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Comparing the economic impact of natural disasters generated by different input-output models. An application to the 2007 Chehalis River Flood (WA)

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Abstract: Due to the concentration of assets in disaster-prone zones, changes in risk landscape and in the intensity of natural events, property losses have increased considerably in recent decades. While measuring these stock damages is common practice in the literature, the assessment of the economic ripple effects due to business interruption is still limited and available estimates tend to vary significantly across models. Given the myriad of proposed input-output models in the disaster literature, this paper reviews the most used methodologies (the traditional Leontief model, Cochrane's rebalancing algorithm, the sequential interindustry model, the dynamic inoperability input-output model and its inventory counterpart) and compares the total losses they generate. We also highlight the nuances of the input-output framework that have been overlooked by applied researchers. As a common benchmark, we analyze the first and higher-order flow effects of the Chehalis river flood that took place in Washington State in 2007. In order to quantify the direct damages, we rely on fine-scale water depth-grids from the U.S. Army Corps of Engineers and the widely used HAZUS software. The results indicate a difference of 69% to 115% in the estimation of total losses across models, hence a careful model selection based on the characteristics of the disaster, of the affected region(s) and on the knowledge of the inoperability and intersectoral interdependency is needed. Such efforts will help us understand the level of vulnerability of our economic systems and be better prepared for future events.

Keywords: Flood, Economic Impact, Input-Output Analysis

1. INTRODUCTION

Major disaster databases (Emergency Events Database (EM-DAT), Natural Hazards Assessment Network (NATHAN), Spatial Hazard Events and Losses Database for the United States (SHELDUS)) tend to compile only *stock losses*, i.e. damages to physical or human capital, as these are routinely collected and reported in the aftermath of a disaster(1). In the case of floods, the National Weather Service is required to provide monetary estimates of damages for all such events in the US, with special attention to property damages(2). They are measured by determining the amount of physical destruction and the associated repair costs. Estimation is performed via engineering models (traditionally damage-depth functions for floods) and the results can be validated through actual post-event assessment from public (local governments) and/or private (insurance companies) entities. Given their availability and the simplicity of the estimation, *stock losses* are widely used in hazard mitigation planning, especially in cost-benefit analyses. However, they offer only an incomplete picture of the economic impacts by not portraying the business interruptions they induce either locally or in their trade partners.

Conversely, *flow losses* provide a more comprehensive view as they account for the direct loss in production due to capital damages (first-order effects according to Rose(3)) and for spillovers to non-affected industries and regions (higher-order effects). These ripple effects can be significant if major industrial chains are disrupted or infrastructure is compromised. For instance, the 1993 Midwest flood halted freight in the Mississippi River, highways and rail lines along the inundated areas leading to $2 billion in losses. Damaged crops in Iowa caused flow losses of $3.6 billion in the state(4). More recently, physical damage from the 2012 Hurricane Sandy caused direct and indirect losses totaling $1.2 billion in New Jersey due to a plunge in tourism spending(5).

In the disaster literature, detailed data on *flow losses* are limited and usually incomplete, as a comprehensive survey would entail tracking businesses inside and outside the affected area for an extensive time length. Most studies on business recovery are geographically constrained to the affected region and qualitative. In addition, few of them provide a long-term assessment that extends beyond the reconstruction phase. Exceptions are Tierney(6) on the impact of the Northridge earthquake in the Greater Los Angeles area and Green *et al*.(7) on the 2007 Chehalis flood in Lewis County which is part of our study area.

Due to these issues, several economic models have been proposed to assess *flow losses*. Most of them are rooted in the Input-Output (IO) framework that models linkages and feedbacks between the productive sectors of an economy. However, a lack of consensus on a preferred model has led to an increasing number of alternative specifications with varying results(8). In order to exemplify the model selection dilemma a practitioner has to face as well as the difference in the various models' capacity to assess sectorial vulnerability and overall losses, which can lead to dramatically distinct disaster relief efforts, we focus on the same event – the 2007 Chehalis flood in Washington State – but under the lens of the five most applied IO models in the literature. They are the traditional Leontief model(4), Cochrane's rebalancing algorithm(9), the sequential interindustry model(10), the dynamic inoperability IO model(11) and its inventory counterpart(12). Moreover, we highlight some common theoretical misconceptions in the application of these models when translating stock damages into flow impacts.

In order to investigate these issues, the next section offers a review of the above models. Section 3 describes the benchmark event and the bridge between physical damages and the IO framework. Section 4 discusses and compares the results of each model, and section 5 concludes and offers some recommendations for future disaster analysis studies.

2. METHODOLOGY

A non-exhaustive literature review of the methodologies used for flow loss estimation is available in Okuyama[13] and Przyluski and Hallegatte[14]. Among those, IO, computable general equilibrium (CGE) and econometric models comprise the most used frameworks in the field. The strength of an econometric approach derives from estimations based on historical data. They provide a statistical base for forecasting, but time-series usually convey limited information on future disasters due to their infrequency and idiosyncrasy. Furthermore, their large majority overlooks interregional effects. As a result, the estimated marginal effects are not generalizable and most models represent partial equilibrium only[15]. CGE models, on the other hand, provide a more comprehensive view of total flow impacts as they capture production chain linkages across various industries and regions as well as the flow of income across industries, factors and institutions. They provide a greater degree of flexibility when modeling supply-demand co-movements, such as allowing non-linear specifications, substitution effects and behavioral responses[16]. Their weakness derives from large data requirements and the technical knowledge needed to build the model. Greenberg *et al.*[15] highlight that the source of many behavioral parameters is usually questionable. When the lack of regional data makes their estimation at the local level unfeasible, they are regularly "borrowed" from national or international studies, which may lead to biases. Oosterhaven[17] adds that it is a challenge to separate short-run input substitution, which is fairly minimal, with more flexible long-run substitution effects.

Furthermore, optimizing behavior assumptions coupled with input substitutability lead these models to underestimate impacts according to Przyluski and Hallegatte[14] and Meyer *et al*.[18].

Despite a more restricted focus on productive activities and rigidity in terms of inputs substitution and prices, the IO framework offers several advantages. It captures the economic linkages between industries and regions, hence allowing to quantify the spread of disruptions in production chains. It also has the benefit of portability in that the same methodology can be applied to structurally different regions and the results can be compared. Its relatively lower data requirement in comparison to CGE models or survey analysis allows for easy deployability, and forecast capacity as simulations on future events or diverse set of constraints can be performed. Regarding the disaster literature, IO also permits an easy integration with external models (e.g. engineering models) and a more accurate portrait of the industrial short-run behavior after disruptions, when rigidities restrict substitution effects[17].

Among the various IO specifications applied in the literature, the traditional Leontief demand-driven model is one of the simplest and most popular (see Miller and Blair[19], for a detailed explanation). It assumes linear production functions with perfectly complementary inputs that are portrayed in the direct input requirement table $\boldsymbol{A}$. Total output is a function of the interdependencies among industries presented in the Leontief inverse matrix $(\boldsymbol{I} - \boldsymbol{A})^{-1}$ and the final demand to be supplied in the period $(\boldsymbol{f})$. Impact analysis is performed by estimating the Leontief inverse, changing the demand vector to reflect conditions post-disaster $(\bar{\boldsymbol{f}}^{*})$ and pre-multiplying it by the original Leontief inverse to obtain the post-disaster output $\boldsymbol{x}^{*}$ (Eq. 1).

$$\boldsymbol{x}^{*}(t) = (\boldsymbol{I} - \boldsymbol{A})^{-1}\bar{\boldsymbol{f}}^{*}(t) \tag{1}$$

Total flow losses per period are easily retrieved by subtracting the pre-disaster output from the post-disaster output. This is the approach used by Changnon[4] to assess the flow impacts of the 1993 Midwest flood and by WSDOT[20] in estimating the total economic impact of the I-5 and I-90 highways closures during the 2007 Chehalis flood.

In the traditional Leontief model, it is assumed that production is simultaneous and contained in each time period, i.e., all the output necessary to attend a given final demand is produced within the time interval without any lag. Moreover, there are no trade constraints nor supply constraints for production. The model is demand-driven so that supply constraints are captured through demand reductions by applying the corresponding capacity constraint (γ_i) to $\boldsymbol{f}$ (Eq. 2).

$$\bar{f}_i^*(t) = \big(1 - \gamma_i(t)\big) f_i \quad \forall i, t \tag{2}$$

This simplified model has severe issues in modeling disruptive events. By assuming constant local input requirement coefficients throughout the aftermath of the disaster, it cannot incorporate input substitution effects due to local supply constraints. The static nature of the model combined with the assumption of production simultaneity limits the scope of the analysis by restricting disruptive leakages within and between production chains and through time. Safety inventories, that traditionally smooth volatile periods, are also not accounted for in the model. Therefore, the recovery process portrayed is negatively biased (i.e. it underestimates losses) as, despite demand changes, the rest of the economy is constant from the pre-disaster scenario.

In order to incorporate supply constraints explicitly in the demand-driven model, Cochrane[9] and Oosterhaven and Bouwmeester[21] propose a rebalancing of the post-disaster IO table. The latter relies on an interregional IO (IRIO) table to recalculate the flows inside and outside the affected region. Given the post-disaster output and trade constraints, a nonlinear programming model that minimizes information gains recalculates the economic flows to support the post-disaster final demand. The implementation of this methodology, however, requires an IRIO table that is usually not readily available to the researcher. As input substitution can only occur with exogenous foreign sectors, the case of a single region requires additional assumptions on trade flexibility. A simpler single-region rebalancing algorithm was introduced by Cochrane[(9)]. It is the one used by HAZUS (HAZard US), a standardized hazard risk assessment tool created by the Federal Emergency Management Agency (FEMA) and widely used in mitigation planning and cost-benefit analysis. The iterative routine checks for excess supply/demand, existing flexibility in inventories and trade, and reallocates production accordingly (Fig. 1).

<< INSERT FIGURE 1 HERE >>

The rebalanced IO table reflects the new steady-state of the economy at each time period. If one assumes no trade constraints nor inventories, the rebalancing algorithm can be directly implemented in the Leontief model by pre-multiplying the input requirement table by a matrix of post-disaster remaining capacity $(\boldsymbol{I} - \boldsymbol{\Gamma}(\mathrm{t}))$, where $\boldsymbol{\Gamma}(\mathrm{t})$ is a diagonal matrix with $\gamma_i(t)$ as the non-zero elements (Eq. 3).

$$\boldsymbol{x}^*(t) = (\boldsymbol{I} - (\boldsymbol{I} - \boldsymbol{\Gamma}(\mathrm{t}))\boldsymbol{A})^{-1}\bar{\boldsymbol{f}}^*(t) \tag{3}$$

This model overcomes the supply-demand incompatibility of the Leontief model, relaxing the previous assumption of constant economic structure and mitigating its bias. Nonetheless, all constraints are exogenously imposed and new production restrictions cannot arise endogenously. Moreover, the static nature of these models still implicitly assumes that the effects of the disruption are contained within the set time interval, as if production was not a continuum. The amount of bias is related to the length of the model's time interval as shorter periods ignore larger intertemporal disruptive "leakages" to future production.

