Resilient infrastructure networks: Managing the impacts of disruptive events on resource movements

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Abstract

Interdependencies between infrastructures which enable the flow resources have the potential to increase the vulnerability of interconnected systems of supply chains to disruption via cascading mechanisms. These interactions are poorly understood as there are limited observations whilst the movement of resources can occur at many spatial scales. It is a complex problem because of both the number of components and the dynamic nature of the systems that allow these to move around.

To analyse the disruption of resource flows within interdependent systems, this paper introduces a resource model that pulls together two established modelling methodologies: input-output modelling and network analysis. Data on supply, demand and flows are typically only provided at coarse spatial scales, so an important development was the disaggregation of regional economic input-output data into smaller spatial units.

The model was tested using a case study of Lerwick in the Shetland Islands. It was found, when flood defences were taken into account, the level of risk from storm surges of various magnitudes was low. The model was able to highlight unknown linkages and reaffirm an increase in vulnerability caused by Just-in-time management strategies and the clustering of like industries. As part of this a flood risk analysis technique was presented which highlighted the potential impacts of floods of varying magnitudes, as well how the flood protection affected the levels of risk caused by these events.

A second case study of the food distribution network in New York was also developed to provide validation through the recreation of the effects post Tropical Storm Sandy.

The research provided a rationale for an encouragement of a move away from just-in-time production to take place and halt the fashion of making supply chains leaner. It also encouraged an increase in cooperation to take place between companies to understand the vulnerabilities within their own supply chains.

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1 Introduction

Cities, regions and countries can be viewed as systems which are made up of numerous stocks and flows such as; direct energy, materials, waste, food, water and transport (BFF, 2002). These resources, and our ability to move them to where they are needed, enable modern lifestyles, and enhance the quality of life and wellbeing of the communities they serve. To deliver these services requires numerous interdependent infrastructures, including energy generation and transmission, water, sanitation, telecommunications and transportation (Rinaldi *et al.*, 2001). Disruption of the movement of resources or its supporting infrastructure therefore has inevitable economic, social and environmental impacts. Numerous examples from extreme events such as Hurricane Sandy and the Chao Praya River Basin flooding in Thailand highlight the need for more effective intervention and management to reduce resource disruption.

To tackle this, a quantitative resource model has been developed that embeds Input-Output (*I*-*O*) (Lifset, 2009) relationships of supply and demand within a spatial network model. These capture the interdependencies within a city or region to enable understanding of how disruption to resource flows may affect the system. The resource model can test the impact of a spatial hazard and test resource and infrastructure management options to reduce the impacts of disruptive events.

1.1 The challenge of understanding resource disruption

Figure 1.1 summarises the movement of resources into and out of Greater London but it does not provide any detail of how these resources are consumed or used by individuals or industrial processes within the region. Work to date on resource modelling has treated cities and their infrastructure as an aspatial ‘consumer unit’ (Figure 1.1). 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).

The importance of this knowledge has been highlighted by recent floods, other natural disasters and human activities, showing 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 helps ensure the health of people, their communities and economy. For example, during the summer and autumn of 2011, Thailand was severely disrupted by prolonged flooding that occurred in the Chao Praya River Basin. The damage was estimated to be more than US$45 billion (AonBenfield, 2012), making it one of the most costly disasters in history.

Similarly, the reduction in energy generation capacity that resulted from the nuclear accident at the Fukushima – Daishi power plant in 2011 lowered the production capacity of Japanese industry. This led to a decrease in the supply of materials and goods to downstream industries – including car assembly plants located as far away as the North East of England (Nanto *et al.*, 2011).

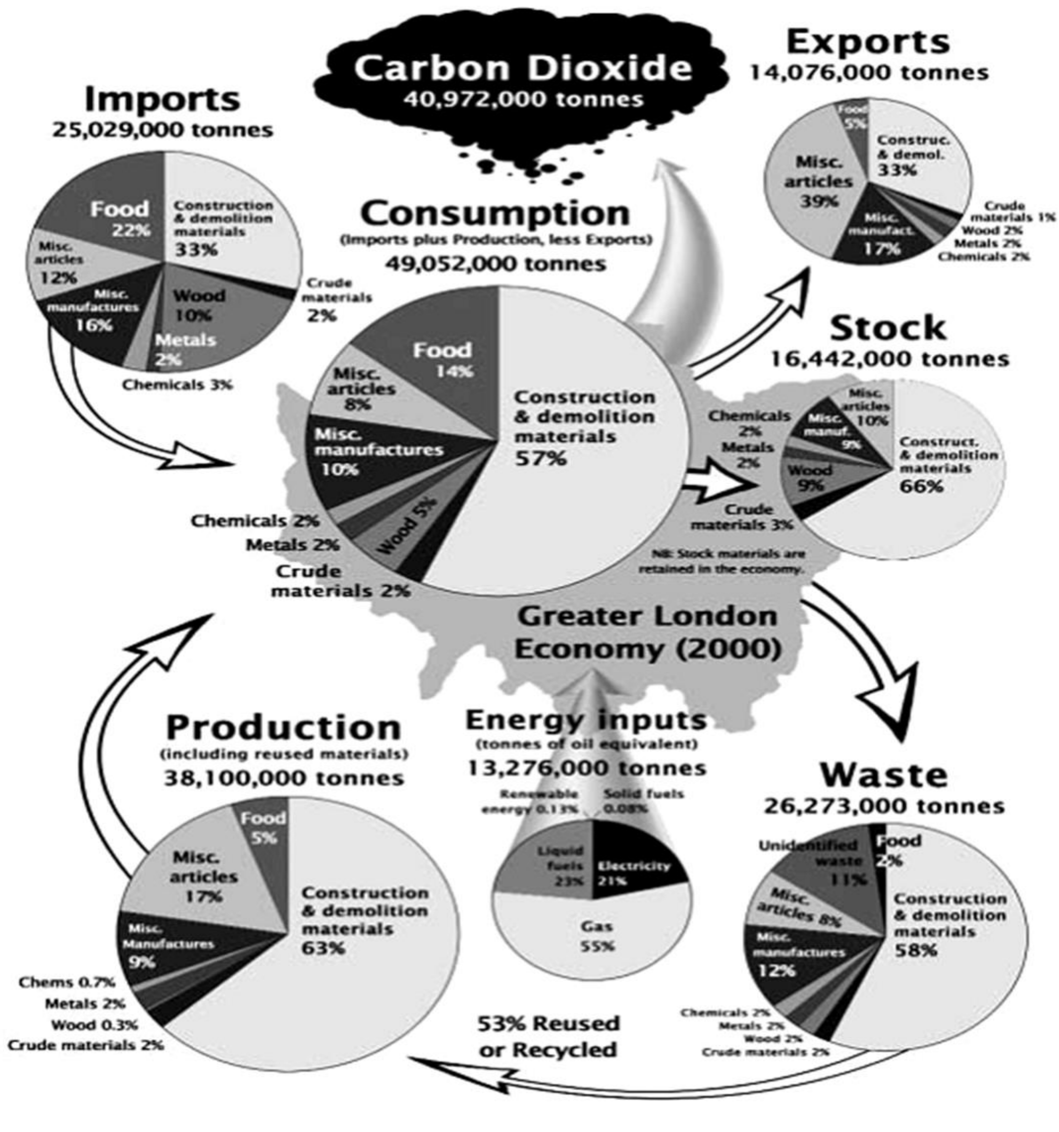

Figure 1.1: ***MFA*** **of Greater London (BFF, 2002)**

In addition, hurricanes Katrina and Sandy both impacted upon resource movements, in New Orleans and New York respectively. A further example is the blockade of six of the nine oil refineries in the UK, which took place over four days in September 2000. This led to a nationwide shortage of fuel; over 3000 petrol stations were reported to have run out. This in turn led to a cancellation of mail delivery, shortage of food availability and other knock on effects.

The number of people affected by disasters is increasing across the globe, and the rise in prevalence of such events poses new challenges for emergency and disaster planners (Nagurney *et al.*, 2011), who will need to understand the problems these disasters will cause to complex supply chain networks. These networks underpin modern society, be it physical networks such as: transportation; logistical and manufacturing networks; energy; and the internet, or other, non-physical networks, such as; financial, social, and economic networks (Nagurney and Qiang, 2012).

Research on such networks has been rejuvenated in recent years because of a string of catastrophic events which have highlighted a requirement to understand the impacts caused by these disruptions. These events have included: the September 11th terrorist attack on the Twin Towers in New York City; the Northeast US and Canadian blackout of 2003; Hurricane Katrina in 2005; the I-35W Mississippi River bridge collapse in 2007; the Mediterranean submarine cable disruption in 2008; and the Sichuan Earthquake and Cyclone Nargis in China (Nagurney *et al.*, 2011).

Focusing on supply chain networks and their related effects after major disruptive events has explicitly emphasised the need to understand the risks posed to such systems. For example, a fire in the Phillips Semiconductor factory in Albuquerque caused mobile phone manufacture Ericsson to lose approximately US$400 million, while their competitor Nokia sourced alternative supplies, which mitigated the impact of this disruption (Latour, 2001). The responses of the two companies differed as Nokia had contingency plans in place, which they followed, whereas Ericsson followed no such action (Mukherjee, 2008). It was therefore important to develop an understanding to how disruption to supply chains could lead to a failure in an interconnected network.

All of the aforementioned examples show that the consequences and vulnerabilities caused by disruptions to supply networks are connectively inherent, even if at first they may seem unrelated or go unnoticed (Sheffi, 2005; Qiang *et al.*, 2009). It is important that a system wide approach is used, when assessing supply chains, to capture the complex interactions (Nagurney and Qiang, 2012). This is partly because supply flows are aided by complex infrastructure networks that have been designed and built, as well as operated, with the assumption that the supply of resources will be continuous (Hodson *et al.*, 2012).It is therefore important to have an understanding of these unknown linkages, in order to increase resilience against such events.

As supply systems become increasingly interdependent, the potential scale of disruption to production, the subsequent cascading disturbance of resource flows and the resultant impact on society becomes increasingly challenging to analyse. Many resources and systems are required to enable modern living, and interdependencies between these resources and the infrastructure which supports their movement are vital. These interactions are poorly understood as there are limited observations. Many approaches, such as material flow analysis (Figure 1.1), only provide a black box view of how resources enter a system and not how these are consumed. In addition, input output analysis is carried out an economy wide scale, when in reality the movement of resources can occur across many spatial scales.

It is a complex problem due to both the number of components and the dynamic nature of the systems that allow them to move around. Current methods for appraising such interactions are based on direct economic benefits and not building resource security. Often the conclusion of these appraisals is that the leaning of supply chains can lead to a lower level of resource resilience. This is exacerbated by the number of apparent uncertainties and no single actor or agency being responsible for monitoring and maintaining the movement of resources.

It therefore becomes important to understand how infrastructure networks mediate and modulate flows of resources around a system with a requirement for a spatial modelling capability. This spacialisation of resource flows allows for the assessment of disruption by spatial hazards such as floods on interdependent supply chain networks within this research.

1.2 Aim & Objectives

The aim of this research is to develop a method for assessing the robustness of resource flows against disruption from spatial hazards. In addition, this research aimed to address recovery; leading to an understanding of the resilience of these flows following such extreme events:

1. Understand the issues relating to disruption of supply chains and investigate different modelling procedures through extensive literature review.
2. Develop a methodology for spatial disaggregation of resource supply and demand quantities and locations.
3. Develop a quantitative, spatial, resource flow model that dynamically links spatially disaggregated information on supply and demand with the infrastructure networks that mediate their flows.
4. Subject this model to a series of disruptive events and test alternative strategies to increase the resilience of urban and regional units and accordingly make recommendations for industry, policy makers and researchers.
5. Demonstrate the use of the model to support flood risk analysis by providing a quantitative assessment of the indirect impacts of extreme events on resource disruption.
6. Validate this resource model against an observed event.

1.3 Overview of thesis

Resource movements have been disrupted by flood events at a range of scales. These resources including water, food, materials and goods are necessities for the wellbeing of both individuals and communities. Yet growing infrastructural and supply chain interdependencies pose significant challenges to those responsible for the conveyance of resources, and flood risk managers aiming to reduce the impacts of extreme events.

The main contribution of this research is the new methodological approach that draws together influences from many different fields of study, for example *I-O* analysis, network analysis, infrastructural interdependencies, urban metabolism, resilience, and supply chain risk management. These different approaches were utilised to provide an understanding of levels of resilience within supply chains and the vulnerabilities within these from hazards such as flooding. This is important as such events are causing more disruption and costing more money than in the past (O'Brien *et al.*, 2006) and the majority of this increase has been seen from meteorological and hydrological events (Birkmann and von Teichman, 2010; Winn *et al.*, 2011).

The literature review of this thesis is split into two parts. Chapter 2 introduces the context of this research. The chapter highlights a number of previous examples of cascading failure due to supply chain disruption and emphasises the need for this research. Chapter 3 reviews methods that have been used in this research, as well as alternatives approaches that were considered but ultimately rejected during the literature review procedure.

Chapter 4 introduces the quantitative resource model that embeds input-output relationships of supply and demand within a spatial network model. This enables the impacts of a spatial hazard, such as a flood event, to be evaluated. The *I-O* model describes the flow and sharing of resources between industrial sectors, capturing interdependencies between elements of the resource system. The elements of these systems interact with each other and with their environment; and are therefore suitable to analysis using network theory.

Initially the model was tested using a case study of the Shetland Islands, described in Chapters 5. The analysis highlights the potential for a single flood event to disrupt the movement of resources in other industrial sectors away from the initial disturbance. Given certain conditions, disruption to some important sectors can rapidly lead to the collapse of the entire system. Resource management strategies were tested to provide a useful insight to flood risk managers and planners; for example locally storing supplies; or planning alternative delivery schedules were shown to reduce the extent of the initial impact, therefore slowing the propagation of disruption through the system.

Chapter 5 also introduces an adapted risk analysis methodology that measures the vulnerability of the economy on the Shetland Island to disruption by storm surge events of different magnitude. This required extension of the spatial disaggregation approach to provide suitably high resolution information for a flood risk analysis. This method provides a rational basis for assessing the risks of resource flow disruption and capturing some of the indirect impacts of extreme events.

Chapter 6 describes a case study in New York City that focuses on the distribution of food following Hurricane Sandy. This case study acts as a form of validation as sufficient information was collated on the disruption of food resource movements to compare actual and modelled results. Chapter 7 then discuses these results while referring back to the examples from the literature reviews, as well as providing some discussion around the validation of the technique developed throughout the research.

Finally, Chapter 8 provides the conclusions of the research. These are split into those relating to the method and those relevant for supply chain managers and academics. A just in time (*JIT*) resource production and movement strategy caused the fastest cascade through the system, and therefore the least resilient approach. On-site storage of stocks increased resilience to disruption, with bulk deliveries providing further stability, although this was dependant on the timing and frequency of deliveries.

2 Background Literature Review

2.1 Introduction

This research, as outlined in Chapter 1, sets out to investigate supply chain resilience. The following chapter presents a review of background literature, and a justification for the research. Included in this is a discussion of the key issues regarding the discourse of resilience; it's current standing in the study of supply chains; and finally some detailed case studies. These case studies highlight the need to develop an understanding of dependencies within supply chains and how the disruption of these linkages leads to cascading failures. Finally, the advantages of the just-in-time (*JIT*) production system are discussed (*JIT* is defined as a resource management strategy in which products are produced or delivered only as required (Merriam-Webster, 2016)).

2.2 Resilience

An understanding of resilience is required because of a noted increase in catastrophes, such as flooding, which have become increasingly devastating (Vogel *et al.*, 2007). This has been attributed to various reasons including increased urbanisation, meaning more people are affected by such events; and climate change potentially leading to a rise in the frequency of extreme weather events (Hammond *et al.*, 2014; Hammond *et al.*, 2015). In response to this is has become imperative to develop an understanding of what resilience is, as this can be used to provide a framework to reduce the loss caused by such disruptive events (Zhou *et al.*, 2010). This will provide a greater understanding of why some cities are more able than others to recover after disruption (Klein *et al.*, 2003).

Resilience is the elastic ability to return to an original state or the capacity to quickly recover from difficulties, (OED, 2010) with its origins coming from the Latin word "resilio" which means to jump back (Klein *et al.*, 2003; Manyena, 2006). It can therefore be defined as the capacity to stabilise and recover from loss (Comfort, 2010; Zhou *et al.*, 2010). Leichenko *et al.* (2010) define urban resilience as the ability of an urban system to withstand a large variety of shocks and stresses. Although this definition is aligned more with the concept of robustness, as it does not take into account "bouncing back" which is integral to the discourse of resilience.

Resilience can also be divided into different attributes. The MCEER (2006) suggest these different components are:

1. Robustness; the amount of force the system can take before performance drops. This attribute was measured by Scott et al. (2006), the authors considered; network flows, link capacity and network topology to develop the Network Robustness Index. This index aids highway planning decisions. This was achieved through developing an understanding of individual links in a network and how disrupting to these affects the wider transport Network.
2. Redundancy; the ability of a system to carry on working after damage has occurred. This is a very important concept in transport planning and takes into account the ability of a network to provide alternative routes in times of disaster, as well as the spare capacity of that network in normal conditions (Xu et al., 2015)
3. Resourcefulness; capability of a system to self-organise after a disruption has occurred. MacKinnon & Derickson (2012) add to this by stating resourcefulness moves the focus of attention to the uneven distribution of resources and promotes the possibilities of community self-determination in response to disruptive events.
4. Rapidity; ability of a system, through learning, to increase its capacity for adaption. Chen & Shinozuka (2004) provide an example of rapidity in practise, it is the ability of a system to provide treatment to any injured in the first day after the event. If rapidity is not present, the injured are left untreated.

The Resilience Alliance discuss three dimensions of resilience; these are: 1) the amount of disturbance which can be absorbed by a system without a large amount of change taking place; 2) the amount a system can self-organise post a disruptive event; 3) the ability, through learning, of a system to grow its adaptive capacity (Klein *et al.*, 2003).

There is no consensus when defining resilience, this means no clear technique exists to measure the concept (Manyena, 2006). Consequently this makes it very difficult to calculate changes in resilience and it also hinders the capacity to predict how differing methods may affect resilience (Gibbs, 2009). As no common indicators exist to measure resilience, the development of such indicators is a necessity to allow for academic debate to be applied to the real world (Cutter *et al.*, 2008). An understanding of who is resilient to what and for how long is required (Gibbs, 2009). Although it is agreed that, for example, a flood resilient city is less affected by extreme flood events than a non-flood resilient city (Hammond *et al.*, 2014; Hammond *et al.*, 2015).

When applying the idea of resilience to a network or system it is viewed as having qualities such as; staying power, adaptability, and a flexible approach, which in turn suggests a system characterised by its dynamism (Pickett *et al.*, 2004), although these systems are highly variable and are prone to change unexpectedly (Ahern, 2011). Early work on resilience within cities focussed on the idea of retaining equilibrium, meaning networks could bounce back to their original state after disruption (Pickett *et al.*, 2004; Leichenko, 2011) with being 'resilient' seen as being able to recover as quickly as possible (Parsons, 2010). In addition to this there is a need to have the capability to adapt and evolve post event; as a resilient system will recognise the risks whilst being highly adaptive (Opstal, 2007).

2.1.1 Robustness

The work carried out in this thesis has a strong focus on one of the attributes of resilience, that is robustness. As mentioned above the term robustness can become confused with that of resilience, therefore it is important to understand the difference between these terms. In general robustness is defined as being *"capable of performing without failure under a wide range of conditions"* (Merriam-Webster, 2016).

Having robustness indicates an ability, for example, of a factory to produce its goods after a disruption has been caused to its production line. It is therefore a very desirable attribute to have in this situation. Kleindorfer and Saad (2005) applied this thinking to supply chains and stated that robustness is determined by the weakest link in a supply chain. Therefore the different aspects of a supply chain need to be assessed to determine the level of robustness apparent, and consideration must be given to the trade off between having robustness and the resulting lowering of effiency this will cause.

As this work is focusing on supply chain networks and systems robustness is defined as such a system's capacity to remain operational following a variety of disturbances, there is then an implication that an understanding is needed on how such a disrupted system responds to differing levels of disturbance (Mens et al, 2011). This resistance and ability to tolerate disruption is different to resilience which is the ability to recover from such disruptions (De Bruijn, 2004a and De Bruijn, 2004b).

Understanding a networks robustness provides an ability to view the effects of a disturbance at one point of time, and therefore a way to understand “what if”. It allows for a focus onto one type of disturbance and/or uncertainty that may affect the modelled system. Finally, it permits for the testing of relevant system responses to disturbances, this provides insight into how different types measures affect the behaviour of the system. This can then lead to improved recovery, and therefore resilience (Mens et al, 2011).

Throughout this research the notion of increasing the robustness, through increasing lag between disruption and effects, is revisited as it is believed this would provide stakeholders to carryout appropriate responses and therefore for increase the resilience of the system.

2.3 Vulnerability and Susceptibility

A second major criticism is the relationship between resilience and other concepts such as vulnerability, as this is not truly appreciated and further hampers the development of a universally accepted definition for resilience. Firstly, resilience can be viewed as an element of vulnerability, relating to how something or someone adapts to a hazard (Pelling and High, 2005). Conversely resilience can be interpreted as the opposite of vulnerability, meaning something which is vulnerable lacks resilience (Cutter *et al.*, 2008).

Manyena (2006) argues that resilience has less of a relationship to vulnerability; if vulnerability is defined in terms of a level of threat or exposure to a hazard. Vulnerability can be seen to be caused by a lack of resilience, meaning an increase resilience will lower vulnerability (Klein *et al.*, 2003). These two points form the backbone of the risk analysis approach developed in this work, the vulnerability is measured in terms of the probability of an event occurring and increasing of resilience to this event will decrease the vulnerability.

Vulnerability can therefore be seen as the degree to which a system is susceptible to floods due to exposure to a risk whilst taking into account the systems with its capacity/incapacity to be resilient, i.e. it's ability to withstand, recover and / or adapt to a disruptive event (Balica et al., 2009; Balica et al., 2013).

Susceptibility can be defined as the level to which parts of a system are exposed to risk (Messner and Meyer, 2006) and this influences the chance that these elements are harmed at times of disruption (Balica et al., 2013). The levels of susceptibility are effected by the characteristics of the modelled, for example, social context of flood damage formation (Begum et al., 2007) such as poverty and education (Balica et al., 2013).

2.4 Adaptive Capacity

This approach to learning was described in Holling's (2001) work on panarchy, which is the concept that explains the evolution of complex adaptive systems. Within this, the main process of learning occurs during the adaptive cycle and is made up of three properties that allow for change:

- The potential for change that exists within a system.
- The amount of interconnected processes and internal control.
- The system's capacity to adapt to disruptive events.

The adaptation occurs within a cycle that has a trajectory and moves from a long stage of slow gathering and transformation of resources to quicker periods in which opportunities for innovation are developed (Holling, 2001). Such learning is a move away from single loop learning (doing things better) towards double loop learning (doing things differently) (O'Brien and Hope, 2010). The disruptive event acts as a trigger for change and initiates a period of a period of rapid reorganization.

This is related to resilience as it is highlights an approach which allows for reorganization and rebuilding after a disruptive event. Once this occurs it provides opportunities for innovation which can either help the system return to pre-event levels or bouncing forward to a new and more desirable state after recovery has been completed.

2.5 Supply Chains

Manufacturing strategies have developed to meet the needs of four important components of consumer goods, these are to; lower cost, improve quality, increase usability, and deliver in a timely manner. Through globalisation and the improvement of transport, IT and services; supply chains have evolved into inter-organisational networks to meet these demands, with the management of costs being the main concern, this could be the cost of; ordering and holding inventory, transportation, production, and assembly (Wang *et al.*, 2009). Within each of these actions there is an inherent risk to the supply chain, as a disruption could occur at any point, and if functionality is affected it could lead to a financial impact (Ponomarov and Holcomb, 2009).

Different supply chains are concerned, therefore, with different cost savings. These can be categorised into three different types: mass customisation networks, allowing for individually tailored products; lean practise which is concerned with the reduction of waste in the supply chain, such as JIT production; and hybrid systems which attempt to do both. Modern supply chains can also be aided by e-commerce and virtual enterprises (Wang *et al.*, 2009). Consequently there is a need to manage supply chains efficiently and effectively to allow them to adapt if disruption occurs (Thun and Hoenig, 2011).

2.5.1 Supply chain disruption

Many corporations throughout the world strive to build a competitive advantage and increase their market share, which can be done through the implementation of various initiatives, such as outsourcing manufacturing and developing product variety (Tang, 2006). This has led to the extending of supply chain networks on an increasingly global scale. In addition, many firms have attempted to make their supply chains more lean (Tang and Nurmaya Musa, 2011) by operating them with lower levels of inventory, and less human and capital investment (Knemeyer *et al.*, 2009). In a stable environment, these endeavours are extremely effective, but because of the factors discussed above, such as uncertain economic conditions, varying consumer demands, and natural and manmade hazards, supply chains have become less stable more at risk of disruption (Tang, 2006).

There are two main types of disruption which can affect a supply chain, these are: issues caused by problems with the coordination of supply and demand; and risks caused by events which interrupt normal activity (Kleindorfer and Saad, 2005). To help lessen the effects of a disruption, supply chains should incorporate both financial and operational mitigation strategies, as well as have contingencies in place to replace effected suppliers or re-route supply lines (Tomlin, 2006). As supply chains get longer and delivery times shorter it becomes imperative to develop ways to understand the effect of such events on supply chains (Kleindorfer and Saad, 2005). The removal of redundancy from the systems have made supply chains less able to reconfigure during disruptive events (Knemeyer *et al.*, 2009).

In order to lessen the impact of disruption to a supply chain, these supply chains need to be understood, and within this an understanding of pinch points in the network is necessary (Christopher and Peck, 2004). It is also important to understand how density and complexity of supply chains, and the importance of various suppliers within those supply chains effect vulnerability (Craighead *et al.*, 2007).

For example, the supply base should be widened to mitigate the risk of a disruption at one production facility cascading through the system (Christopher and Peck, 2004). A move towards multiple suppliers can mitigate the effect of a disruption. An example is Nokia's multisource strategy, which lessened the effects of disruption to the supply of semiconductors, which were necessary for their products (Tomlin, 2006). All of these things can be aided by collaboration and the building of redundancy into systems (Christopher and Peck, 2004).

2.5.2 Supply chain resilience

Wang *et al.* (2009) define resilience for a supply chain as:

"… a system with an objective to survive and maintain function even during the course of disruptions, provided with a capability to predict and assess the damage of possible disruptions, and enhanced by the strong awareness of its ever-changing environment and knowledge of the past events, thereby utilising resilient strategies for defence against the disruptions."

Once again this definition comes short of what is truly meant by resilience, as it does not take into account the ability of a system to recover from shock and therefore is only a measure of the robustness of a system.

In terms of resilience, globalised supply chains can be both a hindrance and an aid in times of disaster. If the majority of a supply chain is found outside of the affected area it can be utilised to replace missing parts and help regain production quicker than if all suppliers were in the affected region (Todo *et al.*, 2014). However, if one element of the supply chain cannot be sourced from outside of the disrupted area, then the shock can be felt throughout the supply chain network (Romero, 2012) showing an inability to function during the course of a disruption.

Companies are, in general, aware of what makes their supply chain vulnerable, although supply chain managers at times fail to implement supply chain risk management. This, coupled with an underestimation of the risks, increases the likelihood of a disruption cascading through a supply chain (Thun and Hoenig, 2011). In order to reduce the chance of this occurring, supply chains must be designed in a way which incorporates effective and efficient responses to disruption, as well as a readiness to implement mitigation strategies (Ponomarov and Holcomb, 2009).

2.6 Working definitions; robustness and resilience

The different discourses which have informed this study all approach resilience in different ways, as outlined above. At times there seems to be a confusion between the concept of robustness and resilience. For simplicity this research will use the following definition of robustness

"Strength, or the ability of elements, systems, and other units of analysis to withstand a given level of stress or demand without suffering degradation or loss of function" (MCEER, 2006).

This definition is the bases of the model developed, which measures how long, and to what extent, the modelled system can still function after a disruptive event. The model has also been developed to add some elements to recovery to it. This therefore pushes it towards a being a full measure of a systems ability to withstand, and bounce back from shock. For the purpose of this study the Cabinet Office's (2014) definition of resilience is used, which is:

"The ability of assets and networks to anticipate, absorb, adapt to and recover from disruption."

2.7 Supply chain disruption examples across different scales

In this section, four detailed case studies dealing with supply chain disruption are introduced. These disruptions occurred across different scales: Sections 2.4.1 and 2.4.2 deal with the disruption to worldwide supply chains; 2.4.3 looks at a National level disruption; and 2.4.5 looks at a city scale.

2.7.1 Great East Japan Earthquake, 2011

On 11th March2011, the Pacific Coast of Tohoku experienced a catastrophic earthquake that uniquely had strong ground motion over large areas and led to a severe Tsunami which caused damage along 670km of Tohoku's Pacific Coastline. The magnitude of the earthquake measured 9.0, and caused a 500km long by 200km wide rupture of the fault zone (Matsuo, 2015). As Japan lies on three seismically active belts it has witnessed many such earthquakes, but this caused a tsunami that resulted in damage to the Fukushima Daiichi Nuclear Power Plant and a wider cascade of disruption than ever observed before (Ghadge *et al.*, 2011)

The earthquake and tsunami were of unparalleled size and were exacerbated by human and political mistakes; the most damaged prefectures were Iwate, Miyagi and Fukushima, leading to national effects (Maya-Ambía, 2012; Krausmann and Cruz, 2013). There were also worldwide consequences, as Japan at this time was the world's third largest economy and was vital in the supply chains of many multinational industries, such as; computers, electronics, and car assembly (Lohr, 2011).

The earthquake, known as both the Great East Japan and Tokoku earthquake, and the resulting Tsunami killed over 1600 people (Krausmann and Cruz, 2013). It caused over US$200 Billion of damage, with roads, bridges, and railways being washed away. In addition, many fishing villages and thousands of boats were destroyed (MunichRe, 2012). Life in Tokyo also experienced a fundamental shock (Ueno, 2013). On top of these disruptions fifteen nuclear reactors were disrupted, including Fukushima Daiichi (Matsuo, 2015).

These disruptions caused unprecedented and extensive damage to supply chains. For example the manufacture of components for digital displays, electronic components, and hard disks was affected (Matsuo, 2015) and with Japan being a leading producer of flash memory, global companies such as Apple felt the supply shortages (Lohr, 2011). These disruptions were caused by numerous factors, but the leading factor was the disruption to electricity production (Ueno, 2013). The resulting evacuations, coupled with uncertainties in the aftermath of the Fukushima nuclear disaster compounded problems caused by the initial disruption. The power grid had a peak shortfall of nearly a third and could only provide 75% of normal supply at other times. As the east and west of Japan have different grids the problem was made worse (Nanto *et al.*, 2011).

This disruption was felt by many large Japanese corporations, who reacted in varying ways. Toyota, Honda and Nissan all halted production in some, if not all, of their Japanese plants. Within the electronics and semiconductor manufacturing sector, Sony closed ten facilities, Texas Instruments, Panasonic, Sanyo and Fujifilm all had to lower output, and Panasonic and Cannon reported injuries to staff. Disruption was also reported in steel and ship building industries (Ghadge *et al.*, 2011).

These national effects also led to global disruption. For example, over a third of Japanese imports to the USA in 2010 were cars and car parts. Toyota had assembly plants which were damaged by the earthquake, whilst other plants were disrupted by the power outages, leading to a reduction in supply. This led to some US based car assembly plants curtailing operations because the required parts from Japan could not be acquired.

Ford was depended on Japanese manufactured electronic components and therefore had to slow production because of disruption to supply. Similar problems were noticed by General Motors, Nissan and Peugeot-Citroen who had to reduce production at US and European assembly plants as they could not get the required semi-conductors from a Hitachi factory based north of Tokyo (Nanto *et al.*, 2011). On top of this, car assembly and export capacity was reduced by 39% in Guangdong-China and 48.5% in Thailand because of the restricted supply of automotive parts (Fujita and Hamaguchi, 2012)

The basic problem was a lack of components within a large number of interconnected industries (Matsuo, 2015).This was made worse by shipping lines reducing the number of vessels sailing to and from Japan because of radiation fears: Hapag-Lloyd halted service to Tokyo, instead unloading in Osaka and shipping goods across land, increasing both time and cost. Extra safety checks in ports receiving goods from Japan also slowed the supply process (Bradsher, 2011)

The interconnected nature of the most affected industries meant a disruption in North Eastern Japan led to supply chain problems throughout the world. The initial disruption was made worse by rolling blackouts in Tokyo leading to a lowering in output of many sectors, as well as a disruption to commuters who struggled to get to and from their places of work as train services were suspended (Ueno, 2013). On top of this, cargo transportation to and from Japan was reduced, making it more difficult for products, such as semiconductors, to reach their intended market.

2.7.2 Chao Phraya River flood in Central Thailand, 2011

In the latter part of 2011 and early 2012, Thailand suffered the country's worst floods for 70 years (Chongvilaivan, 2012). These floods not only had a profound impact on human life (Smith, 2013) but also disrupted the country's manufacturing capacity (Abe and Ye, 2013). It was the most disruptive flood and the fifth largest natural disaster in terms of economic loss since 1950 (Smith, 2013). The estimated losses were around US$45 Billion, with an insurance loss of almost US$15 Billion (Abe and Ye, 2013; Smith, 2013)

Poor urban planning coupled with deforestation, no systems of floodwater management and substandard flood mitigation master plans all attributed to the devastation caused by the floods (Abe and Ye, 2013). The flooding event began at the end of July when Hurricane Nock-ten made landfall in Thailand. The floods resulted in 65 of Thailand's 77 provinces including Bangkok, the capital city, to be declared flood disaster zones in October 2011 (Zevenbergen *et al.*, 2013). The flooding caused over 800 deaths and affected a further 13.6 million people (Komori *et al.*, 2012; Zevenbergen *et al.*, 2013).

With pressures to reduce costs, firms and suppliers in Thailand tend to cluster in a small number of industrial locations. In addition, a *JIT* approach to production increased the vulnerability of the complex global supply chains (Chongvilaivan, 2012; Komori *et al.*, 2012). Seven industrial estates in Ayutthaya and Pathum Thani provinces were severely affected by the flooding; this resulted in huge manufacturing production losses of almost one third, between October 2011 and January 2012 (Abe and Ye, 2013) this equated to over 1000 factories being inundated across central Thailand (Fuller, 2011).

In addition to the direct losses caused by the damage of facilities, a large number of firms were indirectly affected, including nine Japanese car manufactures. In the 1980s, Thailand became a hub for these firms (Fuller, 2011; Kohpaiboon and Jongwanich, 2013). Two of the biggest examples of this were the Nissan and Toyota plants in Thailand, which were unaffected by flood water, but were both forced to suspend operations due to an inability to source all of the required parts from their suppliers, who were directly impacted by the floods (Abe and Ye, 2013). In summary, these disruptions to the supply chains of important parts and components required for the manufacturing process within Thailand compelled other connected industries in areas unaffected by the floods, in both Thailand and the rest of the world, to halt their production lines (Chongvilaivan, 2012).

Toyota was by far the worst affected, as the indirect disruption caused the slowing of production in factories as far afield as Indonesia, Japan, Malaysia, USA, Canada, Pakistan, the Philippines, South Africa and Vietnam. Honda also slowed production at factories across the globe (Fuller, 2011), from the Philippines to Swindon in the United Kingdom (Chongvilaivan, 2012), as its Thailand plant was out of action for nearly six months (Haraguchi and Lall, 2014)

In addition to the disruption within the car manufacturing industry, many other sectors were affected. This was highlighted by a survey of Japanese companies which investigated the impact they felt from the floods in Thailand. Of the companies surveyed, 78% stated they were directly or indirectly affected. In response to the disruption to supply-chains, nearly two thirds of directly affected manufacturers, especially those who manufactured electronic components, had to temporarily relocate their operations to other Asian countries (Abe and Ye, 2013). What was less well documented was the effect on local business, and it was estimated 10,000 – 15,000 SMEs felt some effect of the flooding throughout Thailand (Surminski, 2013).

Supply chain disruptions also had a major impact on another production sector: severe shortage of hard disk drives caused prices to spike and the production of computing equipment to be restricted throughout the world. PC manufactures did not have enough stockpiled components to wait out the flood, and this was exacerbated by the clustering of like industries with the ambition of forming lean *JIT* supply chains (Romero, 2012). As Thailand is the world's second-largest producer of hard disk drives, the lowering of output caused by the flooding caused some resellers and wholesalers to defensively purchase this component. This led to further increases in the prices of hard disk drives to almost double the pre-disaster levels (Abe and Ye, 2013).

2.7.3 United Kingdom fuel protests, 2000

In September 2000, a protest over fuel costs broke out on a national scale in the United Kingdom. The protest was led by a network of British farmers and road hauliers who began an intense movement of direct action to protest at high levels of fuel duty. They followed a similar model to a campaign carried out by farmers, hauliers and fishermen in France, which had led to a lowering of such duty by the French government. The British protesters began by blockading the petrol refinery in Stanlow, Cheshire, and within only a few days created a fuel crisis that paralysed the country, bringing fuel distribution to a virtual standstill (Doherty *et al.*, 2003).

In the eighteen months from January 1999 to June 2000, fuel prices increased by more than 40%. At this time, approximately 75% of the cost of a litre of petrol or diesel was tax and duties. The level of taxation on fuel in in Britain was the highest in Europe, with a steep increase in the price of crude oil adding to the problem (PSEPC, 2005).

The protest was began by a relatively small number of protestors, made up of around 150 – 200 farmers and hauliers from North Wales. Disgruntlement was particularly high among farmers of livestock who were still suffering the effects of the BSE crisis. This coupled with falling livestock and milk prices forced action against the fuel duty increases. The duty on fuel for agricultural machinery and tractors, red diesel, was comparatively low against commercial diesel, but the net price paid had gone up by 9 pence a litre since May 2000 (Doherty *et al.*, 2003).

On Thursday September 7th the price of crude oil rose above US$35 a barrel, a ten year high; this meant a litre a fuel was to rise by 2p per litre compounding the anger felt by consumers who were already paying the highest petrol prices in the world. Direct action was taken and the first oil refinery was blockaded. The following day over 100 trucks staged a "go-slow" protest on the A1 and blockaded the Texaco oil refinery in Pembroke (BBC, 2000a; Korowicz, 2012).

At this point in the protest it was noted that the oil refineries colluded with protesters to cut the country's fuel supply by instructing their drivers not to leave the refineries. This approach was tactical, as it attempted to prevent any future increases in fuel duty (Doherty *et al.*, 2003). It was also noted that some drivers did not wish to cross the unofficial picket lines set up (PSEPC, 2005). Further refinery blockades and protests continued for an extra five days (BBC, 2000a).

The disruption of fuel had profound effects across many sectors in both direct and indirect ways. For example, the transport sector was directly impacted by the "go-slow" demonstrations, which caused temporary traffic delays. In addition, striking truck and taxi drivers compounded the disruption (PSEPC, 2005). The indirect effects were more severe. The transportation sector has a reliance on petrol and diesel, and both public and private systems were interrupted by a lack of fuel. Nearly 30% of private motorists, which is equal to about 23% of the adult population, were forced to stop driving because they were unable to purchase fuel (Travis, 2000). This in turn increased the pressure on public transport due to overcrowding, which was worsened by a reduction in bus services because of limited fuel supplies (Guardian, 2000a).

The day to day functionality of the NHS was also affected by the fuel crisis: ambulance services were disrupted by a lack of fuel; hospitals in the West Midlands were short of food; some hospitals were unable to remove hazardous waste from their sites; and Royal Hull Hospital had run out of stitches for operations (BBC, 2000b). In addition to this, some hospitals had to cancel operations and move to emergency only care (PSEPC, 2005).

A further four sectors also noticed disruption. The first of these was food distribution, caused by both a lack of fuel and panic buying by consumers (PSEPC, 2005). Banks were unable to refill cash machines; and the royal mail had to limit service and cancel next day deliveries altogether (Guardian, 2000b).

The final group which noticed an affect was industrial sectors; including disruptions in the transportation of staff and consumers, meaning people could not get to work, or have the ability to purchase a product. This was made worse by a *JIT* approach to production and the interconnected nature of supply chains. It was felt most of all in the defence, car assembly and steel sectors (PSEPC, 2005).

2.7.4 Hurricane Sandy, 2012

On the 30th October 2012, Hurricane Sandy hit ground in New York City on a city wide scale, causing a 5.1 metre storm surge, the highest since 1851, to engulf the financial district of Lower Manhattan (Chan *et al.*, 2014). This event led to the death of more than 40 people across New York City with the total number of deaths for the North East of the United States reaching 132 (BBC, 2012).

There was also major infrastructure damaged during the storm: the runways of two major airports, John F Kennedy and Newark, were flooded, and the New York Stock Exchange was closed for two days (Chan *et al.*, 2014). In addition, bridges and tunnels connecting Manhattan to the rest of New York were closed, leading to a disruption to the subway system (NYC, 2013).

Sandy affected a very large area, including more than 12 states in New England and the Mid-Atlantic region, with strong winds being reported along it's 1,500km path(CCTV, 2012). New York City's storm warning system was activated nearly 2 days before Hurricane Sandy arrived, leading to the closure of financial markets and the issuing of a warning to local residents to stock up on food and water and protect their property with sand bags, or move to a safer area if possible (BBC, 2012). These measures undoubtedly saved lives (Chan *et al.*, 2014).

In addition to the damage to financial and transportation infrastructure, widespread and prolonged blackouts occurred in the wake of the disaster. In the majority of the areas affected by the Hurricane the power supply was successfully restored after multiple blackouts, but a week after the storm a large number of customers were still affected by the extended power outage; for example in New Jersey over 150,000 customers and New York in the region of 175,000 customers (WRN, 2012). In total, approximately 90% of Long Island was without power and it took from 30 hours to 18 days to fully restore connectivity (Fthenakis, 2013)

These blackouts caused further problems because of the interdependencies inherent in modern supply chains and the dependency on critical infrastructures, which meant that the interruption to electricity supply caused cascading problems throughout other infrastructure systems (WRN, 2012). There were high direct losses caused by Hurricane Sandy to residential and industrial buildings, as well as the electrical supply network. Subsequent supply problems with gas, and business interruption (particularly in transport-dependent industry sectors) led to a large number of indirect losses.

One such example of these indirect losses and disruptions was felt by the food distribution sector in New York City. Initially there were also very heavy direct losses: the storm surge itself destroyed the produce of 80 retailers in Coney Island and Brighton Beach, and nearly all retailers in Rockaways & Broad Chanel lost all produce.

As this sector depends heavily on the transportation network for delivery and distribution of goods, the lack of fuel available in the city, as well as the closure of roads and bridges, meant that supplies could not make it to their intended destinations. This, therefore, led to the Federal Emergency Management Agency (FEMA) setting up hot food distribution sites throughout Manhattan. Food shortages were worsened as perishable food was lost, as the blackouts meant refrigerators could not be used, although in some cases diesel fuel was syphoned from vehicles to power generators (NYC, 2013).

Other impacts were felt on the city's healthcare system: services were disrupted across New York due to the closure of six hospitals and the evacuation of almost 2000 patients. Sandy caused outages across the telecommunication services, either through a loss of power or a damaging of infrastructure, which took up to 11 days to repair. The supply of drinking water was largely unaffected although in areas with power outages pumping stations could not operate, meaning people on the upper floors of high-rise buildings were without running water (NYC, 2013).

Wastewater treatment throughout the city was affected greatly by the loss of power: ten out of 14 treatment plants released partially treated or raw sewage into local waterways, and 42 out of 96 pumping stations required to keep the sewer system moving were temporarily out of service because of either direct damage or a loss of power. Finally, in addition to the closure of bridges, disruption to road traffic, subway, rail and ferry services occurred either directly because of damage caused by the storm surge, or indirectly due to a loss of power. This stranded commuters, meaning people could not get to their place of work (NYC, 2013).

2.7.5 Other Examples

In 2003, a large electricity blackout in the north eastern states of the USA and some areas of South Eastern Canada exposed vulnerabilities within the electric power-grid system. As most aspects of the economy are highly dependent on electric power, the power-grid outage had far-reaching effects, which impaired the ability of critical infrastructures to operate. 50 million people were affected by the blackout which led to commuters being stranded, perishable food going to waste, and water pumping stations going out of action. It also had an effect on other aspects of the transport system, with the panic buying of fuel increasing congestion. The cost of the blackout was estimated at around US$10 Billion (Anderson *et al.*, 2007).

Very soon after the terrorist attacks of September 11th 2001 at the World Trade Center in New York, disruptions to the flow of vital supplies were noticed by manufactures. One such example of this was Ford, who had to shut down production on many of their assembly lines, as trucks bringing supplies from Mexico and Canada were held up at the respective borders. In a matter of hours after the event, Toyota had to stop production in Indiana as they were awaiting components supplied by air from Germany. This problem was caused because the two manufactures operated a *JIT* production system with very little slack in their supply chains to respond to disruptive events (Sheffi, 2001).

In 2005, the devastation caused by Hurricane Katrina kick-started an overwhelming succession of failures in the critical infrastructure of the City of New Orleans and other parts of Louisiana (Leavitt and Kiefer, 2006). These interdependencies let to an estimated US$107 billion of direct losses. When indirect losses caused by the interdependencies within the region were taken into account this rose to almost US$150 billion (Hallegatte, 2008). Examples of such disruption occurred in the oil pipelines and telecommunication systems, which failed because of a loss of power. In addition, contamination of New Orleans water distribution system and inoperable communication and data-gathering equipment during the response phase caused further issues (Santella *et al.*, 2009).

2.7.6 Summary of case studies

From the different case studies we learn four key things:

- Firstly, cascading failures caused by interconnecting supply chains can occur at any scale.
- Secondly, The *JIT* production system was highlighted as a contributing factor in all of the case studies
- Thirdly, clustering of like industries within the supply chain can lead to greater disruption if these areas are affected
- Finally, such disruptions can lead to unexpected indirect effects which need to be understood.

2.8 Just in time production system

In the above examples *JIT* was highlighted as a contributing factor to the severity of all of the cascading failures meaning it is important to understand what this system is and when it was developed.

The approach, which was developed in Japan after the Second World War, came about for three principle reasons: a lack of space, as it was realised the majority of a factory was used up as storage space; the improvement of the quality of production, meaning fewer rejected goods or scrapped batches; and the development of the “Toyota Production System” (Wheatley, 1992).

JIT is an integrated approach which strives to seek manufacturing excellence with the goal of producing a product at a minimum cost (Schniederjans, 1993). It therefore aims to reduce Shigeo Shingo's seven wastes, which are found in; transportation; inventory, motion, waiting, over-processing, over-production, and defect (Sandras, 1989).

The key benefits of *JIT*, as discussed by Malakooti (2013) are:

- Reduction in setup time which allows the company to vastly decrease, or even eliminate, the amount of inventory required to change from one product to another.
- Simplification of inventory flow and the management of this by reducing delays.
- It allows companies to train employees on different parts of production allowing them to move workers to where they are required.
- The scheduling of production is synchronized with demand, therefore if there is zero demand the product is not made.
- Increased emphasis on relationships with suppliers.
- Supply arrives when it is needed meaning the optimal amount of inventory is on site.
- Reduces storage space needed.
- Reduces the chance of inventory breaking or going out-of-date.

JIT pushes for constant improvement and a leaning of the production system at all points to achieve the minimal cost, and therefore increases the profits achievable by the company. Throughout these benefits only one hints at the possibility of problems arising, namely supplier relationship that needs to be strong to avoid any issues occurring, which could slow production.

The most commonly cited example of a *JIT* approach is the Toyota Production System, which is based on the following 14 principles (Jeffrey, 2004):

1. Have a long term philosophy on which management decisions are based
2. The production should be a continuous flow which allows problems to be spotted early.
3. To avoid overproduction, utilise a pull system - supplies are replenished only when used
4. Smooth production removing fluctuations in performance
5. Inbuilt quality control to get it right first time

6. Make processes and tasks standardised, allowing for continuous improvement and employee engagement.
7. Make sure problems are not hidden by using visual controls
8. Technology must be thoroughly tested, reliable, and fit for purpose.
9. Ingrain the philosophy within all staff and develop leaders to teach others.
10. Encourage excellence in people and teams.
11. Respectfully challenge partners and suppliers to improve; providing help when required.
12. Managers should take initiative to understand any situations.
13. Consider all decisions and agree slowly by consensus, implement these decisions rapidly.
14. Learn through persistent reflection and continuous improvement.

These principles form the foundation of their JIT production system and are in place to allow all involved to understand and follow these ideals (Jeffrey, 2004). Although this system has suffered because of its leanness when supply chains have been disrupted. This was noted in the aftermath of the Great East Japan Earthquake and Chao Phraya River flood in Central Thailand: in both cases Toyota had to reduce production because they were unable to source the relevant supplies.

2.9 Summary

Within this Chapter, the background information that identified the need and context of this work has been outlined, building on the justification in Chapter 1. Firstly, issues surrounding the discourse of resilience were discussed: work within this field is hampered by the lack of a common definition.

The removal of robustness from systems makes them more susceptible to disruption from catastrophic events. These can be combated by the introduction of mitigation strategies and contingencies in supply, such as the sourcing of parts from multiple suppliers in different locations.

A number of examples explore the need to understand supply chain linkages to allow cities and infrastructure systems to become more resilient to disruptive events. In all case studies in section 2.7 the *JIT* production system was seen as a contributing factor to the vulnerability of industrial networks. This, therefore, highlighted the need to understand how moving away from this production system would increase resilience. Throughout Chapter 3 alternative methods are discussed to allow for the development of a method that combats some of these issues.

3 Methodological Literature Review

3.1 Introduction

This chapter presents a review of the literature that informed the methodological choices for this research. It begins by focusing on infrastructure research, before looking into the various concepts that can be used to model resource flows along these infrastructure networks. The following methodological approaches were selected for detailed discussion; Input Output (*I-O*) analysis, network analysis, material flow analysis, and risk analysis.

3.2 Infrastructure

The method developed as part of this research models the flow of goods within a chosen infrastructure network, for example transport or electricity distribution. It is, therefore, helpful to have an understanding of what infrastructure is, what the different types of infrastructure are, and what the different forms of can take place. This knowledge informed how the infrastructure was represented within the model, as well as the types of disruption that formed the basis of tested scenarios.

The term infrastructure is defined by the OED (2010) as:

"The basic physical and organisational structures and facilities (e.g. building, roads, and power supplies) needed for the operation of a society or enterprise"

Rinaldi et al. (2001) provide various examples of different infrastructure found within a city including: banking and finance, educational system, electric power, emergency services, food and agriculture, government services, the health care industry, natural gas, petroleum, telecommunications, transportation, water supply, various commodities such as iron and steel, and finished goods.

