Future Property Damage from Flooding – Sensitivities to Economy and Climate Change

Jing Liu
Department of Agricultural Economics, Purdue University
liu207@purdue.edu

Thomas W. Hertel
Department of Agricultural Economics, Purdue University
hetel@purdue.edu

Michael Delgado
Department of Agricultural Economics, Purdue University
delgado2@purdue.edu

Moetasim Ashfaq
Oak Ridge National Laboratory
mashfaq@ornl.gov

Noah Diffenbaugh
School of Earth Sciences, Stanford University
diffenbaugh@stanford.edu

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Jing Liu[1] [1], Thomas Hertel[1], Michael Delgado[1], Moetasim Ashfaq[2] and Noah Diffenbaugh[3]

[1] Department of Agricultural Economics, Purdue University
[2] Oak Ridge National Laboratory
[3] School of Earth Sciences, Stanford University

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Abstract

Using a unique dataset for Indiana counties during the period 1995-2012, we estimate the effects of flood hazard, asset exposure, and social vulnerability on property damage. This relationship then is combined with the expected level of future flood risks to project property damage from flooding in 2030 under various scenarios. We compare these scenario projections to identify which risk management strategy offers the greatest potential to mitigate flooding loss. Results show that by 2030, county level flooding hazard measured by extreme flow volume and frequency will increase by an average of 16.2% and 7.4%, respectively. The total increase in property damages projected under different model specifications range from 13.3% to 20.8%. Across models future damages consistently exhibit the highest sensitivity to future increases in asset exposure, reinforcing the importance of non-structural measures in managing floodplain development.

[1] Corresponding author. 403 West State St., West Lafayette, IN 47907-2056, USA. Email: liu207@purdue.edu, Tel: (+1) 765-543-8959.

1. Introduction

Flooding from extreme rainfall events leads to significant damages. According to the National Climatic Data Center, 17 out of 133 'Billion-dollar' weather disasters in the United States since 1980 were related to flooding. Total estimated losses from these events exceed $60 Billion. While the related mortality rate has fallen rapidly, economic losses from flooding show no sign of abating over time (Serje, 2010; Munich Re Group, 2010). Concerns over the cost of flooding have grown in light of global warming. Accumulating evidence suggests that rising concentrations of greenhouse gases in the Earth's atmosphere observed over the past several decades is consistently associated with changes in a number of components of the hydrological systems such as changing precipitation patterns and widespread melting of snow and ice (Trenberth, 2003). In particular, recent warming of the climate has been speeding up the hydrological cycle, a change that could lead to more violent storms, heavy precipitation events, and potentially more damage from flooding disasters (IPCC, 2007a).

Given the fact that flooding is the source of devastating human and material losses, the question of immediate interest is how much greater will damages grow as extreme weather events become more intense and more frequent. To answer the question properly, one has to know to what extent the increase in damages is attributed to climate change. Although multiple avenues have been explored to assess these questions within the broad context of climate change and disaster management, a consensus has been slow in the making.

In the economic literature, some argue that the time trend in damage is largely fueled by increasing asset values, while anthropogenic climate change has not played a major role so far. This conclusion comes from employing a method popularly dubbed "normalization", in which the original economic loss from disaster is normalized by inflation and growth in wealth. The central interest is to investigate if the adjusted loss record exhibits a long-term trend (Pielke et al. 2008; Neumayer and Barthel 2011; Barthel and Neumayer 2012). A recent review of twenty-two normalization studies reveals that economic loss from various weather-related disasters shows no trend after correcting for growing population and capital accumulation (Bouwer, 2011). However, this line of analysis abstracts from the distinct possibility of mutually offsetting effects: What if the more adverse climate conditions are offset by improved adaptation measures? Without a formal model, it is not possible to separate out these component parts.

Multidisciplinary studies have advanced our understanding of the role of climate change in realized losses by coupling meteorological fluctuations and economic normalization. Sander et al. (2013) find consistent patterns of variability between normalized loss and thunderstorm forcing. The finding suggests that, even after normalization, there may be an upward trend for certain regions and hazards, such that climate impacts are beginning to be evidenced in historical loss data. Nevertheless, the final attribution of climatic variability cannot be assessed because the influence of many levers exacerbating or minimizing the impact of flooding has been left unexamined. Some examples include: the pattern of population growth and asset accumulation in flood prone areas, the manner in which the physical landscape is developed, and the attempts to mitigate losses through policy initiatives (Changnon, 2000). It has been advocated recently that in order to facilitate effective disaster management policies, we need a more inclusive risk-related attribution framework that considers all drivers of risk (Huggel, 2013).

