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Flood footprint of the 2007 floods in the UK: The case of the Yorkshire and The Humber region

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A B S T R A C T

International headlines over the last few years have been dominated by extreme weather events, and floods have been amongst the most frequent and devastating. These disasters represent high costs and functional disruptions to societies and economies. The consequent breakdown of the economic equilibrium exacerbates the losses of the initial physical damages and generates indirect costs that largely amplify the burden of the total damage. Neglecting indirect damages results in misleading results regarding the real dimensions of the costs and prevents accurate decision-making in flood risk management. To obtain an accurate assessment of total flooding costs, this paper introduces the *flood footprint* concept, as a novel accounting framework that measures the total economic impact that is directly and indirectly caused to the productive system, triggered by the flooding damages to the productive factors, infrastructure and residential capital. The assessment framework account for the damages in the flooded region as well as in wider economic systems and social networks. The flood footprint builds on previous research on disaster impact analysis based on Input-Output methodology, which considers inter-industry flows of goods and services for economic output. The framework was applied to the 2007 summer floods in the UK to determine the total economic impact in the region of Yorkshire and The Humber. The results suggest that the total economic burden of the floods was approximately 4% of the region's GVA (£2.7 billion), from which over half comes from knock-on effects during the 14 months that the economy of Yorkshire and The Humber last to recover. This paper is the first to apply the conceptual framework of *flood footprint* to a real past event, by which it highlights the economic interdependence among industrial sectors. Through such interrelationships, the economic impacts of a flooding event spill over into the entire economic system, and some of the most affected sectors can be those that are not directly damaged. Neglecting the impact of indirect damages would underestimate the total social costs of flooding events, and mislead the correspondent actions for risk management and adaptation.

1. Introduction

In recent decades, the frequency and intensity of climate-related natural hazards have both increased. Extreme flooding and flood-related events are leading this trend, and the United Kingdom has been particularly affected by these phenomena (Committee of Climate Change, 2016).

These events have resulted in severe social and economic costs all over the world. Damages to labour and capital productivity after a disaster create knock-on effects that exacerbate the initial losses of the flooded assets, disturbing not only the impacted economic sectors but also other sectors that are indirectly affected through economic mechanisms. This sequence of events can be observed in the 2007 summer floods that occurred in England, which caused a major civil emergency nationwide. Thirteen people were killed and approximately 7000 had to be rescued from flooded areas; 55,000 properties were flooded and over half a million people experienced shortages of water and electricity (Pitt, 2008). The most affected region was Yorkshire and the Humber (Y&H) which accounted for

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Fig. 1. Yorkshire and The Humber region within the UK.
Source: Wikimedia Commons.[1]

65.5% of total national direct damage (region in red in Fig. 1). Approximately 1800 homes were flooded and more than 4000 people were affected. Additionally, more than 64 businesses, schools and public buildings were flooded, and infrastructure services such as roads and electricity substations suffered significant disruptions as well (Ash et al., 2008).

Traditional assessments of economic losses resulting from disasters of this type consider only direct damages to the physical infrastructure (Veen, 2004; Cole, 2003; Steenge and Bočkarjova, 2007). Nevertheless, it has been well documented that knock-on effects are triggered by these direct damages and that they constitute a considerable share of the total socioeconomic burden of the disaster (Cochrane, 1997; Hallegatte and Przyluski, 2010; Veen, 2004). Therefore, accurate flood risk management requires more than proper assessments of losses from capital and labour productivity disruptions; it must also consider the ripple effects of the recovery process, which are dispersed through sectoral and regional interdependencies.

Knock-on effects can arise in two main ways. On the one hand, damages to capital such as roads and offices will interrupt transportation and further disrupt economic activities, while damages to labour – including injuries and death – can be perceived as losses of labour productivity that ultimately prevent economic functioning. During an economic recovery, both capital and labour should be restored. On the other hand, production loss in a single sector, as a result of either capital or labour productivity losses, affects both customer and supplier industries, namely the 'downstream' and 'upstream' sectors. This indicates that an initial economic loss in a single sector can eventually spill over into the entire economic system and even into other previously unaffected regions through sectoral and regional interdependencies.

Flood risk management[2] requires, first, accurate estimates of losses from both capital and labour productive constraints after a flooding. Second, to estimate a flood's indirect effects on the economy, it is essential to consider the ripple effects resulting from sectoral and regional interdependencies. Flood risk management can also reduce vulnerability and increase the resilience[3] of affected regions in the future. (Okuyama, 2009; Rose, 2004; Veen & Logtmeijer, 2003). Third, all accumulated production losses that occur prior to the full recovery of the economy, as well as the costs of capital and labour restoration during the flood's aftermath, should be taken into consideration.

This paper introduces the new concept of *flood footprint* to describe an accounting framework that measures the total economic impact that is directly and indirectly caused to the productive system, triggered by the flooding damages to the productive factors, infrastructure and residential capital; on the flooded region and on wider economic systems and social networks. This framework can not only capture the economic costs derived from capital and labour productivity losses but also account for the post-disaster recovery process. Here, we define the productivity loss, from capital or labour, as the reduction in the production level of equilibrium at pre-disaster conditions due to constraints in the availability of any of the productive factors, which in the case of the Leontief production functions are capital and labour. This type of production functions is a particular case of constant elasticity of substitution production functions, where the level of production is determined as a function of the productive factors.

In the case of the Leontief production functions (used within the IO modelling), or perfect complements, it is assumed that the proportion of productive factors is fixed, or in other words, the technology is fixed and there is no possibility of substitution between de productive factors (Miller and Blair, 2009). Owing to the above, a constraint in the availability of any of the productive factors will have a proportional effect in the level of production. For instance, the reduction of 10% in the availability of labour force, due to transport disruptions, illness, displacements or other factors after a flooding, would represent a decrease of 10% in the level of production.

Additionally, as the *flood footprint* framework is developed based on an Input-Output (IO) model, it is also able to measure the knock-on effects resulting from sectoral and regional interdependencies. The concept of *flood footprint* will therefore improve upon existing flood risk assessment and better assist professionals working on disaster risk assessment, preparation and adaptation.

This paper constitutes the first empirical application of the flood footprint framework to a real past event. It is evaluated the total economic cost (or *flood footprint*) in the region of Yorkshire and The Humber, caused by the 2007 summer floods in the UK. While, a sensitivity analysis is carried out to provide robustness in the results.

This paper is structured as follows. The next section reviews selected literature on disaster impact analysis. Section 3 describes the methodology and rationale of the flood footprint model. Section 4 presents the data gathering and codification methods used to analyse total economic losses in Y&H resulting from the floods in

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[1] Wikimedia Commons (Yorkshire and The Humber region) https://commons.wikimedia.org/wiki/File:Yorkshire_and_the_Humber_in_England.svg.

[2] '[Flood risk management] focuses on reducing the potential adverse consequences of flooding with regard to human health, the environment, cultural heritage and economic activity' (Vanneuvill et al., 2011).

[3] The Intergovernmental Panel on Climate Change (IPCC) defines vulnerability as the 'degree to which a system is susceptible to injury, damage, or harm' and resilience as the 'degree to which a system rebounds, recoups, or recovers from a stimulus' (Burton et al., 2001).

2007. Section 5 presents the main results of the flood footprint assessment. Finally, conclusions are discussed in section 6.

2. Selected literature on the impact assessment of natural disasters

The impact assessment of natural disasters has been a vibrant research area in recent years, many kinds of methodologies are used to do risk analysis based on different theory systems (Chen et al., 2011, 2015; Okuyama, 2007). For example, from the ecological perspective, Chen et al. (2011) developed an information-based model that on the basis of system methodology to assess the ecological risk by eco-environmental hazard. But our research mainly focus on the economic perspective and only consider the economic impact resulted from natural hazard.

2.1. Economic-based methodologies

Based on economic theory, a range of applicable methodologies is applied into natural disaster risk analysis (Okuyama, 2007). However, the pre-eminence of one approach over the others has not yet been decisively determined, and differences in results are influenced by different approaches, assumptions, data, and reference theories (Greenberg et al., 2007). Several methodological adaptations and extensions have arisen, each attempting to overcome the analytical limitations of existing models. The most widely used have been those based on econometrics, Input-Output (IO) analysis, and the Computable General Equilibrium (CGE) model.

