WP 3: Small-scale vulnerability and risk assessment for cities and sectors

D3.3: Analysis of indirect impacts, and benefits of adaptation, to the economy and business supply chains

Reference code: RAMSES – D3.3

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Reference code: RAMSES – D3.3

Short Description:
Deliverable 3.3 examines the indirect impacts of climate events on the urban economy by analysing flooding disruption in London. The disruption of commuting journeys by flooding is simulated, and secondary effects through supply chain disruption assessed using input-output tables. Adaptation options, to reduce such disruptions, are discussed.

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<tr>
<td>ABI</td>
<td>Annual Business Inquiry</td>
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<td>AR5</td>
<td>Fifth Assessment Report</td>
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<td>GLA</td>
<td>Greater London Authority</td>
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<td>GVA</td>
<td>Gross Value Added</td>
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<td>I-O</td>
<td>Input-Output</td>
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<td>IPCC</td>
<td>Intergovernmental Panel on Climate Change</td>
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<td>MSOA</td>
<td>Mid-level Super Output Area</td>
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<td>NACE</td>
<td>Nomenclature of Economic Activities</td>
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<td>ONS</td>
<td>Office of National Statistics</td>
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<td>SIC</td>
<td>Standard Industrial Classification</td>
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<td>UIAF</td>
<td>Urban Integrated Assessment Framework</td>
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<td>VoT</td>
<td>Value of Time</td>
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1 Executive Summary

Climate change impacts to urban areas are often assessed by measuring direct damages to buildings, infrastructure, and people. These effects are more straightforward to simulate and calculate but often there are other, more complex, indirect impacts from climate change. A failure to consider or attempt to capture these effects in damage or impact assessments risks missing a large part of how future climate change will affect our urban areas. The direct effects are often modelled in impact assessment studies of climate change, but such indirect effects are rarely assessed.

Damage to key infrastructure in cities (such as transport networks) from extreme events is often costly to repair. This damage can also, however, result in a reduction in performance of that infrastructure and discomfort or inconvenience for its users. Since such infrastructure underpins the economic and social functions of urban areas, this reduction in performance can also lead to knock-on effects and wider costs to the city. Many economic sectors rely on transport networks for access to the labour market through commuting. Any disruption to commuting flows will lead to a loss of productivity of the economy.

In addition to the first-order effects of a loss of productive hours of work, there may be further effects. The urban economy is an interlinked system forming a co-reliant network of individual businesses and economic sectors. Disruption or damage to one sector can lead to second-order impacts along the business supply chain, with further economic costs due to a reduction in supply to businesses further down the chain. These effects can be captured through Input-Output modelling of the urban economy.

This report looks at the disruption of the urban economy and indirect impacts resulting from pluvial flood events caused by extreme rainfall. This proof-of-concept work is undertaken in the RAMSES case study city of London. Reduction in the performance of the commuting networks for both road and rail journeys are simulated and the indirect impacts on the economy calculated via loss of production. Results are presented for a number of economic sectors and for the economy of London as a whole. Second order effects are addressed using the Input-Output approach from UK national accounts.

It is shown in this deliverable that the total cost of indirect impacts from extreme weather, in the form of pluvial flooding, can be significant. For a 1-in-200 year rainfall event in London, costs of disruption in terms of loss of production could amount to £165m without adaptation. Second-order effects, which are propagated through the economy via business supply chains, can be even larger. Using Input-Output analysis, second order effects from the same event could total £174m.

Possible adaptation options for reducing the impact of such disruptions are discussed. The different stages of intervention in the urban economic system, and the potential effectiveness of soft and hard, green and grey adaptation options discussed. This work leads towards the final synthesis of city-level results to be presented in RAMSES Deliverable 3.4.
2 Introduction

RAMSES Deliverable 3.2 introduced the analysis of climate change risks in cities through an integrated assessment framework. That report demonstrated the unique challenges faced by cities which lead to them being particularly vulnerable to future changes to the climate. The nature of urban areas, with high levels of sealed surfaces, concentrations of people and infrastructure, and interconnected systems, have the potential to exacerbate any changes to risk from climate change alone.

As outlined in the earlier deliverable, several studies have shown that management of urban form and infrastructure provision can mediate a number of climate-related impacts on cities, such as energy use (Newman & Kenworthy 1999), flood risk (Dawson and Hall, 2006), and the intensity of the urban heat island. Such work shows that future vulnerability of cities to climate change is shaped by their operation as a system of interdependent components, the spatial configuration of which alters dynamically over time. It is the examination of these spatial patterns of vulnerability and of climate change impacts that will allow city planners, engineers and other organisations to start to map the most vulnerable spatial locations within cities.

The IPCC Fifth Assessment (AR5) identified the complex nature of climate vulnerability in urban areas (Revi et al, 2014). In particular, it highlights the interactions between climate change and socio-economic change, and the interdependencies in cities which may lead to increased vulnerability. It is widely recognised that future climate change will lead to an increase in the frequency, intensity, and duration of extreme weather events (such as intense rainfall leading to pluvial flooding (Rosenzweig et al., 2011)). The IPCC also make clear that climate change will impact a large cross-section of urban functions, infrastructure, and services, with such impacts occurring both at the location where the climate threat is experienced and, via interdependent networks of resource supply, in other more remote locations (Seto et al., 2012).

The AR5 report also highlights the risk faced by infrastructure in light of future climate extremes, particularly the risk of cascading effects across infrastructure systems. As Hunt and Watkiss (2011) discuss in their wide-ranging review of climate change impacts on cities, in large metropolises such as London, transport links support daily commuter flows from surrounding areas and the movement of goods. As such, any impacts from climate change the supporting transport infrastructure in a city has the potential to have knock-on effects on city populations and the population of satellite towns and the commuter belt. Gasper (2011) shows that extreme weather events will affect interconnected urban systems across multiple economic sectors. These impacts can be both direct (in terms of damage to the infrastructure itself and the cost of reconstruction) and indirect (in terms of the disruption to the functioning of the urban economy as the result of the damage).

Analysis of indirect impacts is central to understanding the broad impacts of climate change and to identify cost-effective adaptation measures. It also forms the basis for understanding the industrial, employment and population drivers behind land use change, which are key determinants of vulnerability to climate change. It has long been recognised that methods of computing direct damage (e.g. based on unit loss per property impacted) under-estimate climate change impacts. In this deliverable, the Urban Integrated Assessment Framework (UIAF) (as described in RAMSES Deliverable 3.2) is extended to analyse the impact of disruption to transport infrastructure, and thus the commuting and business supply routes which are dependent upon them. These outputs will lead to better estimates of the indirect losses associated with climate risks and thus estimates of the cost of climate impacts more broadly. Deliverable 3.2 set out a description of the methodology to be employed in WP3 of RAMSES to
analyse and assess adaptation to climate change at the city scale. This deliverable focusses on one particular aspect of the complex urban system; namely the urban economy, business linkages, and supporting infrastructure, and their vulnerability to extreme events.

2.1 Aim and Objectives

The overall aim of Deliverable 3.3 of RAMSES is to extend develop and demonstrate new methods to analyse the indirect impacts of climate change on urban areas, examining the disruption to business and supply chains.

The objectives of D3.3 are to:

- Spatially simulate, for a RAMSES case study city, disruption to urban infrastructure caused by extreme weather events;
- Determine the indirect impacts of such disruption on businesses in the urban area;
- Understand potential adaptation options to reduce such impacts in the future (ongoing into Deliverable 3.4).

Through achieving these objectives, Deliverable 3.3 will add the capability to the UIAF to examine indirect impacts on the urban economy. The development of this new analysis will be undertaken on the case study city of London. This is a logical choice for a number of reasons:

i. The importance of London as a regional centre, with a strong reliance on a surrounding hinterland for both commuting journeys to serve employment and business supply chains;
ii. Availability of free public data on employment locations, commuting journeys, and regional economic flows;
iii. Excellent stakeholder links for development of future adaptation options.

This report focusses on the disruption of transport infrastructure due to pluvial flooding, and demonstrates a number of climate events and their impact on a number of sectors of the economy. The results of these simulations are presented, and potential adaptation options to reduce these impacts outlined. The final section describes the relevance of these results and how they will be used in Deliverable 3.4 of RAMSES. Whilst this report is readable in isolation, more detail on the methodology may be found in Deliverable 3.2, and the full results of analysis of adaptation options and synthesis across multiple hazards and cities will be available in Deliverable 3.4.

3 Indirect impacts from climate change

Whilst many studies have examined the direct impacts of climate change on urban areas, the indirect impacts are more complex to understand and simulate with models. The reliance of cities on complex networks of infrastructure means that impacts in one location can be felt elsewhere in space and time (Seto et al, 2012). The economic functions of a city, and the lives of its inhabitants, are linked together by such infrastructure networks so disruption to one sector of the economy in one location can have knock-on effects on spatially-separated sectors elsewhere (Hallegatte et al, 2011a). Similarly, the supply of people in the labour force, the commuters, can be disrupted by damage to infrastructure networks and thus productivity adversely affected.
The main potential impact in urban areas to climate change is from the effects of extreme events, such as floods caused by heavy rain, on urban infrastructure (Hunt and Watkiss, 2011). The risk faced by cities from such events, as demonstrated to catastrophic levels by Hurricane Sandy in New York City, has given rise to a number of studies on categorising the wider economic impacts of such events, including the potential for cascading and non-linear effects (ibid). The direct impacts of extreme events on infrastructure are more easily assessed than indirect impacts or cascading failures between interdependent systems (Hallegatte et al, 2011b). RAMSES Deliverable 5.1 identified pluvial flooding as major source of climate risk in London, with events in recent years caused by heavy rainfall leading to disruption to infrastructure and associated major disruption to the service they underpin (Pitt, 2008). Indirect costs to the UK economy were estimated in the range of £3bn (€4.7bn) (Catovsky, 2011), with disruption to electricity, London Underground, road, and water infrastructure.