So far most of the research on flooding damage can be categorized into two classes – to analyze historical trend and to project future damages – using methods deploying different levels of complexity and precision. However, quantitative studies that examine the sensitivities of flooding damage to its causes are limited (Pielke 2007; Brody et al., 2011). This type of sensitivity analysis has practical importance to flooding mitigation and planning. It is of interest to risk managers and policy makers to determine what should be set as a priority – climate change mitigation or building disaster-resilient communities.

This study aims to bridge this knowledge gap by pursuing the following objectives: to identify statistically significant flooding risk drivers as well as their contributions to overall damages; and to examine how flooding damage responds to various combinations of hazard, exposure, and vulnerability conditions. We begin with a Tobit regression model to estimate the impact of flooding risk drivers on damages. These regression estimates are then combined with data on future projections to assess which type of risk factor would contribute the most to increases in flooding losses. In this way, we seek to explore the effectiveness of alternative flood management measures. The assessment considers various scenarios of physical and socioeconomic change in the future to account for uncertainties.

2. Methods and data

2.1 Theoretical framework and empirical realizations

The widely accepted framework for risk analysis is to model risk as the product of the probability of an event and its outcome. The outcome, or damage in the context of natural disasters, is determined by multiple factors including the intensity of a weather event, the value of exposed assets, and their vulnerabilities (Huggel, 2013). Therefore, quantifying risks of natural disasters involves the assessment of hazard probabilities (H), the exposure of people and capital (E), and the vulnerability or susceptibility to harm (V). Conceptually, the relationship can be expressed as:

$$Risk = H \times E \times V.$$

This seemingly simple concept has, however, rarely been empirically studied at a sufficient level of detail to permit accurate assessment of the three components of risk (Bouwer, 2013). Two levels of detail are especially pertinent. One is a comprehensive approach that considers all three dimensions of flooding risk – hazard, exposure, and vulnerability. While many have examined one or two factors, few have included all three in a single framework (Bouwer, 2013). The other is to carefully measure each dimension with an appropriate level of model and data complexity. Modeling flooding risk remains a significant challenge due to uncertainties. However, part of these uncertainties can be resolved by looking at details – improving fundamental understanding of the occurrence of hazards, having knowledge about the growth pattern of exposed people and assets, and assessing the effects of actions taken to reduce risk. At present, our knowledge in this area, in particular regarding the last two components, is fairly limited (Dessai et al., 2009; Hulme et al., 2011).

Recent studies that have begun to address these limitations tend to rely on the integrated assessment method, a technique combining field measurements with computational and modelling systems. Examples include regional studies in the Netherlands (Bouwer et al., 2010), Australia (Schreider, 2000) and Europe (Feyen, 2008; Te Linde, 2011). Almost without exception, a general circulation model is coupled with a hydrological model to assess the likelihood that extreme discharge/runoff will occur. Evolving exposure is normally captured by land use change, change in real gross domestic product (GDP), and change in the number of properties. Vulnerability is typically described by depth-damage functions associated with different land-use categories. These scientific findings made significant advances in covering details and improving accuracy. However, they are often limited to case studies because a large amount of input data is required.

2.2 Measurements of flooding damage, hazard, exposure, and vulnerability

To limit measurement error, we examine only the direct tangible property damage from flooding. We consider county as the principal unit of analysis because it is generally the smallest geographic unit for which socioeconomic data are consistently reported and administrative arrangements are made. County-level damage data in Indiana is extracted from the Spatial Hazard Events and Losses Database for the United States (SHELDUS). SHELDUS uses the National Climatic Data Center's (NCDC) monthly storm data publications as its major data source, and geocodes the event-based damage by the Federal Information Processing Standards (FIPS) code. Because NCDC changed its reporting procedures from category to exact dollar losses in 1995, we restrict the study period to 1995 onwards to maintain consistency. Losses are adjusted to 2011 US dollars to allow for comparability between years. Figure 1 visualizes annual property damage reported in each county during 1995-2012. Damage varies considerably across counties and years. Some large amounts of damage were observed in the late 1990s, 2003, and 2008, among which 2008 was the worst-hit year, with 73 out of 92 counties reporting property losses and the average damage being around 10.9 million $US per county. By contrast, in a dry year like 2012, only 18 counties reported damage, with an average amount of $2000 per county.

