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# Impact of Climate Change on Disruption to Urban Transport Networks from Pluvial Flooding

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**Abstract:** Short-duration, high-intensity rainfall causes significant disruption to transport operations, and climate change is projected to increase the frequency and intensity of these events. Disruption costs of flooding are currently calculated using crude approaches. To support improved business cases for adapting urban infrastructure to climate change, this paper presents an integrated framework that couples simulations of flooding and transport to calculate the impacts of disruption. A function, constructed from a range of observational and experimental data sources, is used to relate flood depth to vehicle speed, which is more realistic than the typical approach of categorizing a road as either blocked or free flowing. The framework is demonstrated on Newcastle upon Tyne in the United Kingdom and shows that by the 2080s disruption across the city from a 1-in-50-year event could increase by 66%. A criticality index is developed and is shown to provide an effective metric to prioritize intervention options in the road network. In this case, just two adaptation interventions can reduce travel delays across the city by 32%. DOI: 10.1061/(ASCE)IS.1943-555X.0000372. This work is made available under the terms of the Creative Commons Attribution 4.0 International license, <http://creativecommons.org/licenses/by/4.0/>.

## Introduction

Floods and convective storms cause significant loss of life and economic damages. The total costs and insured losses from severe convective storms rose by an average annual rate of 9% between 1990 and 2014 (Swiss Re 2015). Cities are particularly vulnerable to such events due to the concentration of people, buildings, infrastructure, and associated impermeable surfaces. Climate change is expected to increase the frequency and intensity of convective rainfall events in many parts of the world (Kendon et al. 2012; IPCC 2014). Coupled with economic development, population growth, and a global trend toward living in urban areas, the impacts of urban flooding are expected to rise. Assessment of climate change impacts is especially important for urban planning because of the longevity of infrastructure (Koetse and Rietveld 2009; Jaroszweski et al. 2014). The availability of new data sets, high-resolution urban flood models, and increased computational power is enabling novel frameworks for advanced urban modeling to assist with such assessments (Jaroszweski et al. 2010; Batty 2013).

In response to a number of flood events over the last decade which caused significant damages and disruption to transport infrastructure, the U.K. government has committed more than £70 billion for improving transport infrastructure through a number of transport projects (Walker 2016). Moreover, *The Brown Review* of transport resilience from the U.K. Department for Transport (DoT 2014a) recommended that transport authorities develop approaches to assess and consider the full cost of disruption within network investment decisions.

This study presents an integrated framework to assess the cost of disruption to transport networks and the benefit of adaptation measures, under current and future rainfall climates. A case study in Newcastle upon Tyne (United Kingdom), where a 2012 flash flood provided important calibration data, is used to demonstrate the methodology. Following this introduction, the paper reviews the background and previous work before describing the methodology. Results from the case study are subsequently introduced before discussing implications for decision makers and setting out remaining challenges.

## Weather and Climate Change Impacts on Roads

Effective and reliable operation of urban transport systems is essential for a city's economic competitiveness and quality of life (Jaroszweski et al. 2010; Chen et al. 2016). Transport has been identified as particularly vulnerable to extreme weather and climate change (Hooper et al. 2014b). The cost of disruption due to flooding has been estimated at £100,000 per hour for each main road affected (Hooper et al. 2014a). Furthermore, roads are among the primary causes of flood-related deaths, as a result of vehicles being driven through flooded roadways (Drobot et al. 2007; Fitzgerald et al. 2010; Jonkman and Kelman 2005).

Road surfaces make up a significant proportion of the urban surface; in London it has been estimated that 8.5% of the surface area of the city is taken up by roads (Webb 2005), whereas on average in North American cities 30% of the urban surface is road (Rodrigue 2013). This is important because roads are typically constructed from impermeable materials and therefore are particularly

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susceptible to surface water flooding. Therefore, intense rainfall coupled with inadequate or poorly maintained local drainage systems can lead to the rapid onset of surface water flooding. This reduces their capacity, either directly as a result of damage rendering the road unusable or as a result of deep floodwater rendering the road impassable. Resultant congestion leads to increased travel times and pollution (Mao et al. 2012). Moreover, the impact of this disruption can extend far beyond the flood extent due to congestion propagating through the transport system (Dalziell and Nicholson 2001; Zio 2016) and into other infrastructure networks (Houghton et al. 2009; Fu et al. 2014). The Intergovernmental Panel on Climate Change (IPCC 2012, 2014) concluded that the frequency of heavy precipitation events is “very likely” to increase over most areas of the world through the 21st century, thereby compounding the challenge of ensuring reliable transport services.

Significant reviews by Peterson et al. (1998) and Jaroszewski et al. (2010) identified mechanisms by which climate change would impact transport networks. Experimental studies (e.g., Shu et al. 2011; Xia et al. 2011, 2014) have analyzed the stability of vehicles in the laboratory by considering the incipient motion velocity as a criterion of stability in flood conditions. Although these studies are based on static vehicles, they provide information used in the depth-disruption function developed for this study (Fig. 3).

Observational studies have investigated the impact of ice, snow, precipitation, and wind on accident frequency or traffic flow (Kyte et al. 2001; Agarwal et al. 2005; Koetse and Rietveld 2009; Jaroszewski et al. 2010; Hooper et al. 2014a; Tsapakis et al. 2013). Travel times are investigated for many weather-related phenomena, but although the impact of precipitation on driver visibility has been considered, the impact of flooding itself has not (Ibrahim and Hall 1994; Kyte et al. 2001; Stern et al. 2003; Chung 2012; Tsapakis et al. 2013). These studies typically have involved coarse categorization of conditions (e.g., either no rain or rain) and have focused on single road corridors. Where multiple categories have been identified (e.g., normal, light, heavy, or very heavy) vehicle speeds are reduced for worse weather. Although interesting, these studies therefore have insufficient granularity to inform climate adaptation decisions, and they do not identify any localized road flooding or relate vehicle speed to flood depth.

A few studies have investigated the impact of flooding in dynamic conditions. These have analyzed the likelihood of road closures or car accidents (Dalziell and Nicholson 2001; Andrey et al. 2003; Chung et al. 2005; Eisenberg 2004) as a result of severe weather, but not the subsequent impacts on vehicle speed and journey time. A number of studies have specifically looked at the impacts of climate change on urban transportation. This includes work by Suarez et al. (2005), who calculated that increased coastal and fluvial flooding would almost double delays and lost trips between 2000 and 2100, and work by Chang et al. (2010), who investigated the impact of increased road closures as a result of fluvial flooding in Portland, Oregon. These and other studies did not consider pluvial flooding and also assumed that a road was either open and running smoothly or closed completely.

A review of the literature has shown that a large proportion of transport disruptions are caused by climatological events, and changes in the climate are expected to further increase the probability of the occurrence and magnitude of such events. Jaroszewski et al. (2014) noted that there are limited studies that relate climate and transport studies, and this review has identified a significant gap in understanding pluvial flood impacts. Until recently, climate change models have been too coarse to assess the impacts of sub-hourly rainfall that is a key driver of pluvial flooding in cities, but Kendon et al. (2012) applied high-resolution models that represent convective processes, making assessment of future pluvial flood

risk more reliable. Observational studies have demonstrated a relationship between the magnitude of a weather hazard and scale of city-wide impact. Therefore to understand pluvial flood risk to transport disruption, and how this might change, requires a simulation approach to test a range of climatic events. Moreover, as recommended by Jongman et al. (2015), this must be able to assess the benefits and costs of adaptation options to manage flood risk.