The effective operation of urban transport systems is essential for a city’s businesses, employees, and economic competitiveness. Any disruption to these systems has the potential to cause severe and far-reaching consequences. Often the interconnected nature of transport infrastructure means that additional effects, such as congestion can exacerbate problems and lead to still higher economic costs (Houghton et al., 2009). By examining such indirect effects, it is possible to analyse the impacts on business through loss of productive hours of employees, disruption to supply chains, and thus loss of earnings. The nature of cities such as London, with large commuter catchments and long daily journeys, means that they are more susceptible to the ill-effects of network disruption as they already feel lower satisfaction with life (Stutzer and Frey, 2008) and thus exhibit lower workplace productivity. Evidence also suggests that there is a relationship between travel time to work and commuting conditions, and poor health and work absences which can have further economic repercussions for employees (Bacon et al., 2009).

RAMSES Deliverable 3.2 described how the UIAF has been extended during Task 3.2 of the project to assess the impact of extreme events on urban transport, by analysing the damage that pluvial flooding from extreme rainfall may cause to transport infrastructure, and thus the knock-on costs to the urban economy. Many cities are aware of a substantial risk to their urban areas from pluvial flooding. Such studies, however, are usually focussed on direct damages, for example inundation of properties and businesses, where there are long-term and wide-ranging economic impacts. There has been little research undertaken into the short-term and indirect impacts that such flooding can cause. For example, pluvial flooding on transport links can often be short-lasting but can lead to substantial impacts on urban functions and thus disruption to the urban economy. Such research is also pertinent, as urban transport networks also serve as lifelines restoration and repairs, with emergency services relying them for access to carry out rescue and emergency assistance. As such, any disruptions to such networks can cause much wider effects (Dalziell and Nicholson 2001).

The Pitt Review into flooding in the UK in 2007 (Pitt, 2008) called for “improved understanding of the level of vulnerability or risk to which infrastructure and hence wider society is exposed”. Much of current transport infrastructure, even in urban areas, is exposed to weather-related hazards (Thornes, 1992). Transport is an increasingly important enabler of urban activity, allowing the movement of workers between residential and employment locations but climate change could potentially impact adversely on the efficient, safe, and cost-effective provision of those services (Jaroszewske, 2014). The impact of climate hazards on transport networks can be measured in a number of ways, but are often divided between direct impacts (e.g. physical damage to the transport infrastructure) and indirect impacts (e.g. disruption to the urban economy caused by sub-optimal network performance) (Walsh et al. 2012). Studies have often examined the direct impacts of flooding on transport infrastructure, but the indirect costs of delays, detours, and trip cancellation may also be substantial (Koetse and Rietveld, 2009). Indirect impacts are more difficult to calculate but their inclusion allows a
better assessment of the true scale and cost of disruption from climate events (Hallegatte et al, 2011b).

Arkell and Darch (2006) examined the potential impacts of pluvial flooding on London’s transport networks and found that there were over 1200 flooding incidents and 200 station closures on the London Underground network between 1992 to 2003, with over half related to surface water flooding caused by extreme rainfall. Much of this research assumes that delays to journeys undertaken by users of urban transport infrastructure are a useful proxy for measurement of disruption. Flooding cost the London Underground approximately €21.4 million in passenger between 1999 and 2004. A pluvial flood event on the 7th of August 2002, caused by an extreme rainfall event of 22mm of rainfall, led to the closure of tunnels at a number of underground stations, streets, and damage to water supply (City of London, 2010). On the road network, flood related traffic disruption during peak periods was estimated to cost at least €146,000 per hour delay on each main road affected, excluding infrastructure damage costs (ibid). The 2000 flood event caused a number of indirect impacts to London, with the disruption of a major commuting rail link between Oxford and London closed by flooding for five days in December. Estimated economic losses, which included lost time for rail passengers during the event and additional lost time during repairs to the infrastructure, were estimated at around £1.2m (€1.9) (LCCP, 2002).

There is little research in the literature that presents methodologies or models that examine the impacts of flooding on urban transport networks from a system-wide point of view (Pregnolato et al, 2016a). As described in Deliverable 3.2, the Urban Integrated Assessment Framework (UIAF) sets out to overcome this by combining a set of models and impact analysis tools linked together in order to analyse the way in which future global and national scenarios of climate change and economic development may impact on cities. One component of the UIAF, namely simulation of disruption to the transport network from extreme weather events and assessment of knock-on effects in the urban economy is employed in this report.

### 3.1 Disruption to the Urban Economy: London case study

London is considered one of the world’s megacities, with an economy mainly based around the finance and business services sectors. London’s economy is underpinned by over 5 million jobs, a number expected to rise by 20% in the next 20 years (GLA, 2016). Ramses Deliverable 5.1 reviewed London’s economy, showing that the metropolitan area’s GDP was in the region of £470.34bn (£563.9bn) in 2014, which equates to around 32% of the UK’s GDP (Brookings Institution and JPMorgan Chase, 2014) and €40,085 per capita (Brookings Institution, 2012). The business and finance sectors make up around 50% of London’s economy, dwarfing the next-largest economic sectors of trade and tourism (12%).

Whilst some of the employees who service these jobs are located within the Greater London Authority (GLA) area, the area made up of 33 boroughs that is governed by the mayor of London, a large number commute into London for employment every day. The City of London and Westminster see a total of 824,000 people commute into their areas for work each day (ONS, 2016). The urban economy therefore relies on the movement of large numbers of people in order to underpin productivity and economic performance. The movement of these people is facilitated by transport networks, the performance of which is vital for the functioning of the urban economy. There are other impacts, both direct and indirect on the urban economy that have been considered and simulated in other RAMSES deliverables, in particular Deliverable 5.2 (impacts on worker productivity due to extreme heat).
In addition to the movement of labour, there is also a need to consider the impact of infrastructure disruption on supply chains and the movement of resources (such as goods, water, energy, materials and waste) at a range of scales. The movement of these resources is vital for the health of urban residents, communities, and businesses. For example, prolonged flooding in Thailand in 2011 caused an estimated US $ 45 billion of direct damages (Aon Benfield, 2012), but also had global effects on the production and supply of a wide range of goods: about 25% of all hard drives in the world are manufactured in Thailand (Munich Re, 2012). Similarly, Hurricane Sandy had various effects on supply chains, with power cuts in New York City leading to the loss of perishable food; the restocking of produce was also hindered by the temporary closure of bridges (The City of New York, 2013). Typically, the impacts of extreme events on a regional economy have been modelled by assuming a uniform drop in production across sectors and not considered the spatial properties of supply, demand and the infrastructure that mediates these (e.g. Crawford-Brown et al., 2013).

There have been calls (for example Resurreccion and Santos, 2012) for risk assessment strategies to reduce the impacts of these disruptions but a crucial first step is to understand and analyse the interconnections and types of resource movement they mediate. To this end, RAMSES has developed an additional risk assessment methodology to examine the impacts of such disruptions to transport infrastructure and thus the indirect impacts to businesses propagated through their supply chains. A model has been developed in the RAMSES project and is presented in this deliverable to provide means of assessing the disruption to urban economies from climate hazards. The particular focus here is on extreme rainfall leading to pluvial flooding impacts on transport networks in the London case study city. The proposed methodology brings together two established modelling techniques: network analysis and input-output (I-O) modelling. The first stage is to assess the disruption to the labour force resulting from the reduction in performance of transport infrastructure in London, and thus the reduction in productive hours in business sectors supplied by that labour. The next stage is use of an I-O model to understand the further knock-on effects to other economic sectors by this first-order impact. Input-Output relationships (see Section 3.3) provide a holistic approach, taking into account both primary and secondary (or lower) interactions within the modelling process (Cordier et al., 2011). Haimes and Jiang (2001) have demonstrated the Input-Output approach to be a powerful tool for risk analysis through incorporation of an inoperability vector which describes the proportion of unrealised production against planned production (Barker and Haimes, 2009).

Using the above methods, two different types of indirect losses to the urban economy can therefore be estimated:

- Disruption to businesses caused by loss in productive hours of work due to increase in commuting times.
- Resultant disruption to businesses caused by a loss of trade between spatially-separated sites.

By combining these methods, a number of differing impacts on the urban economy can be simulated, and the higher-order effects of an initial infrastructure damage calculated. The methodology to simulate these effects will now be described before the application to the London case study is discussed in Section 4, and the results of this application in Section 5.
3.2 Simulating disruption to commuting journeys

The first stage of assessing indirect effects is determining the loss of economic productivity arising from disruption to the labour force during commuting journeys. The method for simulating disruption to commuting journeys was described in detail in RAMSES Deliverable 3.2, with examples for the city of Newcastle upon Tyne in the UK presented in Pregonalato et al. (2016). The UIAF is employed to simulate the effect of pluvial flooding, caused by extreme rainfall, on the transport networks in an urban area. The resultant disruptions are measured in terms of delays to commuting journeys. The main points of the methodology are summarized in this deliverable to ensure readability, but readers are encouraged to refer to Deliverable 3.2 for full details of any particular stage of analysis.

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., 2013). 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 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 Jaroszweski et al. (2010) identified mechanisms by which climate change would impact transport networks.

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 occurrence and the magnitude of such events. Jaroszweski 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 on sub-hourly rainfall that is a key driver of pluvial flooding in cities, but work by Kendon et al. (2012) has 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 therefore to understand pluvial flood risk and its impact at the scale of a city will require a simulation approach that can be used to explore 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.

The cost of disruption due to flooding has been estimated around £100k per hour for each main road affected (Hooper et al., 2014). Furthermore, roads are among the first cause 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, 2010). 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 (Dawson and O'Hare, 2005), whereas on average in North American cities 30% of the urban surface is road (Rodrigue, 2013). This is important as roads are typically constructed from impermeable materials and therefore particularly 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 increased travel times and pollution (Mao et al., 2012). Pluvial flooding can also affect urban public transport networks, particularly buses and rail services.
In the light of the above issues, a modelling framework to assess the impact of flood-related disruptions on the urban transport network has been developed. This framework was outlined in detail, with a full description of all models employed, in RAMSES Deliverable 3.2 but will be summarized here for reference. In order to quantify disruption to transport network performance due to floods, four steps of analysis are required.

