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Flood Footprint Assessment: A Multiregional Case of 2009 Central European Floods

David Mendoza-Tinoco,[1,†] Yixin Hu,[2,3,†] Zhao Zeng,[4] Konstantinos J. Chalvatzis,[5] Ning Zhang,[6] Albert E. Steenge,[7] and Dabo Guan[8,9,*]

ABSTRACT: Hydrometeorological phenomena have increased in intensity and frequency in last decades, with Europe as one of the most affected areas. This accounts for considerable economic losses in the region. Regional adaptation strategies for costs minimization require a comprehensive assessment of the disasters' economic impacts at a multiple-region scale. This article adapts the flood footprint method for multiple-region assessment of total economic impact and applies it to the 2009 Central European Floods event. The flood footprint is an impact accounting framework based on the input–output methodology to economically assess the physical damage (direct) and production shortfalls (indirect) within a region and wider economic networks, caused by a climate disaster. Here, the model is extended through the capital matrix, to enable diverse recovery strategies. According to the results, indirect losses represent a considerable proportion of the total costs of a natural disaster, and most of them occur in nonhighly directly impacted industries. For the 2009 Central European Floods, the indirect losses represent 65% out of total, and 70% of it comes from four industries: business services, manufacture general, construction, and commerce. Additionally, results show that more industrialized economies would suffer more indirect losses than less-industrialized ones, in spite of being less vulnerable to direct shocks. This may link to their specific economic structures of high capital-intensity and strong interindustrial linkages.

KEY WORDS: Climate change adaptation; flood footprint; input–output model

1. INTRODUCTION

The threats imposed by climate change on society have raised alarm all over the world. Europe has been particularly harmed by meteorological and hydrological events, including floods and windstorms. These threats necessitate adaptation strategies capable "[of] responding to current and future climate change impacts and vulnerabilities … within the context of ongoing and expected societal change"

[1]Faculty of Economics, Autonomous University of Coahuila, Saltillo, Coahuila, Mexico.
[2]Department of Statistics and Data Science, Southern University of Science and Technology, Shenzhen, China.
[3]School of Environmental Sciences, University of East Anglia, Norwich, UK.
[4]College of Management and Economics, Tianjin University, Tianjin, China.
[5]Norwich Business School, University of East Anglia, Norwich, UK.
[6]Institute of Blue and Green Development, Weihai Institute of Interdisciplinary Research, Shandong University, Weihai, China.
[7]Faculty of Economics and Business, Global Economics & Management, University of Groningen, Groningen, the Netherlands.
[8]Department of Earth System Sciences, Tsinghua University, Beijing, China.
[9]The Bartlett School of Construction and Project Management, University College London, London, UK.

*Address correspondence to Dabo Guan, Department of Earth System Sciences, Tsinghua University, Beijing 100080, China; tel: +86-13811728771; guandabo@mail.tsinghua.edu.cn.
†These authors contributed equally to this work.

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(Isoard & Winograd, 2013). Such strategies depend on understanding the impacts across regions. In particular, a comprehensive economic assessment must be done in a multiregional approach. This may help to develop more effective adaptation strategies. In this tenor, it is particularly relevant to evaluate the economic long-term effects beyond the original physical destruction from a disaster (Isoard & Winograd, 2013).

Increasingly, academic research has focused in modeling and assessing the economic impacts induced by natural disasters. In this regard, Okuyama and Santos (2014) point out the pertinence of macroeconomic models for impact appraisal of natural disasters, such as the Input-Output (IO) model, computable general equilibrium (CGE) model, social account matrices, and macroeconometric models. In spite of their subjacent constraints, those models are reliable in providing an overview of losses from catastrophic events, and assisting decision making for planning of risk management strategies.

Based on IO theory, we propose to apply the flood footprint framework, a concept and impact accounting framework proposed by Mendoza-Tinoco, Guan, Zeng, Xia, and Serrano (2017) to measure the total economic impact that is directly and indirectly caused by a climate disaster event on the impacted region and wider economic systems. The concept results especially relevant for this work as the main objective is to provide differentiated information between direct and indirect losses, considering the source of the losses in the productive factors. As the word "footprint" demonstrates a dynamic process, it is well suited for describing the flow of flood impacts across economic sectors and regional borders over time, which advantages the model in a comprehensive flood impact assessment. The flood footprint modeling was constructed upon the adaptive regional IO (ARIO) model developed by Hallegatte (2008) and the basic dynamic inequalities (BDI) model built by Li, Crawford-Brown, Syddall, and Guan (2013). The ARIO proposes a framework to consider the influences of damaged capital on industrial production, and BDI provides the way to assess losses in productive capacity due to effects on labor force and residential damage.

We innovatively incorporate a "capital matrix," a concept traditionally used in dynamic IO analysis (Miller & Blair, 2009), with an attempt to translate capital reconstruction in the disaster aftermath into growth of productive capacity. More details in this regard will be introduced in the methodology part (Subsection 3.3.3 called "Capital Matrix").

The article applies this improved flood footprint model to the event of "the 2009 summer flooding in Central Europe," which was caused by intense rainfall in late June 2009 and caused floods across several countries in Central Europe. This refers in particular to 23 regions within Austria, The Czech Republic, and Germany, which suffered the most of the flooding. We apply the analysis to these regions and consider the losses leaked to their respective national economies.

Most of the losses were caused by the overflow of some banks of the river Danube, and some tributaries, such as the Isar and Lech rivers. This disaster was responsible for 13 casualties, including 12 in the Czech Republic and one in Poland. The event also represented the worst Austrian flood in more than a century.

This article applies for the first time the analysis to multiple regions across multiple countries, in comparison with previous studies that focus on a single region or multiple regions within a single country. The analysis uses disaster data from the reassurance company (Munich Re), which enables realistic analysis. The results can contribute to deeper understanding of vulnerabilities and risk hotspots across different regions and economic sectors in Europe, thus assisting in the development of *ad hoc* adaptation strategies.

2. LITERATURE REVIEW

Different economics' techniques have been applied to assess the impacts of disasters. The most commonly used include IO analysis and the CGE model (Greenberg, Lahr, & Mantell, 2007). IO-based models are founded on the basic idea of the circular flow of an economy in equilibrium. IO tables present the interindustrial transactions of an economy in a linear array, allowing the assessment of the knock-on effects from a shock. Moreover, regionalization techniques are well developed, such that regional analysis is feasible. However, IO modeling has been criticized for being rigid, as the proportion of productive factors is considered to be fixed, as are prices (Cole, 2003; Greenberg et al., 2007; Okuyama, 2007, 2008; Rose, 2004). CGE models were developed from IO modeling, partly as an effort to overcome some of the constraints of IO analyses. This means that CGE models allow changes in prices, nonlinear production functions, and flexibility in inputs and import substitutions. However, some critiques of CGE models lie on the large number of parameters to be calibrated, and larger requirements of data in regard to IO models. Both CGE and IO models allow researchers to focus on industrial and regional interconnections at different levels of detail.

However, and in particular, for disaster impact analysis, the main critiques of CGE models refer to the assumption of the economy in equilibrium, a situation that rarely bears in the disaster aftermath (Cochrane, 2004; Greenberg et al., 2007; Okuyama, 2007, 2008; Rose, 1995, 2004; Van der Veen, 2004). That is the main reason to base our research on IO modeling as better suited for disaster impact analysis. It can adequately assess direct and indirect effects in the face of interruptions in the flow of goods and services and the consequent market imbalances, as is usually the case following a disaster. Other important reason is that IO models require considerably less data inputs than CGE models, and the results have proven to be reliable and useful.

Early literature on IO-associated disasters impact estimations can be tracked back in FEMA and NIBS (1999) with the development of a hybrid model called HAZUS, which is based on the IO model and incorporates engineering models with geographical information. It was developed to deal with supply constraints and simulate the recovery path throughout time. Later, Bočkarjova, Steenge, and Van der Veen (2004) adjusted the IO model to incorporate the consequences of reduced productive capacity, bottlenecks, and imbalances in general. With this, the notion of the basic equation was developed to introduce a starting point of the economy with the productive markets in equilibrium before the disaster (Li et al., 2013). Further, they develop the event account matrix, an IO compatible element to assess the shortages in productive capacity of each sector after a disaster.

Van der Veen and Logtmeijer (2005) used a biregional IO model to simulate a flooding and depict the hotspots from flooding events, based on the concepts of vulnerability, dependency, and redundancy. With a Kernel density distribution, it was able to visualize the information using GIS. More recently, Bierkandt, Wenz, Willner, and Levermann (2014) developed a dynamic damage propagation model, based on a multiregional IO table, called Acclimate. They based their analysis on the losses from disruptions in the supply chain, considering economic units as different agents that maximize their gains based on different behavior. Koks, Bockarjova, De Moel, and Aerts (2015) introduced the Cobb–Douglas function to the ARIO model when estimating the production losses caused by labor and capital constraints. This approach is applied to compare the consequences of six hypothetical flood events with different probabilities in the port region of Rotterdam. As the model is dependent on a large number of parameters and assumptions, it leads to relatively large uncertainties in the modeling outcomes. Still, this study constitutes a good comparison for the flood footprint model, as it also incorporates restrictions in the productive capacity of labor using a different approach.

