant because many alternatives are available. However, flooding might lead up to multiple closures in the same area that can potentially fragment a network and make reroutes longer. Table 4 shows the main statistics with regards to the travelled distance in the morning hourly time segments. If we compare the proportion of rerouted vehicles to the proportion of vehicles that had longer routes, it can be observed that rerouting does not necessarily mean travelling longer distances. Between 10:00 and 11:00 a.m. half of the rerouted vehicles registered longer routes. As the route selection was based on travel time rather than distance, it is possible that some vehicles might reduce their travel distance after a change in their route. Another reason could be that if a vehicle is stuck in a traffic jam, by the time, it reaches the flooded road, the road could be open for traffic again.

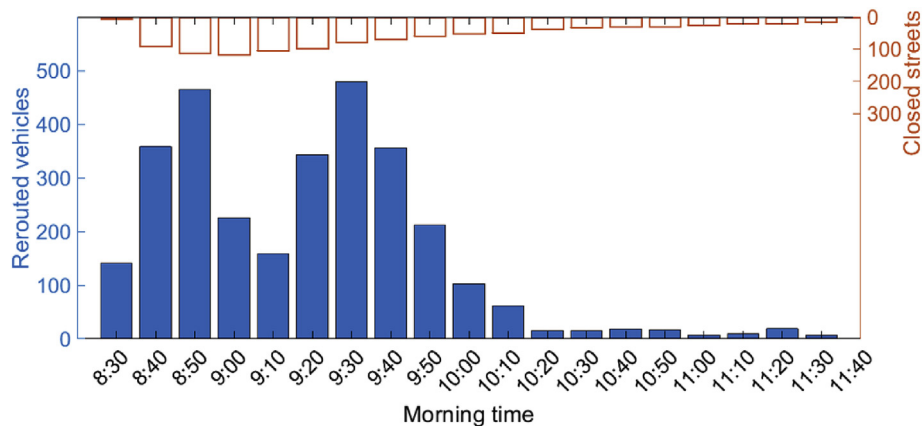Another reason for the discrepancy between the rerouted vehicles



**Fig. 9.** The number of closed streets force the rerouted vehicles in a non-linear way due to changes in traffic demand over time.

**Table 4**
Flood impact on travelled distance.

| Travelled Distance | 8–9 AM | 9–10 a.m. | 10–11 a.m. | 11–12 a.m. | Overall |
|---|---|---|---|---|---|
| Number of vehicles | 7345 | 5238 | 963 | 890 | 14,434 |
| Normal (km) | 32,348 | 22,946 | 3495 | 3118 | 61,903 |
| Flooded conditions (km) | 34,056 | 24,340 | 3543 | 3151 | 65,087 |
| Difference (km) | 1708 | 13,945 | 48 | 33 | 3184 |
| Change (%) | 5.3 | 6.1 | 1.4 | 1.1 | 5.1 |
| Vehicles with longer routes (%) | 11.6 | 19.6 | 10.0 | 5.5 | 14.0 |
| Rerouted vehicles (%) | 14.1 | 34.2 | 20.2 | 5.8 | 21.3 |

and the ones travelling longer distances is related to the way the re-routing mechanism works. If there are no available options to reroute (i.e., no turns on a section of the road), vehicles that are supposed to reroute merely disregard the rerouters and continue on the blocked road. Locations of this behaviour were identified and manually corrected. Disregarding rerouters could occur during the simulation, but the results showed that such cases are unlikely to alter statistics significantly. The additional travelled distance (5.3%) did not rise proportionally with the number of rerouted vehicles (14.1%).