(i) Hazard definition, by means of climate projections and flood modelling.
(ii) Evaluation of the hazard impact in terms of disruptions to the network performance, assessing the delays affecting traffic flows.
(iii) Estimation of cost implications of delays, by assigning a monetary value to the delayed time.
(iv) Assessment of the output of these steps to identify urban interventions (adaptation options) to reduce disruptions and test again.

This analysis can be undertaken for both the current day situation (baseline) and future scenarios in order to identified resilient pathways into the future. The data required to undertake these steps are available for the current time period for most metropolitan areas in Europe and US (e.g. meteorological observations, census data, and spatial network data). For future time periods, outputs from the UIAF can be used to define scenarios of future network configuration, future climate hazard footprints, and future commuting flows. Through a range of scenarios driven by probabilistic data, it is possible to model multiple hazards and thus carry out a risk assessment.

3.2.1 Hazard definition: urban flood simulation

A full description of the CityCAT model as applied in RAMSES is given in Deliverable 3.2. 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 already applied and calibrated for a number of cities. Photos and records from previous high-intensity rainfall events have been used to validate the model for Newcastle (Glenis et al., 2010; Glenis et al., 2013).

Rainfall time-series of precipitation intensity (considered uniform across the model domain in this study) during an event are propagated over the surface using a set of shallow water equations. The surface water flows take into account building locations and their footprint, permeability of the ground, and topography at a high resolution. Water depth and velocity are calculated dynamically throughout the simulation period and reported at each time-step as a grid of cells (in this study at a resolution of 5m) which can be used for further analysis. To reduce computational burden the sub-surface drainage network is not simulated as a dynamic network for this report. The outputs from the flood model are used to calculate impacts on the transport network.

3.2.2 Transport network model

The second element in the modelling framework is a simulation of the transport network in a 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 generalised cost of travel to assess the shortest route between an origin and destination. Free flow speeds on the links are defined using classes from the UK COBA model (Dft, 2004) inferred from attributes in Ordnance Survey Mastermap data, and speed-flow curves are used to simulate congestion.
effects on those links \textit{(ibid)}. These routes are then used for the assignment of trips from observed UK 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 are 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 a reduced speed accounting for congestion. Minor residential roads have been removed from the analysis as it was observed during previous flood events, 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 are simulated since disruption during the morning or evening peak has the potential for the greatest economic disruption (Hallegatte and Przyluski, 2010).

The transport model is applied to simulate all commuting journeys across the Greater London Authority region. Middle-level Super Output Area (MSOA) population-weighted centroids for the 2011 UK census (freely-available from the Office for National Statistics, UK) were used as origins and destinations for a total of 1222 origins and destinations, giving 1.5 million origin-destination pairs and a total of 2.5 million of these journeys, with routes computed for baseline and flood conditions. Following the same process as Ford \textit{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, correspond to the busiest observations. However, only a small proportion of roads have a traffic counter, and commuting flows make up only around 20\% of daily flows on the road network (DfT, 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 is deep flood water block the road entirely.

3.2.3 Transport disruption calculation for road and rail

The third and last stage involves translating flood depth, via the transport network model, into journey travel time increase and ultimately an economic cost. Chen \textit{et al.} (2016) consider the safety of car journeys as a type of flood impact related to the depth of flooding. To better represent the interaction between road users and water depth, Pregnolato \textit{et al.} (2016) developed a depth-disruption function by synthesizing experimental reports (e.g. Ong and Fwa, 2008; Galatioto \textit{et al.}, 2014), safety literature (e.g. Chung and Recker, 2012), experimental data (e.g. Boyce, 2012; Galatioto et al, 2014; Morris et al. 2011), analysis of videos of cars driving through floodwater (Alexandre, 2013), and expert judgment (e.g. Automobile Association, 2015). Data was from the EU, USA, Canada and Australia and for asphalt roads and so comparable (Figure 3). This moves beyond the crude assumption that the road is either open or closed according to a single arbitrary depth threshold, instead relating water depth (between 0 and a critical flood depth where the road is impassable) to safe driving car speed (Figure 1) which is consistent with observations from real flood events that drivers travel slowly through floodwater, including an observed event in Newcastle upon Tyne in 2012 (Newcastle City Council, 2013).

In order to develop the function, flood depth and car velocity were approximated from visual observations of videos, using the elapsed time to estimate vehicle speed and the level of flood water with respect to wheel diameter to estimate flood depth. Key factors in the safety of
vehicles passing through flood water are the clearance of the engine above road level and in the
dimension of the tyres, with lower cars being more at risk than higher vehicles. With some
vehicles, as little as 150mm of water can cause problems with engine failure due to water
entering the air intake. The maximum threshold for safe driving, stopping, and steering (without
loss of control) is identified as 300mm, an approximate measure of the average sill height of a
standard car.

Figure 1: Depth/disruption function relating water depth to safe driving speed for cars.

An upper and lower confidence interval are considered, to include uncertainties due to driving
characteristic and behaviour (e.g. type of car, asphalt or tire, behaviour of the driver, visibility).
Further research is needed to include uncertainties associated to each flood depth level and
different type of cars. Similar curves have been developed for different initial free-flow speeds,
but all functions have a maximum water depth (after which a road is considered closed) at
300mm.

The impact of pluvial flooding on public transport links (e.g. railway lines, underground
stations, or bus routes) is a more-complex problem than that of road disruption, and thus one on
which there is a less information in the literature. It is recognised that future climate change will
lead to greater disruption to the safe and efficient operation of public transport systems across
the world (Tracey et al, 2007; Koetse and Rietweld, 2009). In London, for example, flooding
from extreme rainfall is one of the primary risks facing the underground network from weather-
related hazards (Bull, 2012), alongside extreme temperatures (Jenkins et al, 2014). There have
been incidents of extreme rainfall causing disruption to the London Underground network in
recent years (Bolton, 2015), and such events are expected to happen more frequently in the
future. TfL (2015) have identified track and signal failure from flooding to be of very high
likelihood and medium impact, whilst failure of key infrastructure drainage has been identified as of extremely high impact. Inundation of signalling and electricity supply equipment by pluvial flooding caused by extreme rainfall has been identified as a threat to the London Underground system in particular (ibid).

A further problem caused by surface water and pluvial flooding on the railway network is that of disruption to signalling and train control systems. The Brown Review into the UK’s transport resilience after the winter disruptions of 2013/2014 (DfT, 2014) contained the following passage: “one of the major impacts of flooding on the railway is that standing water short circuits the electrical circuits installed in the track (track circuits) that are used to identify the presence of trains. This disables the automatic signalling, with the normal remedy being to deploy hand signallers on the track side to pass trains until the signalling system is restored. This is a very slow procedure and very substantially reduces the capacity of the line concerned.” Moreover, TfL identified many issues caused by flooding on London Underground infrastructure, such as short circuits in third-rail electrified lines, and lubricant being washed off point equipment. It is evident, therefore, that the operation of railway infrastructure is as important during a flood event as the operation of the railway vehicles themselves.

A number of studies have attempted to identify those links in the public transport network which are at risk from flooding (e.g. Sharada et al, 1999; Hong et al, 2015), but this is generally done by assessing the spatial relationship between flood hazard locations and railway infrastructure locations. As with the road network disruptions above, in most cases railway infrastructure is assumed to be either open or closed depending on the presence or absence of flood water, but reduced performance is not often considered. Koetse and Reitweld (2009), however, acknowledge that studies examining effects of weather or climate change on rail transport and infrastructure are scarce. It is, however, possible for railway infrastructure to remain open with water present depending on the depth and velocity of the way and whether the underlying infrastructure has been damaged by floodwater.

The UK Railway Rulebook (RSSB, 2015a) contains rules for drivers of trains in the UK on how to respond to flooding on railway track. Figure 10 shows the guidance within the rulebook. It can be seen that if flood water on the track is below the base of the ‘railhead’ then normal operating conditions apply. This is, of course, with the caveat that electrical and signalling systems have not already caused damage as described above. The height of the bottom of the railhead on modern track (measured above the top of the railway sleeper) is around 150mm (Arcelor Mittal, 2015). Since the level of complexity for disruption to railway services is much higher than that of private road travel, a set of simplified rules are adopted for the calculation of disruption to railways (both light rail systems and regular heavy rail services) in the RAMSES project. Adopting the RSSB standards for the UK, a set of thresholds is defined to determine the safe speed of passage for trains across the public transport network (see Figure 2). These thresholds are:

- Up to a water depth of 105mm the railway line operates as normal and the everyday speed limit applies
- Between a floodwater depth of 105mm and 150mm a speed limit of 5mph (~8kmph) is imposed on the railway link
- Above a depth of 150mm the railway line is considered closed.
These rules obviously ignore many of the issues highlighted above, in particular the disruption caused by pluvial flooding on signalling and electrical equipment. Whilst these effects are undoubtedly important, they can be considered beyond the scope of this Work Package and the authors recommend that they are addressed in future research projects. Similarly, the velocity of water is an important consideration given its impact on the stability of underlying railway infrastructure during flood conditions. For calculation of impacts of flooding on railways in RAMSES, however, it is assumed that the railway infrastructure is undamaged by the presence of flood water. Again, further research is needed into these important impacts of pluvial flooding on urban transport infrastructure.

### 3.2.4 Assessing the impact of disruption on commuting journeys

In order to assess the disruption to commuting journeys four datasets are required:

(i) Information on the spatial layout of the transport networks, with costs for travelling along links, connectivity between links, and capacity information for each link;

(ii) Information on the weather-related hazard footprints expected under different future climate scenarios;

(iii) Relationship between hazard and network performance;

(iv) Information on the number of users expected to be affected by disruption to each part of the network.