A new approach developed by Oosterhaven and Bouwmeester (2016) is based on a nonlinear programming that minimizes the information gain between the predisaster and postdisaster situation of economic transactions. The model is successful in reproducing the recovery toward the predisaster economic equilibrium. However, it has only been tested hypothetically and further development is to be carried out for applications to real cases, so it is not comparable yet with real case applications as the one in this article. Some aspects of disaster impact analysis are left aside, as the damage to residential capital, or the recovery of productive capacity of labor. It is to be mentioned that this model is based on an interregional IO table.

Related to this approach, Koks and Thissen (2016) developed a dynamic optimization model based on linear-programming model and IO supply-use tables, the multiregional impact assessment model (MRIA), which is able to account for supply constraints. This allows for the appraisal of production losses in the impacted region, required production to overcome the former losses, and production required in a broader region to satisfy demand for reconstruction. The approach shares features with the flood footprint model, which potentially represents a good source of comparison. The hypothetical results for a flood in Rotterdam show that the ratio of indirect/direct losses increases with the intensity of the event, although contrary to our results, the indirect losses remain smaller than the direct losses for all the scenarios. This may be the result of some flexibilities regarding the substitution possibilities in the MRIA.

Further, Oosterhaven and Többen (2017) applied this approach with a multiregional supply-use table to overcome the limitations of fixed industry market shares. They developed a nonlinear programming model and applied it to estimate the economic impacts of a heavy flooding event in Germany in 2013. They provided a methodological reference with the model used in this article, and stated that rigidities in IO models result in overestimation of the induced effects. This is in line with the literature, where it is suggested to consider results from IO models as the upper bound of damages, while considering CGE modeling results as the lower bound (Okuyama & Santos, 2014). For the case study, it is difficult to compare with the case studied here, as different phenomena entail very different damages distribution and value.

Very recently, Koks et al. (2019) bring out a series of scenarios estimation with their previous developed MRIA model. They consider that indirect losses can be offset by flexibility in inputs substitution. Compare with our model, it yields results in the same token regarding the scale relation between direct and indirect losses, where the latter represent a considerable proportion of total losses, but in their case, always lower than the former. A representing comparable result is that most indirectly affected sectors are commerce and utilities, which is in line with the results of our analysis. Still, it is to be tested in real past events to have comparable results with the flood footprint model.

Finally, in an effort to study the worldwide indirect effects of flooding events, Willner, Otto, and Levermann (2018) provide insight of this. They use the so-called deterministic loss-propagation model. Although it is not developed in this article, they provide results of simulations of different scenarios of climate change. Consistently with the reviewed literature and results in this article, they show that indirect losses are a considerable proportion of total losses, which increase in share as the intensity of the event increases.

Flood footprint modeling that was applied in the study was constructed on the ARIO model developed by Hallegatte (2008) and the BDI model built by Li et al. (2013). ARIO proposes a framework to consider the influences of damaged capital on industrial production, and BDI provides the way to assess losses in productive capacity due to effects on labor force and residential damage. From there, our team made improvements on restrictions in supply chain and finally, developed the flood footprint model (Mendoza-Tinoco et al., 2017). This article still adopts a flood footprint model but compared with previous methods, two points are improved. First, the capital matrix concept from IO modeling is incorporated to provide methodological consistency for the transformation from capital accumulation during the process of restoration to the corresponding increase in output flows. It enables more reasonable simulation of the real recovery process than previous models by establishing a more realistic connection between capital investment and productive capacity. Second, data on damaged capital were obtained from the practical survey (NatCatService of Munich Re), which provides more comprehensive information than previous data sources.

3. FLOOD FOOTPRINT MODELING FOR MULTIPLE REGIONS

In this section, the rationale of the *flood footprint* model is described in detail. The following is a diagram of the conceptual framework about the modeling process (Fig. 1). In a modeling overview, we can distinguish the following steps: first, we obtain data about the disaster. Second, the direct economic losses are catalogued in losses of residential assets, industrial capital assets, and labor forces. Third, it is determined how these losses affect the final demand, labor productivity, and industry capacity. Fourth, the economic imbalances among the former categories are determined. In the fifth step, the imbalances determine the reduction in the productive capacity. The reconstruction efforts, for each time-step, are calculated in the sixth step. Finally, if the economy reaches the predisaster equilibrium, the recovery process is finished. Otherwise, we recalculate the economic imbalances between final demand, labor productive capacity, and industry productive capacity, and the process continues.

Regarding the mathematical symbols and formulae, matrices are represented by bold-italic capital letters (e.g., $\boldsymbol{X}$), vectors are represented by bold-italic lowercase letters (e.g., $\boldsymbol{x}$), and scalars are represented by italic lowercase letters (e.g., x). By default, vectors are column vectors, with row vectors obtained by transposition (e.g., $\boldsymbol{x}'$); a conversion from a vector (e.g., $\boldsymbol{x}$) to a diagonal matrix is expressed as a bold-italic lowercase letter with a circumflex (i.e., $\hat{\boldsymbol{x}}$); the operators ".*" and "./" are used to express the element-by-element multiplication and 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 for each region present the interindustrial transactions of the regional economy in a linear array. In mathematical notation, these transactions are defined as:

$$\boldsymbol{x}^r = \boldsymbol{A}^r \boldsymbol{x}^r + \boldsymbol{f}^r, \tag{1}$$

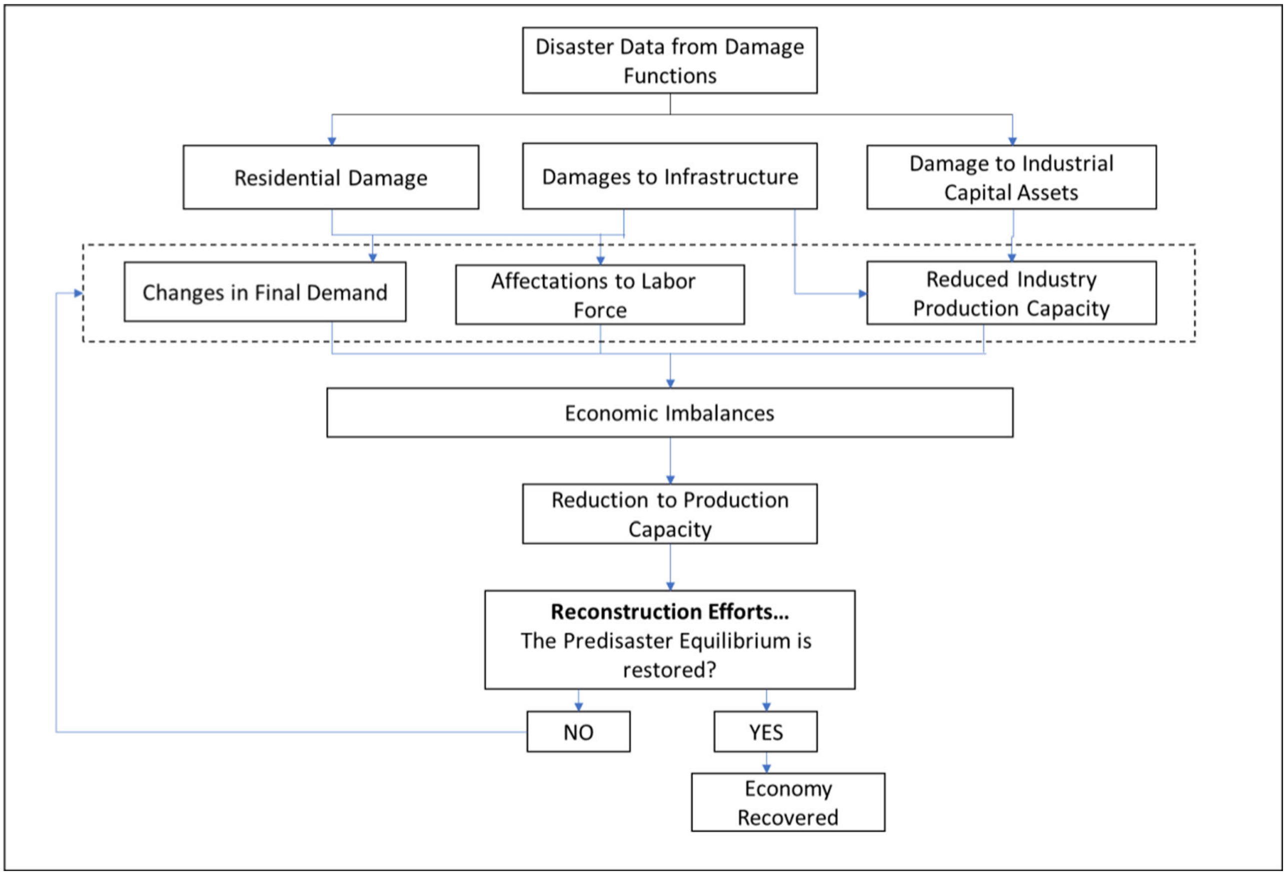

Fig. 1. The conceptual framework of the modeling process.

where $\boldsymbol{x}^r$ is a vector of dimension $n \times 1$ (where n is the number of industry sectors in each region) representing the total production of each industrial sector[1]; and $\boldsymbol{A}^r\boldsymbol{x}^r$ represents the intermediate demand vector, where each element of the matrix $\boldsymbol{A}^r$, $[a_{ij}]$, refers to the technical relation defining the product i needed to produce one unit of product j within region r. Finally, $\boldsymbol{f}^r$ indicates the final demand vector of the products in region r.