3.2.1 Critical infrastructure

Energy, transport, water, waste, and information and communications technology are vital to human well-being and provide necessary services that allow society to function (Otto *et al.*, 2014). The interconnected nature of these infrastructures makes them highly vulnerable to disruption, as problems may stem from one or more of their dependant elements. For example, a water main break could cause a minor disruption, but this in turn could cause a sink hole to develop, resulting in a street closure and consequently a much larger disruption.

The disruptions could develop further if, for example, the sinkhole caused water and natural gas pipelines to fail, leading to fires, which could not be tackled successfully due to a drop in water pressure and supply. This could in turn lead to consciences far exceeding expectations from the initial water main break (Little, 2002).

What is classified as critical infrastructure varies but generally includes: banking and finance, energy, food, health, telecommunications, transport, and water (Ridley, 2011), plus activities such as defence, and the chemical and hazardous materials sector (Min *et al.*, 2007). These are ever changing, complex systems that are highly interdependent, through the widespread use of information and communication technologies and as well as through physical links (Eusgeld *et al.*, 2009a). In the United Kingdom the CPNI (2009), when discussing UK Critical National Infrastructure, stated:

"…there are certain 'critical' elements of infrastructure, the loss or compromise of which would have a major, detrimental impact on the availability or integrity of essential services, leading to severe economic or social consequences or to loss of life."

These different infrastructures also become reliant on one another through various interdependencies within their processes and therefore can be a viewed as a system of systems (Eusgeld *et al.*, 2009b). This relatively new concept strives to describe the integration of numerous independent systems that work together to satisfy a universal goal and within predefined parameters (Karcanias and Hessami, 2011). These form highly complex systems which are adaptive in behaviour and incorporate feedback loops within the system (Eusgeld *et al.*, 2011). As these interdependencies between the different system components increase, the vulnerability of the system also increases (Balducelli *et al.*, 2007) (Figure 3.1).

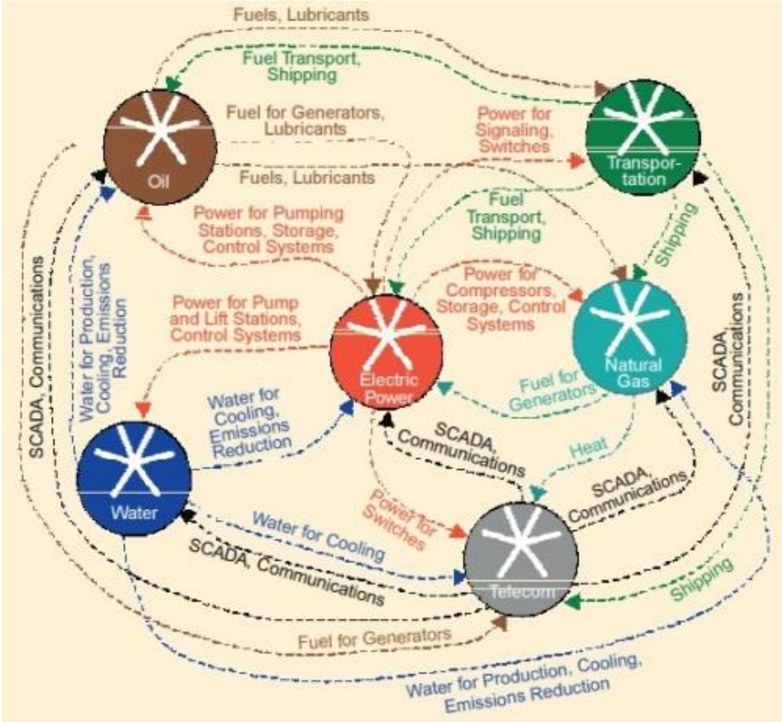

Figure 3.1: Critical infrastructure and their interdependencies (Rinaldi *et al.*, 2001)

3.2.2 Types of disruption

It is important to understand how these infrastructures are connected and what effect a disruption within one or more of these sectors would have on the rest of the system (Zio and Sansavini, 2011). There are various types of disturbance that could cause disruption of supply chains within the urban system; a number of these are listed by Conrad *et al.* (2006):

- Energy blackouts due to insufficient generation, transmission bottlenecks, or equipment failure;
- Telecommunications disruption caused by fire, wind, water, or sabotage;
- Water supply contamination caused by toxic materials;
- Banking and finance liquidity problems, resulting from a disruption to electronic payments;
- Emergency services failing to keep up when a disaster overwhelms response capacity;
- Day to day disruption of operations within government services; and
- Production of food if food supply becomes contaminated

3.3 Input-output analysis

Leontief (1970) introduced the technique as an approach that both describes and explains the output of a chosen sector of an economy. This 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) which is fundamental to the research carried out as part of this thesis.

The basic input output relationship is defined by, where *C* is consumption and demand, *De*.

$$x = Cx + De \tag{3.1}$$

The level of demand is equal to:

$$De = (1 - A)x \tag{3.2}$$

For I-O, the equation must be solved for *x*, where 1 is equal to the identity matrix (*I*), giving:

$$x = (I - C)^{-1}De \tag{3.3}$$

The *I-O* model portrays relationships between industries within an economy. It therefore depicts how an output from one sector may become an input to another. The approach highlights the level of dependency each industrial sector has with every other industrial sector. It also shows how a sector can be both a supplier of outputs to another sector, whilst also being a 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).

I-O accounting is an established technique and it is utilised by national governments to depict their economy. ESA (2010) published *the Supply, use and Input-output tables methodology*. This provided guidelines for the development of national supply and use tables, as well as the Symmetric Input-

Output table. This table can either be produced product by product, or industry by industry. These tables highlight: industrial interdependencies, movements of goods and services within an economy, and imports and exports from the economy.

The interest in this technique for this research stemmed from the need to predict the adverse effects on a network caused by a disruptive event within an interdependent system, as well as the need to evaluate potential techniques to lower the impacts caused by such events (Pant *et al.*, 2011). To do this, such models must show the interdependencies between human activities and ecosystem services, in addition to interactions between them both (Cordier *et al.*, 2011). This provides the ability to predict future scenarios, whilst optimising the system to deal with them (Liang and Zhang, 2011). In addition, this highlights and addresses issues with high levels of uncertainty, and provides a holistic approach that takes into account both core and support services within the modelling process (Cordier *et al.*, 2011).

A major benefit of *I-O* tables is that they provide an insight into the whole economy through the flow of trade, which ultimately links each sector to all others (Leontief, 1986). *I-O* tables take an economy level perspective in order to analyse the economy through disaggregating the total output of economic activities by industry (Giljum and Hubacek, 2009). These tables are made up of various components, that were described fully within Chapter 4. In short, the three main elements of an *I-O* table are:

- The expenditure by a sector in each of the other sectors in the local economy, which is shown in the columns;
- The revenue received by that sector from each of the other sectors, which is shown along the rows;
- The imports, including all expenditures made outside of the local economy; and
- The exports that include all revenue generated from outside of the local economy.

A second advantage of *I-O* is that it is an adaptive approach, which can be used in conjunction with other concepts. For example, an environmental *I-O* analysis carried out by Moll and Acosta (2008) highlighted ten groups of products with both high levels of emissions and wastes, as well as a requirement for a large amount of resources. For these groups, in line with European Union Policy on using natural resources sustainably, various ways to reduce the environmental impacts throughout their lifespan to decouple environmental impacts from resource use were identified. To do this, the environmental *I-O* analysis was combined with NEMA tables (national accounts matrix, including environmental accounts).

A second variation of the approach was to develop an ecological-economic *I-O* model. Cordier *et al.* (2011) applied this technique to a case study of the Seine estuary, which allowed for an estimation of the impacts of the restoration of 50% of fish nurseries that were destroyed between 1834 and 2004. The model took into account the interdependency between the ecosystem service (fish resources) and the life supporting service (nursery habitat) as well as incorporating its impact on human actions. The study also applied principles related to Post-Normal Science, namely addressing uncertainties and establishing holistic properties.

One of the most famous variations of *I-O* modelling was developed by Hallegatte (2008) to assess the economic cost of Hurricane Katrina to New Orleans and the surrounding region. It employed regional *I-O* tables and calculated both direct and indirect losses caused by the disaster. It also incorporated some of the recovery phase, although the author states that it did not model the weeks directly after the disaster very successfully. The model only takes into account interactions within the region studied; it also assumes a steady economy and not how the disaster changed economic activity. Similar assumptions were made within the model described in this thesis.

In addition to the aforementioned benefits, *I-O* has further advantages; first of all it is a long established technique that is well understood and widely used. On top of this, the way that the tables are set out leads to an ability to model scenarios, which is important for this research. *I-O* provides the ability to see the results of these scenarios on a sector by sector basis; this is also fundamental to the developed method (Clarke, 2010).

Certain criticisms exist of the use of *I-O* modelling. One of these is that they lack flexibility, as there is no option within *I-O* models for a producer to find an alternative supplier if there is a disruption to their usual source of supply(Hallegatte, 2008). As *I-O* data and models track the interactions at an economy wide level (Leontief, 1970; Leontief, 1986; Hallegatte, 2012), they do not necessarily take into account a spatial or geographical element of where these interactions actually take place. This is due to the level of aggregation. As the studies are at economy wide levels it becomes impossible to carry out any spatial analysis of the data. Further disadvantages of this approach are that is assumes various constants; for example, it assumes linkages between industries remain the same, and it also assumes that there are no supply constraints (Clarke, 2010). This spatial disaggregation problem is highlighted by Fernandez-Vazquez, et al. (2014) as a frequent problem; as data which is cross classified to include industry and region does not readily exist. This is, therefore, a reoccurring criticism of aggregated *I-O* tables .

The approach developed as part of this research therefore sets out to address these issues, as well as hold on to the benefits of *I-O* analysis. The *I-O* relationships are utilised throughout to depict the supply and demand linkages between different aspects of the economy, and therefore are the backbone of the model developed within this thesis. They provided the raw data that informed the linkages inherent within the resource model, as well as information regarding which sectors were apparent in the modelled economy.

3.4 Network Analysis

A second approach for mapping infrastructure interdependencies is network analysis. The basis of this comes from graph theory. A graph (Figure 3.2) is an object which includes two elements, the first of these are nodes and the second are edges that connect the nodes (Dolan and Aldous, 1993; Wilson, 1996; Rinaldi *et al.*, 2001; Chen, 2003; Salles and Marino, 2012). A graph is an ordered pair consisting of a set of nodes, also known as vertices, and a set of edges; with an edge being related to two nodes (Jungnickel and Schade, 2008). This makes it a perfect tool to model supply chain links between different sites of production.

3.4.1 Graphs

Within a graph the edges can be either undirected, or directed. In an undirected graph, the edges have no orientation. Within a directed graph, on the other hand, the edges connecting the nodes have a direction associated with them (Figure 3.2). A multigraph allows multiple edges to connect the same pair of nodes, as well as loops linking one node to itself (Diestel, 2000; Bang-Jensen and Gutin, 2007; Jungnickel and Schade, 2008). In this research the network was modelled using multigraphs, as more than one route can link the different nodes, and self-loops were also required as certain industries required an input from that industry to operate; for example a power station could not function without electricity.

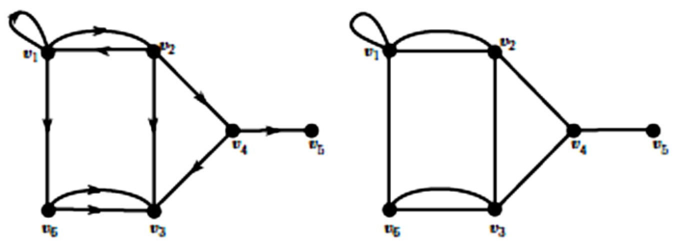

Figure 3.2: Digraph and its underlying graph (Balakrishnan and Ranganathan, 2012)

A subgraph (Figure 3.3) is a subsection of a graph in which all nodes are connected to each other (Jungnickel and Schade, 2008). Related to this a connected component of a graph is a subgraph in which the nodes are connected to each other by edges, but are not connected to any other nodes in the graph (Chen, 2003).

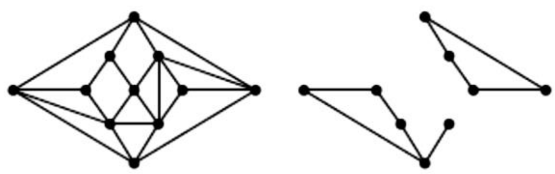

Figure 3.3: Graph and subgraph (Jungnickel and Schade, 2008)

A graph becomes a network when these elements are assigned numerical values (Dolan and Aldous, 1993; Diestel, 2000). These numerical values can take the form of weightings applied to edges and nodes. An example of this could be the time taken to travel along an edge. A node can have both an in-degree and an out-degree showing the number of edges connecting to and from the node. In turn, the degree of the node is the number of edges connected to that node, the higher the degree the more influential the node (Newman, 2004).

3.4.2 Metrics

Connectivity can be measured in various ways and is a technique for assessing the robustness of a network (Diestel, 2000). One way of measuring connectivity is through the clustering property. This uses the assumption that if node *A* is connected to node *B*, which in turn is connected to *C,* it is more than likely that *A* is also connected to *C* (Newman, 2004; Vasudev, 2006; Dueñas-Osorio *et al.*, 2007). The more clustered a network (measured by the clustering coefficient), the more vulnerable it is to cascading failures (Huang *et al.*, 2013). A second measure of connectivity is to calculate the shortest paths; this is done by calculating the mean shortest path lengths connecting each node in turn to all others in the network (Dueñas-Osorio *et al.*, 2007).

The degree centrality is the number of paths less than or equal to k that emanate from a node: this is a good measure of the likelihood of a disruption shifting from one node to another (Kang et al, 2011). It is normalised by the maximum centrality (total number of nodes minus one) (D'Errico *et al.*, 2009; König and Battiston, 2009) and the higher the degree centrality the more likely it is for an event to spread from this node (Salles and Marino, 2012). This, therefore, could be used as a measure of the resilience inherent within infrastructure networks. Within this study the degree centrality was utilised to identify a potential zone to be disrupted in one of the modelled scenarios.

The degree centrality is (Networkx, 2012):

$$\text{for node } n = \textit{degree of } n / N - 1 \qquad (3.4)$$

Nodes which have a greater number of links to other nodes can be considered to be in an advantaged position. This is because they have numerous ties, and therefore alternative means to satisfy their requirements, making them less dependent on other individual nodes. This greater number of links means they could have access to a greater number of the resources found in the network as a whole (Hanneman & Riddle, 2005). However, this does not necessarily increase the robustness, or the resilience, of a network. If, for example, the highly connected node represented the sole power station within a modelled economy, and this power station failed for some reason, the high degree centrality would be detrimental to the robustness of the rest of the network (Salles and Marino, 2012).

The degree centrality has, because of this relationship, been used to measure of the robustness of networks. For example, Pinnaka et al. (2015) used this metric to model the robustness of critical infrastructure networks. The authors utilised the degree centrality to highlight the important nodes within their modelled network; an approach which was utilised within this thesis to select the most important geographic area for a targeted attack (Section 5.8.3). A similar approach was employed by Stergiopoulos et al. (2015), with the authors stating that nodes with the highest degree centrality values display the highest levels of risk, if disrupted, to the reminder of the network.

3.4.3 Types of network

Most real-world networks come under the umbrella of complex networks, which is a large set of interconnected nodes (Lü and Chen, 2005). These networks are everywhere, and can be divided into subcategories: social, information, technological and biological (Rinaldi et al., 2001). Models of complex networks allow for a representation of interdependencies inherent in the network topology; although they are unable to simulate more complicated interactions between nodes (Nan *et al.*, 2013). Complex systems are usually made up of nodes that interact strongly with one another in a nonlinear fashion and the nodes are connected in a complicated web of exchanges that may be largely unknown (Amaral and Ottino, 2004). Various examples of complex networks exist; these include the Internet and electric power grids (Lü and Chen, 2005).

An approach to modelling network interactions is to utilise random networks. This allows for an investigation into how network properties change when varying both their size and topology, although due to their simplified nature they are not accurate representations of real-world networks (Albert and Barabási, 2002; Newman, 2004).

A second approach, slightly closer to real-world networks, is to use small world networks. These are networks which are based on the assumption that geographic proximity of nodes leads to them having effect on the other nodes connected to them, meaning that nodes which are located closer to one anther have a greater effect on each other than if they were further apart (Newman, 2004).

3.4.4 Infrastructure networks

This research is interested in interdependencies within complex interdependent networks that are highly connected (Rinaldi *et al.*, 2001) and therefore very susceptible to disruption. Rinaldi *et al.* (2001) describe four different types of interdependency: physical, in which two entities are dependent on the physical output of the other; cyber, a dependency based on the transfer of information; geographic, when different elements are in close spatial proximity; and logical, a dependence that is not physical, cyber or geographical. Disruption to any of these different types of interdependence can lead to a cascading of failures throughout the network.

Rinaldi *et al.* (2001), follow this up by looking at dependencies which exist to electrical power, giving the example of the power crisis in California (Figure 3.4). As most industries require power, this strong example shows the effects of disruption to interdependent networks; this is highlighted by the disruption to the power network causing cascading failures through many other industries, either directly (first order effects) or indirectly (second and third-order effects).

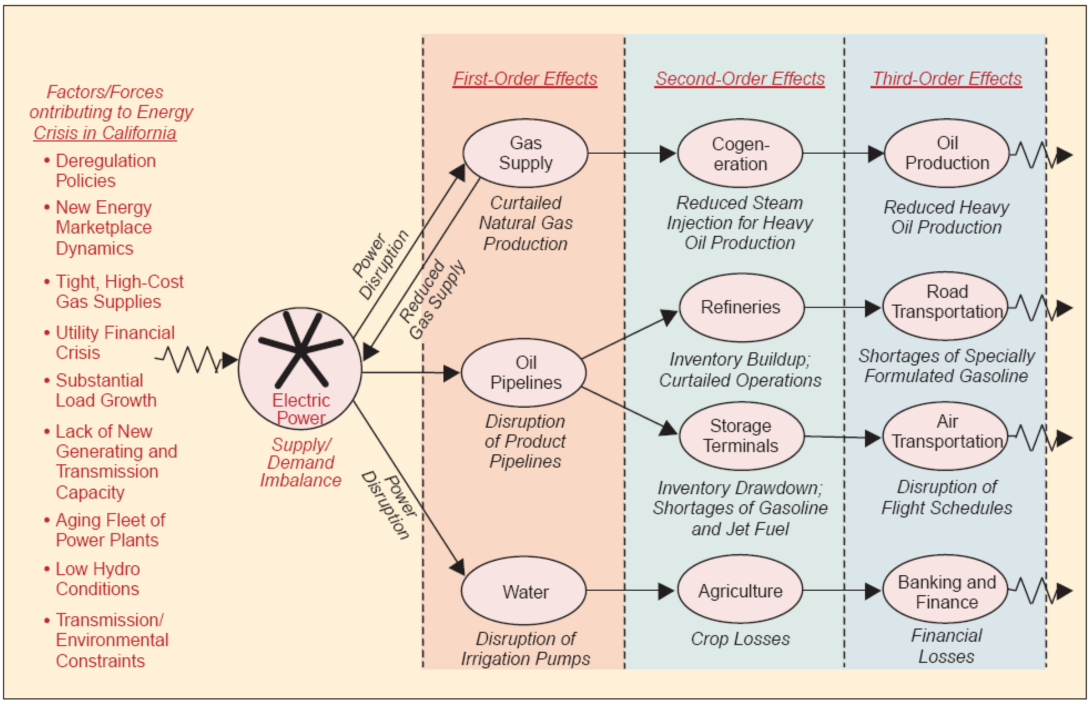

Figure 3.4: Direct & indirect failures caused by the California power crisis in (Rinaldi *et al.*, 2001)

This idea of being able to analyse not only direct, but also indirect, effects of disruption is fundamental to this research. However, it has been addressed slightly differently to allow for the ability to model reserve stock and different delivery patters (Chapter 4).

In addition to the above, Pizzol *et al.* (2013) used network/graph theory to asses a Danish Water Management system, in order to apply theoretic discussion to the real world: this work concluded that network/graph theory was a valuable tool for assessing sustainable use of resources. It is commonplace throughout network analysis for infrastructure systems, such as water systems, to be modelled in such a way. The nodes are typically pumping stations, water towers and electricity substations; and the edges are generally the pipes (Holden *et al.*, 2013). For the purposes of this research, this practice was not followed; instead the links between nodes represented the infrastructure between different sights of production, for example, the roads that allowed supplies to move from one site of production to another.

Recent research into infrastructure networks by Pant *et al.* (2016) has split the type of nodes into three categories. The first of these are the source node, which represent where resources are generated. Next are the intermediate nodes which transmit from the source nodes to other nodes. Finally there are the sink nodes, which receive supplies either from the intermediate nodes, or directly from the source nodes. There are some similarities between the work of Pant *et al*. (2016) and the work carried out in this thesis, the first being that a node can represent both a produce of a resource (source) and a user of a resource (sink). A second similarity is that Pant *et al.* (2016) also use edges to represent a physical piece of infrastructure which links the node, for example a road or electricity cable. The authors trialled their methodology on a case study of Great Britain's rail network and found it provided a valuable analysis tool for highlighting which interdependencies potentially have large impacts on the rail network.

Within Chapter 4, both transportation networks and electrical distribution are studied. Both of these types of network have recently had network theory applied to them, to allow for analysis to take place (Dunn et al., 2014). Examples of these include:

- Transportation Systems

  - Airline networks have been analysed on national scales in China (Wang *et al*., 2011), India (Bagler, 2008), and Australia (Han *et al*., 2008), as well as European wide (Wilkinson *et al*., 2012) and the whole world (Guimera et al, 2005).
  - Subway networks have also gained attention, for example, by Latora and Marchiori (2002) who focussed on Boston's subway network. Lee *et al.* (2008) looked at the Seoul subway network, and the terrorist attacks on the London Underground were the focus of work by Jordan (2008).
  - In addition, and more relevant to this work, road networks have also been addressed using network analysis, for example, by Taylor *et* al. (2006) in Australia and Weber (2016) in the USA

- Electrical distribution systems, which are regarded as some of the most complex human-constructed networks (Costa *et al.,* 2007).
  - Example studies have been carried out on both the North American (Albert *et al*, 2004, and Kinney *et al*., 2005) and European (Sole *et al*., 2008) distribution networks, as well as in the UK (Pakka *et al*., 2016).

3.4.5 Summary

As highlighted above, graph and network theory provide tools to aid investigation into the resilience of supply chain networks. Aspects of the above discussion were, therefore, utilised within the developed resource model. It was important to use such tools to identify key components of a network, to allow for decision makers to implement policies to increase resilience (Nagurney and Qiang, 2012) and therefore understand the vulnerabilities within networks (Eleuterio *et al.*, 2013). This research has built upon the basic application of these methods by using degree centrality to inform which nodes have the most connections, leading to these nodes being targeted for disruption within the developed network model. This allowed for an analysis into how disruption to these important nodes leads to a cascade of disruption through the modelled system (Chapter 5).

3.5 Urban metabolism

Figure 3.5 provides information on the urban metabolism of Brussels, i.e. what the city consumes and the wastes it produces, taken from Duvigneaud and Denayeyer-De Smet's (1977) investigation into urban ecosystems in Belgium. It shows the same basic understanding, but once again no knowledge of how supplies move around the system. It was important within the research for this thesis to develop a method of spatially modelling the flow of resources in order to investigate the effects of disruption to these flows caused by spatial hazards such as flooding.

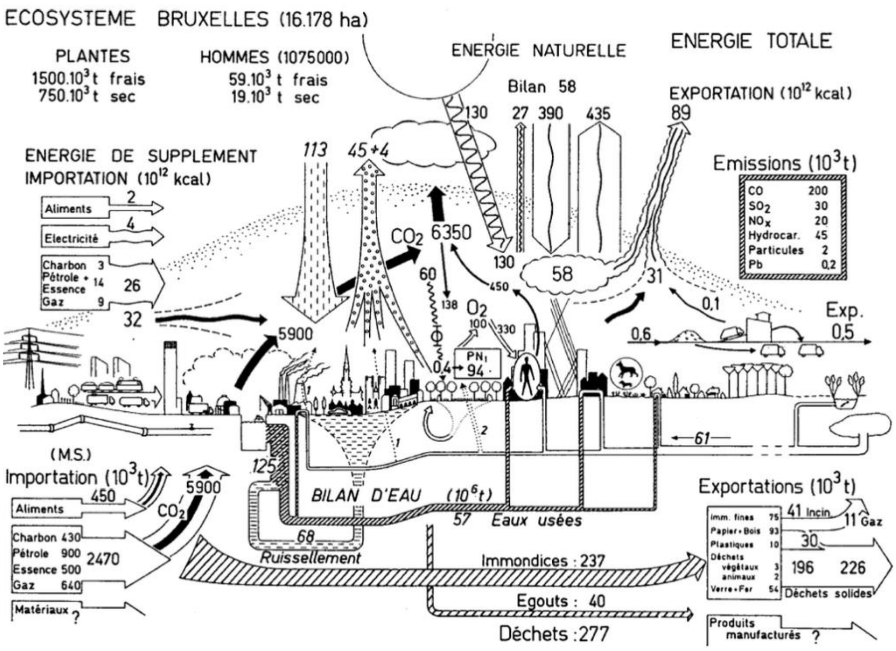

Figure 3.5: The Urban metabolism of Brussels

Studies of the metabolism of an urban area are increasingly conducted (Liang and Zhang, 2012) as they provide a host of benefits. These include giving a holistic view of all inputs, stores, and outputs for an urban area (Kennedy *et al.*, 2011). The approach allows for recommendations to be made that create a more efficient use of materials within a city (Brunner, 2007)

A second benefit of these studies is that they provide a method to understand a city’s metabolism, as most of the products consumed in cities come from other areas. A city can, therefore, be described as an attractor of consumable goods. The knowledge of such flows allows for an understanding of urban functions to be developed, as well as an understanding of what impacts such patterns of consumption can have on a larger scale (Barles, 2009), whilst trying to change the linear metabolism of cities to a more cyclic function. This could lead to waste from one process being an input for another, with stocks maintained and reused to reduce the amount of primary inputs into the system (Brunner, 2007). The metabolism of a city is seen as an interconnected set of flows which are dependent on materials, energy and information inputted from external sources (Gandy, 2004).

Certain issues with the urban metabolism approach do exist, as opposing disciplines use slightly different methodologies and modes to analyse the different stocks and flows which are part of urban activity (Pauleit and Duhme, 2000), The analysis of fluxes and functions within an urban area make it easier to define the different components of urban metabolism (Zhang *et al.*, 2010), allowing for standardisation to occur through concepts such as energy analysis (Pulselli *et al.*, 2009).

Although not directly utilised within this work, the study of urban metabolism offers an alternative data source that can provide the necessary inputs for the developed model. This is done through the use of material flow analysis (MFA) data, which can be displayed in a similar way to I-O tables (Lifset, 2009). Utilising MFA data highlights the direct flows of materials in a more bottom-up approach, rather than focusing on the economic links between different sectors as in I-O tables, which makes these more top-down.

3.5.1 Material flow analysis

To increase the resilience of a system, an understanding of how the system consumes resources is required. In addition, the quantification of material flows and the documentation of industrial processes which make modern society function is required (Hong *et al.*, 2011). To help gain this understanding, material flow analysis (*MFA*) is useful; it is a technique used to measure urban metabolism usually at a national or economy wide level (Eurostat, 2002; OECD, 2008a) but it can also be applied at lower levels (Barles, 2009).

MFA provides a holistic view of how resources are managed, with the goal of minimising wastes and inefficiencies within the supply chain (Browne *et al.*, 2011). It also can focus on a subject whilst allowing for wide-ranging secondary analysis and the development of summary indicators (Eurostat, 2002). *MFA* is based around a mass balance approach which states that inputs are equal to accumulation of materials in the system plus the outputs from it, (Hinterberger *et al.*, 2003; Browne *et al.*, 2011) meaning that matter cannot be created or destroyed (Sheerin, 2002).

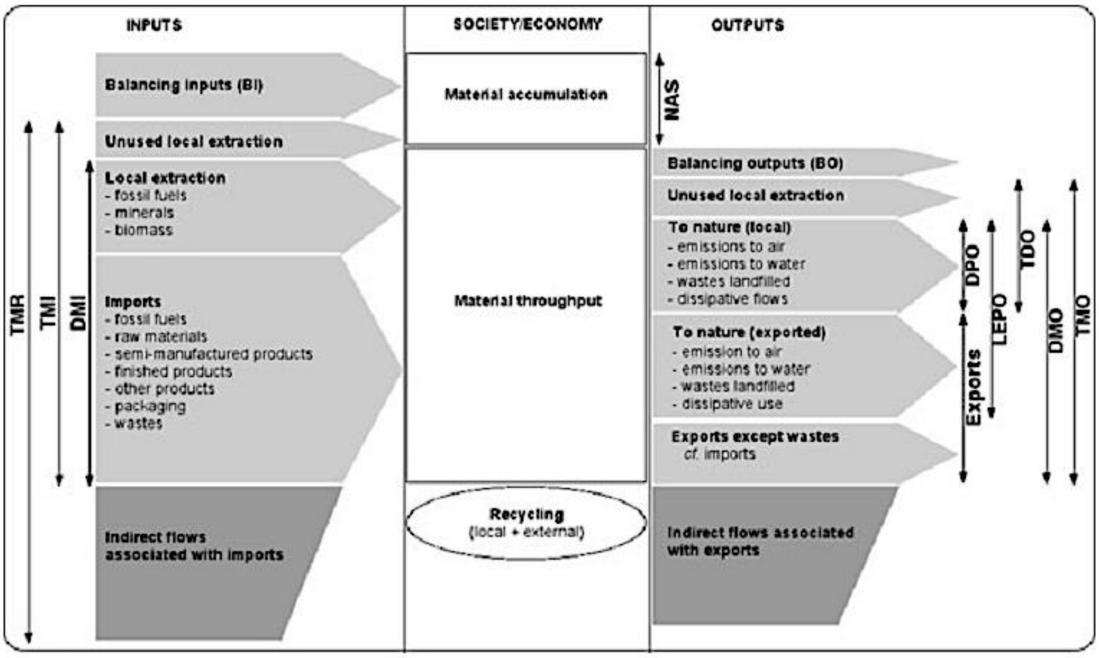

Figure 3.6: Mass balanced approach adapted from methods outlined by Eurostat (Barles, 2009)

Figure 3.6 shows an example approach for a *MFA*, adapted from the approach set out by Eurostat (2001). Similarly to the Brussels (section 3.5) and London (section 1.1) examples, it uses a black box approach to depicting the consumption, meaning that the complex interactions between sites or production are not depicted.

On a basic level, raw materials are extracted from nature, and are the inputs to the system; these are then transformed into products, and finally the outputs re-enter the natural system as waste or emissions (Hinterberger *et al.*, 2003; Weisz *et al.*, 2006). However, the current linear model of production, consumption, waste output seen in cities is unsustainable and does not fit with the patterns shown in natural ecosystems (Huang and Hsu, 2003).

Direct inputs to an economy include resource extraction from within the area being studied and imports from a separate system. The outputs are landfill waste, emissions into air and water, and exports into the system (Sheerin, 2002). This being the case, an *MFA* is affected by varying qualities of data relating to imported products, which can therefore affect the accuracy and validity of the study (Sheerin, 2002; Hong *et al.*, 2011). Another concept that

MFA takes into account is hidden flows; this is unused extraction which does not directly enter the economic system (Kovanda and Hak, 2007).

Many examples of *MFA*s are apparent in the literature ranging in both scope and scale. Huang and Hsu (2003) use *MFA*, coupled with ecological energetic analyses, to investigate the sustainability of urban construction in Taipei. Similarly, Müller (2006) focuses on housing in the Netherlands with the aim of introducing stock dynamics as an approach to predict resource demand and waste generation; urban lifestyles and population being the driving force behind this.

MFA studies can focus on the production of a single product, such as paper. The approach models compositions of raw materials inputs and outputs associated with the lifecycle with this product (Hong *et al.*, 2011). *MFA*s have been applied to larger scales, be it a city or region level, in which the focus is to have a holistic view of the metabolism of the chosen area, such as Limerick (Browne *et al.*, 2011), York (Barrett *et al.*, 2002) and London (BFF, 2002). However, at these lower levels most data is generally disaggregated from national statistics, as in many cases the data does not exist (Browne *et al.*, 2011). *MFA*s are also utilised at an economy wide level, with OECD (2008b) and Eurostat (2001) providing detailed guidance on how this should be carried out. *MFA* can also be used as a comparison tool when looking at material consumption (Weisz *et al.*, 2006) or material flow through major cities (Decker *et al.*, 2000).

MFA is a useful tool for gaining in-depth knowledge of the metabolism of a system, be it the system for the manufacture of a single product, the system by which material flows in and out of a research area or a whole economic system. It takes into account all inputs, including hidden flows, outputs and consumption, and can be used to provide summary indicators as a way of describing the metabolism of the system.

3.6 Risk Analysis

Risk analysis is a formal scientific process for determining the risk of a hazard event to a system (Bahr, 2000; McLauchlin *et al.*, 2004). The process itself is highly subjective and represents the incorporation of science with significant psychological, social, cultural, and political factors (Slovic, 1999).

Risk analysis is a forecasting technique that identifies hazards which may affect a system, carries out a risk assessment determines the significance of the risk, and communicates the risk information to stakeholders (Cohrssen and Covello, 1999), by stating the probability and the expected impact of a hazard (Lee and Pradhan, 2006). The identification of hazards should never be considered to be finished, and should be an on-going process (Redmill and Consultancy, 2001; Redmill, 2002). The events highlighted throughout Chapter 2 emphasise the need for effective risk management.

3.6.1 Hazard and Risk

For the purposes of the following discussion, the terms 'hazard' and 'risk' are defined here. A hazard is something that poses a level of threat to life, health, property, or the environment (Thomas, 2012). Hazards can be either natural, such as an earthquake or a hurricane, or man-made, such as a nuclear disaster (Wolshon and Murray-Tuite, 2013). A hazard is, therefore, something which either exists or not, whereas a risk is the probability of such a hazard doing harm (Hodges, 2009).

A risk is a potential danger (Arnoldi, 2013). Risk, R, must, therefore, include an element of loss, A, which may be multiple in nature. Risk should also take into account how significant a loss might be (larger losses imply a greater risk) and the likelihood, p, of disruption occurring from that event, d. The level of uncertainty dictates how a decision maker responds (Yates, 1992), therefore:

$$R = (p)A(p)d \tag{3.4}$$

Zsidisin (2003) defines supply risk as:

"…the probability of an incident associated with inbound supply from individual supplier failures or the supply market occurring, in which its outcomes result in the inability of the purchasing firm to meet customer demand or cause threats to customer life and safety."

3.6.2 Basic Risk Analysis Approaches

Standard risk analysis approaches can fall into two basic types: quantitative or probabilistic, and pseudo-quantitative. Quantitative approaches attempt to explain the consequences of a hazard in monetary units, time, or potential lives lost, and seek to understand what could happen, how likely this is and what would the consequences be if it were to happen (Kaplan and Garrick, 1981).

While pseudo-quantitative approaches may also assign numbers, these numbers are not necessarily linked to values relating to cost and/or loss of life. An example of this type of approach is a risk matrix that classifies the likelihood and consequences of a risk in separate categories (Markowski and Mannan, 2008).

3.6.3 Vulnerability assessment

In terms of risk assessment, vulnerability is the combination of possible consequences, and uncertainties associated with a given hazard, making risk a combination of both vulnerability and the hazard (Aven, 2007). This definition provided the basis for the flood risk analysis technique developed as part of this thesis; with the risk value being the sum of vulnerabilities for each of the modelled flood magnitudes. The consequences of a natural hazard are generally measured in terms of damage or losses, either as monetary value, or some other metric, such as evaluations based on social values (Fuchs *et al.*, 2007).

A fundamental aspect of the proposed method within this thesis is the assessment of vulnerabilities. Vulnerability assessment can be defined as the methodical inspection of a system to identify those elements or related mechanisms that may be susceptible to a hazard (Rao and Thakur, 2007). Such an assessment should take into account the intensity of hazards and provide information based on the different magnitudes (Deck *et al.*, 2009). A supply chain vulnerability assessment requires a different set of methods and statistics and may be performed separately from standard approaches (Nowakowski and Valis, 2013).

3.6.4 Flood Risk Analysis

Flood risk analysis provides flood managers with an improved understanding of vulnerabilities to flooding and the most effective means of assigning resources to improve performance (Dawson *et al.*, 2005) and is a requirement for flood risk management (Hall *et al.*, 2005).

Within the literature, many approaches to flood risk analysis are proposed. One such method was introduced by Dawson *et al.* (2005). It describes a risk-based sampling technique that removed the need to produce accurate estimates of flood depth and damage, in order to reduce the computing power required to estimate flood risk. The model also had the potential to examine how a system may respond to future external disruptions. For this method, flood risk, “the product of the probability of flooding and the consequential damage”, and economic risk, “an expected annual damage, EAD”, are discussed.

Dawson *et al.* (2005), estimated the probability of distribution flood depths at different dyke locations on a flood plain. As part of this, two types of flood were modelled, overflow and dyke breach. At sites with complex topography, a hydrodynamic model was required. This model simulated floodplain inundation and provided estimates of flood depths. A fragility component was also included to make reference to a dyke’s ability to resist damage within the calculations (Figure 3.7 shows a schematic of the methods used).

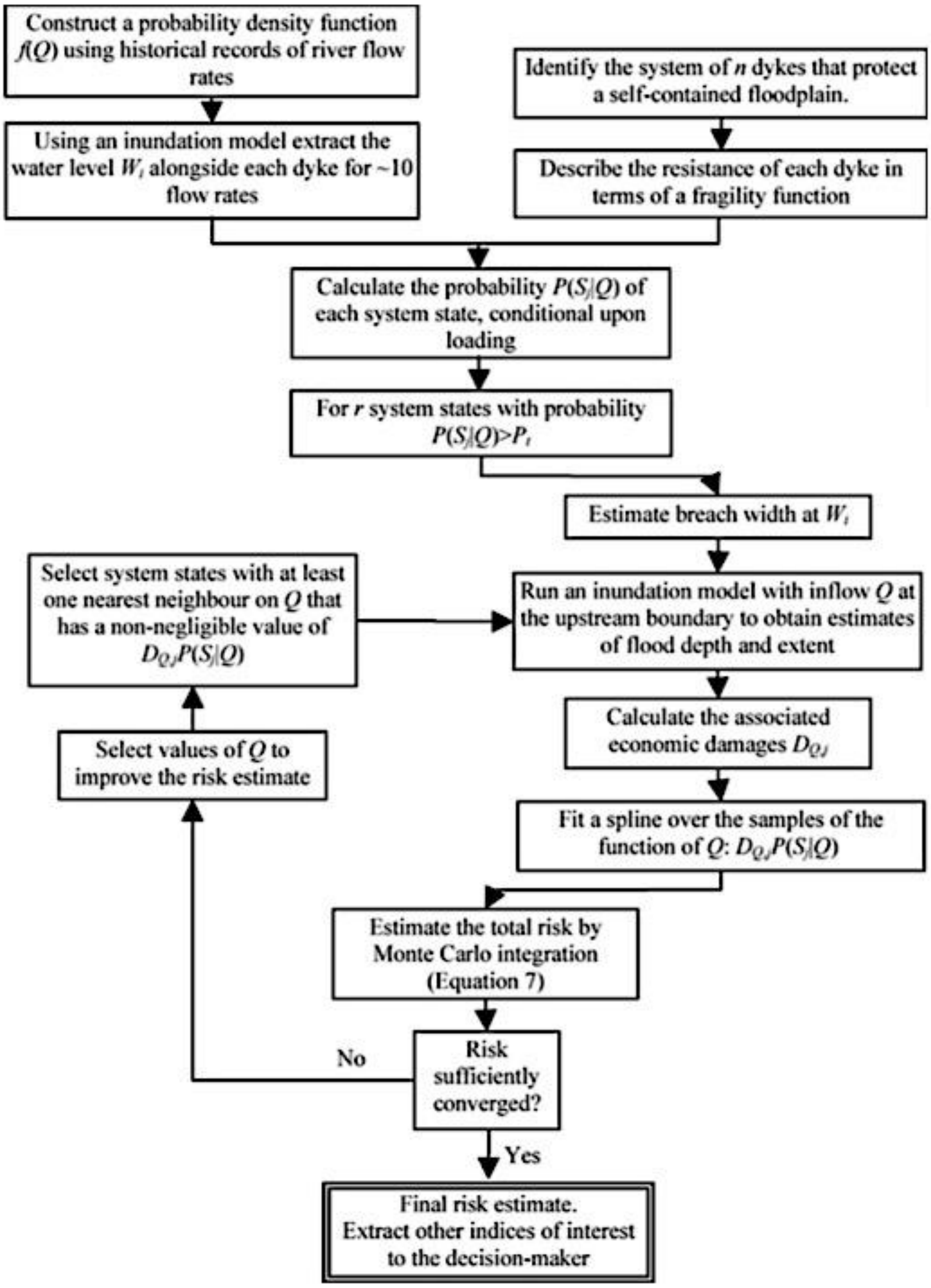

Figure 3.7: Overview of risk-based sampling methodology (Dawson et al., 2005)

On a larger scale, Hall *et al.* (2005) propose a national flood risk assessment model that made use of location, level of protection and condition of flood defences in England and Wales. In addition to this, a dataset with the size of floodplains, topography, population, and asset values was included in the analysis. The analysis predicted that a 20-fold increase in funding for flood risk management would be required by 2080 to mitigate the expected increase in flood risk. Figure 3.8 provides an overview of the methodology used in this study.

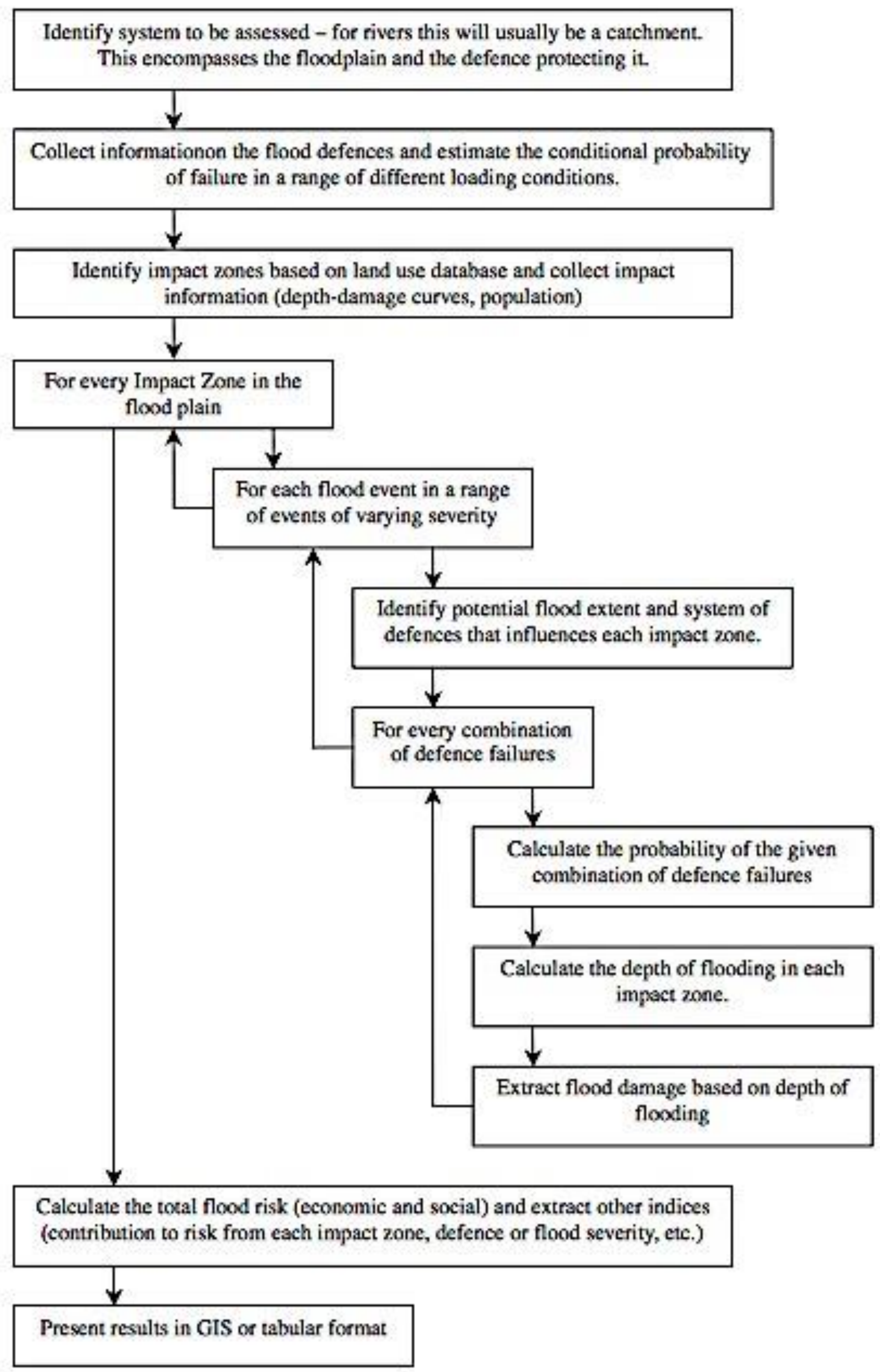

Figure 3.8: Overview of the national flood risk assessment methodology (Hall *et al.*, 2005)

The two examples presented above utilise the vulnerability caused by different depths of flooding and calculate risk based on the probability of these flood events occurring (albeit including other information). This basic approach forms the backbone of the flood risk analysis metric, which is produced by the model developed in this research.

A similar approach in term of an integration of hydrologic and socio-economic factors was proposed by Yoon *et al.* (2014). The research assessed watershed-based flood hazards and vulnerability in the Han River Basin, Korea. The authors found that despite a small sample size and a difficulty sourcing data, they were able to provide a quantitative description of the Han River flood risk, which gave stakeholders and decision-makers a combined approach of risk assessment and management. Figure 3.9 shows the conceptual framework employed for this study.

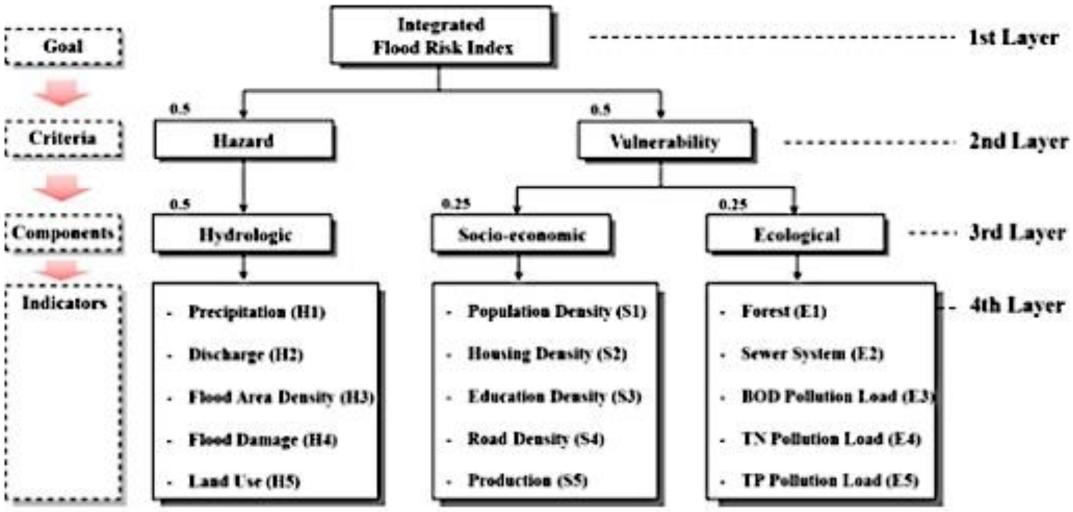

Figure 3.9: Conceptual Framework and Hierarchy for the Flood Risk Index in the Han River Basin, Korea (including weighting factors) Yoon *et al*. (2014)

A further flood risk method was developed by Hallegatte *et al.* (2011), which analysed the risk to Copenhagen from storm surges based on predicted sea level rises. The model incorporated *I-O* analysis to take into account the direct and indirect losses when infrastructure was disrupted. The model identified that the risk of such a hazard occurring would increase, calling for a comprehensive strategy of adaptation and mitigation to manage the effects of climate change to be developed.

3.6.5 Supply chain risk analysis

The main emphasis of supply chain risk analysis is to identify future uncertainties, in order to allow for the practical management of risk-related issues (Norrman and Jansson, 2004). This is usually achieved through a use of multiple qualitative, semi-quantitative or quantitative methods (Cagliano *et al.*, 2012). Supply chain risk analysis is an imperative method to enhance the security of supply chain networks (Toivonen *et al.*, 2009). However, there is no conceptual framework in place which ties together research into this area (Manuj and Mentzer, 2008).

To combat this criticism, Blackhurst *et al.* (2008) when focusing on the automotive industry, developed a framework of risk factors based upon a multi-criteria scoring process. It calculated vehicle part and supplier risk indices with the aim of developing risk assessment and monitoring systems. It was developed in conjunction with the stakeholders from the automotive industry to provide an easy to use system to understand and control their supply base.

A methodology for the identification of supply chain risk was proposed by Neiger *et al.* (2009). It was developed from the incorporation of pre-existing goal modelling and process modelling techniques. It was extended to include a more multi-disciplinary definition of risk that was flexible enough to include the variations caused by the supply chain structure being modelled. The model was able to keep the strengths of the amalgamated approaches to risk analysis, while identifying and representing risks holistically, and also depicting the connections between issues of risk and the goals and activities of business.

Risk analysis is an essential tool for maintaining the functionality of supply chains when disrupted by hazards such as flooding. It provides an ability to identify hazards, highlight vulnerabilities, assess how significant the level of risk is, as well as provide an opportunity to adapt the system to reduce these risks. Risk analysis also provides the opportunity to understand interdependencies within complex supply chains. This is important as underestimating the interdependencies in such networks can cause stakeholders to underestimate the overall risk (Jonkman and Dawson, 2012).

3.7 Spatial data disaggregation

To combat a criticism of *I-O* modelling, a technique for the disaggregation of data has been proposed. This was required because the data was at an economy wide level, therefore without a spatial element. Data disaggregation allowed this data to be output at smaller geographic levels. Hallegatte (2008) disaggregates US wide economic *I-O* data to state level by disaggregating the Gross State Product per industry for Louisiana, post Hurricane Katrina. This, therefore, produced a proportional value for: output, value added, employee compensation, and intermediate consumption. A similar approach to data disaggregation was used for a risk analysis of Copenhagen (Hallegatte, 2012).These investigations by Hallegatte (2008, 2012) were the inspiration for the technique used during this research.