### 4.2.2. Travel time

Several aspects of travel delays must be addressed to understand the differences between the normal and the flooded simulations. A critical element to consider is how to define a delay. The most straightforward answer would be that a delay is registered for a vehicle whenever the flooded simulation has a longer trip than the normal one. However, it is sensible to set up a threshold that defines under what circumstances a trip is delayed. The threshold of travel delays may be determined as a constant value unit or a proportionate value. As Marbella is a small city with short distances and durations of most trips, the proportionate threshold was deemed more appropriate. The discussed statistics consider delays of 10%, 20% and 50% of the original travel time under normal conditions (Table 5). The 50% increase in travel time was not proposed as a threshold, but as a statistic that describes the system.

Depending on the selected threshold for a delay the proportions of delayed vehicles differ, but all keep the same tendency to register the most significant proportion of delayed vehicles between 9:00 and 10:00 a.m. – ranging from 30 to 50% (10% and 20% duration increase threshold). That threshold also determines the average delay of the affected vehicles as a percentage change of individual original trip duration. If a threshold for a delay is 20% increase in trip duration, 25% of the vehicles will experience a two-fold increase in travel time. Similarly, the overall results register 10% of vehicles with delays of more than 50% of their original route duration, and on average these vehicles suffer 300% travel time increase.

The overall trip duration difference between the normal and flooded conditions is 27%, and this is estimated as the difference between the sum of all the trips in both simulations. It is important to underline that although most vehicles suffer from traffic delays, some travel quicker than usual. Roads immediately after the road closure have reduced traffic volumes, and vehicles travel faster. Summing all trips in a system may not be the most appropriate approach, because early trips cannot compensate for individual journey delays. In fact, some authors (HEATCO, 2006) argue that traffic delays, as well as time gains, can equally be regarded as a loss of business time.

### 4.2.3. Fuel consumptions and greenhouse gas emissions

Congestion can have a negative impact on the air quality and efficiency of fuel consumption. The values were evaluated on hourly segments for the whole transportation network. The flood impact on the transport system was again estimated as the difference between normal and flooded conditions. Fig. 10 compares the average hourly change in the most characteristic parameters of the system. Regardless of the threshold for the delay, the percentage of delayed vehicles is not only the most distinctive flood impact but also remains relatively constant over time. Even between 11:00 and 12:00 a.m., when the flood was receding, and many roads were open for traffic, around 30–60% of the vehicles were still delayed. The number of rerouted vehicles and respectively the extra travelled distance was the highest between 9:00 and 10:00 a.m., but the knock-on effect on the whole system sustained the negative impacts to continue evolving in the next time segment with fuel consumption, $CO_2$ and $NO_x$ registering maximums between 10:00 and 11:00 a.m.

### 4.2.4. Flood impacts on trips to and from the hospital

The hospital in Marbella is not located in the flooded areas (Fig. 11), but it is accessed through one of the main roads that flood less than a kilometre away from the hospital. If vehicles are approaching the hospital from the western part of the city, they might need to undergo complicated detours to reach the hospital. The hospital is incorporated
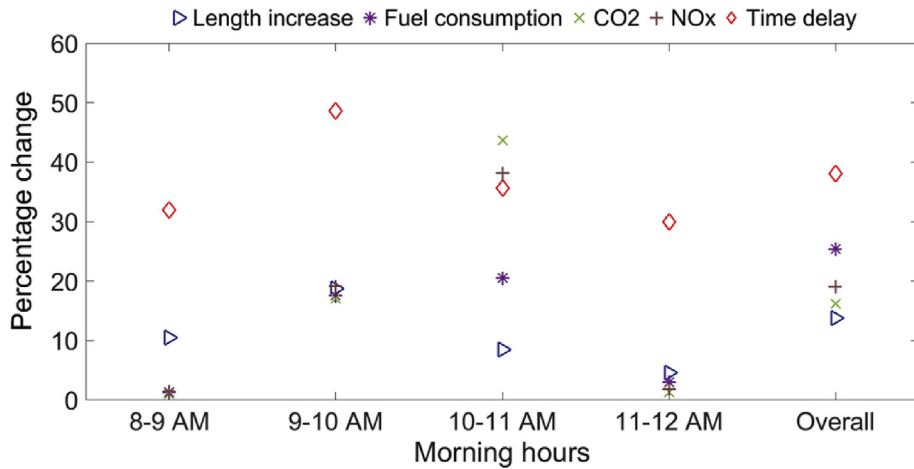
**Table 5**
Flood Impact on travel time.