As highlighted by Cole(22) and Romanoff and Levine(23), the idea of an instantaneous production process is unrealistic, as contractual obligations and production delays can linger in the economic system for several months, thus influencing output inter-temporally. A dynamic approach is therefore needed to accurately assess the total impact of a disaster. One of the first works attempting to incorporate dynamics in disruptive events is the time-lagged model proposed by Cole(22,24) and applied to industrial plants closure. Its core assumption is that the spread of income shocks in the economy suffers different levels of inertia (lags) at various points of the supply/demand chain that the instantaneous model ignores. However, Cole advocates for the endogeneization of all flows in the IO table, which makes the model theoretically inconsistent, not solvable and led to criticism by Jackson *et al*.(25), Jackson and Madden(26) and Oosterhaven (27).

An alternative dynamic formulation is the Sequential Interindustry Model (SIM). Proposed by Romanoff and Levine(23) and based on the series expansion of the Leontief inverse, it introduces production timing in the IO framework. While developed before Cole's model, it was applied to disaster contexts much later(10). In the SIM, industries are classified according to three production schedules: anticipatory, just-in-time or responsive. The former type is related to sectors that produce before orders are placed. They anticipate the demand as their production process is lengthy and goods are standardized. Primary sectors and manufacturing fall in this category. Responsive sectors such as construction receive orders before they start production; while just-in-time sectors have short production lengths, so they can supply demand in the same period. Time is discretized, it is assumed constant, the same for all industries and synchronized across sectors. The Core SIM is derived from the supply-demand identity in the IO table:

$$x_i(t) \equiv \sum_j z_{ij}(t) + f_i(t) \quad \forall i, t \tag{4}$$

Partitioning the traditional input requirement table ($\boldsymbol{A}$) between the different production types ($\boldsymbol{A_a}$: anticipatory; $\boldsymbol{A_j}$: just-in-time; and $\boldsymbol{A_r}$: responsive), we derive one equation for each "pure" production mode:

$$\begin{aligned} \boldsymbol{x}(t) &= \boldsymbol{A_a}\boldsymbol{x}(t+1) + \boldsymbol{f}(t) \\ \boldsymbol{x}(t) &= \boldsymbol{A_j}\boldsymbol{x}(t) + \boldsymbol{f}(t) \\ \boldsymbol{x}(t) &= \boldsymbol{A_r}\boldsymbol{x}(t-1) + \boldsymbol{f}(t) \end{aligned} \tag{5}$$

Then, a mixed model for the economy is derived by combining all production modes:

$$\boldsymbol{x}(t) = \boldsymbol{A_a}\boldsymbol{x}(t+1) + \boldsymbol{A_j}\boldsymbol{x}(t) + \boldsymbol{A_r}\boldsymbol{x}(t-1) + \boldsymbol{f}(t) \tag{6}$$

Notice that the traditional IO model is a special case of the SIM when all industries are just-in-time. Hence, the Core SIM reproduces the same accumulated total losses from the traditional Leontief model but spreads them through time. However, it relies on a set of strong assumptions such as perfect foresight of demand and perfect knowledge of interindustrial requirements(28), of changes in the economic structure and perfect sectoral adaptability to the disruption (no inventories). Romanoff and Levine(29,30) have remedied some of these issues by including inventories, post-disaster technology changes and delivery delays, but their implementation is not straightforward(10). In addition, the system's inoperability in the SIM is inter-temporal only to the extent that intra-temporal impacts are carried over via production lags.

On the other hand, the Dynamic Inoperability Input-Output Model (DIIM) proposed by Lian and Haimes(11) aims at introducing a framework that bridges intra-temporal and inter-temporal inoperability. The DIIM is the dynamic version of the Inoperability Input-Output Model(31,32) that we do not cover in this review given that it offers no methodological advances compared to the traditional IO model(17,33).

DIIM is based on the classic Leontief Dynamic model which assumes that current output accounts for both the production required to attend current demand and any required capital to attend production in the next period via the capital formation matrix $\boldsymbol{B}$ (Eq. 7).

$$\boldsymbol{x}(t) = \boldsymbol{A}\boldsymbol{x}(t) + \boldsymbol{f}(t) + \boldsymbol{B}[\boldsymbol{x}(t+1) - \boldsymbol{x}(t)] \tag{7}$$

While the Leontief's model is a growth model, the DIIM models a recovery process where the economy moves back to the pre-disaster steady-state. Hence, the capital formation matrix is replaced by a resilience matrix $\boldsymbol{K} = \hat{\boldsymbol{k}}$ that represents the speed at which the pre- vs. post-disaster production gap closes (Eq. 8).

$$\xRightarrow{B=-\hat{k}^{-1}} \boldsymbol{x}(t) = \boldsymbol{A}\boldsymbol{x}(t) + \boldsymbol{f}(t) - \boldsymbol{K}^{-1}[\boldsymbol{x}(t+1) - \boldsymbol{x}(t)]$$
$$\Leftrightarrow \boldsymbol{x}(t+1) = \boldsymbol{x}(t) + \boldsymbol{K}\,[\boldsymbol{A}\boldsymbol{x}(t) + \boldsymbol{f}(t) - \boldsymbol{x}(t)] \tag{8}$$

Taking $t = 0$ as the first period post-disaster and $t = T_i$ the time industry i takes to recover to a target (minimal) level of inoperability q_i, the interdependency recovery rate k_i is defined as:

$$k_i = \frac{\ln\left({q_i(0)}\big/{q_i(T_i)}\right)}{T_i(1 - a_{ii})} \tag{9}$$

Notice that Eq. 9 defines an exponential recovery path. Moreover, the leakage of inoperability among industries and their inertia in the system depends on the size of $\boldsymbol{K}$. The larger is $\boldsymbol{K}$, the faster is the recovery. In their original exposition, all matrices are normalized with the pre-disaster total output levels: $\boldsymbol{q}(t) = [\hat{\boldsymbol{x}}^{-1}(\boldsymbol{x} - \boldsymbol{x}^*(t))]$, $\boldsymbol{c}^*(t) = \left[\hat{\boldsymbol{x}}^{-1}\left(\boldsymbol{f} - \bar{\boldsymbol{f}}^*(t)\right)\right]$ and $\mathbf{A}^* = [\hat{\boldsymbol{x}}^{-1}\boldsymbol{A}\hat{\boldsymbol{x}}]$, which yields the model:

$$\boldsymbol{q}(t+1) = \boldsymbol{q}(t) + \hat{\boldsymbol{k}}\,[\mathbf{A}^*\boldsymbol{q}(t) + \boldsymbol{c}^*(t) - \boldsymbol{q}(t)] \tag{10}$$

The connection between intra-temporal and inter-temporal inoperability is embedded in Eq. 10 where an increase in current inoperability creates contemporaneous supply constraints that also influence the next period, hence accounting for both effects. One could criticize the DIIM for assuming all industries operate in anticipatory mode and use the previous period's final demand and production imbalance as the expected output level. Moreover, an ad-hoc proportional rationing rule is implicitly assumed to redistribute reduced output, there are no trade constraints and inventories are not available to mitigate inoperability. With regards to the latter issue, Barker and Santos[(12)] extended the DIIM to include finished goods inventories (I^F) which magnitude defines a sector-specific inoperability p distinct from the overall inoperability q. As such, they introduce a sector-specific recovery coefficient (l_i) similar to k_i in Eq. 9 that informs the speed of recovery from a physical inoperability (Eq. 11).

$$l_i = \frac{\ln\left(p_i(0) / p_i(T_i)\right)}{T_i} \tag{11}$$

Different functional forms could be applied to the recovery function, but Barker and Santos[(12)] use the following:

$$p_i(t) = e^{-l_i t} p_i(0) \tag{12}$$

Initial overall inoperability conditions $q_i(0)$ are determined by the available finished goods inventory in the aftermath of the event ($\boldsymbol{I^F}(0)$) and by supply constraints (sector-specific inoperability post-disaster $p_i(0)$):

$$q_i(0) = \begin{cases} 0 & if\ I_i^F(0) \geq p_i(0)x_i(0) \\ 1 - I_i^F(0)/p_i(0)x_i(0) & if\ 0 < I_i^F(0) < p_i(0)x_i(0) \\ p_i(0) & if\ I_i^F(0) = 0 \end{cases} \tag{13}$$

Hence, the evolution of each industry in the system depends on the remaining inventories in relation to the output constraints (Eq. 14). If inventories are numerous enough to supplant the lost output, then a sector's inoperability will depend solely on its own previous inoperability and on the one of the other sectors (condition 1). In case some inventory remains, but it is not enough to fully overcome the new production constraints, then the level of inoperability is mitigated proportionally (condition 2). If the inventories become depleted in the next period but are still positive in the current period, an additional supply constraint appears in the system, hence increasing the overall inoperability (condition 3). Finally, if there are no contemporaneous inventories, we revert back to the traditional DIIM model (condition 4). Any remaining inventories are updated at the end of each time step.

$$q_i(t+1) = \begin{cases} q_i(t) + k_i\left[c_i^*(t) - q_i(t) + \sum_{j=1}^{n} a_{ij}^* q_j(t)\right] & if\ I_i^F(t+1) \geq p_i(t+1)x_i(t+1) \\ \max\begin{cases} p_i(t+1) - I_i^F(t+1)/x_i(t+1) \\ q_i(t) + k_i\left[c_i^*(t) - q_i(t) + \sum_{j=1}^{n} a_{ij}^* q_j(t)\right] \end{cases} & if\ 0 < I_i^F(t+1) < p_i(t+1)x_i(t+1) \\ \max\begin{cases} p_i(t+1) \\ q_i(t) + k_i\left[c_i^*(t) - q_i(t) + \sum_{j=1}^{n} a_{ij}^* q_j(t)\right] \end{cases} & if\ I_i^F(t+1) = 0,\ I_i^F(t) > 0 \\ q_i(t) + k_i\left[c_i^*(t) - q_i(t) + \sum_{j=1}^{n} a_{ij}^* q_j(t)\right] & if\ I_i^F(t+1) = 0,\ I_i^F(t) = 0 \end{cases} \tag{14}$$

Although the approach above assesses the impact of pre-disaster inventories of finished goods, it does not explain their formation nor accounts for the presence of material and supply inventories. Furthermore, the model lacks different production modes and trade constraints. It still assumes that the external sectors can absorb local imbalances by providing more imports and purchasing excess production. As the latter is unlikely in real situations, overproduction can further decrease local production due to additions to inventories.