Econometric models possess rigorous statistical foundations, which enables forecasting estimations. However, long data series — which are normally at the national level — rarely contain similar past events, which prevents a subnational regional analysis. Additionally, the data hardly distinguish between direct and higher-order — or indirect — losses. These problems hamper the performance of disaster impact analyses (Cochrane, 2004; Greenberg et al., 2007; Hallegatte and Przyluski, 2010; Li et al., 2013; Okuyama, 2007, 2009).

Input-Output based models are founded on the basic idea of the circular flow of the economy in equilibrium. The IO tables present the inter-industrial transactions of the whole economy in a transparent and linear array, which enables the assessment of knock-on effects along the value chain. The analysis remains objective, as the necessary calibration of parameters is usually much lower than in other methodologies. Regionalization of the IO national tables is also possible, thus enabling regional analysis. These characteristics allow the estimation of higher-order losses. Nonetheless, the original IO model presents some limitations: The basic IO model is a static model, the production functions are based on the fixed-proportion approach, the prices are fixed and the substitutions of inputs and imports are not considered. (Cole, 2003; Greenberg et al., 2007; Okuyama, 2007, 2009; Rose, 2004). It is essentially a demand-driven model, and risk uncertainties are not considered in the original version (Cochrane, 2004; Li et al., 2013).

The CGE-based models rely on certain characteristics in overcoming some of the IO rigidities, while retaining the inter-industrial and regional analyses of the IO model. The rigidities are mainly related to the manageability of supply constraints, price changes, non-linearity, and flexibility in input and import substitutions. However, the modelling refinement of CGE models relies on a high number of parameters that are exogenously calibrated. This introduces additional uncertainty and bias into the analysis. In the case of impact analysis, the model assumes that the economy is always in equilibrium, which is one of the main features that the analysis is intended to capture: the economic imbalances and consequences that arise after a disaster.

2.2. Input-Output methodology

Next, we trace the development of IO-based models for impact analysis, as the characteristics of the IO model make it particularly well suited to an economy's situation in the aftermath of a disaster (Cochrane, 2004; Greenberg et al., 2007; Okuyama, 2007, 2009; Rose, 1995, 2004; Veen, 2004).

The first version of the IO model, developed by Wassily Leontief in the 1930s, is a static and demand-driven model. However, the damages caused by a natural disaster impose imbalances in the economy that usually affect the supply side of the productive chain. These imbalances then lead to bottlenecks in production, and damages spill over because of a series of knock-on effects, which ripple through the economic interconnections among industrial sectors and coupled economies. To cope with this, *ad hoc* extensions have been developed to overcome the original rigidities of the IO model and to manage the complexity of natural disaster impact assessment (Cole, 2003; Li et al., 2013; Okuyama, 2007; Rose, 2004).

Initially, to assess the damage to productivity in the industrial sectors, some authors (Y. Haimes and Jiang, 2001; Y. Y. Haimes et al., 2005; J. R. Santos and Haimes, 2004; R. J. Santos, 2006) developed a measure of *expected inoperability* to address the risk inherent in natural disasters. This is a concept based on the system risk or probability of limitations on performing the planned *natural or engineered functions*. Based on this concept, the Inoperability Input-Output model (IIM) assumes a direct relation between the level of transactions and the interdependency among economic sectors. The IIM has been widely used to assess the impact of disasters and has a special focus on disaggregated analysis by economic sector. Nevertheless, some rigidities from the original IO model remain, such as the demand-driven approach, the static analysis and the assumption of economic equilibrium after the disaster, as the IIM is itself a stylized application of the standard IO model (Dietzenbacher and Miller, 2015). In this regard, Oosterhaven (2017) states that the IIM fails to account all the negative impacts from natural disasters and does not consider those positive effects that may arise from additional demand in those sectors/regions substituting the inputs that cannot be supplied by the hit industries.

Leung et al. (2007) and Xu et al. (2011) developed a supply-driven extension for the IIM. These are price models that only capture changes in the prices of the value added factors (labour, taxes, etc.). These models have been useful in the analysis of recovery dynamics after a disaster. Nevertheless, the relation between changes in primary factors' prices and output quantities is not clear. Additionally, Xu et al. (2011) modelled recovery time as an exogenous variable when it is expected to be a result of the impact analysis. Subsequently, J. R. Santos and Rehman (2012) extended the model to estimate the recovery time for the affected sectors based on survey data. One limitation in this model is, however, the absence of institutional allocation options for the remaining resources.

Focusing on post-disaster economic imbalances, Steenge and Bočkarjova (2007) introduce the Event Account Matrix (EAM) concept within IO modelling. This is a mathematical component (a diagonal matrix) whose diagonal-elements express the damaged proportion of each sector's productive capacity.[4] The imbalances and possible bottlenecks after a shock are derived from the information in the EAM, and the recovery path is traced from this point. The model also allows substitutions of *importable* goods and services (Bockarjova et al., 2004; Steenge and Bočkarjova, 2007).

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[4] The rationale of the EAM is disclosed in vector form for this paper, the event account vector (EAV).

Regarding the dynamics of the recovery process, even though the basic IO model is static, Leontief himself developed a dynamic extension (Miller and Blair, 2009; Rose, 1995), and other extensions have subsequently been adapted to address this constraint. Two such examples are the Sequential Interindustry Model (SIM) (Okuyama, 2004; Romanoff and Levine, 1981), a continuous-time formulation of a Regional Econometric IO model (REIM), and the Dynamic Inoperability IO model (DIIOM), a dynamic extension of the IIM (Y. Y. Haimes et al., 2005; Okuyama, 2007; J. R. Santos and Rehman, 2012; R. J. Santos, 2006; Xu et al., 2011). These represent notable progress in overcoming the constraints of models used for disaster impact analysis. However, even these improvements do not address the assumption of economic equilibrium in the aftermath of a disaster.

Stéphane Hallegatte (2008) uses a time-scaled approach to model the recovery path. He developed an Adaptive Regional IO (ARIO) model that considers both the bottlenecks caused by damage to industrial productive capacity and the adaptive behaviour of consumers and producers facing such imbalances. Nevertheless, the model does not consider the bottlenecks resulting from constraints in labour's productive capacity, nor does it consider residential capital damage (Li et al., 2013).

Based on the former ARIO model, Li et al. (2013) laid the foundations for the *flood footprint* model. This incorporates production restrictions – not only based on industrial damage but also considering reductions in productivity as a result of labour damage. The model also considers residential damage, which interacts with the reconstruction process during the competition for available resources and affects the recovery of labour capacity.

An alternative methodology to account the effects from changes in intermediate inputs (as in a flooding event) is developed by Dietzenbacher & Lahr (2013). They apply the method of hypothetical extractions to the analysis of impact assessment. The method proposes to *extract*, partially or totally, the intermediate transactions of a sector within the economy. This is, replacing the row or column of the affected sector with zeros (or smaller proportions of the original value). A new level of production is calculated under this condition. The difference with the original level of production constitutes the effect of the disaster in the economy. The main contribution of this approach is, in a consistent way, considering the forwards effects of a shock within the demand-driven IO model. However, Oosterhaven and Bouwmeester (2016) have argued that the assessment of forward effects with this method is faulty, as what it is measured is the backwards effects of the reduction of intermediate sales of an industry. And not the forward effects of the reduction of inputs from the affected industry to the other purchasing industries. Although it provides with a method to account for supply chain disruptions, within the IO framework, it fails in accounting for other effects when an economy faces a natural disaster, such as the damage in non-productive sectors (or residential damages), and disruptions in productive capacity due to constraints in labour force.

More recently, Koks et al. (2014) have used a Cobb-Douglas function to estimate the direct damages from labour and capital constraints, and the indirect damages incurred during the recovery process are derived through the ARIO model. This approach constitutes a good comparison for the flood footprint model, as it also incorporates restrictions in the productive capacity of labour using a different approach.

A new approach developed by Oosterhaven and Bouwmeester (2016) is based on a non-linear program that minimises the information gain between the pre-disaster and post-disaster situation of economic transactions. The model is successful in reproducing the recovery towards the pre-disaster economic equilibrium. The model has been tested just hypothetically and further development is to be done for applications to real cases. Some aspects of disaster impact analysis are left aside, as the damage to residential capital, or the recovery of productive capacity of labour.