The probability of hazard occurring is mainly governed by the severity and frequency of extreme events. Accordingly, two metrics are used to describe the flooding hazard in a particular year for each county – how large the annually accumulated extreme discharge is and how frequently extreme events occur within a year. To reflect the variation in both space and time, we start with the daily maximum streamflow (discharge) data provided by the US Geological Survey (USGS). The daily summary data is generated from more than 26,000 on-site automated recorders installed across the nation. Among them, 329 are located in Indiana. We define an extreme event as any day in which the daily maximum discharge exceeds the 97.5 percentile of the 30 year (1980-2010) USGS records. Both the severity and frequency metrics are normalized by the number of sites within a county to avoid any inflation caused by the uneven distribution of the monitoring stations.

We use the number of housing units within a county to approximate assets exposed to flooding risks.[2] These data come from the US Census Bureau. Missing years are linearly interpolated using county level average annual growth rate calculated based on that period. To measure exposure, we also control for the county-specific poverty rate to reflect the fact that counties with a larger proportion of impoverished population may have relatively less accumulated wealth and therefore less loss.

Vulnerability, in its most generic sense, conveys the idea of susceptibility to damage or harm, but opinions on how to characterize vulnerability in theory and practice are quite diverse. We find three representative theories from the literature. They consider vulnerability as the potential for loss in a particular setting (Dutta et al., 2003), a condition of being affected by inequalities in resource distributions (Cutter, 2003), and the rigidity resulting from the evolution of science, technology, and social organization

[2] We use units rather than value of properties because home value data provided by the American Community Survey does not cover every county in Indiana during this period.

(Timmerman, 1981). Inspired by these theories, we use a synthetic indicator – the number of flood damage events reported during the past five years – to capture how vulnerable a county is to flooding disasters.[3]

2.3 Econometric model specifications

Since not every county suffered damages every year, damage is a continuous random variable over strictly positive values but takes on the value zero with positive probability. This fits the corner-solution problem described by Wooldridge (2002, p.517-520) and suggests the use of a Tobit regression model. County fixed-effects are added to fit our panel data since the effects of time-invariant variables (e.g., county geographic features) are not of direct interest, but need to be partialed out to avoid confounding the effects of variable flood risk factors. Moreover, in contrast to a random-effects model, the fixed-effects allow for a correlation between time-varying characteristics and omitted variables (e.g., infrastructure, slope, and elevation in our case). It is unlikely that these characteristics are uncorrelated with the level of flood risk. The model is set up as follows:

$$y_{it}^{*} = X_{it}\beta + u_i + \varepsilon_{it}$$
$$y_{it} = \begin{cases} y_{it}^{*} & if\ y_{it}^{*} > 0 \\ 0 & if\ y_{it}^{*} = 0 \end{cases} \tag{1}$$

where y_{it}^{*} is a latent variable used to separate out the distribution of the non-zero damages, and y_{it} is the observed damage. X_{it} contains a set of variables that measure flooding hazard, asset exposure, and vulnerability by county and year. β is a vector of coefficients associated with flood risk factors, u_i is the county-specific effect that is time-invariant, and $\varepsilon_{it} \sim N(0,\sigma^2)$ is the disturbance term.

We hypothesize that the relationship between flooding hazard and incurred damages may be nonlinear, as demonstrated by Figure 2 (a). Damage starts to appear once the volume of water exceeds a certain threshold (section A), reflecting the fact that small amounts of water are not likely to lead to any significant flood damage. Damages continue to climb rapidly as the volume of water increases (section B), but gradually flattens out as the realized damage approaches the maximum asset value of damaged assets (section C). In other words, given a certain level of flood flows, the scale of damage depends on how the hazard is distributed, and the regime in which a particular country finds itself.

[3] We do not consider the adoption of floodplain management regulations and flood insurance under the National Flood Insurance Program (NFIP) and the Community Rating System (CRS) program as vulnerability reduction measures, because these are likely to be endogenous outcomes of historical flooding damages.

In our regression framework, we measure flooding hazard via extreme flows and the frequency of extreme flows. When both measures are included simultaneously, the relationship between flood frequency and flood damage becomes conditional on the flood flows. This interpretation is interesting because, as shown in Figure 2 (b), controlling for total flood flows, damage can either go upward or downward as the frequency of flood events increases. While it appears counterintuitive that an increase in flood frequency may lead to a reduction in total annual damages, we must bear in mind that this relationship is estimated holding constant the total volume of flood water. In effect, the interpretation is that an increase in the number of flooding events spreads out the annual amount of flood waters per year. Depending on where the county is in terms of the damage function (Figure 2 (a)), total damages may either increase, decrease, or first increase and then decrease as shown by the regimes in Figure 2 (b). To model these effects, a quadratic term of flow volume will be considered in our model specification.