## Case Study of Newcastle upon Tyne

The city of Newcastle upon Tyne in the United Kingdom was adopted as a case study. It is a city that is vulnerable to urban flooding, has a dense road network, and contains highly urbanized pockets of land that are almost entirely impervious. These issues are not unique to the city, and it could easily be adopted as a prototype for medium cities in the United Kingdom or other parts of the developed world for analyzing pluvial floods (Wright et al. 2014). A recent example of the risk posed to the city’s infrastructure occurred when a series of convective storms, known locally as *the Toon Monsoon* or *Thunder Thursday*, hit Newcastle on Thursday, June 28, 2012. Approximately 50 mm of rainfall fell in less than two hours, an estimated return period of 1 in 100 years, flooding 377 road links and leading to severe traffic congestion which lasted more than six hours (Newcastle City Council 2013). Although there was some direct damage to the road infrastructure and cars that broke down due to floodwater ingress, this only occurred in very deep floodwater. Photographic evidence of flooding was gathered to assist in calibration and validation of flood models (Fig. 1).

Hourly traffic flows on major road links are recorded by the Tyne and Wear Road Traffic and Accident Data Unit (TADU) by automatic traffic counters (ATCs) and stored in the traffic information database (TRADS). Previous studies and transport project appraisal (Dalziell and Nicholson 2001; Chang et al. 2010; Penning-Rowell et al. 2013) assumed that roads flooded below a depth threshold, typically 3–5 cm, are fully operational and become completely blocked at flood depths above this threshold. Analysis of TRADS and of video footage shows that cars continue to pass through floodwater of far greater depth, albeit at reduced speed (Pregolato et al. 2016b). This highlights the need to improve understanding of the effects of pluvial flooding on urban road networks, now and under future climate change, to maintain transport infrastructure resilience (Walsh et al. 2013).

## Integrated Framework for Urban Flood Risk Disruption

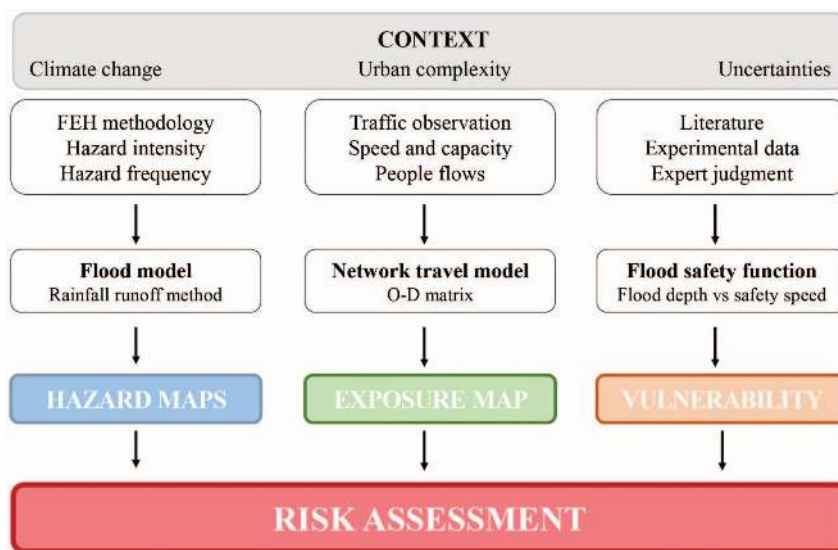
In light of these issues, this paper developed a modeling framework to assess the impact of flood-related disruptions on the urban transport network. The framework combines hazard information from climate and flooding simulations, with analysis of the exposure of the transport network and consideration of the vulnerability of moving vehicles to flood disruption (Fig. 2).

### Hazard Maps: Urban Flood Simulation

For a given scenario of rainfall (duration, intensity), terrain, and boundary conditions, a hydrodynamic model is employed to produce outputs for each time step of the simulation to give flood depths and velocities. The flood model used in this study is the City Catchment Analysis Tool (CityCAT), a two-dimensional hydrodynamic model developed to simulate pluvial inundation at high resolution that is already applied to and calibrated for a number of cities. Photos and records from the Toon Monsoon (Fig. 1) were



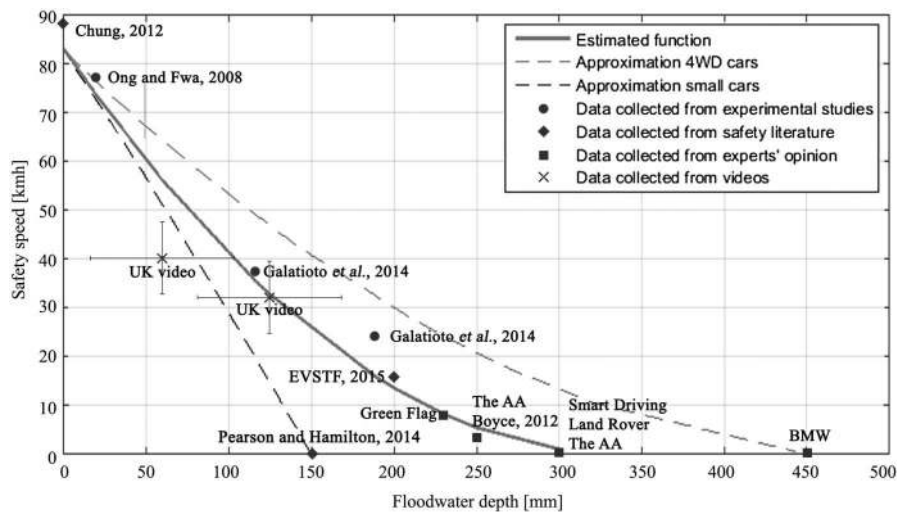
**Fig. 1.** (Color) Newcastle map with photos taken during June 28, 2012; a bow wave shows that vehicles continue to move, albeit slowly, at (b) the Quayside and (d) Chillingham Road, but not in images (a) and (c) where the flood water is too deep (photos courtesy of Newcastle University; map source: Esri, DigitalGlobe, GeoEye, Earthstar Geographics, CNES/Airbus, DS, USDA, USGS, AEX, Getmapping, Aerogrid, IGN, IGP, swisstopo, and the GIS User Community)



**Fig. 2.** (Color) Overview of the modeling framework to assess the impact of climate change on transport disruptions from pluvial flooding

used to validate the model for Newcastle (Glenis et al. 2010, 2013). Rainfall time series of precipitation intensity (considered uniform across the model domain in this study) during an event were propagated over the surface using a set of shallow-water equations. The surface water flows took into account building locations and footprints, permeability of the ground, and topography at a high resolution. Water depth and velocity were calculated dynamically throughout the simulation period and reported at each time step as a raster grid (in this study, at a resolution of 4 m) which can be used for further analysis. To reduce computational burden, the subsurface drainage network was not simulated as a dynamic network. The outputs from the flood model were used to calculate impacts on the transport network (Fig. 3).