Considering the existing models used in disaster impact analysis, this paper applies the new concept of *flood footprint* to measure the total socioeconomic impact that was directly and indirectly caused by the 2007 summer floods in the Y&H region. This new damage accounting framework combines the advantages of existing models used in disaster risk analysis, including the analysis of capital damages by industrial sector as well as labour constraints; it also considers post-disaster economic imbalances and supply bottlenecks. To model the recovery process, the allocation of resources through a rationing scheme is proposed to satisfy the restoration of industrial capital and households' damages. The possibilities of changes in final demand are also accounted for through the modelling of consumers' adaptive behaviour.

3. Flood footprint assessment framework

In this section, the rationale of the *flood footprint* model is disclosed in detail. Regarding the mathematical symbols and formulae, matrices are represented by bold-italic capital letters (e.g., $\boldsymbol{X}$), vectors by bold-italic lowercase (e.g., $\boldsymbol{x}$) and scalars by italic lowercase (e.g., x). By default, vectors are column vectors, with row vectors obtained by transposition (e.g.x'); a conversion from a vector (e.g., $\boldsymbol{x}$) to a diagonal matrix is expressed as a bold lowercase letter with a circumflex (i.e.$\widehat{\boldsymbol{x}}$); the operators '.*' and './' are used to express element-by-element multiplication and the element-by-element division of two vectors, respectively.

The IO model is founded on the basic idea of the circular flow of an economy in equilibrium. The IO tables present the inter-industrial transactions of the whole economy in a linear array. In mathematical notation it is presented as:

$$\boldsymbol{x} = \boldsymbol{Ax} + \boldsymbol{f} \tag{1}$$

Where $\boldsymbol{x}$ is a vector of dimension $1xn$ (where n is the number of industry sectors) representing the total production of each industrial sector,[5] $\boldsymbol{Ax}$ represents the intermediate demand vector, where each element of the matrix $\boldsymbol{A}$, $[a_{ij}]$, refers to the technical relation showing product i needed to produce one unit of product j. Finally, $\boldsymbol{f}$ indicates final demand vector of products.

Based on the IO modelling, the assessment of the damage by the *flood footprint* modelling departs from the *Basic Equation* concept coined by Steenge and Bočkarjova (2007). This is a closed[6] IO model that represents an economy in equilibrium. The equilibrium implies that total production equals total demand with the full employment of productive factors, including both capital and labour, as in equation (2).

$$\begin{bmatrix} \boldsymbol{A} & \boldsymbol{f}/l_T \\ \boldsymbol{l}' & 0 \end{bmatrix} \begin{pmatrix} \boldsymbol{x} \\ l_T \end{pmatrix} = \begin{pmatrix} \boldsymbol{x} \\ l_T \end{pmatrix} \tag{2}$$

$$\text{and} \quad l_T = \boldsymbol{l}'\boldsymbol{x} \tag{3}$$

where $\boldsymbol{l}'$ is a row vector of *technical labour* coefficients for each industry, showing the relation of labour needed in each industry to produce one unit of product.: $\left[\frac{l_i}{x_i}\right]$ l_i is the industrial level of

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[5] In the modelling, it is assumed that each sector produces only one uniform product.

[6] Here, *closed* means that the primary productive factors (labour) are explicitly considered within the model.

employment. The scalar l_T is the total level of employment in the economy.

All inter-industrial flows of products as well as industrial employment are considered as the necessary inputs involved in the production of each unit of output. A linear relation between the productive factors (labour and capital) and the output in each sector is assumed in IO analysis, suggesting that inputs should be invested in fixed proportions for proportional expansion in output.

However, this equilibrium is broken after a disaster, and inequalities arise between productive capacity and demand. In the next section, we introduce the possible sources of these inequalities.

3.1. Sources of post-disaster inequalities

After a disaster, market forces become imbalanced, leading to gaps between supply and demand in different markets. The causes of these imbalances may be varied, and they constitute the origin of the ripple effects that permeate the economy of the flooded region.

3.1.1. Labour productivity constraints

The production functions in the IO model assume a complements-type technology where the productive factors – labour and capital – maintain a fixed relationship in the production process. Constraints in any of the productive factors will produce, therefore, a proportional decline in productive capacity, even when other factors remain fully available. Therefore, labour constraints after a disaster may impose severe knock-on effects on the rest of the economy. This makes labour constraints a key factor to consider in disaster impact analysis. In the *flood footprint* model, these constraints can arise from employees' inability to work as a result of illness or death, or from commuting delays due to damaged or malfunctioning transport infrastructure. In the model, the proportion of surviving production capacity from the constrained labour productive capacity ($\boldsymbol{x}_{\boldsymbol{l}}^{\boldsymbol{t}}$) after the shock is:

$$\boldsymbol{x}_l{}^t = (\boldsymbol{i} - \gamma_{\boldsymbol{l}}^{\boldsymbol{t}}).*\boldsymbol{x}^0 \tag{4}$$

$$\text{and } \gamma_l^t = \left(\boldsymbol{l}^0 - \boldsymbol{l}^{\boldsymbol{t}}\right)./\boldsymbol{l}^0 \tag{5}$$

where $\gamma_{\boldsymbol{l}}^{\boldsymbol{t}}$ is a vector where each element contains the proportion of labour that is unavailable at each time t after the flooding event. The vector $\boldsymbol{i}$ is a vector of ones of the same dimension as γ_l^t, so that the vector $(\boldsymbol{i} - \gamma_{\boldsymbol{l}}^{\boldsymbol{t}})$ contains the surviving proportion of employment at time t. $\boldsymbol{x}^0$ is the pre-disaster level of production.

The proportion of the surviving productive capacity of labour is thus a function of the loss from the sectoral labour force and its pre-disaster employment level. Following the fixed proportion assumption of the production functions, the productive capacity of labour after the disaster ($\boldsymbol{x}_l^t$) will be a linear proportion of the surviving labour capacity at each time step.

3.1.2. Capital productivity constraints

Similar to labour constraints, productive capacity from industrial capital during the flooding aftermath ($\boldsymbol{x}_{cap}^t$) will be constrained by the surviving capacity of the industrial capital. The share of damage to each sector are disclosed in the event account vector (EAV), following Steenge and Bockarjova (2007) Then, the remaining production capacity of industrial capital at each time-step, is:

$$\boldsymbol{x}_{\boldsymbol{cap}}^{\boldsymbol{t}} = \left(\boldsymbol{I} - \gamma_{\boldsymbol{cap}}^{\boldsymbol{t}}\right)*\boldsymbol{x}^0 \tag{6}$$

$$\text{and } \gamma_{cap}^t = \left(\boldsymbol{k}^0 - \boldsymbol{k}^{\boldsymbol{t}}\right)/\boldsymbol{k}^0 \tag{7}$$

where, $\boldsymbol{x}^0$ is the pre-disaster level of production, $\gamma_{\boldsymbol{cap}}^{\boldsymbol{t}}$ is the EAV, a column vector showing the share of damages of productive capital in each industry. $\boldsymbol{k}_0$ is the vector of capital stock in each industry in the pre-disaster situation, $\boldsymbol{k}^{\boldsymbol{t}}$ is the surviving capital stock in each industry at time t during the recovery process.

During the recovery, the productive capacity of industrial capital is restored gradually through both local production/reconstruction and imports.

3.1.3. Post disaster final demand

On the other side of the economic system, final demand may vary for diverse reasons. On the one hand, the recovery process involves the reconstruction and replacement of damaged physical capital, which increases the final demand for those sectors involved in the reconstruction process, namely, the *reconstruction demand*, $\boldsymbol{f}_{\mathbf{rec}}$. On the other hand, final demand may also decrease after a disaster. Based on Li et al. (2013), it has been noted that after a disaster, strategic adaptive behaviour would lead people to ensure their continued consumption of basic commodities, such as food and medical services, while reducing consumption of other non-basic products.

In the model, we consider the adaptive consumption behaviour of households. Here, the demand for non-basic goods is assumed to decline immediately after the disaster, while consumption in industries providing food, energy, clothing and medical services remains at pre-disaster levels.

