Spatiotemporal modelling of flood-related impacts on daily population movement

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Summary

This paper presents research combining spatiotemporal population flow data, flood modelling and network analysis to examine the effect of time of flood onset and flood magnitude on travel across a city for commuters and primary school children. Findings quantify that flood onset time has an effect on the disruption to travel comparable to flood event magnitude.

KEYWORDS: Spatiotemporal modelling, Network Analysis, Risk Analysis

1. Introduction and Background

The majority of fatalities caused by pluvial flash-floods in post-industrial countries concern those travelling in a vehicle (Debionne et al., 2016; Arrighi et al., 2019). The number of people travelling varies greatly over the course of the day, week or year, however mobility aspects are not frequently considered in flood exposure and risk assessments (Debionne et al., 2016; Dawson et al., 2011). This lack of dynamic population consideration means an important aspect of risk is missing when planning for flood events.

Risk is a dynamic phenomenon and varies over both space and time (Mechler & Bouwer, 2014). The 'risk equation' is a common conceptualisation of risk but rarely includes time or space (Hu et al., 2017). Therefore in this paper it is adapted to include both (Equation 1).

$$Risk = f(Hazard_{st}, Exposure_{st}, Vulnerability_{st}) \tag{1}$$

When studying the effect of floods on human populations, the time of flood onset is important as the same hazard event could have different effects due to variation in the exposure and vulnerability components of the risk equation (Freire et al., 2013; Dawson et al., 2011). Exposure is highly time dependent (Aubrecht et al., 2012), for example, a flood occurring during the Monday morning rush hour would mean more people are exposed on the roads than a Sunday morning. There are also

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differences in vulnerability as certain groups of the population are less able to react swiftly to floods, for example young children and the elderly (Smith et al., 2015).

This paper presents a proof of concept for combining spatiotemporal population flow data with flood data and network analysis to quantify the effect of time of flood onset versus size of flood hazard. The hypothesis is that the time of flood onset has an effect on travel disruption comparable to flood event magnitude. Commuters and primary school children are the population groups selected for analysis using a case study for York, UK.

2. Methods

Spatiotemporal population origins were produced in two different ways. (i) For commuters, census data describing output area to workplace zone commutes were combined with Labour Force Survey data to create temporal profiles of numbers of people travelling at a given time. (ii) The origin data for schoolchildren were generated through a spatially weighted Monte Carlo process converting spatiotemporal gridded population data into a set of likely origin centroids. The destinations were the population weighted centroids for the workplace zones and the point location of the primary schools. Inundated areas were delineated through pluvial flood modelling of York using the Flowroute-i^{TM} model (Ambiental Risk Analytics). These data were analysed using ESRI's 'closest facility' algorithm and traffic data from HERE to model driving routes for a specific time of day.

A scenario-based approach was taken to test the hypothesis (Table 1). First a 'baseline' set of data were created to be a control comparison to the flood scenarios. Two factors, time of flood onset and size of flood event, were varied in turn. Three times of flood onset were picked to cover the morning commute, 6am (flood time 1, FT1), 7am (flood time 2, FT2) and 8am (flood time 3, FT3). 1 in 30 and 1 in 100 year flood layers formed barriers to travel at each of these onset times and the output routes saved for comparison to each other and the baseline. The network analysis was conducted at set points during the morning commute (7am, 7:30am, 8am, 8:30am and 9am) to capture variation. The analytical overview for this paper is presented in Figure 1. The origin, destination and flood layer (if applicable) were used in the network analysis, producing shapefiles of the routes taken between each origin-destination pair with distance and travel time. This procedure was repeated for each time step in the scenario.