Synthetic *design storm* events were generated following the standard U.K. procedure from the *Flood Estimation Handbook* (Robson and Duncan 1999) for the current scenarios and extrapolated to the 2080s epoch. To explore the implications due to climate change and potential future rainfall intensity changes, a series of *uplifting factors* were employed. Regional and global climate models are too coarse to fully resolve clouds, moisture, convection, and topography. Convective processes were therefore parametrized as a subgrid process leading to an inability to represent extreme subhourly precipitation (Ban et al. 2015). The computational expense of convection permitting models requires that runs are at the subregional scale if they are to simulate multiple decades (Prein et al. 2015). The uplift factors used here were derived from



**Fig. 3.** Vulnerability curve developed to related floodwater on links and the car speed to drive through it safely (data from Pregolato et al. 2016a)

**Table 1.** Rainfall Intensity of the Simulated Design Storms

| Scenario               | Present epoch          | 2080s epoch |
|------------------------|------------------------|-------------|
| High-probability event | 20 mm/h (1-in-10-year) | 30 mm/h     |
| Low-probability event  | 30 mm/h (1-in-50-year) | 45 mm/h     |

high-resolution climate simulations over the United Kingdom that are able to capture convective storm processes that give rise to pluvial flooding (Chan et al. 2014; Kendon et al. 2014). Dale et al. (2015) derived uplift factors from the high-resolution (1.5 km) climate model using the RCP8.5 climate scenario (IPCC 2014). This analysis projects that the intensity and total rainfall of short-duration events such as the Toon Monsoon will increase. These were not available in previous climate scenario reports (e.g., IPCC 2014) and recently have been made available to the water industry, but to the authors' knowledge this is the first time they have been applied to understanding transport risks. The storms considered are summarized in Table 1.

### Exposure: Transport Network Model

The second element in the modeling framework is a simulation of the transport network in a geographic information system (GIS)-based accessibility model, as outlined in Ford et al. (2015). This model simulates journeys across a transport network, defined by spatial data of links and nodes, using generalized cost of travel to assess the shortest route between an origin and destination. Free-flow speeds on the links were defined using classes from the U.K. cost benefits analysis (COBA) model (DoT 2004) inferred from attributes in Ordnance Survey MasterMap data, and speed-flow curves were used to simulate congestion effects on those links (DoT 2004). These routes were then used for the assignment of trips from observed U.K. census journey-to-work flows using an iterative assignment routine (see De Ortuzar and Willumsen 2011) in order to assess the number of users along any road in the network.

A number of transport processes were represented at reduced complexity to ensure the model is computationally efficient. There is no stochastic variation in the speeds of the vehicles along each link; all traffic on a road link travels at either the maximum free-flow speed or at a reduced speed accounting for congestion. Minor residential roads were removed from the analysis because it was observed during the flood event of June 28, 2012 that the major roads were impacted to such an extent that minor roads were

quickly overwhelmed by the volume of traffic and did not offer alternative route choices. Moreover, this also reflects the lack of perfect knowledge that many road users have, being unaware of alternative minor residential roads away from major or regular routes. Only commuting journeys were simulated because disruption during the morning or evening peak has the potential for the greatest economic disruption (Hallegatte and Przulski 2010). The timing of the June 28, 2012 event was during the evening peak, and so such a situation has been observed.

The transport model was applied to simulate all commuting journeys across the metropolitan county of Tyne and Wear (538 km<sup>2</sup>). Middle Layer Super Output Area (MSOA) population-weighted centroids for the 2011 U.K. census (freely available from the Office for National Statistics, United Kingdom) were used as origins and destinations for a total of 43,681 of these journeys, with routes computed for baseline and flood conditions. Following the same process as Ford et al. (2015) the model was validated for baseline conditions against census journey flows and observations from automatic traffic counters to ensure that the busiest simulated roads corresponded to the busiest observations. However, only a small proportion of roads have a traffic counter, and commuting flows make up only approximately 20% of flows on the road network (DoT 2016), so the validation can only be partial. The impact of flooding was considered by integrating the depth-disruption vulnerability function described in the following section with information on the flood hazard to recalculate (lower) traffic speeds, and where there was deep flood water, to block the road entirely.

### Vulnerability Curve: Traffic Disruption Function

The third and last stage involved translating flood depth, via the transport network model, into journey travel time increase and ultimately into economic cost. Chen et al. (2016) considered *driving safety* as a type of flood impact and recognized that this is related to the depth of flooding. Pregolato et al. (2016a) developed a depth-disruption function by synthesizing experimental reports (e.g., Ong and Fwa 2008; Galatioto et al. 2014), safety literature (e.g., Chung and Recker 2012), experimental data (e.g., Boyce 2012), analysis of videos of cars driving through floodwater, and expert judgment (e.g., The Automobile Association 2016). Data were from the EU, Canada, and Australia and for asphalt roads, and therefore were comparable (Fig. 3). This moves beyond the crude assumption that the road is either open or closed according to a single arbitrary

depth threshold, which is consistent with observations from real flood events that drivers travel slowly through floodwater, including during the Toon Monsoon event (Newcastle City Council 2013).

A baseline transport scenario was initially generated by running the transport model under normal settings (i.e., speeds defined by the speed/flow curves), and then multiple disruption and adaptation scenarios were evaluated. The hazard maps for each flood event showing water depths across the city (Fig. 6) were integrated with the vulnerability curve, enabling the speed reduction according to the depth of floodwater to be calculated for each road link. The uncertainty bounds in Fig. 3 capture a range of vehicle sizes, but with incomplete information available on vehicles in Newcastle and their individual routes, the central estimate of the depth-disruption function was applied to each road link. When network characteristics were modified by hardening one or more links, traffic flows were recalculated and disruptions assessed in terms of additional journey time and delays. This allows an assessment of the effectiveness of one or more adaptation options in reducing network-level disruption from flooding.

By overlaying the water depth from flood simulations onto the road network, vehicle speeds and subsequently journey travel time can be recalculated. A single metric of person-hours delay (PHD) to measure the city-wide disruption is calculated by aggregating all of the delays to each passenger journey across the network

$$\text{PHD} = A^S - A^{\text{BA}}, \quad A = \sum_{i=1}^N \sum_{j=1}^N T_{ij} C_{ij} \quad (1)$$

where  $A^S$  = aggregate journey time across the  $N$  origin and destination zones in the city for scenario  $S$  (BA is the baseline scenario); and  $T$  = number of trips and  $C$  = cost (in time or money) between each origin and destination. Other metrics, such as percentage of roads flooded or severity of damage to infrastructure, could be used to assess the impact, but during the Toon Monsoon the most notable and least-understood impact was the loss of road network performance. The resultant delays, due to rerouting and speed reduction, are used to compare the impacts of scenarios and the benefits of adaptation.

### Economic Impacts of Disruption

Delays can be converted into monetary terms using the value of time (VoT) (Ford et al. 2015; DoT 2014b; De Ortuzar and Willumsen 2011). The additional time required by journeys when the network systems is disrupted means an overall economic cost (e.g., business interruption) which through the use of the VoT can be converted into monetary terms accounting for the time of delay and vehicle operating costs (Ford et al. 2015). The cost per vehicle delayed  $C_{\text{veh}}$  is calculated by

$$C_{\text{veh}} = \Delta T \cdot \text{VoT} \quad (2)$$

where  $\Delta T$  = variation in journey time (h); and VoT = value of time (£/h). The value of commuting time is properly defined as *nonworking travel time*, which differs from *working time* (4 times higher) for business trips or journeys made in the course of work, because commuting trips usually use the commuter's own time. Commuting time includes "all non-work journeys purposes, including travel to and from work" (DoT 2014b). The VoT used in the model was the 2010 market price for commuting time per person, which was £6.81 per hour (US\$10.56 in June 2012 prices).

Although this VoT measure is defined for use in normal road conditions, it can be considered a low bound to the level of economic cost, because the VoT is likely to be higher during disruptive

events (Jenelius et al. 2011; Mattsson and Jenelius 2015). Other impacts could also be quantified, such as the increase in air pollution due to vehicle emissions and a higher total CO<sub>2</sub> for the journey (de Palma and Lindsey 2011; Mao et al. 2012), or social impacts in terms of driver health and well-being (Quah and Boon 2003; Abu-Lebdeh 2015). Using the census journey-to-work data, the individual delay for journeys between each pair of locations can be multiplied by the observed number of commuting trips between those points to give a combined *person-minute delay* for those journeys [Eq. (1)]. This captures the wider effects of the delay to transport links, weighting the delay to journeys by the number of people currently using those portions of the transport network.