A data disaggregation approach was also utilised in order to compile employment forecasts for South East Queensland, Australia. It was carried out by Li *et al.* (2009) as part of a geographically weighted regression analysis. A disaggregated approach was essential, as aggregated data can hide the distribution of economic activities, due to the internal entities of the spatial units being represented as a homologous black box). The approach was also applied to an urban model, which tested planning scenarios in Queensland (Stimson *et al.*, 2012). This technique combined census data and journey to work data, in order to allow the original statistics to be output at a smaller geographic level.

3.8 Summary

In Chapter 2 the background literature was reviewed in order to provide the platform required to carry out the methodological literature review in Chapter 3. This chapter set out to identify appropriate techniques for the development of a resource model that can measure supply chain resilience. From this review, certain aspects from three different mythological approaches were incorporated to form the proposed model.

The first of these was the utilisation of *I-O* tables to inform the supply chain links between different sectors; this was chosen as it contained all of the supply and demand information in one place, allowing for it to be adapted for spatial analysis, while depicting a real world network. This was applied in conjunction with a newly developed technique for the disaggregation of economy wide data to ward level as part of the proof of concept case study.

Secondly, elements from network analysis were added to the model to assess the infrastructure networks which allow stocks and flows to move around supply chain networks. Metrics were chosen because of their simplicity to model within Python, as well as their relevance to the modelling of supply chains.

The final addition to the model was a risk assessment based upon the vulnerability to flood events of different magnitudes. The steps followed to do this are set out in the following chapter. This additional metric provides a tool to compare relative risks between different case studies, as well as highlight a real world application of the developed model.

In Chapter 4 the understanding of the methods is further developed through the presentation of an example case study.

4 Methods

The method developed to model disruption of resource flows is described within this chapter. The approach combines thinking about infrastructure interdependencies with elements of spatial network analysis and is underpinned by input-output (I-O) relationships. The I-O interactions implicitly reveal any interdependencies between different human activities and provide a tool for trialling future approaches as well as allowing for system optimisation (Liang and Zhang, 2012).

As discussed in Chapter 3, the use of I-O allows for the pinpointing of issues caused by supply chain interdependencies, and their disruption. I-O analysis permits a more holistic approach that takes into account all levels of interactions within the system that has been modelled (Cordier *et al.*, 2011), including levels of consumption which occur within an interdependent network (Resurreccion and Santos, 2012).

The I-O relationship describes the input requirements for each site of production from each of the other industrial sectors in the modelled system to yield one unit of its output (Leontief, 1970), thus highlighting the interdependencies that exist between these elements of the same system (Lifset, 2009).The movement of resources around a system is mediated by the infrastructure networks, such as transport, energy, water and waste. As these system elements interact with their environment and one another, they can be analysed using network theory (Amaral and Ottino, 2004).

This chapter describes the key components, algorithms and assumptions of the developed resource model. A synthetic case study is used to illustrate and explain how the model works and has been implemented. A glossary of all of the notation used in this chapter, and throughout the thesis, can be found in Appendix 1.

4.1 Overview of the model

The resource networks modelled are viewed here as a system comprising of numerous stocks and flows. As outlined within Chapter 3 of this thesis, the current understanding of such network interactions treats networks and their infrastructure as a ‘consumer unit’, but does not account for the other influences on resource consumption. The major issue was to understand how infrastructures as well as their interdependencies mediate the flow of resources around, into and out of networks, with infrastructure providing choices and options for resilient (or not) behaviour, and to understand the effects of disruption to resource flows and how this may impact on the rest of a system. This provides the basis for investigating ways to increase resilience and develop adaption options.

The model is made up of three key components that are shown in Figure 4.1:

1. The model domain is divided into a number of zones, *Z*, of analysis. Each zone places resource demands, *De*, on other zones, provides a resource supply, *S*, and holds an onsite stock, *O*.
2. A network model describes the infrastructure links, *IL*, between each zone.
3. A hazard model that can perturb the demand, supply or onsite stocks in zones and/or their flows along the infrastructure links according to the magnitude, *L*, of the hazard event.

Zone 5 is highlighted and within this zone there are two sites of production. For the highlighted site to output its necessary level of supply, inputs are required from various sectors. If the first supplier site does not have any of its products available, the demanding site requests supply form an alternative supplier. If it is unable to source the supply the level of production is affected. This then in turn disrupts upstream industries that require its product, which may then affect the industries they supply and so on. One site of production may produce enough supply to fulfil multiple demands, both inside and outside of the zone it is in.

The model assumes that the network being modelled is a closed system and therefore does not model the imports and exports from the system, focusing on the local interactions as depicted within the local economy section of I-O tables. The relationship is made more complex as the links between the different sites are made by various infrastructures, which is the second layer of the model. In the infrastructures modelled were the transport and electricity network. To receive product from a site there must be a transport link which connects the demanding and supplying sites. If a link was removed due to disruption, certain zones may become disconnected, meaning that sites of production may not be able to receive supply. The current model assumes that resources move along only a single infrastructure network, building on work by Fu *et al.* (2013) and Dunn *et al.* (2013), although in some scenarios the network modelled is transport and in others it is energy networks.

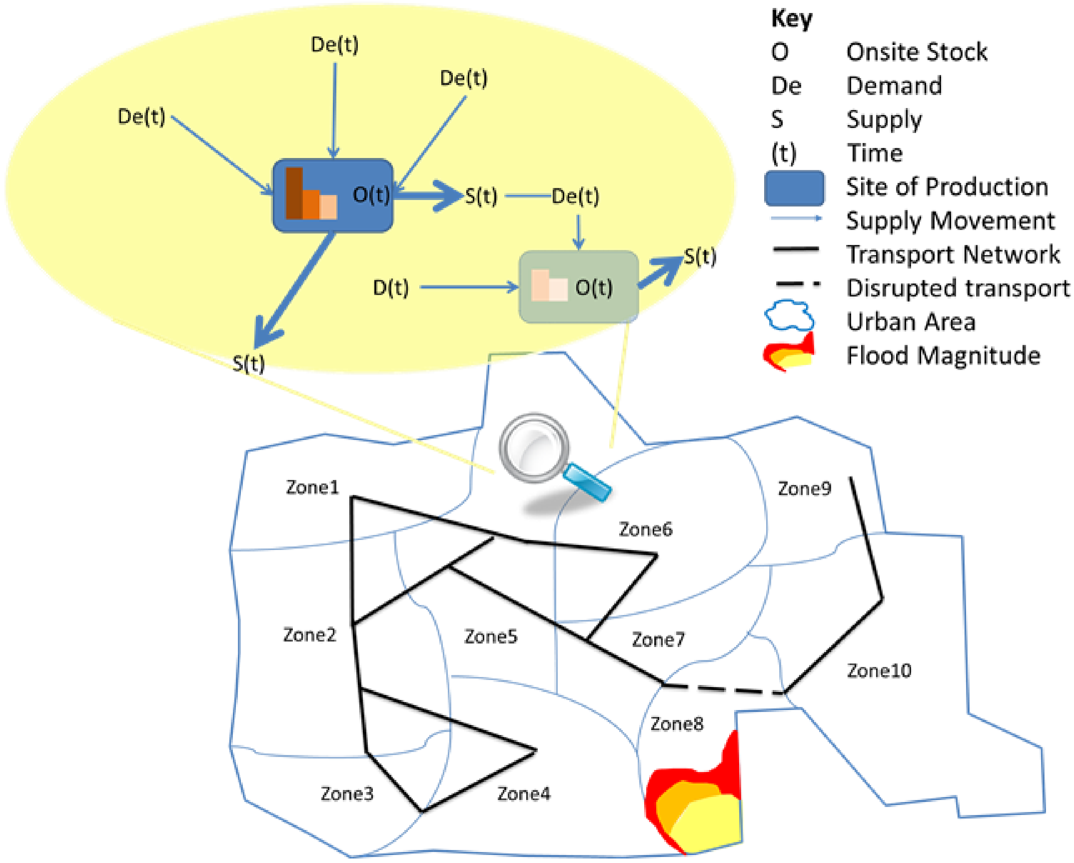

Figure 4.1: Schematic of the key components of the resource model

The scenario parameters and to some extent the flood magnitude was user defined and allowed for the initialisation of the different scenarios utilised within this research. The model overviewed in this section allowed for the impacts of a spatial hazard on the movement of resources to be investigated in an efficient manner. On top of this it enabled the exploration of scenarios and interventions to aid the understanding of network dynamics. The model allowed for the development and design of effective and adaptive supply chain networks to lower the effects of disruption and therefore increase the resilience of these networks.

Figure 4.2 summarises how the model runs through one iteration, depicting the actions which occur either every day, only on a day in which delivery is received, or when the recovery period has begun depending on which scenario was modelled.

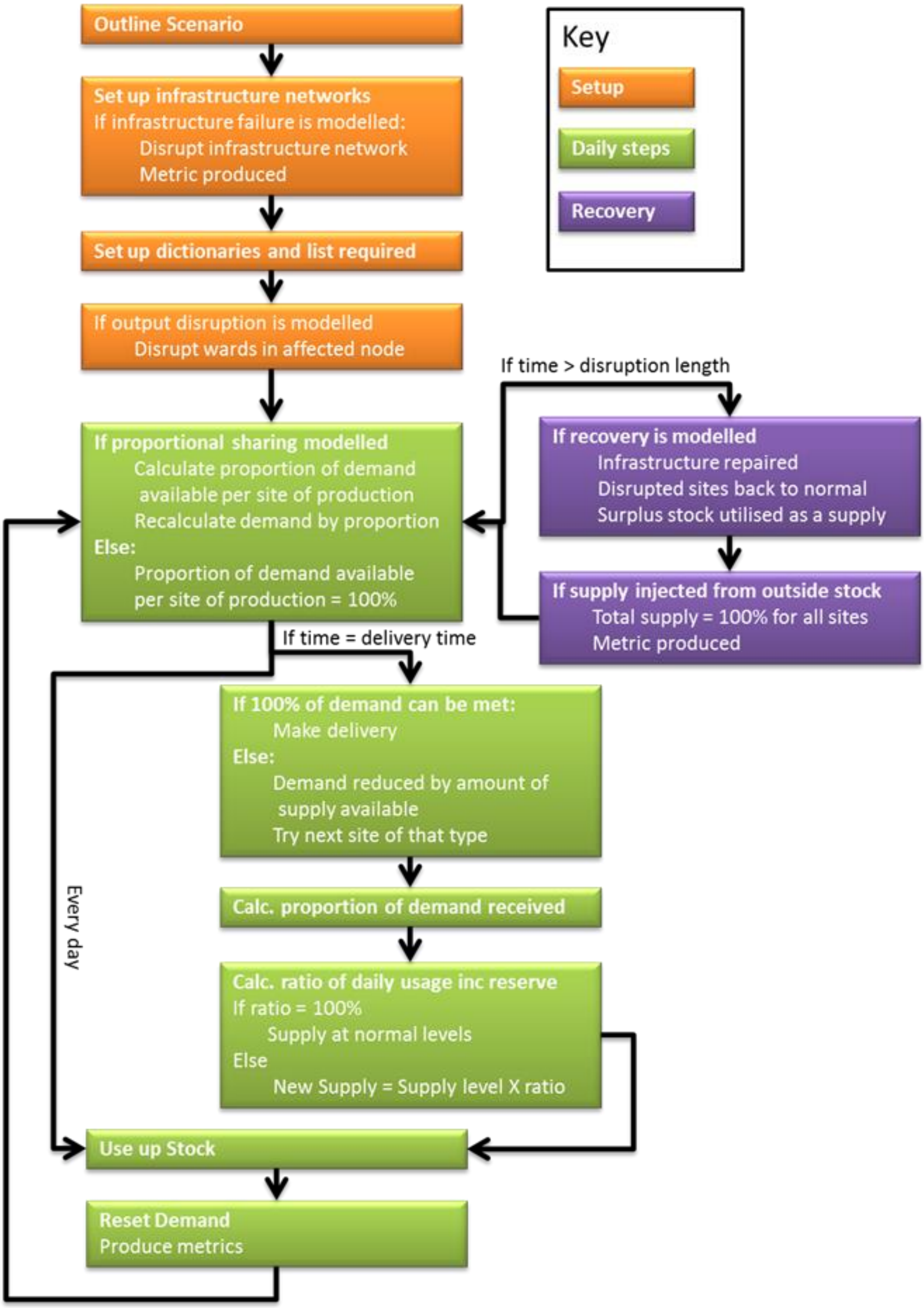

Figure 4.2: A single iteration (day) within the model

Throughout the remainder of this chapter, the different aspects depicted in Figure 4.2 will be elaborated upon, providing a chronological run through of the developed model.

4.2 Setup of the model

Within this section, the data required for the model, as well as how it is formatted, is outlined. On top of this, the set up phase of the model, and the different parameters are also described.

4.2.1 Input-output tables

I-O analysis requires three basic components(Zamora, 2010):

1) A transactions table, showing the monetary flow of goods and services;
2) A direct requirements table, showing inputs purchased from all other sector to produce its output;
3) The total requirements table (direct and indirect requirements), from which multipliers are derived.

These industries make up the columns and rows of the initial transaction table (Table 4.1)

Table 4.1: Basic layout of an I-O table for the example case study

		Intermediate sector, by industry					
		a	B	C	D	e	f
Intermediate sector, by industry	a						
	b						
	c						
	d						
	e						
	f						

Accounting data is added to the table (Table 4.2), going down the columns, highlighting how much one industry spends when purchasing products from another to produce its own products over a stated period of time.

Table 4.2: Example accounting data

		Intermediate sector, by industry					
		a	b	C	d	e	f
Intermediate sector, by industry	a	50	500	500	750	500	0
	b	100	0	0	50	0	0
	c	100	0	100	250	100	0
	d	1000	0	500	300	100	100
	e	500	250	500	750	50	250
	f	1000	250	250	500	150	50

Other aspects are also included within the transaction table. These are the final demands (the purchases by final consumers) and the final payments for inputs not within the intermediate sectors. As the matrix is an integration of revenue and expenditure accounts there should be a balance between the input totals and output totals, as the total outlay is equal to the total output.

The full input-output table is shown on the following page and contains the final demand sectors and primary supply sectors, and provides a statement of accounts for the sectors involved in the example case study (Table 4.3).

Table 4.3: Example of a full I-O table

									Final Demand Sectors					
									Households	Government	Exports	Capital	Final Demand Total (d)	**Total Gross Output**
		Intermediate sector, by industry												
		A	b	c	D	e	f							
Intermediate sector, by industry	a	50	500	500	750	500	0		1000	550	250	150	1950	**4250**
	b	100	0	0	50	0	0		750	500	350	600	2200	**2350**
	c	100	0	100	250	100	0		500	750	1000	100	2350	**2900**
	d	1000	0	500	300	100	100		750	100	100	1000	1950	**3950**
	e	500	250	500	750	50	250		50	100	50	50	250	**2550**
	f	1000	250	250	500	150	50		100	50	50	50	250	**2450**
Intermediate demand (T)									*Final demand (Y)*					
Primary Supply Sectors														
Households		500	300	400	400	500	500							
Government		200	100	100	200	250	700							
Imports		700	650	350	250	100	50							
Capital		100	300	200	500	800	800							
Total		**4250**	**2350**	**2900**	**3950**	**2550**	**2450**							
Value added														

Following the completion of the input-output tables, the next step was to create the consumption matrix, *C,* based on the intermediate demands of the local economy. The output of each sector is listed within a production vector, with a final demand vector listing the values of the goods and services demanded from the productive sectors by the open sector: these are the intermediate demands as the sectors attempt to produce enough goods to meet the final demand vector.

To calculate *C,* each input per column (sector) is divided by the Total Gross Output for that sector. So, for example, the below vector shows the demands required for *sector a*. This sector's Total Gross Output is 4250:

$$\begin{vmatrix} 50 \\ 100 \\ 100 \\ 1000 \\ 500 \\ 1000 \end{vmatrix}$$

Therefore the following calculations take place (4dp):

50 / 4250 = 0.0118

100 / 4250 = 0.0235

100 / 4250 = 0.0235

1000 / 4250 = 0.2353

500 / 4250 = 0.1176

1000 / 4250 = 0.2353

The same process is then repeated for all columns, using the specific Total Gross Output for each sector, giving the following results:

$$C = \begin{pmatrix} 0.0118 & 0.2128 & 0.1724 & 0.1899 & 0.1961 & 0 \\ 0.0235 & 0 & 0 & 0.0127 & 0 & 0 \\ 0.0235 & 0 & 0.0345 & 0.0632 & 0.0392 & 0 \\ 0.2353 & 0 & 0.1724 & 0.0759 & 0.0392 & 0.0408 \\ 0.1176 & 0.1064 & 0.1724 & 0.1899 & 0.0196 & 0.1020 \\ 0.2353 & 0.1064 & 0.0862 & 0.1266 & 0.0588 & 0.0204 \end{pmatrix}$$

Data can then be ascribed to a system, creating a network resource flow model showing the inter-infrastructure flows, as well as providing the raw data for the I-O model used to describe the resource interdependencies (Liang and Zhang, 2011). The above example has 13 sites of production from the six sectors. These sites of productions are shared between the 10 different zones, and was achieved because of the spatial disaggregation outlined in Section 4.2.2. This allowed for multiple sites of production per sector to exist, as well as allowing more than one industrial sector to have sites of production in each zone.

4.2.2 Spatial disaggregation of data

The spatially disaggregating of data provides a spatial element to the analysis, allowing for spatial hazards, such as flooding, to be modelled. To do this, the total demands, *de,* and outputs, *Op,* for each industrial sector are proportionally divided between each zone based on the percentage of employees, *e*, for the site of production in that zone, *z; E* is the total number of employees in an industrial sector, *j* (equation 4.1).

$$Op_z^j = Op_j \, x \, \frac{e_z}{E} \qquad (4.1)$$

For example, *Sector A* has two sites of production; one in Zone 1 and another in Zone 2. They have equal numbers of employees and produce 50% each of the total output for this sector. The entirety of *Sector A* requires the following inputs to produce one unit of its product:

$$\begin{vmatrix} 0.0118 \\ 0.0235 \\ 0.0235 \\ 0.2353 \\ 0.1176 \\ 0.2353 \end{vmatrix}$$

These consumption inputs are then multiplied by the proportion of production found in Zone 1 and Zone 2 (0.5) to give the required inputs as:

$$\begin{vmatrix} 0.0059 \\ 0.0118 \\ 0.0118 \\ 0.1176 \\ 0.0588 \\ 0.1176 \end{vmatrix}$$

The demand placed on each other sector by *Sector A* remains the same but is now split between the two sites. This was then repeated for all other sites of production in each of the zones (Table 4.4). As with industrial supply and demand this makes the assumption, in the light of no higher resolution information, of uniform demand and productivity per capita.

Table 4.4: Adapted consumption matrix, including sector and zone e.g. *a, Zone 1*

a Zone1	a Zone2	b Zone4	b Zone5	c Zone3	c Zone5	c Zone6	d Zone5	d Zone7	e Zone8	f Zone8	f Zone9	f Zone10
0.0059	0.0059	0.1419	0.0709	0.0862	0.0431	0.0431	0.0949	0.0949	0.1961	0	0	0
0.0118	0.0118	0	0	0	0	0	0.0063	0.0063	0	0	0	0
0.0118	0.0118	0	0	0.0172	0.0086	0.0086	0.0316	0.0316	0.0392	0	0	0
0.1176	0.1176	0	0	0.0862	0.0431	0.0431	0.0380	0.0380	0.0392	0.0102	0.0102	0.0204
0.0588	0.0588	0.0710	0.0354	0.0862	0.0431	0.0431	0.0949	0.0949	0.0196	0.0255	0.0255	0.051
0.1176	0.1176	0.0710	0.0354	0.0216	0.0108	0.0108	0.0633	0.0633	0.0588	0.0051	0.0051	0.0102

The final step of this process was to link the data with geographical data based on zone codes shown in Figure 4.1. The sources of and sizes of datasets are different for each case study, although the fundamental preparation remains the same for all.

This allows for the data to be analysed within the model, which is detailed further in the following sections of this chapter.

4.2.3 Infrastructure networks

Before the model parameters are set, the infrastructure network is rebuilt within the model. The infrastructure is a separate layer which links the zones and, therefore, sites of production, to one another. In the example case study the infrastructure being modelled is the transport network (Figure 4.1). The infrastructural links are highly important to the model as they dictate where a demanding site of production can receive its required supply from.

The infrastructure network was rebuilt within the NetworkX module of Python. When NetworkX reads infrastructure networks, such as a road network, from an ESRI shapefile, they tend to treat all junctions as a node and all links between these junctions as edges. As this resource model is simulating interactions between zones, this level of detail is not required and so a simplified network was constructed. This was done, in the example of a road network, by counting all of the roads that linked one zone to another and adding this number of edges to the simplified network.

A multigraph is required, as multiple edges between the same nodes may be required, as well as self-loops. The graph is undirected, to enable resources to flow both ways (although flow is sometimes zero). Other types of infrastructure, such as the electricity network, only allow the flow to follow one direction and are therefore a multidigraph.

4.2.4 Model parameters

To set up the different simulations within the model, certain options are available at the start of the model which can be changed to adapt to the scenario being modelled. These are (with the type of input required in brackets):

- Length of disruption, $t_{l,}$ (number of days).

- Level of disruption, L (value from 0 to 1, for example 0.6 would mean 60% of original output is still produced).
- Infrastructure failure, *IF,* (Yes or No).
- The zone which was disrupted, z, (name of zone).
- Rationing of supply *Ps*, (Yes or No).
- Amount of reserve stock in days, $t_{r,}$ (0 if not modelled).
- Delivery frequency, t_n. (number of days)
- Recovery modelled, *Rv* (Yes or No).
- Injection of resources, *I,* (Yes or No).

4.3 A standard day in the model (no disruption)

For a standard day in the model, with no disruption, the following parameters are set:

- $t_{l,} = 0$
- $L = 1$
- *IF* = No
- z = na
- *Ps* = No
- $t_{r,} = 0$
- $t_n = 1$
- *Rv* = No
- *I* = No

This means that there are no disrupted sites of production, the model is delivering stock every day, and each site of production has no reserve.

4.3.1 Pre-daily iterations

At this point of the model, before the daily iterations begin, each site of production, *i,* has some supply, *S*, which is a factor of time, *t*. This supply is the sum of all the demands from the K number of sites that require this input; with *k* equalling site of production placing the demand (taken from the disaggregated I-O table, with daily usage, *U*, being equal to demand) *De* on *i*.

$$S_i(t) = \sum_{k=1}^{K} De_k \qquad (4.2)$$

In addition, each site of production has a value termed original supply, *Os*:

$$Os_i(t) = S_i(t) \qquad (4.3)$$

The reserve level, *Re*, at site of production *i* for demands *j* at the start of a day is calculated as:

$$Re_{ij} = De_j\ (t_r) \qquad (4.4)$$

The model also has an assumption that a delivery has taken place and, therefore, the non-disrupted sites of production, *i*, have enough onsite stock, *O*, of demands, *j*, to keep production at 100% until the next delivery date. For example, if deliveries are made every day, this value will be zero plus the amount of reserve, *Re,* for *j.* Whereas, if the deliveries are made every 3 days, this value will be 2 times (t_{d-1}) the original demand, *De,* meaning that on the day of delivery the onsite stock will equal zero plus the amount of reserve, *Re,* for *j*

$$O_{ij} = De_j(t_{d-1}) + Re_j \qquad (4.5)$$

Finally, supply, *S*, is recalculated for any disrupted sites of production, *i*, in the disrupted zone, *z*:

$$S_{iz}(t) = Os_{iz}L \qquad (4.6)$$

4.3.2 Daily iteration

Once this information is in the model, it then checks to determine whether rationing, *Ps*, is being modeled. On a standard day, rationing is not being modelled and so Ps_j

= *1,* and the demands, *De*, at each site of production *k*, for each demand type *j* are calculated as:

$$De_{kj} = Ps_j De_{kj} \qquad (4.7)$$

The next step in the model is the delivery, with the supply, *S*, at site of production, *i*, of product *j,* being reduced by the amount demanded, *De*, by site of production *k*:

$$S_{ij} = S_{ij} - De_{kj} \qquad (4.8)$$

j is then added to the onsite stock, *O*, at site of production *k*:

$$O_{kj} = O_{kj} + De_{kj} \qquad (4.9)$$

This demand is then met, and $De_{kj} = 0.00$. The model then calculates the minimum proportion, $\hat{p}$ of demands, *j*, received onsite, *O,* at site of production *k* based on the usage, *U*, per day:

$$\hat{p}_k = min(\frac{O_{kj}}{U_{kj}}) \qquad (4.10)$$

The model assumes that all different inputs to a site are a limiting factor on production. For example, if one site requires four inputs; receives 100% of three, but 0% of the fourth then zero production would take place at that site. This is similar to Liebig's law which states that the maximum possible output is not dictated by the total amount of available resources, but by availability of the scarcest resource, which is, therefore, a limiting factor (Danger, *et al.,* 2008).

This is then used to calculate the supply, *S*, available for the next delivery, based on the original supply, *Os*, value for *k*:

After the delivery, the onsite stock, *O*, of *j* is then used up in such a way as to make sure *j* does not run out before the time of the next delivery t_n. Therefore, usage, *U* is recalculated at site of production *k* as:

$$U_{kj} = \frac{O_{kj}}{t_n} \quad (4.11)$$

And onsite stock, *O becomes:*

$$O_{kj} = O_{kj} - U_{kj} \quad (4.12)$$

Finally, *De* and *U* are reset to their original value before the iteration begins again. Throughout this process the model does loops to check if a path exists between a site providing a service and/or commodity, and another site which demands this input. If there is a path connecting the two, then the demand can be met, assuming sufficient supply is available. If there is no path, or there is insufficient supply, the model loops through and checks the next site of production which may potentially satisfy the demand.

4.4 Disruption of output

The first type of disruption simulated within the model is disruption to output in all sites of production, *S*, in a particular zone, *z*. This means that the initial values for these sites of production are changed during the initial set up phase.

The formula for supply and demand, *De*, at site *i* becomes, with *L* being the level of disruption:

$$S_{zi} = Os_{zi} \times L \quad (4.13)$$

$$De = U_{zi} \times L \quad (4.14)$$

The model also assumes onsite stock for these sites is, $O_{zi} = 0.00$.

4.4.1 Just-in-time (JIT)

Just-in-time (JIT) production means that inputs were required every day, treating the deliveries as a constant flow of goods or services at each time step (day). Therefore, in normal circumstances, the sum of supply, *S*, at each site, *i*, is equal to sum of all demands, *De*, made on that site.

$$\sum_{i=1}^{n} S_i = \sum_{i=1}^{n} De_i \qquad (4.15)$$

Once the supply, demand, and onsite stock are set, the model then runs through the same process as in Section 4.3.2, until it gets to the delivery. At this point there is an 'if' statement which checks if 100% of demand is met. If it can be, it follows the process set out above. If It cannot be, the supply, S = 0.00 and the demand, and onsite stock are:

$$De_{kj} = De_{kj} - S_{ik} \qquad (4.16)$$

$$O_{kj} = O_{kj} + S_{ik} \qquad (4.17)$$

The model then continues to follow the process set out in 4.3.2, and as there is a shortfall in supply, this affects the rest of the calculations and, therefore, the output of individual sites of production which require a supply from one of the disrupted sites. This then in turn, in following iterations, means that more sites become disrupted, and they cannot supply the sites which demand their product and so on.

4.4.2 Modified Just-in-Time

In the model's basic state, it assumes that all sites work on a *JIT* supply basis. This strategy moves away from this by adding a level of reserve, *Re*, which was calculated by demand, *De*, for *i*, multiplied by the number of days the reserve would last for, t_r. The reserve can be accessed when normal supplies are interrupted. The model assumes that there is space on site for the storage of reserve. Reserve levels in terms of a service is assumed to mean that this input can be forgone for a few days, before it affects the output at the site of production.

$$\sum_{i=1}^{n} Re_i = De_i \; x \; t_r \qquad (4.18)$$

A second way of modifying *JIT* was through the rationing of supply. When this is simulated, instead of using *Ps = 1.00*, *Ps* is calculated for the levels of supply, *S*, for each type of demand, j. Ps is the sum of all of this supply from all sites of production J, over the non-disrupted values, Os:

$$Ps_j = \frac{\sum_{j=1}^{J} s_j}{\sum_{j=1}^{J} Os_j} \qquad (4.19)$$

Changing this value means that demand is reduced, based on the proportion of available supply from one sector. For example, if sector A usually has two sites producing 50 units of a product each, and one of these sites were to be disrupted by 50% and could only produce 25 units, then the total output for the sector would be reduced to 75%. The rationing value then affects the demand values derived from equation 4.7, meaning that each demanding site of production would only be able to receive 75% of their usual demands.

The rationing is important as it attempts to stop certain supplies running out. This is done because one assumption programmed into the model is that if a supply runs out, and reserve has been depleted, then all sites requiring this supply halt production.

4.4.3 Bulk deliveries

The second resource management strategy simulated within the model introduces batch deliveries. For example, a site may receive enough of its demands, *De*, of product, *j,* to last three days every third day. This assumes that all deliveries by all suppliers happen at the same time and with the same frequency between deliveries, t_d, for all of the sites of production. S_j is equal to the total amount of j available in the economy.

$$\sum_{j=1}^{n} S_j = De_j x\ t_d \qquad (4.20)$$

This has a major effect on the daily iteration outlined in Section 4.3.2. Prior to the delivery phase there is a check carried out to see if time, $t = t_d$. If these two times are equal, the normal path is followed. If they are not equal, the model jumps straight to the utilising of available stock.

4.4.4 Recovery

To develop the model from a measure of robustness, a simple recovery element was added. At the start of each daily iteration, a check is carried out to see if time, $t = t_l$, with t_l being the modelled length of disruption. If this isn't the case, then the daily iteration carries on. If they are equal, then the recovery loop is followed. The first aspect of this recovery loop allows the sites of production, which were originally disrupted, to have the potential to output at 100% again (if stock is available). Secondly, any surplus reserve, *Re*, of *j* which may be available in the system is utilised to boost available supply, *S*, in that sector.

$$S_j = S_j + Re_j \tag{4.21}$$

A further development of the recovery model was the injection of supply into the system, to cover any shortfall. This development assumes that firstly, the amount of resource required is distributed evenly between the sites which produce that supply, and secondly, that there is enough resource to cover whatever shortfall there may be between original demand levels and the amount of supply currently available:

$$S_i = Os_i \tag{4.22}$$

When modelling recovery, it was assumed that all disruption to either the sites of production within a zone, or to an infrastructure network, ended at the same time, meaning that all sites attempted to return to pre-disruption levels of production simultaneously.

4.5 Disruption of infrastructure

The second type of disruption simulated within the model is the disruption of an infrastructure network. This was carried out in the initial set up phase of the model, by removing various edges which linked one zone to another. This in turn could potentially lead to failure cascading more quickly through the system.

4.5.1 Recovery

As mentioned above, disruption to infrastructure affects the way the recovery model works. Once the model reaches the recovery phase, all of the removed edges are re-added. This then allows the whole infrastructure network to act as one, meaning that resources can move freely around the system once again.

A development of the recovery model was to withhold the use of reserve until the disruption has ended, this is because once a a sub-network is formed the model assumes the sites of production in this network will stop producing, and therefore their reserve will remain unused. This final strategy was used during infrastructural failure scenarios to investigate how the timing of using reserve stock affected recovery after disruption. Within this scenario, as reserve was available, onsite stock was not utilised as an extra source of supply.

4.6 Metrics

This study is not seeking to evaluate indirect economic impacts (Hallegatte, 2008), so simple metrics were used to aid understanding of the interdependencies and the processes of disruption, as well as compare the effectiveness of alternative resource management strategies:

1. The number of days after the initial disruptive event before a site of production is disrupted
2. The proportion of ward of production output, $\hat{p}$ *(op),* as a percentage of baseline (normal) levels (*b*) per individual site of production
3. The mean production output as a proportion of baseline, *Op,* as a percentage for the whole study period for the whole of the Shetland Islands. Calculated as:

$$Op = \frac{\sum \hat{p}(op)}{\sum \hat{p}(op)}\ x\ 100 \qquad (4.23)$$

The latter two metrics are often used as a proxy to measure the resilience of networked systems (Salles and Marino, 2012).

The following metric of resilience, which was used within this study, was more complex and focused on the structure of the network:

4. The centrality was measured to illustrate the robustness of the network (Yazdani *et al.*, 2011), as well as where the critical nodes to the network lie and how this changes as the failures pass through the system.

4.6.1 Risk Analysis

The risk analysis approach was developed to provide a metric that can easily be compared between different parts of a case study, as well as allowing for comparison to take place between different networks.

Flood risk data was plotted for the selected zone. This data highlighted areas at risk of flooding and the probabilities of different storm surge levels. The flood depth data was then mapped. The simplified map shows the areas affected by different depths of flooding caused by the different magnitudes of events for the separate probability levels.

A vulnerability, *V*, analysis was carried out by quantifying the impact of floods of differing magnitudes in the area of interest. The following steps were done to calculate V:

1. The first step in the vulnerability analysis was to set the parameters of the model. For this example, no reserve stock was available and deliveries were made every day. Finally, it was assumed that the different sites of production worked together and shared resources proportionally by initial demand.

2. For each mapped probability level, the percentage of industrial area inundated was calculated.
3. The model was then run until the disruption stabilised (Figure 4.3). The number of days this took and the levels of output were recorded.
4. Once the reduction in resource stocks, production capacity, and network transportation capacity was quantified, the model was re-run to explore how far the disruption proliferates and was repeated for a full range of flood levels to produce a vulnerability curve.
5. The vulnerability curve was plotted showing the level of disruption caused by the modelled magnitude.
6. The steps above are summarised using the equation below, which was used to calculate the vulnerability, defined as the proportion of resource flows remaining at equilibrium. This is a worst case measure, as recovery from the disruption may have started by this point:

$$V = \frac{\sum_{i=1}^{N} De_i(t=t_e)+S_i(t=t_e)}{\sum_{i=1}^{N} S_i(t=t_o)+ S_i(t=t_o)} \qquad (4.24)$$

The equilibrium time is the number of days after the initial disruption that the level of disruption stabilises – the lowest point on Figure 4.3.

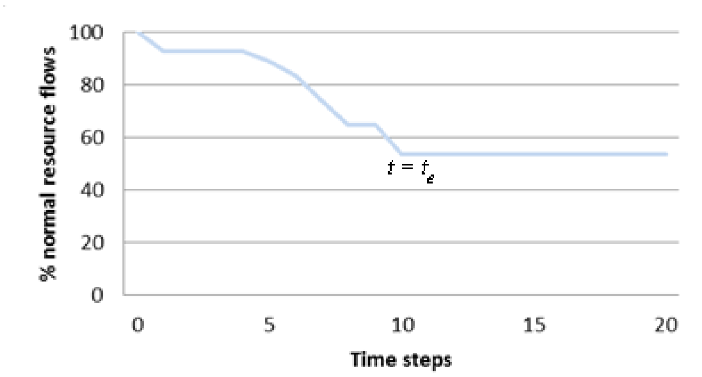

Figure 4.3: An indicative model output, showing the percentage of total resource flows (compared to normal operating conditions) across the system after a disruptive event.

The overall risk of the modelled zone is the area underneath the line on the vulnerability graph. This was calculated by finding the sum of the disruption level for each of the modelled flooding events, multiplied by the likelihood of that flood event taking place. Dawson and Hall (2006) stated, *R*, is a function of probability, *p*, and impact, *D*. Here the impact is measured in terms of disruption to usual output of the modelled economy. Water depth, *w*, is assumed to be the dominant driver of disruption:

$$R = \int \rho(w) D(w) \qquad (4.25)$$

4.7 Sensitivity testing

One approach to validation was to recreate real world events, and a second was through sensitivity analysis. Sensitivity analysis was utilised in order to gain an understanding of how the model was performing, highlight any issues and validate the model. Sensitivity analysis was used to determine how the model reacted to the changing of certain key parameters (Starkey, 1992), such as the amount of reserve and time between deliveries that is required to make sure the model operates as expected.

4.7.1 Sensitivity testing during the development of the model

The following two figures are from the early stage of the model, and show the testing of different levels of reserve (Figure 4.4) and the different lengths of time between deliveries (Figure 4.5). The data used was an unmodified version of the Shetland Island Input Output tables, i.e. there is no spatial disaggregation of data for different wards. The upper group of results shows an industry that was not very connected (marine engineering - ME), and the second shows a highly important sector (distribution - D). The industries disrupted were done so at 100%, meaning that no input was received from either, in the respective model runs. This was done in order to facilitate the interpretation of the results, as it constrains the behaviour of the model, so that the only variables are the changes in reserve levels and the lengths of delivery time.

Figure 4.4 shows the effect that changing reserve levels has on the percentage of normal output within the modelled economy. The results of this are quite straight forward and can be summed up by stating that the more reserve available on site, the longer the lag between the disruption and the effects of that event are felt. The more reserve in the system, the more robustness is evident, as the levels of redundancy are increased.

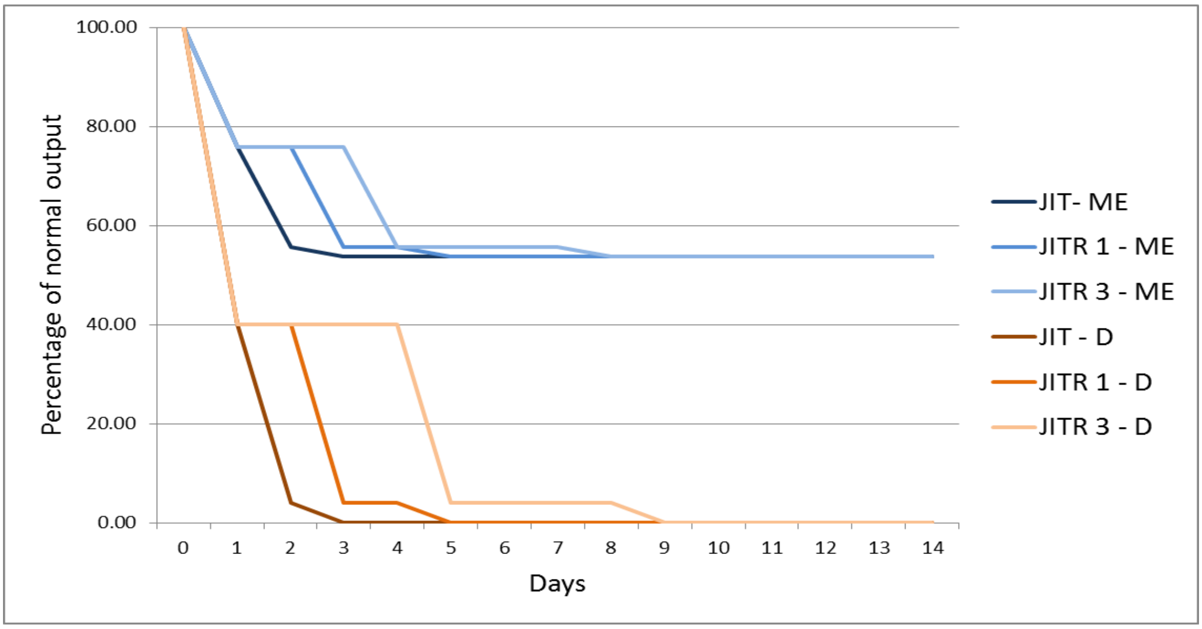

Figure 4.4: Reserve set at 0 days, 1 day, and 3 days

Figure 4.4 keeps reserve levels at either 0 or 3 days, and shows the effect that varying the length of time has on the percentage of normal output. Once again it should be stressed that the more stock delivered to a site at a time (i.e. within a single, bulk delivery), the more resilience is noted. However, it is worth mentioning here that the model assumes a delivery was received just before the disruption took place. If a delivery was due the day after the disruption, the levels of resilience and the lag between disruption and effect will be shorter, as the site of production will not have the available stock to cover any disruption to delivery.

The additional resilience created by increasing the sizes of deliveries provides potential ‘breathing room’ for local authorities, flood risk managers and other stakeholders. It allows them more time to identify alternative mechanisms for ensuring the continued supply of critical resources, as well as repairing facilities and infrastructure. However, although results are similarly sensitive to change, increasing reserve is the more robust option, as this is not dependant on when the last delivery took place.

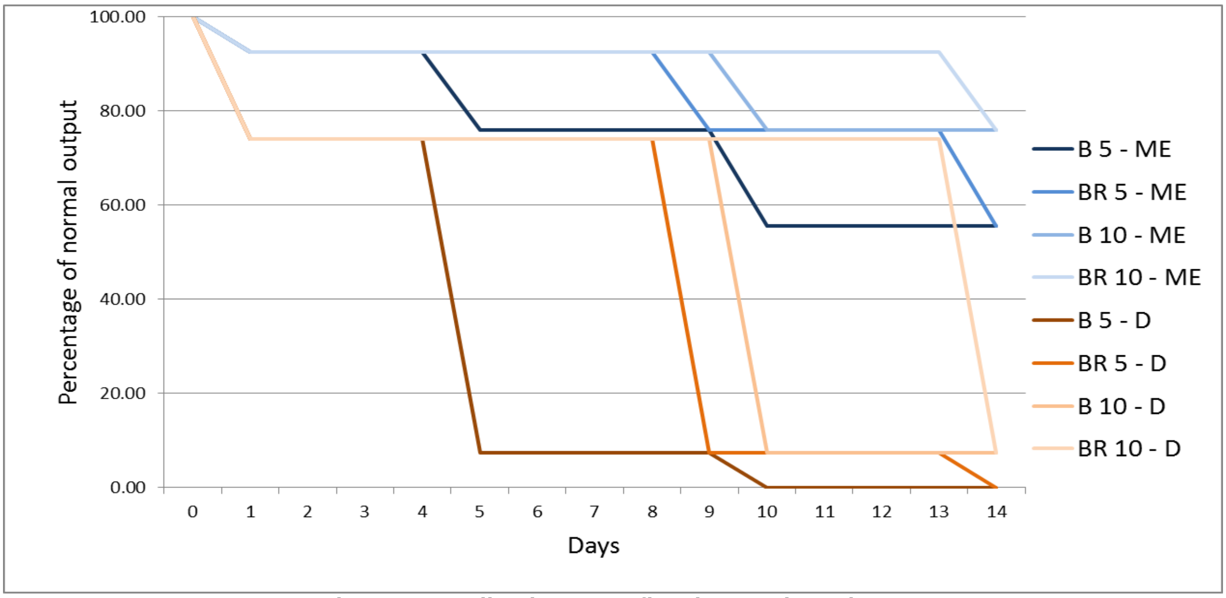

Figure 4.5: Deliveries every five days and ten days

The information gained from these simulations, and the simulations carried out in Chapter 5, provided an initial insight into what actions and changes would increase the level of resilience in such systems. It also provided the basis of the development of the different scenarios set up as part of the main case studies, and the design of the experiments carried out, as it became important to understand how changing the sensitivities at the same time, along with other parameters, would affect more complex, spatially disaggregated datasets.

The final insight that these tests provided was the difference in results caused by the relative importance of certain industries. In the basic economy which was modelled, the distribution sector had indirect connections to all of the other sectors, which therefore led to an entire failure of the system. This showed how “important” sectors could have wide ranging affects, but also provided the need to spatially disaggregate the data, as distribution is not a single input based in one location. It therefore became important to understand how having many inputs would alter these results.

4.8 Summary

This Chapter introduced a new resource flow model to analyse the disruption of resource movements during extreme events. The design of the model was influenced by the literature review in Chapter 3, and combines network analysis and I-O analysis to disaggregate regional resource supplies and demands, and attribute the associated movements of resources to infrastructure networks. The model can be used to assess and improve supply chain resilience to two types of disruption that result from extreme events: reduction of output, and removal of infrastructure which links different sites of demand and production. To test different resilience strategies, the model was designed to allow the analysis of a number of different resource and infrastructure management strategies. Those strategies that create a lag between disruption and effect provide a longer window for businesses, communities and emergency responders to implement some form of corrective action.

To facilitate the introduction of the model, a ‘proof of concep’ case study was used. The following chapters introduce more detailed results, and provide analysis in the demonstration of the model in the Shetland Islands and New York City.

5 Case study: Shetland Islands

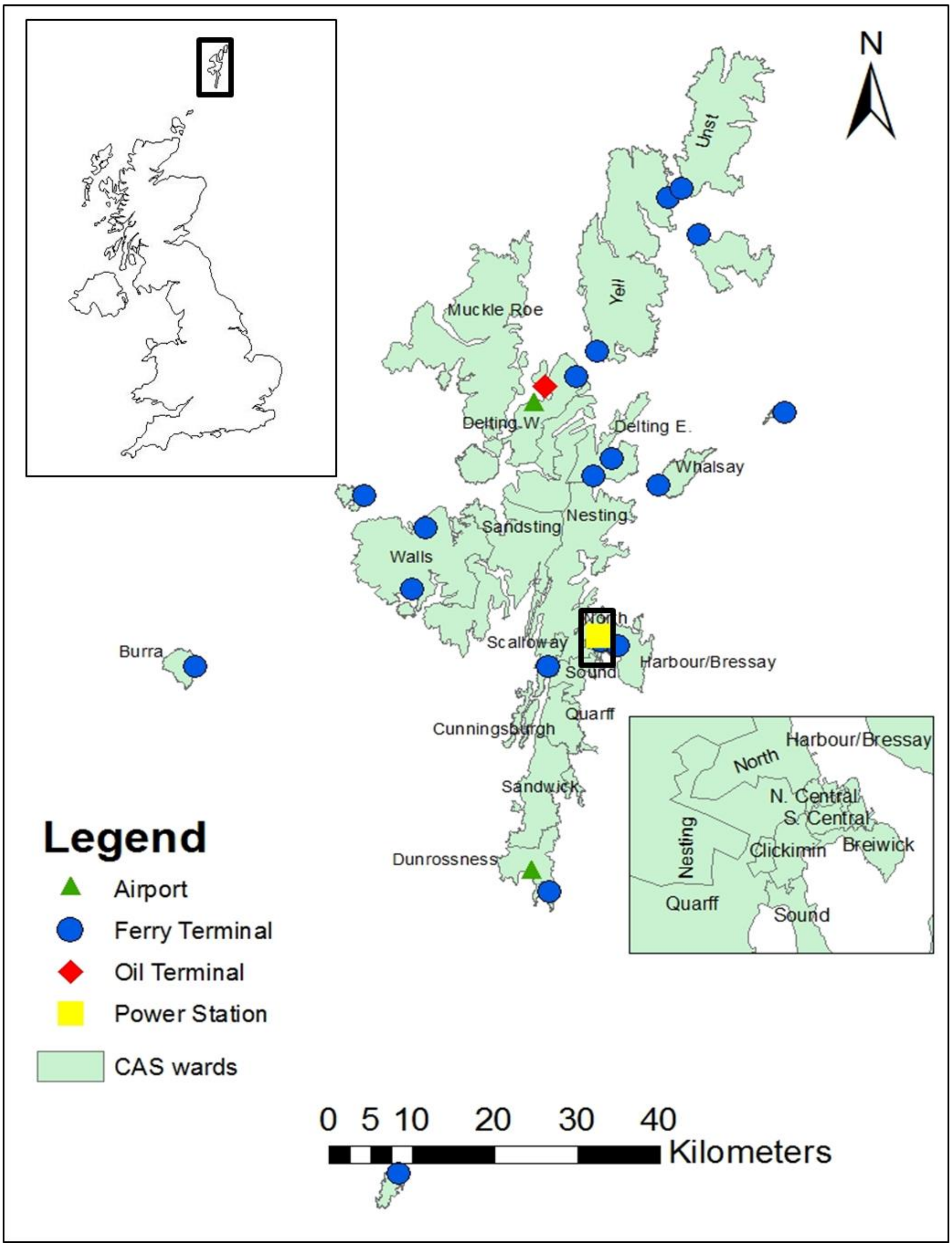

Figure 5.1: Map of the Shetland Islands showing CAS Wards used during the analysis; ferry terminals, regional airports (not intra Island), oil terminal and power station. Insert shows Lerwick.

5.1 Introduction to the case study

This case study of the Shetland Islands was developed to test and demonstrate the methods and concepts outlined in Chapter 4. It investigates infrastructural interdependencies within an interconnected system by exploring the networks that deliver the required stocks and flows around the Shetland Islands. The case study focuses on how disruption to these stocks and flows might affect the whole system as a result of the interdependencies between sites. The study then aims to identify ways of building resilience to disruptive events by taking advantage of the lag between the occurrence of a disruption and the time when a reduction in supply becomes apparent. This was carried out through the testing of different policy adaptations within the quantitative urban resource model to examine how changes to the system affect overall resilience

The Shetland Islands are the most northerly local authority in the UK, with a population of around 22,000 people in 2009 (SIC, 2009). The islands comprise 16 inhabited islands, in a chain of over 100, with a combined area of 1,450km^2 (SIC, 2013). The most southerly point of the Shetland mainland is approximately 160km from the closest point on mainland Scotland (SIC, 2012). The relative isolation of the islands limits the number of external resource interactions; the internal economic flows have been well documented over a number of years, and the co-location of many industries reduces the internal spatial complexity of flows on the island. This data is based solely on intra-region industrial interactions, therefore imports and exports to or from the islands are not taken into account.

Within the Shetlands there are 22 wards (Figure 5.1), which are used as the output level for this analysis. The characteristics of these 22 wards vary greatly across the islands. The largest urban area of the Shetlands is the capital, Lerwick. It has a population of 7000 people and another 4000 thousand live within 10 miles. This area covers nine of the 22 wards.

As part of the data preparation for this study, any site of production with output less than one per cent of the total for that industry was removed, to simplify the adapted input-output (*I-O*) table. This meant that Sound, which is mainly residential, has no modelled sites of production. In contrast, important wards modelled include: Delting East and Lunnasting which is home to Sullom Voe Oil Refinery; and Dunrossness where the main airport on the Island is located.

A number of simulations were tested, the first set of these analysed a disruption to each ward individually. Production in each ward was disrupted by fifteen per cent and the model was run in each of the following basic states (Section 5.3):

1. A non-managed approach in which supply was taken on a first-come, first-served basis.
2. Rationing, in which the available supply was shared out between each of the demanding sites as a percentage of that sites original supply
3. Recovery was added to the model with simulations once more done for both the non-managed and managed approaches
4. Recovery with injection of supply was added to the model, with simulations done again for both the non-managed and managed approaches

For each of these scenarios the following resource management strategies were also tested for four approaches outlined above, and explained in Section 4.6:

- JIT production (*JIT*): every day each site of production received a delivery of all resources required in order to produce one day's worth of goods. This was chosen as it is assumed to be the least robust strategy and, therefore, a worst case scenario.
- JIT production with some reserve (*JIT/Re*): enough reserve stock to cover one day's worth of production was added to each site, meaning that the site then had the resources for two days of production. This modification of *JIT* was

tested as a means to increase the lag between the disrupted event and the impact on production.