Recovery in household consumption is driven by two complementary processes. For consumption adaptation, we consider a short-run tendency parameter ($\mathbf{d}_1^t$), which is modelled as the rate of recovery in consumption at each time step. The rationale here is that consumers restore their consumption according to market signals about the recovery process. Likewise, a long-run tendency parameter ($\mathbf{d}_2^t$) is calculated as a *recovery gap,* i.e., the total demand minus the total production capacity compared against the total demand at each time step. These two parameters are calculated for each sector. So, the expression for dynamic household consumption recovery is:

$$\boldsymbol{f}_{hh}^t = \left(\mu^0 + \boldsymbol{d}_1^t + \boldsymbol{d}_2^t\right).*\boldsymbol{c}^0 \tag{8}$$

where the parameter μ^0 is a scalar which expresses the reduced proportion of household demand (a parameter similar to the EAV) over time, and the vector $\mathbf{c}^0$ represents the pre-disaster level of household expenditure on products by industrial sector.

The rest of the final demand categories recover proportionally to the economy, based on the share of each category regarding pre-disaster final demand. It should be noted the trade-off of resources allocation between final demand and the reconstruction process. The adapted total final demand ($\boldsymbol{f}^t$), then, is modelled as follows:

$$\boldsymbol{f}^{\boldsymbol{t}} = \sum_k \boldsymbol{f}_{\boldsymbol{k}}^{\boldsymbol{t}} + \boldsymbol{f}_{\boldsymbol{rec}}^{\boldsymbol{t}} \tag{9}$$

where $\mathbf{f}^t$ is the adapted total final demand at each time step t, including the reconstruction demand for damaged industrial and residential capital ($\boldsymbol{f}_{\boldsymbol{rec}}^{\boldsymbol{t}} = \boldsymbol{f}_{\boldsymbol{cap}}^{\boldsymbol{t}} + \boldsymbol{f}_{\boldsymbol{hh}}^{\boldsymbol{t}}$). It also includes the final demand for all final consumption categories, indicated by the summation $\sum_k \boldsymbol{f}_k^t$, where the subscript k refers to the vector of each category of final consumption: $k = 1$ is for the adapted household consumption ($\boldsymbol{f}_{hh}^t$), $k = 2$ is for government expenditure, $k = 3$ is for investment in capital formation, and $k = 4$ is for external consumption or exports.

The adapted total demand for each sector, ($\boldsymbol{x}_{td(i)}^t$), can thus be calculated as follows:

$$x_{td(i)}^t = \sum_{j=1}^{n} a_{ij} x_{td(i)}^t \; + f_i^t \tag{10}$$

Equations (4)–(10) describe the changes on both sides of the economy's flow – production and consumption – where imbalances in the economy after a disaster arise from the differences in the productive capacity of labour, the productive capacity of industrial capital, and changes in final demand. From this point, the restoration process starts to return the economy to its pre-disaster equilibrium production level.

3.2. *Post-disaster recovery process*

The following section describes the process of recovery. Here, an economy can be considered as recovered once labour and industrial production capacities are in equilibrium with total demand and production is restored to the pre-disaster level. How to use the remaining resources to achieve pre-disaster conditions is modelled based on a selected rationing scheme.

The first step is to determine the available production capacity in each period after the disaster. Within the context of Leontief production functions, the productive capacity is determined for the minimum of either productive factor, capital and labour, as shown below:

$$\boldsymbol{x}_{tp}^t = min\left\{\boldsymbol{x}_{cap}^t, \boldsymbol{x}_l^t\right\} \tag{11}$$

Secondly, the level of the constrained production capacity is compared with the total demand to determine the allocation strategy for the remaining resources and for reconstruction planning. The rules of this process constitute what it is called the *rationing scheme*, described below.

3.2.1. *Rationing scheme*

The recovery process requires allocating the remaining resources to satisfy society's needs during the disaster's aftermath. Thus, the question of how to distribute and prioritize the available production based on the remaining capacity of industry or final customer demand becomes essential, as recovery time and indirect costs can vary widely under different rationing schemes.

This case study used a *proportional-prioritization* rationing scheme that first allocates the remaining production among the inter-industrial demand ($\boldsymbol{A}\boldsymbol{x}_{tp}^t$) and then attends to the categories of final demand.[7] This assumption is built on the rationale that business-to-business transactions are prioritised, based on the observation that these relations are stronger than business-to-client relationships (Stéphane Hallegatte, 2008; Li et al., 2013).

Thus, when calculating the productive possibilities of the next period, actual production is first compared with inter-industrial demand. Defining $o_i^t = \sum_j A_{ij} x_{tp(j)}^t$ as the production required in industry i to satisfy the intermediate demand of the other industries, two possible scenarios may arise after the disaster (Hallegatte, 2008):

The first scenario occurs if $x_{tp(i)}^t < o_i^t$, in which case the production from industry i at time t in the post-disaster situation ($x_{tp(i)}^t$) cannot satisfy the intermediate demands of other industries. This situation constitutes a bottleneck in the production chain, where production in industry j is then constrained by $\frac{x_{tp(i)}^t}{o_i^t} x_{tp(j)}^t$, where $\frac{x_{tp(i)}^t}{o_i^t}$ is the proportion restricting the production in industry j, $x_{tp(j)}^t$.

This process proceeds for each industry, after which there must be consideration of the fact that industries producing less will also demand less, in turn affecting and reducing the production of other industries. The iteration of this process continues until production capacity can satisfy this *adapted* intermediate demand and some remaining production is liberated to satisfy part of the final and *reconstruction* demand and increase the productive capacity the next period. This situation leads to a partial equilibrium, where level of the adapted intermediate demand is defined as $\boldsymbol{A}\boldsymbol{x}_{tp}^{t^*}$, where the asterisk in $\boldsymbol{x}_{tp}^{t^*}$ represents the adapted production capacity that provides the partial equilibrium, and is smaller than the actual production capacity ($\boldsymbol{x}_{tp}^t$) from equation (11).

This process continues until the total production available at each time, $x_{tp(i)}^t$, can satisfy the intermediate demand at time t, o_i^t.

The second scenario occurs when $x_{tp(i)}^t > o_i^t$. Then, the intermediate demand can be satisfied without affecting the production of other industries.

In both cases, the remaining production after satisfying the intermediate demand is proportionally allocated to the recovery demand and to other final demand categories in accordance with the following expressions:

$$\left(\boldsymbol{x}_{tp}^{t*} - \boldsymbol{A}*\boldsymbol{x}_{tp}^t\right) \cdot * \boldsymbol{f}_k^0 \cdot \Bigg/ \left(\sum_k \boldsymbol{f}_k^0 + \boldsymbol{f}_{rec}^t\right) \tag{12}$$

$$\left(\boldsymbol{x}_{tp}^{t*} - \boldsymbol{A}*\boldsymbol{x}_{tp}^t\right) \cdot * \boldsymbol{f}_{rec}^t \cdot \Bigg/ \left(\sum_k \boldsymbol{f}_k^0 + \boldsymbol{f}_{rec}^t\right) \tag{13}$$

Equation (12) refers to the distribution of product to the k categories of final demand, while equation (13) refers to the proportion of available product that is designated to reconstruction.

The expression ($\boldsymbol{x}_{tp}^t - \boldsymbol{A}*\boldsymbol{x}_{tp}^t$) refers to the production left after satisfying the intermediate demand, and $\sum_k \boldsymbol{f}_k^0$ refers to the total final demand in the pre-disaster period, so that the production left after satisfying intermediate demand is allocated among the categories of final demand following the proportions of pre-disaster condition, plus the consideration of the reconstruction needs for recovery ($\boldsymbol{f}_{rec}^t$). Note that for the first scenario, the expression $\mathbf{A}*\mathbf{x}_{\mathrm{tp}}^{\mathrm{t}}$ becomes $\mathbf{A}*\mathbf{x}_{\mathrm{tp}}^{\mathrm{t}*}$ and represents the *adapted intermediate demand*, where $\boldsymbol{x}_{tp}^{t^*}$ is smaller than the actual production capacity, $\mathbf{x}_{\mathrm{tp}}^{\mathrm{t}}$.