| Travelled Time | 8–9 AM | 9–10 a.m. | 10–11 a.m. | 11–12 a.m. | Overall |
|---|---|---|---|---|---|
| Number of vehicles | 7345 | 5238 | 963 | 890 | 14,434 |
| Normal (h) | 829.0 | 491.0 | 73.7 | 59.9 | 1456.6 |
| Flooded conditions (h) | 1068.1 | 582.2 | 80.9 | 65.0 | 1851.3 |
| Difference (h) | 239.1 | 91.2 | 7.1 | 5.1 | 394.7 |
| Change in duration (%) | 28.8 | 29.0 | 9.7 | 8.6 | 27.1 |
| Proportion of vehicles with **10%** delay | 32.0 | 48.6 | 35.7 | 29.9 | 38.1 |
| Average Delay/Journey time (%) | 106.4 | 67.9 | 30.9 | 29.2 | 80.1 |
| No change vehicles (%) | 48.6 | 47.8 | 61.9 | 69.7 | 55.6 |
| Proportion of vehicles with **20%** delay | 21.2 | 33.5 | 19.7 | 14.9 | 25.6 |
| Average Delay/Journey time (%) | 153.0 | 91.8 | 44.3 | 41.3 | 113.5 |
| No change vehicles (%) | 75.5 | 65.0 | 78.9 | 84.7 | 72.4 |
| Proportion of vehicles with **50%** delay | 9.7 | 12.7 | 5.0 | 3.4 | 10.0 |
| Average Delay/Journey time (%) | 299.6 | 191.2 | 85.0 | 78.5 | 238.4 |

**Fig. 10.** Average hourly percentage changes between normal and flooded conditions for different parameters. The various thresholds of time delay (10% threshold) are shown with a diamond.

in the traffic model as an employer and is attracting twice as many trips as it is releasing. The total number of trips going to and from the hospital was 499, which was 3.5% of the total number of trips during the simulation. The vehicles travelling to and from the hospital are not emergency vehicles, because the transport model could not differentiate special access conditions on closed streets. Therefore, instead of modelling ambulances, the model simulates trips to the hospital from personnel or patients.

Table 6 presents the average values of base parameters for hospital trips and the overall simulation, and the impact of flooding on the trips to the hospital was more severe than on average in every aspect. More than 50% of the trips to and from the hospital were rerouted which is significantly higher than the 21% for the whole simulation. Most likely the higher proportion of vehicles being rerouted was due to the hospitals' accessibility being impeded from the flood. Having a low increase in travelled distance and a significant increase in travel time is

**Table 6**

Comparison between average parameters of the vehicles going to and from the hospital and simulation averages. The percentage changes are computed per vehicle under normal and flooded conditions.

|  | Hospital (to and from) | Simulation average |
|---|---|---|
| Rerouted Vehicles (%) | 53.9 | 21.3 |
| Trip Length Increase (%) | 5.9 | 5.1 |
| Trip Duration Increase (%) | 57.3 | 27.1 |

sure evidence for the presence of severe congestion in the system. The major knock-on effects on the system indicated that even not flooded critical infrastructure should be considered in flood analysis, as their services may be indirectly impacted by the flood conditions.