- Batch deliveries (*B*): every three days, each site received enough stock to last for three days of production. This allowed for a testing of different delivery strategies to take place.
- Batch deliveries with some reserve (*B/Re*): enough reserve stock to cover one day's worth of production was added to each site. This modification of batch deliveries to was tested as a means of increasing the lag between the disrupted event and the impact on production.

On top of these resource management strategies, recovery strategies were also tested. These utilised available stock in the system to help return production to pre-disruption totals, or injected new supply into the system to make sure this occurred.

In total, 12 scenarios (not including injection of supply) took place per disrupted ward, these were:

- Batch (B), batch with recovery (B/Rv), batch with reserve (B/Re), and batch with recovery and reserve (B/Re/Rv);
- Just-in-time (JIT), just-in-time with recovery (JIT/Rv), just-in-time with reserve (JIT/Re), and just-in-time with recovery and reserve (JIT/Re/Rv); and
- Rationing of batch with reserve (PS/B/Re), rationing of batch with recovery and reserve (PS/B/Re/Rv), rationing of JIT with reserve (PS/JIT/Re), and rationing of JIT with recovery and reserve (PS/JIT/Re/Rv).

This was done to allow for a comparison to the resilience of each of the wards during the different scenarios. In Section 5.4, a detailed analysis of the results of the least resilient wards is carried out; this also includes a comparison with a highly robust / resilient ward. In Section 5.5, a detailed risk analysis is outlined, using the costal wards of Lerwick.

The second type of disruption modelled was caused by infrastructure failure (Section 5.6); to do this, certain infrastructure links were removed. The first links to be removed were all of the ferry links, and secondly a failure in the electricity network was modelled. Finally, roads that were highlighted as pinch-points during the semi-structured interviews were blocked. Again, for each of these scenarios the four basic simulations outlined above were modelled, as well as simulations that withhold using reserve (*WR*) until recovery has begun.

The next set of scenarios investigated the effects of combination events; both output in a ward and infrastructure were disrupted (Section 5.6.5). The first two of these investigated a road closure and reduced output in that ward, and finally, disruption to all of the coastal wards in Lerwick took place, with the addition of ferries from Lewick being unable to sail.

The case study itself is split up into different scenarios (Table 5.1), in which each has a hazard which leads to a modelled type of disruption. This disruption comprises either a lowering of production in the effected ward, failure of infrastructure, or a combination event (causing both a lowering of production and infrastructure failure in one ward). Each scenario is then split up into different simulations in which one or more resource management strategies is employed to allow for analysis to take place.

To aid understanding of the different simulations carried out within the different types of scenario, Tables 5.1 and 5.2 and the resource management strategies are used, to provide a unique identifier for each simulation. For example, SI01HB_JIT (SI = Shetland Islands) would be a simulation from the unmanaged basic scenario (01), with disruption occurring in Harbour and Bressay (HB) and *JIT* resource management being used.

Table 5.1: Different scenarios tested within this Shetland Islands (SI) case study

Code	Scenario	Hazard	Disruption mechanism	Section

01	Basic / unmanaged	Disrupted output	Lowered Production	5.4-6
02	Injection of supply	Disrupted output	Lowered Production	5.5
03	Risk Analysis	Storm surge	Lowered Production	5.7
04	Ferry disruption	Storm	Infrastructure failure	5.8.1
05	Blackout	Disrupted output	Infrastructure failure	5.8.2
06	Road Closures	Flood	Infrastructure failure	5.8.3
07	Road Closures	Flood	Combination event	5.8.4
08	Lerwick	Storm surge	Combination event	5.8.5

Table 5.2: Wards analysed in detail with two letter code used for generating the unique ID. In the infrastructure failure scenarios where disruption occurs on links between wards *NF* or *RB* is used.

Ward	Code	Ward	Code
Clickimin	CL	North Central	NC
Cunningsburgh & Sandwick	CS	North	NO
Delting East & Lunnasting	DL	Sansting, Aithsting and Weisdale	SA
Dunrossness	DN	Sandwick, Levenwick & Bigton	SB
Delting West	DW	Scalloway	SW
Harbour and Bressay	HB	*No Ferries*	*NF*
Lerwick	*LW*	*Road Blockage*	*RB*

5.2 Data Requirements

The case study required data from multiple sources, to allow for a clear analysis of the relationships between components of an interdependent network. The different data sources were manipulated to allow common fields to be related to one another. For example, common industrial sectors are required for the *I-O* tables and Business Register and Employment Survey *(BRES)* Data, and it is necessary that Ward codes are linked between the geographic data and the disaggregated *I-O* table. 1997 – 2007 CAS Wards were used to match the data format used by the Shetland Island Council in their publications.

The *I-O* table was sourced from “An Analysis of the Shetland Economy based on Regional Accounts for 2010-11”. The report was commissioned by Shetland Council in 2011 to presents findings from an economic analysis of the Island’s economy. The data was presented in *I-O* tables, and allowed for the inclusion of detailed information on the industrial sectors of the economy (Dyer *et al.*, 2013). These *I-O* tables provide an all-inclusive illustration of the goods and services which flow within a the economy per year, providing a detailed picture of industrial interdependencies as well as the links between producers and consumers (Scotland.gov, 2013).

The second data requirement was the *BRES,* which are annual employment statistics available on a ward level, which detail the locations of e employees' workplaces (NomisWeb, 2014).

In order to gain an insight into the actual current state of resilience planning on the Shetland Islands, face-to-face interviews with members of the resilience team within the Shetland Island Council were carried out. This provided useful information on vulnerabilities and the types of disruptive events which can occur, and also gave a general feeling of what life is like on the Islands. The interviews followed an unstructured pattern, allowing for respondents to add further detail when required (Grix, 2010). The approach also allowed for the interview to remain more informal, aiding the quality of discussion.

The interview respondents were chosen as they were identified as the people who would most likely be able to provide significant information in aid of this research (Creswell, 2009). As the respondents were experts within the Council, they were able to provide an understanding of why the Council carried out the *I-O* study, and also highlight vulnerabilities within the transport network.

Information was gaining during these interviews that ultimately led to the development of certain scenarios within this work. For example, it was stated that during large storms the ferry services lining the different Islands cannot run; and pinch points in the road network were also highlighted. In addition, it was noted that flooding was not a significant problem for most of the wards but at times coastal flooding could cause problems.

Finally, "The Shetland Island Council Strategic Flood Risk Assessment" provided the data required to map the areas at risk of flooding on the islands. The report was carried out as part of the Shetland Local Development Plan (LDP). The LDP aims to assist in both the preservation of the built and natural environments, as well as support economic growth and provide information to aid the planning process (SIC, 2013).

5.3 Disaggregating of data

Using the approach outlined in section 4.3.2, the *I-O* data was spatially disaggregated to be used within the resource model. This enables the physical connections between supply and demand to be better represented within the model. Spatial downscaling is also essential to understand the impact of spatially variable events such as flooding.

The first step of the process was to acquire the *BRES* data from NomisWeb. The data was supplied as a CSV file with a column for each if the wards within the study area. Each row showed the number of employees in each sector within that ward. The next step was to use the percentage, which is the raw count normalised according to the total number of employees per sector across the whole economy, *E,* from the *BRES* data e_s, to calculate the total output per sector per ward. To do this, the proportion of employees, e, was used as a proxy for estimating the proportion of supply, *S*, and demand, *De*, from each industrial sector, *j*, in each of the zone, *z*:

$$S_{z,j} = \left(\frac{e_s}{E}\right) De_j \; ; \; De_{s,j} = \left(\frac{e_s}{E}\right) S_j \qquad (5.1)$$

This, therefore, means that the total inputs and outputs for each industry is proportionally divided between each ward based on the percentage of employees from a specific sector found in each ward. This is then repeated for all other wards. The demand placed on each other sector by another sector remains the same but is now split between the sites of production which represent that industrial sector, as described in Section 4.4.2.

5.4 Initial Results

Within this section, the results of the initial scenario set out in Section 5.1 are presented. In each simulation the output of a single ward is reduced by 15%. The simulations are then run again, but for a different ward. This continued until all wards had individually been disrupted.

5.4.1 Results by simulation

Figure 5.2 shows the percentage of production for all of the wards during each of the basic simulations of the model (based on 85% production for all sites in the disrupted ward). The first thing to note is the obvious grouping of simulations of the same type, for example, the four box plots for *JIT* simulations show a much lower level of output on average for the entire economy than the simulations using batch deliveries (*B*).

When the addition of rationing (*PS*) of available resources is added to the *JIT* simulations there is improvement in some of the simulations, but the median value is still very similar to the initial *JIT* simulations, meaning that in some cases the simulation performs well but in others it does not. This is shown by the very long length of box (depicting a high interquartile range). This result is an indicator of the importance of the ward in terms of both the total levels of production and also the output of individual sites of production then a large proportion of the overall output from the Shetland Islands is removed and therefore the system is unable to withstand this shock and therefore rationing does not make a large difference in the results.

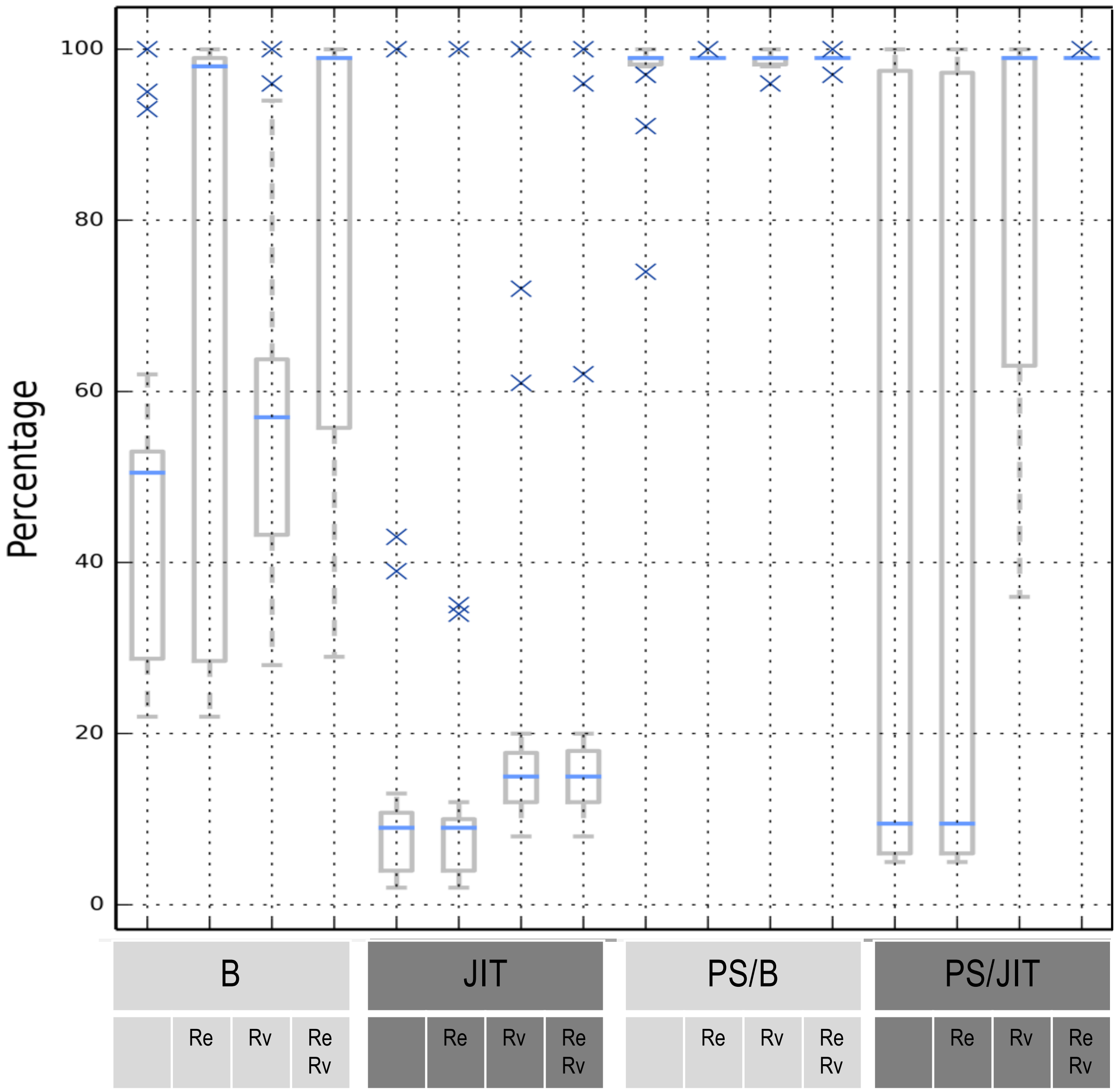

Figure 5.2: Box and whisker plot showing the percentage output for . The box represents the first and fourth quartile, whiskers 2nd and 98th percentile and the crosses are outlying results.

When focusing on the *B* simulations, the four box plots are considerably higher (35%) than those of the initial four JIT simulations. A greater level of recovery was also noted in the simulations in which it was modelled (returning to almost 100% production). When *PS* is added to *B,* the level of production throughout the month long simulations is only a fraction under 100%, showing much higher levels of resilience than in the basic simulations.

This is highlighted further in Table 5.3, which shows the first day in which effects are noticed outside of the disrupted ward for the basic simulations of the model (without recovery and injection of supply). It clearly shows that the addition of reserve to all simulations increases the lag, with bulk deliveries also slowing the effects.

Table 5.3: Number of days between disruption and initial effects on production, and the mean production output of the Shetlands for the whole study period

	Mean day first effects felt after disruption	Mean output of whole of the Shetlands (%)
B	4	45.29
B/Re	5	56.40
JIT	2	10.91
JIT/Re	3	19.36
PS/B	25	97.59
PS/B/Re	28	99.11
PS/JIT	9	34.17
PS/JIT/Re	22	83.8

Finally, if rationing of resources is encouraged, only small disruptions are observed throughout the whole island, and only within three out of the four simulations. This is shown by the high mean output, which indicates much greater levels of resilience. The modification of *JIT* to include either a reserve stock, rationing of supply, or both, makes a scenario much more robust to disruption then when just following a pure *JIT* model.

The longer the lag between initial disruption and the effects outside of the disrupted ward, the higher the levels of resilience. A longer lag also allows for corrective actions, such as the sourcing of supply from outside of the local economy, to take place (see Section 5.3.2).

5.4.2 Recovery

One clear result which can be seen in Figure 5.2 is the recovery model in most cases, apart from *JIT* simulations leads to a bounce back towards the original output levels by the end of the modelled period. This can be seen most clearly in the batch delivery scenarios. In the scenarios which are just measuring robustness (i.e. no recovery is modelled), median values for output are slightly above 50%, whereas when recovery is included these results show an overall output for the study period at around 98%, i.e. overall only 2% of resource movement is lost. This therefore shows a very high level of resilience when these scenarios are modelled. High levels of resilience are also noted in the Batch with Rationing runs that include a recovery component. Similarly, when the *JIT* with rationing strategy includes rationing or reserve components, the resilience to disruption is extremely high, with around 99% of all resource flow occurring for all of the simulations carried out using these criteria.

5.4.3 Injection of supply from outside of the local economy

Figure 5.3 is the mean percentage of supply which needs to be injected into model run to bring production back to 100% per run type. These follow a similar pattern to the mean production box plots. The least resilient simulations were *JIT* this was because these simulations exhausted resources quickly. In most of rationing simulations the amount injected was lower, in some cases, less than 1% of supply, as resources were not exhausted in these simulations. *PS/JIT* with exhibits a large spread across the wards; as discussed in 5.4.1 this is a function of both the connectivity and volume of resources produced by the sectors in each ward. This modification of *JIT* does show vast improvement to robustness in some cases, making it a viable option to increase robustness.

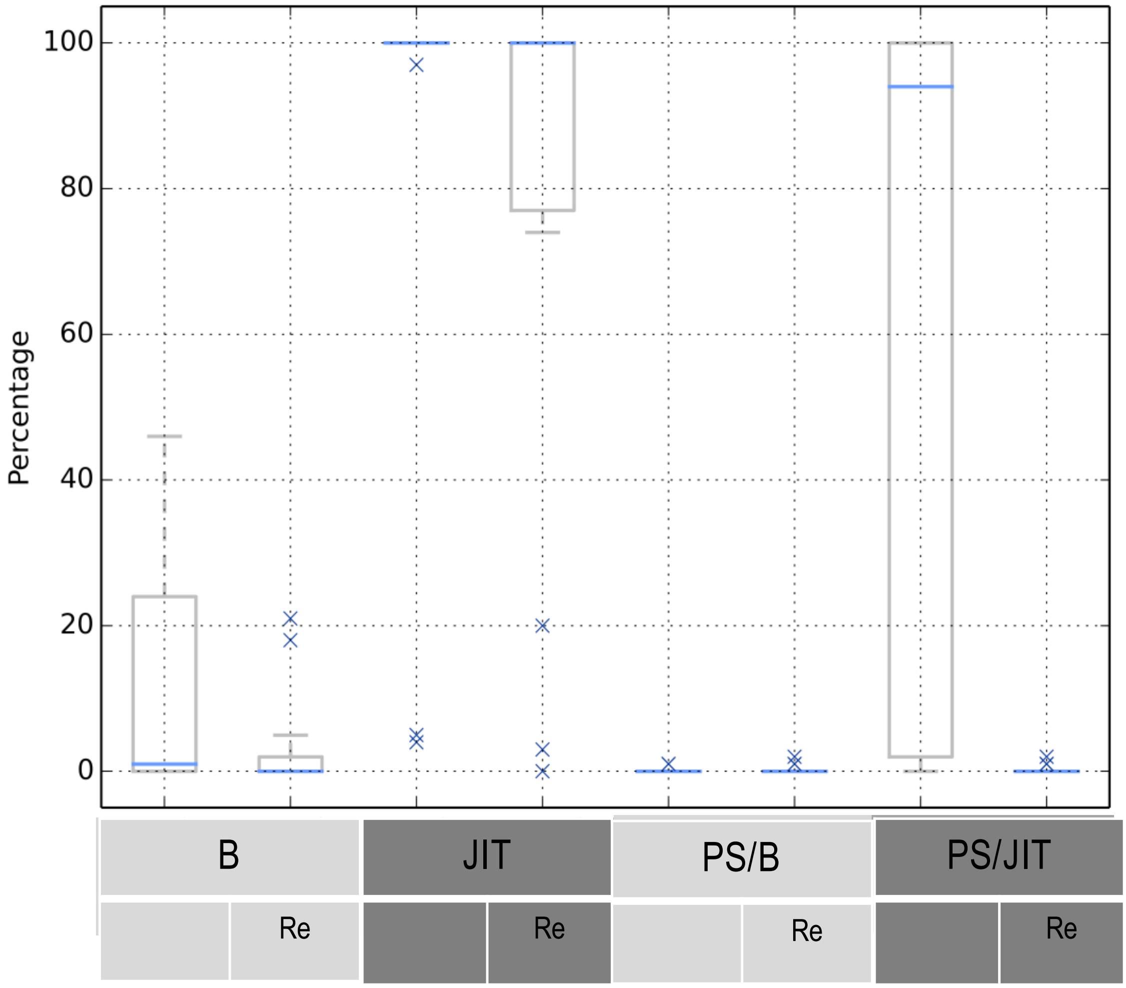

Figure 5.3: Box and whisker plot showing the percentage of supply required to return production to 100%. The box represents the first and fourth quartile, whiskers 2nd and 98th percentile and the crosses are outlying results.

5.5 Results by ward

By way of example, the following simulations have been highlighted to show how results can be viewed by ward. Figures 5.4-5.7 highlight these basic differences in performance for the Sandsting, Aithsting and Weisdale ward. The first set of four maps (Figure 5.4) focus on SI01SA_JIT. These simulations show a low level of resilience, with disruption cascading through the system quickly (production dropped to zero by day 5). Within this example, the 14 different sectors had their supply disrupted at the start of the scenario, as they had sites of production in the disrupted ward.

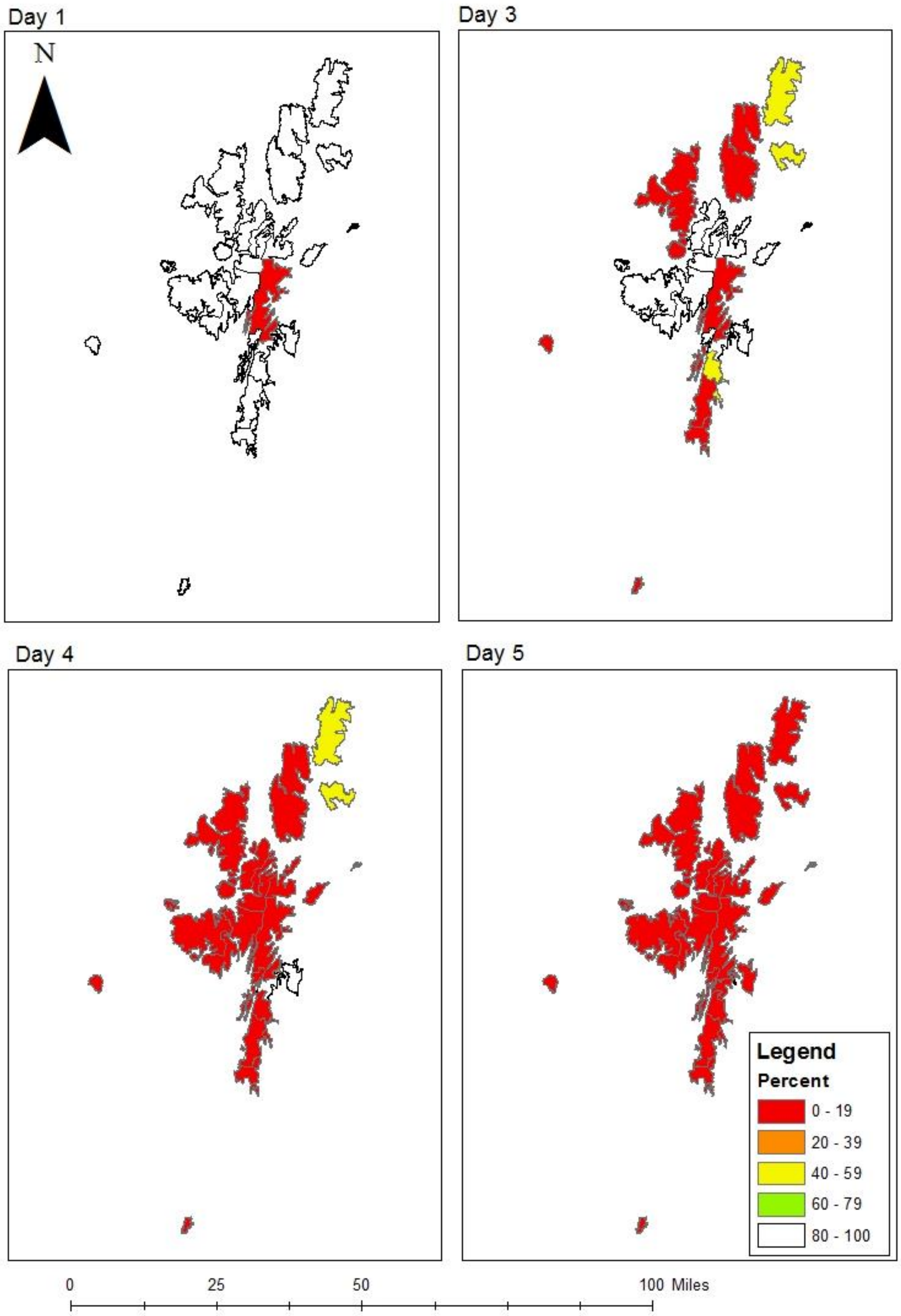

Figure 5.4: Percentage of production by ward for JIT simulation after the Sandsting, Aithsting and Weisdale ward was disrupted (SI01SA_JIT)

A move from *JIT* production (SI01SA_B) increased the resilience levels and added a lag between disruption and the cascading of this through the system (Figure 5.5). In this simulation, the lag between the initial disruptive event and this disruption causing all sites of production to cease activity has been lengthened by 19 days because of the change to the resource delivery strategy.

T he key difference between the results shown in Figures 5.4 and 5.5 is the speed in which the disruption cascades through the system. In 5.4 it takes five days for output in all wards to drop below 20% of normal, whereas in 5.5 it takes 24 days. This increase in lag between the initial disruption and the production levels being impacted is caused by the additional robustness within the system resulting from the move away from *JIT*.

To add further resilience, a small amount of reserve stock (SI01SA_B/Re) was included as part of an additional simulation (Figure 5.6). In the depicted example there was enough reserve to last one day of production if delivery of that input ceased all together. There was a clear difference in performance between the results shown in Figure 5.5 and 5.6. The addition of reserve increased robustness and provided an extra three days of breathing room before the system collapsed completely.

Within the bulk deliveries approach, once supply has been received the model calculates how much can be produced per day until the next delivery, without running out of any of the required inputs for that sector. This means that the received delivery was divided by the number of days between deliveries (in this case, three days).

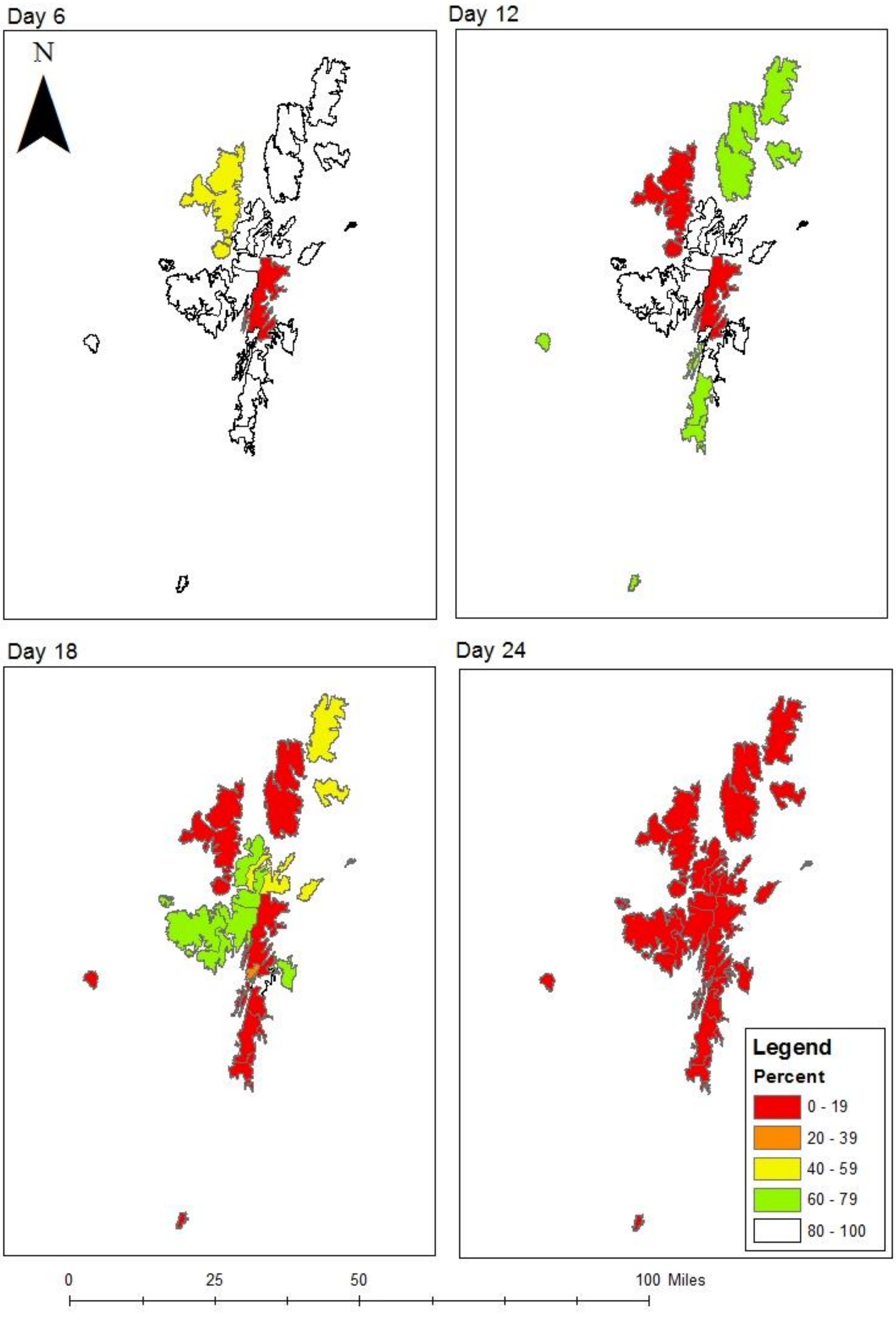

Figure 5.5: Percentage of production by ward for bulk delivery simulation after the Sandsting, Aithsting and Weisdale ward was disrupted (SI01SA_B)

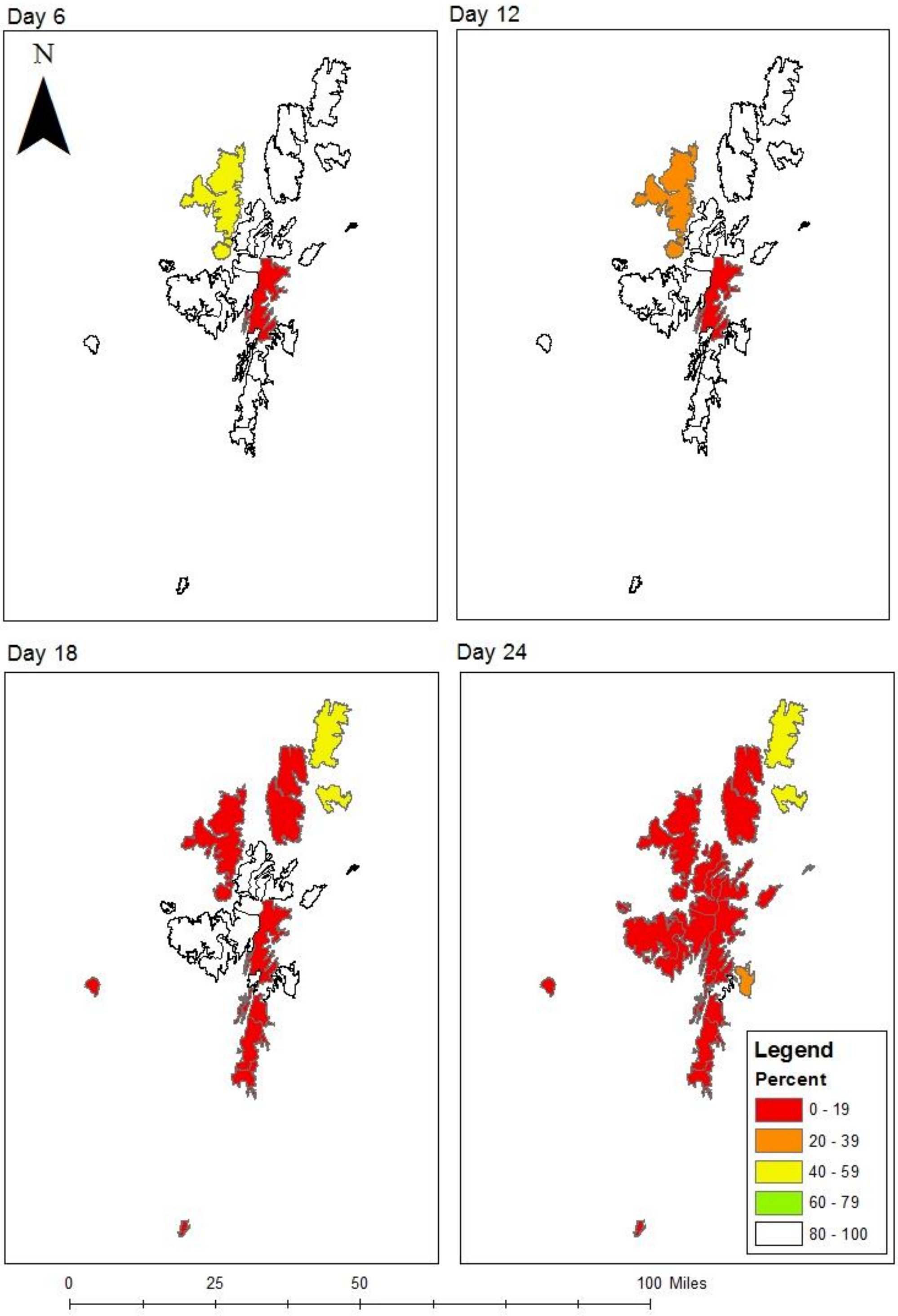

Figure 5.6: Percentage of production by ward for bulk delivery with reserve simulation after the Sandsting, Aithsting and Weisdale ward was disrupted (SI01SA_B/Re)

Figure 5.7 shows the simulations which incorporate rationing of resources within the Sandsting, Aithsting and Weisdale ward. If supply was limited to 85% then the site requiring this input could only request 85% of their usual inputs. Rationing was also introduced as an attempt to lower the chance of a supply running out. This was run in conjunction with bulk delivery, and reserve. This simulation approach consistently performed the best and increased the amount of time it took for disruption to cascade through the system, and therefore increasing resilience.

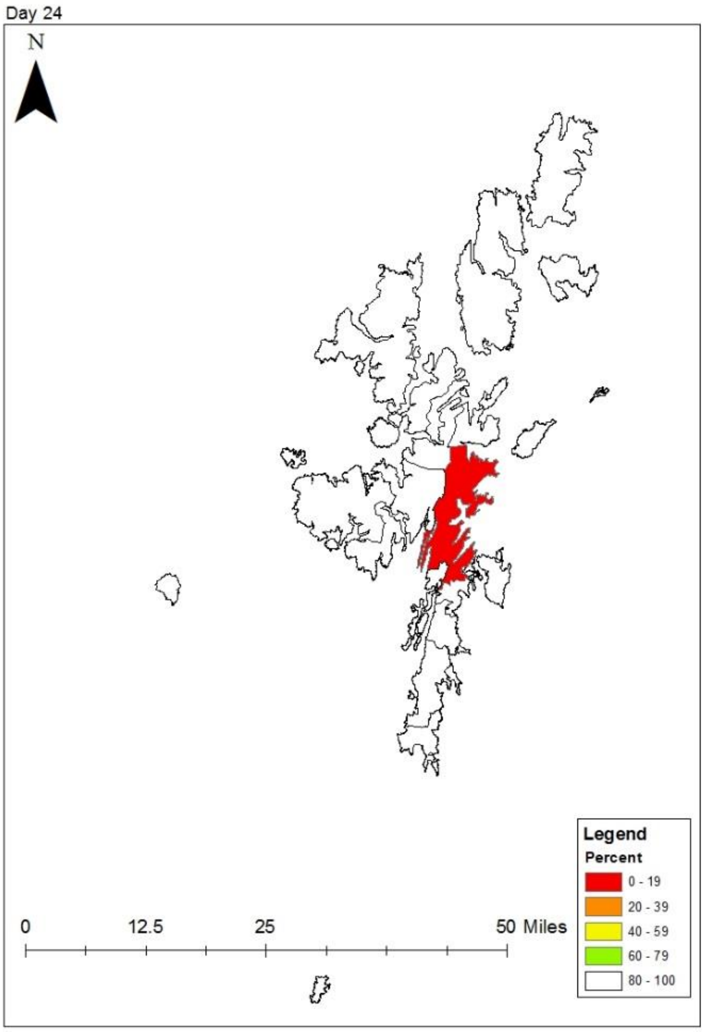

Figure 5.7: Percentage of production by ward for rationing with bulk delivery with reserve simulation after the Sandsting, Aithsting and Weisdale ward was disrupted (SI01SA_PS/B/Re)

5.6 Least resilient wards

The simulations for disruption within various wards across the Shetlands have shown lower levels of resilience than others, as represented by their lower mean output. These results are shown in Table 5.4. The wards in question are; North Central, Harbour and Bressay, North, Delting West, Delting East and Lunnasting, Scalloway, Walls, Sandness and Clousta, Sandwick, Levenwick and Bigton, and Dunrossness. In comparison a ward with higher levels of resilience, Clickimin (Lerwick), is also discussed.

Table 5.4: Lag between disruption and initial effects and mean production output for the whole modelled month across the Shetland Islands

	Percentage of sectors present in ward	Mean output of whole of the Shetlands (%)	Number of simulations leading to total collapse	Number of simulations which stabilise above 80% output
Clickimin	34	85.29	4	8
Delting East & Lunnasting	53	53.99	8	3
Delting West	59	38.34	9	3
Dunrossness	53	41.51	9	3
Harbour & Bressay	78	43.28	9	3
North	69	41.63	9	3
North Central	56	42.49	9	3
Sandwick, Levenwick & Bigton	44	47.68	8	4
Scalloway	65	55.43	7	5
Walls, Sandness & Clousta	56	52.78	7	4

5.7 Resilience in Lerwick

The results for disruption for twelve simulations in Clickimin (SI01CL), located in Lerwick are shown in Figure 5.8. As a first observation, only simulations with a *JIT* approach lead to the failure of the entire network (Table 5.4) with batch deliveries stabilising production to 80%. A basic improvement in overall output is also noticed within the *JIT* and batch delivery simulations, when there is the addition of reserve stock. Output does not reach its lowest level for a further 11 days, by which time enough reserve stock for one day of production is held on site. This, therefore, provides a lag before disruption is felt to allow for corrective action to take place, increasing adaptive capacity and, therefore, resilience.

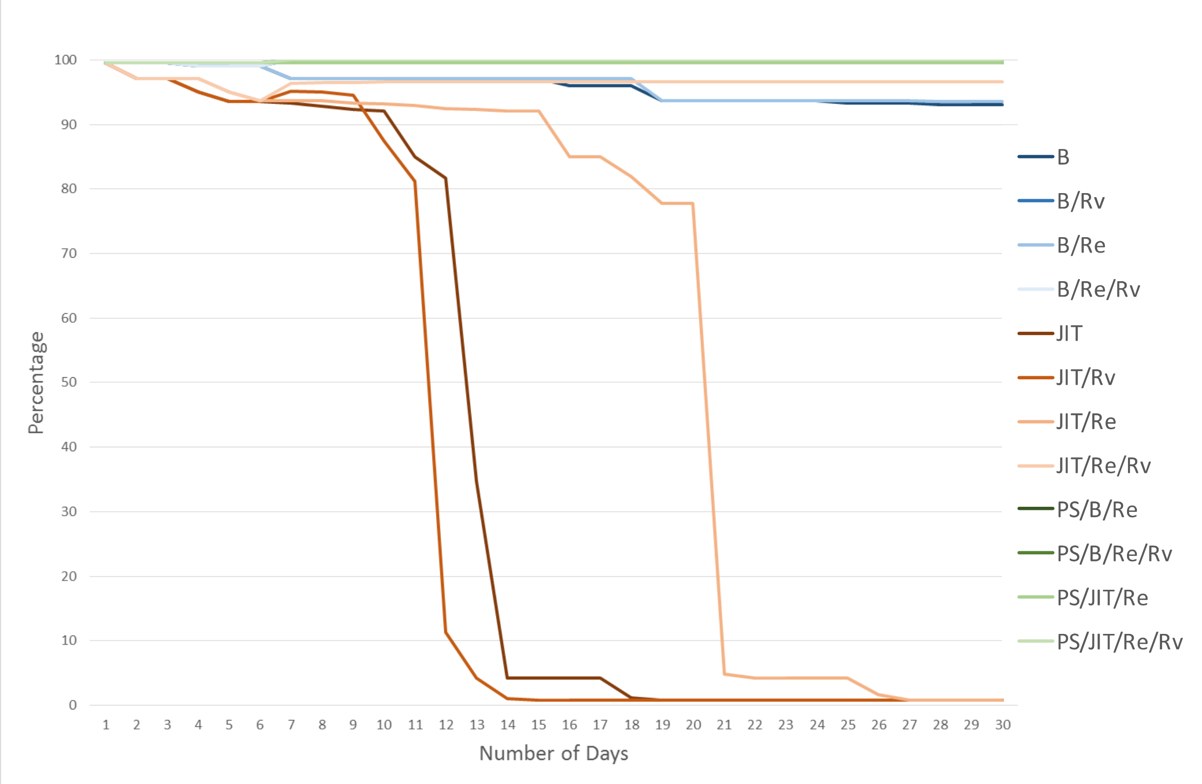

Figure 5.8: Scenario results for disruption to Clickimin (SI01CL)

In comparison to this, Figures 5.9-5.11 show much lower levels of resilience for wards North Central (SI01NC) (mean output of 42%), Harbour and Bressay (SI01HB) (mean output of 43%), and North (SI01NO) (42%). Within these results, poor performance can partly be explained by the modelling assumption that one resource is a limiting factor on production (Section 4.2). The results reinforced what was noted during flooding in Thailand, when the reduction in hard drive production led to a fall in PC and laptop manufacturing output around the world (Chongvilaivan, 2012) i.e., for this case study if one site required four inputs, received 100% of three, but 0% of the fourth, then zero production would have taken place at that site.

In all four of Figures 5.9-5.11 the results show that modifying *JIT* by combining either reserve stock, recovery and/or rationing of available supply leads to much greater robustness and resilience throughout the whole economy. The number of days between disruption and a major drop in production increases from 1 day up to 10-12 days. This would, therefore, provide stakeholders with time to source other suppliers and implement any plans they may have to keep production as high as possible.

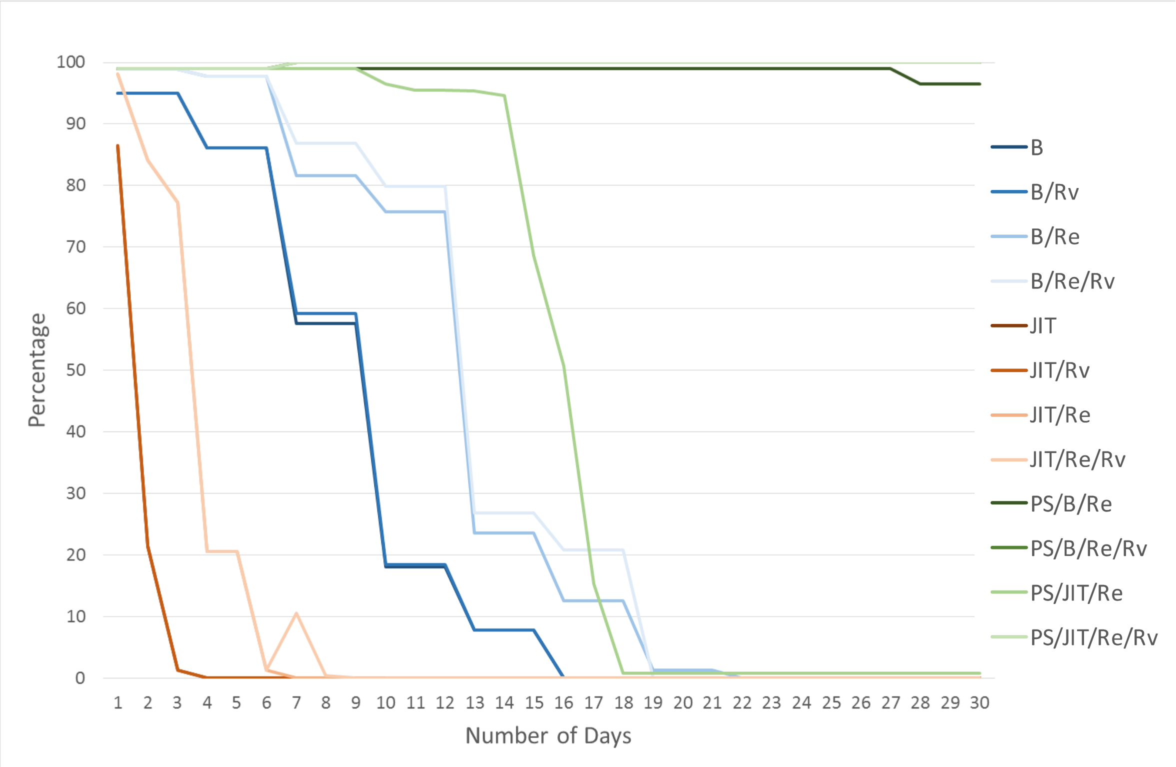

Figure 5.9: Scenario results for North Central (SI01NC)

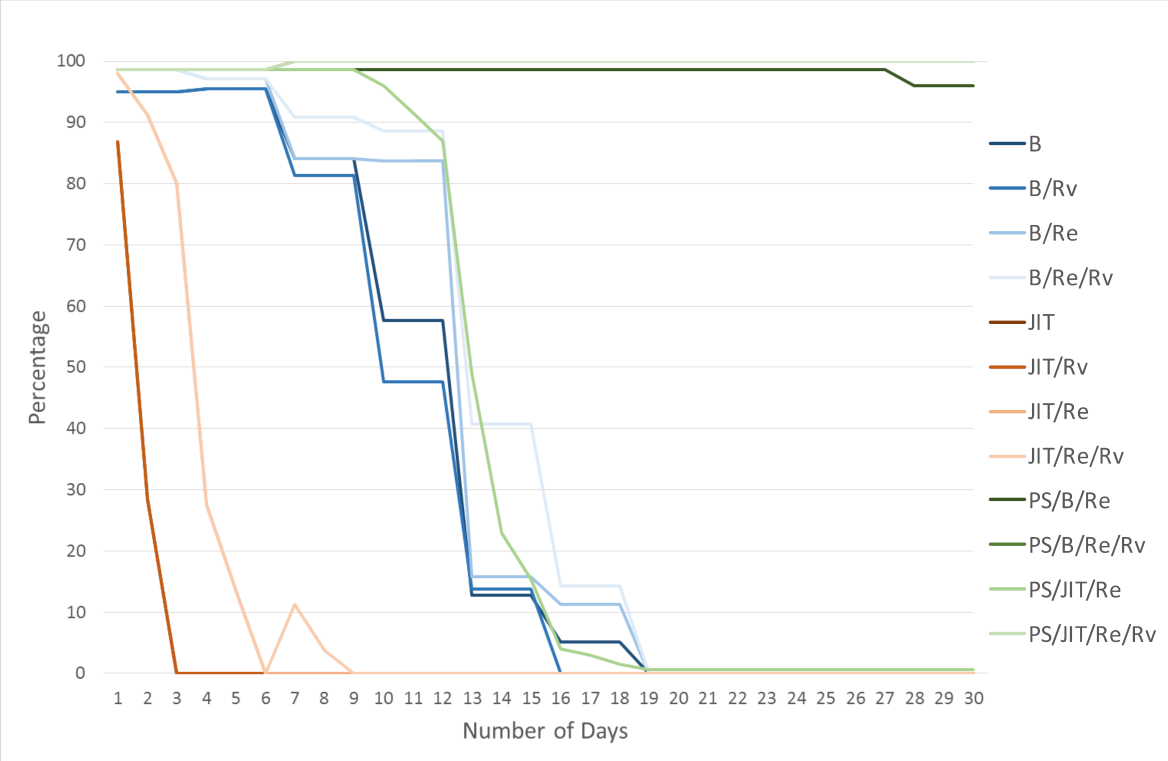

Figure 5.10: Scenario results for disruption to Harbour and Bressay (SIO1HB)

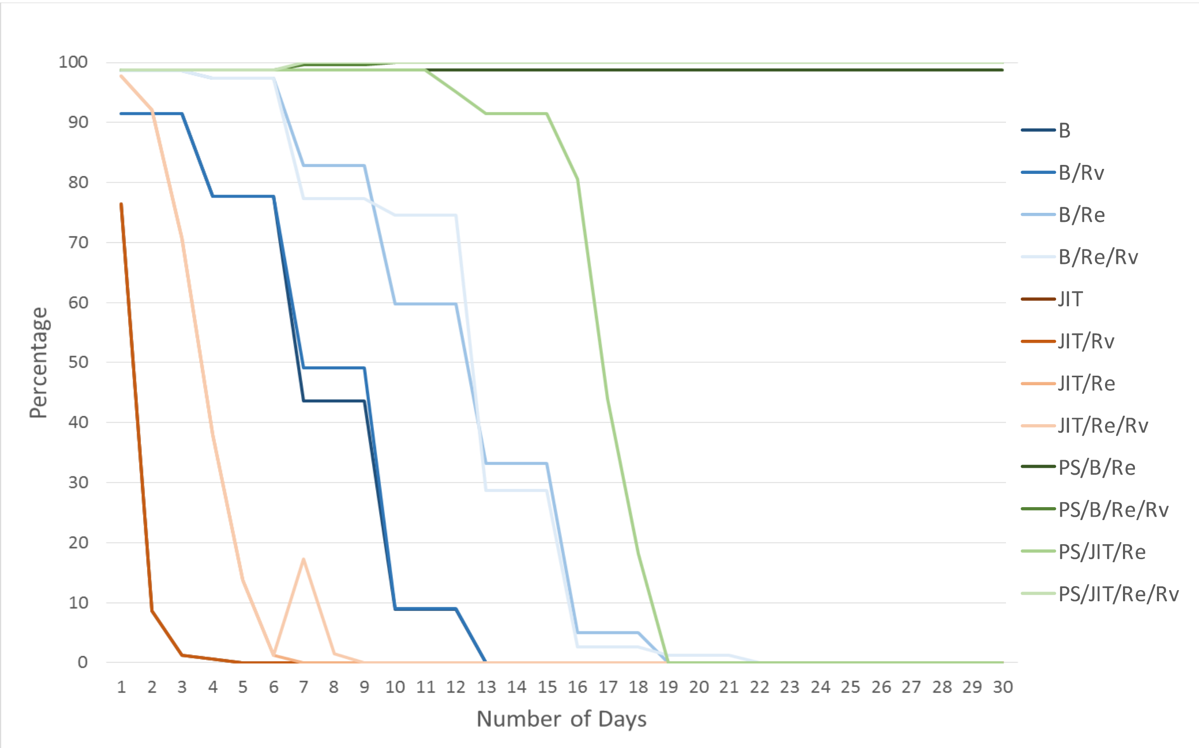

Figure 5.11: Scenario results for disruption to North (SI01NO)

The number of days between initial disruption and production dropping off is much longer in Clickimin, taking at least 14 days with the worst performing simulation (*JIT*) and with only four simulations leading to failure of the network, whereas in North Central, Harbour and Bressay, and North *JIT* simulations fail after 3-4 days and in all three of these cases 9 of the simulations cause a total failure. This implies a greater level of robustness when disruption takes place within Clickimin. The lower levels of robustness in North Central, Harbour and Bressay, and North is the high number of industries located in these wards are highly connected to other industries throughout Shetland, as well as these wards having a number of sites of production located within them that produce high a percentage of the total output for their sector.