2.4 Estimation strategy

The model is estimated using a standard Tobit model with county indicators.[4] We are interested in the expected value of flood damage (Equation (2)) and the marginal effects of risk factors on the expected damage (Equation (3)):

$$E[y_{it}] = \Phi\left(\frac{X_{it}\beta}{\sigma}\right)[X_{it}\beta + \sigma\lambda_{it}(\alpha)] \qquad (2)$$

$$\frac{\partial E[y_{it}]}{\partial x_k} = \Phi\left(\frac{X_{ti}\beta}{\sigma}\right)\beta_k \qquad (3)$$

$\lambda_{it}(\alpha) = \frac{\phi(X_{it}\beta/\sigma)}{\Phi(X_{it}\beta/\sigma)}$ is the inverse Mills ratio that controls for the probability of a non-zero flooding damage event. Note that the β_k parameters are not equal to the marginal effects of X on the outcome due to the nonlinearity of the model.

2.5 Sensitivity Analysis

Our goal is to show how sensitive flooding damage is to different combinations of changing risk factors. To this end, we first use historical data to establish the statistical relationship between disaster loss and each

[4] Honoré (1992) proposes the trimmed least absolute deviations (LAD) and least squares (LS) estimators for this type of model. In particular, the fixed effect is controlled by piecewise subtraction of the mean from the original value along the nonlinear distribution, and is not explicitly estimated. We do not favor these estimators because they are unable to uncover the full set of estimates that are required for the damage projection. Furthermore, Greene (2004) shows that the coefficients obtained by estimating the Tobit model with indicators are not severely biased, and that this bias diminishes as the panel dimension of the data increases. Estimates of our model using the LAD estimator yield qualitatively similar estimates to those reported below.

flood risk factor. Assuming the relationship remains unchanged, we are interested in predicted loss under a series of future scenarios and how the prediction responds to the variation of scenarios. Here the constant correlation assumption is applied to avoid further uncertainty being introduced. Comparing across scenarios, the component that, when perturbed, leads to the largest reduction in predicted damage, is interpreted to have the greatest potential to mitigate flooding loss.

3. Results

3.1 Summary statistic

The dependent variable in the reduced-form Tobit regression is county level annual property damage ($US, 2011 price throughout the paper if not otherwise mentioned) from flooding during the period of 1995-2012. Here we use population-normalized damage ($US per hundred people); simply using total damages would yield variation caused by differences in populations across counties. Table 1 provides the data summary statistics. Because for some county-year observations the USGS stream flow data is missing, we end up with an unbalanced panel of 965 observations. On average, annual flood loss per capita is 24 $US. There are about 11 extreme days in a year. The average count of houses in a county is 34,938. Indiana counties have a mean poverty rate of 10.4% during this period. Within a five-year interval, each county reported 5.28 damages, or at least one damage event per year.

3.2 Estimated correlation between loss outcome and risk factors

To test the nonlinear hypothesis discussed above and to check the robustness of the estimates, we try different specifications denoted by model (1) to (4). Table 2 summaries the Tobit maximum likelihood estimates. We find that more hazardous flooding corresponds to larger damages, no matter whether the degree of hazard is measured by volume or frequency metric (models (1) and (2)). In model (3), the negative sign associated with the squared flow term indicates a concave increasing (i.e. increases but at a reduced rate) flow-damage function. Further, when holding constant the flow volume, more extreme events relates to larger damage, which suggests Indiana counties are likely to reside in regime B or C demonstrated in Figure 2(b).

More housing units, a proxy for larger exposure, leads to more damages. Although still statistically significant, this effect is less precisely estimated than the other factors perhaps because the frequency tells little about spatial distribution and value of assets. It has been pointed out that the spatial resolution of population and properties actually exposed to flooding disaster is either lacking or not sufficiently detailed, and should be addressed in future research (Pielke, 2007; Dorland et al., 1999; Schreider et al., 2000).

Controlling for the total number of establishments, a higher poverty rate is linked to less per capita wealth accumulated and thus lower damage. Finally, more damage events in the past is positively correlated with a larger per capita damage, suggesting the flooding stress is chronic. Comparing across model specifications, our estimation is reasonably robust, with most of the coefficients highly significant.

3.3 Sensitivity analysis

The purpose of the sensitivity analysis is to compare the projected damage in 2030 under different scenarios and see which one shifts the projection the most. To construct the scenarios, we vary three factors – hazard (H), exposure (E), and vulnerability (V) at two levels – historical (0) and future (1). Future exposure (E_1) is linearly extrapolated based on the evolving pattern over 1995-2012. Future vulnerability (V_1), however, is more difficult to gauge given its multidimensional nature and the substantial uncertainty associated with it. Therefore, a 10% increase is assigned to this variable. Next, we explain how the future hazard (H_1) is constructed.