It can be seen from the previous sections, the datasets (i)-(iii) are provided for future time periods by components of the UIAF as described above. Dataset (iv), information on users of each transport link, is provided in part through the inclusion of journey-to-work matrices, either from observed data (e.g. census records) or model outputs from the zonal population model. Whilst, as mentioned previously, commuting journeys only make up around 50% of transport...
trips during the peak hours, information about other journeys (e.g. school trips, leisure trips, or shopping trips) are not provided by readily-available data or produced by the UIAF. Accurate data on the home-to-work commute is more often available than data on other trips (Boussauw and Witlox., 2009). Whilst it is recognised that these other trips are important, commuting trips are particularly crucial to the functioning of the local economy, and they are often rigid in terms of route taken and time allowed (ibid). It is therefore proposed that for disruption and cost calculations undertaken in RAMSES, readily available journey-to-work data be used from the 2011 UK census for the London case study city.

The methodology for the simulation of disruption to commuting journeys is depicted in a flowchart in Figure 3. The steps taken can be summarised as follows:

1. The generalised cost transport model is run for private and public modes to obtain an estimate of origin-destination travel costs (in units of time) between spatial zones in each case study city given unperturbed (baseline) network conditions.
2. An extreme rainfall event is simulated using the CityCAT flood model for each case study city to obtain a time series of flood water depth and velocity maps across the model domain.
3. These flood water maps are overlaid in GIS with a spatial representation of transport networks (road and public transport) to obtain an estimation of the expected flood depth on each network link.
4. Using the depth/damage functions described above, the speed on the network is adjusted to reflect safe passable speeds for the given depth of water present.
5. The cost of travel between spatial zones is recalculated using the new perturbed networks speeds.
6. The change in cost between flood-disrupted and normal conditions is calculated for every origin-destination pair in the model domain.
7. The change in travel cost will be multiplied by the number of persons making each trip in order to estimate the total Person-minute delay for each flood scenario and for each socio-economic scenario.
Figure 3: Flowchart for method to calculate disruption on commuting journeys.

The time epoch at which the maximum disruption is present during the CityCAT simulation has been selected, in order to analyse the greatest effect on commuting journeys. This can be done in a number of ways (e.g. the maximum number of cells above a given threshold, the maximum average water depth on the transport network) depending on the nature of the modelled area and the volume of water present. Whilst the linking of a dynamic transport model with the dynamic CityCAT simulation has been considered, it has been decided to continue with a simpler single time-step analysis at this stage. The results presented in this report assume the largest disruption is present at the final time step of the simulation.

A baseline transport scenario is 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 are evaluated. The hazard maps for each flood event showing water depths across the city (see Figure 13 for an example used in the London case study) are 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 Figure 1 capture a range of vehicle sizes, but with incomplete information on vehicles in Newcastle and their individual routes the central estimate of the depth-disruption function has been applied to each road link. When network characteristics are modified by hardening one or more links, traffic flows are 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 Minutes Delay (PMD) to measure the city-wide disruption is calculated by aggregating all of the delays to each passenger journey across the network:
\[ PMD = AS - A^{BA}, \quad A = \sum_{i=1}^{N} \sum_{j=1}^{N} T_{ij} C_{ij} \]  

(1)

where \( AS \) is the aggregate journey time across the \( N \) origin and destination zones in the city for scenario \( S \) (\( BA \) is the baseline scenario), \( T \) is the number of trips and \( C \) the 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 observed events the most notable and least understood impact is the loss of transport network performance. The resultant delays, due to rerouting and speed reduction, are used to compare the impacts of scenarios and the benefits of adaptation.

### 3.2.5 Economic impacts of disruption

Location of employment are linked to locations of residence through commuting flows. Simulating disruption to these flows along the transport network allows an estimation of the disruption caused to the economy by the inability for workers to reach their place of employment. As has been seen earlier in Section 3, this can often lead to very large economic effects, even for short duration climate-related disruptions. These the economic costs of these delays can be calculated in two ways: 1) direct assessment of delay costs using a Value of Time approach, or 2) assessment of the economic impacts of the delays at workplace locations through a loss of productive time and second-order knock-on effects.

The first approach gives an assumed cost for each journey by converting lost time due to commuting disruption into a monetary value. 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 (see Equation 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.

Delays can be converted into monetary terms using the Value of Time (Ford et al., 2015; Dft, 2014a; De Ortuazar 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 a Value of Time (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 \( C_{veh} \) is calculated by:

\[ C_{veh} = \Delta T \cdot VoT \]  

(2)

where \( \Delta T \) is the variation in journey time (hr) and \( VoT \) is the value of time (£/hr). The value of commuting time is properly defined as “Non-Working Travel Time”, which differs from “Working Time” (4 times higher) for business trips or journeys made in the course of work, as commuting trips usually use the commuter’s own time. Commuting time includes “all non-work journeys purposes, including travel to and from work” (DfT, 2014a). The 2010 market price for “Commuting time” per person is £6.81 per hour (US $ 10.56 at June 2012 prices). Whilst this Value of Time measure is defined for use in normal road conditions, it can be considered a low-bound to the level of economic cost, as the Value of Time 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 CO2 for the journey (de Palma and Lindsey, 2011; Mao et al., 2012), or social impacts in terms of driver health and wellbeing (Quah and Boon, 2003; Abu-Lebdeh, 2015).
An alternative approach to assessing the economic costs of disruption is to estimate indirect impacts through the reduction in productive hours at employment locations served by commuting trips. By examining such trips from the destination end of the journey, an indication of the impact of the disruption on business function can be calculated. The total reduction in production at zone \( j \) (\( p_j \)) caused by a disruption to mode \( m \) is assumed to be the sum of all delays (\( \Delta T \)) from all origins (\( i \)) locations from where workers travel to the employment zone \( j \) by mode \( m \):

\[
p_{jm} = \sum_{i=0}^{n} \Delta T
\]

(3)

\[
D_j = \frac{p_j}{WT} M
\]

(4)

To calculate the economic disruption \( D \) in zone \( j \), the proportion of the working time for all employees lost due to commuting delays is calculated (Equation 4). This is given by the ratio of total lost time from disruption to commuting journeys to that zone to the sum of all daily working time in that zone (employees in the zone multiplied by the average working hours in a day (8 hours)). This value is then multiplied by the proportion of all jobs in the zone served by the mode of transport being disrupted (\( M \)). This gives a measure of the cost of disruption to that zone’s economic output. In the census commuting flows it is not possible to discern which journey is linked to which employment sector, so disruptions are assumed to be felt equally across all economic sectors, with employees in all sectors disrupted equally. Thus, the productive hours of all economic sectors in each zone are reduced proportionally by lost hours from this process. This gives an estimation of the total first order impact of transport disruption at that location. Second order impacts to the economy can be calculated by the methodology described in the next section.

3.3 Vulnerability of Business Supply Chains

Businesses are linked together in space through supply chains. In London’s service-based economy, most of these supply-chains rely on the provision of services from one sector to another (e.g. the ICT sector underpinning the financial sector). These supply chains are complex networks underpinned by infrastructure, and any disruption to one sector can lead to a knock-on impact on the sector which rely upon it. Risks caused by unexpected events, such as pluvial floods, are one of the forms of impact that may interrupt normal business activity (Kleindorfer and Saad, 2005). To help mitigate against these disruptive effects, supply chains often incorporate mitigation strategies and contingencies to replace effected suppliers or re-route supply lines (Tomlin, 2006).

One means of analysing the interdependence and supply chains between business sectors is through the use of the Input-Output (I-O) Model. Leontief (1970) developed the I-O approach to
describe the activity and output of a given sector of an economy, which is related to the associated intensities of activities in other sectors within the same economy. I-O modelling can be used to represent interdependencies between elements of a system (Lifset, 2009), as critical industries share significant resources with the flow of goods and information constantly taking place between these different sectors (Pant et al., 2011). The levels of outputs and interdependencies, both desirable and undesirable, can be analysed and described as part of a network (Leontief, 1970) of interconnected businesses. I-O accounting is an established technique used by national governments to describe their economy. ESA (2010) published the Supply, Use and Input-output Tables methodology, which provides guidelines for the development of national supply and use tables, as well as the Symmetric Input-Output table. These tables highlight: industrial interdependencies, movements of goods and services within an economy, and imports and exports from the economy.

The I-O model describes relationships between sectors in the economy, and therefore how an output from one sector may be used as an input to another. The approach highlights the level of dependency each industrial sector has with every other industrial sector, and thus how each sector is both a supplier of outputs to some sectors and consumer of inputs from others (Ten Raa, 2009). The demand for outputs from one sector can be influenced by the sectors it supplies. For example, if the demand for construction rose then the demand for outputs from various parts of the manufacturing industry, as a supplier to construction, is also likely to go up. These inter-industry linkages can be used to investigate the knock-on effects caused by changes in demand (The Scottish Government, 2015).

The I-O approach is useful to estimate the impact of disruptive climate events on the urban economy, particularly in terms of knock-on secondary effects to spatially-distinct businesses. (Pant et al., 2011). Hallegatte (2008) used an application of I-O modelling to assess the economic cost of Hurricane Katrina to the city of New Orleans and its surrounding region. The study employed regional I-O tables and calculated both direct and indirect losses caused by the disaster. Since the I-O model describes the flow of resources between different industrial sectors it is able to capture interdependencies between elements of a system (Lifset, 2009) and the flow of goods and information constantly takes place among these different industrial sectors (Pant et al., 2011). Infrastructure systems, including transport, energy, and ICT, mediate the movement of these resources through networks and link together spatially-separated locations of industrial and commercial activity.