Based on the IO modeling, the assessment of economic losses by *flood footprint* modeling departs from the basic equation concept (Steenge & Bočkarjova, 2007). This is a closed[2] IO model that represents an economy in equilibrium. This equilibrium implies that total production equals total demand, with the full employment of productive factors, including both capital and labor, as in Equation (2):

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

and

$$l_T^r = \boldsymbol{l}'^r \boldsymbol{x}^r, \tag{3}$$

where $\boldsymbol{l}'^r$ is a row vector of technical labor coefficients for each industry in region r, showing the relation between the labor needed in each industry to produce one unit of product. The scalar value l_T^r is the total level of employment in each region-economy.

All interindustrial flows of products, as well as industrial employment, represent the necessary inputs involved in the production process. A linear relation between the productive factors (labor and capital) and the output in each sector is assumed in IO analysis, suggesting that inputs should be invested in fixed

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

[2] Here, "closed" means that the primary productive factors (labor) are explicitly considered within the model.

proportions for a proportional expansion in the 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. Postdisaster Inequalities of Economy

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 economies of the flooded region.

3.1.1. Labor Productive Constraints

Continuing with the assumption of a fixed relationship between productive factors during the production process implies that constraints in any of the productive factors will produce a proportional decline in productive capacity, even when other factors remain fully available. Therefore, labor constraints after a disaster may impose severe knock-on effects on the rest of the economy. This makes labor 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 this model, the proportion of surviving productive capacity from the constrained labor productive capacity ($\boldsymbol{x}_l^{r,t}$) after a shock for each region r is defined as:

$$\boldsymbol{x}_l^{r,t} = \left(\boldsymbol{i} - \boldsymbol{\gamma}_l^{r,t}\right) .^{*} \boldsymbol{x}^{r,0} \tag{4}$$

and

$$\boldsymbol{\gamma}_l^{r,t} = \left(\boldsymbol{l}^{r,0} - \boldsymbol{l}^{r,t}\right) ./\boldsymbol{l}^{r,0}, \tag{5}$$

where $\boldsymbol{\gamma}_l^{r,t}$ is a vector where each element contains the proportion of labor that is unavailable at each time t after the flooding event in region r. The vector $\boldsymbol{i}$ is a vector of ones of the same dimension as $\boldsymbol{\gamma}_l^{r,t}$, such that the vector $(\boldsymbol{i} - \boldsymbol{\gamma}_l^{r,t})$ contains the surviving proportion of employment at time t in region r. $\boldsymbol{x}^{r,0}$ is the predisaster level of production in region r.

The proportion of the surviving productive capacity of labor is thus a function of the losses from the sectoral labor forces and its predisaster employment level. Following the assumption of the fixed proportion of production functions, the productive capacity of labor in each region after a disaster ($\boldsymbol{x}_l^{r,t}$) will represent a linear proportion of the surviving labor capacity at each time step, as defined in Equation (4).

3.1.2. Capital Productive Constraints

Similar to labor constraints, the productive capacity of industrial capital in each region during the aftermath of flooding ($\boldsymbol{x}_{cap}^{r,t}$) will be constrained by the surviving capacity of the industrial capital. The share of damage to each sector is directly considered as the proportion of the monetized damage to capital assets in relation with the total value of industrial capital for each sector, which is disclosed in the event account vector (EAV) for each region ($\boldsymbol{\gamma}_{cap}^{r,t}$), following Steenge and Bockarjova (2007). This assumption is embodied in the essence of the IO model, which is the Leontief-type production functions. That is, as capital and labor are considered perfectly complementary as well as the main production factors, and the full employment of those factors in the economy is also assumed, we assume that damage in capital assets is directly related with production level and therefore, value added level.

Then, the remaining productive capacity of the industrial capital at each time step in region r is defined as:

$$\boldsymbol{x}_{cap}^{r,t} = \left(\boldsymbol{i} - \boldsymbol{\gamma}_{cap}^{r,t}\right) .^{*} \boldsymbol{x}^{r,0} \tag{6}$$

and

$$\boldsymbol{\gamma}_{cap}^{r,t} = \left(\boldsymbol{k}^{r,0} - \boldsymbol{k}^{r,t}\right) ./\boldsymbol{k}^{r,0}, \tag{7}$$

where, for each region r, $\boldsymbol{x}^{r,0}$ is the predisaster level of production and $\boldsymbol{\gamma}_{cap}^{r,t}$ is the EAV, a column vector reflecting the share of damage to productive capital in each industry. $\boldsymbol{k}^{r,0}$ is the vector of capital stock (CS) in each industry in the predisaster situation, and $\boldsymbol{k}^{r,t}$ is the surviving CS in each industry at time t during the recovery process.

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

3.2. Postdisaster Final Demand

On the other side of the economy, the final demand may vary for diverse reasons in each region. 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 in region r, $\boldsymbol{f}^{r}_{rec}$. On the other hand, final demand may also decrease after a disaster. Li et al. (2013) noted that after a disaster, strategic adaptive behavior can lead people to continue their consumption of basic commodities, such as food and medical services, while reducing their consumption of other nonbasic products.

In the model, we consider the adaptive consumption behavior of households. Here, the demand for nonbasic goods is assumed to decline immediately after a disaster, while the consumption of industries providing food, energy, clothing, and medical services remains at predisaster levels.

Recovery in household consumption is driven by two complementary processes. For the adaptation of consumption, we consider a short-run tendency parameter ($\boldsymbol{d}^{r,t}_{1}$), which is modeled as the rate of recovery in consumption at each time step. The rationale here is that consumers restore their consumption based on market signals about the recovery process. Likewise, a long-run tendency parameter ($\boldsymbol{d}^{r,t}_{2}$) is calculated as a recovery gap, i.e., the total demand minus the total productive capacity compared to the total demand at each time step. These two parameters are calculated for each sector. Therefore, the expression for dynamic household consumption recovery in each region r, ($\boldsymbol{f}^{r,t}_{hd}$), is:

$$\boldsymbol{f}^{r,t}_{hd} = \left(\mu^{0} + \boldsymbol{d}^{r,t}_{1} + \boldsymbol{d}^{r,t}_{2}\right) .^{*} \boldsymbol{c}^{r,0}, \tag{8}$$

where the parameter μ^{0} is a scalar value that expresses the reduced proportion of household demand (a parameter similar to the EAV) immediately after the floods, and the vector $\boldsymbol{c}^{r,0}$ represents the predisaster level of household expenditure on products by industrial sector in region r.

The rest of the final demand categories recover proportionally to the economy based on the share of each category relative to the final demand prior to the disaster. It should be noted that there is a tradeoff in the allocation of resources between the final demand and the reconstruction process. Then, the adapted total final demand in region r, ($\boldsymbol{f}^{r,t}$), is modeled as follows:

$$\boldsymbol{f}^{r,t} = \sum_{k} \boldsymbol{f}^{r,t}_{k} + \boldsymbol{f}^{r,t}_{rec}, \tag{9}$$

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

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

$$\boldsymbol{x}^{r,t}_{td} = \boldsymbol{A}^{r} \boldsymbol{x}^{r,t}_{td} + \sum_{k} \boldsymbol{f}^{r,t}_{k} + \boldsymbol{f}^{r,t}_{rec}. \tag{10}$$

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

3.3. Postdisaster Recovery Process

This section describes the process of recovery. Here, a regional economy can be considered to have recovered once labor and industrial production capacities are in equilibrium with the total demand, and production is restored to its predisaster level. It is important to mention that the model, as it is based on IO modeling, considers the same economic structure before the disaster and during recovery. This modeling characteristic is behind the assumption that the economy is recovered once the predisaster production level and equilibrium is reached. This assumption may be closer to the short run analysis and enables straightforward benchmarking. By modeling the recovery to the predisaster level, we can learn from its results about how much direct and indirect costs can be avoided in the future if disasters of similar kinds were mitigated or properly adapted. Such information would facilitate the cost–benefit analysis of alternative disaster mitigation or adaptation measures, and therefore smarter decision making in pathways to a more resilient future. However, it is to be mentioned that this represents a model rigidity in the case of general equilibrium effects, when structural changes in the economy are expected, as in the long run. Therefore, for our analysis, using the remaining resources to achieve predisaster conditions is modeled under a selected rationing scheme.

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

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

Second, the level of the constrained productive capacity is compared with the total demand to determine the allocation strategy for the remaining resources to both the final demand and reconstruction planning. The rules of this process constitute the *rationing scheme*, which is described below.

3.3.1. Rationing Scheme

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

For this case study, we applied a *proportional-prioritization* rationing scheme that first allocates the remaining production to address interindustrial demand ($\boldsymbol{A}^r\boldsymbol{x}_{tp}^{r,t}$) and then attends to the categories of final demand.[3] This assumption is based on the rationale that business-to-business transactions are prioritized, which in turn is based on the observation that business-to-business relationships are stronger than business-to-client relationships (Hallegatte, 2008; Li et al., 2013).