To closely reflect future hazard (H1) to the largest possible extent, we rely on a series of fine-scale (one-eighth degree) daily water runoff data simulated by the Community Climate System Model Version 3 (CCSM3).[5] Figure 3 displays the change of county-level flooding hazard from 1960-1999 to 2000-2039. Comparisons based on the 40-year average suggest more severe and more frequent extreme events in the future, with a larger degree of increase in the severity.

Figure 4 presents the predicted flooding damages under varying future possibilities. Scenario $H_0E_0V_0$ serves as a baseline, which has the same degree of flooding risk as current levels. Taking model (1) as an example, the result is interpreted as follows. After having all the risk factors updated to their future level $H_1E_1V_1$, we expect annual state damage to increase by 15.5% from 287 to 332 million $US. If, however, allowing only exposure to be updated to future levels (scenario $H_0E_1V_0$), the expected damage increases by 9.6% from 287 to 315 million $US.

[5] As described in Meehl et al. (2006), these CCSM3 realizations are identified by the National Center for Atmospheric Research (NCAR) as ensembles c, e, bES.01, fES.01 and gES.01. The five realizations were generated using a standard atmosphere-ocean general circulation model (AOGCM) ensemble method, with each realization initialized from a different point in the pre-industrial control simulation, and all ensemble realizations prescribed identical atmospheric constituent concentrations over the historical and scenario periods. The five CCSM3 realizations therefore differ only in the atmosphere, land and ocean conditions at the time of initial industrial-age forcing. The global warming in the CCSM3 A1B ensemble falls near the middle of the Coupled Model Intercomparison Project phase-3 (CMIP3) ensemble, with the CMIP3 ensemble showing warming of 1.0 to 1.7 ˚C above the late twentieth century baseline at the end of the 2030s (Meehl et al., 2007b), and the CCSM3 ensemble showing warming of 1.1 to 1.3 ˚C (Meehl et al., 2006).

Several interesting points emerge from our analysis. First, simulated damage outcomes exhibit the highest sensitivity to a larger exposure in all four models. In other words, properly managing floodplain landscape may provide the largest potential of flood damage control. Almost without doubt, real estate wealth will continue to accumulate in the next few decades, and probably even faster on floodplains due to the "safe development paradox" – a (false) sense of security brought by regulations that inadvertently increases the tendency of residing on flood-prone areas. So our finding reinforces the emphasis on more prudent land-use planning that can direct development away from high flood risk zones.

Second, we find empirical support for the concave flow-damage function. An otherwise linear approximation misses the apex, and thus may understate the effect of more rising weather hazard on flood damage. In our simulated results, this is translated into a less sensitive response to the increasing extreme event intensity (Figure 4 model 3). After taking into account the curvature, we find fairly consistent sensitivity patterns from different model specifications (Figure 4 model 1, 2, and 4), which is sensible because two flood hazard metrics - extreme flow volume and frequency - are derived from the same set of data and essentially point to an integrated description of extreme events. Our projected damages from the different models overlap over a reasonably narrow range despite the varying width of the confidence intervals. Understanding the shape of the damage function helps to identify the allocation of investment which yields the largest marginal benefit given a budget constraint.

4. Concluding remarks

Using a unique dataset for Indiana counties during the period of 1995-2012, we estimate future flooding damage explained by risk factors – weather hazard, property exposure, and vulnerability. We find that per capita property damage from flooding has a statistically significant positive correlation with more intensive and frequent flooding events, a larger number of housing units, and is larger in areas with a history of flooding. Furthermore, we compare how sensitive the projections are to different combinations of these factors. The most significant change occurs when the exposure factor is perturbed.

An immediate implication is that promoting non-structural measures plays a critical role in flood damage control in Indiana. Policies like enforcing zoning regulations and building codes can reduce exposure to flood hazard, which would provide the largest room for change according to our regression and simulation results. In view of the chronic nature of floods, the treatment calls for a comprehensive flood management strategy that improves pre-disaster preparedness as well as post-disaster response and recovering capability especially at a local level and among disadvantaged populations. It is also important to note that economic losses are also sensitive to more severe weather hazards – the second most important element of risk. Moreover, the change of precipitation patterns can be abrupt (within a decade or over the span of a few years), such that crossing some threshold or “tipping point” can come faster than expected, prepared, or budgeted. Future strategy forces a more reactive than proactive approach to adaptation.