80% of the Marine Engineering sector is found within the ward of North Central: disruption to this sector had a knock on effect on other important sectors throughout the island, namely port and harbour activities, sea transportation, fishing, and oil supply (Table 5.5). Once these connected sectors are disrupted they cannot produce at the same levels, leading to further failure throughout the system. For example, once port and harbour services are disrupted highly connected sectors like retail and wholesale start to see their operations affected. This causes a rapid cascade of failure through the whole system.

Table 5.5: Interconnections between industries within the Shetland Islands and number of sites of production per industry

	Number of wards	Sectors directly supplied	Number of inputs required
Agriculture	4	10	21
Fish Catching	6	4	17
Aquaculture	12	6	18
Oil Terminal	1	1	17
Mining & Quarrying	3	7	12
Fish processing	5	13	16
Other food & drink processing	9	17	18
Marine engineering	4	6	16
Textiles & crafts	7	11	16
Other manufacturing	9	24	11
Electricity, gas & water supply	6	30	16

Construction	11	30	20
Wholesale	6	17	11
Retail	8	21	11
Accommodation	12	20	17
Catering	11	21	19
Ports and Harbours	8	11	4
Transportation, sea	6	19	15
Transportation, land	10	26	8
Transportation, air	2	26	18
Oil Supply Services	1	4	19
Communication & supply	16	21	15
Financial Services	2	24	4
IT/computer related & real estate	10	23	17
Technical, Professional, other business services	15	28	9
Public administration	15	18	15
School Education	17	0	15
College Education	4	1	10
Health	7	3	16
Social work	13	5	9
Other community services	16	24	16

The reasons for high vulnerability within Harbour and Bressay (Figure 5.11) were similar to that of North Central a large and diverse range of sectors, including several important sectors (Financial Services, IT/computer related and real estate services and technical, professional, other business services) (Table 5.4). This means that when disruption occurs within this ward, all of these sectors (and, therefore, the majority of sectors within the whole Shetland economy) are affected, even before connections are taken into account. Consequently, this began to affect some of, what were expected to be, the more resilient simulations.

Within North, similar to Harbour and Bressay, there are a large number of different sectors represented, in this case 22. Four of these produce more than 50% of the output for that sector; wholesale, other manufacturing, land transportation and construction (Table 5.5).

5.7.1 Other wards with low resilience

Disruption to Delting West (SI01DW); Delting East and Lunnasting (SI01DL); Scalloway (SI01SW); Walls, Sandness and Clousta (SI01WC); Sandwick, Levenwick and Bigton (SI01SB); and Dunrossness (SI01DN) led to lower levels of resilience. These results are shown in Table 5.5, which highlights the sectors which have the most connections to other sectors; he greater the number of connections, the lower the level of resilience. It also shows how many sites there are within each industry across the Islands; the greater the number of sites, the higher the level of resilience in output for that sector. This is countered if the majority of output is actually found in one area, as described in some of the examples below.

Delting West is a sparsely populated ward at the North of the Main Island. Within this ward is Scatsta Airport, which is the main hub for commercial air travel to and from the island. It also provides the majority of support for North Sea Oil operations associated with the Island. In total there are around 19 different sectors represented in the ward, albeit most of their outputs equate to less than 10% of the output for their own sector. Of the 32 sectors which make up the modelled economy, 26 of them require some sort of input from air travel at some point, highlighting the importance of this ward and why, when disrupted, its resilience is lower than that of most of the other wards on the Island.

Delting East and Lunnasting is home to the North Sea Oil terminal on the Shetland Islands. If disruption occurs to production at the oil terminal electricity generation can be affected, as the Shetlands are not on the national grid. If electricity production reduces, all other sectors on the Island will be disrupted, which lowering resilience within the ward. The ward is also home to 20% of the Island's aquaculture. A lowering in supply of farmed fish firstly affects the fish processing industry but also the supply of food to catering and accommodation sectors as well as households on the Islands. The other eleven represented industries in this ward contribute less than

10% to their respective sectors, so are less likely to cause cascading failures throughout the system.

The regional accounts of Shetland show an input into the electricity production sector from fish processing: this relationship was therefore reflected in the model. 20% of the fish processing industry is located within Scalloway and, consequently, disruption to this industry can cascade through to electricity production.

As outlined above, disruption to electricity production has the potential to disrupt all other sectors on the island. Fish products have various industrial uses, one of which is the production of industrial lubricant, although it is unknown if such lubricant is used within electricity production in the Shetlands. Conversely the expenditure on processed fish products from the local economy could easily be for the purchasing of food to be sold / consumed in the staff canteen. If this were the case, it is unlikely that such disruption to electricity production would actually take place.

More than 50% of the agriculture which takes place on the Shetlands occurs in Walls, Sandness and Clousta. A reduction in supply here has effects on food and drink processing, textiles and accommodation, schools, as well as health care and households. A limit in the supply of food could have more profound effects than those highlighted in this model and would realistically lead to a swift intervention from outside of the island chain. This would be similar to the response of FEMA in the aftermath of hurricane Sandy, in which they set up hot food distribution centres throughout Manhattan (NYC, 2013).

The predominate industry in Sandwick, Levenwick and Bigton, which is found in the southern areas of the main island, is food and drink processing (excluding fish processing). As more than 30% of this industry is found in this ward, it’s disruption has a large effect on food supplies modelled, with the same issues arising to those outlined when discussing Walls, Sandness and Clousta.

Dunrossness is the southernmost ward on the mainland and also incorporates Fair Island. Within this ward the other main passenger airport of the Islands is located. Although 13 sectors are apparent in Dunrossness, all of these sectors aside from one employ less than 10% of the total for that sector. This one sector is Ports and Harbours; 25% of the employment in this sector within the Islands being in this ward. Disruption to this sector leads to disruption in many other sectors, such as: oil supply services, fishing, aquaculture, wholesale and retail. Although, the model assumed that each site of production within a sector all had the same links with other sectors. This is not entirely the case. The majority of these services would take place at the port, within the oil terminal itself and not on the smaller harbours servicing the different islands.

5.8 Infrastructure failures & combination events

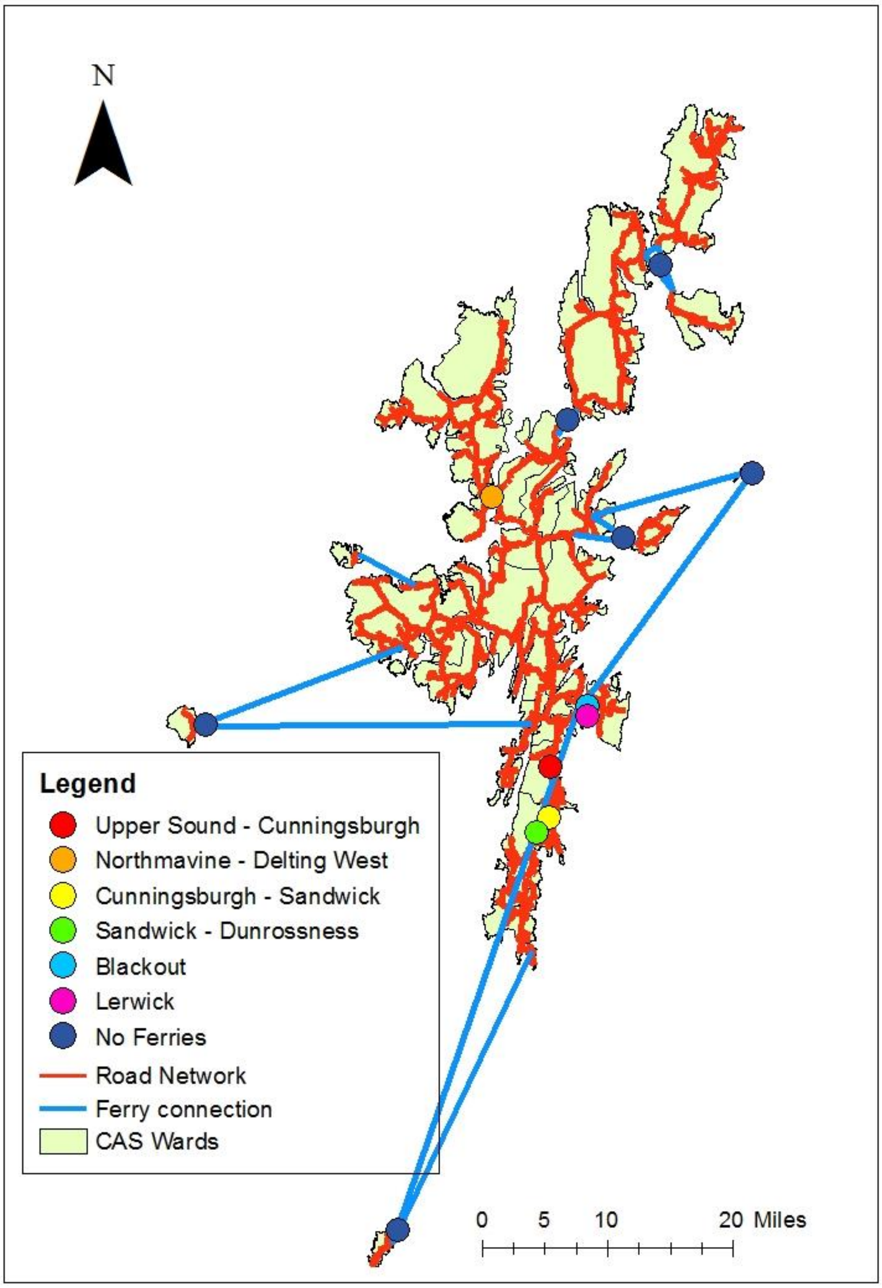

Figure 5.12: Locations of disrupted Infrastructure

5.8.1 Disruption to all ferry services

The first failure focused on the ferries being disrupted due to bad weather; the locations of the ferry routes affected are shown in Figure 5.12. Figure 5.13 shows the mean production for the different simulations ran. There was a similar basic pattern in the results: SI04NF_JIT was least robust, SI04NF_B next and finally the greatest rubust with the addition of a rationing of resources was SI04NF_PS/B.

Within these simulations, the idea of withholding reserve until infrastructure returned to normal was tested. If a site of production cannot get one of its required inputs it ceases production, even if reserve is available. Once the infrastructure returns to normal output returns to 100%, even if a node ceased production due to lack of stock, it could return to 100% output because the level of reserve was set as enough stock for one day of production. SI04NF_JIT/RE/WR (and other *JIT* simulations) returns output to pre-disruption levels. For the bulk deliveries simulation there is not enough reserve to last until the next delivery, and so there is initial recovery before production drops off.

The results show that the withholding of reserve provides production sites with the ability to increase production back to pre-event levels: this vastly increases the resilience of the economy to these modelled scenarios. When an infrastructural link is removed it causes different sub economies; the larger economy can carry on but this is not the same with the disconnected part. So once the supply of one input is reduced, it would be more sensible for production to cease until the supply lines are reconnected.

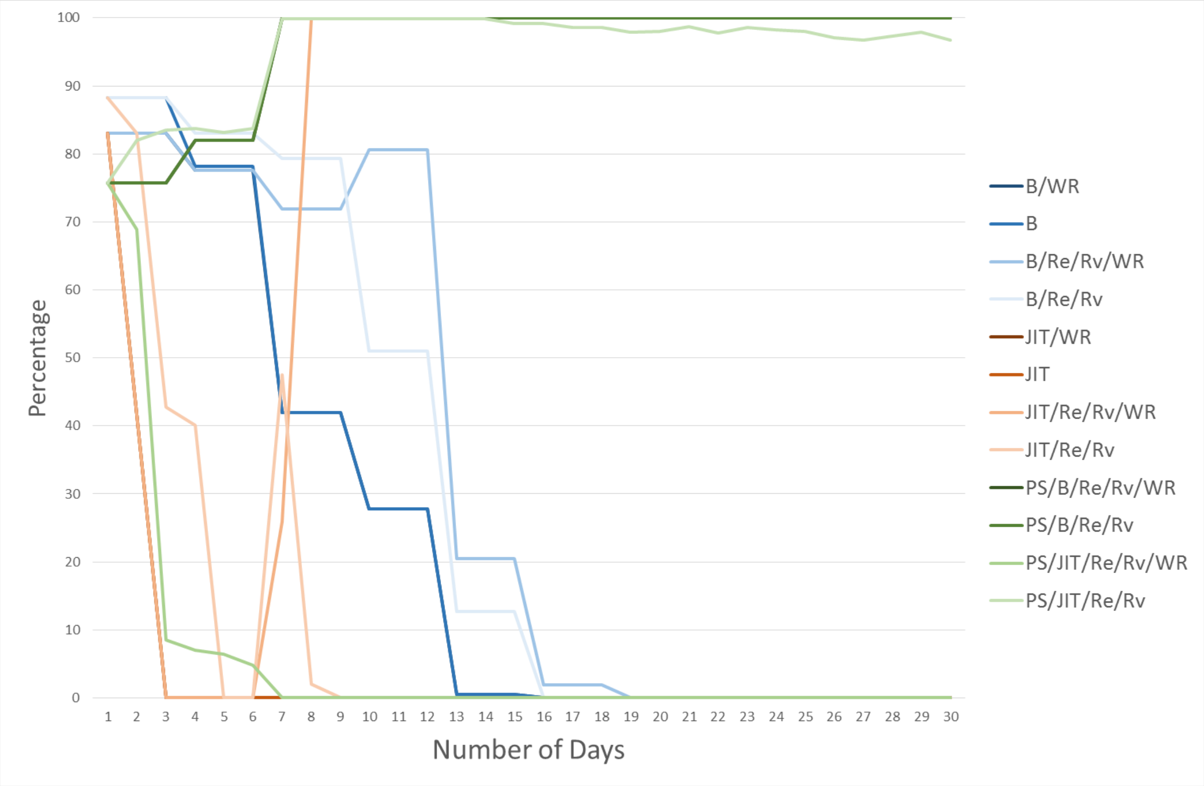

Figure 5.13: Scenario results for disruption to ferries linking different wards

5.8.2 Centrality to inform next scenario

To help inform the case study the centrality of the different wards was measured based on the road (and electricity distribution – it was assumed the electricity network followed the road layout) network (Figure 5.14). The higher the value the more central that node is to the network. Harbour and Bressay had the joint highest centrality, leading it to be chosen for the simulation of a blackout, which involved removing all of the edges (representing electricity distribution) linking this ward to other wards, as it is a good measure of the likelihood of a disruption shifting from one ward to another.

The centrality for Harbour and Bressay became zero, as it was no longer connected to other wards. This in turn reduced the centrality value in all of the wards which were initially connected to Harbour and Bressay as they had lost this connection. In total, the connections to six different wards were removed. Although the subgraphs created contained one (Harbour and Bressay) and 21 nodes (the rest of the wards) respectively, meaning the blackout itself would not travel further than the effected ward. In summary, all of the disruption to output that occurred was due to the lowering of production in Harbour and Bressay (Section 5.6.3). This was not the case in the other infrastructure failure scenarios. The removal of the wards created subgraphs which contained more than the disrupted ward. The sites of production in these wards, therefore, stopped producing because they could not receive all of the required inputs, increasing the size of the initial disruption (Sections 5.6.4 and 5.6.5).

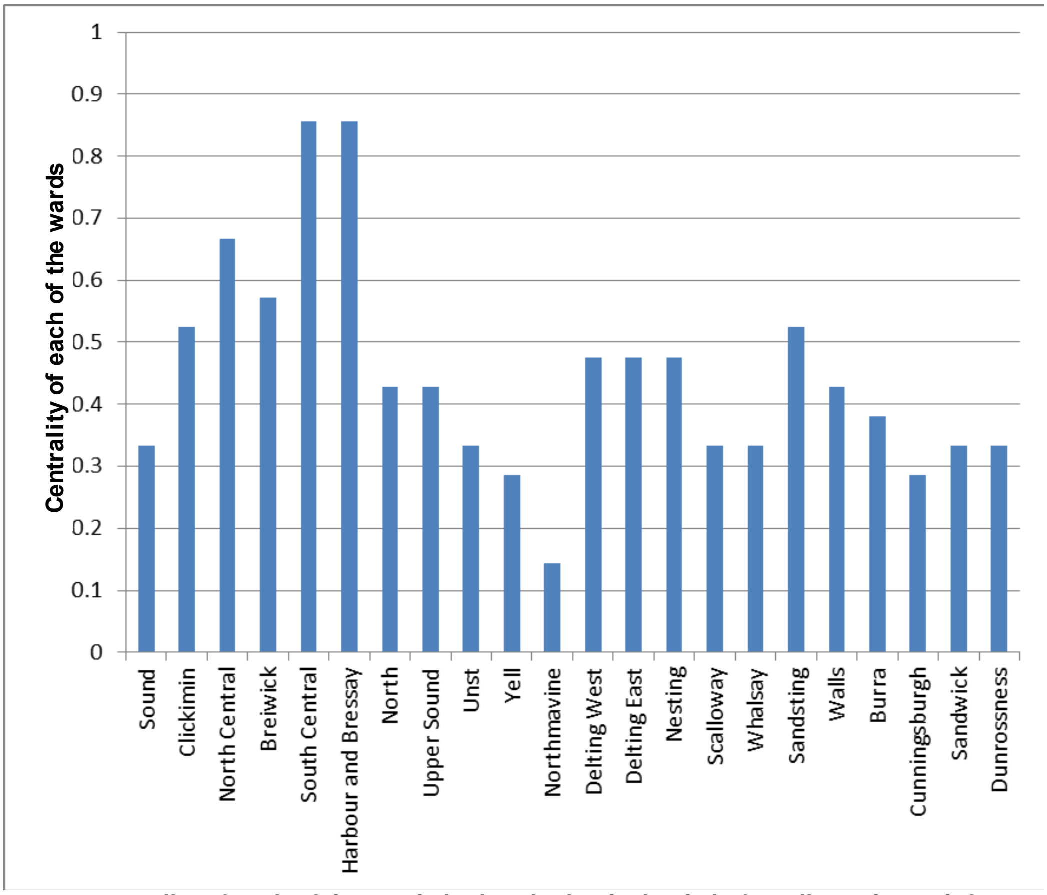

Figure 5.14: Centrality of each of the wards in the Shetland Islands before disruption to infrastructure network (certain ward names shortened to fit on the chart)

5.8.3 Electricity outage

The following scenario (SI05HB) was based on a blackout occurring in ward Harbour and Bressay. Location of electricity cables is not mapped but through the semi-structured interviews it was noted that in most parts of Shetland the network follows the roads, and electricity generators for back up are more prevalent than on the mainland. Therefore, for the purpose of the model this was assumed to be the case. As part of this scenario, zero production took place in Harbour and Bressay.

The results shown in Figure 5.15 once again highlight the importance of when to utilise reserve stock. For the simulations which utilised *JIT* as one of the resource management strategies, withholding the reserve stock until the disruption ended led to a return to pre-disruption production levels within a day of the electircty supply returning to normal. In all other cases this did not happen; for example, in the cases of SI05HB_PS/B/Re/Rv and SI05HB_PS/B/Re/Rv/WR a new equilibrium was found. In these cases batch delivery lowered resilience, as the sites of production used up stock for longer before ceasing production; whereas SI05HB_PS/JIT/Re/Rv/WR stopped production straight away and was able to return to 100% output after the event.

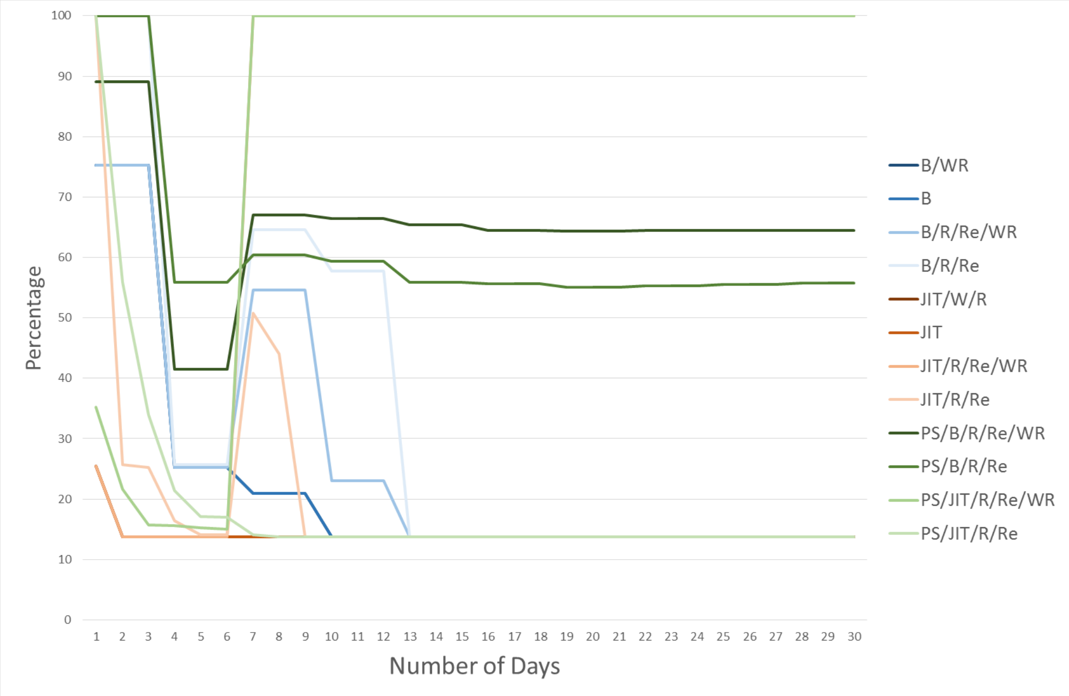

Figure 5.15: Scenario results for a blackout within Harbour and Bressay

The withholding of reserve vastly improved resilience and is most clearly seen with SI05HB_PS/JIT/Re/Rv/WR, which returned to full output. The network was unable to recover at all when reserve was used up before the disruption ended, As is shown in the case of SI05HB_PS/JIT/Re/Rv.

Harbour and Bressay, as discussed earlier in this chapter, is a highly connected ward that is home to many important, highly connected industries. In addition, such an outage has an effect on other infrastructure; in this case the road network would be disrupted as traffic signals would be out of action.

5.8.4 Road blockages

The following three scenarios all focused on a disruption to the road network. This was carried out by a targeted removing of edges from the network. The removed edges were chosen as they were highlighted as "pinch points" during the two interviews. The term "pinch point" was used by one of the respondents to describe a section of road that, if disrupted, would split the island's road network into two separate parts.

The first of these disruptions was made by blocking the road that linked Upper Sound, Gulberwick and Quarff to Cunningsburgh and Sandwick (SI06RB). These wards are located on the main island to the south west of Lerwick. The results for this disruption show a similar outcome to those discussed above (Figure 5.16). That is, the simulations which withheld the use of reserve until after the disruption had ended were able to return to 100% output, with other simulations showing some initial recovery before production falls away.

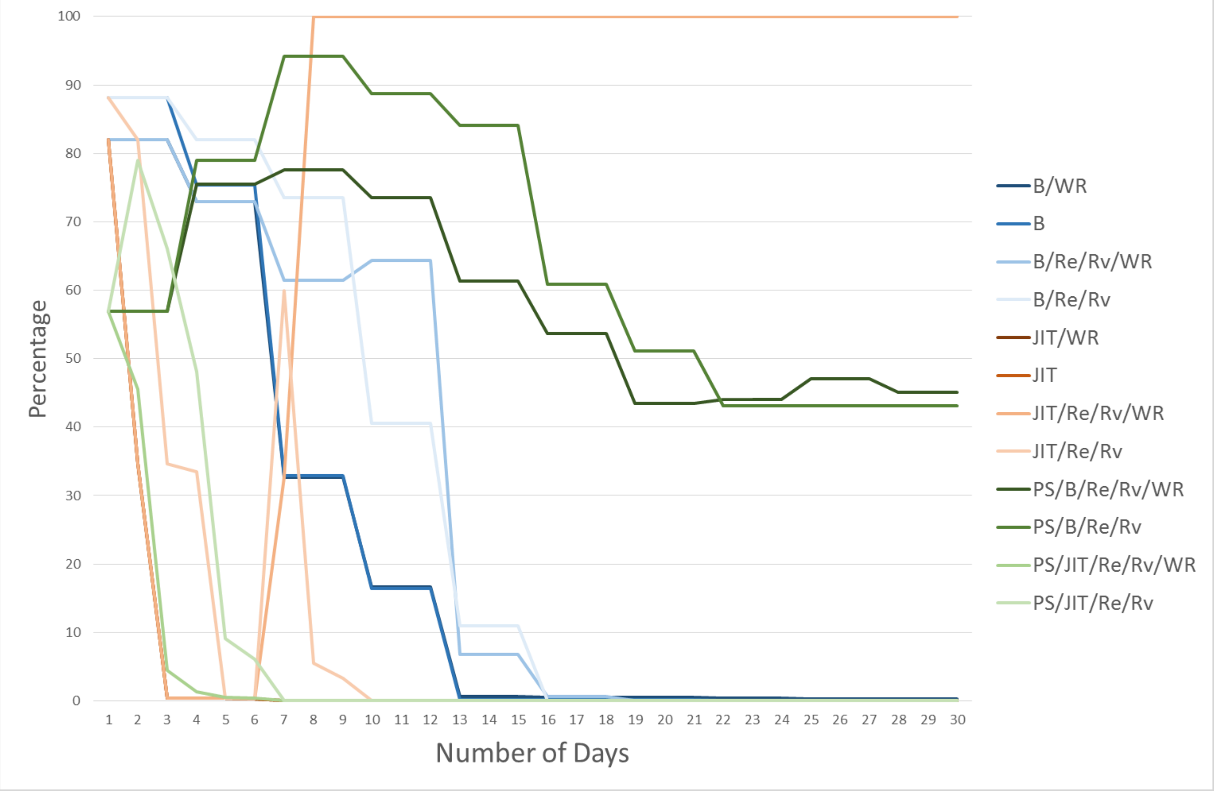

Figure 5.16: Scenario results for disruption to road between Upper Sound, Gulberwick and Quarff, and Cunningsburgh and Sandwick

The removal of the edge (road link) from the network produced two subgraphs, the first of which had 19 wards and the second had three. The smaller of the subgraphs included the three most southern wards: Cunningsburgh and Sandwick; Sandwick, Levenwick and Bigton; and Dunrossness. Production in this subgraph dropped to almost zero in most of the simulations, as there is no connection to all of the desired inputs for the sites of production in these wards, therefore causing production at most sites to cease.

The final two scenarios for road blockages followed the same pattern, although the smaller subgraph was given one ward less for each scenario, as the removed edge was essentially just further south along the same road.

5.8.5 Combination events

Two combination events (CE) were also ran. The first of these combination events was based around a transport network "pinch point" between wards Northmavine, Muckle Roe and Busta, and Delting West (SE07RB). As part of this scenario it was also assumed that production in this ward dropped to 85%, in combination with the disruption to infrastructure.

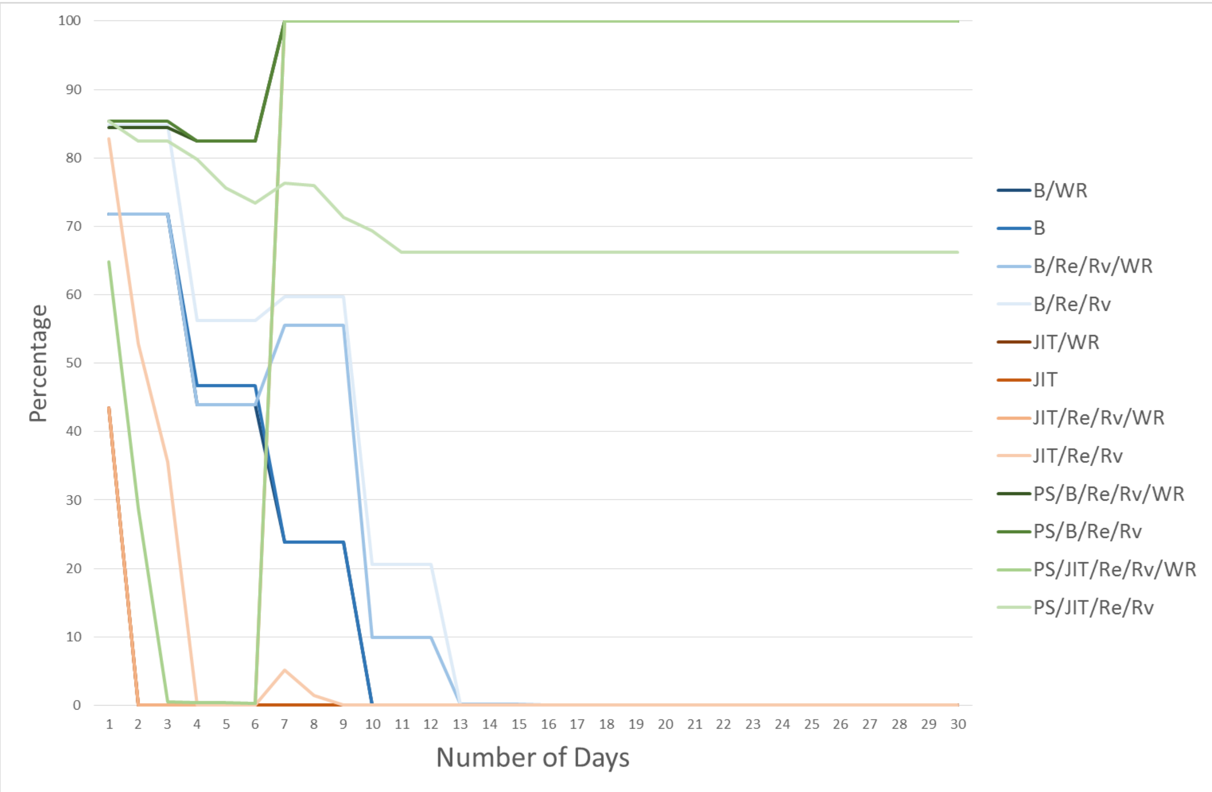

Figure 5.17: Scenario results for disruption during Northmavine, Muckle Roe and Busta, and Delting West CE

This disruption caused two sub graphs to develop within the transport network. This meant that sites of production within Northmavine, Muckle Roe and Busta were unable to receive what they required, which dropped production in this ward to zero (Figure 5.17).

When the results from this modelled CE were compared to the basic results for disruption in Delting West (SE01DW) (Figure 5.18), a clear difference in output for the whole modelled economy was noticed, with the results for the SE07RB (a) dropping off quicker and having a lower overall output than those in SE01DW (b).

The disruption to the road network in combination with the lower levels of production did, as expected, lead to a slight lowering of the resilience of the whole network. The mean output for the whole of the Shetlands for SE07RB and initial runs was 42%, compared to 59% when only output was lowered. This was caused by, as mentioned above, the sites in Northmavine, Muckle Roe and Busta stopping production, but also production in other wards was indirectly affected, as those same sites do not fell throughout the network. While this caused some initial recovery in some simulations, the recovery was not sustained in all but one case (SE07RB_PS/B/Re/Rv), as some supplies ran out due to the temporarily creation of two sub-networks.

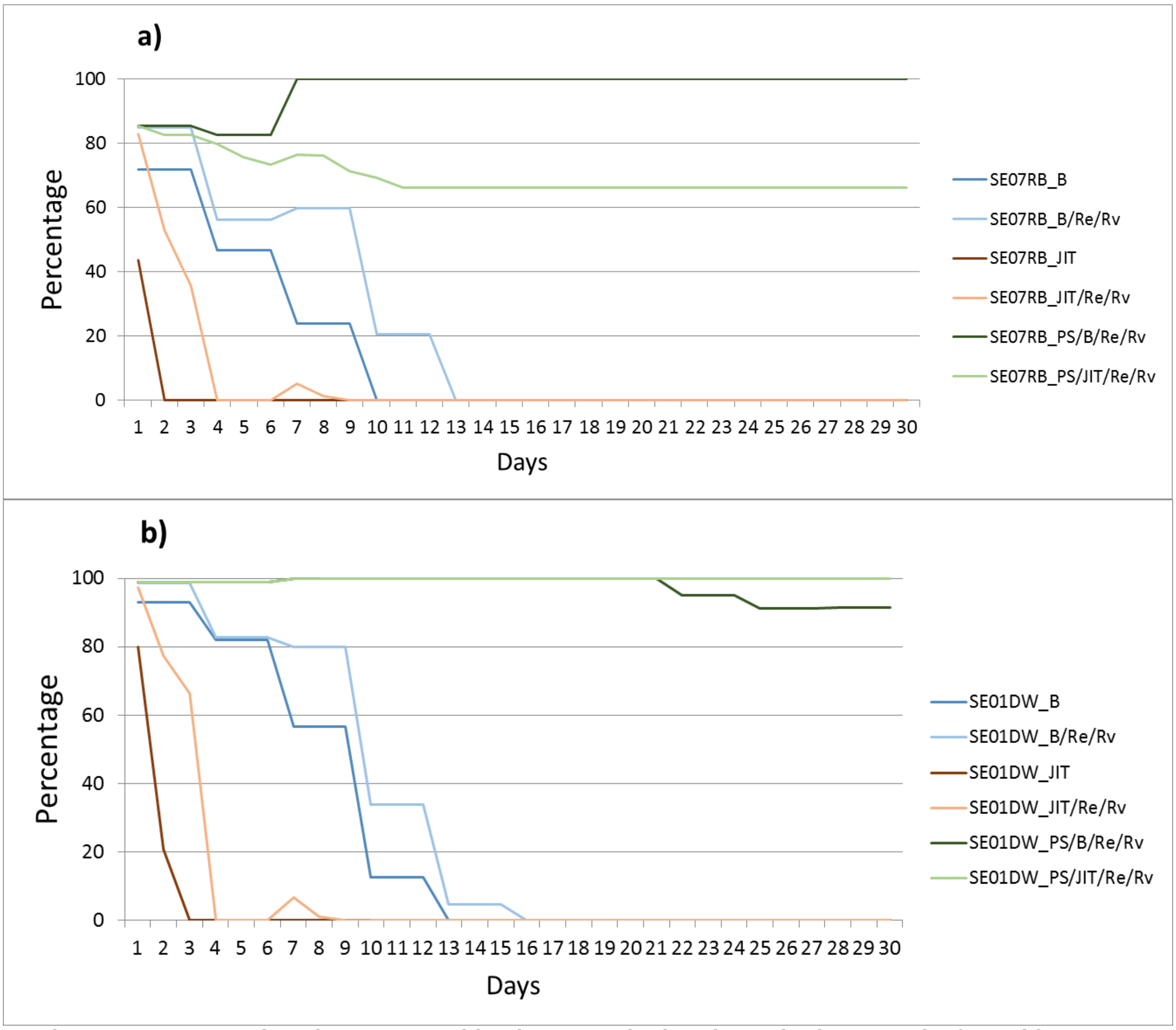

Figure 5.18: Comparison between combination event (CE) and standard run results for Delting West

The second of the combination events was based upon the Lerwick Risk Analysis discussed below (Figure 5.19). The scenario was based upon a one-in-200-year storm surge, which caused disruption to production in the four modelled wards. On top of this it was assumed that such an event could damage the harbour facilities, meaning that disruptions to the ferries leaving Lerwick were also factored into the scenario (SE08LE). The majority of the Island’s economic activity takes place within the four disrupted wards, and the flood event modelled lowered output within these wards to 65%; therefore, having significant impacts on Shetland as a whole.

Within these four wards, just over 25% of the sites of production included within the model were located, only five of which were not initially disrupted. In many cases these sites are the largest producers in their individual sectors. All of these things combined make the observed resilience for all simulations, including the rationing, very low, implying an increased vulnerability to the modelled hazard. Once again, the withholding of reserve on SE08LE_JIT/Re/Rv/WR allowed for full recovery to occur.

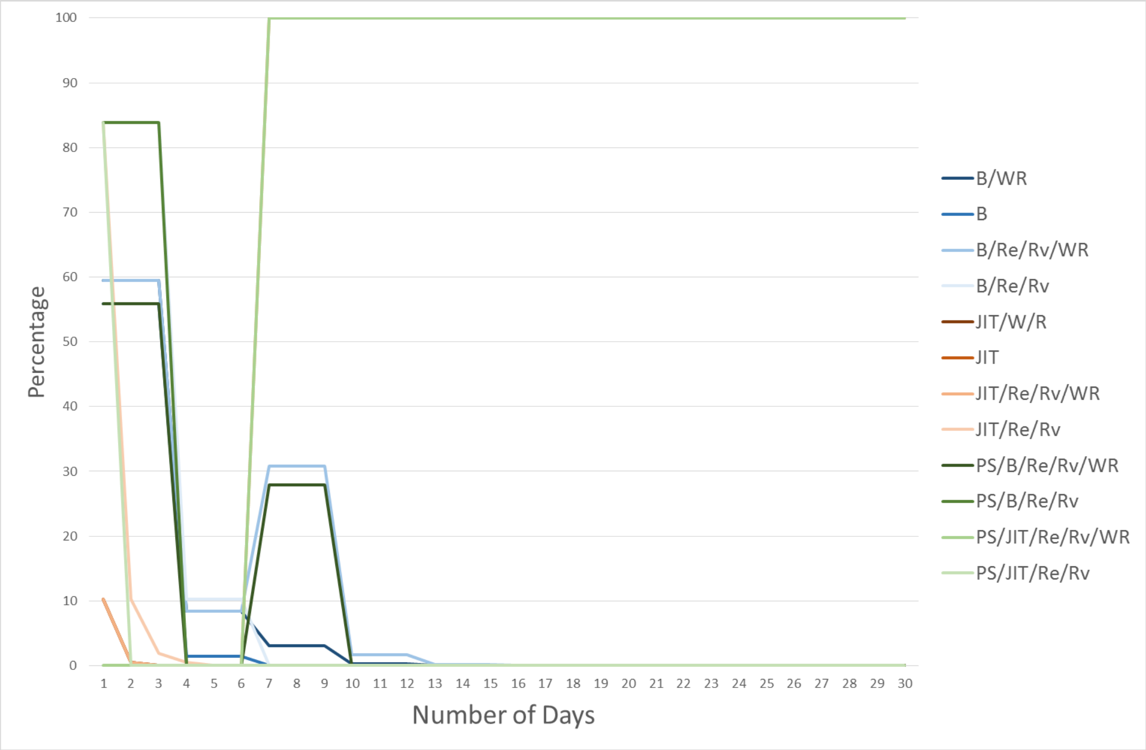

Figure 5.19: Scenario results for disruption during Lerwick Combined Event

5.9 Lerwick: Risk Analysis

A risk analysis can be used to provide a rational basis for comparing different locations, hazardous events, and management strategies. Lerwick, the capital city of the Shetlands, is the case study location and the only town on the archipelago. As part of this risk analysis, four costal wards were assessed, first individually and then combined together in one larger assessment. These wards are shown in Figure 5.20 and comprised Clickimin (SI03CL), North Central (SI03NC), Harbour and Bressay

(SI03HB), and North (SI03N0) (The wards have more than one area shown on the map as they are fragmented slightly within Lerwick).

As part of the risk analysis of Lerwick, not all of the wards shown on the map were involved. Wards Upper Sound, Gulberwick and Quarff, and South Central have no coast line and sit too high above sea level to be at risk of being flooded at any of the modelled depths. Wards Sound and Breiwick were not included in the analysis as they contain no industrial sites, and very few properties were at risk to any of the mapped flood depths.

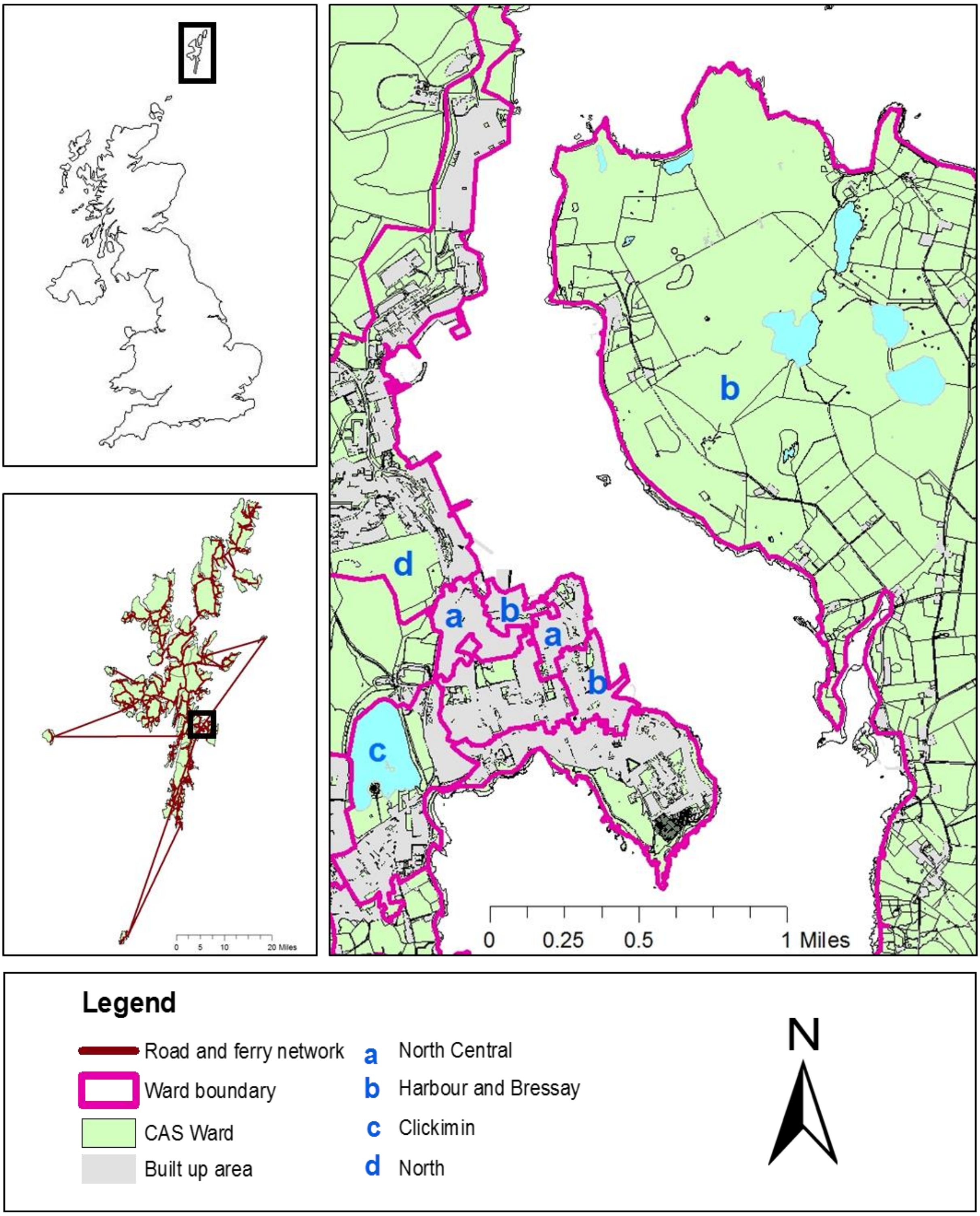

Figure 5.20: Lerwick study area

5.9.1 Vulnerability analysis

The first step in the risk analysis was to ascertain the vulnerability to the hazard being investigated, in this case a storm surge. The depths for different magnitude of flood are shown in Table 5.6, which was taken from the Shetland Island Strategic Flood Risk Assessment (SIC, 2013). The flood depth was measured in metres above ordnance datum (mAOD).

Table 5.6: Flood probability and lowest mean output during risk analysis simulations for the whole of the Shetland Islands post disruption and the probability for flooding at stated depth to take place

Probability	1	0.1	0.05	0.005	0.003	0.001	0.0001
Flood depth	1.59	1.69	1.79	1.87	1.89	1.99	2.09
Clickimin SI03CL_a-f	99.33	99.16	99.16	99.16	99.16	99.16	99.16
North Central SI03NC_a-f	14.33	14.33	14.32	14.32	14.30	14.30	14.29
Harbour and Bressay SI03HB_a-f	37.17	37.17	34.90	34.90	20.36	18.16	15.72
North SI03NO_a-f	33.25	29.58	27.82	21.28	21.28	21.28	18.15

Table 5.6 also shows the results of the vulnerability analysis. As mentioned above, Clickimin is mostly a residential ward and, therefore, the range of disruption caused by the different flood depths to output is negligible: from 0.67% (SI03CL_a) for a one-in-one-year event, to an 0.84% (SI03CL_f) reduction in normal output for all other flood events.

North Central ward is shown as the most vulnerable: the low depths of flooding have the potential to cause substantial disruption. For a one-in-one-year event, production for the whole island was predicted to drop to 14.32% (SI03NC_a). This ward is very important in terms of economic output as it has, amongst others: 79% of the marine engineering; 46% of Public administration - Local/Central; 32% of IT/computer related and real estate services; and 20% of Financial Services. All of these sectors are highly connected, meaning that disruption cascades quickly from them to those that they supply with products or services.

Harbour and Bressay is another very important ward for the economy of the Shetland Islands, as 32 out of 39 sectors modelled have some level of output within this ward. For a one-in-one-year flood, the level of production throughout the whole of Shetland drops by 62% (SI03HB_a).

The pattern of disruption in North for the different magnitudes of flood is very similar to that of North Central: 67% (SI03NC_a) production loss in the whole of Shetland for a one-in-one-year flood; 78% for a one-in-200-year event (SI03NC_c); and 81% for the highest magnitude flood mapped (SI03NC_f).

5.9.2 Risk analysis

Flood risk is a function of probability and impact, as outlined in Section 4.6.1. Here the impact is measured in terms of resource disruption, and water level is assumed to be the dominant driver. Figure 5.21 shows the plotted vulnerability for the four wards at each depth of modelled flood. As the probability of a flood event decreases left to right on the graph. For example, the probability of a 1.59m flood is 1 (a 1-in-1 year flood), as such an event is expected every year, so vulnerability is high, whereas the probability of a 2.09m flood is 0.0001 (a 1-in-10,000 year flood) so the vulnerability is low.

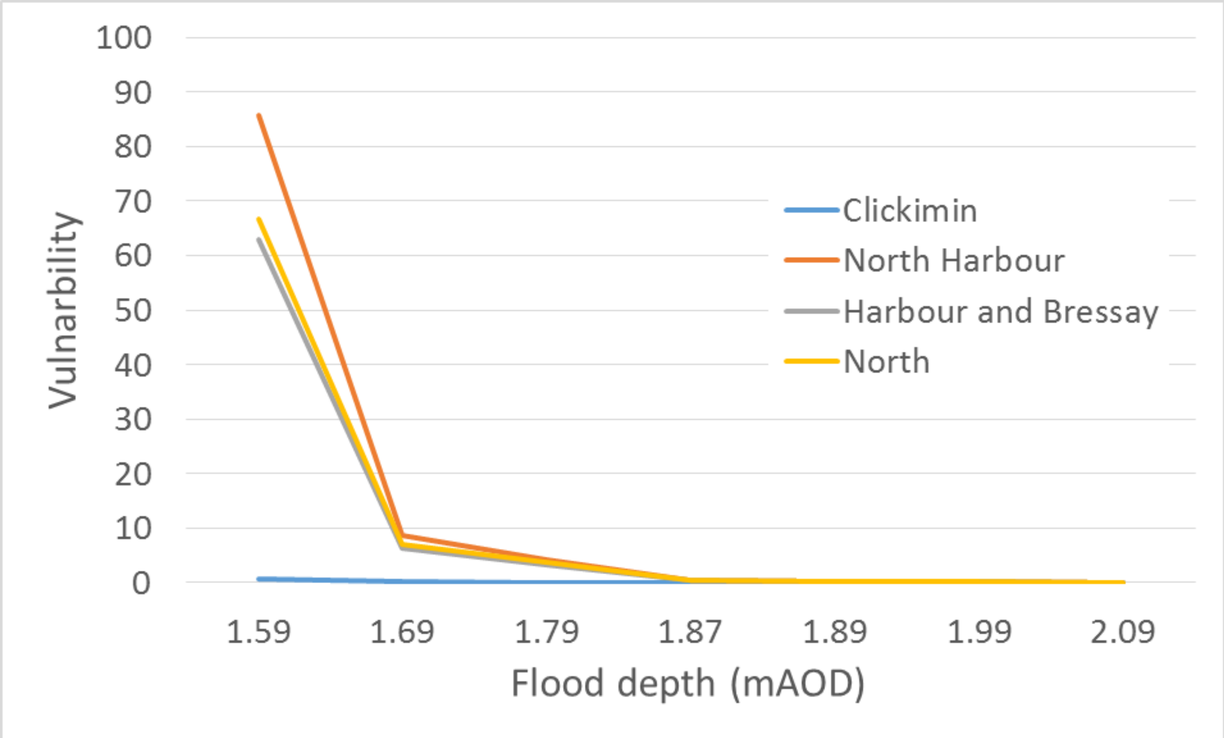

Figure 5.21: Vulnerability of production in the Shetland Islands coastal by flooding of different depths in the coastal wards of Lerwick

The *R* value for each of the wards is the area divided by the sum of the risk values calculated for each of the flood depths (probability of the event multiplied by the vulnerability).

Table 5.7: Level of risk, *R*, to overall output to the Shetland Islands after flooding in each of the wards, with and without flood defences.

	R	*R* after factoring in flood defences
Clickimin	0.81	0.01
North Central	99.30	0.78
Harbour and Bressay	73.02	0.65
North	78.12	0.71

As expected, Clickimin's level of risk (Table 5.7) to the coastal flooding hazards modelled is very low (0.808). Flood defences in Clickimin are capable of protecting against floods of a magnitude of up to a one-in-200-year event (1.87mAOD), and when these are taken into account the risk posed by any flood in this ward is approximately zero.

The three remaining wards all follow a similar pattern, a relatively high risk posed by the relatively low magnitude events (less than one in 200 years - 1.87mAOD) and a much lower risk thereafter.

As flood defences are in place in Lerwick, assuming they are well maintained and fit for purpose, the level of risk posed in this area to coastal flooding is negligible. This affirms with information gathered during the semi-structured interviews in which one respondent stated “flooding isn’t a big issue on the Shetlands”.

5.10 Summary

It is imperative to recognise and maintain the flow of vital food, materials, water and other resources to ensure community resilience, before, during and after any disruptive event. This case study presented a proof of concept, results, and insights from the developed resource model. It couples spatially disaggregated information on consumption and demand for resources, within a network model. This enabled an understanding to be developed of how disruption to the output in one ward cascades through the system to affect other sites of production.