A summary of the main characteristics of each of the models presented above is available in Appendix 1. In terms of issues regarding the application of IO models, two important misconceptions are recurrent in the empirical literature. First, since the IO framework is defined in terms of flows, stocks should not enter directly in the models. For instance, Hallegatte[34,35] allocates housing stock losses as direct output losses to the financial and real estate sectors. Moreover, since the total output of any tertiary sector represents payment for services provided within the time span of the table, housing damages have no connection to this sector in the IO framework but for the services of processing insurance claims. Second, transportation, retail and wholesale sectors are derived from margins, hence a transaction between sectors or final demand has two components: the portion paid to the industry that produced the good/service, and the portion covering shipping and sales costs. A clear implication is that these sectors cannot hold finished goods inventories because they only provide services. (12) mistakenly allocate finish good inventories to retail and wholesale sectors using BEA's inventory-to-sales ratio. Similarly, Koks *et al.*[8] mistakenly assume that materials and supplies inventories for trade sectors represent merchandise for sale so that they find, unsurprisingly, that unrestricted inventories in retail have little effect in mitigating flood losses. Moreover, reconstruction stimuli should also account for these margins as correctly highlighted in HAZUS' technical manual[36]. Therefore, researchers willing to apply the IO framework should be aware of the methodology's nuances and avoid the above misconceptions.

Finally, another important factor that has not been considered in any of the available models in the literature is the role of seasonality in the economic structure. Intra-year fluctuations in production capacity have a significant impact on the magnitude and extension of the impacts by affecting inventory levels and the sectoral adaptive response. In Avelino[37], it is shown that the bias in output multipliers from using an annual table instead of quarterly tables is up to 6% in either direction.

3. CASE STUDY: THE 2007 CHEHALIS FLOOD

In order to compare the results of the five IO methodologies listed above, we will rely on the same benchmark event: the 2007 Chehalis Flood in the state of Washington. Over December 1-4 2007 a system of storms formed by an atmospheric river hit the U.S. West Coast and led to a record-breaking 14 inches of precipitation at the Willapa Hills which feed the main stems of both the Chehalis and the South Fork rivers. The surrounding areas experienced an additional 3-8 inches of rain. This event led to landslides, failed levees, overtopped dikes(38) and floods in western Washington and Oregon. Traditionally, this region experiences an average precipitation of 7-13 inches for the entire October to March period(38). Most of the damage was concentrated alongside the Chehalis River Basin, southwest Washington. The flood extent is shown in Fig. 2 below.

<< INSERT FIGURE 2 HERE >>

The counties of Grays Harbor, Thurston and Lewis were the most affected and were declared major disaster areas on December 8, 2007. Around 75,000 customers lost power and several roads became impassable(7). The cities of Centralia and Chehalis, both in Lewis County, sustained the most damage with 25% and 33% of their respective area inundated. It affected more than half of the commercial land-use and 32% of the industrial zones in the Centralia-Chehalis Urban Growth Area. The direct building damage in the county was assessed at $166 million. In addition, around 10,702 acres of the 22,919 acres of agricultural land in western Lewis County were flooded at an estimated reseeding cost of between $188-$490 million[39].

Damage to Interstate 5, the main corridor connecting Portland to Seattle, led to its closure to all traffic for 4 days. Flow losses estimates were calculated using a combination of business surveys and traditional IO analysis via IMPLAN (see section 3 of WSDOT[20] for a full discussion). Besides the $5 million in physical damage, WSDOT[20] estimates that $47 million in economic activity, $2.4 million in state tax revenue and $14.6 million in personal income were lost due to this event.

However, when it comes to flow losses due to building damages, only a qualitative survey on local businesses was conducted[7]. The study in Centralia and Chehalis comprising flooded and non-flooded businesses revealed that more than 80% of them had below average sales two weeks after the event and a third after two months. The main disruption channels reported were a loss of accessibility by road and a temporary absence of employees. Sales plunged due to flood-affected households and a smaller discretionary spending from non-impacted individuals. Nonetheless, businesses related to redistribution and recovery efforts showed above average sales in the survey. Overall, 31% of the local businesses expected to fully recover in a year and 20% in more than two years[7].

The tri-county region impacted by the 2007 Chehalis flood has contrasting characteristics. While Grays Harbor and Lewis counties are more primary based economies with a significant commercial logging sector, Thurston County is a service based economy and is part of the Seattle-metro area. Economic data for 2008 indicates that, in terms of total output and employment, Thurston is the largest and the most diversified economy among the three (Fig. 3). Lewis and Grays Harbor have similar sized economies with a combined output that is a third of Thurston's.

The largest employers in Lewis County are government (17%), retail (13%) and manufacturing (13%) sectors. Grays Harbor experiences a somewhat similar economic structure (24%, 11% and 13% respectively) whereas government and retail are the largest employers in Thurston County (34% and 11% of the jobs respectively). Most of the imported inputs in all counties are from the manufacturing sectors and payments for transportation services.

<< INSERT FIGURE 3 HERE >>

A Multiplier Product Matrices analysis[40] reveals that in our study area agriculture in general and its commercial logging activity in particular are the most intertwined sectors in terms of backward and forward linkages. We also find that manufacturing exhibits significant forward and backward linkages in Grays Harbor (especially between “Commercial Logging” and “Sawmills and Wood Preservation” sectors), while the service sectors are the most interconnected in Lewis and Thurston. As a result, any disruption affecting these key sectors will lead to additional inoperability in the other local sectors.

3.1. Connection with the Economic Models

Our methodology is composed of three components: flood water-depth grids from the atmospheric model, stock damages from the engineering model (HAZUS) and flow losses from the economic model (IO model). In this paper, the floodplain and water-depth maps are derived from the U.S. Army Corps of Engineers (USACE) and are used in HAZUS to estimate the physical damages to buildings, vehicles, crops and infrastructure via depth damage functions and reconstruction timing. Both first and higher-order effects are then estimated using the range of IO models described above. Total flow losses in terms of output, income and jobs are calculated. The relationship between all these components is shown in Fig. 4.

<< INSERT FIGURE 4 HERE >>

This study relies on a fine scale estimate of floodplain and water-depth maps derived from the 2007 event. Observed data collected by the USACE from gauges along several river branches in the Chehalis basin were used in HEC-RAS to generate a water-depth map for the area[41]. The engineering model (HAZUS) uses this water-depth grid to determine the total stock losses in each affected county. It has been the most widely applied model in the literature evaluating economic losses and performing cost-benefit analysis as it offers a balanced trade-off between modeling capability and required technical engineering knowledge[42].

HAZUS determines the percentage of damaged square footage by occupancy class at the census block level. Then, capital stock damages are measured in terms of repair costs, inventory, content, crop losses and vehicle replacement costs. Transportation infrastructure damage is only evaluated in terms of impacted bridges, so a comprehensive assessment of transportation disruption is lacking. The software provides estimates of first-order flow losses in business interruptions and rental income based on average sales data for the occupancy class. We detract from the latter and estimate both first and higher-order flow losses using the county's IO table to have more accurate results.

Natural disasters create constraints to production, thus leading to negative economic impacts. However, the reconstruction efforts that follow stimulate the local economy. Capacity constraints $\mathbf{\Gamma}(\mathrm{t})$ are determined by assuming a homogeneous productivity per square foot for each industry in a specific county and that industries operate at full capacity before the disaster. Using information on crop losses, on damaged squared footage from the General Building Stock (GBS) as well as information about the economic sectors these buildings belong to (HAZUS occupancy class classification is matched to NAICS classification), we set the capacity constraints based on the pre-disaster total output by industry (Fig. 5). When it comes to agriculture's output, it is reduced proportionally to the share of crop and livestock output in the county. Livestock losses are not considered independently as they are not reported by HAZUS.

<< INSERT FIGURE 5 HERE >>

The reconstruction demand $\boldsymbol{R}(t)$ is determined by repair costs to the GBS, to the lifelines and the replacement of building content and vehicles. While the first two generate construction stimuli, the last two support demand in manufacturing. Given the reduced size of the affected counties, all the reconstruction stimuli are allocated outside the area. Following the HAZUS methodology, we assume that manufacturing orders include a margin to be split 20%-80% between transportation and wholesale (Fig. 6).

<< INSERT FIGURE 6 HERE >>

The total square footage per industry before the disaster (s_i^T), the damaged square footage (s_i^D) and the timing of the disruption are used to determine the capacity constraints and the reduced local final demand in the economic model. We also assume that recovery is proportionally distributed through time according to the restauration timeframe provided by HAZUS. Details on these elements appear in tables 14.1, 14.5 and 14.12 of FEMA[36]. Based on this information, we define the level of inoperability of a particular industry i at time t as:

$$\gamma_i(t) = \frac{s_i^D(t)}{s_i^T} \tag{15}$$

As mentioned on Eq. 3, the matrix $(\boldsymbol{I} - \boldsymbol{\Gamma}(\mathrm{t}))$, where $\boldsymbol{\Gamma}(\mathrm{t})$ is a matrix with $\gamma_i(t)$ in the main diagonal, represents the available production capacity for each industry at each time period in the post-disaster phase.

Recovery efforts are compiled in the vector $\boldsymbol{R}(t)$. Due to labor restrictions and displacement, final demand reduces from the pre-disaster level ($\boldsymbol{f}$) to $\bar{\boldsymbol{f}}$. We assume that the expenditure structure remains fixed in the post-disaster period and that demand decreases proportionally to the plunge in income. Thus, in order to account for both capacity constraints and reduced household expenditure due to wage loss, we define the demand vector in the post-disaster period ($\bar{\boldsymbol{f}}^*$) as:

$$\bar{f}_{\boldsymbol{i}}^*(t) = \min\Big(\big(1 - \gamma_i(t)\big)f_i, \bar{f}_i(t)\Big) \qquad \forall i, t \tag{16}$$

Finally, we do not explicitly model interregional trade, but assume that given the small size of the affected counties' economy relatively to the state of Washington, all imports are produced by the rest of the state and their production leads to negligible positive feedback to the affected counties. Notice that the assumption of fixed prices holds here due to the small size of the affected region.

Direct losses are estimated in HAZUS-MH version 3.0 using the default dasymetric datasets and assuming a warning time of 48h. It implies a 35% loss reduction in building damage according to the embedded Day Curve. No reduction in vehicle damage is assumed as no reliable source of information is available. As the software informs both day and night losses for vehicles, we follow the flood timing reported in NOAA[43] and select day losses for Grays Harbor and Thurston and night losses for Lewis County.

We use the 2008 IO tables extracted from IMPLAN at a 16 sectors aggregation level. The sectors are presented in Table I alongside the assumptions used in the SIM and DIIM models. This level of aggregation was chosen to minimize incompatibilities when bridging HAZUS' occupancy class classification and NAICS classification used by IMPLAN as shown in Appendix 2.