The final remark is that, although the analytical method employed here is universal, the inferences drawn from this particular analysis only pertain to the State of Indiana. The primary reason for this caution is that flood appears to be a highly localized phenomenon tied to physical, economic, and social characteristics of a community. When moving to, for instance, the southern US where future extreme weather hazard is expected to be more severe than in the Midwest, it is likely that the impact as well as the pattern of sensitivity to each risk component will be altered.

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Table 1. Summary statistics

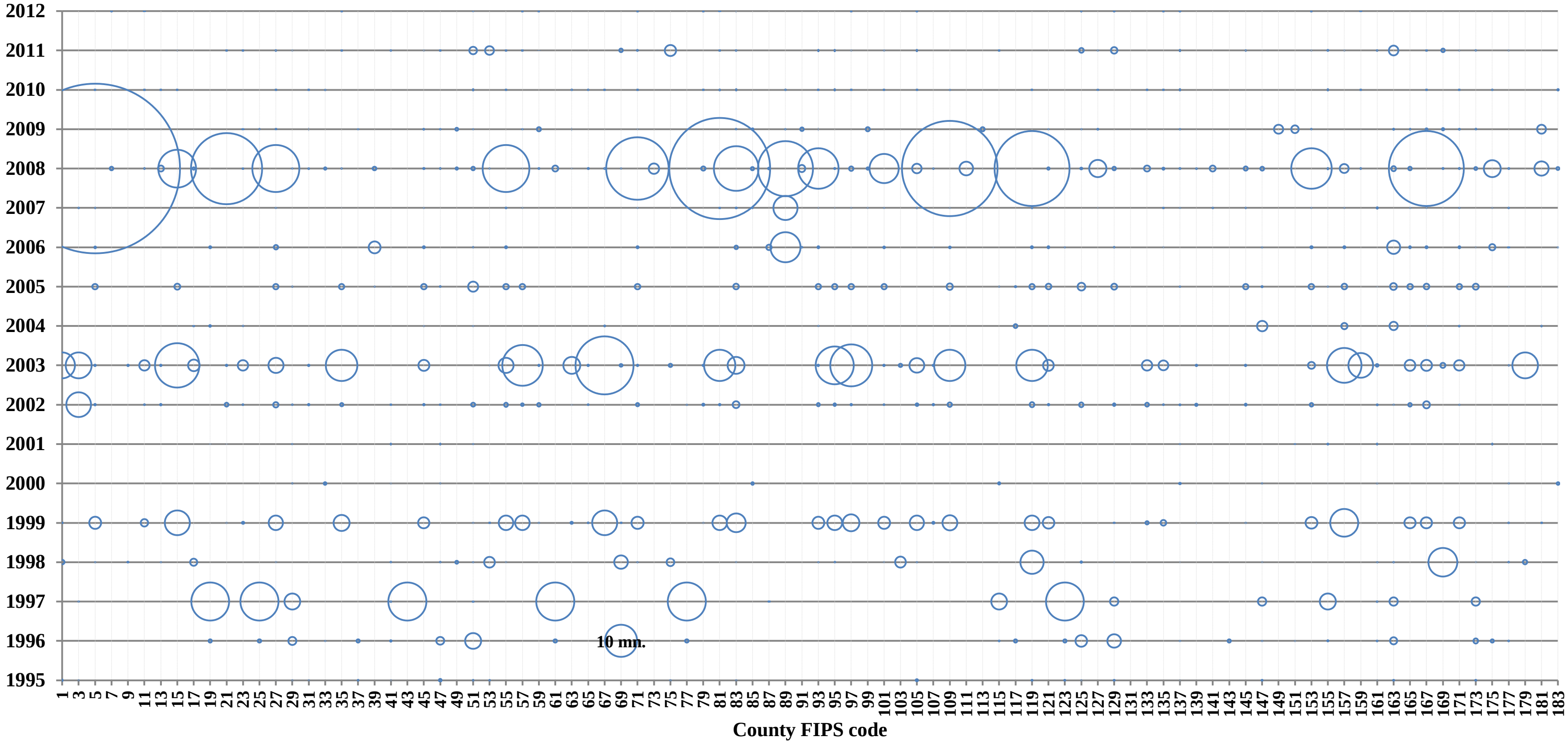
Variable	N	Mean	Std Dev	Min	Max
Annual property damage from flooding, $US/100 persons	965	2389.39	17113.17	0.00	344388.83
Total volume of flow from extreme days, 10,000 ft^3/second	965	16.44	52.48	0.02	744.06
Total number of extreme days, days/year	965	11.03	7.38	1.00	44.00
Total housing units, 100 units	965	349.38	606.05	34.25	4241.11
Poverty rate, %	965	10.44	3.29	2.99	22.24
Total number of damages recorded during the last 5 years	965	5.28	6.03	0.00	36.00