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

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

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

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

The second scenario occurs when $x_{tp(i)}^{r,t} > o_i^{r,t}$. 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:

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

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

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

The expression ($\boldsymbol{x}_{tp}^{r,t} - \boldsymbol{A}^r\boldsymbol{x}_{tp}^{r,t}$) refers to the production left after satisfying the intermediate demand, and $\sum_k \boldsymbol{f}_k^{r,t}$ refers to the total final demand at time t, such that the production left after satisfying the intermediate demand is allocated proportionally between the categories of final demand, in addition

[3] Here, we assume that the productivity of any one productive factor does not change during the recovery process, as is the case with Leontief production functions. We also assume that the disaster occurs just after time $t = 0$ and that the recovery process starts at time $t = 1$.

to considering the reconstruction needs for recovery ($\boldsymbol{f}_{rec}^{r,t}$). Note that for the first scenario, the expression ($\boldsymbol{x}_{tp}^{r,t} - \boldsymbol{A}^r \boldsymbol{x}_{tp}^{r,t}$) becomes ($\boldsymbol{x}_{tp}^{r,t^*} - \boldsymbol{A}^r \boldsymbol{x}_{tp}^{r,t^*}$), which represents the production left after satisfying the adapted intermediate demand, where $\boldsymbol{x}_{tp}^{r,t^*}$ is smaller than the actual productive capacity, $\boldsymbol{x}_{tp}^{r,t}$.

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

3.3.2. 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 the reconstruction demand. Additionally, if the reduced productive capacity is not able to satisfy the final demand of 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 always be available for provision at the maximum rate of imports under predisaster conditions. Third, there are some types of goods and services that, by nature, are usually supplied locally (e.g., utilities and transport services), thus making it infeasible to make large-scale adjustments over the timescale of disaster recovery. Finally, imports are assumed to be constrained by the total importability capacity, which is defined here as the survival 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 to transport, so that if the production value of sectors related to transport services is contracted by $x\%$ in time t, the imports will contract by the same proportion, in reference to the predisaster level of imports, $\boldsymbol{m}^{r,t}$:

$$\boldsymbol{m}^{r,t} = \left(\frac{x_{tran}^{r,t}}{x_{tran}^{r,0}} .^* \boldsymbol{m}^{r,0} \right), \tag{14}$$

where for each region r, $\boldsymbol{m}^{r,0}$ is the vector of predisaster imports, $x_{tran}^{r,0}$ and $x_{tran}^{r,t}$ are the scalars denoting the predisaster and postdisaster production capacities of the sectors related to transport, respectively. The subscript $tran$ refers to aggregated transport sectors by land, water, and air. If the sectors related to transport are two or more, then $x_{tran}^{r,0}$ is the sum of the product of those sectors at their predisaster levels, and $x_{tran}^{r,t}$ is the sum of those sectors at time t during recovery, as obtained from the vectors of productive capacity, $\boldsymbol{x}^{r,0}$ and $\boldsymbol{x}_{tp}^{r,t}$.

3.3.3. Capital Matrix

This section describes the incorporation of the *capital matrix* to the analytical framework of the *flood footprint* to achieve a methodologically consistent transformation from capital investment to productive capacity. The *capital matrix* is traditionally used in IO analysis to simulate economic growth by capital accumulation (Miller & Blair, 2009). We consider the investment in restoration to be an exogenous variable, thus allowing for recovery planning. In this article, the *capital matrix* is adapted within the original flood footprint framework, where investment in recovery is allocated based on the share of demand for reconstruction relative to other categories of final demand. As in the single regional flood footprint (Mendoza-Tinoco et al., 2017), it is assumed that the surviving production is allocated to the different categories of final demand once the intermediate demand is satisfied.

The capital matrix, $\boldsymbol{K}$, is introduced as a square matrix where each element, $k(i, j)$, represents the amount of capital produced by sector i to increase the productive capacity of sector j by one unit. Therefore, the elements of column j represent the amounts of products needed from all sectors to produce an extra unit of product in sector j (Miller & Blair, 2009). It should be noted that the recovery process requires the repair and/or replacement of damaged CS and households. During this process, the productive capacity increases through both local production and the allocation of imports to the reconstruction investment. Note that the reconstruction of households occurs through the consumption of final products to the reconstruction sectors.

The capital investment for reconstruction in each region, $\boldsymbol{K}^r \Delta \boldsymbol{x}_{cap}^{r,t}$, is computed as the share of the reconstruction demand relative to the total final demand, multiplied by the production remaining after satisfying the intermediate demand:

$$\boldsymbol{K}^r \Delta \boldsymbol{x}_{cap}^{r,t} = (\boldsymbol{x}_{tp}^{r,t} - \boldsymbol{A}\boldsymbol{x}_{td}^{r,t}) \times \left(\boldsymbol{f}_{rec}^{r,t} ./ \left(\sum_k \boldsymbol{f}_k^{r,t} + \boldsymbol{f}_{rec}^{r,t} \right) \right). \tag{15}$$

It must be noted that the investment in capital restoration entails both the technical requirements of capital by industry disclosed in the capital matrix, $\boldsymbol{K}^r$, and the amount of productive capacity that is added the next time, $\Delta \boldsymbol{x}_{cap}^{r,t}$.

Similarly, the share of imports that are invested in reconstruction capital can be expressed to estimate their contributions to increase the productive capacity during the reconstruction process. Once the amount of imports designated for capital investment is determined using Equation (16), the restoration of productive capacity from imports, $\Delta \boldsymbol{x}_m^{r,t}$, can easily be obtained:

$$\boldsymbol{K}^r \Delta \boldsymbol{x}_m^{r,t} = \boldsymbol{m}^{r,t} .^* \left[\boldsymbol{f}_{rec}^{r,t} \cdot \left(\sum_k \boldsymbol{f}_k^{r,t} + \boldsymbol{f}_{rec}^{r,t} \right) \right]. \quad (16)$$

Then, the total investment in capital restoration during each period is:

$$\boldsymbol{K}^r \Delta \boldsymbol{x}^{r,t} = \boldsymbol{K}^r \times \left(\Delta \boldsymbol{x}_{cap}^{r,t} + \Delta \boldsymbol{x}_m^{r,t} \right). \quad (17)$$

Multiplying by the inverse of the *capital matrix* provides the industrial productive capacity that is added during the next period, $\Delta \boldsymbol{x}^{r,t} = \Delta \boldsymbol{x}_{cap}^{r,t} + \Delta \boldsymbol{x}_m^{r,t}$.

Thus, for the next period, the production possibilities from industrial capacity are defined by the following expression:

$$\boldsymbol{x}_{cap}^{r,\ t+1} = \boldsymbol{x}_{cap}^{r,t} + \Delta \boldsymbol{x}^{r,t}. \quad (18)$$

This allows us to reformulate the function of the vector $\boldsymbol{f}_{rec}^{r,t}$ in terms of a Leontief capital matrix $\boldsymbol{K}^r$. Substituting the term in Equation (18) ($\Delta \boldsymbol{x}^{r,t}$) in terms of the capital matrix yields the total demand requested by the economy during each period of the recovery process:

$$\boldsymbol{x}_{td}^{r,t} \ = \ \boldsymbol{A}^r \boldsymbol{x}_{td}^{r,t} + \sum_k \boldsymbol{f}_k^{r,t} + \boldsymbol{K}^r \Delta \boldsymbol{x}^{r,t}. \quad (19)$$

The iterative process starts again and runs until the total demand and total production in each region are in equilibrium and at the same predisaster levels.

There are several points that should be mentioned here. Regarding the construction of capital matrices, the CS data are disaggregated to show how the CS of each sector is built up, i.e., the CS of sector i is the sum of the capital products from those sectors involved in capital formation, $\sum j^*$, where * corresponds to those sectors involved in capital formation. Next, a concordance matrix was also used to match the sector disaggregation from the EU KLMS data with the 14-sector disaggregation used in this article (see Tables A1–A3). To maintain data coherence, the totals of the capital matrices were rescaled to match the CS data in the NEG dataset. Thus, in the aggregate, the capital/product relationship remains in the NEG database. Finally, to obtain a set of coefficient matrices, $\boldsymbol{K}^r$, each element of the jth column was divided by the output of the jth industry to show the proportions of the products required to build the CS that increases the productivity of the jth sector by one unit. One matrix for each country was built, which represents the average capital productivity for all regions within the country.

3.4. Total Flood Footprint

Finally, the total flood footprint of the event, $\boldsymbol{ff}$, is considered to represent the sum of the flood footprints of all affected regions:

$$\begin{aligned} \boldsymbol{ff} &= \sum_r \left(\boldsymbol{va}_{dir}^r + \boldsymbol{va}_{ind}^r \right) \\ &= \sum_r \left[\boldsymbol{f}_{rec}^{r,0} + \left(T^r .^* \boldsymbol{x}^{r,0} - \sum_t \boldsymbol{x}_{tp}^{r,t} \right) \right], \end{aligned} \quad (20)$$

where T^r is the time calculated for recovery in each region, $\boldsymbol{va}_{dir}^r$ and $\boldsymbol{va}_{ind}^r$ represent the direct and indirect losses in each region respectively.