The benefit of climate adaptation actions are usually realized over multiple years. The net present value (NPV) of the benefits in terms of risk reduction is one criterion for deciding which action is more cost effective. Net present value computes the long-term costs and benefits, discounted to present-day rates to account for inflation. The NPV of the benefits in terms of risk reduction,  $\text{NPV}_r$ , is calculated by summing the disruption cost,  $D(x)$ , and likelihood,  $\rho(x)$ , of a range of flood events:

$$\text{NPV}_r = \sum_{i=1}^N \frac{\int \rho(l_i) D(l_i) dx}{(1+r)^i} \quad (3)$$

In line with HM Treasury (2013) guidelines, a life span,  $N$ , of 50 years for infrastructure and a discount rate,  $r$ , of 3% were used.

### Climate Change Scenarios

Potential changes to rainfall intensity over Newcastle benefit from high-resolution climate model simulations (Kendon et al. 2014) that have been analyzed using the approach described by Dale et al. (2015) in Table 2. Low, central, and high projections of change are made to a range of rainfall events—showing, for example, that a 30-mm, 1-h storm in the present epoch would be 36–42 mm, with a central estimate of 38.4 mm, in the 2030s. The central estimate is used in this analysis.

### Prioritization of Adaptation Interventions

In order to ensure resilience of urban areas in the future, infrastructure must be adapted to cope with such change in future extreme events (IPCC 2014). The vulnerability of the road transport network of Newcastle upon Tyne to pluvial flooding was assessed by Pregolato et al. (2016b), with multiple locations at risk from rainfall-induced flooding (and therefore in need of adaptation) identified in the city. One strategy to make infrastructure in those locations more robust is to intervene with measures of hard engineering, such as improved drainage or raising the level of the link. Such strategies are referred to in this paper as *link hardening*. When a link is considered hardened in this study, it means that such a link has been made completely invulnerable to flooding. There are

**Table 2.** Uplift Factors Derived from High Resolution Climate Simulations for Low (L), Central (C), and High (H) Climate Scenarios (Data from Dale et al. 2015)

| Duration<br>(h) | Epoch |    |    |       |    |    |       |    |    |
|-----------------|-------|----|----|-------|----|----|-------|----|----|
|                 | 2030s |    |    | 2050s |    |    | 2080s |    |    |
|                 | L     | C  | H  | L     | C  | H  | L     | C  | H  |
| 1               | 20    | 28 | 40 | 24    | 44 | 75 | 45    | 50 | 60 |
| 3               | 12    | 15 | 16 | 18    | 29 | 41 | 35    | 53 | 76 |
| 6               | 5     | 7  | 10 | 8     | 17 | 30 | 35    | 51 | 75 |

many options available for hardening a link (e.g., better drainage or road elevation), and the results for one such option are presented in the “Results” section, along with a simple cost–benefit analysis.

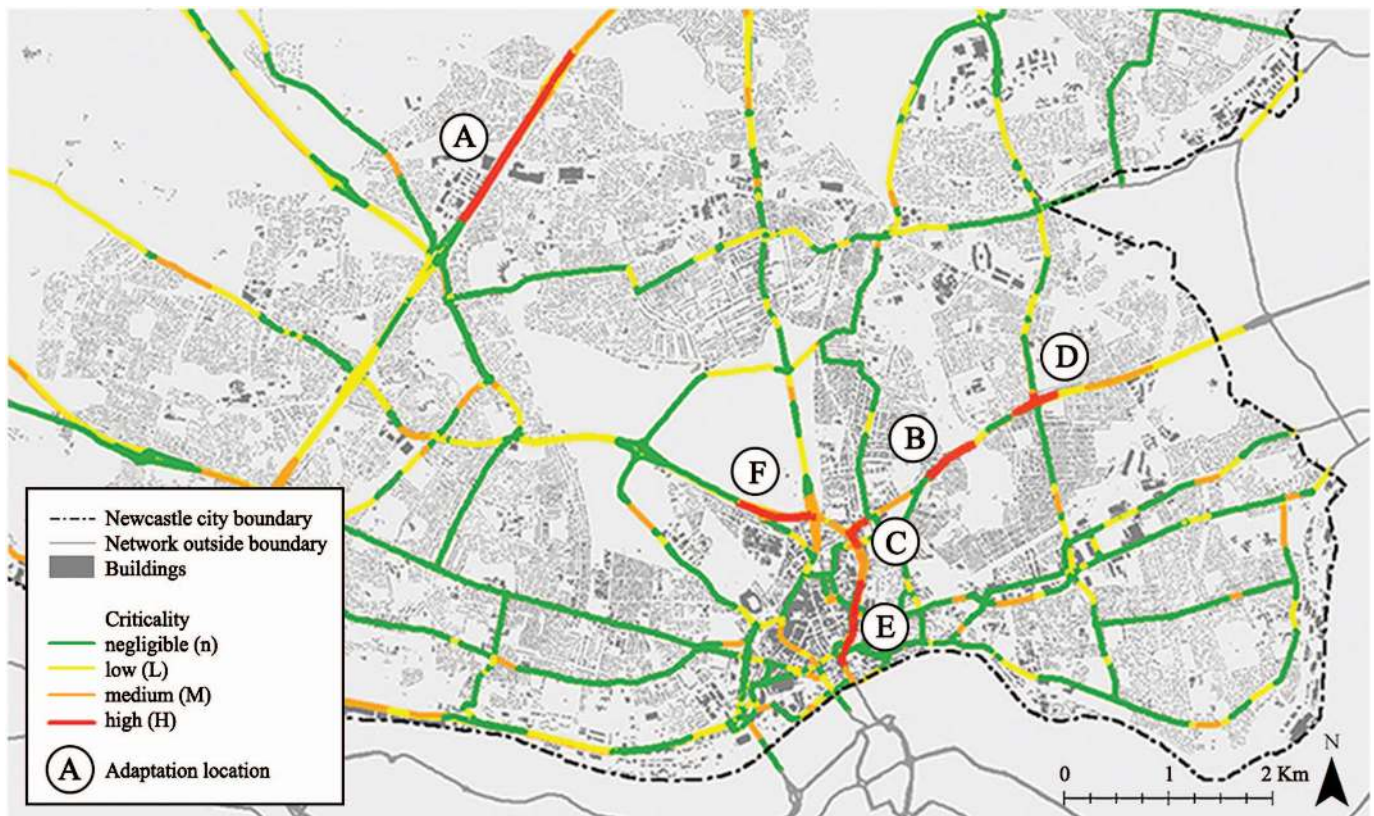
During the analysis process, network metrics are used to select the critical links in the network and target adaptation options. The most at-risk locations in the road network are identified through a matrix (Larsen et al. 2010; Naso et al. 2016; Pregolato et al. 2016b) combining the hazard, i.e., the depth of water on the road, and the exposure, i.e., the average daily traffic flow along the road (Fig. 4). Network measures, such as betweenness centrality, have been used in other studies to identify critical locations (Pregolato et al. 2016b) based on their topological importance, although that approach has not been adopted here.