Table 2. Tobit estimates

Parameter	(1) Estimates		(2) Estimates		(3) Estimates		(4) Estimates	
Total frequency of extreme days, days/year	817.28	***	800.69	***				
Total volume of flow from extreme days, 10k ft3/second			52.59	***	76.15	***	377.04	***
Squared volume of flow from extreme days, 10k ft3/second							-0.59	***
Total housing units, 100 units	3.50	**	2.92	*	3.90	**	4.95	**
Poverty rate, %	-2551.78	***	-2669.62	***	-1962.89	***	-1913.64	***
Total damage events reported during the last 5 years	546.00	***	657.65	**	665.75	***	332.58	**
Sigma	27601	***	26679	***	28283	***	25950	***
Observations	965		965		965		965	

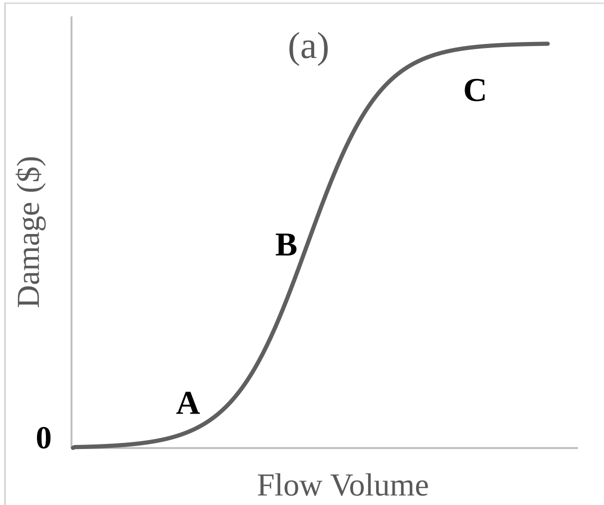
Note: Model (1) – (4) differ only in the measurement of flooding hazard. * denotes significant at 10%, ** significant at 5%, *** significant at 1%. Coefficients for county indicators are not reported.

Figure 1. County property damage from flooding, Indiana, 1995-2012



The size of the bubble is proportional to the scale of the damage. Damage experienced by county # 69 in year 1996 demonstrates a loss of 10 million $US. Horizontally, bubbles tell the prevalence of damage in a certain year and compare the scale of the damage across counties. Vertically, they demonstrate how often counties were hit by flooding during this period and on which year the largest damage was reported.

Figure 2. Theoretical relationship between property damage and flooding hazard measurements.



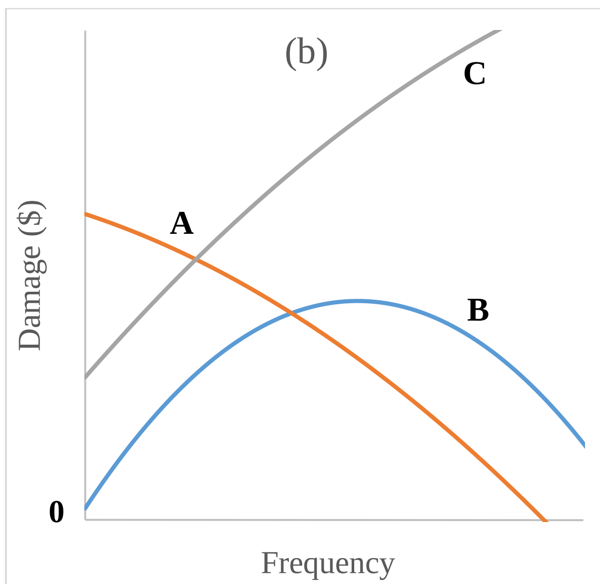


Figure (a) depicts the nonlinear response of damage to accumulated annual flood flow, featured by three regimes. Figure (b) illustrates the possible response of damage to increasing flooding frequency in each regime. When annual flow volume is low (regime A), splitting it into more events tends to reduce total damage since each event has less damaging power. Conversely, when flow volume reaches a high level that approaches or exceeds the maximum damage potential (regime C), splitting one enormous event into multiple but still large events permits more damage realizations, which potentially increase total damage. Regime B contains other possibilities between the two extreme cases