The sectors with a higher number of interdependencies have a far greater and more rapid cascading disruption of the wider network. This is because losing a more connected sector accelerates cascading effect and makes it more significant overall, as well as more connected sectors are more likely to be impacted. A *JIT* approach to resource production and movement caused the fastest cascade through the system. On-site storage of stocks increased resilience to disruption, with bulk deliveries providing further stability in both cases. This stability was increased further by introducing a rationing response during a disruption where wards could only request a proportion of their requirements based upon the level of available stock. This increased robustness is shown to provide potential ‘breathing room’ for the identification of alternative mechanisms for safeguarding the continued supply of resources, as well as repairing disrupted elements. Even for the *JIT* resource management strategy which, on its own, is the least resilient, the incorporation of rationing, with batch delivery and reserve can significantly improve its overall resilience by as much as 90% for *JIT* and 50% for batch deliveries.

The infrastructure failure scenarios were chosen because of either a likelihood of them occurring (ferries not being able to run), a pinch point in the transport network, or to simulate a disruption within an economically crucial ward (electricity blackout). The main conclusion to take from these events is that the utilising of reserve stock is crucial for recovery when the assumption of a closed economy is taken into account.

During the simulations in which reserve was withheld until after the disruption, recovery was more likely to return to pre-event levels than if it were used straight away. If a power cut was to occur, it would be reasonable to assume that in some cases the level of demand would also reduce as production would cease until power returns. In these cases, the need to use reserve straight away will be reduced and could therefore aid recovery. This was the most resilient response to infrastructure failures and combination events.

The model was then adapted to quantify the risk to resource disruption across the Shetland Islands as a result of flooding in one location. The non-linearity of the disruption function highlights the need to capture interdependencies in such a way. This was because what seem to be relatively small disruptions within one ward can lead to much larger affects throughout the whole of the Shetlands.

The level of risk found within the case study, especially when the flood defences were taken into account, was very low. This conclusion is reinforced by information gathered within the unstructured interviews. Both respondents suggested that the impact of flooding within these locations was generally insubstantial, because of the rock armour flood protection as well as the topography of the land. The elevation above sea level rises quickly as you move inland, meaning that even a one-in >10,000-year flood event would not lead to many more buildings being engulfed compared to the more common flood magnitudes. However, the case study has demonstrated the feasibility of incorporating resource disruption into existing flood risk assessment approaches.

As the model case study was based on a closed system, it takes away the opportunity for the sites of production within the Shetlands to source products from other places, which would have an effect on the level of resilience within the modelled network.

A second limitation of the case study comes from the level of data available. Although the disaggregation method provides data to a ward level, if finer grain data were available then the results would be more accurate. The model assumed that there is only one site of production per industry per ward, and all of the different sites from a sector have similar productivity levels. Both of these assumptions are inaccurate, but without the required data they had to be made.

The final limitation based on assumptions relates to the delivery of goods. The model treats all products and services the same, meaning that they were delivered uniformly. This was done because data showing how often certain products and services are required by each individual site of production does not exist.

6 Case Study: New York City – Hurricane Sandy

This chapter introduces a second case study, this time to analyse the model against the disruption to resource movements in New York City caused by Hurricane Sandy. The major effects of Hurricane Sandy are outlined in Section 2.4.4. The case study does not model all sectors of NYC economy, unlike in the previous chapter, but instead focuses on some of those reported in detail in the aftermath of Hurricane Sandy. The focus of the case study is food distribution, which was a well-publicised impact. Factors discussed, therefore, include fuel, wholesale, retail and households.

This study addresses two shortcomings of the method introduced so far, by providing an opportunity for validation against an event, and demonstrating the transferability of the model to other contexts and geographies. Building on the insights from the Shetland Island case study, recommendations are made for increasing the resilience of NYC to similar extreme events.

Figure 6.1 provides a timeline of key events which took place in the lead up Sandy impacting on New York City, its impacts, and the relevant aspects of recovery which took place.

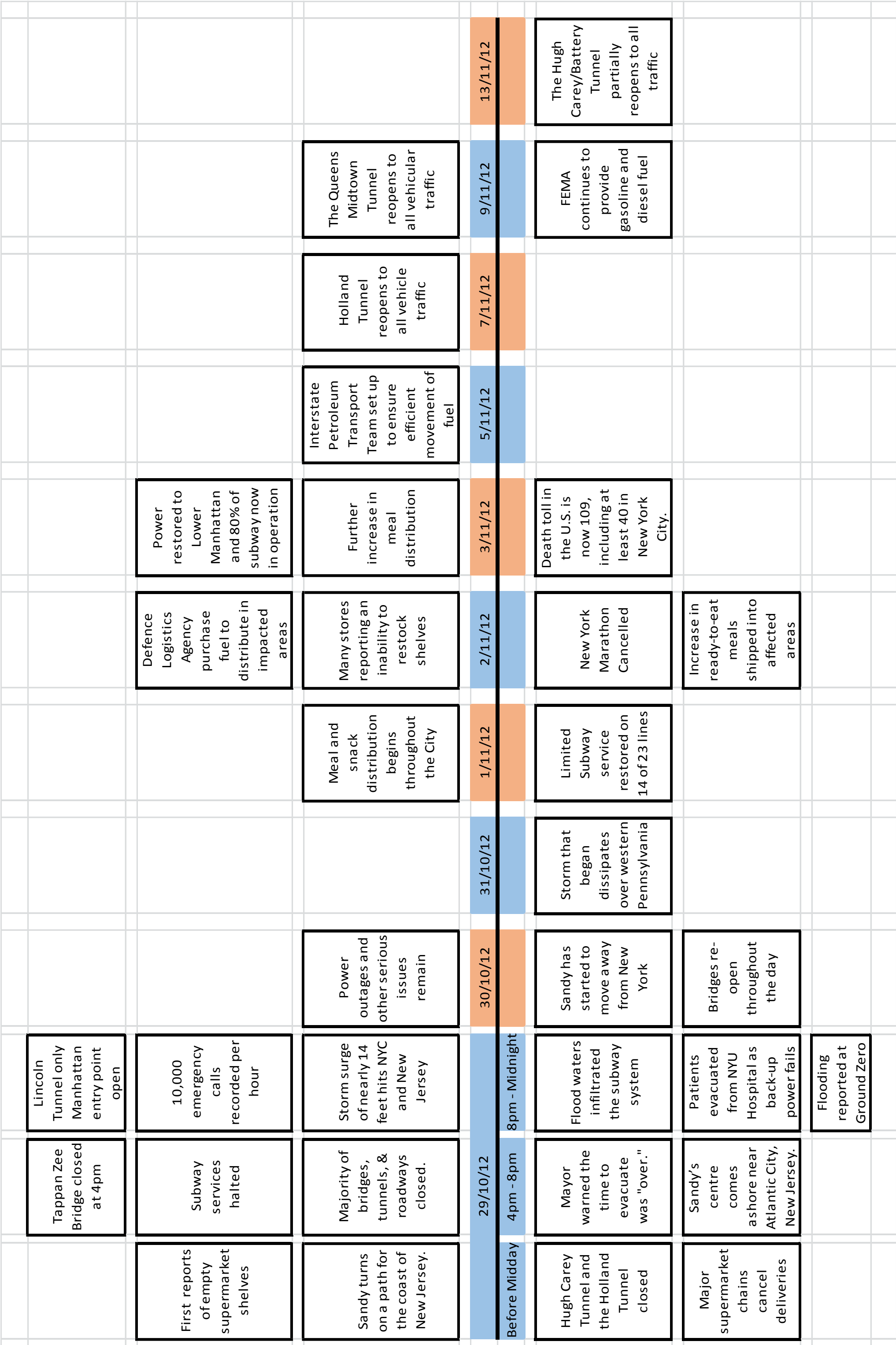

Figure 6.1: Sandy Timeline of events in New York City (Diaz, 2012; Drye, 2012; FEMA, 2014)

6.1 Methods

The case study focuses on five sectors within New York City's economy; all other aspects of the model were implemented in the same way as in Chapter 5. The sectors modelled were distribution, oil, wholesale, retail, and households. This was done to enable a validation against reported data, which was not available for all sectors. A simplified *I-O* table (Table 6.1) was developed around the proportion of demand for each of the sites. For example, there are 71 community districts in NYC. A broad assumption was made that one retail outlet provides 100% of food to the households in that district.

Table 6.1: Overall I-0 Relationships for NYC Area

	Oil	Distribution	Wholesale	Retail	Households
Oil	0	1	0	0	0
Distribution	1	0	5	0	0
Wholesale	0	0	0	71	0
Retail	0	0	0	0	71
Households	0	0	0	0	0

In this example, the oil industry required inputs from distribution, and in turn provided an input to the distribution sector. Distribution was then required to move produce from the wholesale food markets to the retail outlets. Finally, the retail outlets provided an input into the households. This is a highly simplified view of the interactions between the sectors; the oil industry and distribution industry were represented by one site of production for the sector, and the wholesale industry had five sites.

The model resolution is 'community district' (i.e. used as the equivalent to the 'output level' in Chapter 5), of which there are 71 across five boroughs in New York City (Figure 6.2). Each of these, therefore, has a column for household and retail in the *I-O* table, resulting in the model comprising 71 retails nodes and 71 household nodes.

Within the city there are also five major food wholesale markets. The largest of these is Hunts Point (Figure 6.3) which handles 60% of the food that passes into New York City (NYC, 2013). It was assumed the remaining 40% was shared equally between the other four sites as this information was not provided.

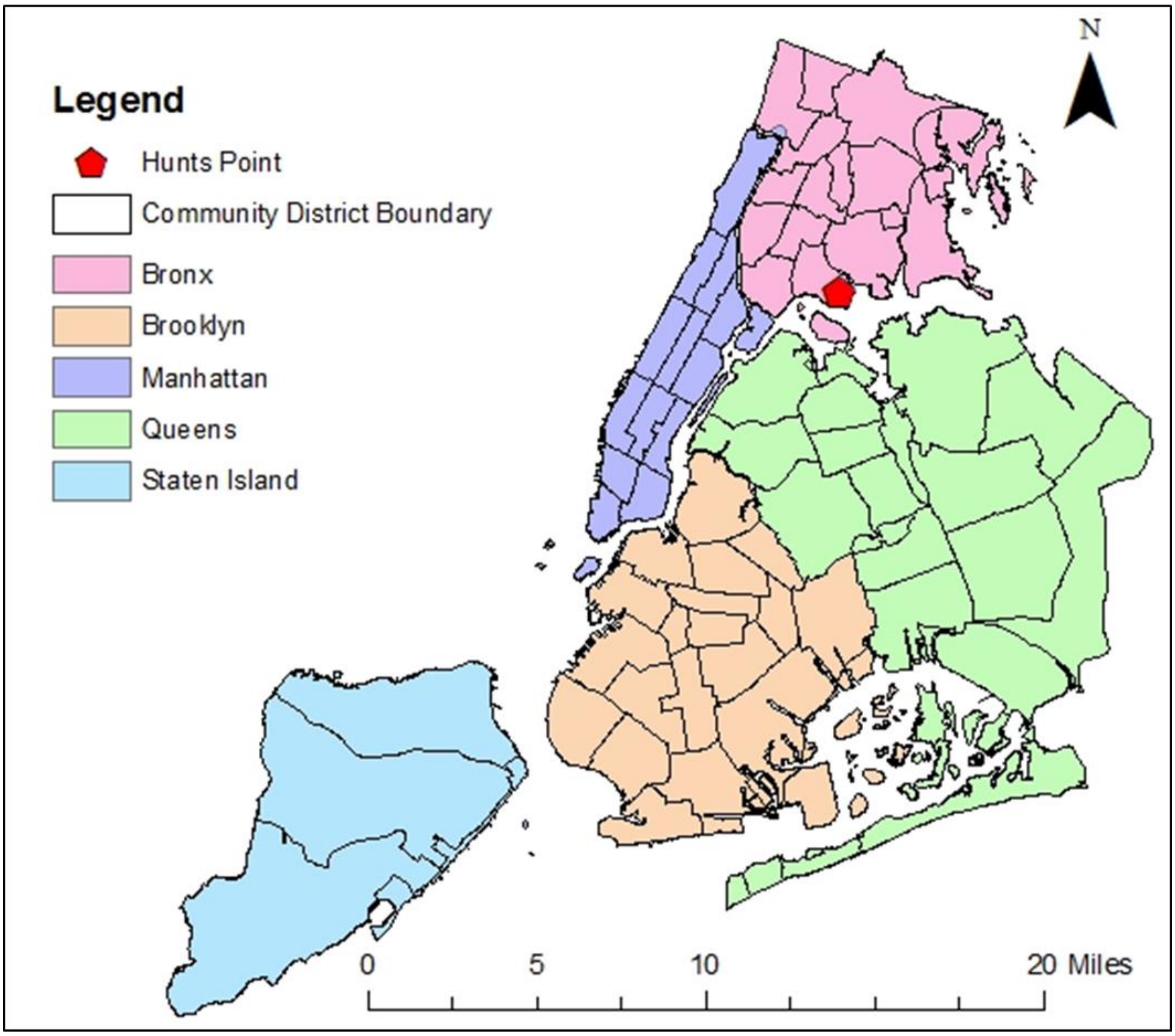

Figure 6.2: Map of the five boroughs of New York City including community district boundaries

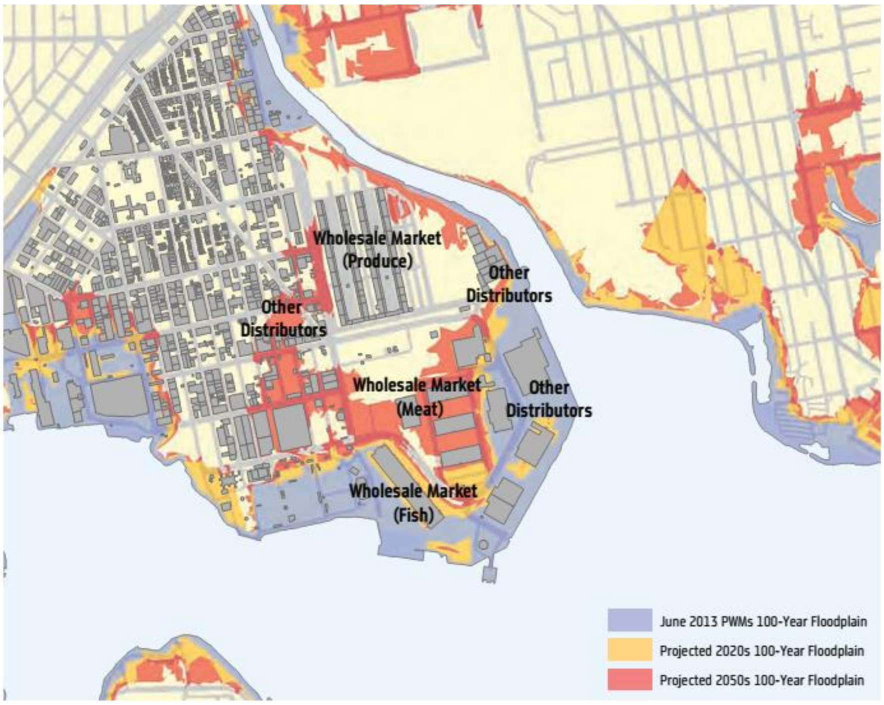

Figure 6.3: Hunts Point vulnerability to flooding (from NYC, 2013)

Additional model elements for oil and distribution were created, allowing simulation of the supply of fuel for delivery vehicles throughout the study area. Table 6.2 shows the total supply produced by each sector. This relates to the total number of sites that required each input, derived from Table 6.1.

Table 6.2: Total output per sector

Oil	Distribution	Wholesale	Retail	Households
1	77	71	71	0

The difference in the implementation of the model compared to Chapter 5 was the structure and formatting of the input data. Separate output CSVs were generated by sector, to facilitate analysis of different model simulations. An examination of various newspaper articles revealed that there were two to three days' worth of food available within New York City (Dietrich, 2012), therefore three days was set as an appropriate level of food reserve within wholesale, retail and households. In addition, *JIT* approach to food supply management was assumed due to its perishable nature.

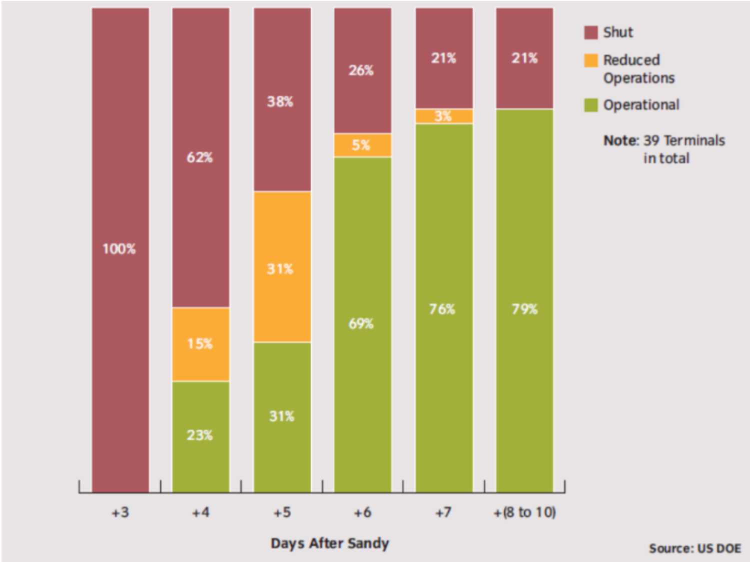

Figure 6.4: New York Metropolitan Area fuel terminals operational status after Hurricane Sandy (NYC, 2013)

The initial simulations were set up to recreate the food shortages which were reported post Hurricane Sandy, these involved:

1. Disruption of the supply of fuel to the city (Figure 6.4) as this was highlighted as the major factor that caused the disruption to food distribution post Sandy (NYC, 2013).
2. As above, plus modelling a closure of all the bridges and tunnels in the city for one day, which was similar to real life events.
3. A closure of the bridges and tunnels that connect Manhattan to the rest of the city only; for a prolonged period, all of the connections shown in Figure 6.5 were removed from the model.
4. A diversification of the supply of oil from one input to two; this was done to test highlight the effects of diversifying a supply base.

Simulations 4-7 simulated a different extreme event which completely closed the Hunts Point Wholesale Market. The simulations were:

5. JIT with three days' worth of reserves, three days was chosen as this was the number of days' worth of food reserves that was available post Sandy (Dietrich, 2012).
6. Rationing of supply with JIT and three days' reserve, modifying JIT to increase the robustness.
7. As 5-6, plus a more even share of food distribution between the five hubs in NYC.

The location of Hunts Point in the coastal floodplain, and the proportion of food resource that passes through it, makes it particularly important from a flood risk management perspective.

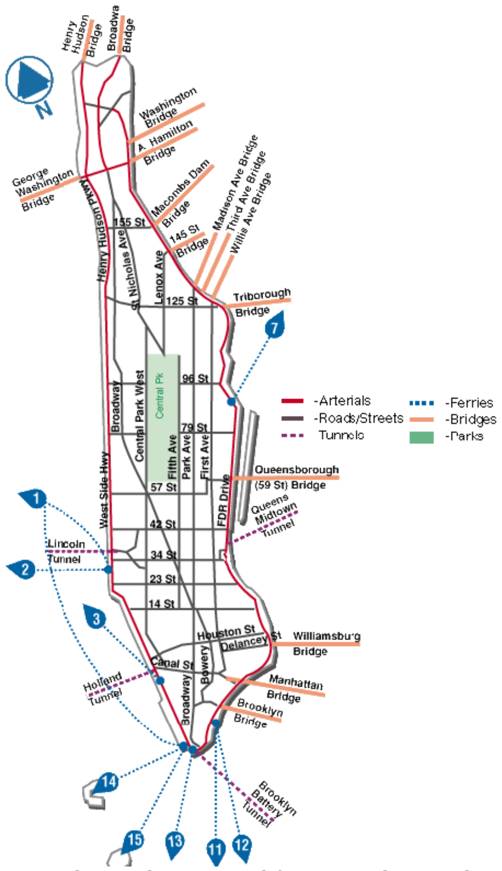

Figure 6.5: Crossing points to and from Manhattan (ParkIt, 2010)

The final three simulations focused on a hypothetical flood which completely closed the Hunts Point Wholesale Market. The simulations were: JIT with three days' worth of reserves; rationing of supply with JIT and three days' worth of reserves; and as the second scenario, but with an understanding of how long the disruption would last, meaning that reserve could be shared out over this time. Hunts Point was chosen as not only does 60% of New York City's food pass through its markets, but also as its vulnerability to storm surges is set to increase (NYC, 2013) (Figure 6.3).

Finally, Figure 6.6 shows the road network of New York City; in a similar way to the Shetland Island case study in Chapter Five it was simplified, meaning that the community districts were counted as nodes and the road network as the links between these nodes. It was assumed that the closure of bridges would be the only road infrastructure failure that could cause separate sub-networks to be created.

This simplification took place as the road infrastructure network is very resilient, with many different routes available. This being said, the bridges between islands provide a weakness within the network, which is investigated in Section 6.3.1, although ferries and subway tunnels provide alternatives if bridges are closed for prolonged periods of time.

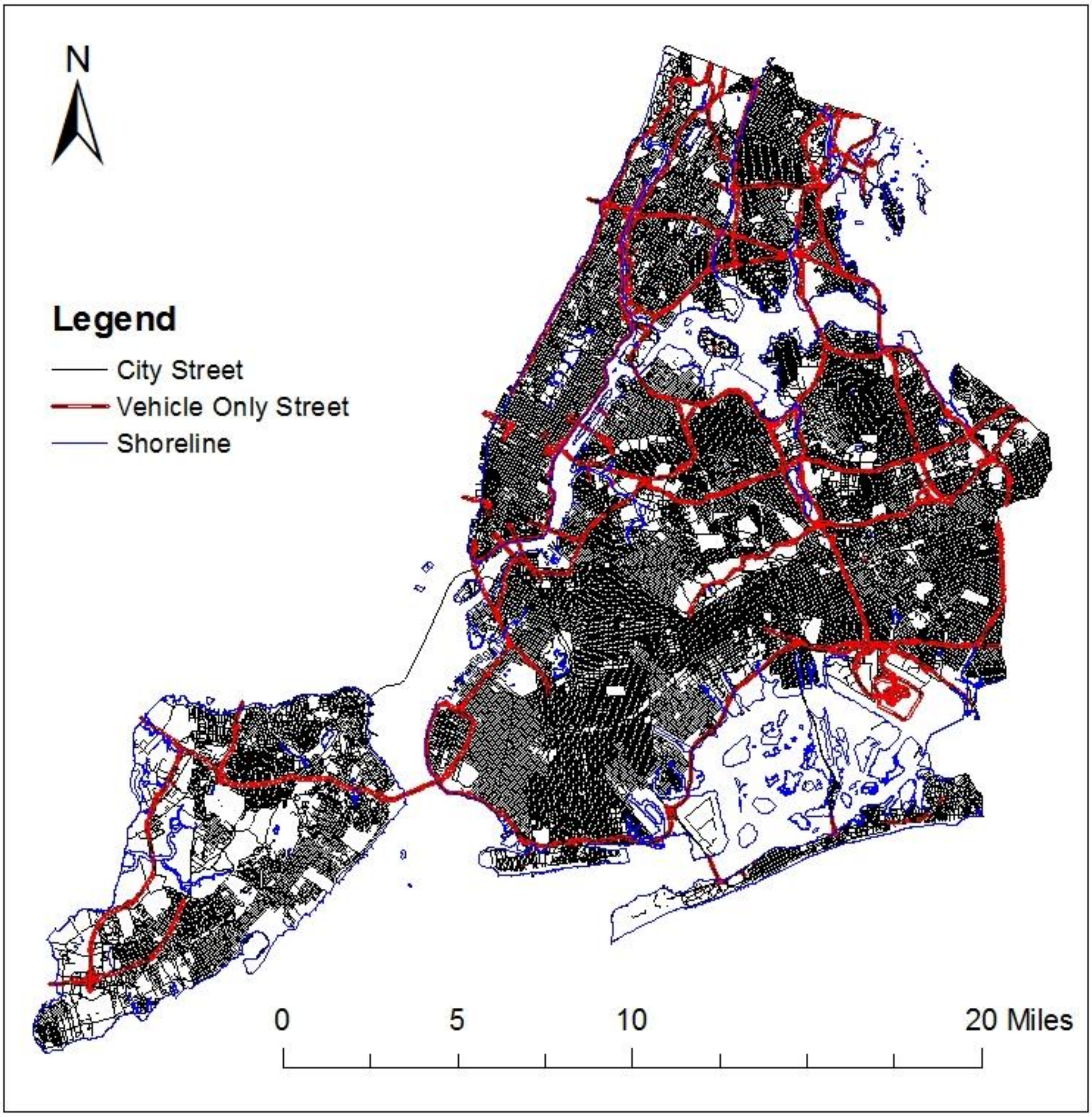

Figure 6.6: Road network in New York City.

Similarly to the previous chapter, an identifier has been generated for different scenarios. For example, NY01FD refers to the basic food distribution scenarios, 02 refers to scenarios which test diversified supply, HP is for the Hunt's Point Scenarios and MH for those based in Manhattan.

6.2 Model parameters

Information from ‘grey literature’ such as news articles and blogs was required to set up this analysis. There are $criticisms of grey literature, including lack of peer review and unclear information provenance (McAuley *et al.*, 2000), and so such sources were only used when others could not be located. Background information from the aforementioned sources is outlined in Table 6.3, which shows the variable parameters of the model and the sources of information that dictated how each parameter was set.

Table 6.3: Model parameters for NYC case study

Parameter	Value (days)	Main source	Comment
Length of disruption	9	NYC, 2013	9 days of disruption to fuel distribution
Level of disruption	100%	NYC, 2013	Complete disruption
Delivery Time	1	Assumption	Reasonable due to NYC’s size
Amount of reserve	3	Dietrich, 2012	Food to last 2-3 days (grey literature)
Infrastructure to fail	1	FEMA, 2014	Bridges and tunnels
Hunts Point example only			
District disrupted		NYC, 2013	Highlighted the vulnerability of area
Level of disruption	100%	Assumption	All output would be affected by a flood

Recovery was not included in this case study, as data relating to the restocking of food to Hunts Point and other distribution warehouses is not available. Any investigation into this would, therefore, be based entirely on assumptions.

6.3 Disruption to New York City’s food distribution (FD)

The initial simulations modelled in this case study were used to recreate the effects of Hurricane Sandy and test the effects of diversifying the oil supply. The model assumed that all fuel came into the city from one external node. As shown in the

Shetland Island case study (Chapter 5) resilience can be increased by widening the supply base of an input. Therefore, the model was run firstly using the same data as above for the 12 standard simulations (Figure 6.7) and secondly the same but with oil being supplied from two external nodes (Figure 6.8). In both cases the results show the percentage of usual output for the whole system.

In figure 6.7, eight out of the 12 simulations lead to a full collapse in the system, as the movement of food around New York City is prevented by the unavailability of fuel. The bulk delivery simulation combined with rationing of supply was the most robust, as this resulted in the biggest lag between the disruption and the supply of oil running out (NY01FD_PS/B). Rationing of supply slightly slowed the collapse of the food supply network. The steps in the results show the lag in supply caused by the three days' worth of reserve at each of the stages.

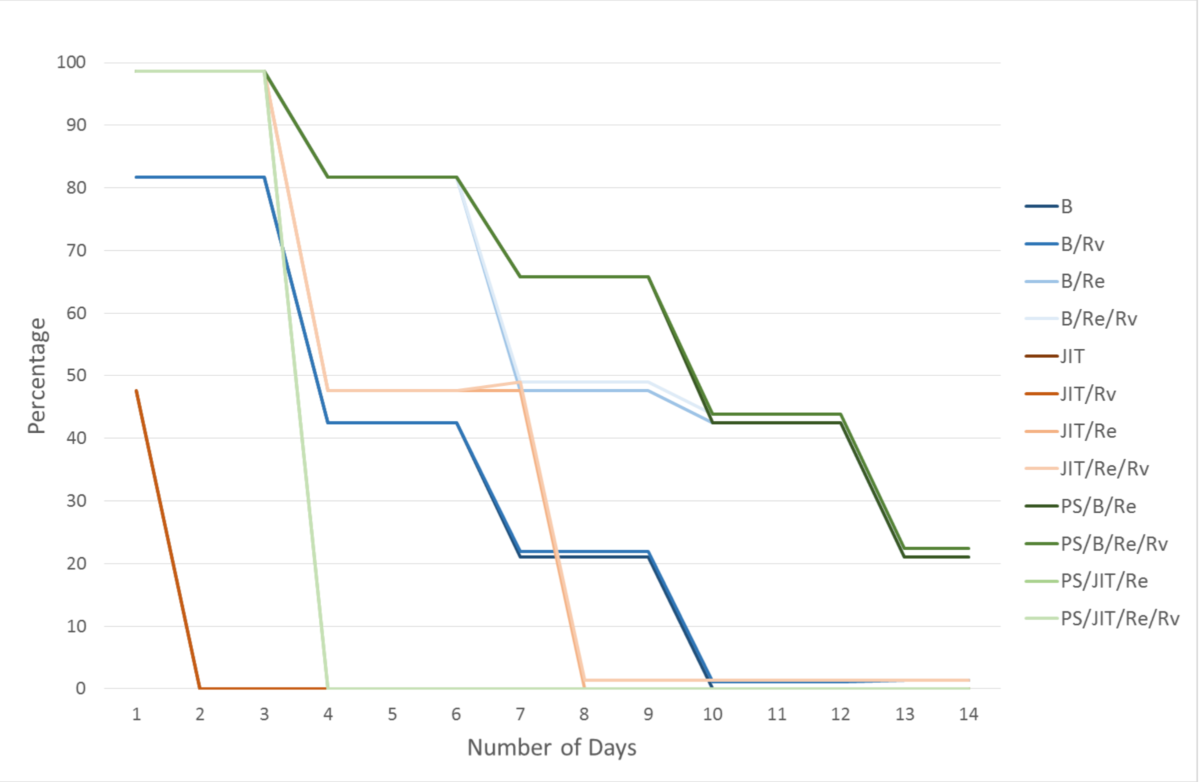

Figure 6.7: Graph showing the results for 100% disruption to the fuel supplied to New York City as a percentage of normal, baseline, output (NY01FD)

The addition of a second external supply of fuel to the supply network (Figure 6.8) enabled 50% of usual demands to be met, increasing the overall resilience of the simulations. This aim of this scenario was provide a hypothetical example of what would happen if a more robust fuel supply network existed (Figure 6.4). NY02FD_JIT performed the worst, but still resulted in almost 50% of normal food supply being available within the city. Bulk deliveries added further resilience to the network by rationing supply.

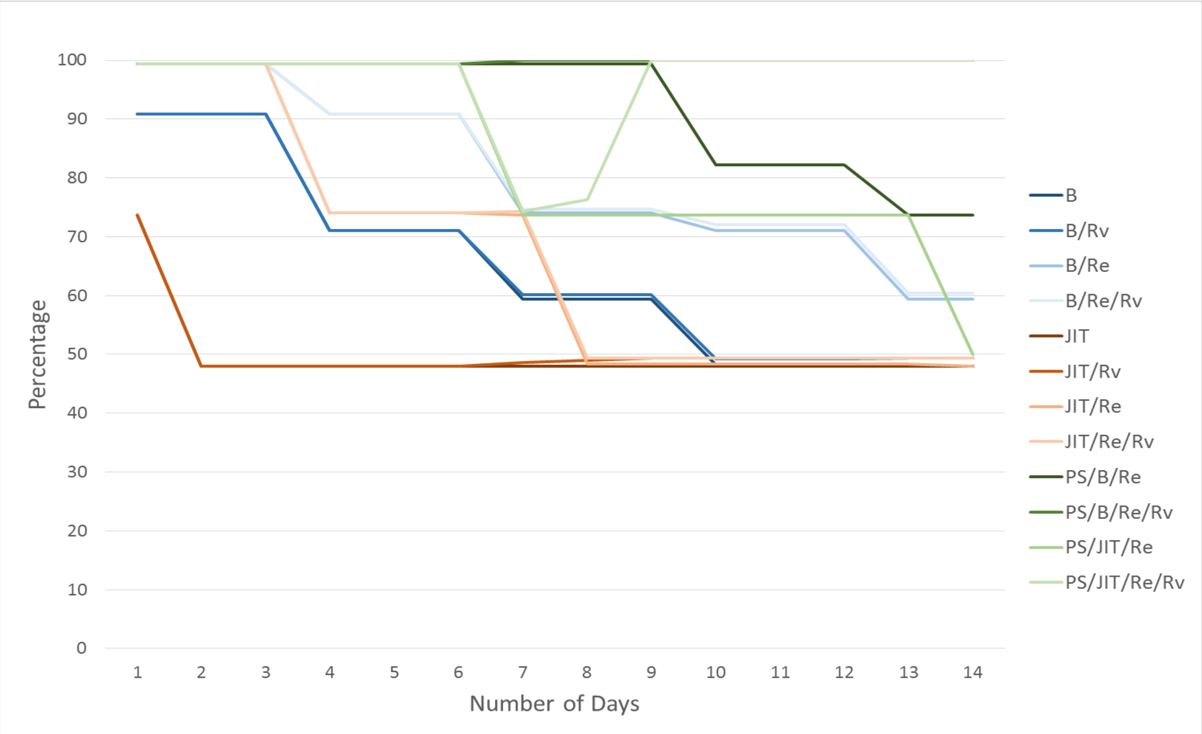

Figure 6.8: Graph showing the results for disruption to the fuel supplied to New York City as a percentage of normal, baseline, output from a diversified supply base (NY02FD).

These results reinforce the reoccurring themes outlined throughout this thesis. Firstly, pure *JIT* reduces the level of robustness and resilience in a resource network. Secondly, bulk deliveries and rationing of supply provide increased levels of resilience. Finally, a more diverse supply base increases the level of robustness. A modification of *JIT* once again provides a robust outcome, which may overcome some problems such as storage space. The percentage output for simulation *PS/JIT/Re/Rv* remained above 50% for two weeks, whereas the unmodified JIT dropped to 50% of output in two days.

The next stage of this case study solely considers the availability of food during Hurricane Sandy (NY02FD). In order to do this, *JIT* is chosen for the bases, as it is assumed that food deliveries are mainly carried out in this manner due to the perishable nature of the product and the premium cost of onsite storage, resulting from the scarcity of space within New York City.

The model was run again for the whole city of New York. Two further scenarios were tested: the first assumed that the ability to distribute produce was hampered by a lack of fuel, and the second added the closure of bridges and tunnels throughout New York for one day. These model simulations were chosen to recreate the events post Sandy.

The results for both showed no difference: this was because the disruption to bridge infrastructure was for a shorter period of time than that of the distribution to fuel. This fits with what was found during Sandy: initially it was the closure of bridges and tunnels that caused disruption to the movement of food to and from Manhattan and other islands, but the main problem after the event was the inability to refuel delivery vehicles, meaning that produce could not get from the wholesalers to the retail outlets (DeAngelis, 2012; Wilkie *et al.*, 2012; NYC, 2013).

Figure 6.9 shows the results for the diversified fuel supply (NY02FD), which assumed two external inputs to the system instead of one. This presented a much greater robustness in terms of the distribution of fuel. 50% of fuel supply was making it into the city for these scenarios, as well as approximately 50% of the food getting to the retail stores and therefore to the households. This once again highlighting the increased robustness resulting from having a wider supply base.

There is a three-day lag within the model that shows food within households running out three days later than in retail outlets. This assumes that no rationing takes place to extend how long the food lasts for. If 50% of the oil is not disrupted, then 50% of deliveries will still be able to take place, lowering the affects of the disruption. This shows the importance of getting supply from more than one place to increase the robustness of such networks.

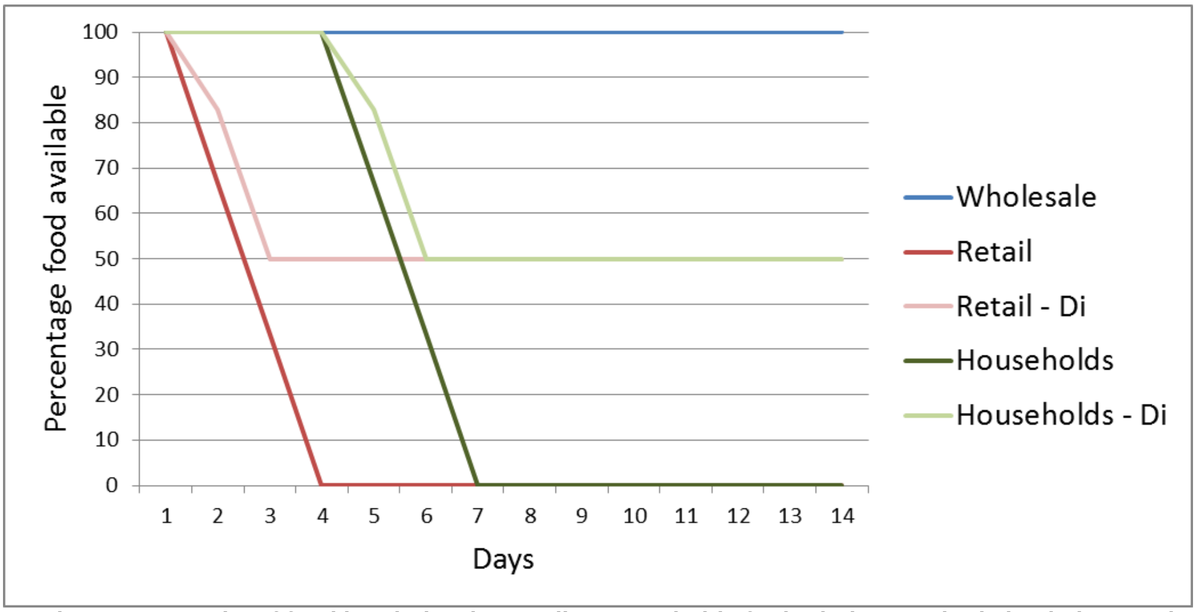

Figure 6.9: Stocks of food in Wholesale, Retail & Households for both the standard simulations and simulations with a diversified (Di) supply of oil (NY01FD & NY02FD).

During the disruption throughout the days following Sandy, the Red Cross, FEMA and other organisations handed out ready-to-eat meals and snacks to those who were short of food. This began three days after Sandy, during which 2,300 donations were handed out on the first day, 25,000 by the second day and over 350,000 on the third day. This continued until the 11th day after Sandy, by which time the trend of the cumulative number of meals handed out had reached over 3.7million (throughout the whole of the affected area, as figures solely for NYC were not available) (FEMA, 2014).

Figure 6.10 shows a trend line based on these figures, the line shows that there is some negative correlation between the actual number of hot meals given out post Sandy and the proportion of food demand met within the modelled simulation. As the number of days goes up after disruption the number of meals handed increases, whereas the proportion of food demand met from usual sources decreases.

This, therefore, implies that the people affected may have been able to either stock up before the disruption, or ration their food consumption during the period of disruption, meaning that their reserves of food where able to last longer than would usually be the case, or a mixture of both. Without a detailed understanding of how much food was held on average by each household it is, of course, impossible to accurately model the effect of the food shortages. The model results show a worst case scenario that would take place if no corrective action (in addition to the modelled level of reserve) and changing of consumption habits had taken place.

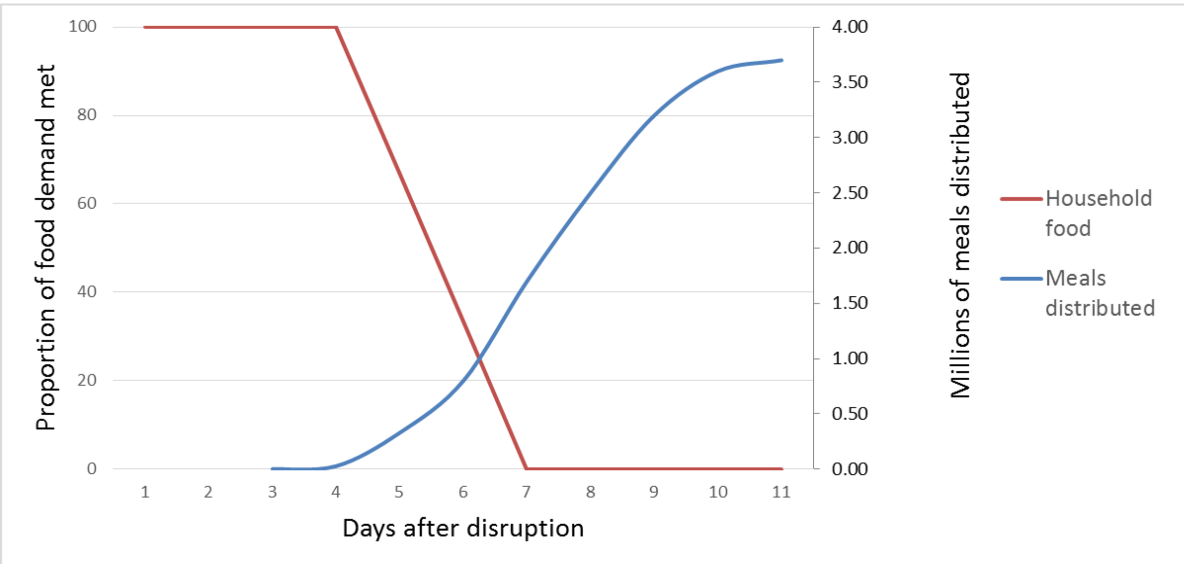

Figure 6.10: Modelled results for households with number of meals distributed (NY01FD) (FEMA, 2014)

6.3.1 Prolonged bridge closures to and from Manhattan (MH)

The next set of simulations focused on the closure of bridges and tunnels connecting Manhattan to the rest of New York; although it is very unlikely that all of the connecting routes would be lost for such a long period of time. In the modelled simulations it was nominally chosen as six days. Post Sandy itself, bridges were only closed for a relatively short period of time, reopening on the day following the storm (Figure 6.1).

The majority of food distribution in New York City in this scenario (Figure 6.11) functioned as normal, meaning that produce was able to be moved from wholesale markets to retail outlets, and finally to households, without disruption. In Manhattan, a similar drop in food levels to that of the first two modelled simulations was noticed. As there is a food distribution centre on Manhattan the speed of the disruption slowed slightly, until the stocks here were exhausted. The stepped nature of the results was caused by the household’s reserve being used after supplies were exhausted from the local distribution hub.

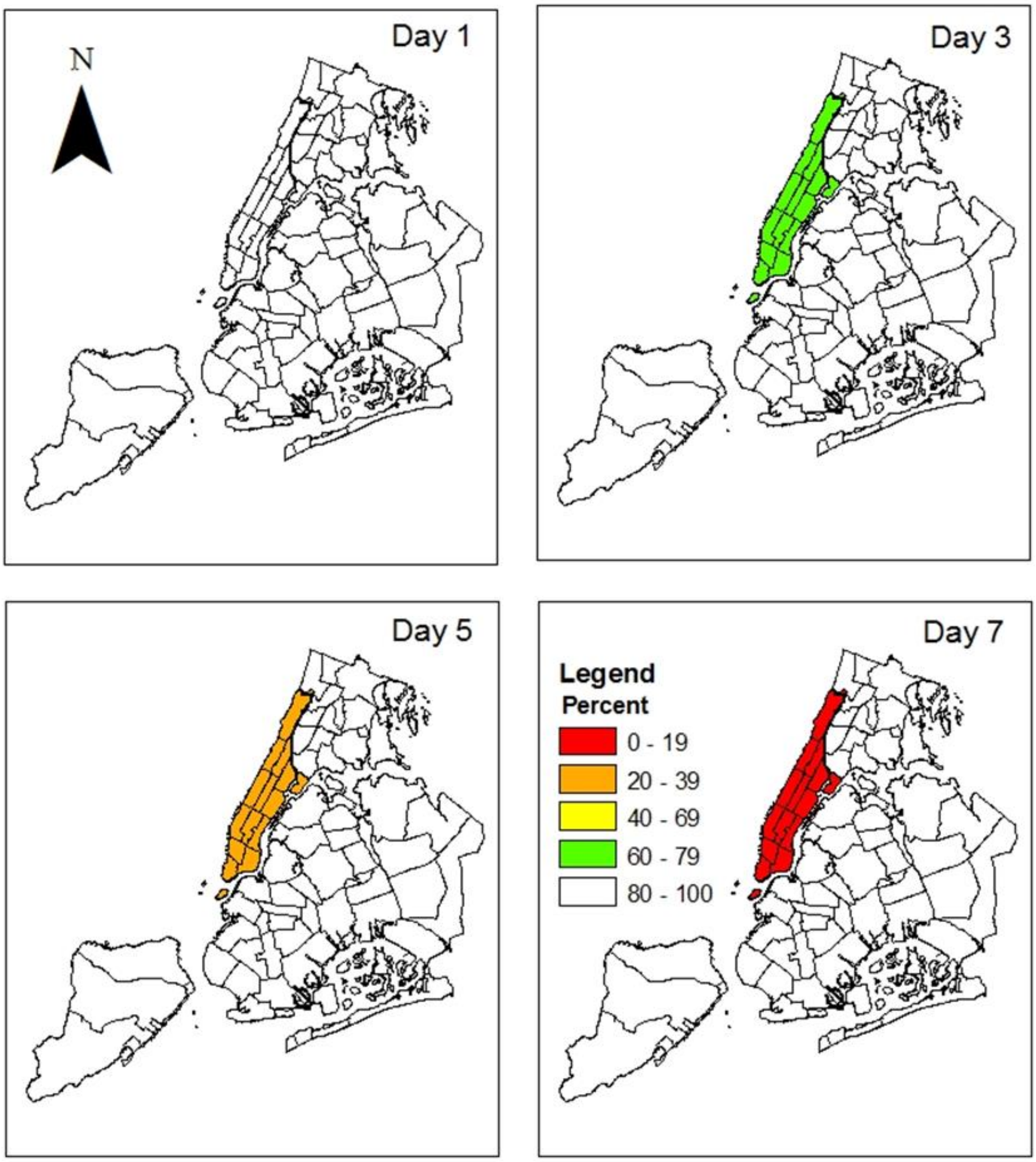

Figure 6.11: Percentage of available food supply available in each community district after the modelled prolonged bridge and tunnel closures between Manhattan and the rest of New York City (NY01MH)

The effect of the closure was to split distribution and transport networks into two sub-networks, which would act independently from one another. The larger of the two networks was left with a surplus of produce, whereas in Manhattan there was a shortfall. It could be assumed, therefore, that if such a scenario played out in the real world, corrective actions to move produce to Manhattan would take place. This could be done either by rerouting the available infrastructure or injecting supplies into the system via other means; an obvious example would be to ship produce in from the main areas of New York on the ferries.

6.4 Flooding of the Hunts Point food distribution centre (HP)

The final scenarios which make up this New York case study investigate the effects of a hypothetical storm surge flood of the Hunts Point food distribution hub, as the vulnerability of Hunts Point was highlighted by NYC (2013).

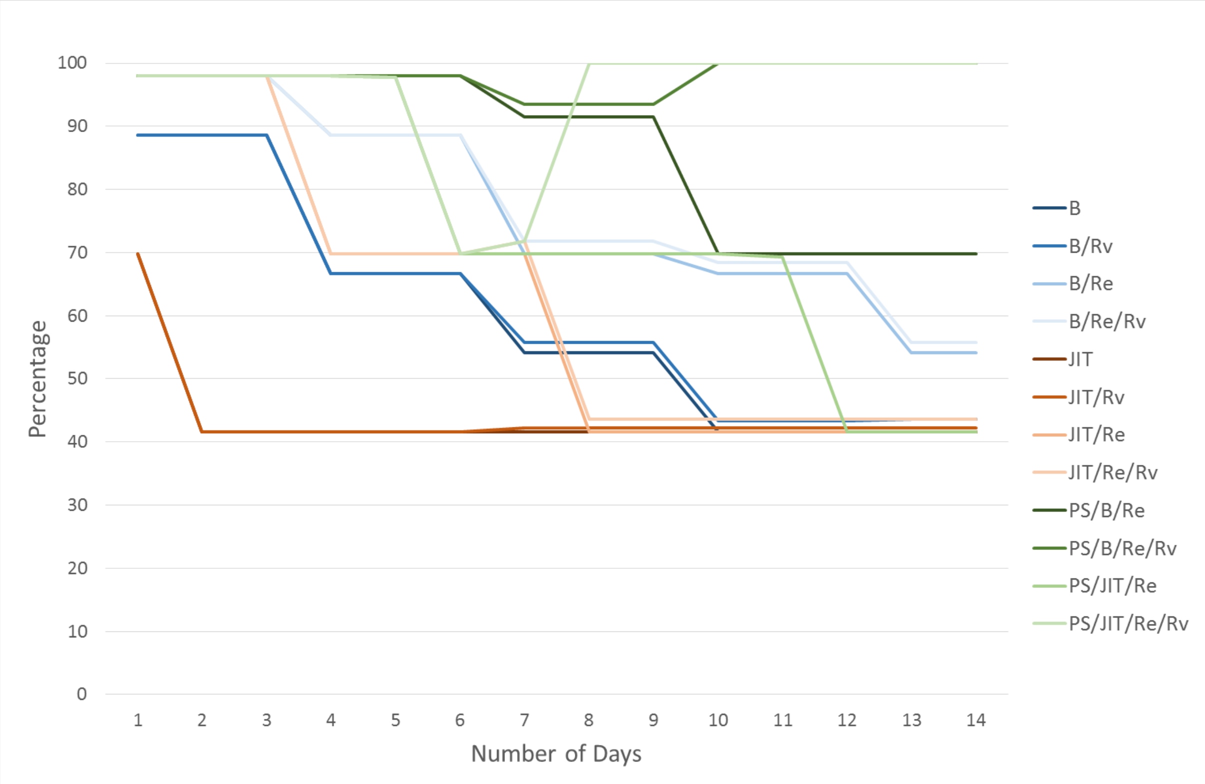

Figure 6.12: Output as a percentage of base line within the food distribution network after a flood causing output to cease at Hunts Point (NY01HP).

Figure 6.12 shows the results of the various modelled simulations, which were based on the premise that Hunts Point would not be able to input any food into the distribution network. Approximately 60% of this sector is situated at Hunts Point, it is unsurprising to see the majority of simulations dropping to an output level of food distribution of just over 40%. NY01HP_JIT and NY01HP_JIT/Re simulations are shown falling to this level the quickest (within 2-6 days depending on whether reserve was modelled or not).

A bulkier delivery slows the cascading of failure noticed after disruption. When no reserve is modelled the lowest point is reached on the 10th day after disruption; with reserve total output is still approximately 55% 14 days after disruption. Finally, rationing gives further stability, and also allows for recovery in the two simulations in which reserve is also available. Once again *PS/JIT/Re/Rv* is shown to offer a viable approach to resource management, as it shows a much greater lag between initial disruption and output being affected; for this simulation it was 4 days longer than the pure *JIT* approach.