Table 1 Scenarios run during the analysis

Scenario Name	Description
Non-flood Baseline	Network analysis with no flood layer included as a baseline.
Flood time 1, 30yr flood	Network analysis with flood layer for a 1 in 30 year event, flood onset at 6am.
Flood time 2, 30yr flood	Network analysis with flood layer for a 1 in 30 year event, flood onset at 7am.
Flood time 3, 30yr flood	Network analysis with flood layer for a 1 in 30 year event, flood onset at 8am.
Flood time 1, 100yr flood	Network analysis with flood layer for a 1 in 100 year event, flood onset at 6am.
Flood time 2, 100yr flood	Network analysis with flood layer for a 1 in 100 year event, flood onset at 7am.
Flood time 3, 100yr flood	Network analysis with flood layer for a 1 in 100 year event, flood onset at 8am.

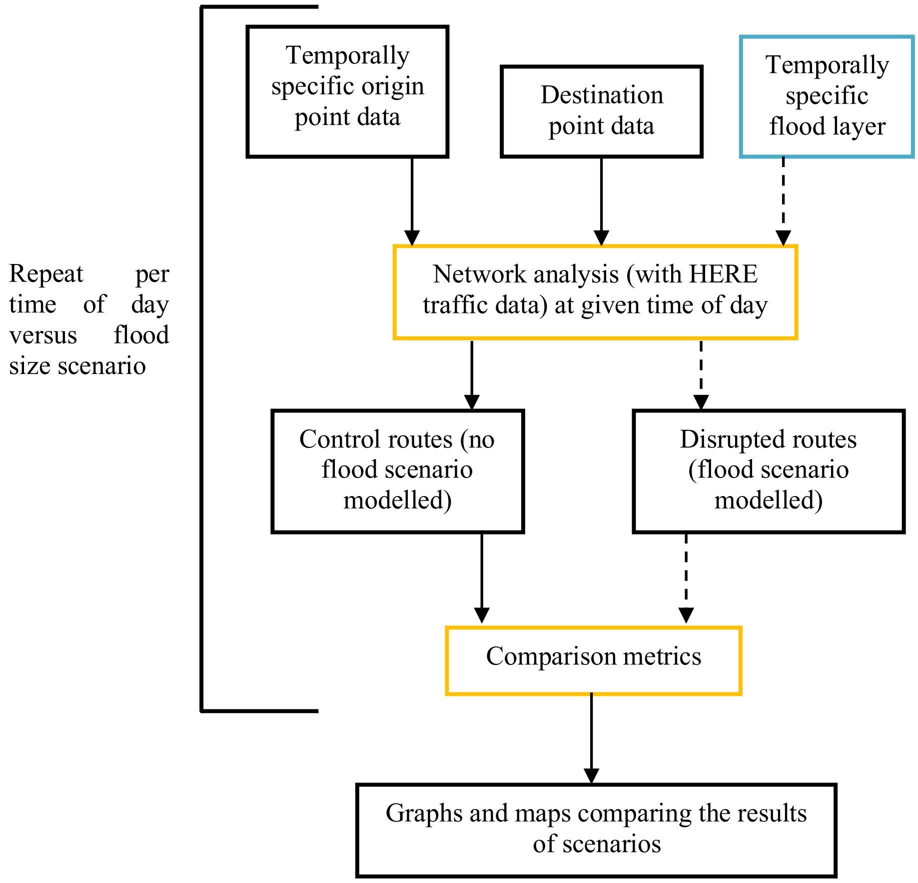

Figure 1 Diagram of analysis workflow. Black boxes indicate inputs and outputs, the blue box optional flood data, the yellow boxes processes and the dashed arrows steps included for flood scenario analysis.

3. Results and Discussion

Three examples of the results from the analysis are given. Firstly, Figure 2 compares road travel between the baseline and a flood scenario, the FT1 1 in 30yr scenario. Whilst there are similarities in road usage volumes, with the city centre and ring road most used, a northern part of the ring road is flooded in Figure 2b and longer routes are taken outside of the city to avoid flooding.