To understand resource flows across infrastructure networks, the transport modelling approaches described above have been extended through economic modelling to capture inputs, $I$, outputs, $O$, as well as stocks, $S$ and flows through time, $t$. The model enables a range of alternative resource management strategies to be explored (Figure 4).
I-O relationships describe the input requirements per unit of output, or what each sector requires from the other sectors in a system to produce one unit of its product (Leontief, 1970). This describes the interdependencies between different sectors, underpinned by supporting infrastructure. The input output relationship is defined as:

\[ x = \hat{C}x + d \]  \hspace{1cm} (5)

where \( x \) is the desired production, \( \hat{C} \) is the consumption matrix and \( d \) is the final demand. The equilibrium production is calculated using:

\[ x = (I - \hat{C})^{-1}d \]  \hspace{1cm} (6)

where \( I \) is the identity matrix and \((I - \hat{C})^{-1}\) is generally referred to as the Leontief Inverse, or the total requirements matrix (Hawkins et al., 2007) which captures both the direct and indirect input requirements into the system (Duchin and Levine, 2008).

An I-O relationship highlights how different industrial sectors are affected by impacts in other parts of the system. For example, industry A requires \( x \) from industry B and \( y \) from industry C. In turn industry A supplies industries B, D and E with \( z \) of its own outputs. Thus, a disruption in supply from Industry B will have a knock-on effect to production in A, which subsequently cascades back to industry B and also industries D and E.

Each industrial site is represented as a node in the network, and connected via a link to other relevant sites if an I-O relationship exists. So for example in Figure 4, the magnified view of one node shows it has three inputs, which provide a given quantity of a resource at each time step. In this instance, the singular output acts as an input for another industrial activity. The model also contains reserve stocks at each of the sites; enabling each different site to have different stocks of resources level. In a service-based economy, as in London, such stocks are less important.

The vulnerability of a given urban system to hazards like floods is influenced by the spatial distribution of networks and sites across urban areas. Businesses are located at specific spatial locations, often very small sites in relation to the extent of the urban area, and connected to transport networks that supply and link them. Typically input/output data is not provided at a spatial resolution that is suitable for impact analysis within areas of heterogeneous activity. Thus, an important step is the spatial disaggregation of input/output data from large spatial scale (often aggregate totals for a given city) to smaller spatial units.
This disaggregation has been undertaken in the UK using data from the Annual Business Inquiry (ABI) which records the number people employed within a specific industry Mid-level Super Output Area (MSOA) level. These zones are consistent with the transport analysis described above. The following steps are then undertaken to carry out a vulnerability assessment of the urban economy to a given hazard.

First the supply and demand for modelled sectors of the economy at zonal scale are estimated by:

a) Filtering ABI data (or equivalent) at SIC 4 digit classification level to include only the modelled sectors,

b) Manipulating these sectors to match the input/output sectors that match the records from the regional accounts of the urban area being modelling.

c) Using the count of employees from the ABI \(e\) for each site of production \(s\) in each zone to estimate the proportion of the total number of employees in that sector within the whole economy \(E\).

d) Multiplying the proportion of employment for each sector against the vector of demand \(d\) for that sector (column within the input/output table) to give the individual demands for each modelled site of production at a zonal level.

e) Multiplying the ABI proportion for all sites of production by the total supply \(S\) for each sector to give the individual supply \(i\) available from each site of production

The resulting individual demand and supply at a spatial site is therefore given by equations (7) and (8)

\[
d(s) = \left( \frac{e(s)}{E} \right) D \tag{7}
\]

\[
i(s) = \left( \frac{e(s)}{E} \right) S \tag{8}
\]

Next the disruption to the economic activity at a given location due to pluvial flooding is calculated using Equation 4 above. This gives a first-order calculation of the impact on the economy. By the use of Input-Output tables for the UK (ONS, 2017), the second-order impact of this disruption on further business sectors is calculated by reducing the production of businesses which rely on the first-order disrupted sectors for their production. Using this method, threats to spatially-disparate businesses and economic sectors that are linked through supply chains can be examined through the use of Input-Output analysis.

Further disruption is likely when the network links (in this case, transport is considered) between business sectors are damaged. For example, if the transport network is affected by floods as described above, the ability for staff, communication, or goods to move between two industrial sectors is also diminished. In order to estimate such disruption, the business locations inferred from employment data can be linked to network analysis in a similar way to the calculation of commuting routes described above (the least cost route between two business locations along the transport network). If this route is then disrupted and the cost of the journey increased, this will reflect is a proportional reduction in the supply of goods and services (i.e. the flow in the input/output table) between these two industrial sectors, normalised by the number of jobs in the supply sector at the origin location. In some cases, these I-O relationships represent physical flows of goods between economic sectors.

The techniques outlined above have been applied to the RAMSES case study city of London to demonstrate the methods for calculating indirect impacts of climate events on the urban economy and business supply chains. This is possible due to the availability of commuting and economic Input-Output data for the London case study. Such detailed economic analysis will not be undertaken in other case study cities. The results of these analyses will now be presented. Further work on testing of
adaptation options to reduce these impacts is ongoing in WP3 of the project, and will be presented in Deliverable 3.4.

3.4 Adaptation options for reduction of indirect impacts

RAMSES Deliverable 3.2 highlighted the adaptation options available to reduce the flood risk in urban areas. These adaptations were categorised into:

- Hard adaptation: physical measures installed or alterations to infrastructure to reduce the risk from climate disruption. These can be in the form of Grey adaptation (traditional engineering approaches to infrastructure), or Green adaptation (nature-based approaches like green roofs or sustainable urban drainage systems).
- Soft adaptation: manages the use of the infrastructure through changes to behaviour or practice to reduce the vulnerability of the population to climate disruption.

As discussed in the earlier deliverable, Task 2.4 of RAMSES (‘Adaptation measures and corresponding indicators for resilient architecture and infrastructure’) examined potential adaptation measures that can be employed to improve the resilience of the urban system. This work identified a number of possible interventions for different climate threats and different components of city infrastructure. The adaptation options highlighted in RAMSES Deliverable 2.4 for flooding and to improve the resilience of transport infrastructure are summarised in Table 1. There are other adaptation options presented in Deliverable 2.4 but these options have been selected as it is possible to include them in simulations of flooding hazard (through pluvial flood modelling), transport network configuration or performance (through transport modelling).

<table>
<thead>
<tr>
<th>Resilient Transport Infrastructure</th>
<th>Multiple transport modes</th>
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<tr>
<td>Non-motorised transport</td>
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<tr>
<th>Flood Adaptation (SUDS)</th>
<th>Blue roof</th>
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<td>Green roof</td>
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<td></td>
<td>Mixed use flood management zones (green)</td>
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<td></td>
<td>Permeable pavements</td>
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<td></td>
<td>Rainwater harvesting</td>
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<td>Urban lakes and water bodies/urban trees and parks</td>
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<th>Flood adapted planning</th>
<th>Flood adapted construction</th>
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<td></td>
<td>Flood adapted location</td>
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<td></td>
<td>Critical infrastructure location</td>
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Table 1: Possible adaptation measures for flooding and urban infrastructure identified in RAMSES Deliverable 2.4.

The extension of analysis to include aspects of disruption to the urban economy increases the number of possible adaptation options that can be tested during the analysis process. In addition to these options identified in Table 1, there are additional possibilities for soft adaptation which could reduce the impacts outlined in the previous section. The intervention point differs for each of these types of adaptation, giving the option of portfolios of measures being deployed at different points in the urban system to maximise the resilience to both direct and indirect effects.
Figure 5 shows the possible points of intervention in the urban system to reduce disruption from pluvial flooding impacts. In general, green adaptation options intervene between the source rainfall and transmission of rainwater along surface pathways, thus reducing the hazard severity experienced. Grey adaptation options intervene at the reception of the surface water flow on critical infrastructure (e.g. transport network links) reducing the vulnerability of those links to a given hazard level. Soft adaptation options intervene at the operational level of the network, thus reducing the exposure of each network link to disruption by reducing criticality. Figure 5 shows the various points of intervention in the methodology described earlier.

Work presented in Pregnolato et al (2016) shows the use of network measures such as betweenness centrality to assist in targeting adaptation options to the most effective locations in the transport system. Critical links can be selected through a matrix combining hazard severity (flood depth) and exposure (the number of journeys using the link in the network) to provide an indication of how severely a link could be impacted by a flooding event. This allows an estimation to identify and prioritise critical locations in the transport network and thus provides insights into the local and global benefits of different adaptation strategies across the system.

Such a methodology can be used to assess the potential of well-targeted engineering interventions in comparison to green and blue infrastructure. It also allows the prioritisation of limited financial resources to improve transport network resilience. This is particularly important as flood risk management investments typically have a much higher benefit cost threshold than transport infrastructure investments (see RAMSES Deliverable 5.3 for adaptation cost curves for flood protection infrastructure). By capturing the value to the transport network from flood management interventions, it is possible to create new business models that provide benefits, and enhance the resilience of, both transport and flood risk management infrastructures.

![Figure 5: Points of intervention for adaptation measures in reducing disruption from pluvial flooding to the urban economy.](image-url)
The simulation of adaptation options is part of Task 3.4 and these results will be presented in the final deliverable from WP3, Deliverable 3.4. A summary of the options being simulated are, however, presented here for completeness.

Green adaptation options are tested during the modelling of pluvial flooding using the CityCAT model. Of the measures catalogued in Task 2.4, a subset are being simulated for London during Task 3.4 to estimate the reduction in the indirect impacts of flooding on the urban economy and business supply chains. The options being tested include:

- Blue roofs – the addition of water tanks to certain buildings in the model domain. These buildings are being identified during work with stakeholders in the Environment team at the GLA.

- Green roofs – the addition of vegetation to building roofs to capture and store water. Such roofs also have co-benefits in reducing urban temperature and improving biodiversity. The buildings with green roof potential are being identified with GLA stakeholders.