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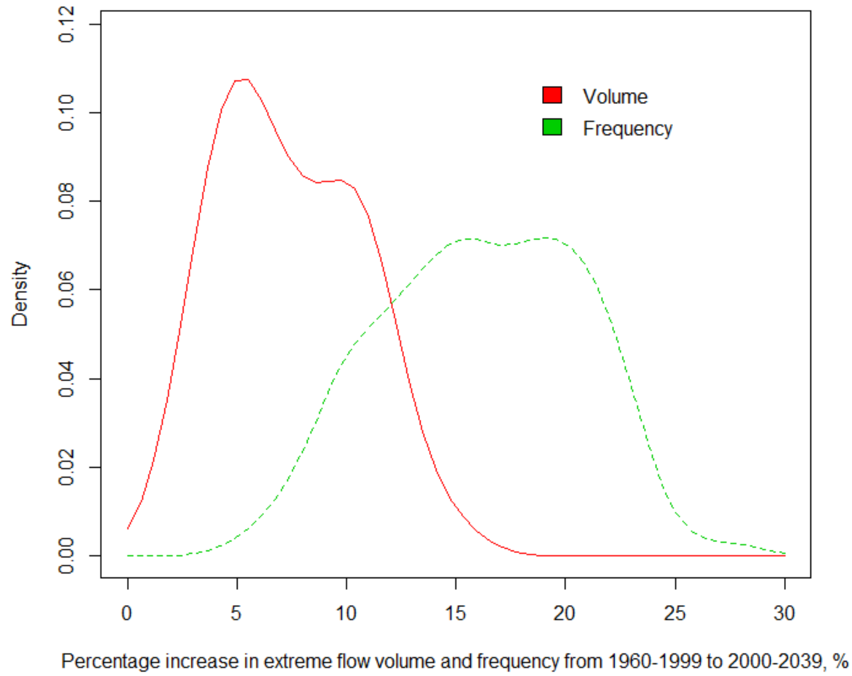
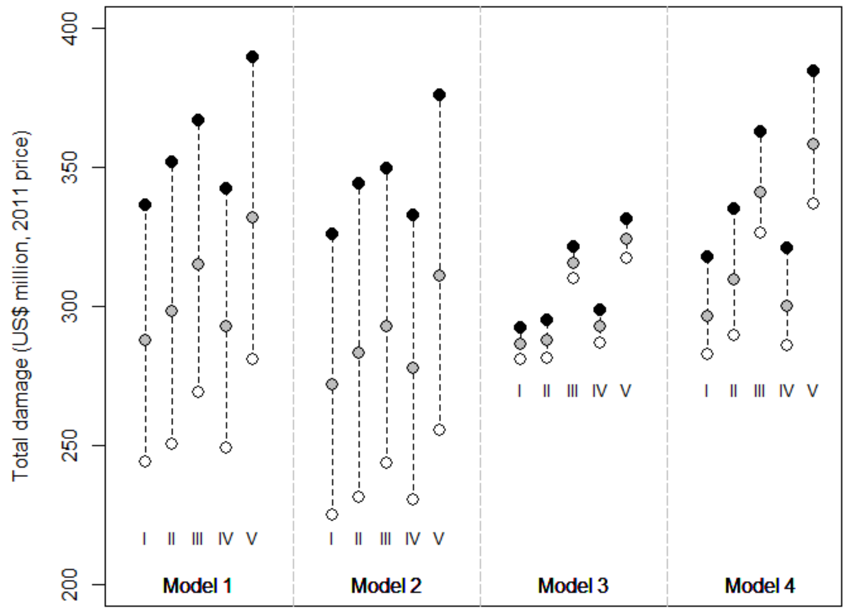
Figure 3. Change in flooding hazard measured by the frequency and volume metrics of extreme events



Kernel density plot of percentage change (2000-2039 mean relative to 1960-1999 mean) in extreme flow volume and frequency based on data for 92 Indiana counties. The humps in the density plot indicate that most counties will experience a 5 to 10 percent increase in extreme flow volumes, and 15 to 20 percent increase in extreme flow frequency.

Figure 4. Sensitivity analysis of projected property damage from flooding



Projected damage for Indiana in 2030, under scenarios varying flooding hazard (H), asset exposure (E), and vulnerability (V) at historical (0) and future (1) levels. Scenarios I and V represent $H_0E_0V_0$ (baseline) and $H_1E_1V_1$ (fully updated). Scenario II, III, and IV – for $H_1E_0V_0$, $H_0E_1V_0$, and $H_0E_0V_1$, respectively – allow one factor to be perturbed while keeping the others constant. Grey circles represent the mean. Black and white circles represent the upper and lower bound of 95% confidence interval. Model 1 and Model 2 have larger confidence intervals than the other two because the frequency metric is less variable (contains less information) than the volume metric.