Secondly, Figure 3 compares the average travel time to an example destination between all scenarios. FT1 has the highest average travel times, higher than the baseline at all given time points, with FT2 rising above the baseline after 7:30am. In Figure 3a the increase in travel time for FT2 is similar to FT1 from 8:30am, and in Figure 3b average travel time rises but not enough to reach FT1. In both Figure 3a and 3b, the results for FT3 match the baseline until 9:00am where there is a slight increase from the baseline. The pattern of results is similar between Figure 3a and 3b, but with a greater increase in travel time seen in 3b as the flood magnitude has increased.

Finally Figure 4 is a summary of the effect of each disruption scenario on the city. The time lost was calculated by aggregating the additional travel time per origin-destination pair and, if a journey to a destination was not possible, the time for a full work/school day. This gives the total time lost at workplaces and schools due to flood disruptions. Commuters have more time lost partly due to higher numbers of commuters and workplaces meaning more journeys take place. It shows that the disruption is greater from FT1 for both magnitudes, and the decrease in time lost is greater when changing the time of flood onset than changes in the flood magnitude. This therefore provides evidence to support the hypothesis that flood onset time has a comparable effect to flood magnitude.

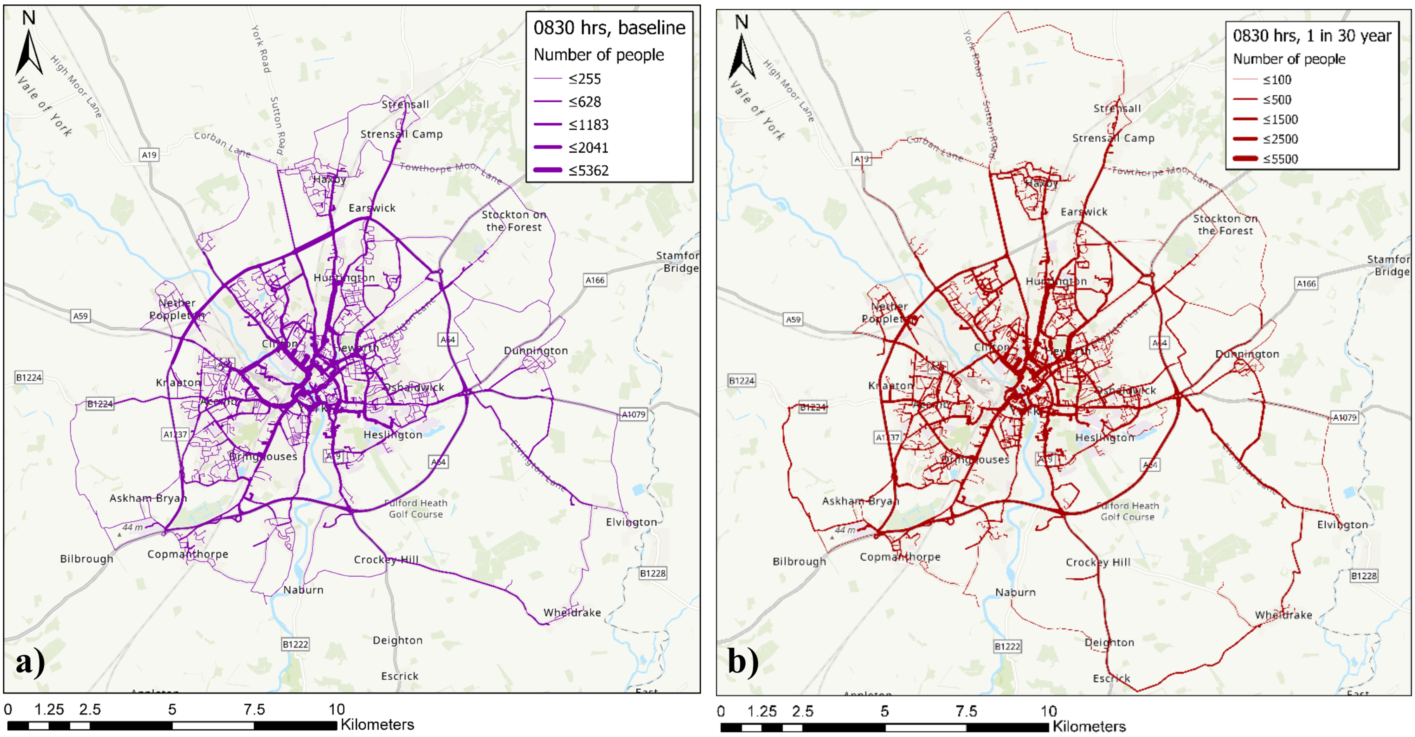

Figure 2 Road usage maps for 8:30am, a) non-flood baseline conditions and b) 1 in 30 year flood at flood onset time 1 (FT1) (6am).