Additionally, we assume that part of the unsatisfied final demand is covered by imports, some of which contribute to the recovery when allocated to *reconstruction demand*.

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[7] We assume here that the productivity of any of the productive factors does not change during the recovery process, as is the case with Leontief production functions. We also assume that the disaster happens just after time t = 0 and that the recovery process starts at time t = 1.

3.2.2. Imports

In the *flood footprint* model, imports help in the reconstruction process by supplying some of the inputs that are not internally available to meet *reconstruction* demand. Additionally, if the damaged production capacity is not able to satisfy the demand of final consumers, they will rely on imports until internal production is restored and they can return to their previous suppliers.

There are some assumptions underlying imports. First, imports will be allocated proportionally among final demand categories and reconstruction demand. Second, commodities from other regions are assumed to be always available for provision at the maximum rate of imports under the pre-disaster condition. Third, there are some types of goods and services that, by nature, are usually supplied locally (such as utilities and transport services), making it infeasible to make large scale adjustments over the time scale of disaster recovery. Finally, imports are assumed to be constrained by the total *importability capacity,* which here is defined as the survival productive capacity of the transport sectors (see equation (14)). The assumption is that the capacity of transporting goods is proportional to the productive capacity of the sectors related with transport, so that if the production value of sectors related with transport services is contracted by x% in time t, the imports will contract by the same proportion, in reference to the pre-disaster level of imports, $\boldsymbol{m}^t$.

$$\boldsymbol{m}^t = \left(\frac{x^{*(t)}_{tran}}{x^0_{tran}} * \boldsymbol{m}^0\right) \tag{14}$$

where $\mathbf{m}^0$ is the vector of pre-disaster imports, and $\mathrm{x}^0_{\mathrm{tran}}$ and $\mathrm{x}^{*(t)}_{\mathrm{tran}}$ are the scalars denoting the pre-disaster and post-disaster production capacities of the sectors related with transport. The subscript *tran* refers to aggregated transport sectors by land, water and air. If sectors related with transport are 2 or more, then $\mathrm{x}^0_{\mathrm{tran}}$ is the sum of the product of those sectors at pre-disaster level, and $\mathrm{x}^{*(t)}_{\mathrm{tran}}$ is the product of those sectors at time t during recovery, obtained from the vectors of productive capacity, $\mathbf{x}^0$ and $\mathbf{x}^{*(\mathrm{t})}$, respectively.

3.2.3. Recovery

Decisions to return to pre-disaster conditions can be complex and varied. Here, we have assumed a way of adapting to a condition of balanced production and demand. That is, we pursue a partial equilibrium for productive capacities at each time period – through the rationing scheme – and then follow a long-term growth tendency towards the pre-disaster level of production – through the reconstruction efforts.

It should be remembered that the recovery process implicates the repair and/or replacement of the damaged capital stock and households. During this process, production capacity increases both through local production and through imports allocated to *reconstruction demand.*

Then, the productive capacity of each industry for the next period incorporates the rebuilt capacity of the last period:

$$x^{t+1}_{cap(i)} = x^t_{cap(i)} + \Delta x^t_{cap(i)} \tag{15}$$

$$\text{where: } \Delta x^t_{cap(i)} = g_i\left\{\left[m^t_i + \left(x^t_{tp(j)} - \sum_{j=1}^{n} a_{ij}x^t_{tp(j)}\right)\right] * \left[f^t_{cap(i)} \Big/ \left(\sum_k f^0_{k(i)} + f^t_{rec(i)}\right)\right]\right\}$$

where g_i encloses the functional relation (or ratio) between capital and production to each sector, and the argument of the function represent the amount of resources invested in capital reconstruction by sector. And where $m^t_i + (x^t_{tp(j)} - \sum_{j=1}^{n} a_{ij}x^t_{tp(j)})$ is the total product (regional and imported) allocated to final consumption, while the expression $f^t_{cap(i)} \,/\, (\sum\limits_k f^0_{k(i)} + f^t_{rec(i)})$ refers to how much of that product is allocated to capital reconstruction each time period.

Note that the proportion of affected capital –the EAV– changes for each sector by the amount:

$$\gamma^t_i - \gamma^{t+1}_i = \frac{\left[m^t_i + \left(x^t_{tp(i)} - \sum_{j=1}^{n} a_{ij}x^t_{tp(j)}\right)\right] * \left[f^t_{cap(i)} \Big/ \left(\sum_k f^0_{k(i)} + f^t_{rec(i)}\right)\right]}{f^0_{rec(i)}} \tag{16}$$

The new level of production is compared with the level of labour capacity at the next time-step. Then, the process described above is repeated until an equilibrated economy of the pre-disaster production level is reached.

The driving forces of recovery are constituted, then, by the progressive restoration of the productive capacity of industrial capital by means of internal production and imports allocated to *reconstruction* demand, by the restoration of the labour force, and by the recovery of final demand.

3.3. Flood footprint modelling outcomes

The flood footprint model provides us with the outcomes of diverse economic variables over the course of the recovery process. All results are provided at each time-step during restoration and at a disaggregation level of 46 industrial sectors. The time that each variable and sector requires to achieve its pre-disaster level is, likewise, provided by the model.

Results of the *direct* and *indirect damages* constitute the principal outcomes of the model.

The *direct damages* account for the value and the proportion of the damages to the physical infrastructure, both to industrial and residential capital. To determine these, we construct the EAV with the proportion of damage to the capital stock as the cost of reconstruction. The model, in turn, translates the damage from this *stock variable* into damages to productivity, a *flow variable.*

The *indirect damages* account, period by period, for non-realised production owing to constraints in both productivity and demand, i.e., the cascading effects from the *direct damages.*

The model delivers the dynamics of recovery for other variables, including industrial productive capacity as rebuilt capital; labour productive capacity, which is linked to the restoration of residential capital and transportation facilities; the contribution of imports to the economy during the recovery process (as the proportion of final demand satisfied by external suppliers and of production allocated to reconstruction, both of which are processes also linked to the process of transport restoration); and final demand, as the restoration of levels of consumption in each category, which is influenced by adaptive behavioural modelling for the case of household consumption.

It should be considered that the trajectories of the variables' recoveries are influenced by the assumptions and decisions considered for reconstruction, such as the establishment of the rationing scheme. On the other hand, a sensitivity analysis of the parameters is performed to obtain robust results and to determine how the results are influenced by changes in the parameters.

4. Data gathering and codification

The Flood Footprint model requires two sets of data: economic data about the affected region and information about the disaster. All of the values are for 2007, and when they are monetary they are in millions of pounds (£million) at 2009 prices. A monthly time scale is used for the temporal analysis, and the sectoral disaggregation uses 46 economic sectors (see sectors disaggregation in the EAV provided in the appendix).

4.1. *Economic data*

The economic data include information on capital stock, final demand, employment, and inter-industrial transactions. All the information is at the regional level, and when available it was obtained from official data; otherwise, a regionalization was carried out.

Capital stock data are only available at the national level. The regionalization consisted of obtaining the productivity of each sector at the national level and then adjusting by regional output, assuming the same productivity as the national average. The regional dwelling capital is the proportion of housing in the region multiplied by the national dwelling capital. For the region of Y&H, this accounts for 8%.

The categories for final demand, i.e., households, government, capital, imports and exports, were obtained from the UK-Multisectoral Dynamic Model (MDM) by Cambridge Econometrics Ltd,[8] a macro-econometric model used to analyse and forecast environmental, energy and economic data for twelve regions in the UK. The data used for the analysis were for the region of Y&H and 46 industry sectors.

Employment data are usually available at a very detailed regional scale; thus, these data were obtained directly from official data. However, the sectoral disaggregation was not consistent with the rest of the data. To match the data with the 46-sector disaggregation, a weighted distribution was followed based on both national employment and the value-added data from the MDM.

For inter-industrial transactions data, a regionalised matrix of technical coefficients had to be derived from the national IO tables following the methodology developed by Flegg and Webber (2000), owing to the lack of regional tables (see supporting information for the regionalization technique). The transactions' values are obtained later by multiplying the regional matrix of technical coefficients by the regional output.