4. DATA

This model requires information about disaster damages and the economic structures of the affected regions. This case is related to the use of damage functions to generate the values of EAVs. The analysis of the 2009 Central European Floods uses information from 23 regions across Austria, the Czech Republic, Germany, and Poland. The regional scale for this analysis is at the NUTS2 level. All data are disaggregated in 14 industrial sectors (see Table A1), and monetary values are given in millions of euros at 2007 prices.

4.1. Disaster Damages

The disaster data on direct damages in the affected regions were provided by the NatCatService,[4] the Natural Hazards Assessment Network (NATHAN)[5] of Munich Re, and the Emergency

[4]NatCatService: https://natcatservice.munichre.com/.

[5]NATHAN: https://www.munichre.com/en/reinsurance/business/non-life/nathan/index.html.

Events Database (EM-DAT),[6] using damage function curves. Here, we only give a brief description of these curves for informative purposes, as they are not developed as part of this analysis. In general, damage functions consider the average depth of flood waters in a squared meter as the key input variable, and translate this disaster parameter into asset damage in monetary terms following the synthetic method described in Penning-Rowsell et al. (2014). By this case, the set of damage functions is taken from the Dutch HIS-SSM (Kok, 2004), as a proxy (or average) of damage functions in Central Europe. These curves relate to the characteristics of the hazard (e.g., water depth in the case of flooding); the exposure to the hazard, expressed as the affectations to physical assets (by land use or building type); and the vulnerability of the economy, as the maximum value of the damage for the affected assets (by industry category). This provides the distribution of the value of the damages by industry.

Then, these data are transformed into EAVs, namely, the share of damage to the industrial capital, through dividing the physical damage by the total CS for each industry. The following is the seven-step procedure of data preparation taken to develop the EAVs (Triple E Consulting, 2014).

First, estimated total damage (ETD) from Munich Re database is taken at the national level. These data do not consider lost working days of labor, permanent loss of human capital, and nonmarket effects.

Second, a fixed share of 5% of damage lost is assigned to lost inventory and emergency relief costs. Inventory costs include destructed unsold finished goods, unused intermediate products, unused raw materials, and agricultural products, among others.

Third, the ETD is regionally distributed on a CS basis, supported upon auxiliary information describing the share related to household CS or public/business CS. Annual gross fixed capital formation data per country is considered to account these shares. CS related to household is not considered for production capacity. This yields the estimate total cost related with lost production capacity (LPC), weighted by the share of public/business CS, which is the relevant for LPC.

Fourth, the ETD from LPC is evenly distributed to NUTS2 regions per country, those affected by the disaster. This yields the ETD by LPC at NUTS3 region level. It is to be mentioned that the geographical scope is based on the Munich Re.

Fifth, the economic structures of affected NUTS2 regions are determined based on value added data from Eurostat.

Sixth, the absolute reduction of production capacity is calculated from ETD by LPC per sector in a region, based on secondary information (local reports on damages) and damage functions.

Seventh, the EAVs are constructed with the shares of damaged capital from the CS of each sector.

4.2. Input–Output Tables

The regional IO tables provided for this analysis use information from the RAEM-Europe model, which is a regional-economic model for EU27 (Ivannova, Bulasvskaya, Tavasszy, & Meijeren, 2011). The raw data emanate from Eurostat's statistics.[7] Later, the RAEM model regionalizes it at NUTS2 level and aggregates the information from 14 different industry categories. The variables considered by the RAEM include output, labor, CS, intermediate consumption, final consumption, and imports. It should be noted that this is a multiple regional IO model for several regions in several countries, and not a multiregional IO model, and economic linkages among countries are only through imports.

The RAEM was previously modeled for Dutch regions, using coefficients from bi-regional IO matrices. The RAEM model is a spatial CGE model developed to consider indirect effects from infrastructure (transport) projects across different regions. It was further extended by Ivannova et al. (2011) to the regional level across the EU.

It is to mention that there are other multiregional IO models and tables for EU regions, as the Project for the EC Institute for Prospective Technological Studies (JRC-IPTS) by Thissen, Lankhuizen, and Jonkeren (2015), which developed a multiregional model for the EU, considering intranational and international flow trade, regionalizing from supply and use tables. This is, as the RAEM, consistent with national accounts. It would be interesting to compare both data sets for consistency, although that is out of the scope of this article. Then, RAEM data were used for this article as it was the available data.

[6]EM-DAT: The Emergency Events Database – Université catholique de Louvain (UCL) – CRED, D. Guha-Sapir – www.emdat.be, Brussels, Belgium.

[7]Eurostat: http://ec.europa.eu/eurostat.

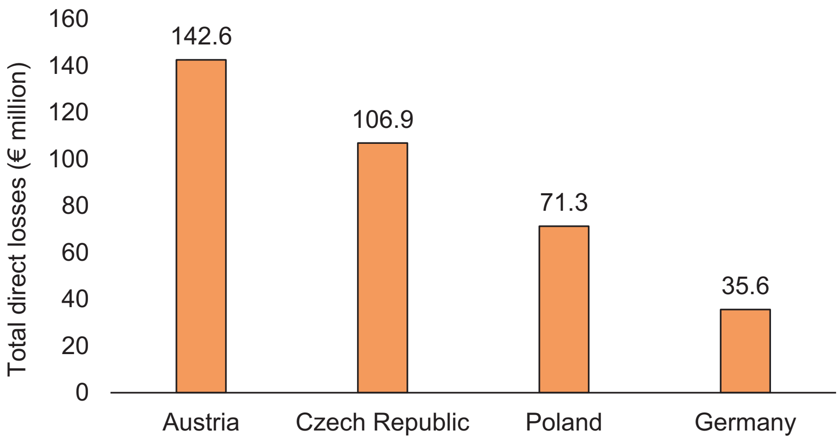

Fig. 2. Values of material damage by country.

4.3. Capital Matrix

The capital matrix contains information about how much CS, as a productive factor, is needed for production in each industry, as well as which sectors are involved in the construction of this capital. In the case where a disaster destroys part of the CS, the capital matrix provides the "recipe" with which to rebuild the CS and, consequently, the productive capacity.

The CS data used to construct the capital matrices were taken from the EU KLEMS database, which is publicly available at http://www.euklems.net (The Conference Board, 2016). The data used here are from the file "Real fixed capital stock (2010 prices)" and are available at the national level. In countries where data were not available, data from another country were used as proxies (see Table A2). It is to be mentioned that capital matrices are elaborated with national data, as regional data for fixed CS are not available. The obtained coefficients for the national capital matrices are applied for all regions within a country. This certainly represents a source of uncertainty; however, national capital matrices can be considered as the national average composition for fixed CS.

4.4. Labor Losses

As data on labor constraints in the aftermath of a disaster are scarce or nonexistent, proxy variables were used to develop an exogenous labor loss curve. For this purpose, the proxy variable used was the damage to the transport sector and affected households. The labor constraints were defined as 1 in 10,000 employees unable to attend work, and 1% of the working population was delayed by an average of half an hour during the first month. The amount of labor unavailable for traveling came out from the proportion of damage to residential capital and the proportion of employees by household. This was extrapolated to the regional population. The proportion and time of labor delayed are related with damage to the transport sector. Labor is fully available by the third month. A sensitivity analysis was carried out to test the stability of the parameters.

5. RESULTS

5.1. Direct Economic Impacts of the 2009 Flood Event

The floods mainly caused material damage to businesses, residential properties, roads, railways, power stations, the water industry, and crops. The total value of these damaged assets was estimated to be €356 million, comprising the entire direct economic losses. These losses were distributed across four countries (Fig. 2). The initial direct losses of industrial capital in the four Central European countries accounted for €238 million, which is equivalent to 0.004% of the total CS among the affected regions. In addition, direct losses of residential capital across all affected regions accounted for a total of €118 million. The maps in Fig. 3 show the regional distribution of each category of losses among the 23 affected regions within Austria, the Czech Republic, Germany, and Poland.