The matrix was applied to identify and rank the criticality of road stretches in Newcastle’s road network. The six most critical stretches, where both the exposure (i.e., traffic flow) and hazard (i.e., water depth) were in the highest categories, were selected for analysis of adaptation options. Road stretches can comprise a number of neighboring links and nodes (e.g., protective measures would not be taken for just one spur of a roundabout). These stretches, shown in Fig. 5, in order of criticality are

- A: main A1 road bypassing the city to the west;
- B: section of the Coast Road (A1058), the main route entering the city from the east;
- C: convergence of A167, Great North Road (B1318), and the Coast Road (A1058);

|                              |                     | Exposure: AWG [veh/day] |                           |                        |                  |
|------------------------------|---------------------|-------------------------|---------------------------|------------------------|------------------|
|                              |                     | minor<br>0-20000        | moderate<br>20001 - 40000 | major<br>40001 - 60000 | severe<br>>60000 |
| Hazard: water height<br>[mm] | minor<br>0-100      | n                       | L                         | L                      | M                |
|                              | moderate<br>101-200 | L                       | L                         | M                      | M                |
|                              | major<br>201-300    | L                       | M                         | M                      | H                |
|                              | severe<br>>300      | M                       | M                         | H                      | H                |

**Fig. 4.** Criticality assessment of road links, according to the magnitude of the hazard and exposure of vehicles; road links are subsequently categorized as n = negligible; L = low criticality; M = medium criticality; and H = high criticality



**Fig. 5.** (Color) Location of the critical links in Newcastle upon Tyne’s road network, identified using the criticality matrix in Fig. 4 (map source: Esri, DigitalGlobe, GeoEye, Earthstar Geographics, CNES/Airbus, DS, USDA, USGS, AEX, Getmapping, Aerogrid, IGN, IGP, swisstopo, and the GIS User Community)

- D: further section of the Coast Road;
- E: A167 Central Motorway, the main route through the city center; and
- F: A167 Central Motorway, northwest section.

Eleven different adaption scenarios were considered and simulated using the framework. Each of the six options was tested independently (i.e., LH\_A, ..., LH\_F). Five additional scenarios considered the cumulative effect of adaptation portfolios that included the next most critical link (i.e., LH\_A, LH\_AB, ..., LH\_ABCDEF).

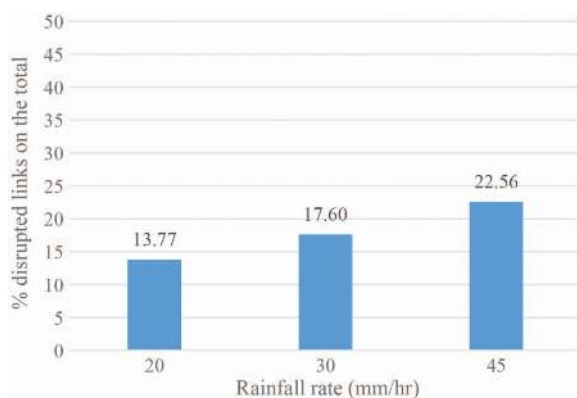
## Results

Fig. 6 shows the percentage of road links affected by flooding under the different levels of rainfall intensity, and Fig. 7 shows the floodwater depth and the speed reductions on the network for a small area of Newcastle for different rainfall rates.

To help understand the calculation, disruption to a single journey between links is first considered by way of an example illustrated in Fig. 8. The route taken under baseline (BS) conditions for a nearly circular journey between five stops along the network is plotted in Fig. 8(a). When flooded by a high probability in the present epoch with no adaptation (NA), the route must be modified to avoid roads that are deeply flooded in order to find the fastest alternative route [Fig. 8(b)]. The successive introduction of each hardened stretch of road (Stretches B, C, and E, introduced previously) is shown in Figs. 8(c–e). With all three stretches of road hardened, the route corresponds to the baseline, although the travel time is increased due to shallow flooding on some unprotected stretches of the route, as shown in Table 3. For this single journey, the disruption caused by floodwater adds approximately 15 min to the journey time without adaptation.

The impact of a range of flooding events, including those similar to the June 28, 2012 storm, on the road network were assessed for the whole urban system. Disrupted journeys were calculated for every pair of origins and destinations across the network, and results were aggregated across the domain. Results for a range of hazard events, climate epochs, and adaptation strategies are summarized in Tables 4–6.

Table 4 shows that adaptation decreases delays to travelers under all scenarios. For present-epoch higher-probability, low-intensity events, adaptation can reduce the PHD for all journeys



**Fig. 6.** (Color) Proportion of road links affected by a 1-h rainfall event of different intensities; the proportion of links increases with intensity as might be expected, but the depth of flooding on links also increases, which has a nonlinear impact upon journey times

across the network by up to 50%. The addition of individual adaptation measures provides benefits, but these are much higher for the two most-critical stretches of road than for the other four locations. However, when implemented in combination, the return from the interventions with the lower criticality score is far larger, and each successive intervention provides additional benefit. The same adaptations provide a lower proportional benefit under lower-probability, higher-intensity events, although their effectiveness varies depending on the number of junctions protected. This highlights the need for an understanding of the importance of particular hotspots in the road network in order to prioritize adaptation investments.

A number of complexities are also highlighted in the results, demonstrating the need for system-level analysis of the transport network. For example, hardening Links A, B, and C provides the same benefit as hardening just A and B, because Link C feeds directly into Link F. Any benefit from hardening Link C is only returned if Link F is also hardened. It can also be seen from the results that the overall package of adaptations is proportionally more effective under the future lower-probability event than under the future higher-probability event.

Particularly effective is the hardening of Link A, the strategically important city bypass road. This is most beneficial for more-extreme events because a number of alternative high-capacity routes remain open during less-severe events, and therefore avoiding this road during such events is a possibility for drivers. Under more-extreme events those alternative routes also become severely disrupted, and thus protecting Link A becomes a more-effective option once more. This again highlights the importance of considering system-scale analysis of network disruption rather than link-based disruption and adaptation assessment.