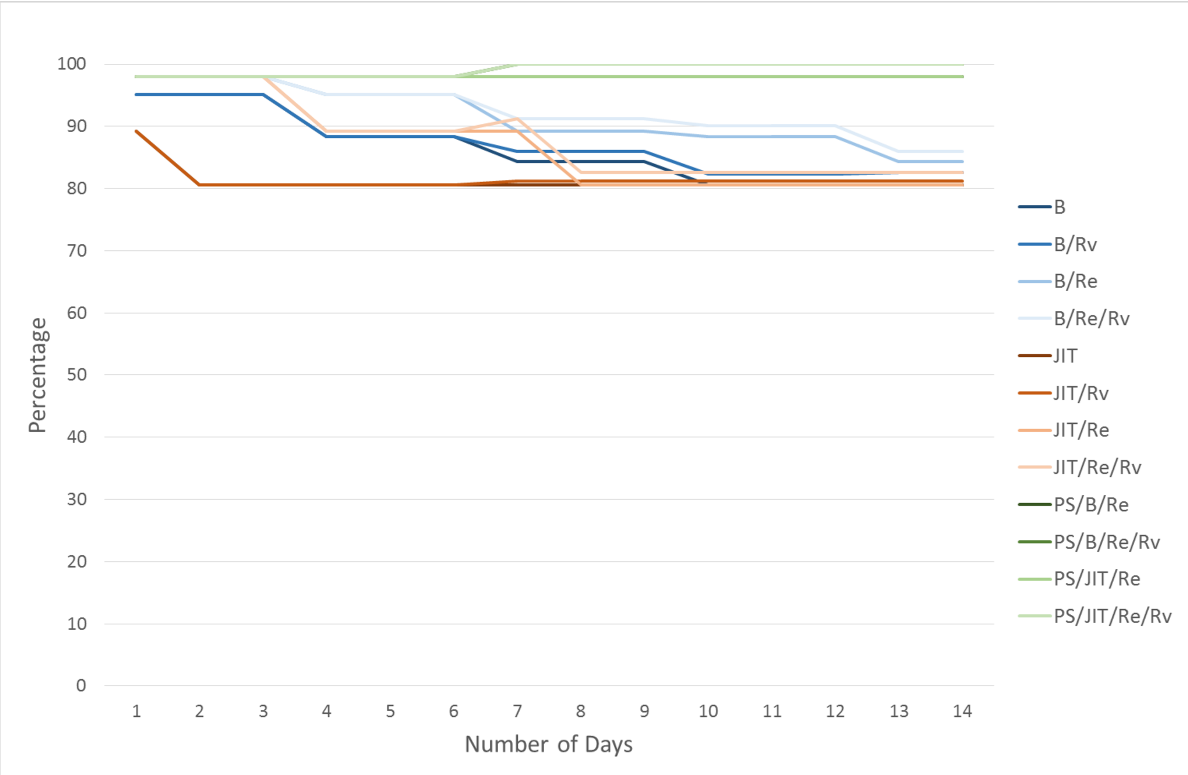

Figure 6.13: Output as a percentage of base line within the food distribution network after a flood causing output to cease at Hunts Point, but with the dominance of Hunts Point reduced (NY02HP).

Figure 6.13 shows the same simulations but with food distribution spread evenly between the five hubs of New York City. Consequently, a disruption to Hunts Point means that the overall output of food distribution is over 80% in all of the shown simulations. Again, these results follow the same basic pattern outlined above, but this time show a much higher level of resilience to such a flooding event. This is because of the wider supply base, which supports the ideas outlined in both Chapter 2 and Chapter 5, i.e. getting inputs from more than one supplier increases the level of resilience within a network.

Within the rest of the chapter Hunts Point and disruption of food distribution from this wholesale depot becomes the focus. These simulations sections highlight the potential policy relevance of this model. It took into account a known issue and provided an estimation of the effects such a disruption would have on food distribution throughout New York City.

This model could assist policy makers in making informed decisions when developing ways to reduce risks, with a key recommendation being to reduce the importance of Hunts Point within New York's food distribution network by increasing redundancy within the system.

6.5 Summary

This, second case study, highlights the versatility of the model, and also provides a means to verify the resource model. The case study was carried out by modelling a small number of sectors as a tool to recreate what could happen in a real world event, even with a limited amount of data available.

After Sandy the distribution of food was hampered because the supply of diesel and petrol to New York City was disrupted. This meant that the food could not get from the wholesale markets to retail outlets, and finally to households (NYC, 2013). This same pattern was seen reproduced in these results. On top of this, a disruption to the bridges connecting to Manhattan highlighted further vulnerabilities. The final simulations showed a vulnerability to the food distribution network at Hunts Point. As this site controls more than half of the food coming into New York City, a flood in the area would have major effects. It is, therefore, important to plan for such an issue by increasing the robustness of a network to this sort of event. This could either be done through the building of physical defences to protect the site or by the system sharing output between the different hubs within the city.

The stripped down data used in this case study helps to show the importance of oil in seemingly unconnected sectors; in this case food retail. The inability to get fuel into New York City post Sandy led to the difficulties noted in moving food from wholesale markets to retail outlets. This was reflected in the results of this case study. This problem was exacerbated further when power cuts caused the perishable food to go bad, further limiting the availability of food. This was not included in the model as it treats all food as one commodity, therefore does not separate between perishable and non-perishable goods.

Table 6.4: Summary of results from disruption to oil supply and Hunts Point, for standard and diversified (Di) simulations (calculated over 14 days)

	Mean Overall Output	Mean Equilibrium Point
Oil Supply Disruption (NY01FD)	35.26%	7 days
Oil Supply Disruption (NY02FD)	74.66%	10 days
Hunts Point Disruption (NY01HP)	70.07%	10 days
Hunts Point Disruption (NY02HP)	90.75%	10 days

Table 6.4 provides summary statistics from the two comparable simulations modelled within this case study. The mean overall output is the average output for all of the different simulations of the model in each of the scenarios. In both cases, the diversification of the supply base (either by adding an extra supplier of fuel or by

sharing output equally between the five food distribution hubs) leads to much higher levers of resilience to disruption. The mean equilibrium time shows how long before the networks output stabilises after production across all of the modelled simulations. In the oil supply simulations, the addition of a second supplier is shown to slow the cascading of disruption.

The simple case study shows the ability of the model to recreate real world events. Firstly, the modification of *JIT* to include rationing and reserve is a viable solution to increase the robustness of the food distribution network, as it may be a cheaper option than having bulkier deliveries, due to the cost of storage space (this point is discussed further in the next chapter). Secondly, the importance of having more than one supplier for an input is shown as an important factor when increasing robustness. Post Sandy, the distribution of fuel was the major cause of disruption to the food distribution in New York, so having secondary suppliers, or redundant suppliers, would have increased the robustness of this part of the network. This was highlighted by the results of simulating 50% of oil supply coming from an alternative, unaffected sources, which increased the robustness by 50%.

7 Discussion

This Chapter draws together and discusses the knowledge gained throughout the preceding chapters. A number of cross-cutting issues have been identified, and are discussed in Section 7.1 onwards:

1. Resource management strategies
2. Economic implications
3. Practical challenges of resource management
4. Learning post extreme event
5. Governance issues
6. Scaleability and transferability
7. Validation and uncertainties

7.1 Resource management strategies

The model developed, and applied, in previous chapters of this thesis has been tested against a number of resource management strategies and considered a number of post-disruption recovery options in order to both understand and enhance resilience. The results from the two case studies show that just-in-time (*JIT*) approach to resource management reduces system resilience. This conclusion was also backed-up by the literature, which identified *JIT* as a contributing factor to cascading failure of resource movements in all of the major examples described in Section 2.4.

7.1.1 Minimise Just-in-Time resource management

In all of the systems modelled, a pure *JIT* approach inhibited the levels of robustness and resilience. This was seen by the small number of days after the initial disruptive event before the sites of production and the economy as a whole were affected (these metrics were outlined in Section 4.5). Across all of the *JIT* simulations within the Shetland case study, overall output was less than 10%. This showed very low robustness to disruption. When recovery was also modelled, overall output did not change, and no recovery took place. This shows the resilience of these techniques to be very low, and therefore an ineffective way to respond to disruptive events.

The results of the model were backed up by reviews of observed events which took place after the Great East Japan Earthquake, which occurred on the 11th March 2011, From the 14th to the 26th March Toyota had to close all of its domestic plants, and on the 15th it also reduced all production in overseas plants. It was announced that it would take until June for Toyota's production rates to return to pre-earthquake levels. This disruption was caused by both a lack of parts and also a lack of information on which parts would be available when production resumed. It took Toyota a week to put together a list of 500 parts from 200 locations which would be difficult to source. While Toyota understood the availability to its first and second tier suppliers, they did not understand the complexities further down the supply chain (Matsuo, 2015).

The developed model is designed to test different scenarios, as shown throughout this study, to allow stakeholders to develop strategies which would increase the robustness and resilience of their supply chain through understanding it's complexities as well as the linkages further upstream in the supply chain. This is likely to take the approach of a balancing act between the benefits of having a lean supply chain and the levels of risk apparent to that supply chain. One way of doing this is through the modification of the *JIT* approach to include some on site stock and rationing of resources. In both the Shetland and New York case studies this was shown to provide a viable alternative to *JIT*.

Unexpected linkages became apparent within the results of the Shetland case study (Chapter 5) and disruption was amplified by problems within seemingly unconnected industries. The model therefore provides a means to investigate linkages further down the supply chain. The finer grain the data used to set up the model, the more useful it can become in investigating vulnerabilities. This is because it is important to understand not only the downstream links but also where these sites of production are located, as large scale disruptions such as a flood or earthquake can affect multiple suppliers simultaneously leading to larger disruptions and making it more difficult to mitigate such events.

7.1.2 Avoid spatial clustering of like industries

A secondary type of vulnerability was highlighted after the Chao Phraya River flooded in Central Thailand. To save on costs, clustering occurred between sites of production from within the same sector, within the industrial areas of Thailand (Chongvilaivan, 2012; Komori *et al.*, 2012).

As shown in the model, results from the Shetland Islands case study (Chapter 5) and the Hunts Point scenario (Section 6.4), if one industry (even if represented by many companies) is predominantly located in one area, the amount of disruption felt upstream in the supply chain increases as the output of the whole sector is affected. This was reinforced within the Shetland Islands case study, which showed that disruption to areas which held a high proportion of one sector's industrial output led to very rapid failure throughout the whole system. When oil production was disrupted it affected electricity production for the whole island, because of a total failure in electricity supply. This again highlighted very low levels of robustness to disruption. If more than one site provided fuel for the power station, a partial service could have been provided, avoiding complete disruption to the island's resource movement and economic activity.

It points of supply are geographically spread out, then other arrangements can be made to keep resources moving. For example, Nokia was able to source semiconductors from another location after the Albuquerque factory fire but Sony Ericsson was not, providing Nokia with a competitive edge (Latour, 2001) as a result of their more resilient supply chain.

It would be up to the individual companies to assess the level of risk is caused by getting all of an input from clustered industries. If the risk is deemed to high, then they must locate alternative supplies from outside of the same vulnerable area. It would be necessary to take into account all aspects of this to come to a sound decision. This is shown by the Lerwick Risk Analysis (Section 5.9), in which the vulnerabilities to flooding seem very high until the flood defences are taken into account and the actual levels of risk are found to be negligible.

7.1.3 Stockpiling of resources

To help build resilience and lessen the chances of supply disruption cascading through a system a “move back” towards the principles of Just-in-Case (*JIC*) production, may be beneficial. The results of this analysis show that the addition of redundancy to a system is advantageous when concerned with the effects of disruptive events. The addition of a day of reserve stock in the Shetland Island case study showed overall output for the whole study period increasing from 9% (*JIT* simulations) to 17%. Here, redundancy was added to the system through the addition of reserve stock to each of the sites of production. Matsuo (2015) highlights the need for this redundant inventory to mitigate risks, and also goes further by suggesting that redundant suppliers who could step into the breach if the usual flow of goods is disrupted should be introduced.

JIC production can be considered an opposite of *JIT,* in that it is a push system which moves on products from one stage to another, whether they are required or not (L'Abbe Wu, 1989). It also provides a slack in the production system by increasing onsite inventory (reserve), which can then be utilised if a disruption to supply occurs, therefore leading to an effective management of supply and demand uncertainties (Christopher and Peck, 2004).

This was shown within the results of both the Shetland Islands and New York City case studies. In both cases the addition of extra onsite inventory led to an increase in resilience after a disruption occurred. It provides redundancy to the system, and also allows time for the sites of production to locate alternative supplies or for the blockage in the supply chain to be rectified, therefore lessening the effect of the event. The main disadvantage of this approach is the economic implications, discussed in Section 7.2, as these could prevent this option from being economically viable.

7.1.4 Bulk deliveries

One of the major disadvantages of *JIT* is the reliance on suppliers to deliver their product on time, and this was shown to be a recurring issue throughout the case studies outlined in Section 2.4. In all cases a *JIT* production system was disrupted by an extreme event that led to a cascading of failure throughout either the local, regional, or global economy. The results of the Shetland Island case study highlight the vulnerabilities caused by this approach (Section 5.3).

The analysis trialled an approach for supplies to be delivered in bulk and at set intervals. This increased the level of resilience apparent within a local economy by lengthening the lag between the disruption occurring and the production at a given site being affected by on average four days when adding reserve to the pure *JIT* and bulk simulations (enough reserve to cover one day of no inputs). The ability to increase the lag in supply loss after an extreme event is central to creating resilience, as it will provide time to take corrective action, and therefore lower the impact of disruptive events

The number of days between disruption and its effects being noticed by the site of production is one of the key resilience metrics used within this study. Section 5.3 shows that in the Shetland case study, bulky delivery strategies outperformed *JIT* strategies, with overall output closer to 50% across the whole case study. With the addition of one day of reserve stock this went up to above 98%. This was reinforced by the mean production metric showing the usefulness of building redundancy when developing resilience within supply chains (Carvalho and Cruz-Machado, 2011).

Within these scenarios, adding the recovery element of the model showed a cleared improvement and a bounce back towards the original output levels across the modelled economy of the Shetland Islands. This showed that it was a very resilient approach, even before improving this further by adding a rationing of resources across the network.

7.1.5 Modification of JIT

A reoccurring theme throughout this thesis is the realisation that a modification to the *JIT* approach can at times produce both very robust, and very resilient results. The addition of some reserve stock, as well as the rationing of supplies after a disruptive event is a viable alternative to the points outlined in 7.1.3 and 7.1.4. Such an approach could circumnavigate some of the economic and practical challenges outlined in Sections 7.2 and 7.3.

Although it must be noted that this approach did not perform well across the board, as shown within the very wide range of results in Figure 5.2 in chapter 4. It shows percentage of output ranged from 38% - 100% depending on the ward where disruption occurs. This compares very favourably with the results from the pure *JIT* which showed output all results under 20%. The modification of *JIT* with reserve and rationing can be seen as an easy uptake option to increase the resilience, as with the recovery model included output was at around 99% for all simulations using this approach. Making it one of the more resilient methods for dealing with disruption and with some coordination between sites of production it could provide increased resilience and robustness throughout a supply chain network.

7.1.6 Flood risk Analysis and management

As part of this study a risk analysis technique was developed; as described in Section 4.5. This provides a consistent metric, which accounts for the magnitude, frequency and impacts of the flood events. The technique can be applied to different locations and management strategies. Such an approach is very important as it allows stakeholders to understand the level of vulnerability within their system through taking into account all downstream and upstream activities that are related to their own activity. As highlighted in Chapter 3, such interdependencies are often ignored, which leads to an underestimation of the level of risk inherent within a system (Jonkman and Dawson, 2012).

Risk analysis is about providing a rational, consistent approach that accounts for the impact and likelihood of disruption. Typically, such an approach is used to identify direct damages, but in this case it has been extended to take into account resources and indirect losses. The approach outlined within this study provides an ability to identify hazards, highlight vulnerabilities, assess how significant the level of risk is, and provide an opportunity to adapt the system to reduce these risks.

The developed framework is entirely generic and would, therefore, work with any hazard, with differing magnitudes. It could also integrate risk to employment, as employment can be treated as an input to a site of production, and therefore part of the supply chain.

The Lerwick Risk Analysis (Section 5.9) highlighted the effectiveness of building infrastructural resilience to a specific type of risk, so for example sea defences protect many parts of the coast in and around Lerwick. The results of the Lerwick risk analysis showed that the risk of resource disruption is reduced by two orders of magnitude by the presence of flood defences.

The secondary case study focused on food distribution in New York post Hurricane Sandy (Chapter 6). In this study, an extreme surge that inundated Hunts Point food distribution hub was considered (Section 6.4). This was chosen as NYC (2013) reported that this site is vulnerable to flooding, and that the risk of flooding may increase in the future. The report also set out proposals for an integrated flood protection system for the area of Hunts Point, which would incorporate aspects of both natural and engineered flood defences capable of withstanding a one-in-200-year storm surge event.

7.2 Economic Implications

It is important to consider the financial implications of these suggestions, which have not formed part of this model. A move away from *JIT* would be likely to lead to additional costs, such as, an increased need for extra warehouse space for reserve stock. For example: in 2006 the average cost of land in New York was $366.08 per square foot (Haughwout *et al*., 2008), which suggests a significant rise in overheads if retails wish to increase their square footage to allow for further reserve and/or a move to bulkier deliveries. The actual cost would be dependent on the levels of reserve to be housed, the nature of the business and the size of the product to be stored. It would also be dependent on the shelf life of the required inputs. This may be prohibitive to many enterprises in terms of cost, but also availability of space.

The second major cost would come from encouraging companies from the same sectors to no longer cluster together. Clustering enhances the economic competitiveness of the industries as they produce greater levels of economic growth, more jobs and better paid jobs, increased levels entrepreneurial activity, and higher levels of intellectual property (Chatterji *et al.*, 2013). Although as noted during the modelling process, this can cause problems within supply chains. If companies were encouraged to base themselves in different locations, they would lose out on the advantages of clustering in the same area as like businesses and transport costs would also increase.

Companies and organisations should analyse the costs associated with making their supply chains more resilient against the perceived risk of serious disruption taking place. If the results of their risk assessment show that the costs associated with disruption are low, no change may be needed. For large interconnected systems it may be beneficial for down and upstream suppliers to work together to add the required redundancy to the system. This approach is made more difficult as, for example, in the United Kingdom the Treasury Green Book (HM Treasury, 2014) makes only limited consideration of resilience. This creates a systemic problem as it is difficult to provide a business case for resilience.

These economic implications are external to the model and would be highlighted as part of a cost benefit analysis. Such an analysis would benefit from the results of a model like this, which shows the risk to production at individual production sites as well as providing a range of levels to which production could drop, based on the type of resource management strategy employed.

7.3 Practical challenges of resource management

Practical issues exist around increasing reserve and having bulkier deliveries, as for example, some products require large amounts of storage space and some have a short shelf life. Bulky deliveries of certain products, such as chemicals, can also lead to increased safety concerns, as if an accident were to occur, spillages, for example, may be larger and therefore more difficult to clean up / contain (Trowbridge, 2006).

When focusing on the bulkier deliveries, practical issues may also reduce this approach to increase resilience, as the effectiveness of this approach depends on: the size of the delivery (how long the supplies should last for), the frequency of the delivery; and when the delivery takes place in terms of the disruption, i.e. if the delivery occurred the day before the disruption, as per the model, robustness would be higher as more stock would be on site, whereas if the delivery were due the day after the disruption robustness would be reduced, leading to a quicker cascading of failure through the network.

Another issue is caused by the scale of extreme events. The Great East Japan Earthquake in 2011 and the resulting tsunami (Section 2.7.1) affected large parts of Japan, and disrupted links within and between industries both inside Japan and internationally. Despite Japan's awareness and preparedness for such events, supply chain managers were ultimately unable to mitigate everything. The adoption of a risk based approach, which takes into account the likelihood and consequences of hazards, as well as accepting that there are certain unknowns that cannot be predicted, would force a consideration of big events and what options may exist if issues cannot be "designed out" of the supply chain.

Finally, returning to the two case studies undertaken in this research, another key practicality is where employees live, and how the ability for them to get to their place of work, or not, affects the level of resilience apparent in a supply chain. For example, if employees in Shetland were unable to get to work in Lerwick due to a disruption to the ferries (Section 5.8.1), their absence from the production site would be likely to further amplify the proliferation of resource disruption throughout this scenario.

7.4 Learning post extreme event

After Hurricane Katrina the government of New York State carried out a thorough investigation into the effects of the disaster and what future improvements could be made to increase resilience. As is highlighted in Section 2.4, learning post extreme event is necessary to increase resilience. Such learning allows for the development of an adaptive capacity that provides opportunities for change, and for resilience to be increased.

A trigger for change and learning is often the occurrence of a disaster or disruptive event, as it can be seen an opportunity to take advantage of a period of rapid reorganisation. This was certainly the case in New York, with *"A Stronger, More Resilient New York"* (NYC, 2013) being the foundation of this post Sandy. Holling, (2001) suggests that such events provide the correct conditions for experimentation and innovation to develop with the specific aim of increasing resilience. This should be used as a template by others to follow post an extreme event, to allow for resilience to be increased as well as encourage everyday life to return to an acceptable state.

7.5 Governance issues

A further source of discussion is the need to identify who is responsible for resource resilience within interconnected systems. One of the major issues post Sandy was an inability to get fuel into New York City, as refineries away from the metropolitan area had been disrupted; these were beyond the influence of the city One way the government of New York City could stop this happening again would be to invest in methods such as sea defences around refineries or, as suggested by Matsuo (2015), having redundant suppliers which are not called upon until they are required after a disruptive event.

In a supply chain such as that of Toyota, the responsibility for understanding the resilience of that supply chain is most likely shared between the manufacturer, i.e. Toyota, and the companies that supply it. For successful governance it would be important for Toyota, in this example, to understand both the down and upstream linkages, as well as to press suppliers into incorporating measures targeted at increasing robustness into their own processes.

On the Shetland Islands, governance should be shared between manufacturer and local authority, but in this case, Shetland Island Council plays an important part. This is seen through the installation and maintenance of flood defences around the Islands. Along with an understanding of resource vulnerabilities (as highlighted in Chapter 5), this would help improve resource resilience on the Shetlands.

7.6 Scaleability and transferability of the resource model

Within the two case studies the transferability of the model is shown as a benefit. The basic model was largely unchanged, the only changes being those related to the format of the data received. The same basic approach was used to analyse a small scale local economy (Shetland) and an individual sector in a much larger scale example (Hunt's Point, NYC).

Within both case studies it was found that the unmodified *JIT* approaches yielded low levels of resilience and, therefore, it would be interesting to apply this approach to a global supply chain for a large multinational corporation, such as Toyota. However, this would be hampered by both the availability of data (as it is commercially sensitive) and the processing speed of the model itself. This second issue could be mitigated slightly by simplifying the approach, if the aim of the project were solely to highlight vulnerabilities in the system.

The approach would also be transferable to small scale studies, such as an analysis of resource movements between wards in a hospital, with the aim of producing a more effective system through the identifying and locating of vulnerabilities.

7.7 Assumptions and uncertainties

Limited availability of data for this analysis causes significant uncertainties, as well as challenges for validation. The Shetland case study used data relating to the local economy as a whole, so therefore needed to be disaggregated down to lower levels of geographical output. Conversely, the data used for the New York case study was derived from qualitative statements and figures reports, newspaper articles, blogs, and government publications.

Ideally, data would be available at a site-of-production level, noting what supplies were required, where they were obtained from, and in what way limiting an input would affect the output from that site. On top of this, information regarding what product that site supplies, the availability of resources, and the delivery patterns, would also help develop a sound understanding of resource flows. This in turn could incorporate transport models to simulate this resource movement, whilst also allowing for targeted disruptions to be tested.

Another uncertainty within the modelled simulations occurred when the rationing of available resources took place. Within these simulations it was assumed that all of the components within an economy would follow the same management strategy, which would increase the network's resilience and, therefore, keep output in the economy as high as possible. To make this a reality, stakeholders would have to work together and develop integrated business continuity plans, which would come into place after a disruption. With numerous competitors utilising the same suppliers this would be very difficult if not impossible to implement, as the market would drive who gets the available resource. For example, the cost of hard drive motors drastically increased after the flooding in Thailand, which meant that computer manufacturers who were able to pay the most got the available components (Chongvilaivan, 2012; Komori *et al.*, 2012).

In some cases, rationing of supply could take place on an ad-hoc basis, but real world examples of this happening have not been found in the literature and would require a more an extensive survey. Saying this in the simplified New York case study it would be appropriate to ration food to allow for all members of a population to receive a share, and a form of rationing was shown through the distribution of meals to those who needed it most post Hurricane Sandy (NYC, 2013).

7.8 Summary

Within this chapter, issues relating to resource management strategies were discussed. This discussion led to the recommendation to reduce *JIT* resource management, by incorporating both larger bulkier deliveries and onsite stockpiling of resources. It was also recommended that spatial clustering of like-industries be avoided.

From the initial discussions, economic and practical challenges of resource management were introduced, in addition to governance issues. These included the cost of such changes, as well as the suggestion that it would be impossible to design out all vulnerabilities. The way in which affected parties learn from disruption is also discussed and linked back to information gathered during Chapter 2 of this thesis.

The discussion then moves to the model itself in terms of the scalability and transferability of the model. The validation within this chapter shows that this aim has been successfully met. The developed model has provided an approach to test interdependencies, whilst also incorporating policy tests to increase the amount of lag between disruption and when the effects are noticed. The model was informed through a development of an understanding of the wider issues relating to the disruption of supply chains; background research and an investigation of different modelling procedures was carried out by completing an extensive literature review.

The aim of this research was to develop a method for assessing the robustness of resource flows against disruption from spatial hazards. In addition, this research aimed to address recovery, leading to an understanding of the resilience of these resource flows following an extreme event. to the study centred on building robustness and resilience to disruptive events through taking advantage of a lag and between the disruption of supply, and the time when this becomes apparent. This lag should provide time for a corrective action to take place, they success of which depends on the length of the lag.

One major case study was identified (Shetland, Chapter 5), which allowed for the application of a quantitative urban resource model incorporating aspects from *I-O* and network analysis. This was supplemented by the simplified case study discussed in Chapter 6 (New York City). In both of the modelled examples, different policy tests were analysed and the implications of these discussed, including the economic implications of moving away from a *JIT* method of production. A number of case studies were also discussed within the literature review (Chapter 2), albeit in much less detail.

The move to a more *JIC* approach through an increase of reserves is an underlying recommendation to answer the research question set out at the start of this thesis: how can the resilience to disruption of resource flows be increased within an interdependent network? Another viable approach which increases robustness by reducing the impact of disruptive events, is to modify *JIT* strategies by including some onsite reserve stock, to ration resources after a disruption. This modified approach showed very high levels of resilience once recovery was modelled and, therefore, could be the preferable option when taking into account the other factors, such as the economic implications discussed in this chapter.

8 Conclusion

8.1 Introduction

In this final chapter, the aims and objectives of this research are revisited. Conclusions are drawn from the methodological approach and the two r case studies. Additionally, the theoretical and policy implications of the work are considered, before making recommendations for industry and policy-makers, and identifying future research priorities.

8.2 Revisiting the aims and objectives

The aim of this work, set out in Chapter 1, has been to identify strategies to improve the resilience of urban and regional units to resource flow disruption that is caused by extreme events. This has been achieved by developing and applying a systems approach, in order to model the resource and infrastructure interdependencies within regions. The impact of events, such as flooding, on these resource flows is assessed and used to identify resource management strategies that are more robust to disruptions. Finally, recovery strategies are considered to understand how the system can be made more resilient. To meet this aim, a number of objectives were set out, how the thesis has met each of these objectives is considered in Sections 8.2.1 to 8.2.6 below.

8.2.1 Understand the issues relating to the disruption of supply chains and investigate different modelling procedures through extensive literature review.

Resource movements have been disrupted by flood events, at a range of scales. These resources, which include water, food, materials and other goods, are necessities for the wellbeing of both individuals and communities. Growing infrastructural and supply chain interdependencies pose significant challenges for those wishing to transport resources, and flood risk managers aiming to reduce disruption to resource movements. A huge number of resources are relied upon every day by individuals and communities in the modern world. While basic resources comprise water and food, many other goods are also to be necessities. One of the main impacts of disasters, such as flooding, is the disruption of resource movement, and growing infrastructural and supply chain interdependencies are increasing the challenges faced by flood risk managers attempting to lessen these impacts.

When reviewing the background literature (Chapter 2) it was found that work on resilience is affected by having no common definition and little understanding of where it fits with other approaches. It was also noted that the slimming down of supply chains removes both the robustness and redundancy from systems, making them more susceptible to disruption from catastrophic events. In addition, the discussed examples showed a need for an understanding of the supply chain linkages to be developed to allow for systems to become more resilient to disruptive events.

Within the methodological literature review, appropriate techniques for the development of the resource model were identified. From this review, certain aspects from three different methodological approaches were identified as useful for a resource model. The first of these was the utilisation of input-output (*I*-O) tables and the calculation of direct and indirect costs, to inform the supply chain links between different sectors. Secondly, elements from network analysis were added to the model to assess the infrastructure networks. The final addition to the model was a risk assessment based upon the vulnerability to different magnitudes of flood events.

8.2.2 Develop a methodology for spatial disaggregation of resource supply and quantities and locations of demand.

A new approach to the disaggregation of *I-O* data is set out in Section 5.2.2. It utilises Business Register and Employment Survey (*BRES*) data to estimate the industrial output of a single census ward based on the number of employees per sector in that ward, and took inspiration from work carried out by Hallegatte, (2012), Li *et al.* (2009) and Stimson *et al.* (2012).

This approach allowed for a disruptive event to be modelled spatially, and provided the basis for the two case studies (Chapters 5 and 6). If the data had been available at a finer grain (individual sites) it could have allowed for more detailed network analysis (Section 3.5.2), especially regarding the role of resilience measures.

Major criticisms of *I-O* modelling were highlighted in Chapter 3. The first of these was their lack of flexibility. For example, there is no option within *I-O* models for a producer to source a supply from an alternative source if there is a disruption to their usual source. The model outlined in this research addresses this through spatially disaggregating the *I-O*, giving numerous sites of production for each sector and simulating the effects of spatial hazards.

The incorporation of both backward ripple effects was also important within the model to address issues with other modelling approaches which linked demanding sites to just one supplier (Hallegatte, 2013). This provides a truer picture of an economy as it allows for alternative supplies to be sought wherever available. It occurs when a site cannot produce their product, and they subsequently lower their demands on their suppliers, freeing up supply for other sites.

As *I-O* data and modelling track the interactions at an economy wide level (Leontief, 1970; Leontief, 1986; Hallegatte, 2012) they do not necessarily take into account a spatial element. This is once again addressed by the disaggregation of *I-O* tables to a lower geographic level. In this case it was done to ward level, but if employment statistics had been available at a site of production level it would also have been possible to do this.

Within the literature about resilience (Section 2.2) it was highlighted that it was important to understand who is resilient to what and for how long they are resilient

(Gibbs, 2009). The model allows for different sorts of hazard to be tested; for example, it tested resilience to both a lowering of output in individual wards during the Shetland Case study, and to disruption to the infrastructure that moved these resources around. It also provided an idea of how long sites of production could function after a disruptive event.

8.2.3 Develop a quantitative, spatial, resource flow model that dynamically links spatially disaggregated information on supply and demand with the infrastructure networks that mediate their flows.

The methodological literature review (Chapter 3) investigated how other studies had approached the problem set out in the Chapter 1. From this review a hybrid approach was put forward. This took the use of *I-O* tables and the calculation of direct and indirect costs, and used them to inform the supply chain links between different sectors. This was applied in conjunction with the technique for the disaggregation of economy wide data to ward level.

Within all of the case studies set out in Chapter 2, the amount of cascading disruption and the financial costs caused by these highlighted the need for an approach which was able to:

1) Investigate supply chain linkages;
2) Understand the importance of various supplies (Craighead et al., 2007);
3) Locate and investigate pinch-points (Christopher and Peck, 2004),
4) Identify supply chain risks (Rao and Goldsby, 2009); and
5) Reduce the likelihood of underestimating the risk (Jonkman and Dawson, 2014).

The approach described throughout this research provides a simple, repeatable method which can address previously highlighted crisitisms of the discourse. Within both the Shetland and Sandy case studies, the model is able to investigate linkages, while also being able to pick out which supplies are important and therefore could reduce the robustness of the system if disrupted In addition, , pinch points were investigated throughthe removal of edges from the transport network. Finally, the risk analysis metric allows for both the identification of risk and, as it also takes into account the indirect effects of disruption, the reduction in the liklihood of the risk being underestimated.

The methods chapter (Chapter 4) outlined this new technique, which utilised aspects of network analysis and *I-O* analysis to assess and improve supply chain resilience to two types of disruption. The first of these was a reduction of output and the second was the removal of infrastructure which links the different sites of production. As part of this, different policy tests were also modelled in order to generate a lag between disruption and when it is noticed, allowing for stakeholders to implement some form of corrective action.

Within the introduction to this research (Chapter 1) it was highlighted that the current standing in research into resource movements around an economy tends to use a black box approach, without reference to how resources are used within the system. It was also noted that there is a lack of a spatial element to most of the example approaches set out in Chapter 3. This, therefore, provided the niche in which this research focused: the development of a spatial resource model that addressed these two fundamental issues.

The model successfully addresses this by moving away from one large black box representing a local economy (Sections 3.4.1 and 3.7) and splitting this box up into many smaller black boxes, CAS Wards in the Shetland Islands and Community districts in New York City. These smaller black boxes allow for some geographic analysis, such as the Lerwick Risk Assessment in Section 5.5.

8.2.4 Subject this model to a series of disruptive events and test alternative strategies to increase the resilience of urban and regional units and accordingly make recommendations for industry, policy makers and researchers.

Policy options identified from the literature review (Chapter 2) were parameterised within the model to consider options to increase resilience.

The resource model utilises spatially disaggregated information on consumption and demand for resources, within a network model. Results presented in Chapters 4 and 5 provided an understanding how disruption to the output in one ward cascades through the system to affect other sites of production.

This phenomenon of cascading failure, which was observed during real events reported in the literature review, demonstrates how the use of a *JIT* resource production and movement strategy leads to the fastest cascading failures through the system. The addition of onsite stock to each site of production provided a lag in time between the disruption and the output being affected (which was to be expected), therefore simulating more of a "just-in-case" (*JIC*) approach. The *JIT* approach led to a mean output for the whole economy of less than 20% for all simulations (Shetland Islands Case Study – Chapter 5).

A move away from *JIT* production increases the resilience within the system. The addition of bulk deliveries provides further robustness; with higher levels of output noticed after the disruption. This increased average output by 15% after disruption, showing much greater levels of resilience. Resilience is further increased by the addition of reserve stock and the rationing of supplies, and further aided by the addition of rationing of the available stock per sector, making these the most resilient simulations tested during the study with mean outputs above 90%.

An alternative approach to this that achieved high levels of resilience in all of the cases considered was the modified *JIT* strategies. Within these simulations, recovery was modelled and the approach simulated included some onsite reserve and rationing of supply. Thus extending analysis from considering the robustness of resource strategies and the infrastructure networks that mediate them, to consideration of recovery and resilience. This approach also showed increased levels of resilience, albeit with a wider range of results. Such an approach could provide a viable method to improve both resilience and robustness whilst maintaining a lean supply chain and therefore the benefits associated with *JIT*.

The infrastructure failure scenarios showed that if reserve stock is not used immediately to try to maintain production and resource movements within *JIT* simulations, but instead used to stimulate recovery, the system recovers to 100% output. In the simulations in which reserve stock was used immediately, output remained higher, but in the majority of cases did not return to pre-disruption levels.

The second major vulnerability was having a non-diverse supply base: this was addressed in the New York case study. The diversification of oil supply more than doubled the levels of resilience, and the diversification of food supply added 20% to the output after the simulated disruption to Hunts Point.

The analysis highlighted the potential for a single flood event to disrupt the movement of resources in other industrial sectors, away from the initial disturbance; in certain conditions and if certain important sectors are affected, this can rapidly lead to collapse of the entire system.

These case studies highlight the adaptability of the resource model as well as its ability to simulate the impact of hazards across a range of spatial scales and magnitudes. This provides a bridge between macro and micro level studies which, as noted in Chapter 2, has been considered a weakness of the previous work in this field.

8.2.5 Demonstrate the use of the model to support flood risk analysis by providing a quantitative assessment of the indirect impacts of extreme events on resource disruption.

.A final development of the model was its use within a flood risk analysis technique. The first aspect of this was to assess the vulnerability of the Shetland Islands economy to flood hazards at differing magnitudes, with the risk value being the sum of vulnerabilities for each of the modelled flood magnitudes multiplied by the frequency of the event.

The model was also adapted to quantify the risk to resource disruption, to allow for the development of a risk analysis technique. This provided a consistent metric, which permits for the risk at different locations, and relating to different hazards, to be compared. The technique can also take into account defences already in place to provide a true picture of the risk to industrial output caused by a disruption to resource flows at various different magnitudes. It therefore identifies supply chain risks, while reducing the likelihood of underestimating these risks.

This extension of the model provides a rational basis for assessing the direct and indirect impacts of a disruption to interdependent supply chain networks, and allows them to be compared within the same framework, which has often been seen as lacking in other approaches. It also allowed for an investigation of the benefits of different measures in terms of reducing the direct and indirect impacts of such events.

8.2.6 Validate this resource model against an observed event.

The Shetlands Islands were chosen as the first case study. The local council has up-to-date *I-O* tables of the intra-region industrial interactions in the local economy, which made this study possible. The study site was convenient as the internal economy of the Islands has been well documented and many of the industries are co-located geographically, which reduced the complexity of the spatial interactions that needed to be represented in the model.

Initial validation took place through sensitivity tests to understand the model's response and behaviour, but this could not include analysis of the event dynamics due to insufficient data. The disruption of food and fuel distribution after Hurricane Sandy was successfully modelled to provide a secondary validation. The model's results showed an indirect relationship between the number of hot meals distributed after Sandy and the modelled disruption to the food distribution network. This provided an increased level confidence in the results of both case studies. The Sandy case study was then taken further by running other simulations to investigate how the resilience of the food distribution network could be increased.

8.3 Challenges and opportunities for the future development of the resource model

Challenges and opportunities for the development of the specific resource model introduced within this research. Within this method a data disaggregation method was successfully implemented by taking advantage of *BRES* data to estimate production levels within different sectors at a smaller level of geographic output. This allowed for an investigation into the importance of different wards and the links that exist between them.

The model also successfully brought together aspects of study from different fields, to create a multi-disciplinary approach. It was inspired by work within the field of industrial ecology to develop a tool that could provide a big picture of supply chain resilience: this helped to explain the links between the modelled networks and their environments, which assisted in the development of a more resilient system.

The risk analysis technique that was developed followed the accepted approach for such techniques, and so the following exercises were carried out: hazard identification; risk assessment; determination of the significance of risk, through the vulnerability assessment; and reporting of risk, within the case study. The method was set up to firstly highlight the risk to the supply network within the Shetlands from floods of different magnitudes. Due to the adaptable nature of this method, it could be reused on different case study locations, but more importantly to different types of hazard.

Two limitations of the methodological approach were highlighted when carrying out the case study of the Shetland Islands. The first of these was that the model assumed that Shetland was a closed system. This took away the opportunity for the sites of production within the Shetlands to source products from other places outside of the local economy. Had this been considered, the level of resilience within the modelled network may have been different, although given the geography of the Shetlands this was a more acceptable assumption than with many other potential sites.

The second limitation was based on assumptions relating to the delivery of goods. The model treated all products and services the same, meaning they were delivered uniformly, on the same day and the same size of delivery, this was done because data showing how often certain products and services are required by each individual site of production does not exist.

A major limitation to the scope and effectiveness of the modelling is the availability of high resolution resource flow data. The Shetland Islands were chosen for the case study as the council regularly (every 10 years) carries out an input-output survey of the local economy. The data was as low level as readily available but it was still necessary to disaggregate it to smaller levels of geographic output. Ideally the model would have *I-O* data at individual site level, to allow for the model to take into account the individual requirements of each site. This could be combined with address data, meaning that the exact location of different sites would be known and an accurate depiction of the flow of materials involved within the network could, therefore, be made. This would¸ however, lead to a much larger number of nodes within the model, which could then cause issues with the processing speed of the model.

The employment statistics used to disaggregate the data provided the number of employees from each sector in a ward. This was used to estimate the proportion of each sector's output by ward. It therefore assumed that that there is only one site of production per industry in each ward, and that all of the different sites from a sector have similar productivity levels. In both case studies this was inaccurate, but without the required data those assumptions had to be made.

8.4 Recommendations for industry

The first of the recommendations for industry is to move away from *JIT* management strategies. This approach caused for a quick and rather drastic cascading of disruption in all of the modelled wards within the case study of the Shetland Islands. A move to a *JIC* approach would allow for such networks to increase their resilience, by adding robustness through the addition of reserve stock and bulkier deliveries to the system. In most situations, however, the business case for such an approach would need to be understood and the associated costs for such a change would also need to be taken into account. Issues relating to resource resilience should therefore become an essential part of the decision making process, meaning that a business should understand their vulnerabilities and how disruption to their output could affect the companies they supply, as well as how such disruption may cascade to other sections of the economy.

A second recommendation is to encourage companies to work together, by providing information on the availability of products which may be sourced from more than one location. This would allow companies to proportionally share what resources are available, which would in turn lessen the effects of disruption. As part of this strategy, companies should attempt to source components or important products from more than one geographic location, and so, avoid problems such as those caused during the floods in Thailand when many clustered factories producing similar components were affected by the same disruptive event. Other examples of this were also found in the literature; for example, the case of Ericsson and Nokia after the disruption to the supply of components for the production of mobile phones.

If this attitude were adopted, the modification of *JIT* would be a viable approach to increase both resilience and robustness at individual sites of production, and therefore for the economy as a whole. As discussed in Chapter 7, such an approach would require some onsite stock, as well as the ability to ration supplies after disruption. When this was applied in the full model, recovery levels were very high and, therefore, resilience was also very high. This is because most of the modelled industries were able to bounce back to pre-disruption output within the modelled time period.

These recommendations could become the basis of an industrial code of conduct or resource chain management guidance, with the advice being catered for different industries taking into account the current resilience of that industry's supply chain. The approach could also be used by large corporations, such as Toyota, to test and accredit the resilience of the supply chains of the companies which provide the parts for their assembly lines.

8.5 Recommendations for policy makers

The New York City case study (Chapter 6) shows the need for policy makers to understand vulnerabilities within networks, such as food distribution. This was recognised by the government of New York City, who understood the need to build resilience into this network through the building flood of defences to protect the Hunts Point food distribution network. More generally, there is an urgent need for local authorities and national governments to undertake resource security assessments.

Carrying out a risk analysis, such as the approach demonstrated in Chapter 5, should be standard practice when resource relevant development is being considered in areas of flood risk. This, coupled with a requirement to report on such activities, would allow for policy makers to impose resilient building techniques onto organisations to increase resource security, as well as provide incentives for organisations to invest in activities to increase robustness. A risk analysis, such as the Lerwick Risk Assessment (Section 5.5), can be used to analyse the effectiveness of flood defences at protecting the economic activity of an area, as well as to provide an input to a cost benefit analysis. A cost benefit analysis can provide an understanding of what magnitude of disruption that it is cost effective to defend against, which can be useful information when planning future defences.

Policy makers should use such information to diversify the locations from which inputs are sourced. For example, aside from Hunt’s Point there are four other wholesale markets which serve New York. It would vastly increase the resilience of the food distribution network if some of Hunt’s Point’s capacity was shared with each of these, allowing the system as a whole to cope better with disruption.

A review of the background literature (Chapter 2) identified real world evidence that the sourcing of a resource from a single geographic location reduces resilience to disruptive events. For example, this phenomenon was apparent during the 2011 flooding in Thailand, and in the aftermath of Albuquerque factory fire, as well as in the two main cases studies (Chapters 5 and 6). In these case studies it was found that having either: a single source for an input, such as oil for the power station on the Shetland Islands; or a dominant supplier, such as Hunts Point in New York City, can very quickly lead to disruption throughout the modelled networks. In the cases of the Thailand floods and the issues with food distribution in New York City, resilience would have been increased if like industries had not been clustered together on floodplains, supporting a recommendation that in future, such developments be avoided.

8.6 Recommendations for future research

In this section various recommendations for future research that could utilise the methods developed in this thesis are set out.

8.6.1 Integration with other systems

One useful development would be to recode the model into a more modular approach. This would then allow it to be incorporated into larger, integrated systems, with modelling approaches such as that of Walsh et al. (2011), to facilitate testing a wider range of resilience issues.

The developed model could also be combined with other modelling approaches, for example, with more detailed flooding models, which could provide a more in-depth and accurate representation of the flood risks. The approach could also be incorporated into existing models that look at interdependencies of critical infrastructure, allowing for an investigation into how supply chain disruption may affect these systems, or conversely, how disruption to critical infrastructure may affect the movement of resources.

8.6.2 Scaling up analysis

The model could also be applied at different scales and scopes; for example, the investigation of the material flows that are essential for the day-to-day functioning of a hospital, and the vulnerabilities and bottlenecks that hinder it from running smoothly.

Along the same theme, it would be interesting to apply this method at a national scale. For example, the model could be used to recreate the events that occurred during the fuel protests of the year 2000 (Section 2.4.3). With such a method, national level vulnerabilities, comprising various different hazards and combinations of multiple hazards, could be highlighted. Policy adaptations could then be made to protect against these hazards, and the potential increase in resilience could be tested.

On a global scale the model could lead to a tracking of a single multinational corporation's supply chain. Within this, a risk assessment could take place at each of the sites of production, to identify where resilience is low, and test ways of improving this; for example, by diversify supply geographically, by increasing reserve, or by encouraging suppliers to work together. An assessment such as this would also allow corporations to understand who supplies their suppliers in greater detail, which was a problem for Toyota after the Great East Japan Earthquake in 2000. This information would help to increase the resilience further downstream in the supply chain, and subsequently increase the resilience of Toyota, or other global operation.

8.6.3 Recovery modelling

The development of a more detailed recovery model would also benefit the approach, as at the moment it does not take into account everything that a more specific model would, such as sites of production bringing in supplies from outside of the local economy. The current model also does not allow a situation in which the disruption affects different industries for varying amounts of time to be simulated.

A recovery model fitting the above description could be used to aid disaster response. This could be done by applying the tool as a post-event assessment tool, and the tool could, therefore, help find relationships within a system that may have been unknown.

Such a model should take into account: the amount of time needed to repair any damage caused by the disruption; the ability to bring in supplies from outside of the modelled economy, if and when they are needed; and the affects the events may have had on the local population, for example, has some of the workflow left the area?

8.6.4 Use of real time observations

Live data provides exciting opportunities for most avenues of research. Having access to live data in this field could allow for a move to finer spatial scales, where the focus would be on the individual sites of production. This could assist in the development of a true representation of the interaction between sites of production, and the infrastructure that aids in the movement of resources around a system. It would also allow for the development of an agent based version of this model, which would depict the individual attributes of each of the sites within a modelled economy.

Data which details the individual sites of production would remove the many small black boxes and provide an understanding of resource movement and usage at a micro level. This could mean that policy makers, and emergency planners could work with stakeholders in developing individual approaches to increase a site's resilience, whilst contributing to the resilience of the system as a whole.

Real time tracking of resources and the routes they follow would allow for real time decision making. Therefore, as soon as a disruption occurred, a decision could be made utilising transport models to plan new routes, predict traffic and, if needs be, provide options for the resourcing of goods from an unaffected location. This could lessen the effects on supply chains and the movement of resources, and increase the resilience to extreme and disruptive events.

The final two recommendations would have to incorporate better understanding and modelling of IT systems, and how these are (or could be) utilised to manage resource flows. Such systems could be modelled in such a way to allow for real time re-routing of resource flows during a simulation, enabling demands to be met and therefore resilience to be further increased.

8.7 Summary of research

This research was carried out to develop an innovative methodological approach for the spatial analysis of disruption to movement of resources. This is required because of the increasing number of disasters which cause a cascading of failure throughout supply chain systems, at regional, national and global scales. Business practises of leaning the supply chain and geographically clustering like-industries was seen as a contributing factor to the severity of cascading disruption across all of the discussed examples.

Previous approaches do not take into account spatial elements of disruption. The developed quantitative resource model took influence from I-O analysis, network analysis, infrastructural interdependencies, industrial ecology, resilience, and supply chain risk management, as well as introducing a data disaggregation technique that allowed for the spatialisation of the analysis. The basic model outlined in this research measured the robustness to disruptive events, but with the addition of a recovery aspect of the model it starts to become a measure of "*the ability of assets and networks to anticipate, absorb, adapt to and recover from disruption",*(Cabinet Office, 2014) and therefore a measure of resilience.

In both of the two major case studies, it was noted that just-in-time approaches were the least resilient, but that the addition of bulkier deliveries, rationing of resources and applying on-site reserve stock increased resilience, through adding both robustness and redundancy to the systems modelled. Therefore, although the literature focuses on *JIT* not being a resilient approach to resource management, the findings of both case studies show that with subtle adaptations and organisation between different elements of the supply chain, a modified *JIT* approach becomes a viable approach to increase the levels of resilience to disruptive events. It was also noted that a diversification of supply across separate geographic locations, increased resilience.

A further development of the approach was the introduction of a risk analysis technique, which looked at the cascading disruption caused by hazards at varying magnitudes. This technique also allow for an investigation into the effectiveness of any protection against these hazards that may be already in place.

It is vital to recognise and maintain the flow of vital food, materials, water and other resources, to ensure community resilience before, during and after any disruptive event. This research has presented preliminary results and insights from a new resource model that couples information on consumption and demand for resources, within a network model. Both the New York and Shetland case studies show that a generic, scale free approach that can be applied to very diverse case studies. With the addition of the risk analysis technique, a generic metric can also be output, meaning that comparative studies can take place.

The research carried out as part of this provided recommendations for industry, policy makers, and academics, with the goal of increasing resource resilience.

The method successfully brought together aspects from many different discourses, to create a multi-disciplinary approach. It outlines a technique with the ability to asses, as well as predict, the damage caused by a disruptive event. Within this thesis, the results from the described research have been presented for a new resource model. The resource model couples consumption and demand information within a network model. This has enabled an understanding of resource flows and disruption in time and space. It provides stakeholders with a tool to test strategies which lessen the risks, and therefore utilise these developed approaches to increase resilience to a variety of disruptive events.