Table 7 shows how different thresholds of delay can interpret the situation in the traffic model. Regardless of the threshold, the trip to the
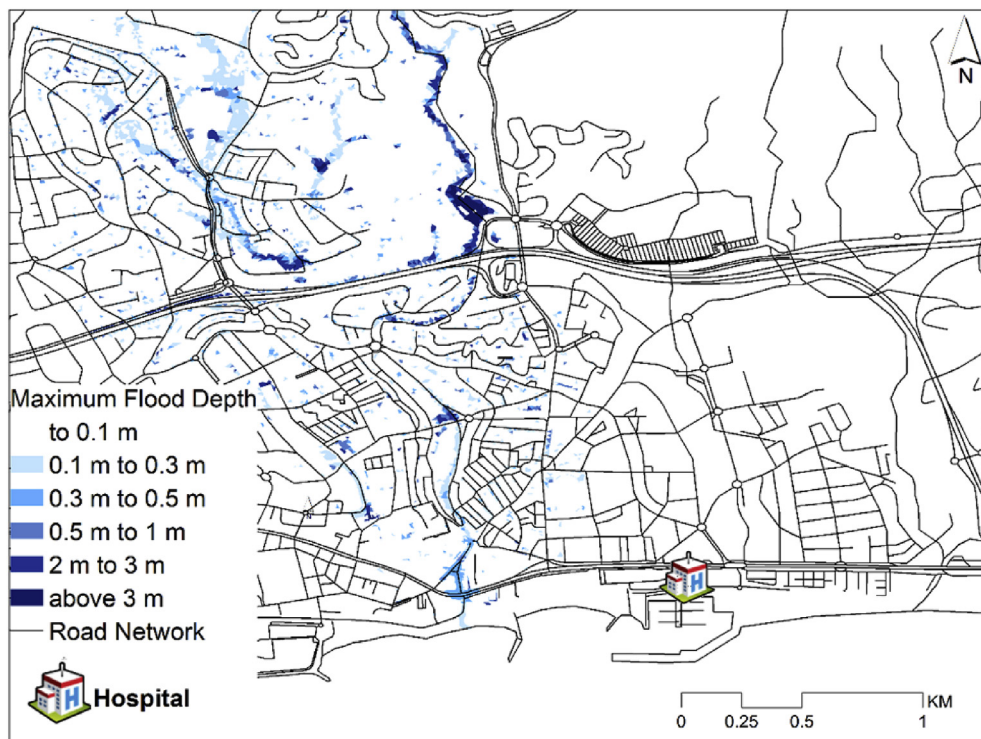


**Fig. 11.** Location of the hospital and the flooded areas in the city.

**Table 7**
Proportion of delayed vehicles and their respective average delay according to different thresholds defining a delay.

| Threshold | Proportion of affected vehicles | | Average delay duration | |
|---|---|---|---|---|
| | Hospital | Simulation average | Hospital | Simulation average |
| 10% | 42.3 | 38.1 | 167.7 | 80.1 |
| 20% | 35.4 | 25.6 | 213.6 | 113.5 |
| 50% | 16.8 | 10.0 | 387.3 | 238.4 |

hospital was slightly more likely to be delayed than any other trip. But when it comes to discussing the average delays, there are substantial discrepancies. Nearly 17% of these vehicles travelling to the hospital have increased their travel time five-fold. In general, the results indicate that there is around a 50% chance that a vehicle will encounter doubled travel times. This situation is detrimental for both patients and staff going to the hospital during a disaster event and can potentially have drastic consequences on the effectiveness of the emergency services.

*4.2.5. Road speed changes due to the flooding*

Except for the statistics of vehicles experience during the flood, the spatial variation of the flood impacts is critical for the understanding and management of the transport system. To achieve this, the traffic conditions on each street were aggregated for hourly intervals of time. As the primary goal was to identify and quantify the differences between the normal and the flooded conditions, the presented maps show the speed differences between the above two. The speed decrease means that for a particular road in the flooding conditions traffic was slower than for the same road in the standard conditions.

Fig. 12 is a map of the average speed differences between the normal and the flooded conditions and indicates the locations of roads that consistently received a speed reduction for the period of 8:00 to 12:00 a.m. These locations were marked with numbers 1–6 on the map, and it can be argued that these were the most vulnerable parts of the transport network. Numbers one and two were both associated with Av.