<< INSERT TABLE I HERE >>

The inventory data for the DIIM are based on the December 2007 inventory-to-sales ratio for manufacturing reported by the Federal Reserve Bank of St. Louis[44], as suggested in Barker and Santos[12]. This not-seasonally-adjusted ratio is 1.23 for the period under study. It is homogeneously applied to all counties. Data for wholesale and retail are not considered as these sectors' activities are recorded as margins, so they cannot hold finished goods inventories (although they can hold "materials and supplies" and "work-in-progress" inventories, which data are not available).

3.2. Stock Damages Estimates via HAZUS

Physical damages are estimated at $680 million. As expected, the largest impact is in Lewis County. A breakdown of damages is provided in Table II. The only available counterfactual for direct losses is from Lewis County[39] where the total building losses (structure + inventory) were assessed at $166.2 million. Our HAZUS-based estimates lead to a figure of $150.9 million. This difference can be explained, in part, by the fact that our model estimates the total number of damaged structures at 439 when 957 of them were actually reported[39]. Five fire stations were affected during the flood, at a total repair cost of $6 million[39]; however, HAZUS does not report any impact.

<< INSERT TABLE II HERE >>

When it comes to the estimated square footage of damage per industry, most of the affected area is concentrated in Lewis County, followed by Grays Harbor and then Thurston (see Fig. 7). Agriculture, construction and health services are the main impacted industries, the latter being almost exclusively located in Lewis. In Grays Harbor and Thurston, agriculture is the main affected sector. These results appear in figures 8-10 below.

<< INSERT FIGURE 7 HERE >>

<< INSERT FIGURE 8 HERE >>

<< INSERT FIGURE 9 HERE >>

<< INSERT FIGURE 10 HERE >>

4. RESULTS AND DISCUSSION

Considering the disruption timing set by default in HAZUS, we estimate a total direct output loss of $26.3 million over 25 months. First-order effects are the same across models. Health services, agriculture and manufacturing are the most affected sectors. Given the economic structure of the counties, Lewis has the most losses in the service sectors and Thurston the most losses in government activities (Fig. 7). Such loss of output translates into a $10.5 million decrease in direct labor income (Fig. 11).

<< INSERT FIGURE 11 HERE >>

Next, we use the five specifications described in Section 2 to estimate higher-order effects. The full results by model, county and sector are available in Appendix 3. It is clear that in all counties the accumulated losses are in-between the lower bound given by the Leontief model and the upper bound calculated by the DIIM (Fig. 12, 13 and 14). This difference varies from 69% to 115% in Thurston and Grays Harbor respectively depending on which sectors are the most affected in each county and on their local linkages (Appendix 4). The results make it also obvious that, due to the truncation of intertemporal effects, static models suffer from a negative bias.

<< INSERT FIGURE 12 HERE >>

<< INSERT FIGURE 13 HERE >>

<< INSERT FIGURE 14 HERE >>

When it comes to monthly losses by county (Fig. 15, 16 and 17), Cochrane's model consistently shows the highest production plunges in the initial post-disaster periods when the economic structure is the most impaired. This highlights the importance of accounting for both capacity constraints and their implication to local interdependence. As the economy rebounds and returns towards its original steady state, Cochrane's model approaches the traditional IO model estimates.

Moreover, as the Leontief and Cochrane models are static, the initial inoperability does not spread inter-temporally, so there is a large loss in the first post-disaster months that fades quickly. The SIM distributes losses in time due to perfect foresight, so the efficient output path begins pre-disaster and involves lower reductions in output. While we are aware that an event like the one studied here cannot be expected, it is important to recall that the SIM is originally designed for positive shocks. The DIIM creates an inertial inoperability effect that extends the length of the disruption. The exponential recovery assumption determines the shape of the curve.

In the case of Grays Harbor, the primary sector is the one sustaining the most stock damages (2.7%) and also the one with most backward and forward linkages in the local economy. As a result, the inoperability it generates spreads significantly to other sectors. This reflects in the

37% difference between Leontief's and Cochrane's estimates (the largest difference of all counties). It now becomes clear that if highly interdependent sectors are affected and the economic structure is kept fixed, the bias is exacerbated. Besides agriculture and construction, government, manufacturing and professional services are indirectly affected. Notice also that by considering manufacturing inventories in the model, the total losses calculated by the inventory DIIM (noted Inv-DIIM) can be mitigated by 5.6%.

<< INSERT FIGURE 15 HERE >>

Lewis County is the most affected county with major damages to the health sector (4.6%), construction (2.8%) and agriculture (2.5%). Due to the high amount of direct losses, almost all of its sectors suffer some indirect negative impact, although the low interdependence of the affected sectors leads them to experience the largest losses. As such, health services are estimated to have lost between $12.2-19.3 million, while losses in manufacturing and agriculture sum up to $2.0-4.1 million and $1.2-3.0 million respectively. Contrary to Grays Harbor, the difference in accumulated losses generated by the Leontief and the Cochrane models is significantly lower (only 8%) as their local linkages are reduced. Recovery is slower due to a long reconstruction time in the health sector while most other sectors rebound within 6 months.

<< INSERT FIGURE 16 HERE >>

Despite a similar pattern of damages in Thurston and Grays Harbor whereby agriculture and construction sustain the most stock reductions, total flow losses in Thurston are significantly different due to differences in the economic structure. The agricultural sector is not integrated in the local economy as in Grays Harbor since Thurston is mainly service based and manufacturing inventories do not attenuate flow losses. As a result, the DIIM and the Inventory DIIM yield the same estimates. Moreover, the inoperability does not spread as much as in Grays Harbor County, so the flow losses are concentrated in the agriculture and construction sectors only (compare Fig. 17 with 15).

<< INSERT FIGURE 17 HERE >>

In summary, we compile the estimates for stock damages, flow losses and recovery time for each county. Thurston is the fastest county to recover with an overall negative impact of $4 million. Conversely, Lewis' $37 million losses spread throughout 2.5 years until full recovery (Table III). Notice the significant variation in high-order effects between lower and upper bound estimates.

<< INSERT TABLE III HERE >>

When it comes to the positive economic impacts from reconstruction, we find that the rest of Washington receives a direct stimulus of $680 million. It leads to a total impact of $957 million in that area. A comprehensive net effect on who bears the costs of reconstruction or on the investment/expenditure decisions it leads to is out of the scope of this paper. If we assume that all of the aid is external and that the regional economies return to their pre-disaster steady-state, the total net effect for the state as a whole is positive: it is composed of a $52 million loss in the affected counties and of a $ 905 million gain in the rest of Washington.

5. CONCLUSIONS

Although stock damages are well understood, flow impacts taking place in the post-disaster period tend to be overlooked[8,18]. As a result, mitigation strategies for future events are myopically applied to the affected economies only as if they had no spatial and temporal linkages. This partial account of impacts ignores the interconnectivity of modern production chains and may lead to significant negative effects to non-affected regions.

The disaster literature has several models to assess flow losses and most of them are rooted in the IO framework. However, there exist no consensus on a preferred methodology. Therefore, researchers are often faced with a model selection issue based on the characteristics of the disaster, of the affected region(s) and on their assumptions on the mechanics of the local economy.

In this paper, we use fine-scale characteristics of a single event, the 2007 Chehalis flood (WA), to calculate the flow losses that are generated by the five most commonly used models in the disaster literature. The results highlight their bias under different economic structures, level of industrial interdependency in affected sectors and amount of inoperability. We find that for each county the accumulated losses are in-between the lower bound given by the Leontief model and the upper bound calculated by the DIIM. This difference varies from 69% to 115% in Thurston and Grays Harbor respectively depending on which sectors are the most affected and on their local linkages. Static formulations (traditional IO and HAZUS) underestimate the losses by ignoring the presence of intertemporal externalities. They truncate the inoperability impacts at each time period, which leads to a significant bias in the event of large disruptions as the recovery period is deemed shorter than it actually is. Moreover, modeling changes in the sectoral interdependencies between the pre- and post-disaster period is paramount when industries with strong backward and forward linkages are impacted. Finally, we show that the role of inventories depends on the external dependency of the affected sectors, so that estimates for mainly tertiary-based regions may not change significantly whether inventories are modeled or not.

We also highlight that most of the common theoretical inconsistencies in the disaster literature derive from issues in integrating stock damages into a framework developed for flow analysis. Stocks should be introduced as primary inputs constraints (capital, labor, land) to analyze losses and later be converted into reconstruction stimuli via repair information to assess positive impacts. Furthermore, transportation and trade sectors are recorded as margins; hence IO practitioners should not consider that they hold finished goods inventories. Beyond these points of caution, we believe that the IO framework is still rich of opportunities for further methodological developments. For instance, efforts focusing on integrating both input and output inventories into a single framework and on developing a dynamic rebalancing of the local industrial linkages after a disruption are certainly needed. In addition, the role of the time of the event, of the seasonality in the economic structure and its implication on sectoral interdependency, inventories and resilience have been largely ignored in the literature. A solution for the former issue is to rely on intra-year IO tables that better reflect the industrial relationships at the time of the disaster. As shown by Avelino[37], highly seasonal sectors such as agriculture and services exhibit significantly different linkages across quarters, which are not captured using annual tables.

While the additional complexity of such extensions seems to conflict with the short timing emergency and disaster relief efforts have to work under, the more accurate and detailed analysis they generate informs us better of the current vulnerability of our economic systems and allow us to adapt more suitably to future events[13].

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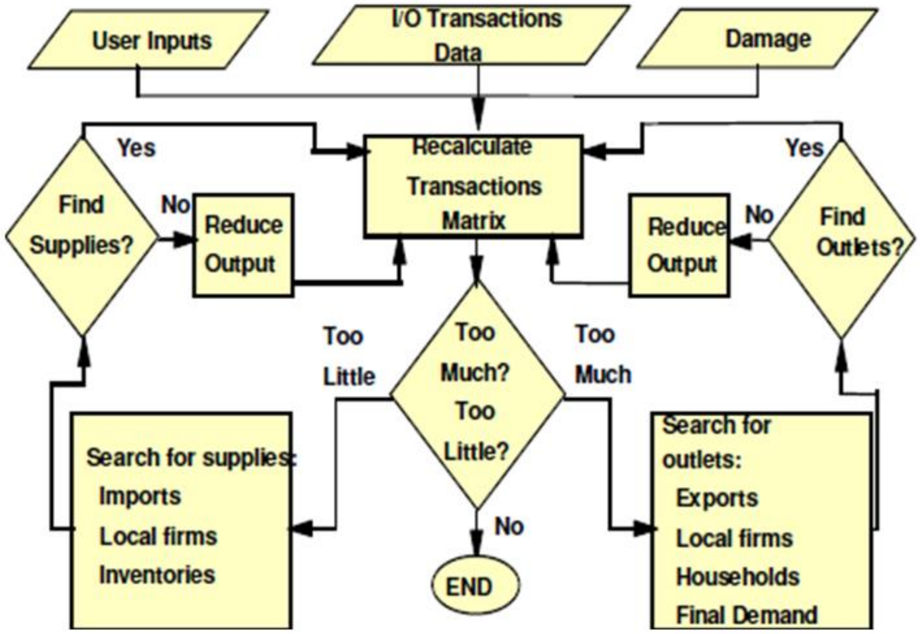