- Permeable pavements – increasing the permeability of pavements across the model domain. This is being undertaken in a uniform way by increasing the porosity values of surfaces in the CityCAT model.

- Urban greenspace (parks/flood management zones) – current greenspace has been identified in London and simulations are testing the effectiveness of increased greenspace on reduction to pluvial flood impacts.

Grey adaptation options are being tested through modification of the attributes of individual transport links in the network to improve their resilience to flood impacts (see Section 4.1.1). The options from D2.4 being tested in the transport disruption model are:

- Installation of rainwater tanks: Simulating the removal and storage of a portion of surface water through the construction of tanks at some location along the pathway, thus interception surface water before it causes an impact on transport links.

- Flood adapted location: moving critical transport links in order to reduce flood risk by raising them above the level of flood water (i.e. making them impervious to flooding)

- Flood adapted construction: reducing the impact of flood water on critical transport links through modification of the depth/disruption relationship (e.g. to simulate the effect of improved drainage on transport links).

Soft adaptations are implemented through the exposure component of the process, by adjusting the behaviour of transport users on the network. These include:

- Altering the transport networks and generalised cost formulation to make alternative, more resilient modes of travel more attractive. For example, scenarios of improved public transport provision or improved walking and cycling infrastructure are being examined as such modes are expected to be more resilient to surface water flooding than private car travel.

- Increasing the number of people working from home, and thus reducing the criticality of the transport network for business commuting.

- Spatial planning options, such as mixed-use developments, to reduce commuting distances and thus exposure to and reliance on transport networks of businesses and the labour force.

These adaptation options are each applicable at different scales but also managed by different actors in the urban system. Soft adaptation options are managed by urban planners and infrastructure managers (e.g. public transport operators) to manage the use of the in situ
networks. Hard adaptation measures are managed by flood risk managers and engineers to alter the physical characteristics of infrastructure and their resilience. Thus different governance arrangements can potentially be tested using this framework to assess the most effective adaptation portfolios for reducing future climate risk. The results of this analysis testing, and synthesis of results of all WP3 tasks, will be presented in Deliverable 3.4. The planning of adaptation can be assisted by the RAMSES Deliverable 8.2, which presents a transition model for moving towards a more resilient future.
4 London Case Study Results

As described above, the Greater London Authority area contains 5 million jobs. Figure 6 shows the spatial distribution of these jobs across the city. It can be seen that the majority of these jobs are located in three major employment locations: central London (A), the Docklands Area (B), and Heathrow Airport (C). These locations differ in their nature: the vast majority of employees in central London commute into the area each day from other zones in the region (up to 800,000 each day into the City of London alone), predominately by public transport modes. The Docklands area sees a large number of commuters but also has a number of employees living in the local area. The Heathrow Airport zone sees a large number of people travelling to work there each day, but the majority of these travel by private transport (road).

![Figure 6: Total employment in each MSOA in the Greater London Authority area](image)

Figure 7 shows the distribution of total population in each of the corresponding MSOA areas across the GLA area. As can be seen, the locations of higher population do not correspond directly with location of employment. Thus, transport networks are required to facilitate the access of these workers to locations of high employment. These transport networks, for both private (road) journeys and public transport (integrated bus, rail, and Underground networks), are shown in Figures 8 and 9. It is these networks which are at risk from pluvial flooding and whose function must be maintained in order to avoid losses in the urban economy.
Figure 7: Population per MSOA area across the GLA region.

Figure 8: Network of major roads across the GLA region as used in the disruption analysis.
Figure 9: integrated public transport network as used in the disruption analysis.

The methodology described above was applied to the case study city of London in order to simulate the impacts of a pluvial flooding event on the urban economy. For this study, London has been defined by the Greater London Authority (GLA) area, made up of the 33 boroughs of London. As outlined above, London’s economy is reliant on commuting to and within the urban area to support economic activity. Whilst a large number of commuting journeys into this area originate outside the boundary of the administrative region, they have not been simulated at this demonstration stage (see Discussion section). Instead, disruptions to the commuting journeys within the GLA area, and a 5km buffer area around the GLA area, are simulated to reduce computational complexity and data requirements, but this analysis still simulates a total of 4.89 million jobs and their commuting flows. Jobs across 19 industrial sectors as defined by the UK SIC (NACE) classification (Companies House, 2015). These sectors are listed in Table 2.

<table>
<thead>
<tr>
<th>Sector</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>Agriculture, Forestry and Fishing</td>
</tr>
<tr>
<td>B</td>
<td>Mining and quarrying</td>
</tr>
<tr>
<td>C</td>
<td>Manufacturing</td>
</tr>
<tr>
<td>D</td>
<td>Electricity, Gas, Steam and air conditioning</td>
</tr>
<tr>
<td>E</td>
<td>Water supply, sewerage, waste management and remediation activities</td>
</tr>
<tr>
<td>F</td>
<td>Construction</td>
</tr>
<tr>
<td>G</td>
<td>Wholesale and retail trade; repair of motor vehicles and motorcycles</td>
</tr>
<tr>
<td>H</td>
<td>Transport and storage</td>
</tr>
<tr>
<td>I</td>
<td>Accommodation and food service activities</td>
</tr>
</tbody>
</table>
The number of jobs in each of these sectors is recorded at MSOA level. Figure 10 shows the proportion of all of London’s jobs in Sector K (Financial and Insurance Activities). As can be seen, a large proportion of jobs in this sector are concentrated in a small number of spatial locations (the City of London, and Canary Wharf areas). This means that any disruption to transport services to those employment locations will have significant impact on the function of that sector of the economy.

Figure 11 shows the journey-to-work flows to the Canary Wharf MSOA ward from all other wards in the metropolitan area demonstrating the wide spatial area from which employees in that zone travel. Note that whilst some links go beyond the GLA boundary in Figure 11, only
those journeys within a 5km buffer of London are simulated as described above. The MSOA with code E02006854 attracts workers from almost 2000 other zones across the UK, with a total of 77,000 workers registered as travelling to that zone for work by train in the census journey-to-work data. Those workers starting their journey within the GLA by all modes (private and public) are simulated in these results.

Figure 11: Journey-to-work flows to the Canary Wharf MSOA (E02006854) from other MSOAs in the London metropolitan area.

By contrast, Figure 12 shows the proportion of employment in the GLA area in each MSOA zone in Sector P (Education). As can be seen from the map, the employment in this sector is much more evenly-distributed across the region, with a small proportion of total jobs in each zone. The major universities in the centre of London are obvious but a large number of other jobs are also present in MSOA zones across the GLA. This makes this sector as a whole much more resilient to any potential disruption to commuting travel.
These individual maps show the spatial interconnections between residence and employment in the London case study city, and the reliance on transport networks for commuting across the region.

### 4.1 Pluvial Flood Risk

Whilst pluvial flooding may lead to specific local impacts (e.g. inundation of buildings) causing impacts on businesses at the small scale, in this task the impacts have been examined at city scale. This is to allow for the examination of system-wide impacts across urban areas and testing of adaptation options across a broad spatial domain. The CityCAT flood model has been run to simulate the surface water flooding resulting from a design storm of 200 year return period and a duration of 60 minutes across the whole GLA area at a 5m resolution. This results in around 50 million data points per time step throughout the simulation. In order to allow modelling across such a wide area, the resolution of the modelling is limited to 5m which means that assessments of small-scale local impacts is not possible, but it allows for a broad-scale assessment of regions at risk from pluvial flooding across the urban area. Whilst it is possible to model fine-scale impacts of surface water and pluvial flooding on individual urban infrastructure component such as transport links or residential dwellings (see Zhou et al (2012) and Galatioto et al (2014) for studies of this type) in detail, for a city-wide study a more systemic approach is needed.

The outputs from the CityCAT model for the design storm event are overlaid with the spatial representations of both the private (road) and public (bus, London Underground, and rail) networks to understand which portions of each network are disrupted by the flood event. The
The final time-step of the flood event is taken as the point at which the disruption to the network is at its greatest. The process for calculating transport disruption is as follows:

1. The water depth value of every cell in the simulation within 5m of a transport link is assessed in relation to the threshold values outlined in Section 3.2.3. The maximum water depth of all of the points within this distance is assigned to each transport link in the network (79,000 links for road, and 644,000 links for public transport) for input into the disruption calculation.
2. The travel speed, and thus time, for each link is recalculated according to the disruption specification in Section 3.2.3.
3. The origin-destination journey cost for every pair of MSOA population-weighted centroids in the GLA area is calculated, first for the baseline unperturbed situation, and then for the flood-disrupted case. Difference in travel time (i.e. delay) is computed.
4. The difference in time is multiplied by the number of people recorded making that data in the latest (2011) UK census journey-to-work tables to give the PMD value for that origin-destination pair.

Figure 13 shows an indicative time step during the simulated design storm event over the London domain. The flood depths resulting from this simulation range from 0 to 5.5m. These depths must be treated with caution: a simulation of this scale over such a large domain is limited by a number of modelling assumptions: there is no simulation of the drainage network in the city, so water may pool more rapidly in some areas than would be expected in reality; the spatial resolution of land-use information is limited to the 5m resolution of the grid cell, so thus small areas of greenspace may be omitted; and the DEM employed in the simulation may omit small topographic features which may exacerbate or mitigate against the development of pluvial flood conditions across the model domain. This issues are being addressed during the application of CityCAT to case study cities and the testing of adaptation options and will be reported separately in RAMSES Deliverable 3.4.

![Figure 13: CityCAT output for London model domain showing flood depths at 5m resolution.](image_url)
Figure 14 shows the points around a transport link above the threshold for road closure, demonstrating how information from the CityCAT model runs is assigned to the transport network in order to calculate disruptions. As can be seen, each transport link can be affected by a number of different flood depths, so the maximum depth along each link is recorded at this stage of the process.