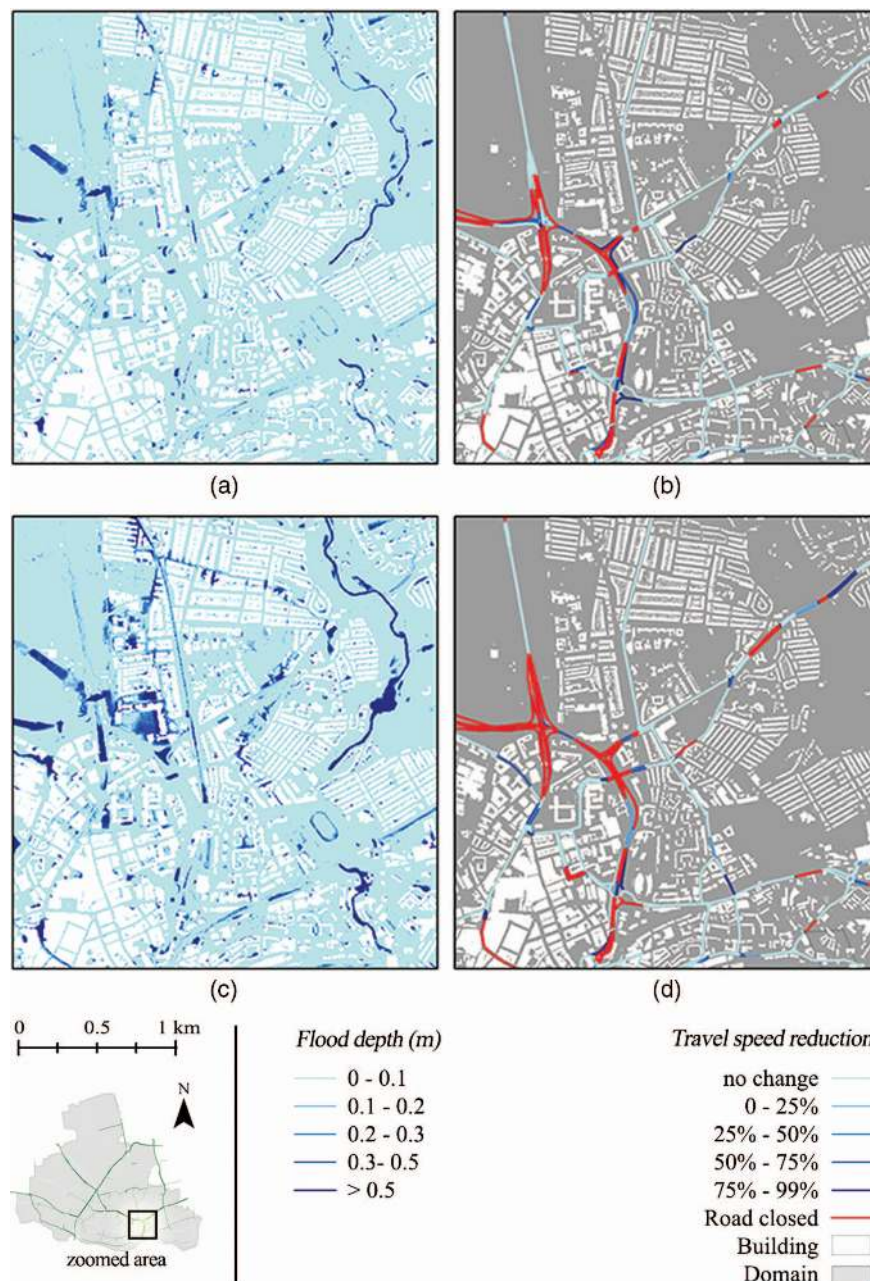
Calculating the cost of disruption in monetary terms allows a cost–benefit analysis to be undertaken. Possible adaptations for link hardening include the installation of stormwater attenuation tanks, which could be provided by storm crate systems or underground tanks that manage surface water runoff. Data from a number of companies offering such systems has been collected, showing costs of approximately £100 per cubic meter of water to be removed, including excavation work and delivery cost. The cost of holding the volume of water that drains onto the road stretch (calculated from the flood model) is shown in Table 5, although these do not include maintenance costs, which were not available.

The NPV was calculated using Eq. (3), and the timeframe within which the benefits exceed the investment is shown in Table 6. The return in terms of reduced risk improves as more intervention options are considered, although it takes longer to realize the return on investment. However, the net benefit that accounts for the initial capital costs is greatest for just two interventions (LH\_AB).

## Discussion

Previous studies in the literature have shown that the relationship between adverse weather and traffic flow is complex and has been poorly understood. Using an integrated framework, this paper coupled inundation modeling, transport network modeling, and a function that relates flood depth to driving speed. The results assess the impact of a range of flooding, climate, and adaptation scenarios and show that the impacts of traffic disruption from extreme flooding can be effectively mitigated through targeted adaptation at key stretches of the road network. This approach demonstrates that increases in rainfall intensities lead to a nonlinear increase in journey time as a result of the spatial heterogeneity of the flood hazard and the many network interactions of journeys across the transport





**Fig. 7.** (Color) (a) Flood depths for 1-in-10-year event in the present epoch; (b) the associated decrease in traffic speed; (c) flood depths for 1-in-200-year event in the present epoch; (d) the associated decrease in traffic speed; this area includes the location of adaptation locations C, E, and F from Fig. 5 (map source: Esri, DigitalGlobe, GeoEye, Earthstar Geographics, CNES/Airbus, DS, USDA, USGS, AEX, Getmapping, Aerogrid, IGN, IGP, swisstopo, and the GIS User Community)

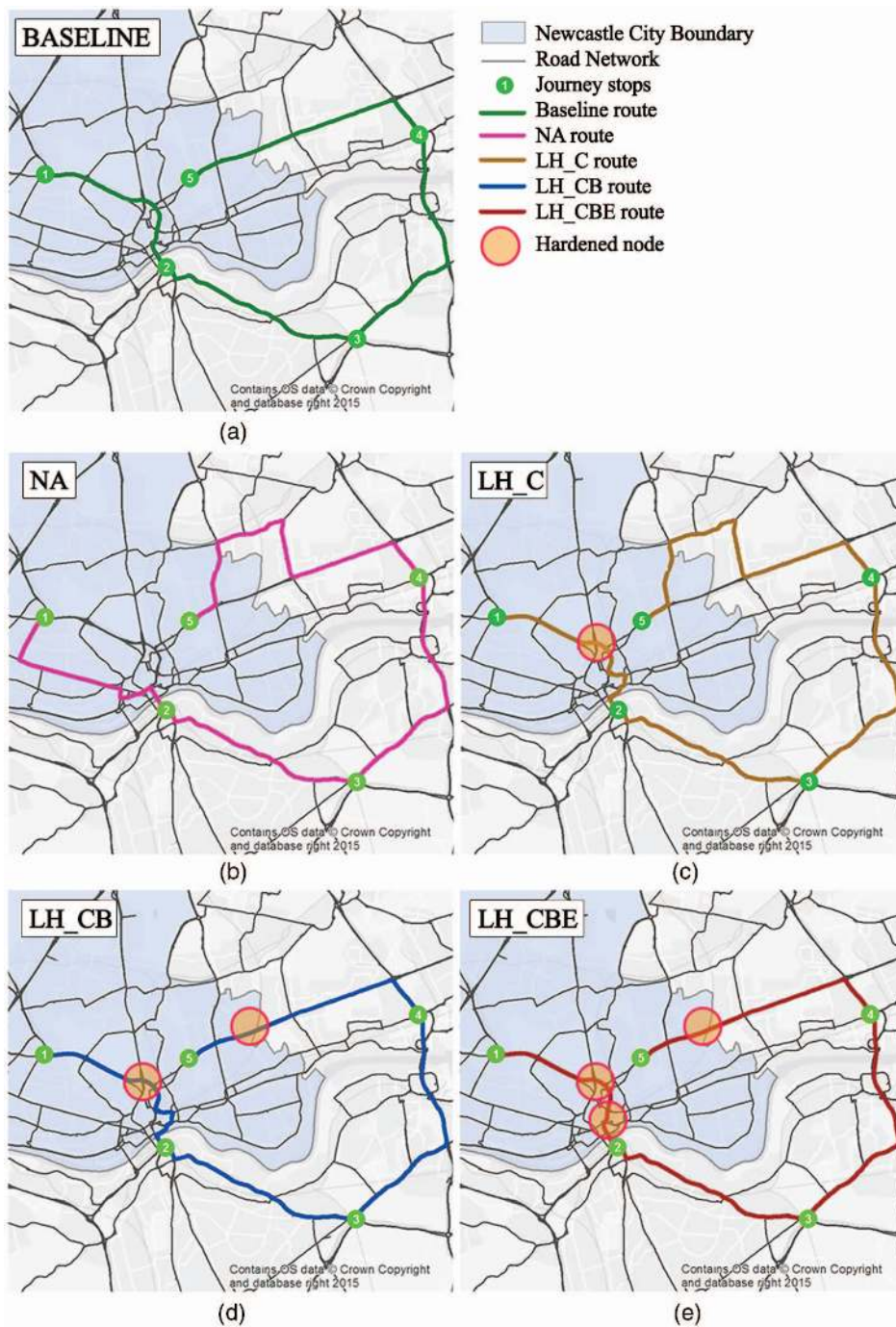
system. Without adaptation intervention in the transport system, Newcastle and cities with similar urbanization properties will experience increased transport disruption by the end of this century because of climate change, with travel time increases of more than 50% for more extreme events.