Figure 1. Cochrane's rebalance scheme(9)

Figure 2. Flood-depth grid for the Chehalis Basin

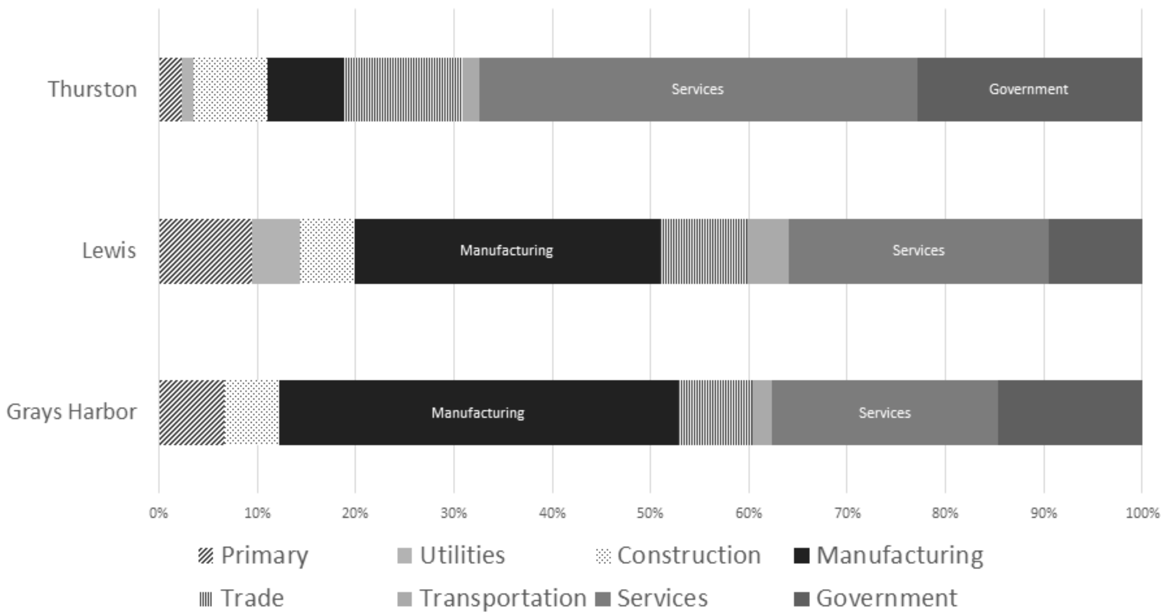

Figure 3. Share of output by sector, 2008

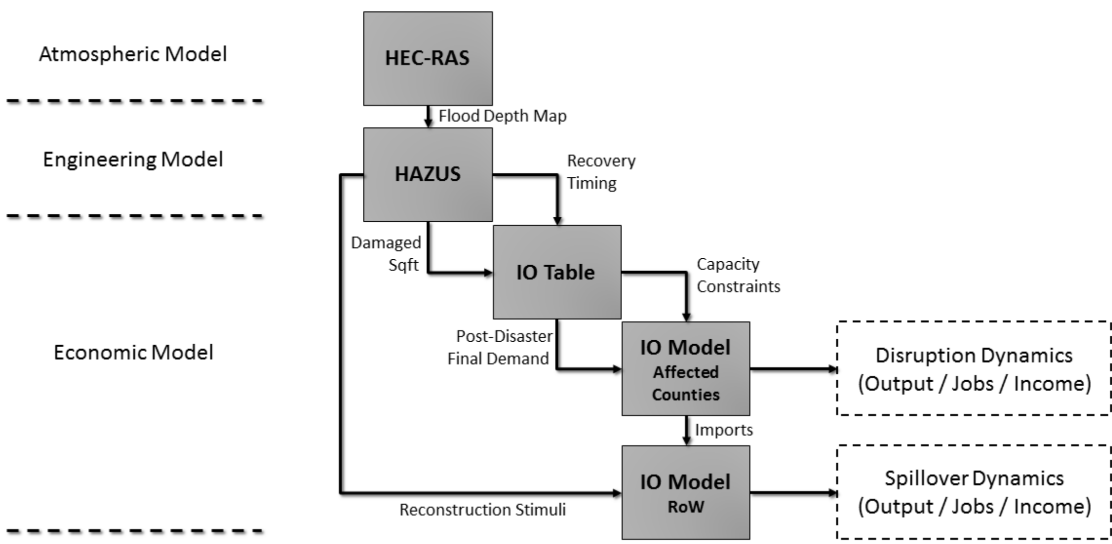

Figure 4. Modeling approach overview

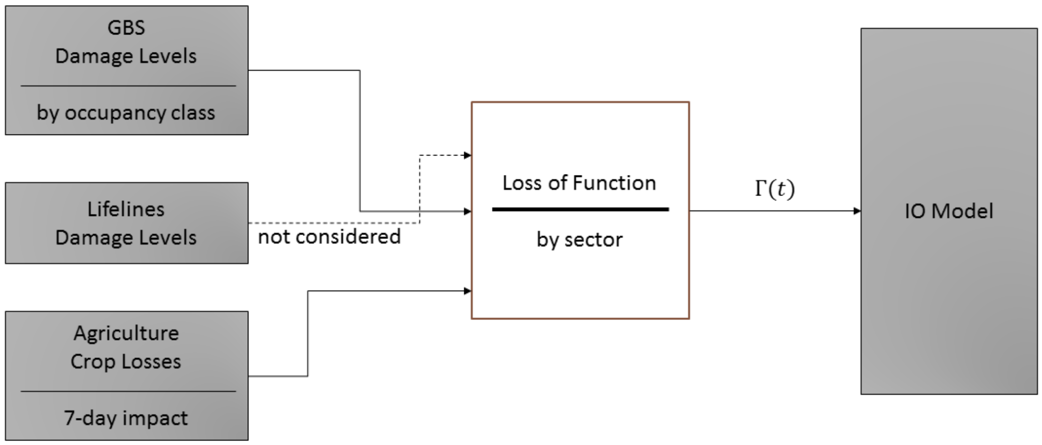

Figure 5. Bridge HAZUS-IO for Capacity Constraints

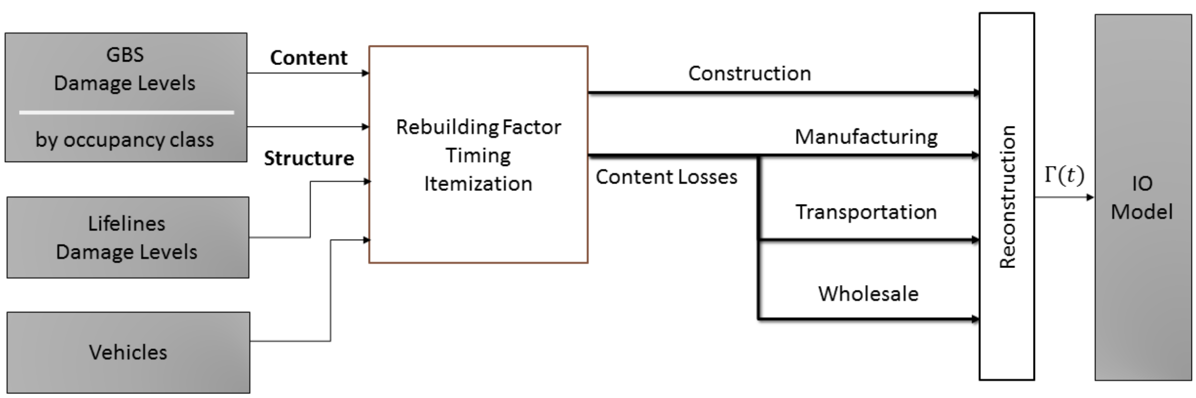

Figure 6. Bridge HAZUS-IO for Reconstruction Stimuli

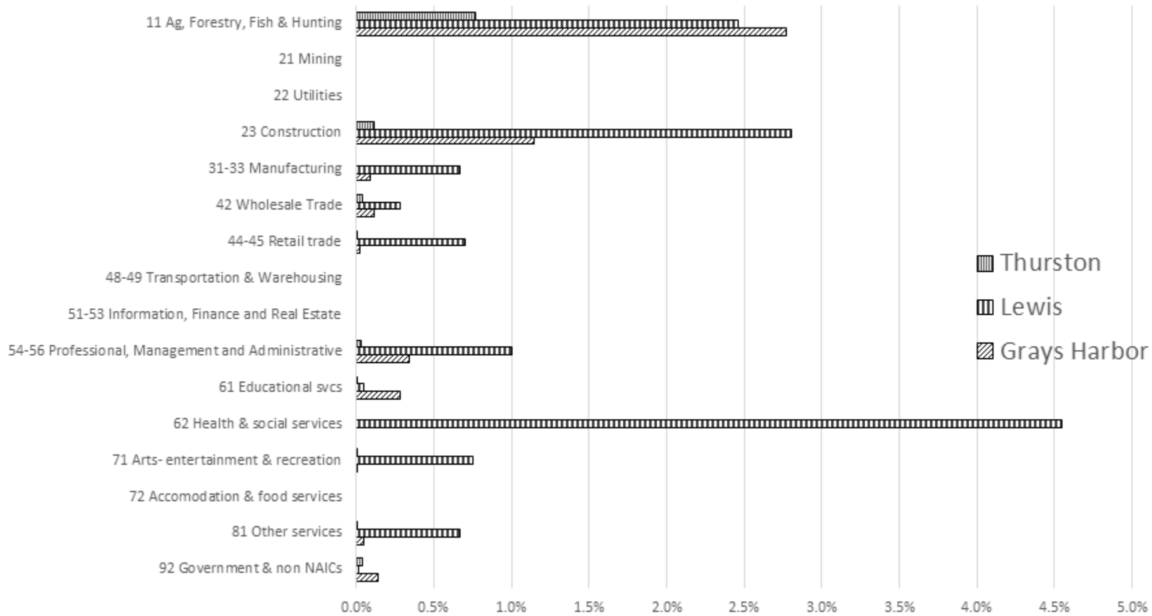