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Appendix

Appendix 1

Glossary

Bulk deliveries	*B*	Deliveries of *x* amount of a required supply made every *x* days.
Daily stock usage	*U*	How much of an input a site of production uses per day
Demand	*De*	How much a site of production requires of a specific product.
Demanding site	*k*	The site which is demanding some of a site of productions supply.
Disruption / Impact	*D*	The impact of the disrupting event.
Disruption level	*L*	Potential maximum level of output which can take place around the whole economy.
Employees per zone	*e*	Number of employees from a specific sector in an individual zone.
Equilibrium time	t_e	The number of days after the initial disruption that the level of disruption stabilises.
Industrial sector	*j*	Specific industry from the *I-O* table.
Infrastructure failure	*IF*	When a IL is removed from the modelled infrastructure
Infrastructure links	*IL*	The infrastructure links between different sites of production
Infrastructure network	*IN*	The infrastructure network rebuilt within networkx for use within the model.
Injection of supply	*I*	Supply added to the modelled economy from outside of the system to allow output to reach normal levels.
Input output	*I-O*	The accounting method utilised to show the interactions between different elements an economy.
Just in time	*JIT*	Resource management strategy in which products are produced or delivered only as required.
Length of disruption	t_l	Number of days that the modelled disruption lasts.

Number of nodes	N	The number of sites of production
Onsite stock	O	Amount of stock available on site in a site of production
Original supply	Os	The amount of supply output from a site of production at normal output levels.
Output	Op	The amount of products output per modelled zone
Probability	p	The likelihood of something taking place.
Proportion	$\hat{p}$	Equal share based on other values.
Rationing	Ps	Proportionally sharing available supply between the different demanding sites of production.
Recovery	Rv	Phase in the model that takes place after the disruption has ended
Reserve	Re	Level of back-up stock available at a site of production
Risk	R	The sum of the disruption level for each of the modelled flooding events, multiplied by the likelihood of that flood event taking place.
Supply	S	The amount of supply output from a site of production
Supplying site	i	The site of production providing a supply to meet a demand
Time	t	Number of days within the model
Time of delivery	t_d	The number of days between deliveries.
Time reserve will last	t_r	Number of days reserve will last for if all supply of that stock ceases.
Time until next delivery	t_n	Number of days until the next delivery.
Total employees	E	Total number of employees in a specific sector.
Vulnerability	V	Quantification of the impact of floods at differing magnitudes in the area of interest
Water depth	w	The level of flood water modelled
Zone	z	The geographic area of which the disaggregated *I-O* tables represent

Appendix 2: User documentation

Requirements:

- setupCVS.py – This is a python script that sets up the output files populated with the results from the model (Appendix 3)
- full_auto.py – This is the model itself (Appendix 4)
- para.csv – a csv with the completed parameters for each simulation ran
- nodeType.csv – three columns showing; the node type, zone name, and amount of supply available at that site of production.
- nodeDemand.csv – the input – output consumption matrix of the local economy

NB The number of rows in nodeType should equal the number of columns in nodeDemand, with: row 1 in nodeType corresponding to column 1 in nodeDemand, 2 to 2, 3 to 3, etc.

Instructions

1) Paste a copy of setupCVS.py, full_auto.py, para.csv, nodeType.csv and nodeDemand.csv into a folder
2) Double click on setupCVS.py
3) Fill in the parameters you want to test in para.csv (the headings should not be saved in the csv just the values)

A	B	C	D	E	F
infraFail	injection	disruptedWard	propShare	recovery	done
Yes / No	*Yes / No*	*Yes / No*	*Yes / No*	*Yes / No*	*No*
G	H	I	J	K	L
merge	useReserve	deliveryTime	reserve	disruptionTime	disruptionLevel
Yes	*Yes / No*	*interger*	*interger*	*interger*	*decimal 0-1*

4) In the same CSV also fill in the file names where each matric will be saved. The examples below show the (again titles should not be saved in the csv).
   - resilience metric,
   - mean production per type of simulation,
   - percentage production at each site of production
   - demand proportion per type of simulation,

- mean demands per type of simulation,
- injection amount per site,
- mean production per ward,
- mean demand per ward
- The name of the simulation
- The sites of production that failed on each day of the simulation

M	N	O	P	Q
resilience	meanproduction	percentproduction	demandproportion	meandemand
resilienceB1.txt	*meanproductionB.csv*	*percentproductionB1.csv*	*demandproportionB1.csv*	*meandemandB.csv*
R	S	T	U	V
injectAmount	mpWard	mdWard	runName	disruptedBy
injectAmount.csv	*27C01mp.csv*	*md27C01.csv*	*B1*	*disruptedByB1.txt*

5) The infrastructure is rebuilt within the model and this is done simply using networkx.
    a. To change the number of nodes edit line 51 in full_auto.py
    b. To add or remove connections edit line 52 in full_auto.py
    c. To change the names of the nodes edit line 49 in full_auto.py
    d. To change the names of the sectors modelled edit line 48 in full_auto.py
6) Double click on full_auto.py to run the model
7) Results are saved in the CSVs created in the same folder as the script
    a. Resilience metric is saved in a text. These will only change if infrastructure connections are removed
    b. Mean production / demand per simulation type shows the results for separated out into similar simulations with just the disrupted ward changing
    c. Mean production / demand per ward shows the results for the different simulations carried out for one zone, therefore the zone stays the same but simulation parameters change
    d. Percentage production per site shows the output level between 0-1 for each site of production. A separate file is produced for every simulation.
    e. Inject amount per sector shows the amount of stock that would be required to be added to the system for all sectors to return to full production. A separate file is produced for every simulation.
    f. The disrupted by text file gives a list of the sectors affected per day of the simulation.

Appendix 3: Setup CSVs

```
# -*- coding: utf-8 -*-
"""
Created on Wed Oct 15 15:15:20 2014

@author: a3041464
"""

from numpy import genfromtxt
#runs = genfromtxt("runs.csv", dtype = str, delimiter=",")



################################################################################
#####~~~~~~~~~~~~~~~~~~~~~~~~~~SET UP SCENARIO~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~####
################################################################################
#x=1
#while x < len(runs):
para = genfromtxt("para.csv", dtype = str, delimiter=",")
r=0
while r < len(para):
    meanproduction = para[r][13]
    meandemand = para[r][16]
    injectAmount = para[r][17]
    mpWard = para[r][18]
    mdWard = para[r][19]

    newHeader = ["DisruptedWard", "Run name",
        "1","2","3","4","5","6","7","8","9","10","11","12","13","14",
        "15","16","17","18","19","20","21","22","23","24","25","26","27","28","29"
        ,"30","31","32"]
    newHeader2 = ["DisruptedWard", "Run name",
        "1","2","3","4","5","6","7","8","9","10","11","12","13","14",
        "15","16","17","18","19","20""21","22","23","24","25","26","27","28","29", "30"]
    newHeader3 = ["Run name",
"1","2","3","4","5","6","7","8","9","10","11","12","13","14","15","16","17",
        "18","19","20","21","22","23","24","25","26","27","28","29","30"]
    nh = ",".join(newHeader)
    nh2 = ",".join(newHeader2)
    nh3 = ",".join(newHeader3)
    writer = open(meanproduction,'wb')
    writer.write(nh2)
    writer.close
    writer2 = open(meandemand,'wb')
    writer2.write(nh2)
    writer2.close
    writer3 = open(injectAmount,'wb')
    writer3.write(nh)
    writer3.close
    writer4 = open(mpWard,'wb')
    writer4.write(nh3)
    writer4.close
    writer5 = open(mdWard,'wb')
    writer5.write(nh3)
    writer5.close
    print r+1, "of", len(para)
    r+=1
#    x+=1
```

Appendix 4: Full Auto

```
# -*- coding: utf-8 -*-
"""
Created on Wed Jul 30 18:13:20 2014

@author: Shaun Brown
"""
import numpy as np
from numpy import genfromtxt, loadtxt
import decimal
import networkx as nx
from decimal import *
from scipy.stats import mode

para = genfromtxt("para.csv", dtype = str, delimiter=",")
r=0
while r < len(para):
    time = 0
###############################################################################
#####~~~~~~~~~~~~~~~~~~~~~~~~~~SET UP SCENARIO~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~####
###############################################################################
    infraFail = para[r][0]
    injection = para[r][1]
    disruptedWard = para[r][2]
    propShare = para[r][3]
    recovery = para[r][4]
    done = "No"
    merge = "Yes"
    useReserve = para[r][7]
    deliveryTime = int(para[r][8])
    timeUntilDelivery = int(para[r][8])
    reserve = int(para[r][9])
    disruptionTime = int(para[r][10])
    disruptionLevel = decimal.Decimal(para[r][11])
    resilience = para[r][12]
    meanproduction = para[r][13]
    percentproduction = para[r][14]
    demandproportion = para[r][15]
    meandemand = para[r][16]
    injectAmount = para[r][17]
    mpWard = para[r][18]
    mdWard = para[r][19]
    runName = para[r][20]
    disruptedBy = para[r][21]

###############################################################################
#####~~~~~~~~~~~~~~~~~~~SET UP INFRASTRUCTURE NETWORK~~~~~~~~~~~~~~~~~~~~~~~~####
###############################################################################
    datazones = ("27C01", "27C02", "27C03", "27C04", "27C05", "27C06", "27C07", "27C08",
"27C09", "27C10", "27C11", "27C12",
        "27C13", "27C14", "27C15", "27C16", "27C17", "27C18", "27C19", "27C20", "27C21",
"27C22")
    sectors = ("Agriculture", "Fish Catching", "Aquaculture", "Oil Terminal",
        "Mining & Quarrying", "Fish processing", "Other food & drink processing", "Marine
engineering",
        "Textiles & crafts", "Other manufacturing", "Electricity", "gas & water supply",
"Construction",
        "Wholesale", "Retail", "Accommodation", "Catering", "Ports & Harbours", "Sea
Transportation",
        "Land Transportation", "Air Transportation", "Oil Supply Services", "Communication &
supply services",
        "Financial Services", "IT/computer related & real estate services", "Technical
Professional other business services",
```

```
        "Public administration Local/Central", "School Education", "College Education",
"Health", "Social work & other services",
        "Other community social & personal services")
    G = nx.MultiGraph()
    G.add_nodes_from([0,21])
        G.add_edges_from([(0, 0), (0, 1), (0, 1), (0, 1), (0, 7), (0, 7),  (1, 1),(1, 2), (1,
3), (1, 3), (1, 4),(1, 4),(1, 4),
        (2, 2), (2, 4),(2, 4), (2, 5),(2, 5),(2, 5), (2, 5),(2, 5),(2, 5), (2, 6),(2, 6),(2,
6), (3, 3), (3, 4),(3, 4),(3, 4),(3, 4),
        (3, 4),(3, 4), (3, 5), (3, 5), (4, 4), (4, 5), (4, 5), (4, 5), (4, 5), (4, 7), (5,
5),(5, 6),  (5, 5),(5, 16), (6, 6),(6, 7),
        (6, 13),(6, 13), (7, 7), (7, 13), (7, 19),(7, 19), (8, 8), (8, 8), (8, 9), (8, 9),(8,
9), (9, 9), (9, 11), (10, 10),(10, 11),
        (11, 11), (11, 12),(11, 12),(11, 12),(11, 12), (11, 16),(11, 16), (12, 12),(12, 13),
(12, 15), (12, 15),(12, 15), (13, 13),
        (13, 14), (13, 14), (13, 16), (13, 16), (14, 14), (14, 18),(14, 18),(14, 18), (15,
15), (15, 15), (16, 16), (16, 17), (16, 17),
        (16, 17),(16, 17), (17, 17),(17, 17),(17, 18), (18, 18), (18, 18), (19, 19), (19, 20),
(19, 20), (20, 20), (20, 21), (20, 21),
        (20, 21), (21, 21), (21, 21)])
###############################################################################
#####~~~~~~~~~~~~~~~~~~DISRUPTION OF INFRASTRUCTURE~~~~~~~~~~~~~~~~~~~~~~####
################################################################################
    writera = open(resilience,'wb')
    writera.write("Before Disruption" + "\n")
    writera.close
    writerb = open(resilience,'a')
    writerb.write("Sub Graphs" + "\n")
    writerb.write(str(nx.connected_components(G)) + "\n")
    writerb.write("k-connectivity" + "\n")
    writerb.write(str(nx.average_neighbor_degree(G)) + "\n")
    writerb.write("Degree Centrality" + "\n")
    writerb.write(str(nx.degree_centrality(G)) + "\n")
    writerb.close
    x = 0
    while x < len(datazones):
        G.node[x] = datazones[x]
        x += 1
    ebunch=[(6, 7), (7, 6)]
    if infraFail == "Yes":
        G.remove_edges_from(ebunch)
    else:
        pass
    subgraphs = {}
    y = 0
    while y < nx.number_connected_components(G):
        subgraphs.setdefault((y), nx.connected_components(G)[y])
        y+=1
    writerc = open(resilience,'a')
    writerc.write("After Disruption" + "\n")
    writerc.write("Sub Graphs" + "\n")
    writerc.write(str(nx.connected_components(G)) + "\n")
    writerc.write("k-connectivity" + "\n")
    writerc.write(str(nx.average_neighbor_degree(G)) + "\n")
    writerc.write("Degree Centrality" + "\n")
    writerc.write(str(nx.degree_centrality(G)) + "\n")
    writerc.close
################################################################################
#####~~~~~~~~~~~~~~~~~~~~~~~~SET NODE ATTRIBUTES~~~~~~~~~~~~~~~~~~~~~~~~~~~~####
################################################################################
    conMatrix = loadtxt("nodeDemand.csv", dtype=(Decimal), delimiter=",")
    nodeT = genfromtxt("nodetype.csv", dtype = int, delimiter=",", usecols = (0))
    location = genfromtxt("nodetype.csv", dtype = str, delimiter=",", usecols = (1))
    supply = genfromtxt("nodetype.csv", dtype=(Decimal), delimiter=",", usecols = (2))
    inputs = len(conMatrix)
    numberOfNodes = len(conMatrix[0])
```

```
subGraphSites = {}
z=0
while z < nx.number_connected_components(G):
    subGraphSites.setdefault((z), [])
    for x in subgraphs[z]:
        y = 0
        while y < numberOfNodes:
            if location[y] == G.node[x]:
               subGraphSites[z].append(y)
            y+=1
    z+=1
originalDemand ={}
siteDemand = {}
conDict = {}
totalSupply = {}
originalSupply ={}
newSupply = {}
usage = {}
siteLocation = {}
demandType = {}
sectorSupply = {}
newDemand = {}
onsiteStock = {}
removedDemand = {}
disruptedDict = {}
distSect = {}
proportion = {}
sectorDist = {}
missing = {}
valueList = {}
stockPerStep = {}
injectionAmount = {}
totalSector = {}
minProportion = {}
nodeType = {}
totSup = {}
keyList2 = []
typeOfSite = []
mpList = []
stopProduction = {}
reserveAmount = {}
spsRatio = {}
spsMinRatio = {}
sitesPerSector = {}
sitesPerSubGraph = {}
sectorSupply = {}
totSec = {}
originalStock = {}
demandProportion = {}
distReserve = {}
initialDisTFail = {}
initialDisruption = {}
nodeFailure = {}
idDone = {}
nfDone = {}
minDP = {}
mpList = []
mdList = []
list1 = ["Disrupted", "Failed"]

x=0
while x < numberOfNodes:#len(conMatrix):
    totSup[x] = deliveryTime*(decimal.Decimal(supply[x]))
    x+=1
for TYPE in nodeT:
    sectorSupply.setdefault((TYPE), []) #set type of sector as key
```

```
    x = 0
    while x < len(nodeT): #less than number of sites of production
        y = 0
        while y < len(sectorSupply.keys()): #less than the number of sectors
            if nodeT[x] == sectorSupply.keys()[y]: # if the type of node matches type of
sector
                sectorSupply[y].append(decimal.Decimal(totSup[x])) #value = the totalSupply
for that site of production
            y += 1
        x += 1
    for sector in sectorSupply.keys(): # for each sector
        totSec.setdefault((sector), []).append(np.sum(sectorSupply[sector])) #the supplies for
each sector are added together to give the supply

    y=0
    while y < inputs: #len(conMatrix[x]):
        typeOfSite.append(y)
        y+=1

    z=0
    while z < nx.number_connected_components(G):
        totalSupply.setdefault((z), {})
        newSupply.setdefault((z), {})
        originalSupply.setdefault((z), {})
        disruptedDict.setdefault((z), {})
        siteLocation.setdefault((z), {})
        conDict.setdefault((z), {})
        originalDemand.setdefault((z), {})
        onsiteStock.setdefault((z), {})
        demandType.setdefault((z), {})
        valueList.setdefault((z), {})
        usage.setdefault((z), {})
        proportion.setdefault((z), {})
        distSect.setdefault((z), {})
        missing.setdefault((z), {})
        siteDemand.setdefault((z), {})
        newDemand.setdefault((z), {})
        removedDemand.setdefault((z), {})
        stockPerStep.setdefault((z), {})
        spsRatio.setdefault((z), {})
        spsMinRatio.setdefault((z), {})
        injectionAmount.setdefault((z), {})
        sectorDist.setdefault((z), {})
        totalSector.setdefault((z), {})
        nodeType.setdefault((z), {})
        minProportion.setdefault((z), {})
        stopProduction.setdefault((z), {})
        reserveAmount.setdefault((z), {})
        sitesPerSubGraph.setdefault((z), {})
        distReserve.setdefault((z), {})
        originalStock.setdefault((z), {})
        demandProportion.setdefault((z), {})
        minDP.setdefault((z), {})
        initialDisruption.setdefault((z), {})
        initialDisTFail.setdefault((z), {})
        nodeFailure.setdefault((z), {})
        idDone.setdefault((z), {})
        nfDone.setdefault((z), {})
        for key in totSec.keys():
            totalSector[z].setdefault((key), []).append(totSec[key][0])
        for x in subGraphSites[z]:
            totalSupply[z].setdefault((x),
[]).append(deliveryTime*(decimal.Decimal(supply[x])))
            newSupply[z].setdefault((x), []).append(deliveryTime*(decimal.Decimal(supply[x])))
```

```
            originalSupply[z].setdefault((x),
[]).append(deliveryTime*(decimal.Decimal(supply[x])))
            valueList[z].setdefault((x), []).append(deliveryTime*(decimal.Decimal(supply[x])))
            disruptedDict[z].setdefault((x), "No")
            stopProduction[z].setdefault((x), "No")
            distReserve[z].setdefault((x), "Yes")
            idDone[z].setdefault((x), "No")
            nfDone[z].setdefault((x), "No")
            siteLocation[z].setdefault((x), []).append(location[x])
            injectionAmount[z].setdefault((x), []).append(decimal.Decimal("0.00"))
            nodeType[z].setdefault((x), nodeT[x])#.append(nodeT[x])
            minProportion[z].setdefault((x), [])
            spsMinRatio[z].setdefault((x), [])
            initialDisruption[z].setdefault((x), [])
            initialDisTFail[z].setdefault((x), {})
            nodeFailure[z].setdefault((x), [])
            minDP[z].setdefault((x), decimal.Decimal("0.00"))
            q = 0
            while q < 2:
                initialDisTFail[z][x].setdefault((list1[q]), [])
                q+=1
            y=0
            while y < inputs: #len(conMatrix[x]):
               conDict[z].setdefault((x), []).append(decimal.Decimal(conMatrix[y][x]))
               usage[z].setdefault((x), []).append(decimal.Decimal(conMatrix[y][x]))
               proportion[z].setdefault((x), []).append(decimal.Decimal("0.00"))
               distSect[z].setdefault((x), []).append(decimal.Decimal("1.00"))
               missing[z].setdefault((x), []).append(decimal.Decimal("0.00"))
               originalDemand[z].setdefault((x),
[]).append(deliveryTime*(decimal.Decimal(conMatrix[y][x])))
               siteDemand[z].setdefault((x),
[]).append(deliveryTime*(decimal.Decimal(conMatrix[y][x])))
               newDemand[z].setdefault((x),
[]).append(deliveryTime*(decimal.Decimal(conMatrix[y][x])))
               removedDemand[z].setdefault((x), []).append(decimal.Decimal("0.00"))
               spsRatio[z].setdefault((x),
[]).append(deliveryTime*(decimal.Decimal(conMatrix[y][x])))
               demandType[z].setdefault((x), []).append(y)
               sectorDist[z].setdefault((y), "No")
               sitesPerSubGraph[z].setdefault((y), 0)
               sitesPerSector.setdefault((y), 0)
               demandProportion[z].setdefault((x), []).append(decimal.Decimal("1.00"))
               reserveAmount[z].setdefault((x),
[]).append(reserve*(decimal.Decimal(conMatrix[y][x])))
               if deliveryTime == 1:
                   onsiteStock[z].setdefault((x),
[]).append(reserve*(decimal.Decimal(conMatrix[y][x])))
                   stockPerStep[z].setdefault((x),
[]).append(reserve*(decimal.Decimal(conMatrix[y][x])))
                   originalStock[z].setdefault((x),
[]).append(decimal.Decimal(conMatrix[y][x]))
               else:
                   onsiteStock[z].setdefault((x),
[]).append(reserve*(decimal.Decimal(conMatrix[y][x])) + (deliveryTime-
1)*(decimal.Decimal(conMatrix[y][x])))
                   stockPerStep[z].setdefault((x),
[]).append(reserve*(decimal.Decimal(conMatrix[y][x])) + (deliveryTime-
1)*(decimal.Decimal(conMatrix[y][x])))
                   originalStock[z].setdefault((x), []).append((deliveryTime-
1)*(decimal.Decimal(conMatrix[y][x])))
               y+=1
            x+=1
        for site in nodeType[z].keys():
            for sector in sitesPerSector.keys():
                if nodeType[z][site] == sector:
                    sitesPerSector[sector] += 1
```

```
                    sitesPerSubGraph[z][sector] +=1
                else:
                    pass
################################################ DISRUPTION
################################################
        for ward in siteLocation[z]: # for every ward
            if disruptionLevel < decimal.Decimal("1.00"): # if disruption in network
                if siteLocation[z][ward][0] == disruptedWard: #if the site location is in the
disrupted ward
                    totalSupply[z][ward][0] *= disruptionLevel #level or production is
multiplied by disruption level for each site in the ward
                    newSupply[z][ward][0] *= disruptionLevel
                    disruptedDict[z][ward] = "Yes" # disruption dict becomes yes
                    demand = 0
                    while demand < inputs: # while less than the number of sectors
                        siteDemand[z][ward][demand] *= disruptionLevel
                        newDemand[z][ward][demand] *= disruptionLevel
                        distReserve[z][ward] = "No"
                        stockPerStep[z][ward][demand] = (stockPerStep[z][ward][demand]-
reserveAmount[z][ward][demand])*disruptionLevel
                        if demand == nodeType[z][ward]: # if equals node tyoe of disrupted
site
                            sectorDist[z][demand] = "Yes" # sector disrupted becomes yes
                        demand += 1
                else:
                    pass
            else:
                pass
        z+=1

    z=0
    while z < nx.number_connected_components(G):
        if infraFail == "Yes":
            for key in sitesPerSector.keys():
                if sitesPerSector[key] > 1:
                    if sitesPerSector[key] > sitesPerSubGraph[z][key]:
#print key
                        sectorDist[z][key] = "Yes"
                    else:
                        pass
                else:
                    pass
        else:
            pass
        #timeuntil delivery needed for batch deliveries
        for key in stockPerStep[z].keys(): # for each site of production
            stock = 0
            while stock < inputs: #les then the number of sectors
                if deliveryTime > 1:
                    stockPerStep[z][key][stock] /= (timeUntilDelivery-1) # amount to be used
up each timestep
                else:
                    pass

                if usage[z][key][stock] > decimal.Decimal("0.00"):
                    spsRatio[z][key][stock] = stockPerStep[z][key][stock]/usage[z][key][stock]
                else:
                    spsRatio[z][key][stock] = decimal.Decimal("1.00")
                stock += 1
        for key in stockPerStep[z].keys():
            spsMinRatio[z][key] = min(spsRatio[z][key])
     #   print spsMinRatio
################################################ SETUP CSVS
###################################################
        writerz = open(percentproduction,'wb')
        writerx = open(demandproportion,'wb')
```

```
        keyList = conDict[z].keys()
        for key in keyList:
            keyList2.append(str(key))
        z+=1
    newHeader = ",".join(keyList2)
    writerz.write(newHeader + "\n")
    writerz.close
    writerx.write(newHeader + "\n")
    writerx.close
    writery = open(disruptedBy,'wb')
    writery.close
    numberOfSubgraphs = nx.number_connected_components(G)

    while time < 30:
        print time
        ratioList = []
        injectList = []
        meanDemandList = []
        vl = []
        dp1 = {}
        demandProp = []
        subSectorSupply = {}
        disTotalSector = {}
        subTypeDict = {}
        z=0
        while z < nx.number_connected_components(G):
            subTypeDict.setdefault((z), [])
            dp1.setdefault((z), {})
            for site in typeOfSite:
                if site in nodeType[z].values():
                    subTypeDict[z].append("Yes")
                else:
                    subTypeDict[z].append("No")
                for node in onsiteStock[z].keys():
                    if subTypeDict[z][site] == "No":
                        if originalDemand[z][node][site] > decimal.Decimal("0.00"):
                            if onsiteStock[z][node][site] == decimal.Decimal("0.00"):
                                stopProduction[z][node] = "Yes"
                            elif useReserve == "No":
                                stopProduction[z][node] = "Yes"
                            else:
                                pass
                        else:
                            pass
                    else:
                        pass
            z+=1
        if infraFail == "Yes":
            if time%deliveryTime == 0:
                if time >= disruptionTime:
                    if recovery == "Yes": #if being moddled
                        if done == "No": #has stock been utilised previously, if yes then loop
finishes
                            G.add_edges_from(ebunch)
                        else:
                            pass
                    else:
                        pass
                else:
                    pass
            else:
                pass
        else:
            pass
        z=0
        while z < nx.number_connected_components(G):
```

```
    ################################################################################
    #####~~~~~~~~~~~~~~~~~~~~~~~~~~RECOVERY~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~####
    ############################ Delivery Step ###################################
            if time%deliveryTime == 0:
                if time >= disruptionTime:
                    if recovery == "Yes": #if being moddled
                        if done == "No": #has stock been utilised previously, if yes then loop 
finishes
                            if merge == "Yes":
                                n = 1
                                while n < numberOfSubgraphs:
                                    totalSupply[0].update(totalSupply[n])
                                    originalSupply[0].update(originalSupply[n])
                                    disruptedDict[0].update(disruptedDict[n])
                                    conDict[0].update(conDict[n])
                                    originalDemand[0].update(originalDemand[n])
                                    onsiteStock[0].update(onsiteStock[n])
                                    demandType[0].update(demandType[n])
                                    valueList[0].update(valueList[n])
                                    spsRatio[0].update(spsRatio[n])
                                    spsMinRatio[0].update(spsMinRatio[n])
                                    usage[0].update(usage[n])
                                    proportion[0].update(proportion[n])
                                    distSect[0].update(distSect[n])
                                    missing[0].update(missing[n])
                                    siteDemand[0].update(siteDemand[n])
                                    newDemand[0].update(newDemand[n])
                                    removedDemand[0].update(removedDemand[n])
                                    stockPerStep[0].update(stockPerStep[n])
                                    injectionAmount[0].update(injectionAmount[n])
                                    sectorDist[0].update(sectorDist[n])
                                    newSupply[0].update(newSupply[n])
                                    nodeType[0].update(nodeType[n])
                                    minProportion[0].update(minProportion[n])
                                    stopProduction[0].update(stopProduction[n])
                                    reserveAmount[0].update(reserveAmount[n])
                                    demandProportion[0].update(demandProportion[n])
                                    idDone[0].update(idDone[n])
                                    initialDisruption[0].update(initialDisruption[n])
                                    nfDone[0].update(nfDone[n])
                                    nodeFailure[0].update(nodeFailure[n])
                                    originalStock[0].update(originalStock[n])
                                    n+=1
                                for key in minProportion.keys():
                                    if key >= nx.number_connected_components(G):
                                        del(minProportion[key])
                                        del(totalSupply[key])
                                        del(originalSupply[key])
                                        del(disruptedDict[key])
                                        del(conDict[key])
                                        del(originalDemand[key])
                                        del(onsiteStock[key])
                                        del(demandType[key])
                                        del(valueList[key])
                                        del(spsMinRatio[key])
                                        del(usage[key])
                                        del(proportion[key])
                                        del(distSect[key])
                                        del(missing[key])
                                        del(siteDemand[key])
                                        del(newDemand[key])
                                        del(removedDemand[key])
                                        del(stockPerStep[key])
                                        del(injectionAmount[key])
                                        del(sectorDist[key])
                                        del(totalSector[key])
```

```
                                        del(newSupply[key])
                                        del(nodeType[key])
                                        del(stopProduction[key])
                                        del(spsRatio[key])
                                        del(reserveAmount[key])
                                        del(demandProportion[key])
                                        del(idDone[key])
                                        del(initialDisruption[key])
                                        del(nfDone[key])
                                        del(nodeFailure[key])
                                        del(originalStock[key])
                                merge = "No"
                            else:
                                pass
                            for site in originalDemand[z].keys(): #every site of producion
                                disruptedDict[z][site] = "No" # disruption dict now finished
                                stopProduction[z][site] = "No"
                                for key in sectorDist[z].keys(): # for every sector
                                    sectorDist[z][key] = "No" # disruption dict now finished
                                    distSect[z][site][key] = decimal.Decimal("1.00") #
disruption dict now finished
                                    if useReserve == "Yes":
                                        if nodeType[z][site] == demandType[z][site][key]: #if
type of node matches the type of resource
                                            if onsiteStock[z][site][key] > 0: #if the
onsitestock is greater than zero
                                                if originalStock[z][site][key] <
onsiteStock[z][site][key]:
                                                    newSupply[z][site][0] +=
(onsiteStock[z][site][key]-originalStock[z][site][key]) #onsitestock which  matches nodeType
is added to supply
                                                    totalSupply[z][site][0] +=
(onsiteStock[z][site][key]-originalStock[z][site][key])
                                                    onsiteStock[z][site][key] = 0 #onsitestock
then becomes zero

                            done = "Yes"
                            useReserve = "Yes"
                        else: # recovery not moddled
                            pass
                    else:
                        pass
                else:
                    pass
            z+=1
        z=0
        while z < nx.number_connected_components(G):
            if time%deliveryTime == 0:
                subSectorSupply.setdefault((z), {})
                for x in nodeType[z]: # while x is less than the number of sites of production
                    for y in sectorDist[z].keys(): #while y is less than the number of sectors
                        subSectorSupply[z].setdefault((y), [])
                        if nodeType[z][x] == subSectorSupply[z].keys()[y]: #if the node type
is the same as the sector type

subSectorSupply[z][y].append(decimal.Decimal(totalSupply[z][x][0])) #add new supply created
per timestep to the dict
                for sector in subSectorSupply[z].keys(): # for each sector
                    w = 0
                    while w < mode(nodeT)[1]:
                        if len(subSectorSupply[z][sector]) < mode(nodeT)[1]:
                            subSectorSupply[z][sector].append(decimal.Decimal("0.00"))
                        w += 1
                for sector in subSectorSupply[z].keys(): # for each sector
                    disTotalSector.setdefault((z), {})
```

```
                    disTotalSector[z].setdefault((sector),
[]).append(np.sum(subSectorSupply[z][sector])) #the supplies for each sector are added
together to give the supply
                for node in originalDemand[z].keys(): #for every site of production
                    for TYPE in disTotalSector[z].keys(): #while type is less than number of
different sectors
                        if totalSector[z][TYPE][0] > decimal.Decimal("0.00"):
                            if disTotalSector[z][TYPE][0] >= totalSector[z][TYPE][0]:
                                missing[z][node][TYPE] = decimal.Decimal("0.00")
                            elif decimal.Decimal("1.00") -
(disTotalSector[z][TYPE][0]/totalSector[z][TYPE][0]) > decimal.Decimal("0.00"):
                                missing[z][node][TYPE] = decimal.Decimal("1.00") -
(disTotalSector[z][TYPE][0]/totalSector[z][TYPE][0]) #missing is the proportion of stock below
usualy levels of poduction
                            else:
                                missing[z][node][TYPE] = decimal.Decimal("1.00")
                        else:
                            pass
            z+=1
        z=0
        while z < nx.number_connected_components(G):
            if time%deliveryTime == 0:
                if time >= disruptionTime:
                    if injection == "Yes":
                        for site in originalDemand[z].keys():
                            stopProduction[z][site] = "No"
                            for demand in sectorDist[z].keys():
                                distSect[z][site][demand] = decimal.Decimal("1.00")
                                if nodeType[z][site] == demandType[z][site][demand]:
                                    if totalSector[z][demand][0]-disTotalSector[z][demand][0]
> decimal.Decimal("0.00"):
                                        injectionAmount[z][site][0] =
(totalSector[z][demand][0]-disTotalSector[z][demand][0])/sitesPerSector[demand]
                                    else:
                                        injectionAmount[z][site][0] = decimal.Decimal("0.00")


                        for site in originalDemand[z].keys():
                            for demand in sectorDist[z].keys():
                                totalSupply[z][site][0] = originalSupply[z][site][0]
                                if nodeType[z][site] == demandType[z][site][demand]:
                                    disTotalSector[z][demand][0] = totalSector[z][demand][0]
                                    sectorDist[z][demand] = "No"
                                    disruptedDict[z][site] = "No"
                    else:
                        pass

                else:
                    pass

            z+=1
    ################################################################################
    #####~~~~~~~~~~~~~~~~~~~Working out Proportion~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~####
    ############################ Delivery Step ###################################
        z=0
        while z < nx.number_connected_components(G):
            if time%deliveryTime == 0:
                for site in originalDemand[z].keys(): #for every site of production
                    demand = 0
                    while demand < inputs: #while less than number of sectors
                        if disruptedDict[z][site] == "Yes": #if the site is from disrupted
ward
                            proportion[z][site][demand] = decimal.Decimal(disruptionLevel)
#proportion is equal to set disruption level
                        elif propShare == "Yes": #if proportional sharing taking place
```

```
                           if sectorDist[z][demand] == "Yes": #if the sector is disrupted but
site not in disrupted ward
                                if nodeType[z][site] == demand: #if node type is the same as
disrupted sector
                                    TYPE = 0
                                    while TYPE < inputs: #while less than number of sectors
                                        if usage[z][site][TYPE] > decimal.Decimal("0.00"):
                                            if sitesPerSubGraph[z][TYPE] == 0:
                                                if onsiteStock[z][site][TYPE] /
usage[z][site][TYPE] < decimal.Decimal("0.01"):
                                                    proportion[z][site][TYPE] =
decimal.Decimal("0.00")
                                                else:
                                                    proportion[z][site][TYPE] =
decimal.Decimal("1.00")
                                            elif sectorDist[z][TYPE] == "Yes":
                                                if nodeType[z][site] == TYPE:
                                                    proportion[z][site][TYPE] =
decimal.Decimal("1.00")
                                                else:
                                                    proportion[z][site][TYPE] =
decimal.Decimal(disTotalSector[z][TYPE][0])/decimal.Decimal(totalSector[z][TYPE][0])
#proportion becomes that value
                                            else:
                                                proportion[z][site][TYPE] =
decimal.Decimal("1.00") #for other sites in disrupted sector proportion = 100%
                                        else:
                                            proportion[z][site][TYPE] =
decimal.Decimal("1.00")
                                        distSect[z][site][TYPE] = decimal.Decimal("0.00")
#once set changes to zero so isnt changed in next step
                                        TYPE += 1
                           else:
                                TYPE = 0
                                while TYPE < inputs: # while less than number of sectors
                                    if distSect[z][site][TYPE] == decimal.Decimal("1.00"): #if
not disrupted
                                        if totalSector[z][TYPE][0] > decimal.Decimal("0.00"):
                                            if
disTotalSector[z][TYPE][0]/totalSector[z][TYPE][0] < decimal.Decimal("1.00"): #if percentage
is less than 1
                                                proportion[z][site][TYPE] =
decimal.Decimal(disTotalSector[z][TYPE][0])/decimal.Decimal(totalSector[z][TYPE][0])
#proportion becomes that value
                                            else:
                                                proportion[z][site][TYPE] =
decimal.Decimal("1.00") # else it is 1 (cant be greater than 1)
                                        else:
                                            proportion[z][site][TYPE] =
decimal.Decimal("1.00")
                                    else:
                                        pass
                                    TYPE += 1
                        else:
                            TYPE = 0
                            while TYPE < inputs: # if not proportional sharing value is always
1.00 apart from sites in disrupted ward
                                proportion[z][site][TYPE] = decimal.Decimal("1.00")
                                TYPE += 1
                        demand += 1
                for key in proportion[z].keys():
                    minProportion[z][key] = min(proportion[z][key])
                    if minProportion[z][key] < decimal.Decimal("0.05"):
                        stopProduction[z][key] = "Yes"
                if propShare == "Yes": #if proportional sharing taking place
```

```
                for node in demandType[z].keys(): #for every site of production
                    testa =  np.greater_equal(onsiteStock[z][node], missing[z][node]) #if
available (left over stock since previous delivery) stock is greater than missing
                    for demand in demandType[z][node]: #for each type of supply (sector)
                        if testa.all() == True: #if all results from testa are true
                            newDemand[z][node][demand] =
proportion[z][node][demand]*originalDemand[z][node][demand] #new demand is proportion of
original demand (as reserve stock to make up value to 100%)
                        elif minProportion[z][node] > decimal.Decimal("0.00"):
                            newDemand[z][node][demand] =
minProportion[z][node]*originalDemand[z][node][demand] #if no reserve proportion is smallest
value as that limits what can be produced
                        else:
                            newDemand[z][node][demand] = decimal.Decimal("0.00")
            for node in demandType[z].keys(): #for each site of production
                for demand in demandType[z][node]: #for each type of input
                    removedDemand[z][node][demand] = originalDemand[z][node][demand] -
newDemand[z][node][demand] #removed demand is the difference between normal demand levels and
new ones after disruption

################################################################################
#####~~~~~~~~~~~~~~~~~~~~~~~~~~NEW DELIVERY~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~####
############################ Delivery Step #################################
            for node in demandType[z].keys(): #for each site of production
                for demand in demandType[z][node]: #for each type of input
                    for TYPE in nodeType[z].keys():
                        if demandType[z][node][demand] == nodeType[z][TYPE]: #if demand at
node = the supply from another node
                            if stopProduction[z][node] == "No":
                                if proportion[z][node][demand] == 1:
                                    if siteDemand[z][node][demand] <=
totalSupply[z][TYPE][0]: #if there is enough supply to meet demand
                                        totalSupply[z][TYPE][0] -=
siteDemand[z][node][demand] #total supply reduces by amount of demand
                                        onsiteStock[z][node][demand] +=
siteDemand[z][node][demand] #onsitestock recives 100% supply
                                        siteDemand[z][node][demand] = 0 #demand is met so
becomes zero
                                    else: #if supply is less than demand
                                        siteDemand[z][node][demand] -=
totalSupply[z][TYPE][0] #site demand is reduced by whatever the available stock value is
                                        onsiteStock[z][node][demand] +=
totalSupply[z][TYPE][0] #onsitestock still gets all supply available
                                        totalSupply[z][TYPE][0] = 0 #at this site of
production becomes zero
                                else: #if prooprtion is less than 1
                                    if newDemand[z][node][demand] <=
totalSupply[z][TYPE][0]: #if if there is enough supply to meet the newdemand
                                        totalSupply[z][TYPE][0] -=
newDemand[z][node][demand] #total supply reduces by amount of newdemand
                                        onsiteStock[z][node][demand] +=
newDemand[z][node][demand] #onsitestock recives 100% supply
                                        newDemand[z][node][demand] = 0 #new demand reduced
to zero
                                    else: #if supply is less than demand
                                        newDemand[z][node][demand] -=
totalSupply[z][TYPE][0] #new demand is reduced by whatever the available stock value is
                                        onsiteStock[z][node][demand] +=
totalSupply[z][TYPE][0] #onsitestock still gets all supply available
                                        totalSupply[z][TYPE][0] = 0 #at this site of
production becomes zero
                                        #print "there", node, demand, "newDemand",
newDemand[z][node][demand]
                                    siteDemand[z][node][demand] =
newDemand[z][node][demand] + removedDemand[z][node][demand] #site demand becomes whats left of
new demand plus the removed demand
```

```
                                else:
                                    pass
                            else:
                                pass
            z+=1
################################################################################
#####~~~~~~~~~~~~~~~~~~~~~~~~RATIO OF SUPPLY RECIEVED~~~~~~~~~~~~~~~~~~~~~~~~####
########################### Delivery Step ######################################
        z = 0
        while z < nx.number_connected_components(G):
            if time%deliveryTime == 0:
                for node in stockPerStep[z].keys():
                    timeUntilDelivery = deliveryTime #set time until delivery to equal
delivery time
                    for demand in demandType[z][node]:
                        if useReserve == "Yes":
                            #print "here", node, demand
                            if disruptedDict[z][node] == "Yes":
                                if usage[z][node][demand] > decimal.Decimal("0.00"):
                                    if ((onsiteStock[z][node][demand]-
reserveAmount[z][node][demand])/timeUntilDelivery)/usage[z][node][demand] > disruptionLevel:
                                        stockPerStep[z][node][demand] =
usage[z][node][demand]*disruptionLevel
                                    else:
                                        stockPerStep[z][node][demand] =
(onsiteStock[z][node][demand]-reserveAmount[z][node][demand])/timeUntilDelivery
                                else:
                                    stockPerStep[z][node][demand] =decimal.Decimal("0.00")
                                #print "there", node, demand, "stockPerStep",
stockPerStep[z][node][demand], "usage", usage[z][node][demand]
                            elif onsiteStock[z][node][demand] > decimal.Decimal("0.00"):
                                stockPerStep[z][node][demand] =
onsiteStock[z][node][demand]/timeUntilDelivery #amount of stock per time step is
                            else:
                                stockPerStep[z][node][demand] = decimal.Decimal("0.00")
                        else:
                            if onsiteStock[z][node][demand] > decimal.Decimal("0.00"):
                                stockPerStep[z][node][demand] = (onsiteStock[z][node][demand]-
reserveAmount[z][node][demand])/timeUntilDelivery #amount of stock per time step is
                            else:
                                stockPerStep[z][node][demand] = decimal.Decimal("0.00")
                        if usage[z][node][demand] > decimal.Decimal("0.00"):
                            spsRatio[z][node][demand] =
stockPerStep[z][node][demand]/usage[z][node][demand]
                        else:
                            spsRatio[z][node][demand] = decimal.Decimal("1.00")

                for key in stockPerStep[z].keys():
                    spsMinRatio[z][key] = min(spsRatio[z][key])
                for node in stockPerStep[z].keys():
                    if disruptedDict[z][node] == "Yes":
                        if disruptionLevel < spsMinRatio[z][node]:
                            spsMinRatio[z][node] = disruptionLevel
                        elif spsMinRatio[z][node] < decimal.Decimal("0.01"):
                            spsMinRatio[z][node] = decimal.Decimal("0.00")
                            #stopProduction[z][node] = "Yes"
                        else:
                             pass
    ################################################################################
    #####~~~~~~~~~~~~~~~~~~~~~~~~~~~~CREATE SUPPLY~~~~~~~~~~~~~~~~~~~~~~~~~~~~~####
    ############################ Delivery step #####################################
                for i in conDict[z].keys():
                    if spsMinRatio[z][i] >= decimal.Decimal("1.00"):
                        totalSupply[z][i][0] += originalSupply[z][i][0]
                        newSupply[z][i][0] = originalSupply[z][i][0]
```

```
                else:
                    totalSupply[z][i][0] += (originalSupply[z][i][0] * spsMinRatio[z][i])
                    newSupply[z][i][0] = (originalSupply[z][i][0] * spsMinRatio[z][i])
    ###############################################################################
    #####~~~~~~~~~~~~~~~~~~~~~~~~~~~~DELIVERY DONE~~~~~~~~~~~~~~~~~~~~~~~~~~~~~####
    ############################ Every Timestep ##################################
            else: # not a delivery time
                if z == 0:
                    timeUntilDelivery -= 1
                else:
                    pass
    ###############################################################################
    #####~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~USE STOCK~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~####
    ############################ Every Timestep #################################
            for i in conDict[z].keys():
                for j in demandType[z][i]:
                    if spsMinRatio[z][i] >= decimal.Decimal("1.00"):
                        onsiteStock[z][i][j] -= decimal.Decimal(usage[z][i][j])

                    elif spsMinRatio[z][i] > decimal.Decimal("0.00"):
                        onsiteStock[z][i][j] -= decimal.Decimal(stockPerStep[z][i][j])
                    else:
                        stopProduction[z][i] = "Yes"
            z+=1
        z=0
        while z < nx.number_connected_components(G):
            if time%deliveryTime == 0:
                for node in demandType[z].keys(): #for each site of production
                    demand = 0
                    while demand < inputs:
                        if originalDemand[z][node][demand] > decimal.Decimal("0.00"):
                            demandProportion[z][node][demand] = 1-
(siteDemand[z][node][demand]/originalDemand[z][node][demand])
                        else:
                            demandProportion[z][node][demand] = "na"
                        demand+=1
                    demand = 0
                    while demand < inputs:
                        if demandProportion[z][node][demand] == "na":
                            pass
                        else:
                            dp1[z].setdefault((node),
[]).append(demandProportion[z][node][demand])
                        demand+=1
                for key in demandProportion[z].keys():
                    minDP[z][key] = sum(dp1[z][key])/len(dp1[z][key])
            z+=1
        z=0
        while z < nx.number_connected_components(G):
            for key in stockPerStep[z].keys():
                for demand in demandType[z][key]:
                    if spsRatio[z][key][demand] < decimal.Decimal("1.00"):
                        if idDone[z][key] == "No":
                            TYPE = 0
                            while TYPE < len(sectors):# nodeType[z].keys():
                                if demandType[z][key][demand] == TYPE:
                                   initialDisTFail[z][key]["Disrupted"].append(sectors[TYPE])
                                TYPE+=1
                    if spsRatio[z][key][demand] == decimal.Decimal("0.00"):
                        if nfDone[z][key] == "No":
                            TYPE = 0
                            while TYPE < len(sectors):# nodeType[z].keys():
                                if demandType[z][key][demand] == TYPE:
                                    initialDisTFail[z][key]["Failed"].append(sectors[TYPE])
                                TYPE+=1
            z+=1
```

```
        z=0
        while z < nx.number_connected_components(G):
            for node in demandProportion[z].keys(): #for each site of production
                demand = 0
                while demand < inputs:
                    if len(initialDisTFail[z][node]["Disrupted"]) == 0:
                        pass
                    else:
                        idDone[z][node] = "Yes"
                    if len(initialDisTFail[z][node]["Failed"]) == 0:
                        pass
                    else:
                        nfDone[z][node] = "Yes"
                    demand+=1
            z+=1
    ################################################################################
    #####~~~~~~~~~~~~~~~~~~~~~~~~~RESET DEMAND~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~####
    ############################## Every Timestep #################################
        z=0
        while z < nx.number_connected_components(G):
            for i in conDict[z].keys():
                for j in demandType[z][i]:
                    siteDemand[z][i][j] = decimal.Decimal(originalDemand[z][i][j])
    ################################################################################
    #####~~~~~~~~~~~~~~~~~~~~~~~GENERATE METRICS~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~####
    ############################## Every Timestep #################################

            for key in valueList[z].keys():
                if originalSupply[z][key][0] > decimal.Decimal("0.00"):
                    valueList[z][key][0] =
decimal.Decimal(newSupply[z][key][0])/decimal.Decimal(originalSupply[z][key][0])
                else:
                    valueList[z][key][0] = decimal.Decimal("1.00")
                demandProp.append(str(minDP[z][key]))
            for key in valueList[z].keys():
                for value in valueList[z][key]:
                    vl.append(value)
                    ratioList.append(str(value))
            if time%deliveryTime == 0:
                if time == disruptionTime:
                    if injection == "Yes":
                        for key in injectionAmount[z].keys():
                            injectList.append(str(injectionAmount[z][key][0]))
                            injection = "no"
                        iJ = ",".join(injectList)
                       # print "injectionAmount", injectionAmount
                        iJL = disruptedWard + "," + runName + "," + iJ
                        writer4 = open(injectAmount,'a')
                        writer4.write("\n"+iJL)
                        writer4.close
                    else:
                        pass
                else:
                    pass
            else:
                pass

            meanProduction = decimal.Decimal((sum(vl))/(len(vl))*100)
            for key in minDP[z].keys():
                meanDemandList.append(minDP[z][key])
            meanDemand = sum(meanDemandList)/(len(meanDemandList))*100
            z+=1
        mpList.append(str(meanProduction))
        mdList.append(str(meanDemand))
    ########################################## SAVE RESULTS
######################################
```

```
    writerz = open(percentproduction,"a")
    rL = ",".join(ratioList)
    dP = ",".join(demandProp)
    writerz.write(rL + "\n")
    writerz.close
    writerx = open(demandproportion,'a')
    writerx.write(dP + "\n")
    writerx.close
    if recovery == "no":
        if meanProduction == decimal.Decimal("0.00"):
            time = 30
        else:
            time += 1
    else:
        time += 1
z=0
writery = open(disruptedBy,'a')
writery.write("Initial Disruption" + "\n")
while z < nx.number_connected_components(G):
    for i in initialDisTFail[z].keys():
        listID = []
        j=0
        while j < len(initialDisTFail[z][i]["Disrupted"]):
            listID.append(initialDisTFail[z][i]["Disrupted"][j])
            j+=1
        if len(listID) > 0:
            lID = ",".join(listID)
            k=0
            while k < len(datazones):
                if nodeType[z][i] == k:
                    lID2 = "Node "+ str(i) + " in " + datazones[k] + ":" + lID
                    writery.write(lID2 + "\n")
                k+=1
          #  print lID2
    z+=1
z=0
writery.write("" + "\n")
writery.write("Node Failure" + "\n")
while z < nx.number_connected_components(G):
    for i in initialDisTFail[z].keys():
        listNF = []
        j=0
        while j < len(initialDisTFail[z][i]["Failed"]):
            listNF.append(initialDisTFail[z][i]["Failed"][j])
            j+=1
        if len(listNF) > 0:
            lNF = ",".join(listNF)
            k=0
            while k < len(datazones):
                if nodeType[z][i] == k:
                    lNF2 = "Node "+ str(i) + " in " + datazones[k] + ":" + lNF
                    writery.write(lNF2 + "\n")
                k+=1
    z+=1
writery.close
mP = ",".join(mpList)
mD = ",".join(mdList)
mPL = disruptedWard + "," + runName + "," + mP
mPL2 = runName + "," + mP
mDL = disruptedWard + "," + runName + "," + mD
mDL2 = runName + "," + mD
writer2 = open(meanproduction, "a")
writer2.write("\n" + str(mPL))
writer2.close
writer5 = open(meandemand, "a")
writer5.write("\n" + str(mDL))
```

```
    writer5.close
    writer6 = open(mpWard, "a")
    writer6.write("\n"+str(mPL2))
    writer6.close
    writer7 = open(mdWard, "a")
    writer7.write("\n"+str(mDL2))
    writer7.close
    print r+1, "of", len(para)
    r+=1
print "KAPOW", "THWACK", "ZOWIE", "BAM"
```