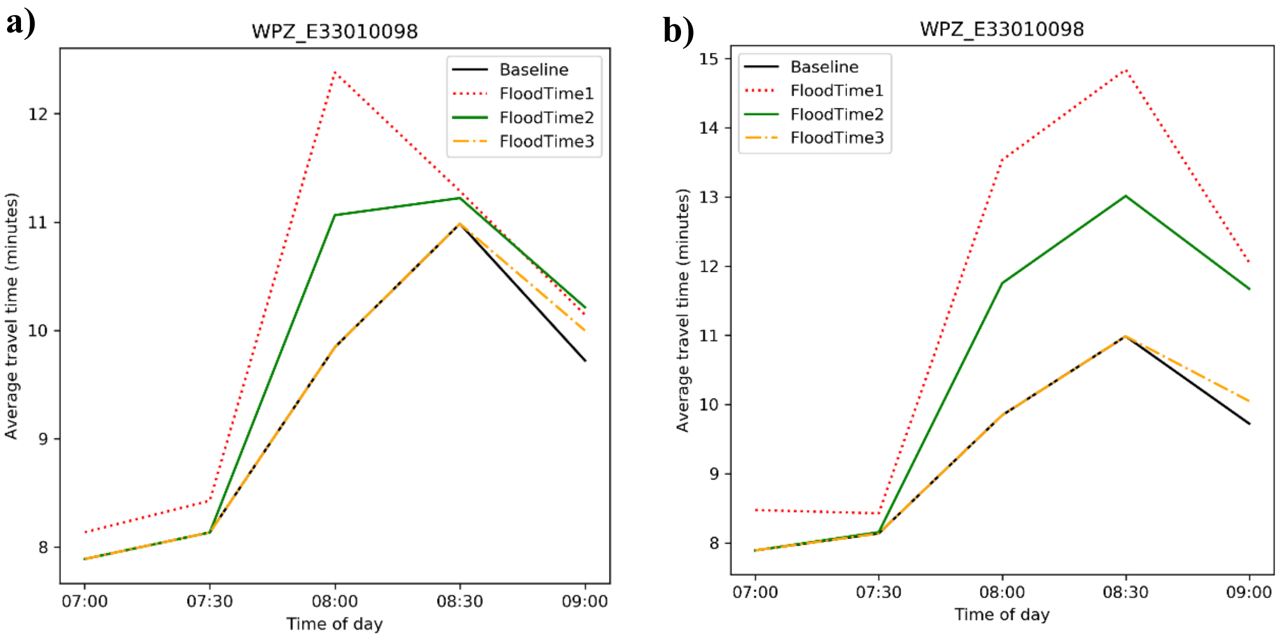

Figure 3 Average travel time of origins to an example destination (Workplace zone E33010098) for each flood magnitude a) 1 in 30 b) 1 in 100. The three flood onset scenarios plus the baseline are shown in each.