![Figure 14: Detailed view of CityCAT flood depth points related to transport network links](image)

The water depth from CityCAT outputs is then used in the depth-disruption relationships outlined in Section 3.2 to calculate new travel speeds for each transport link under the presence of flood water. These speeds are then used in a calculation of new routes and travel times for commuting journeys across the GLA area.

### 4.1.1 Example of disruption to transport trips

The full analysis simulates all observed journeys to work in the wider Greater London Authority area. In order to demonstrate the methodology employed in the full system-scale analysis in more detail, a single journey is described here, showing the impact of flooding on urban transport function, and thus the increase in cost via rerouting and delays. The results of this test are illustrated in Figure 15: the first panel (upper left corner) shows firstly the Baseline route taken in the simulation on a journey between five locations on the road network. These stops are visited in order and the route between them can be seen to follow the major roads in the city and the lowest cost path between the destinations. Under the No Adaptation (NA) simulation, the route was modified as a result of the journey avoiding flood disruption on the network and thus finding an alternative faster route, using secondary streets.
The panels in Figure 15 demonstrate a potential adaptation option for a number of links in the network to return those links back to their previous performance (see Section 3.4 for a discussion of possible adaptation options). The successive introduction of each adapted, or ‘hardened’, link (LH_1 to LH_3) results in the route returning to a closer approximation of the original Baseline route, as the adaptation maintains the performance of the link to a level closer to the original travel time. This simple example assumes an adaptation returns the link performance to its unflooded state.
Since the disruption due to flooding causes re-routing of the journey, measures of time delay and additional length can be captured to assess the level of impact. Values for this example route are shown in Table 3. These show that, for this single example journey, the disruption caused by floodwater adds around 15 minutes to the journey time. This does not include congestion effects, which will exacerbate the problem, especially since the diversionary routes are likely to be lower-classification roads. This re-routing also assumes that users of the network making the journey have perfect knowledge and are able to divert to the next lowest-cost route. It can be seen, therefore, that this delay is effectively the ‘best case scenario’ and the delay in reality will be longer than this. The full system-scale analysis presented in the remainder of this section follows the same approach, but the disrupted journeys are calculated for every pair of origins and destinations across the network.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Disruption</th>
</tr>
</thead>
<tbody>
<tr>
<td>Label</td>
<td>No. of adapted links</td>
</tr>
<tr>
<td>BS</td>
<td>N/A</td>
</tr>
<tr>
<td>NA</td>
<td>0</td>
</tr>
<tr>
<td>LH_1</td>
<td>1</td>
</tr>
<tr>
<td>LH_2</td>
<td>2</td>
</tr>
<tr>
<td>LH_3</td>
<td>3</td>
</tr>
</tbody>
</table>

*Table 3: Impact of disruption and ‘adaptation’ on routes through the road network shown in Figure 15.*

### 4.2 Impact calculations

Once the disruption to transport networks is simulated using the above methodology, the resulting indirect impacts to the urban economy can be calculated. These impacts can be assessed and visualised in a number of ways:

- The aggregate impact of transport disruption from a flood event can be assessed for a given economic sector, examining the spatial interdependencies between main locations of activity and commuting flow or business supply chains. This can be done through a series of spatial visualisations of the impact at each stage in the impact chain.
- The aggregate impact of first-, second-, or nth-order impacts across all economic sectors can be assessed through numerical measures of lost productivity throughout the whole study area. This can be used to compare the relative vulnerability of each sector to a given event.

The resulting impact is calculated using Equations 3 and 4 and recorded for every origin, destination, and origin-destination journey. First the indirect impacts on one spatially-distributed employment sector will be presented, followed by aggregated results for all economic sectors in the GLA economy.
4.2.1 **Indirect impacts to economic sectors**

The Financial and Insurances Activities sector (Sector K) of the London economy is the 7th largest in terms of total employment but contributes to around 20% of London’s annual GDP (GLA, 2016). This important sector is spatially-concentrated in a small number of employment areas (see Figure 6), making it particularly vulnerable to disruptions to commuting journeys. The disruption to this sector has been calculated using the above methodology for the London case study, giving the total indirect economic impact of one rainfall event (1 in 200 year return period). Table 4 shows the disruption results for the four MSOA zones with the highest employment in Sector K which make up 70% of London’s total jobs in this sector. The total employment can be multiplied by 480 to give the total average minutes of daily work in that zone, and thus the ratio of lost time in the form of the Total PMD for all journeys by private or public transport modes into the zone calculated (as in Equation 4). This is normalised by the proportion of employees travelling by the modes being disrupted (i.e. only those employees who travel by private car or public transport are affected, not those walking, cycling, or using other modes).

<table>
<thead>
<tr>
<th>Zone ID</th>
<th>Zone Name</th>
<th>Total Sector K Employment</th>
<th>Proportion of Commuters</th>
<th>Total PMD</th>
<th>Proportion of economic output lost</th>
</tr>
</thead>
<tbody>
<tr>
<td>E02000001</td>
<td>City of London 001</td>
<td>162000</td>
<td>47.0%</td>
<td>12068065</td>
<td>12.16%</td>
</tr>
<tr>
<td>E02006854</td>
<td>Tower Hamlets 033</td>
<td>60000</td>
<td>52.6%</td>
<td>5948525</td>
<td>19.17%</td>
</tr>
<tr>
<td>E02000977</td>
<td>Westminster 018</td>
<td>17000</td>
<td>56.7%</td>
<td>5344153</td>
<td>11.24%</td>
</tr>
<tr>
<td>E02000972</td>
<td>Westminster 013</td>
<td>7000</td>
<td>52.1%</td>
<td>4647271</td>
<td>10.87%</td>
</tr>
</tbody>
</table>

Table 4: Results for disruption to road and public transport networks for the four zones with highest employment in the Financial and Insurance Activities sector (Sector K).

These results show that for these four MSOA zones, the proportion of economic output lost can be seen to be in the region of 10-20% for the simulated day in question. The Gross Value Added (GVA) per year of London’s finance sector was around £60.5 billion in 2012 (GLA Economics, 2015). Assuming that the proportion of GVA in the sector is distributed across all workers evenly, the proportional contribution of each sector’s employees to total GVA, and therefore the estimated GVA per MSOA can be calculated. Table 5 shows the proportion of London’s total employment in Sector K in each of the four zones above, and thus the total estimated daily GVA (annual GVA / 365) for each of those zones. The total lost GVA, assuming disrupted time for employees is time which is unproductive, is given in the final column. The disruption to these four zones alone for a single day could cost up to £15.93 million in lost GVA to London’s economy.

<table>
<thead>
<tr>
<th>Zone Name</th>
<th>Total Sector K Employment</th>
<th>Proportion of Total London Employment in Sector K</th>
<th>Total Daily GVA in Zone</th>
<th>Total Lost GVA for One-day Flood Event</th>
</tr>
</thead>
<tbody>
<tr>
<td>City of London 001</td>
<td>162000</td>
<td>46.00%</td>
<td>£76.175m</td>
<td>£9.27m</td>
</tr>
<tr>
<td>Tower Hamlets 033</td>
<td>60000</td>
<td>17.03%</td>
<td>£28.213m</td>
<td>£5.40m</td>
</tr>
<tr>
<td>Westminster 018</td>
<td>17000</td>
<td>4.82%</td>
<td>£7.993m</td>
<td>£0.90m</td>
</tr>
</tbody>
</table>
Table 5: Lost economic output from disruptions to commuting journeys in the four zones with the highest employment in Sector K.

The disruption caused by this event is not limited to the four zones summarised above. By summing the total disruption to all sectors in the same way it is possible to calculate the total economic cost to each economic sector in the modelled area. This is limited by the available data from the UK Regional Accounts (ONS, 2016) which are aggregated to a slightly different set of sectors from the NACE classification (Sectors ABDE are aggregated together, as are Sectors R and S). Table 6 shows the total first-order disruption to each of the remaining sectors for the simulated flood event resulting from delays to commuters as both a total and as a percentage of that sector’s daily GVA.

<table>
<thead>
<tr>
<th>Sector</th>
<th>Description</th>
<th>Total First Order Disruption Cost</th>
<th>% GVA Loss</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>Manufacturing</td>
<td>£6.550 million</td>
<td>29.90</td>
</tr>
<tr>
<td>F</td>
<td>Construction</td>
<td>£10.631 million</td>
<td>25.58</td>
</tr>
<tr>
<td>G</td>
<td>Wholesale and retail trade</td>
<td>£17.562 million</td>
<td>24.45</td>
</tr>
<tr>
<td>H</td>
<td>Transportation and storage</td>
<td>£10.847 million</td>
<td>28.41</td>
</tr>
<tr>
<td>I</td>
<td>Accommodation and food</td>
<td>£5.432 million</td>
<td>19.94</td>
</tr>
<tr>
<td>J</td>
<td>Information and Communications</td>
<td>£16.187 million</td>
<td>17.63</td>
</tr>
<tr>
<td>K</td>
<td>Financial and insurance activities</td>
<td>£24.819 million</td>
<td>14.98</td>
</tr>
<tr>
<td>L</td>
<td>Real estate activities</td>
<td>£19.037 million</td>
<td>18.93</td>
</tr>
<tr>
<td>M</td>
<td>Professional, scientific, and technical</td>
<td>£16.909 million</td>
<td>16.91</td>
</tr>
<tr>
<td>N</td>
<td>Administrative and support</td>
<td>£10.603 million</td>
<td>20.65</td>
</tr>
<tr>
<td>O</td>
<td>Public administration and defence</td>
<td>£6.043 million</td>
<td>17.42</td>
</tr>
<tr>
<td>P</td>
<td>Education</td>
<td>£11.070 million</td>
<td>23.50</td>
</tr>
<tr>
<td>Q</td>
<td>Human health and social care</td>
<td>£10.201 million</td>
<td>22.50</td>
</tr>
</tbody>
</table>

Table 6: Aggregate disruption costs for all economic sectors in UK Regional Accounts for flood event simulated in London

The sum of these individual economic sector disruptions gives a total first-order indirect economic impact of £165.9 million.