Fig. 3(A) depicts the distribution of direct losses of industrial capital. Austria was the most affected country, as it experienced 38% of all losses in this

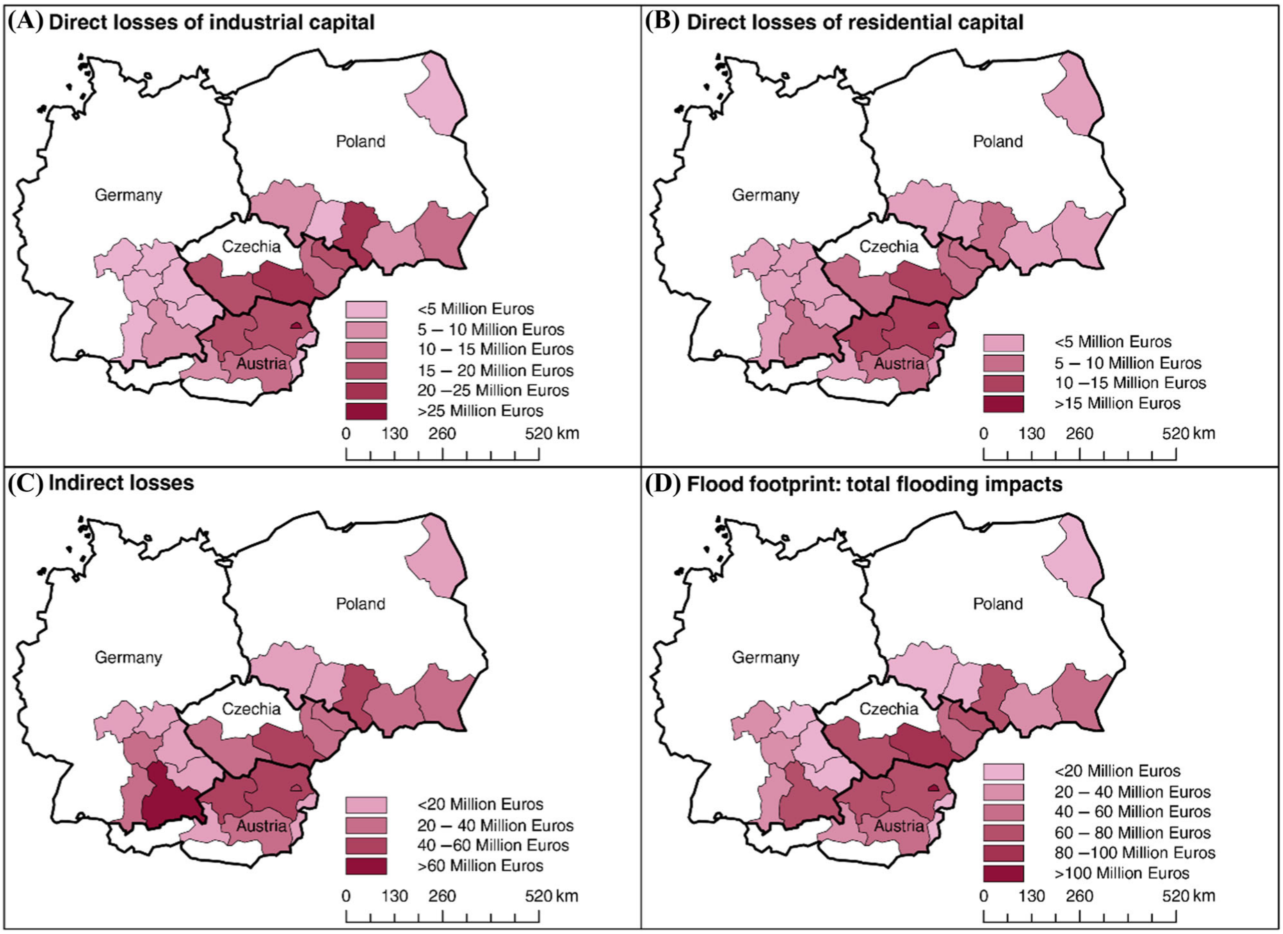

Fig. 3. Regional distribution of impacts of the 2009 flooding in Central Europe.

category (ca. €91 million). Within Austria, Vienna (the darkest region) was the most strongly affected region, accounting for 32% of direct industrial losses. The distribution of losses of the industrial capital of the other countries includes the Czech Republic with 31%, Poland with 23%, and Germany with 8%. Two other notable affected regions are Jihovýchod in the southeastern Czech Republic (€23 million) and Śląskie in southern Poland (€20 million).

Fig. 3(B) shows the distribution of direct losses caused by residential capital damage. Again, Austria was the most affected country, as it experienced 44% of the total losses in this category (ca. €52 million). The three most affected regions are localized within Austria: Vienna (the darkest region), Niederösterreich (Lower Austria), and Oberösterreich (Upper Austria) experienced 32%, 21%, and 20% of the national residential losses, respectively. Other seriously affected regions outside Austria include Jihovýchod in the Czech Republic (ca. €10 million), Oberbayern (Upper Bavaria) in Germany (ca. €7 million), and Śląskie in Poland (ca. €6.5 million). Notably, the losses in Oberbayern represent 40% of the residential losses in Germany, while those in Śląskie represent 38% of the residential losses in Poland.

5.2. Indirect Economic Impacts of the 2009 Flood Event

The indirect losses accumulated during the recovery added an additional €663 million to the flood footprint of the event. Therefore, the final flood footprint for the 2009 flooding in Central Europe amounts to over €1 billion. For comparative purposes, this is equivalent to 0.04% of the German annual GDP in 2009. The indirect losses caused by constraints in labor and industry are shown in

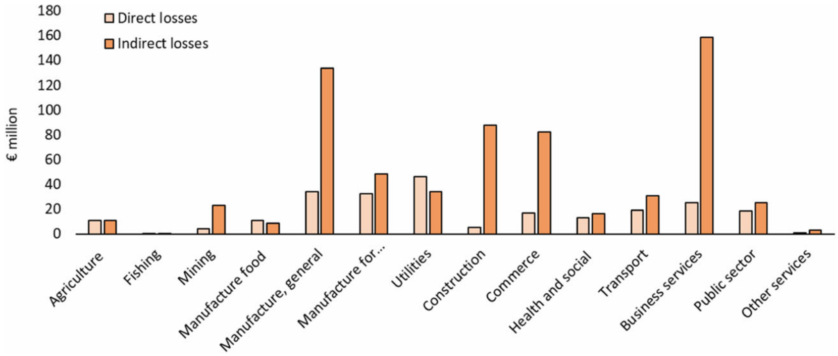

Fig. 4. Distribution of direct and indirect impacts by economic sector.

Fig. 3(C), which constitute two-thirds (65%) of the total flood footprint. The most affected country is Austria, with 31% of total indirect losses (€205 million), while the most affected region is Oberbayern in Germany, which accounts for 36% (€63 million) of national indirect losses. Other notable regions include Vienna and Austria, whose losses represent 29% (€59 million) of national indirect losses, as well as Jihovýchod in the Czech Republic (€49 million) and Śląskie in Poland (€43 million).

5.3. Total Flood Footprint of the 2009 Flood Event

The total economic impacts of the disaster are added up in the flood footprint concept. The total economic impacts include all costs incurred due to direct and indirect losses. The geographical distribution of the flood footprint is presented in Fig. 3(D). This footprint shows that Austria experienced the largest proportion of losses, accounting for over one-third of the total flood footprint (€347 million). The Czech Republic contributes over one-quarter of all losses (€268 million), while Germany and Poland contribute 21% (€211 million) and 19% (€193 million), respectively. For comparative purposes, relative to their respective national 2009 GDPs, the flood footprint in Austria represents 0.12%, in the Czech Republic represents 0.15%, in Germany represents 0.015%, and in Poland represents 0.03%.

Fig. 4 depicts the direct and indirect losses across each of the 14 industrial categories. It must be noted that direct losses of residential capital are excluded from these figures, as they do not affect the productivity of industrial capital. The sectors that are most affected by direct losses are utilities, manufacture (general), and manufacture for recovery. These three sectors account for 47% of the total direct losses (€112.5 million). On the other hand, indirect losses were accrued in business services, which is the most affected sector, accounting for approximately one-quarter of total indirect losses (€159 million); followed by the manufacture (general) (€134 million), construction (€87.5 million), and commerce (€82 million) sectors. These four sectors account for 70% of the total indirect losses. It is probable that functioning of these sectors is highly dependent on support from other sectors and therefore they are more vulnerable to the direct shock that affects the overall economy.

Fig. 5 shows the distribution of direct and indirect losses by economic sector for each affected country. In Austria, direct losses in industries account for €91 million, while indirect losses account for €205 million. Approximately half of direct losses are concentrated in the utilities (€19.5 million), business services (€12.5 million), and manufacture general (€11.3 million) sectors. On the other hand, 60% of indirect losses are concentrated in the business services (€49.5 million), manufacture general (€40 million), and construction (€33 million) sectors.

In the Czech Republic, direct losses account for €73 million and indirect losses account for €161 million. Manufacture for recovery (€14.7 million), utilities (€13.4 million) and manufacture general (€11.8 million) represent 54% of direct losses. In terms of indirect losses, 47% are concentrated in the manufacture general (€43.8 million) and business services (€31.2 million) sectors.

In Germany, direct losses account for €19 million and indirect losses account for €176 million. The manufacture for recovery (€3.3 million), business services (€2.9 million), and utilities (€2.8 million) sectors represent 47% of direct losses. On the other hand, the business services sector represents one-third of indirect losses (€57 million).