Figure 7. Initial inoperability by county

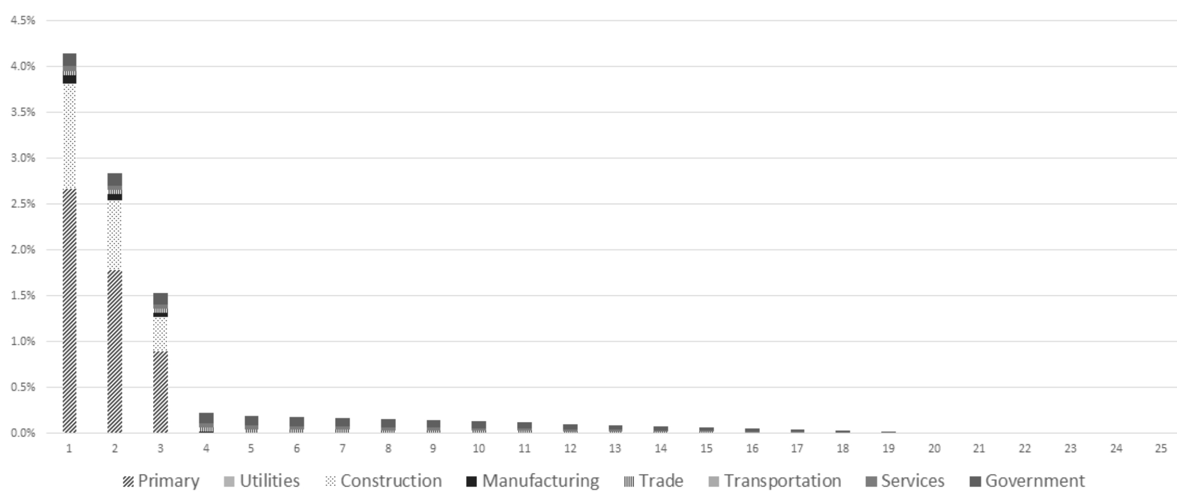

Figure 8. Sectoral inoperability by month, Grays Harbor County

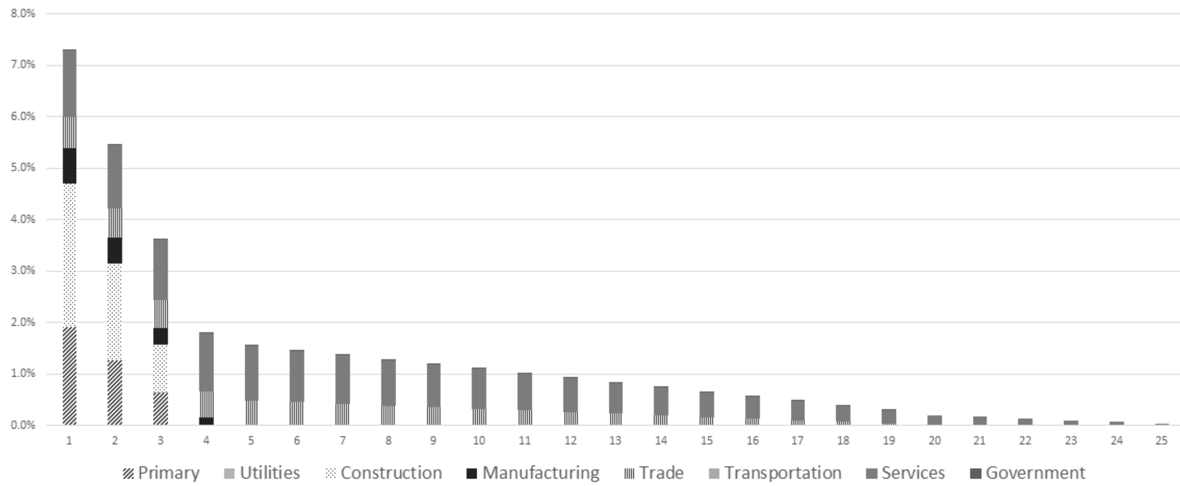

Figure 9. Sectoral inoperability by month, Lewis County

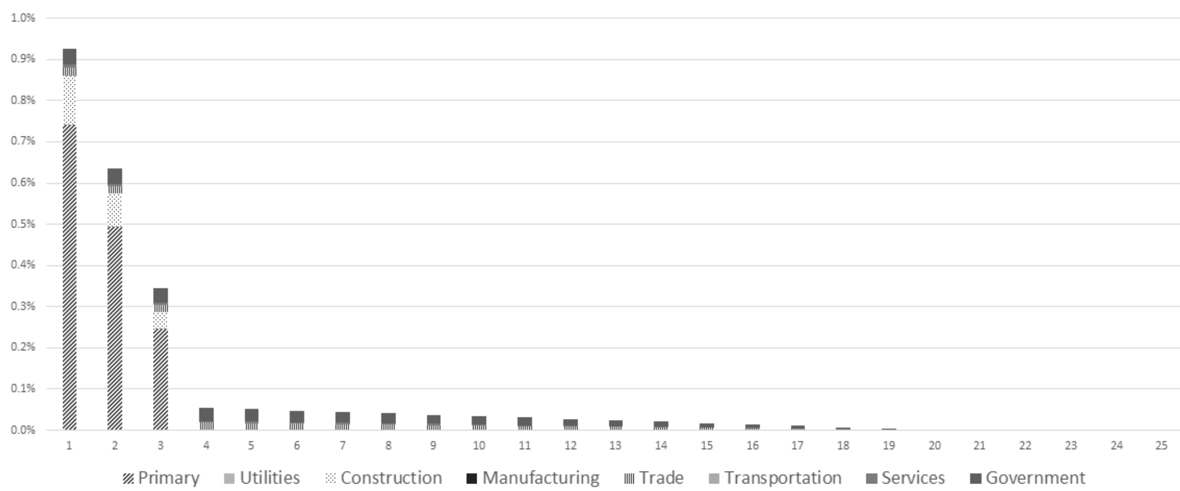

Figure 10. Sectoral inoperability by month, Thurston County

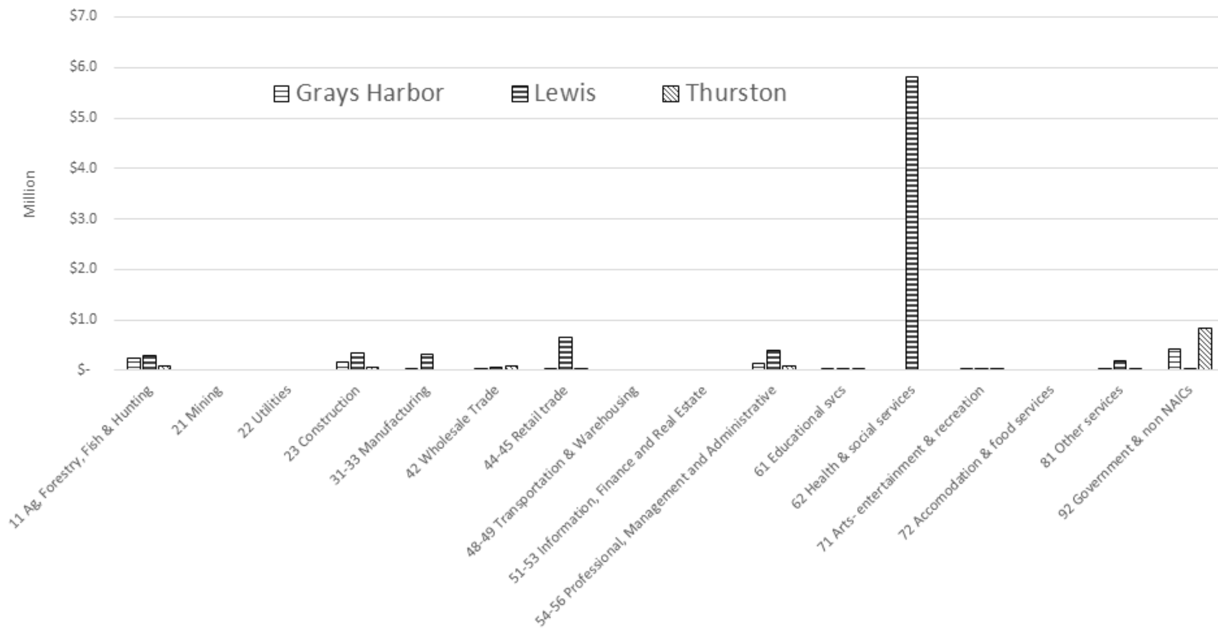

Figure 11. First-Order Effects: direct labor income loss due to business disruptions