Ramón y Cajal, and they appeared before and after the flooded roads. It is important to note that the street was closed due to flooding for only 30 min, but the traffic disruption lasted 4 h with road segments being reduced with 40–75 km/h. Location 3 registers slow traffic under normal circumstances according to Google Maps Traffic (Fig. 5, p. 9) during flooding conditions the traffic problems were exacerbated for an extended period. The road was flooded for only 10 min between 8:40 and 9:50 a.m. and the traffic delays ware more likely to be associated mainly with the knock-on effects on the whole system rather than the localised flooding. Locations 4 and 5 are both ramps/sliproads from or to the motorway. Although the motorway shows no significant delays throughout the simulation, the sliproads to and from it had constant speed reductions. The speed decreases on location 6 were entirely related to the flooding that passes through that area. The flooded road was the best way to reach the rest of the city from that isolated by hills neighbourhood. The flood fragments parts of the network from the rest of the Marbella for 40 continuous minutes, and this is the most dangerous situation for the residents.

The knock-on effects of the restrictions in the network capacity resonate through the whole system, and they continue to evolve even after the system perturbation has seized. It is generally arduous to predict where the congestion will accumulate but several locations received consistently slower traffic throughout the simulation.

**5. Conclusions**

This research described an interdisciplinary approach to integrating flood and traffic models to assess the impact of flooding on an urban transportation network. The results suggest that congestion does not evolve proportionally with the reduction of traffic supply and the knock-on effect on the traffic system may be revealed with a delay. It is noteworthy that this research is not prescriptive about the system performance. However, its results captured trends and characteristics of flooded transport systems that were not described previously.

-Representing the flood characteristics in the traffic model has been an essential aspect of the research. The static integration of the flood
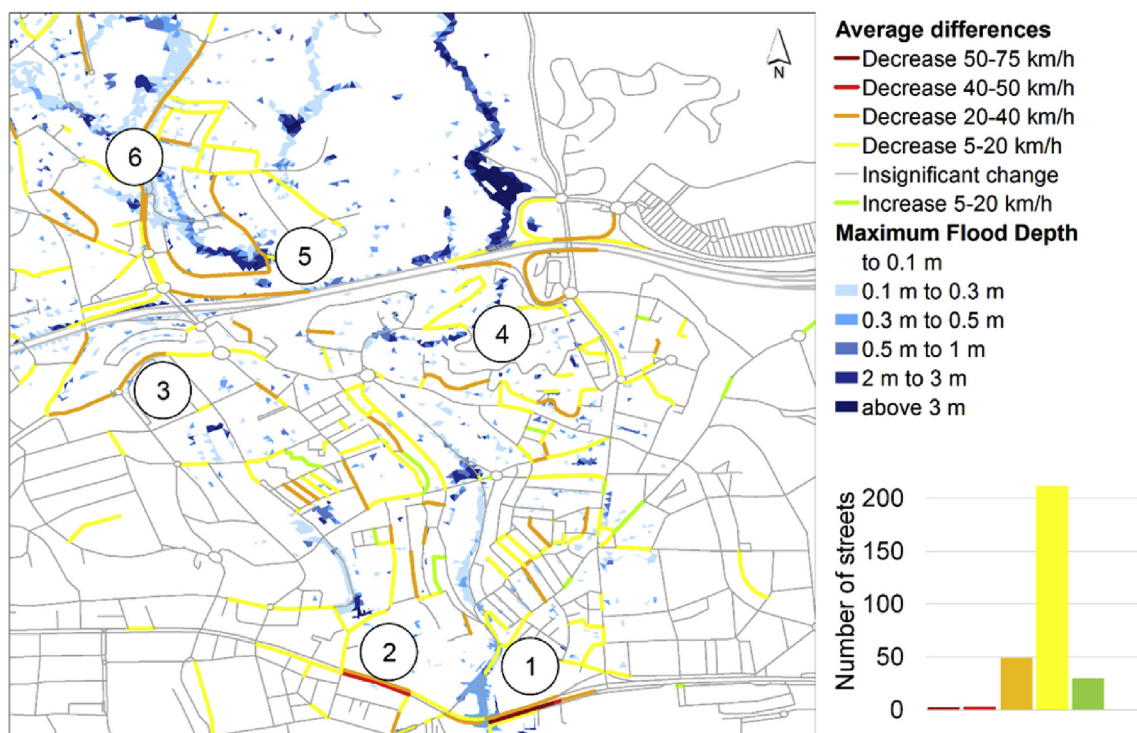