### Implications for Transport and Flood Risk Managers

The methodology in this paper was developed with standard tools and practitioner appraisal methods in mind. For example, any flood or transport model could be used. Similarly, the calculation of the generalized cost of travel and value of time is in line with U.K. government guidance, ensuring that the results are of direct value

to the policy appraisal process (DoT 2004; EA 2010; HM Treasury 2013; DoT 2014b), but this stage of the calculation is readily adapted to suit other national approaches (e.g., FHWA 2001).

The framework provides a means of assessing the benefits, in terms of reduced disruption, of flood risk management and highway drainage interventions. To date this has not been considered in flooding appraisals in such a comprehensive way. Moreover, the method provides a mechanism for city-wide screening of priority locations for climate change adaptations based upon analysis of road networks and traffic properties. The results for Newcastle show that just two interventions provide a substantial reduction in transport disruption. This may seem unintuitive; however, both are important roads for commuters and are susceptible to surface water



**Fig. 8.** (Color) Journey from Point 1 to Point 5, via Points 2, 3, and 4; the route is calculated for (a) baseline (i.e., no flooding) conditions; (b) flooding with no adaptation; and (c–e) a range of adaptation scenarios that correspond to the locations shown in Fig. 5 (map source: Esri, DigitalGlobe, GeoEye, Earthstar Geographics, CNES/Airbus, DS, USDA, USGS, AEX, Getmapping, Aerogrid, IGN, IGP, swisstopo, and the GIS User Community)

**Table 3.** Additional Journey Time and Distance after Rerouting Caused by Flooding, for the Present Epoch High Probability Event Considering the Journey Shown in Fig. 7

| Adaptation strategy | Disruption |                     |
|---------------------|------------|---------------------|
|                     | Time (min) | Journey length (km) |
| BS                  | 24         | 27                  |
| NA                  | 39 (62.5%) | 32 (18.5%)          |
| LH_C                | 35 (45.8%) | 30 (11.1%)          |
| LH_CB               | 30 (25.0%) | 27 (0.0%)           |
| LH_CBE              | 29 (20.1%) | 27 (0.0%)           |

flooding, but, crucially, if they are blocked, alternative routes are limited and markedly longer. This rate of return from two adaptation interventions is not expected to be the same in every city because the transport network structure and level of redundancy, travel patterns, and topographies will be different, but application of the criticality analysis is shown to prioritize investment interventions effectively. The analysis also shows the importance of considering a range of events because of the different flood footprint and depths, which alter the viability and possible travel speed of different routes. Furthermore, by considering multiple events it is possible to identify a balance of the costs and benefits from the size

**Table 4.** Total Person-Hour Delay (PHD) for the Model Domain, Economic Cost of the PHD, and Economic Benefits Provided by Adaptation Scenarios Measured in Terms of a Reduction in PHD

| Scenario                  | Setting |                       | Present |                |                         | 2080s   |                |                         |
|---------------------------|---------|-----------------------|---------|----------------|-------------------------|---------|----------------|-------------------------|
|                           | Label   | Number links hardened | PHD     | Delay cost (£) | Benefit (per event) (£) | PHD     | Delay cost (£) | Benefit (per event) (£) |
| Higher probability events | NA      | 0                     | 13,650  | 92,954         | 0                       | 19,446  | 132,424        | 0                       |
|                           | LH_A    | 1                     | 9,265   | 63,092         | 29,862                  | 14,637  | 99,680         | 32,744                  |
|                           | LH_B    | 1                     | 11,987  | 81,632         | 11,322                  | 17,727  | 120,723        | 11,701                  |
|                           | LH_C    | 1                     | 13,517  | 92,051         | 903                     | 19,161  | 130,486        | 1,938                   |
|                           | LH_D    | 1                     | 13,615  | 92,716         | 238                     | 18,885  | 128,606        | 3,818                   |
|                           | LH_E    | 1                     | 13,515  | 92,035         | 919                     | 19,364  | 131,870        | 554                     |
|                           | LH_F    | 1                     | 13,635  | 92,857         | 97                      | 19,442  | 132,400        | 24                      |
|                           | LH_AB   | 2                     | 8,066   | 54,929         | 38,025                  | 13,160  | 89,620         | 42,804                  |
|                           | LH_ABC  | 3                     | 7,783   | 53,002         | 39,952                  | 13,160  | 89,620         | 42,804                  |
|                           | LH_ABCD | 4                     | 7,746   | 52,750         | 40,204                  | 12,586  | 85,711         | 46,713                  |
| LH_ABCDE                  | 5       | 7,406                 | 50,435  | 42,519         | 12,461                  | 84,859  | 47,565         |                         |
| LH_ABCDEF                 | 6       | 6,850                 | 46,649  | 46,306         | 12,256                  | 83,463  | 48,961         |                         |
| Lower probability events  | NA      | 0                     | 19,446  | 132,424        | 0                       | 32,363  | 220,390        | 0                       |
|                           | LH_A    | 1                     | 14,637  | 99,680         | 32,744                  | 20,617  | 140,400        | 79,990                  |
|                           | LH_B    | 1                     | 17,727  | 120,723        | 11,701                  | 30,526  | 207,882        | 12,508                  |
|                           | LH_C    | 1                     | 19,161  | 130,486        | 1,938                   | 32,099  | 218,593        | 1,796                   |
|                           | LH_D    | 1                     | 18,885  | 128,606        | 3,818                   | 32,264  | 219,719        | 670                     |
|                           | LH_E    | 1                     | 19,364  | 131,870        | 554                     | 32,264  | 219,719        | 670                     |
|                           | LH_F    | 1                     | 19,442  | 132,400        | 24                      | 32,356  | 220,342        | 48                      |
|                           | LH_AB   | 2                     | 13,160  | 89,620         | 42,804                  | 18,920  | 128,845        | 91,545                  |
|                           | LH_ABC  | 3                     | 13,160  | 89,620         | 42,804                  | 18,920  | 128,845        | 91,545                  |
|                           | LH_ABCD | 4                     | 12,586  | 85,711         | 46,713                  | 18,296  | 124,596        | 95,794                  |
| LH_ABCDE                  | 5       | 12,461                | 84,859  | 47,565         | 18,158                  | 123,656 | 96,734         |                         |
| LH_ABCDEF                 | 6       | 12,256                | 83,463  | 48,961         | 17,726                  | 120,714 | 99,676         |                         |

Note: NA is the no adaptation scenario, and LH\_x denotes adaptation in single or multiple sites, corresponding to the locations shown in Fig. 4.