In Poland, direct losses account for €54 million and indirect losses account for €121 million. The sectors in Poland that are most affected by direct

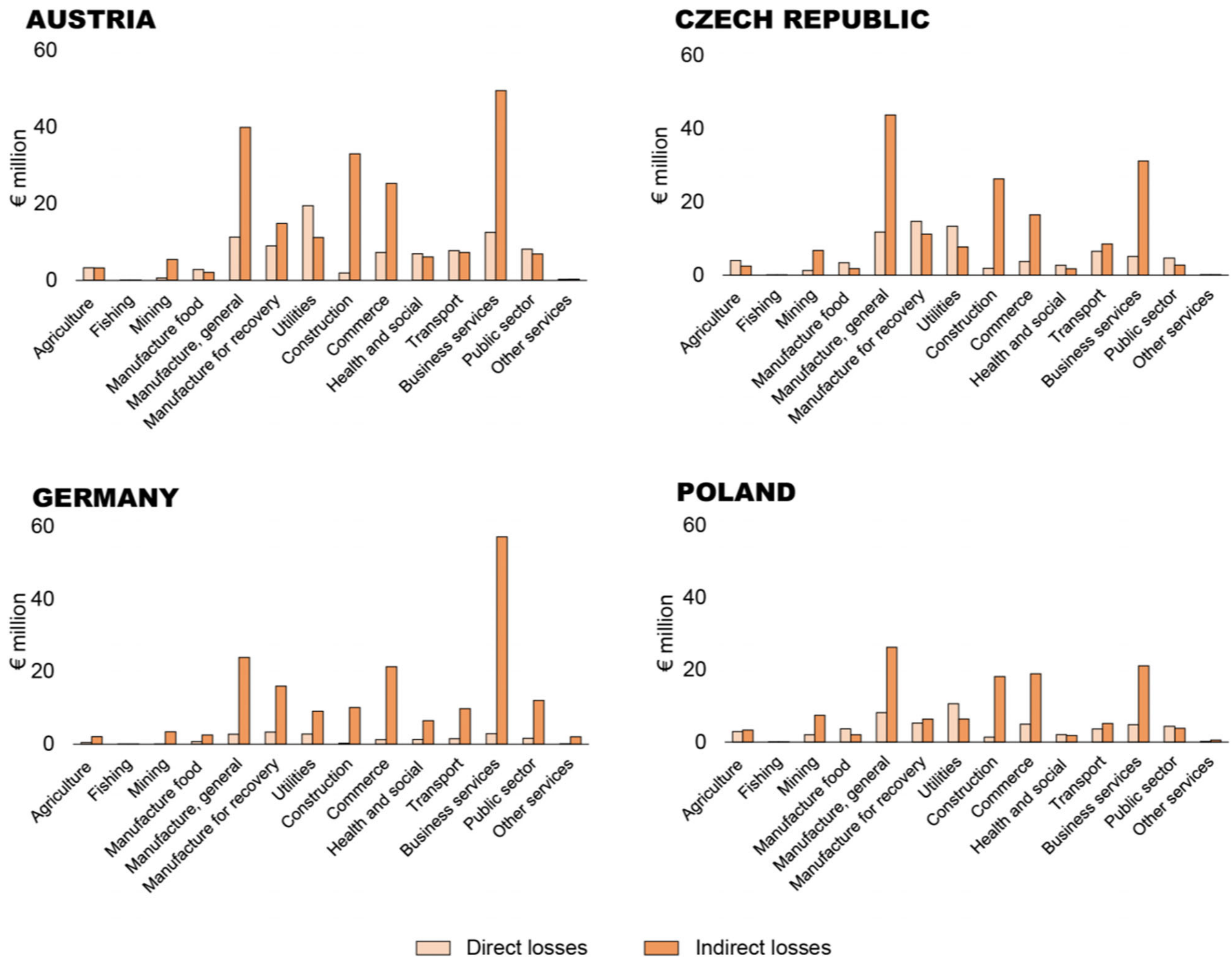

Fig. 5. National distribution of direct and indirect losses by industrial sector.

losses are utilities (€10.6 million) and manufacture general (€8.1 million), which together represent 35% of the total direct losses. Approximately 70% of indirect losses are accumulated in the manufacture general (€26.3 million), business services (€21.1 million), commerce (€18.9 million), and construction (€18.1 million) sectors.

5.4. Sensitivity Analysis: 2009 Floods in Central Europe

A sensitivity analysis was carried out on the model parameters related to the loss curve of labor, and behavioral changes in final demand. The sensitivity analysis comprises the upward and downward variation of 30% of the parameters in intervals of 5%. Related to final demand, the variation of parameters comprises the decreased proportion of consumption in nonbasic products. While for labor, the variation of parameters comprises the proportion of labor not available for traveling, and the proportion and time of labor delayed by transport constraints. Here are the results of a global sensitivity analysis, that is, the results of variations in all parameters at the time. This is because changes in final demand parameters gave nonsignificant changes in results.

The error bars in Fig. 6 show the standard error by industry sector from the sensitivity analysis. On average, the standard error is 11% different from the mean values. The maximum error, in relative terms, is found in the business services sector, which represents a deviation of 13% from its mean value. The maximum error, in absolute terms, is found in the manufacture general sector, which shows a deviation of €17 million. The standard error of the overall result (the variation in total indirect losses for all

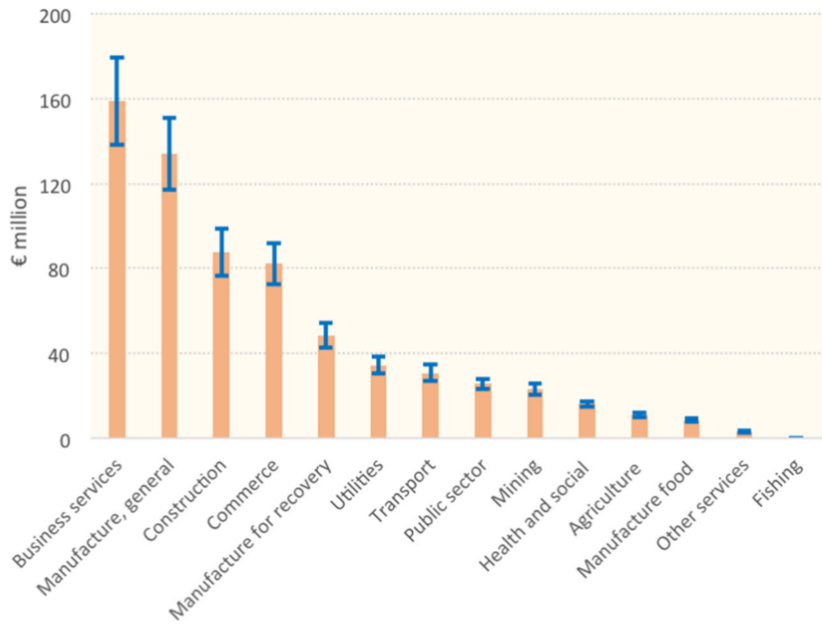

Fig. 6. Sensitivity analysis by sector.

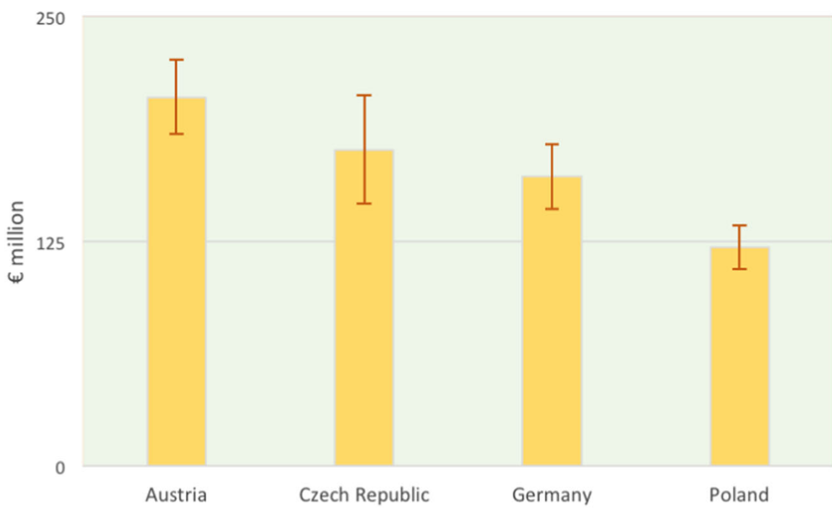

Fig. 7. Sensitivity analysis by country.

sectors in all regions) is 12% different from the mean (± €662 million).

In Fig. 7, the error bars represent the variation given by the standard error from the sensitivity analysis, by country. It can be noted that the distribution of the error is more heterogeneous than by sector. This is mainly due to the variation being distributed among fewer categories. The maximum error, in relative terms, is found in Germany, which represents a deviation of 17% regarding the mean values. The maximum error, in absolute terms, is found in Germany as well, which represents a deviation of €30 million (37% of total standard error).

The sensitivity analysis shows that the model is relatively stable, and the results can be considered robust, as variations in the model parameters cause less than proportional changes in results. In this case, a variation of ± 30% in parameter values results in a standard error equivalent to 12% of the mean value of the total indirect losses of the event.