4.2. *Disaster data*

Ideally, the disaster data comprise information of damages to industrial capital, residential capital, and infrastructure; reductions in labour capacity; and changes in final demand.

The main source for the disaster data is the UK Environmental Agency, and the information for the analysed event is disclosed in the report ‘Economic Impacts of Flood Risk on Yorkshire and Humber. Cost of 2007 Floods’ (Ash et al., 2008).

For damages to industrial capital, the report states a total cost of £380 million for business premises, stock, equipment, etc. Additionally, the £470 million of damages to infrastructure are allocated to *infrastructure* sectors, namely Transport, IT services, Electricity & Gas, Water & Sewerage & Waste, PAD, and Education and Health sectors. As the sectoral disaggregation was for 15 categories, an allocation of damage to each sector was made through a weighted distribution based on the share of the sector in the regional economy. These data were compared with stocks of industrial capital to determine the proportion of affected productive capacity, i.e., the values of the EAV (see Appendix for the values of the EAV for each industry).

Regarding residential damage, 10,759 houses were reported flooded, representing 0.6% of total housing in the region. Total household damages were estimated at £340 million by the UK Environmental Agency.

Labour constraints, about which hard data are unavailable, were derived from the number of flooded houses multiplied by the average number of working people per household. Additionally, commuting delays were proportionally related to damage in the transport sectors. This resulted in one tenth of the proportional effect in transport, as a proportion of affected labour, and a delay of 1 h in commuting for 1.5% of the regional population.

Finally, as information on changes in final demand is very scarce, we follow a sensitivity analysis over different levels of reduction in non-basic products. The values for the analysis show a decrease of 0.25% in households' demand for non-basic industries and a recovery time of 6 months with positive and marginally decreasing growth, i.e., a higher recovery rate for the first periods, which slows down at the end of the recovery.

5. Results

5.1. *Total economic loss for Yorkshire and The Humber region*

The Y&H region is located in the north-western region of the UK. The annual GVA in 2007 was over £88 billion (at 2009 prices), which represents around 7% of total UK's value added for that year. Likewise, there are around 2.6 million employees in the region, which constitute over 8% of the total UK's labour force.

According to the flood footprint analysis, it takes at least 14 months for the economy of the Y&H region to return to its pre-disaster situation after the 2007 summer floods in the UK (Fig. 2); this recovery entails both achieving economic equilibrium and returning to pre-disaster production levels. This entails a total economic loss of £2.7 billion, which is equivalent to 3.2% of the regional annual gross value added (GVA).

In differentiating direct economic loss from indirect economic loss, Fig. 2 compares the shares of each category. The direct economic loss (including industrial and residential infrastructure damages) accounts for 1.4% of the yearly GVA (nearly £1.2 billion), of which the majority corresponds to industrial and infrastructural damages (71%). The indirect economic loss – including all non-realised product flow owing to productivity and demand

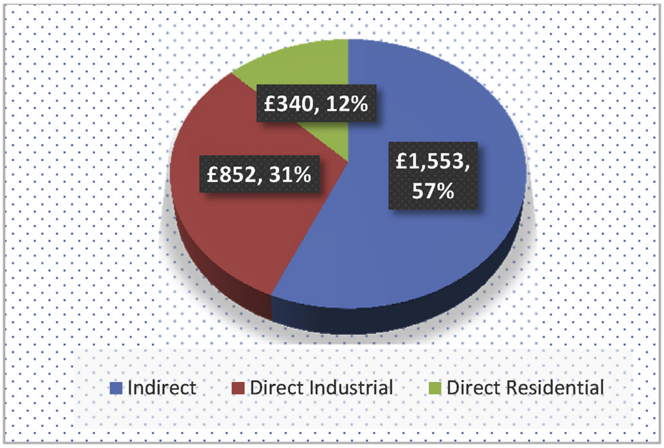

Fig. 2. Flood Footprint damage composition (£million).

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[8] http://www.camecon.com/how/mdm-e3-model/.

shortages – accounts for an additional 1.8% of the city's GVA, at around £1.5 billion. This represents 57% of the total flood footprint.

5.2. Economic recovery

The present section describes the progress of the economic variables involved in the recovery process.

Figure 3a) depicts the accounting of the cumulative damage during the recovery process. The area in purple, which indicates the distance between the final demand met by the available production at each time step and the pre-disaster level, represents the total indirect damage over the course of the recovery process. It can be noted that the initial shock represents a decrease of 0.4% of the productive capacity. The shape of the curve shows a fast recovery in the beginning, especially in the first 4–5 months, at which time the economy has recovered approximately 90% of its damaged productive capacity. It must be noted, however, that the recovery-curve shape is influenced by the rationing scheme chosen for the modelling, where the inter-industrial and recovery demand is prioritised over other final demand.

Figure 3b) displays the recovery process of productive capacity, including both labour and industrial capital capacities. The figure indicates that industrial capital constraints constitute the main source of production disruptions in the first period after the disaster, being responsible for the 0.4% fall in productivity. However, this recovers rapidly, and labour disruptions happen to be the main constraint on productive capacity.

Fig. 3 c depicts the dynamics of final demand in the aftermath of the disaster. The green line indicates the adaptation and recovery process of the final demand. This variable includes the adapted behaviour of final consumers and the reconstruction demand. On the other hand, the red line shows how much of that adapted demand can be supplied by the actual constrained capacity of production. Part of the demand that cannot be satisfied by internal production is supplied through imports, as the black line illustrates.

Finally, Fig. 3 d indicates the inequalities that remain between the level of production required by the final demand during the recovery process and the product supply from the surviving production capacity during the aftermath.

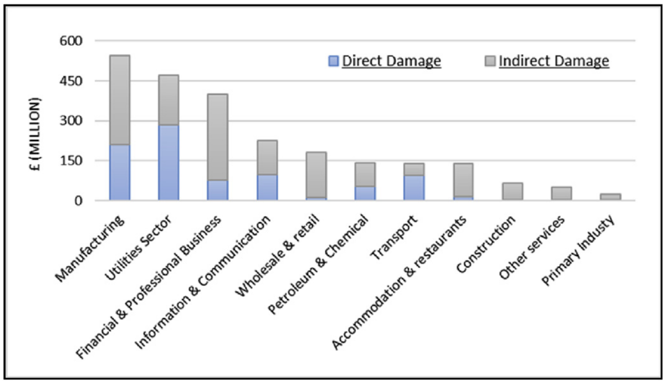


Fig. 4. Sectoral distribution of damage.