4.3 Second-order effects

The first-order indirect impacts described in the previous section show that there is the potential for substantial economic effects from climate-related disruption to commuting in London. The first-order impacts also demonstrate that the economic effects can be felt in spatial locations disparate from the location of the climate hazards. There is also the potential, however, for lower-order effects to be propagated through business supply chains. As described in Section 3.3, the use of Input-Output tables can help to identify the links and co-dependencies between different economic sectors, and thus estimate these lower-order effects to the economy.

These second-order effects can propagate along business supply chains to be felt in areas far removed from the initial first-order effect. Figure 6 showed the spatial concentration of jobs in Sector K (Finance) in the Greater London authority area. From the UK Supply and Use tables (ONS, 2016) it is possible to estimate the level of dependency of other sectors of the economy in London on Sector K. Two of the sectors on which the Financial sector most heavily relies for its production are Sector J (Information and Communications Technology (ICT)), which contributes 14% of intermediate demand from Sector K, and Sector M (Professional, Scientific,
and Technical Services) on which Sector K is reliant for 20% of its production. Figure 16 shows the locations of the proportion of London’s jobs in the ICT sector; it can be seen that the spatial location of these jobs differs from those in Sector K as shown in Figure 6. Thus, any second-order impact in Sector K from disruption in Sector J will be felt in spatial locations remote from the first-order impacts. In contrast, the majority of jobs in Sector M (Figure 17) are located close to the Sector K jobs, so the spatial propagation of impacts will be less noticeable.
In order to calculate second-order impacts the steps in Section 3.3 are undertaken for London. Using the UK’s Supply and Use Tables, it is possible to obtain national accounts of the intermediate demand for each sector’s products from all other economic sectors. The demand is aggregated to the same 19 NACE classes outlined above (from which Sectors A, B, D, E, R and S are again eliminated in these results due to differing levels of aggregation in the UK National Accounts). The total consumption values (in Millions of GBP) are normalised to a proportion of each sector’s total output to provide an estimation of how reliant each sector is on each other sector. Table 8 shows the proportion of economic output from each row which is reliant upon input from each column. For example, column K shows the proportion of the output from each sector A-S which is required as intermediate inputs to products from Sector K (e.g. 1 unit of output from Sector K is made up of 0.14 units of input from Sector J).

By using the values in this table it is possible to estimate the second-order impacts of a reduction in performance of a given sector on all other sectors in London’s economy. The values in Table 6 give a measure of the proportional loss to each economic sector arising through commuting delays. Reducing the intermediate input of each economic sector from all other sectors by this loss in productive hours gives a measure of the reduction in productivity arising due to a loss of inputs further down the supply chain. For example, Sector K is reliant on Sector J for 14% of its economic output. The productive hours of Sector J are reduced by 17.63% due to the pluvial flooding of the transport links serving the locations where Sector J’s economic activity takes place. Thus, the performance of Sector K is reduced by 17.63% of 14%, or 2.45% by the loss of supply of services from Sector J. This equates to an additional second-order loss in GVA of 2.45% of the daily output from Sector K (which is estimated at £165.68m) and thus an additional second-order loss of £4.2m resulting from disruption to Sector J productivity.

The results of this second-order analysis for all I-O relationships in the London economy are presented in Table 7. It can be seen that in many cases the second-order disruption is greater in terms of GVA loss than the initial first-order loss from commuting disruption. This demonstrates the complex nature of the interconnected urban economy and the need to consider the economic structure of cities in order to capture the full extent of climate-related disruption.
Table 7: Results of Second-order analysis of disruptions using Input-Output analysis of business supply chains.
<table>
<thead>
<tr>
<th>Sector</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>E</th>
<th>F</th>
<th>G</th>
<th>H</th>
<th>I</th>
<th>J</th>
<th>K</th>
<th>L</th>
<th>M</th>
<th>N</th>
<th>O</th>
<th>P</th>
<th>Q</th>
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</thead>
<tbody>
<tr>
<td>A</td>
<td>0.21</td>
<td>0.00</td>
<td>0.04</td>
<td>0.00</td>
<td>0.04</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.03</td>
<td>0.00</td>
<td>0.00</td>
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Table 8: Input-Output estimations from UK NACE economic sectors as a proportion of each column’s total output.
5 Discussion and Conclusions

This deliverable has presented a set of methodologies for assessing the indirect impacts of climate change on the urban economy, using the RAMSES case study city of London as a demonstrator. The report outlined the pressing need to consider the wider impacts of climate events on the function of urban systems and the users of infrastructure such as transport networks. By combining climate, transport, and economic Input-Output modelling the methodology allows the estimation of the indirect costs of pluvial flooding at both first- and second-order levels.

The analysis presented here has highlighted the complex relationships between the spatial locations of where people live and work, the networks of transport that underpin those relationships. These relationships link residential locations to employment sites and different employment sites to one another. A further layer of complexity is the spatial nature of the disruption itself, driven by the intensity of rainfall events, the urban form and surface water flow, and the location of exposed elements of the transport infrastructure. All of these complexities can be explored through the framework presented here.

Whilst these spatial distributions present challenges in capturing the added complexity in a modelling framework, they also present more opportunities for adaptation. They allow the examination of adaptation from systemic changes at the city-scale right down to individual components of infrastructure. They also allow the testing of non-traditional ways of managing adaptation through different stakeholders, testing adaptations by urban planning, transport economics, or business practices as well as through traditional engineering approaches. This means that adaptation is not just about making adaptation tougher and more resilient, but thinking about changes to employment locations, land-use policies, examining the potential of mixed-use developments and switching transport modes. These options will be explored in full in the next RAMSES deliverable from WP3, D3.4.

The analysis presented here does make a number of assumptions to simplify analysis and allow the task to be achieved within the time allowed. The transport model used in this proof-of-concept study provides a low-complexity representation of human behaviour in response to flood disruption. In the transport analysis component, it is assumed that all travellers have perfect knowledge of the network, allowing them to use the next-best option to get to their destination. This provides a benefit computationally, allowing the city-scale macro effects of disruptions to millions of commuter journeys, but the results presented here should be considered to be the lower-bound of possible total disruptions to transport (and thus the cost to the urban economy).

The transport model also assumes that all lost time due to disruptions is unproductive (i.e. that travellers cannot use wifi-enabled devices to work during delays) and thus lost to business. There is an assumption that the distribution of lost time is equal across the study area and that all jobs are equally important or productive. Travellers are assumed to be unable or unwilling to switch to alternative modes; regardless of the level of disruption the option to switch from public transport to driving will not be taken. It is also assumed that the modal split of journeys to a destination is equal across all sectors and job types, regardless of socio-economic group or occupation. Many of these assumptions are required because of the aggregate nature of the data used in this methodology and representations at zonal level. Some of these assumptions could be addressed through the use of agent-based modelling, representing individual travellers’
choices, requirements, and actions were data for parameterisation available.

Whilst it is recognised that extreme rainfall and flooding events can pose a danger to human life, the impacts of such effects are not counted in the economic evaluation presented here. There are approaches (e.g. the human capital approach) to quantify the economic costs of loss of life, but these are considered direct impacts. There are other non-fatal outcomes, however, such as healthcare costs or absenteeism, which could be considered in this approach but have not been factored in during this study. Such impacts are difficult to capture in an I-O model and difficult to quantify in economic terms. They are obviously something that could be considered in further work.

For the Input-Output analysis, no consideration has been made of stocks in the system, with a just-in-time production strategy assuming. Given the high proportion of intellectual and digital, rather than physical, supply chains between business locations this is considered a safe assumption, but it does not assume that work can be delayed without penalty or loss of production or that there are alternative strategies to mitigate against the disruption. In some cases there may be physical flows of goods which are disrupted, but data on these are difficult to acquire. This method could therefore be improved by factoring in the concept of stocks, goods flows, and storage (as described in Section 3.3), and such options give further scope for adaptation and resilience through changing business practices.

Validation of models of systems in equilibrium, such as transport and economic models, during disruptive events is challenging because of the infrequency of events, limited observations on system responses, and unpredictable human responses. The approach adopted here, using vulnerability curves to simulate the reduction of performance, allows some degree of uncertainty in the response of infrastructure to flood water. The exact impact of the event, however, is reliant on the initial conditions of the system and human decisions, such as the choice about whether or not to accept a delay or cancel a journey. Such uncertainties could be addressed using Big Data, such as automatic traffic counts or mobile phone records during such events. To this end, discussions are in progress with a mobile phone operator over the use of anonymised records collected during disruptive weather events to determine whether such data could help parameterise the models used here.

The results presented in this paper only analyse a single flood event of 1-in-200 year return period in the London case study city. Work is underway, however, on the simulation of further events to capture a range of climate extremes. Use of ‘uplift factors’ determined through the running of high-resolution climate simulations over limited time periods are also being tested to capture the expected increase in frequency and severity of intense rainfall events under climate change. Such simulations are also giving an opportunity to test the various adaptation measures outlined in this report under different future climate scenarios, and thus establish a measure of their effectiveness at reducing indirect impacts on urban systems.

The work in this deliverable is ongoing into the final tasks of WP3 in RAMSES, and will be presented in Deliverable 3.4. This will include simulations of flooding impacts in the remaining two RAMSES case study cities (Bilbao and Antwerp), testing of a suite of adaptation options for the reduction of these impacts (both direct and indirect) on the cities in question, and a synthesis of the findings. The UIAF will be able to test the effectiveness on the reduction of impacts of a wide range of adaptation strategies, including alternative land-use and spatial planning strategies, distribution of industries and supporting transport infrastructure, and protections of infrastructure systems to reduce vulnerability to flooding. This work feeds is in conjunction with WP5 to estimate the economic costs of climate change adaptation, and will feed into the outputs of WP8 on transition models towards resilience and sustainable cities.
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