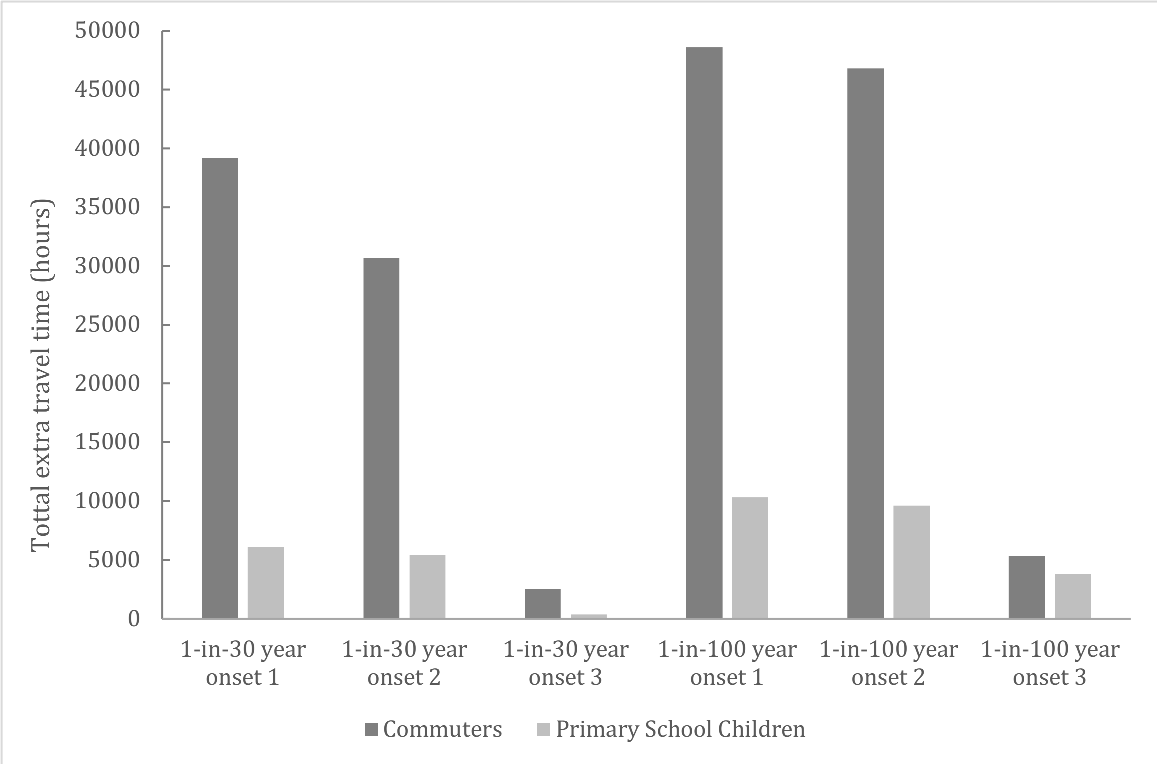

Figure 4 The total time lost (hours) at all destinations in each flood scenario in York. Dark grey represents the time lost by commuters at workplaces and the light grey the time lost by school children at schools.

4. Conclusion

These results show that there are spatial and temporal differences in the impact of flooding on road travel, with time of flood onset and magnitude affecting the average travel time to a destination. This workflow could be applied to other cities and types of hazard for risk assessments including spatiotemporal population data.

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6. Biography

Kate Rawlings is a final year PhD student in the School of Geography and Environmental Science at the University of Southampton. Her research interests include risk theory, geospatial network analysis and the impact of natural hazards on travel.

Jim Wright is a Professor in Geographical Information Systems in the School of Geography and Environmental Science at the University of Southampton. His research examines how geospatial data can be used to tackle public health and environmental management problems.

Alan Smith is a Lecturer in Environmental Management in the School of Geography, Earth and Environmental Sciences at the University of Plymouth. His research interests include, spatiotemporal population mapping and modelling, hazard risk assessment and applied GIS.

Sally Brown is Deputy Head of Department for Life and Environmental Sciences at Bournemouth University. She is interested in coastal geomorphology, the impacts of sea-level rise on a range of settings and climate change adaptation at local to global scales, plus the long-term sustainability of coastal zones.

Jeremiah J Nieves focuses on spatio-temporal modelling of populations and urban growth at high-resolution using machine learning methods and remote sensing with applications in planning, public health, sustainability, and disaster risk reduction. He is finishing his PhD and has been a WorldPop researcher since 2014.

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