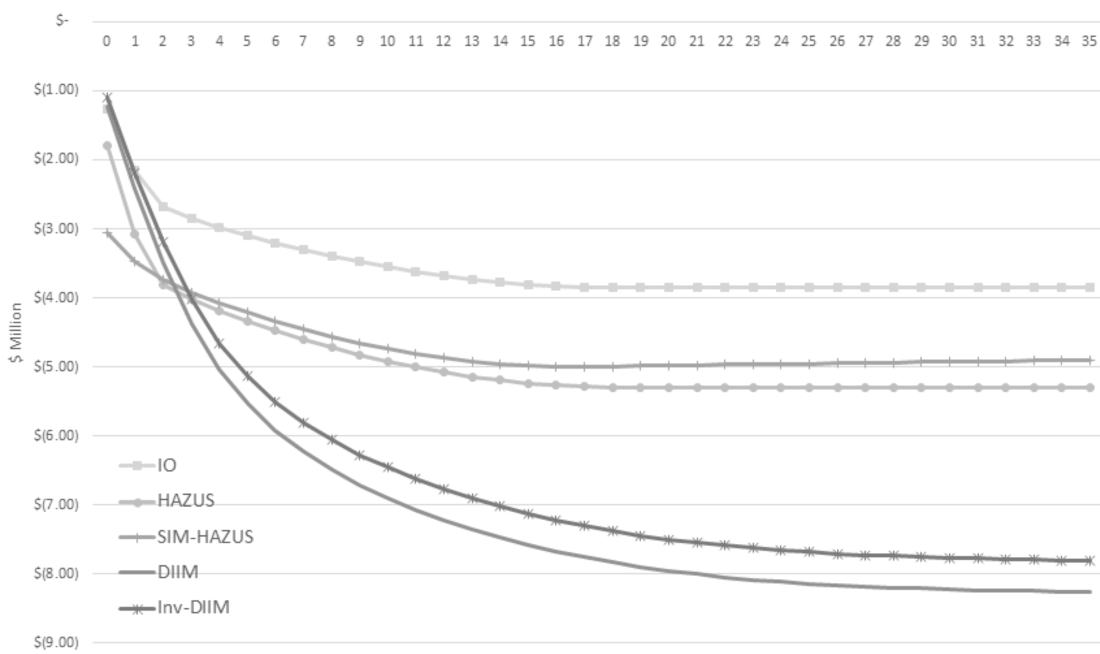

Figure 12. Accumulated flow losses by model, Grays Harbor

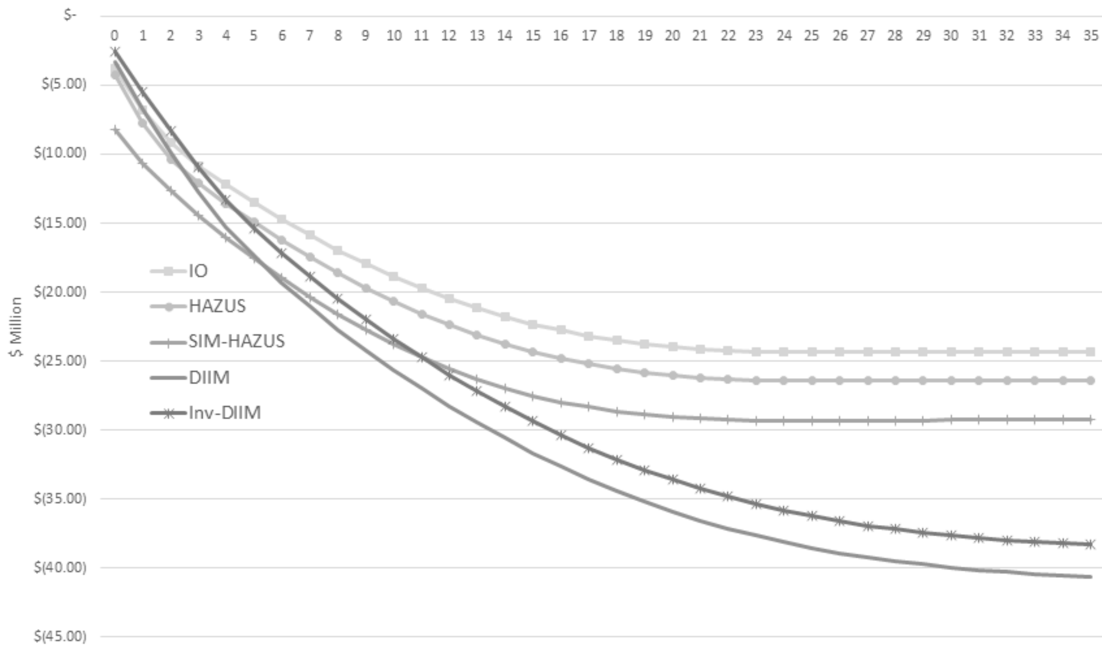

Figure 13. Accumulated flow losses by model, Lewis

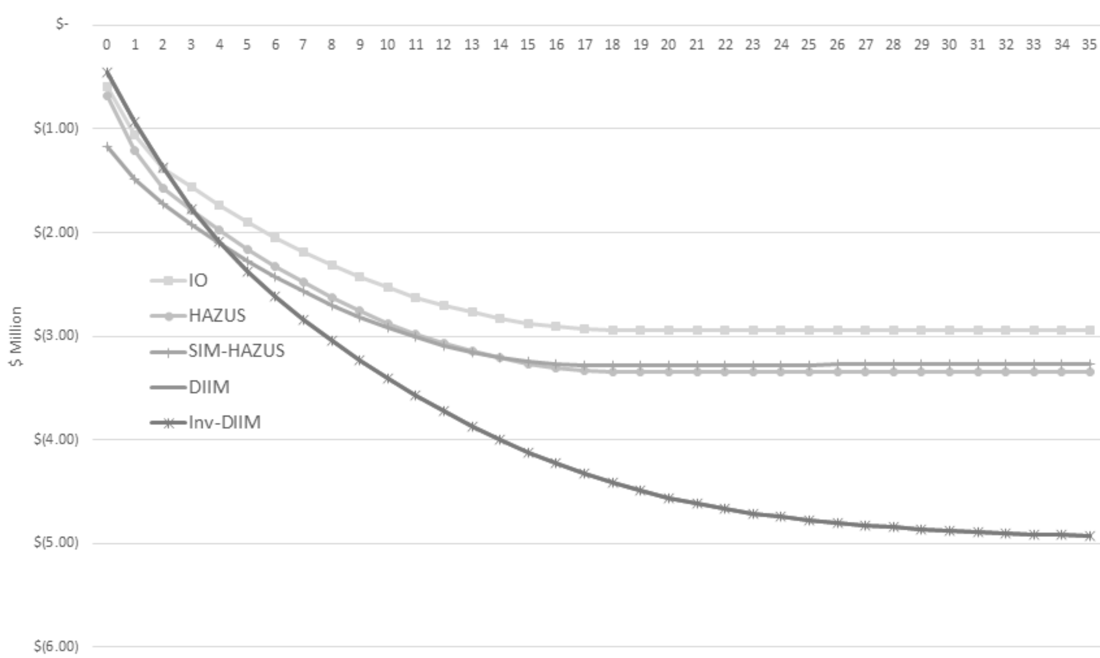

Figure 14. Accumulated flow losses by model, Thurston

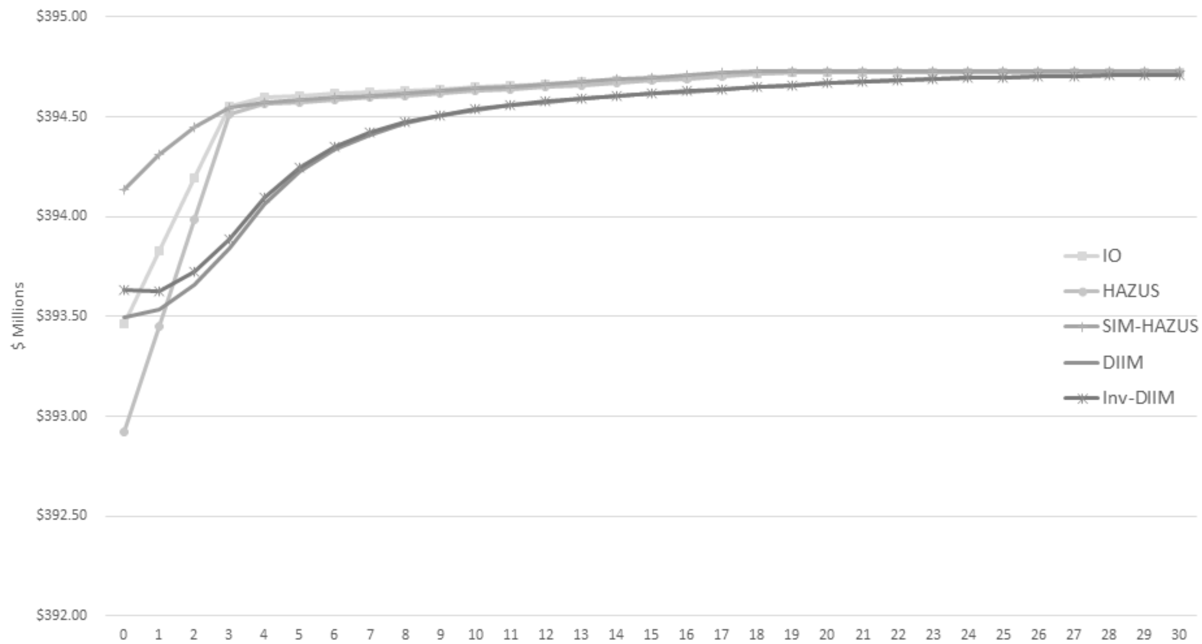

Figure 15. Monthly flow losses by model, Grays Harbor

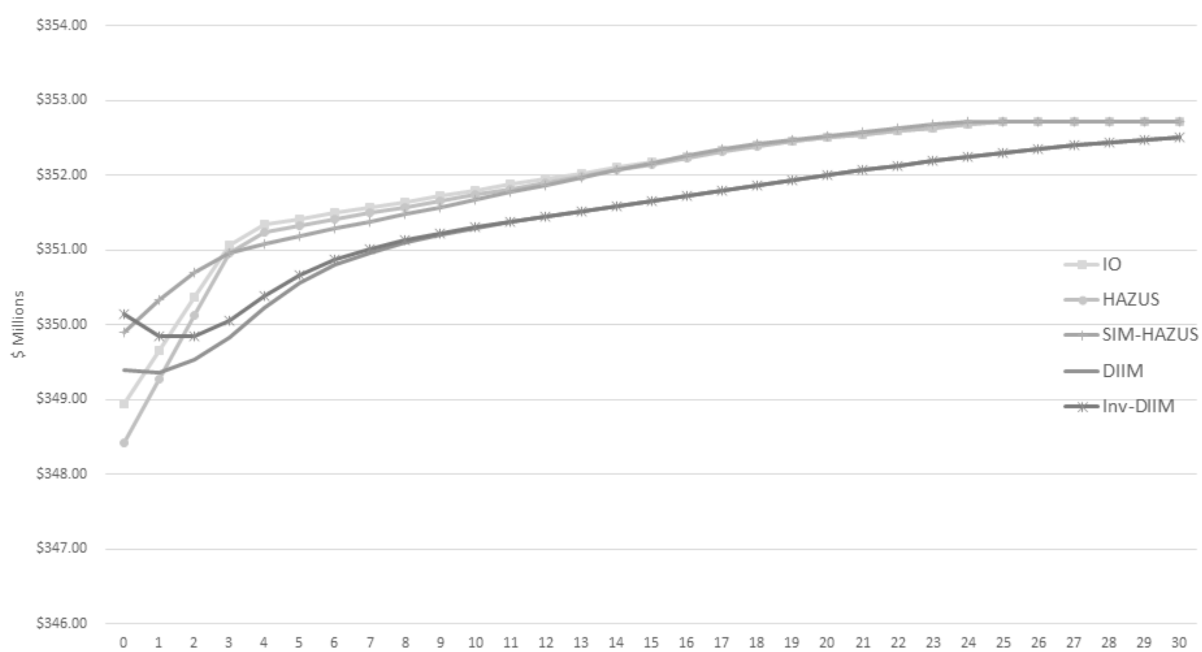

Figure 16. Monthly flow losses by model, Lewis

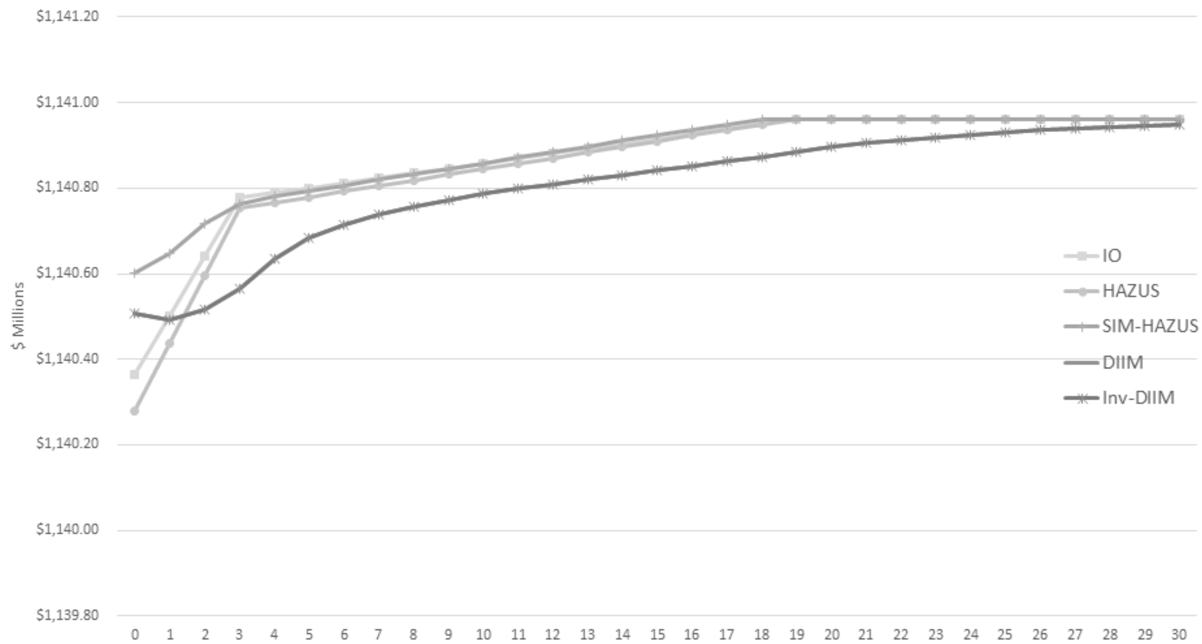

Figure 17. Monthly flow losses by model, Thurston

Table I. Input-output table disaggregation and assumptions

IO Sectors	Production Mode	Hold Inventories
11 Ag, Forestry, Fish & Hunting	Anticipatory (3 months)	Yes
21 Mining	Anticipatory (3 months)	Yes
22 Utilities	Just-in-Time	No
23 Construction	Responsive (1 month)	Yes
31-33 Manufacturing	Anticipatory (1 month)	Yes
42 Wholesale Trade	Just-in-Time	No
44-45 Retail Trade	Just-in-Time	No
48-49 Transportation & Warehousing	Just-in-Time	No
51-53 Information, Finance and Real Estate	Just-in-Time	No
54-56 Professional, Mgmt. and Adm.	Just-in-Time	No
61 Educational Services	Just-in-Time	No
62 Health & Social Services	Just-in-Time	No
71 Arts-Entertainment & Recreation	Just-in-Time	No
72 Accommodation & Food Services	Just-in-Time	No
81 Other Services	Just-in-Time	No
92 Government & non-NAICs	Just-in-Time	No

Table II. Direct Physical Damage by County, in 2008 Thousand dollars

	Grays Harbor	Lewis	Thurston
Agriculture			
Crops	$ -	$ -	$ -
Building Stock			
Capital Stock Losses			
Building Loss	$ 71,449	$ 142,845	$ 22,282
Contents Loss	$ 52,366	$ 192,622	$ 23,731
Inventory Loss	$ 977	$ 8,079	$ 357
Vehicles			
	$ 18,413	$ 46,452	$ 9,601
Infrastructure			
Transportation	$ -	$ -	$ -
Utilities	$ 26,719	$ 31,567	$ 20,040
Essential Facilities			
Fire Station	$ -	$ -	$ -
Police Station	$ -	$ -	$ -
Hospitals	$ -	$ -	$ -
Schools	$ 7,412	$ 4,657	$ -
Total Physical Damage			
	$ 177,336	**$ 426,221**	**$ 76,011**

Table III. Summary of Results, Lower and Upper Bounds

	Grays Harbor	**Lewis**	**Thurston**
Stock Damages	$ 177.34	$ 426.22	$ 76.01
Flow Losses	$ 3.86 - $ 7.84	$ 24.38 - $ 39.03	$ 2.95 - $ 4.97
First-Order	95% - 47%	84% - 53%	73% - 43%
Higher-Order	5% - 53%	16% - 47%	27% - 57%
Full Output Recovery*	10 months	30 months	3 months

*Below 1% inoperability

Appendix 1 – Main features of alternative input-output methodologies

	IO	HAZUS	SIM	DIIM	Inv-DIIM
Type	static	static	dynamic	dynamic	dynamic
Causality	demand-driven	demand-driven	demand-driven	demand-driven	demand-driven
Constraints	demand	demand supply trade	demand	demand	demand supply
Inventories	no	no	no	no	yes
Production	simultaneous	simultaneous	time dependent	simultaneous	time dependent
Market Clearing	Implicit	implicit	implicit	implicit	implicit
Prices	constant	constant	constant	constant	constant
Behavior	perfect foresight	perfect foresight	perfect foresight	perfect foresight	perfect foresight

Appendix 2 – Bridge between IO disaggregation and HAZUS occupancy classes

IO Sectors	**HAZUS Occupancy Classes**
11 Ag, Forestry, Fish & Hunting	AGR1
21 Mining	-
22 Utilities	-
23 Construction	IND6
31-33 Manufacturing	IND1, IND2, IND3, IND4, IND5
42 Wholesale Trade	COM2
44-45 Retail Trade	COM1
48-49 Transportation & Warehousing	-
51-53 Information, Finance and Real Estate	COM5
54-56 Professional, Management and Administrative	COM4