6. DISCUSSIONS

6.1. Cascading Effect: Indirect/Direct Ratios

The ratio between indirect and direct losses provides useful information about the cascading effect

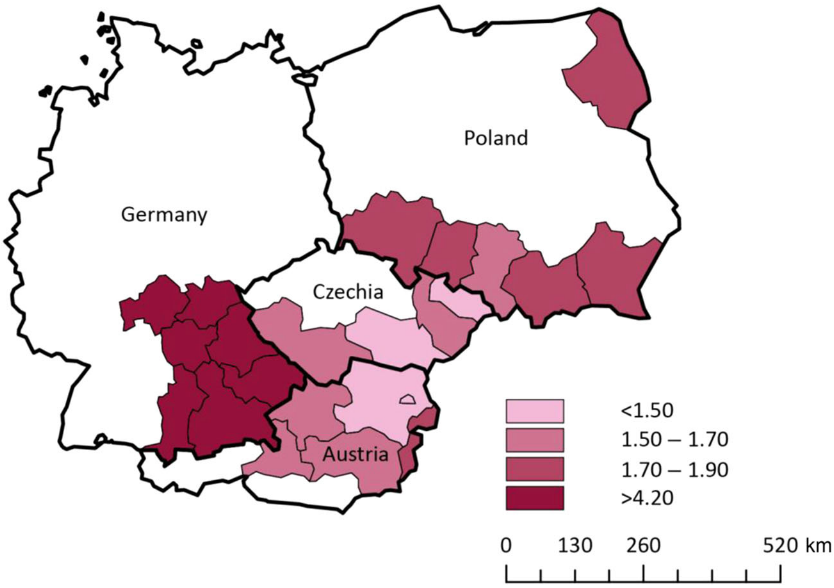

Fig. 8. Regional distribution of indirect/direct ratios in Central Europe.

of the floods through the production chain. The cascading effect refers to the additional amount of output loss caused by one unit of direct shock. It is incurred through two mechanisms: (1) reduced productive capacity due to direct damage to *industrial capital*; and (2) retardation in output recovery due to direct damage to *residential capital* that competes for resources for reconstruction with other economically vital industries. As shown in Section 5.2, the total amount of indirect losses caused by the 2009 flooding is estimated to be €663 million, reaching 186% of direct losses (including losses in both industrial and residential capital). The result is consistent with that in Hallegatte (2008), which shows that the indirect losses range between 50% and 250% of the direct losses. In general, IO models tend to overestimate the ratio compared with other related research. Recent approaches of those using linear and nonlinear programming, as in Koks and Thissen (2016) and Oosterhaven and Többen (2017), showed that the ratios of indirect/direct losses are smaller, although in a sense they are more related with CGE than with IO modeling, in the words of the former; and it is also recognized in disaster impact analysis that CGE models provide lower levels of indirect losses compared with direct losses. Therefore, as mentioned by Okuyama and Santos (2014), results from IO models can be seen as an upper bound of losses estimation, while CGE models would provide the lower bound.

6.2. Comparative Analysis Between Regions

The multiple regional method used in this study allows to examine the regional differences in response to flooding. As shown in Fig. 8, regions in Germany generally have much bigger indirect/direct ratios than other regions, indicating larger cascading effects. Results show that ratios in Germany are 4.93 on average, more than three times bigger than those in other regions (cluster at 1.52). Such a gap might be related to the difference in economic structures between affected regions. According to data collected from the World Bank website, in 2009, the medium and high-tech industry (including construction) accounted for a larger part of the manufacturing industry in Germany than that in Austria, Czech, and Poland (58% vs. 43%, 41% and 38%, respectively, in value added).[8] Development of these industries, e.g., computer, electronic, and optical manufacturing, requires not only large amounts of capital investment, but also massive input of primary products from other industries, which altogether increases the level of capital intensity and strengthens the interindustrial links of German's economy. For one thing, higher capital intensity implies that the employee productivity is higher than economies/industries that are less capital intensive, and direct impacts that affect labor in capital-intensive economies/industries will have severe effects on productive capacity, therefore, leading to high economic losses. For another,

[8]Source of data: https://data.worldbank.org/.

in economies with stronger interindustrial links, industries rely more on intermediate input to maintain production, which makes them more vulnerable to disasters that harm intermediate production through direct shock to industrial capitals, and thus higher incurring losses along the production chain.

Furthermore, comparing Figs. 3(A) and (C), Oberbayern, the region located in the southeast of Germany, stands out among all the regions by showing significant cascading effect of flooding shock. In Oberbayern, a less-than-medium level of direct losses (€14.43 million) has caused the largest amount of indirect loss (€62.55 million) among all the regions, and its ratio between indirect and direct losses is also among the top of all affected regions. This may be because Oberbayern is the largest regional economy (in terms of GDP) among 23 regions. Oberbayern's regional output is 76,694 million euros in 2008, which is almost 2.5 times the amount of the second largest regional economy—Vienna (Wien) among 23 regions.[9] Flood footprint in Oberbayern is 76.98 million euros, accounting for the largest part (36.42%) of total German footprint.

To sum up, it can be inferred that the cascading effect in large and developed economies would become much more significant than that in small and less-developed ones. In other words, large and developed economies, like regions in Germany, although less affected by direct asset damage, would suffer more indirect losses, because they are typically highly capital-intensive and strongly interindustrial related, making the adverse shock have a more severe and widespread impact through the production chain.

6.3. Caveats

Even though the model used for the analysis in this article is able to depict the direct and indirect damages by region and economic sector in a robust way, there are still some rigidities in the model that prevent the consideration of certain aspects of the recovery process. First, it is to point out explicitly that IO models work with Leontief-type production functions, which does not consider substitution between industries, while it has been experienced in real life that producers may work with different technologies that requires a different composition of inputs. This assumption is related with the fixed technology along the recovery time. It has been noticed that disasters bring the opportunity of incorporating newer technology in the recovery process, which may increase the productivity and hence the recovery speed. These two factors may act speeding the recovery process, thus reducing the indirect damages.

Second, the model does not consider the possibility of switching external suppliers, which would imply the permanent loss of clients for those business that experienced production shortfalls. This factor would increase the indirect damages.

7. CONCLUSIONS

In this study, we have introduced damage functions and capital matrix to the flood footprint model and successfully applied this improved method to a past extreme climate event—the 2009 European Floods—in a multiple regional framework. We can draw three important conclusions from our results and discussions. The first conclusion is that indirect losses constitute a major part of the total flood footprint. For the 2009 Central European Floods, the indirect losses represent around 65% of the total losses, which is consistent with the results of previous IO-based studies and provides the upper bound among those of other models. The second conclusion is that most of the indirect losses come from industries that are at the end of the production chain and closely connected with other industries. Our results show that 70% of indirect losses come from four industries, which are business services, manufacture general, construction, and commerce. Production of these industries shows high reliance on intermediate input from other sectors. The last important conclusion is that large and developed economies would experience higher levels of cascading effect than small and less-developed ones. The cascading effect is measured by the ratio between indirect and direct losses caused by the floods, which according to our results varies among the affected regions. The ratios in large and developed economies, like regions in Germany, are averagely more than three times bigger than those in other regions. These regions, although less vulnerable to the direct shock of the floods, suffer more indirect losses than others, owing to their specific economic structures with high capital intensity and strong interindustrial links. Furthermore, the model has proven to be reliable through the sensitivity analysis.

The application of the flood footprint model to multiple European regions across national borders allows us to not only consider the total economic impacts of the disaster, but also make comparisons

[9] Source of data: https://ec.europa.eu/eurostat/data/database.

regarding different economic structures at both national and subnational levels. This analysis is especially useful for establishing disaster adaptation policies in the context of the European Union, where adaptation policies seek "umbrella" strategies to reduce the climate risk to all involved regions.

A possible implication from this analysis is that, at regional level, adaptation strategies must consider financial resources flow from more developed countries to those less developed, to protect industries in the latter to avoid input shortages, which cause large indirect damage to the former. This implies a change in climate change studies paradigm, which states that mitigation should be at global scale, while adaptation at local scale.

The main contribution of this study is that the introduction of capital matrices adds methodological consistency, as it translates capital accumulation into productive capacity restoration in a more realistic way than previous research, which leads to more reliable results. Beyond that, we have employed data from practical surveys of the NatCatService of Munich Re, which is a more comprehensive data set than previous ones.

In the future research, the flood footprint model might be applied to a wider range of disaster groups other than flooding, as long as the direct damage can be transformed into percentage losses of productive capacity using damage functions. This means that the flood footprint model can be extended to a disaster footprint model. Damage functions also allow the integration of flood modeling with other research techniques to assess the impact of projected hazards under a variety of socioeconomic scenarios. However, the influence of interregional trade in a multiregional framework needs to be incorporated in future studies to analyze the spillover effects of indirect losses to other regions.

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APPENDIX

Table A1. Industrial Sectors Used for Analysis

Industrial Sectors		
Agriculture	Manufacture for Recovery	Transport
Fishing	Utilities	Business services
Mining	Construction	Public sector
Manufacture food	Commerce	Other services
Manufacture general	Health and social	

Table A2. Availability of Capital Data for Affected Countries

Countries	Availability of Capital Data (Yes/No)	Country Used as Proxy
Austria	Yes	–
Belgium	No	The Netherlands
Czech Republic	Yes	–
Germany	Yes	–
Spain	Yes	–
France	No	Germany
Italy	Yes	–
Lithuania	No	Czech Republic
Luxembourg	No	Germany
Latvia	No	Czech Republic
The Netherlands	Yes	–
Poland	No	Germany
Portugal	No	Spain
United Kingdom	Yes	–

Table A3. Sectors Involved in Capital Formation

Code in EU KLEMS Database	Description
K_IT	Computing equipment
K_CT	Communications equipment
K_Soft	Software
K_TraEq	Transport equipment
K_OMach	Other machinery and equipment
K_OCon	Total nonresidential investment
K_RStruc	Residential structures
K_Other	Other assets

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