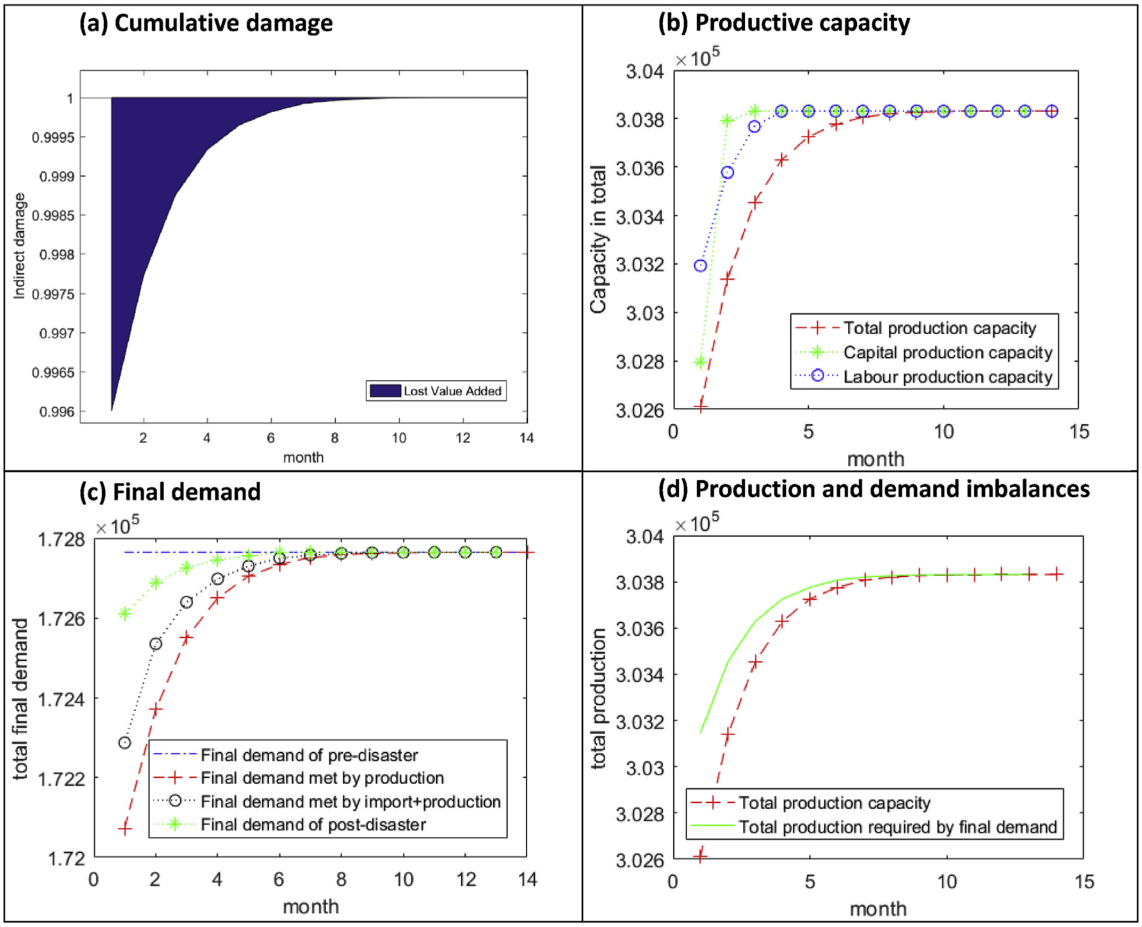


Fig. 3. Recovery process.

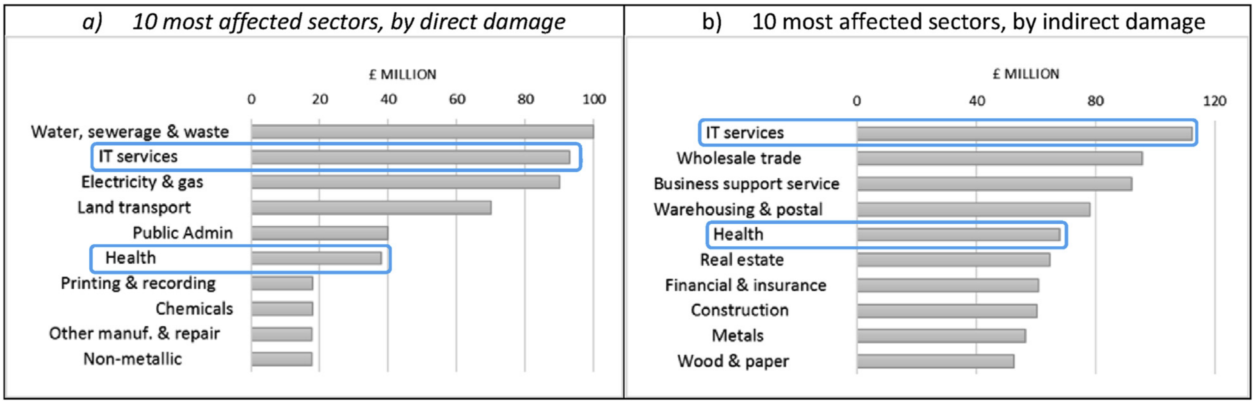


Fig. 5. The most affected sectors by different damage categories: Direct and Indirect damage.

5.3. *Sectoral analysis*

Because it is based on the IO model, one of the strengths of the flood footprint framework is its capacity to provide an analysis at the industrial sector level. This is especially useful for disentangling the distribution of the knock-on effects as they propagate through the impacted economy and through other economic systems. Additionally, this capacity of the flood footprint framework becomes very convenient when planning for flood risk management and adaptation policies.

Fig. 4 shows the distribution of the *flood footprint* for both direct and indirect damages among ten industrial groups. The proportions of direct and indirect loss present high heterogeneity among the sector groups. For example, Manufacturing is shown to be the most

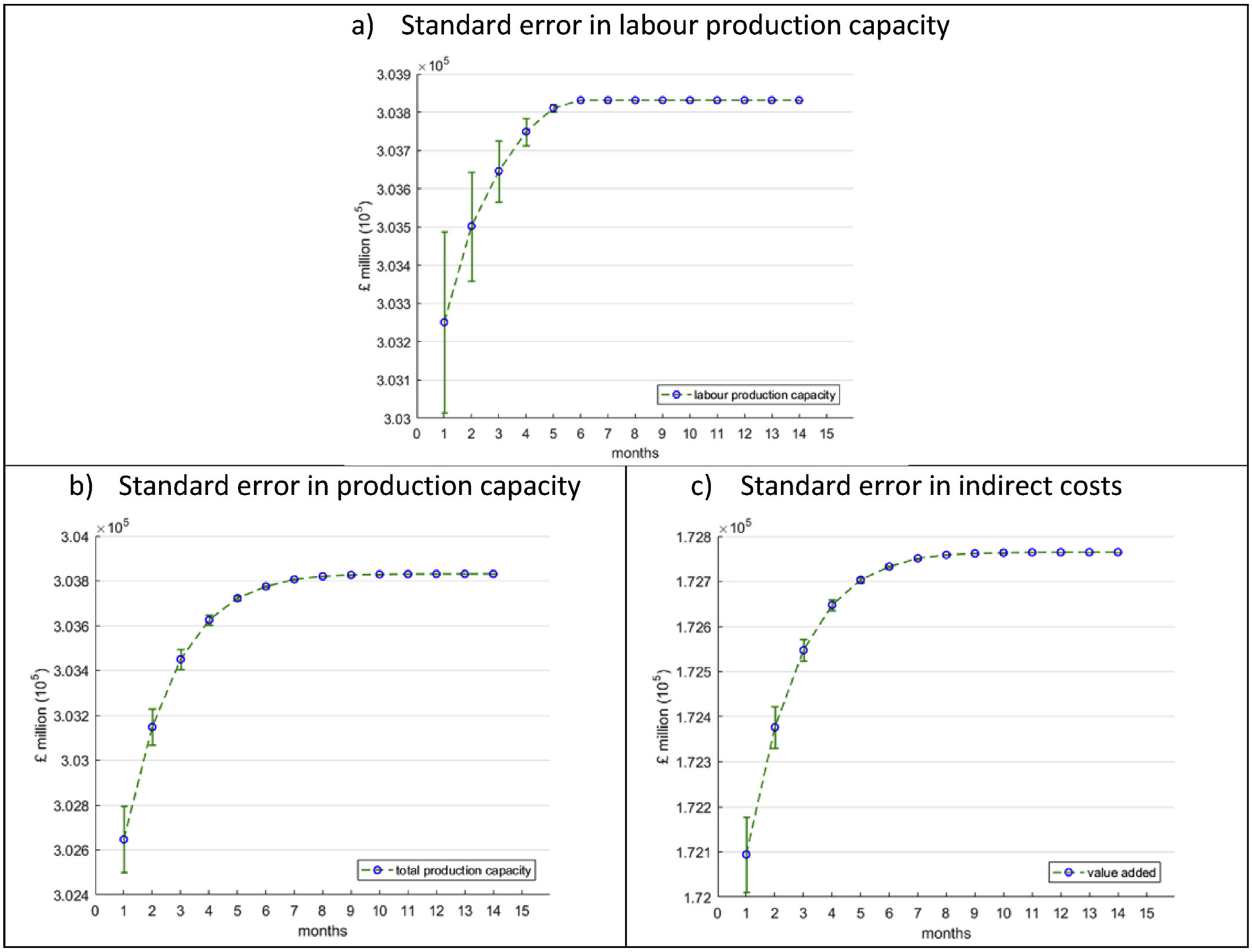


Fig. 6. Sensitivity analysis for labour parameters.

affected sector, with a share of indirect loss 60% higher than direct loss, and the total damages in this group account for 23% of the total *flood footprint*. The utilities sector suffers major direct damages (£190 million), as infrastructure damages are allocated among this sector. The Financial & Professional sector is the most indirectly affected, with 21% of total indirect damages, while just 9% of total direct damages are concentrated in this group (see Fig. 5).