**Table 5.** Cost of Each Adaptation Strategy If Designed to Handle a Given Rainfall Event

| Scenario                  | Label     | Current   | 2080s     |
|---------------------------|-----------|-----------|-----------|
|                           |           | Cost (£)  | Cost (£)  |
| Higher probability events | LH_A      | 278,468   | 516,508   |
|                           | LH_AB     | 337,404   | 644,220   |
|                           | LH_ABC    | 412,588   | 773,932   |
|                           | LH_ABCD   | 453,332   | 884,692   |
|                           | LH_ABCDE  | 564,980   | 1,070,672 |
|                           | LH_ABCDEF | 749,888   | 1,422,928 |
| Lower probability events  | LH_A      | 516,508   | 717,336   |
|                           | LH_AB     | 644,220   | 919,284   |
|                           | LH_ABC    | 773,932   | 1,276,732 |
|                           | LH_ABCD   | 884,692   | 1,520,408 |
|                           | LH_ABCDE  | 1,070,672 | 1,801,076 |
|                           | LH_ABCDEF | 1,422,928 | 2,365,464 |

**Table 6.** Net Present Value (NPV) of the Benefits in Terms of Reduced Risk of Disruption

| Node      | Capital cost of intervention (£) | NPV of risk reduction (£) | Net benefit (risk reduction – capital cost) (£) | When benefit exceeds investment (years) |
|-----------|----------------------------------|---------------------------|---|---|
| LH_A      | 717,336                          | 3,779,023                 | 3,061,687                                       | 5.5                                     |
| LH_AB     | 919,284                          | 4,568,182                 | 3,648,898                                       | 5.5                                     |
| LH_ABC    | 1,276,732                        | 4,619,257                 | 3,342,525                                       | 8.5                                     |
| LH_ABCD   | 1,520,408                        | 4,842,145                 | 3,321,737                                       | 9.5                                     |
| LH_ABCDE  | 1,801,076                        | 4,950,972                 | 3,149,896                                       | 11.5                                    |
| LH_ABCDEF | 2,365,464                        | 5,166,280                 | 2,800,816                                       | 15                                      |

of adaptation at each road stretch. Although designing for more extreme events is more costly, the returns are greater and provide greater resilience to projected changes in rainfall.

Because this analysis only considers the benefits in terms of disruption, and not other benefits associated with urban flood management, it is likely that the overall returns would be higher. Previous work by Pregnolato et al. (2016a) showed that green infrastructure provides notable benefits across the city. However, because these are more diffuse interventions than the targeted adaptation options considered here, although they provide a city-wide reduction in flood levels they are less effective at mitigating the impacts on the transport system. There are a range of other options that could be tested in future work—e.g., upgrading the urban drainage network. Extension of the impact analysis to use land-use transport modeling to consider future urban development and socioeconomic change would provide future traffic flows and enable testing of other adaptation options, such as a modal shift away from private cars, increased home working, or adding redundancy to the road network.

### Implications of Uncertainties and Future Development

Although the use of the high-resolution climate simulations (Dale et al. 2015) provides a marked improvement on other transport impacts studies, these currently use only a single climate scenario. Because the scenario modeled by Dale et al. (2015) is a higher-emissions scenario, the change in flood frequency in the 2080s might be considered an upper estimate, although Sanford et al. (2015) note that global emissions are proceeding along, and even exceeding, this trajectory.

The transport model used here provides a low-complexity representation of driver behavior—e.g., it does not consider

vehicle-to-vehicle interactions at road junctions, and assumes that travelers have perfect knowledge of the network and associated journey disruptions. This provides a computational advantage while still capturing the macroscale transport interactions that this work seeks to understand; however, the disruption estimates are therefore expected to be a lower bound.

An agent-based transport model could be used to better capture micro effects, albeit at additional computational cost. Dynamically linking an inundation and transport model would allow a simulation of disruption over the course of the flood event and an understanding of when transport patterns return to normal after the rain, which would vary according to the magnitude of the flood. Similar approaches have already been implemented to understand the risk of drowning (e.g., Dawson et al. 2011). The effect of blockages such as broken-down vehicles that continue to obstruct roads after waters recede could also be captured. However, this is unlikely to be significant in the context of an extreme event because the transport model used here does not route vehicles through very deep water, and although these obstructions may cause local disruption they are unlikely to be significant in the context of a city-wide flood. Nevertheless, the framework applied here enables assessment of the peak disruption impact, thereby providing important information for policy makers to determine the benefits of adaptation options on the transport network.

Validation of transport models during disruptive events is challenging because weather extremes are relatively infrequent, and therefore provide limited observations. The vulnerability curve used here captures within uncertainty bounds the observations from a range of studies based on data from similar asphalt roads for a range of vehicles. The model replicates the types of delays reported by commuters and accurately captures the areas that flooded during the Toon Monsoon event (Newcastle City Council 2013). However, the exact impact of any particular event is sensitive to initial conditions such as the number of vehicles on the road and driver choices about whether to delay their journey. The presence of traffic sensors enables the automatic counting of vehicles, at least for a portion of the road network. Incorporation of this data and other emerging data sets from driver monitoring systems offers the potential for a far richer understanding of vehicle response during disruptive events and should greatly improve the validation and calibration of this type of model (Jenelius and Mattsson 2012; Batty 2013; Kermanshah et al. 2014; Osei-Asamoah and Lownes 2014; Kermanshah and Derrible 2016).

The models and data used in this study are readily available for many locations around the world, enabling the approach to be readily transferred to other cities. Moreover, although this study focuses on the flood risk to the road network, the framework could be applied to other weather-related phenomena (e.g., wind gusts, heat waves) and other transport networks (e.g., the railway network). This would require an appropriate hazard model and a relationship between the hazard and disruption (e.g., a rail-buckling function that is conditional on temperature) to support the system-wide analysis of their direct and indirect impacts.

## Conclusion

Flooding poses significant challenges to urban planners around the world. Urban transport networks are particularly vulnerable to flooding caused by extreme rainfall. Moreover, projected changes in climate will increase the frequency of extreme flooding events, and the current trend in many cities is for increased demand on the road network. However, understanding the efficacy of potential adaptations is far from straightforward. Because financial resources

are typically limited for local communities, it is crucial to understand the nature and vulnerabilities of the road network and how they may change in the future in order to prioritize limited available investment funds to protect the most important assets.

This paper presents an integrated framework that couples flood modeling with transport network simulations to quantify disruptions from flooding. The analysis takes advantage of new high-resolution climate simulations that provide uplift factors for intense rainfall events. A depth-disruption function was developed which provides a more realistic representation of vehicle speed through floodwater than the binary *blocked or full speed* assumption used in current appraisal processes.

Application of the framework to a case study in Newcastle upon Tyne in the United Kingdom shows that projected changes to rainfall could see the 1-in-10-year event flood increase the proportion of road links flooded from 14 to 18%. However, because of network effects and increased depth of flooding, the effect on disruption is nonlinear and increases by 43% for the 1-in-10-year present-epoch event and by 66% for the 1-in-50-year present-epoch event. By targeting adaptation interventions at the most critical stretches of the road network, in terms of traffic flows and flood depth, the framework is used to propose a cost-effective prioritization of intervention options. In this case study the risk reduction increases as more interventions are included, but the overall benefit (i.e., risk reduction minus capital costs) is maximum for just two interventions (strategy LH\_AB), which reduces travel delays across the city for the 1-in-50-year present-epoch event by 32%. Although different cities will exhibit different properties, the framework and principles for prioritizing adaptation are transferable, and the outputs have been shown to be compatible with existing infrastructure appraisal processes.

When limited resources for flood risk management are available, this method enables quantification of the indirect impacts of flooding on transport delays and a strategy for prioritizing investment to maximize returns. Because hard engineering measures are expensive and effective only in protecting a particular infrastructure asset, alternative options should be considered alongside these engineering interventions as part of a more sustainable approach to flood risk management. Green infrastructure and other strategies to replicate natural flow processes bring additional cobenefits. Given the longevity of transport infrastructure, the additional headroom this provides for existing transport drainage systems will provide greater flexibility in developing long-term adaptation strategies for climate change.

A number of challenges remain to reduce some of the uncertainties in the integrated framework, but this work provides an important first step to improve understanding of transport disruption from flooding and demonstrates an effective approach to prioritizing adaptation investment. Future development of this approach could reduce uncertainties by increasing a number of the processes represented, although this comes at a computational expense. A focus should be on accessing and analyzing big data from flood events in cities around the world to produce better validation data on the relationship between flooding and traffic disruption.

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