61 Educational Services	EDU1, EDU2
62 Health & Social Services	RES6, COM6, COM7
71 Arts-Entertainment & Recreation	COM8, COM9
72 Accommodation & Food Services	RES4
81 Other Services	COM3, COM10, REL1
92 Government & non-NAICs	GOV1, GOV2

Appendix 3 – Comparison of total losses by sector and by county, 2008 constant dollars

	Grays Harbor County					Lewis County					Thurston County				
	IO	HAZUS	SIM	DIIM	Inv-DIIM	IO	HAZUS	SIM	DIIM	Inv-DIIM	IO	HAZUS	SIM	DIIM	Inv-DIIM
11 Ag, Forestry, Fish & Hunting	$ (0.98)	$ (1.79)	$ (1.81)	$ (2.92)	$ (2.90)	$ (1.18)	$ (1.77)	$ (2.14)	$ (3.01)	$ (2.92)	$ (0.36)	$ (0.46)	$ (0.47)	$ (0.90)	$ (0.90)
21 Mining	$ (0.00)	$ (0.00)	$ (0.00)	$ (0.00)	$ (0.00)	$ (0.02)	$ (0.02)	$ (0.21)	$ (0.04)	$ (0.03)	$ (0.00)	$ (0.00)	$ (0.00)	$ (0.00)	$ (0.00)
22 Utilities	$ (0.00)	$ (0.00)	$ (0.00)	$ (0.00)	$ (0.00)	$ (0.39)	$ (0.40)	$ (0.61)	$ (0.52)	$ (0.49)	$ (0.02)	$ (0.02)	$ (0.02)	$ (0.02)	$ (0.02)
23 Construction	$ (0.47)	$ (0.53)	$ (0.56)	$ (1.17)	$ (1.17)	$ (1.07)	$ (1.16)	$ (1.50)	$ (2.59)	$ (2.59)	$ (0.20)	$ (0.21)	$ (0.27)	$ (0.48)	$ (0.48)
31-33 Manufacturing	$ (0.44)	$ (0.52)	$ (0.69)	$ (0.97)	$ (0.57)	$ (2.00)	$ (2.08)	$ (3.80)	$ (4.11)	$ (2.10)	$ (0.03)	$ (0.03)	$ (0.12)	$ (0.04)	$ (0.04)
42 Wholesale Trade	$ (0.09)	$ (0.17)	$ (0.17)	$ (0.22)	$ (0.20)	$ (0.35)	$ (0.46)	$ (0.44)	$ (0.62)	$ (0.57)	$ (0.21)	$ (0.27)	$ (0.27)	$ (0.38)	$ (0.38)
44-45 Retail trade	$ (0.16)	$ (0.17)	$ (0.09)	$ (0.21)	$ (0.21)	$ (1.74)	$ (1.84)	$ (1.83)	$ (2.92)	$ (2.91)	$ (0.15)	$ (0.16)	$ (0.11)	$ (0.20)	$ (0.20)
48-49 Transportation & Warehousing	$ (0.03)	$ (0.04)	$ (0.05)	$ (0.05)	$ (0.05)	$ (0.19)	$ (0.20)	$ (0.48)	$ (0.28)	$ (0.26)	$ (0.02)	$ (0.02)	$ (0.03)	$ (0.02)	$ (0.02)
51-53 Information, Finance and Real Estate	$ (0.35)	$ (0.41)	$ (0.26)	$ (0.50)	$ (0.50)	$ (2.43)	$ (2.52)	$ (1.81)	$ (3.11)	$ (3.07)	$ (0.42)	$ (0.44)	$ (0.34)	$ (0.50)	$ (0.50)
54-56 Professional, Management and Administrative	$ (0.21)	$ (0.47)	$ (0.47)	$ (0.51)	$ (0.51)	$ (1.12)	$ (1.84)	$ (1.88)	$ (2.25)	$ (2.21)	$ (0.22)	$ (0.38)	$ (0.37)	$ (0.43)	$ (0.43)
61 Educational svcs	$ (0.01)	$ (0.01)	$ (0.01)	$ (0.01)	$ (0.01)	$ (0.06)	$ (0.07)	$ (0.03)	$ (0.07)	$ (0.07)	$ (0.02)	$ (0.02)	$ (0.02)	$ (0.03)	$ (0.03)
62 Health & social services	$ (0.16)	$ (0.16)	$ (0.05)	$ (0.16)	$ (0.16)	$ (12.19)	$ (12.32)	$ (12.32)	$ (19.31)	$ (19.31)	$ (0.20)	$ (0.20)	$ (0.13)	$ (0.20)	$ (0.20)
71 Arts- entertainment & recreation	$ (0.02)	$ (0.02)	$ (0.01)	$ (0.03)	$ (0.03)	$ (0.18)	$ (0.20)	$ (0.19)	$ (0.30)	$ (0.30)	$ (0.02)	$ (0.02)	$ (0.01)	$ (0.02)	$ (0.02)
72 Accomodation & food services	$ (0.06)	$ (0.07)	$ (0.05)	$ (0.08)	$ (0.07)	$ (0.41)	$ (0.42)	$ (0.35)	$ (0.48)	$ (0.47)	$ (0.06)	$ (0.06)	$ (0.06)	$ (0.07)	$ (0.07)
81 Other services	$ (0.06)	$ (0.07)	$ (0.07)	$ (0.10)	$ (0.10)	$ (0.81)	$ (0.89)	$ (0.90)	$ (1.38)	$ (1.37)	$ (0.03)	$ (0.04)	$ (0.05)	$ (0.04)	$ (0.04)
92 Government & non NAICs	$ (0.79)	$ (0.87)	$ (0.86)	$ (1.35)	$ (1.35)	$ (0.25)	$ (0.27)	$ (1.01)	$ (0.36)	$ (0.36)	$ (0.98)	$ (1.02)	$ (1.02)	$ (1.64)	$ (1.64)
	$ (3.86)	**$ (5.30)**	**$ (5.16)**	**$ (8.30)**	**$ (7.84)**	**$ (24.38)**	**$ (26.45)**	**$ (29.52)**	**$ (41.34)**	**$ (39.03)**	**$ (2.95)**	**$ (3.34)**	**$ (3.29)**	**$ (4.97)**	**$ (4.97)**

Note: we use Cochrane's rebalancing algorithm as the base for the SIM.

Appendix 4 – Comparison of total losses by sector and county