**Fig. 12.** Average speed changes between normal and flooded conditions between 8 a.m. and 12 a.m.

and traffic models gave only a binary representation of flooding and can be a satisfactory solution only if the flood develops very slowly and has a duration of several days. Since all previous research papers in that area have used such an approach to the problem, this paper also applied it as a method. The aim was to explore options to construct it as realistic as possible, but even in the 50 min flood propagation event, the results of additional travel time were around ten-fold more than in the dynamic integration. Perhaps the case study proved particularly difficult for static integration considering the long history of flash flood events. All things considered, the static integration of the models did not describe in depth the events that unfold while a transport system is flooded with a 100-year return period event. Therefore, it was deemed more appropriate the conclusions about flood impacts on road transportation to be based on the dynamically integrated flood and traffic models.

The flooded conditions cause severe disruptions to the transportation system. Here are some of the interesting findings of the research:

- The knock-on effect of the capacity reductions is overarching in both time and space. The locations of closed streets cannot be directly associated with areas of traffic disruptions, because traffic jam may accumulate far from the flooded areas.
- At the beginning of the flooding, the system was capable of absorbing the capacity restrictions until it reached a tipping point, after which it started deteriorating rapidly. Identifying and understanding this tipping point might be crucial for transport managers.
- Some roads will inevitably become faster in a situation of disruption. While some roads receive significantly higher traffic volumes, others, usually located immediately after closure, would have fewer vehicles. If these roads have one-way traffic, the latter can be even exacerbated.
- Even though it is difficult to predict where the system will struggle mostly, the results allow the identification of vulnerable locations that have experienced consistent speed reductions over time.
- The number of rerouted vehicles can be translated into some vehicles that travel extended distances, which can be defined as a direct consequence of the flood. As the number of delayed vehicles is two to three times more than the number of vehicles travelling longer distances, it gives additional confidence that the knock-on effects are essential for the assessment of the flood impacts on transportation.
- Thousands of drivers suffered delays during the 3 h flood event. The greenhouse gas emissions during the peak of flood event can increase by 40% per hour for $CO_2$ and $NO_x$.
- The long hospital delays are a good example of how indirect impacts can propagate in many levels in an urban environment. Therefore, it is essential to develop contingency plans involving critical services operations, even if the critical infrastructure may not be in direct risk of flooding.

The monetisation of the potential intangible impacts indicated they did not appear to be costly compared to other types of flood impacts (such as direct tangible damage). Nevertheless, that does not rule this research out as unimportant, because it highlights potential problems that sometimes can be addressed only with contingency planning. When considering intangible impacts, there are many aspects of the transport system that has to be focused on. For example, how to monetise a delayed trip of a doctor to the hospital, an ambulance struggling to reach emergencies on time, or the notion of frustration that the thousands of delayed drivers may experience. Therefore, indirect and intangible impacts must find their rightful place in ex-ante or post-event analysis. As these impacts may have substantial consequences but are hard to monetise, future developments in investigating how relatively inexpensive measures can increase the resilience of the transport system would be necessary to enhance urban crisis management. Therefore, various ex-ante mitigations or ex-post interventions can be

implemented to assess their influence on the transport system performance.

## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2019.05.013.

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