At a more disaggregated level (46 sectors), Fig. 4 depicts the ten most affected sectors for direct (a) and indirect (b) economic losses, respectively. The major direct damage is concentrated in those sectors forming the *Utilities Sector* group. The most affected sector is Water, Sewerage & Waste, accounting for 35% of direct economic loss in the Utilities Sector group and 12% of the total direct damage. Regarding indirect damages, the IT services sector, from the Information & Communication group sector, was the most damaged, accounting for 86% of this group's losses and 11% of the total indirect damages.

Finally, it is noteworthy that two sectors appear in both categories: the IT Services and Health sectors. This indicates they are among the most vulnerable sectors in the region. The flood footprint in these sectors accounts for 13% of the total flood footprint.

5.4. Sensitivity analysis

Uncertainty in the model mainly comes from the lack of data in labour and final demand variables, and some assumptions applied to calibrate the correspondent parameters. To prove the robustness of the results, a sensitivity analysis is performed on labour and final demand parameters.

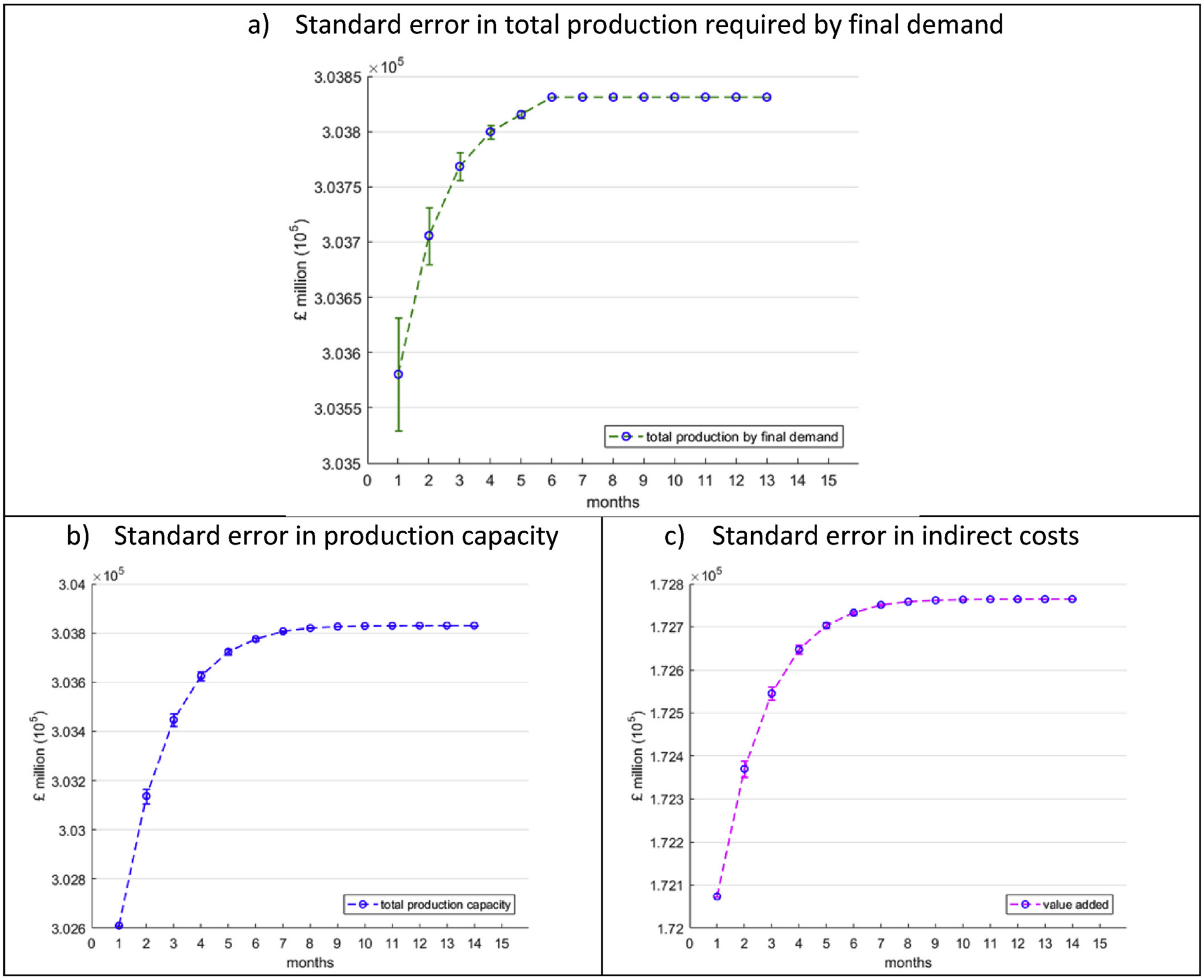
The sensitivity analysis comprises the upwards and downwards variation of 30% of the parameters in intervals of 5%.

5.4.1. Changes in labour parameters

The variation of parameters comprises the proportion of labour not available for traveling, and the proportion and time of labour delayed by transport constraints.

The results of the sensitivity analysis, as presented in Fig. 6, show that variations in labour parameters have a less-than-proportional effect in indirect costs and the total production capacity, and these are decreasing over time. Other variables are not affected by variations in labour parameters.

The standard deviation of the total variation of labour productive capacity is about £483 million, which causes a standard



a) Standard error in total production required by final demand

b) Standard error in production capacity

c) Standard error in indirect costs

Fig. 7. Sensitivity analysis for final demand parameters.

deviation of £297 million in total production capacity, and a standard deviation of $168 million in indirect damages.

5.4.2. Changes in final demand

The variation of parameters comprises the decreased proportion of consumption in non-basic products.

The results of the sensitivity analysis, as presented in Fig. 7, show that variations in final demand parameters have a less-than-proportional effect in indirect costs and the total production capacity, and these are decreasing over time. Other variables are not affected by variations in labour parameters.

The standard deviation of the total variation of total production required by final demand is about £96 million, which causes a standard deviation of £93 million in total production capacity, and a standard deviation of $54 million in indirect damages.

6. Conclusions

The increasing frequency and intensity of weather-related disasters require more accurate and comprehensive information on damages. This will support better risk management and adaptation policies to achieve economic sustainability in the affected cities in the upcoming years. For instance, the 2007 summer floods caused a national emergency in England, and Yorkshire and the Humber was the most affected region.

This paper is the first study to apply the flood footprint framework to a real past event, the 2007 summer floods in the Yorkshire and The Humber region. This analysis supports the important lesson that losses from a disaster are exacerbated by economic mechanisms, and that knock-on effects (or indirect damage) constitute a substantial proportion of total costs and that some of the most affected sectors can be those that are not directly damaged. For this case study, the proportion of indirect damages accounts for over half of the total flood footprint. The sensitivity analysis proves the stability of the model and the robustness of results.

This research provides a quantitative evidence for policy stakeholders that any direct damage may incur significant indirect impact along the economic supply chain. The climate change adaptation policy should start to consider minimising indirect impact, especially those sectors hidden in the supply chain which are vulnerable to labour loss, such as the services sectors. Not considering the indirect effects would mislead for actions in flood risk management and would lead to an inefficient use of resources.

There are, however, some caveats that must be noted. The current study is subject to some degree of uncertainty. First, data scarcity is the main source of uncertainty, making the use of strong assumptions unavoidable in certain cases. Engineering flood modelling and GIS techniques have been rapidly evolving in recent years, providing new sources of information with great precision and constructing the so-called damage functions,[9] although this progress has demanded substantial computing, time and monetary resources. The implementation of these techniques in future research would considerably improve the accuracy of the analysis. Second, although the model effectively accounts for knock-on effects in the affected regional economy, global economic interconnectedness requires us to move the analysis towards a multi-regional approach if we are to make an exhaustive impact assessment. Finally, additional research on labour and consumption recovery would greatly improve the analysis, as these are areas that have attracted less attention from researchers.

Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.jclepro.2017.09.016.

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[9] 'Damage functions show the susceptibility of assets at risk to certain inundation characteristics, currently mostly against inundation depth' (Messner et al., 2007).

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