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ORIGINAL PAPER

Assessing Illinois's flood vulnerability using Hazus-MH

Jonathan W. F. Remo[1] · Nicholas Pinter[2] · Moe Mahgoub[1]

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Abstract In this study, we developed a flood vulnerability index to help planners screen the relative flood vulnerability across the entire state of Illinois at the county, jurisdictional, and census block scales. Our flood vulnerability index was comprised of a deterministic flood loss assessment using the Federal Emergency Management Agency's Hazus-MH multi-hazard loss estimation software, coupled with a parametric social vulnerability index developed from US Census data. The flood-vulnerability screening revealed that approximately half (46 %; 8500 km^2) of Illinois's 18,500 km^2 special flood hazard areas (i.e., 100-year floodplain) had low flood vulnerability (i.e., few people affected, with little or no flood losses). This finding substantially reduces the area that Illinois planners may need to focus their mitigation efforts. The relative flood vulnerability across the three spatial scales evaluated in this study generally mirrored each other (i.e., counties with high flood vulnerability had a substantial number of its jurisdictions and census blocks with high flood vulnerability). However, the census block-level analysis revealed that counties and a substantial number of jurisdictions with moderate-to-low relative flood vulnerability often had pockets (one to a few census blocks) of high relative flood vulnerability. This suggests flood-vulnerability screening should be performed to at least the census block scale to ensure pockets of vulnerability are not overlooked. Jurisdictional flood loss ratios (flood losses proportional to total floodplain exposure) in Illinois were generally largest in rural

Nicholas Pinter was formally affiliated with Department of Geology, Southern Illinois University Carbondale, Carbondale, IL 62901-4323, USA during his study.

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✉ Jonathan W. F. Remo
diamict@siu.edu

[1] Department of Geography and Environmental Resources, Southern Illinois University Carbondale, Carbondale, IL 62901-4323, USA

[2] The Department of Earth and Planatery Sciences, University of California Davis, Davis, CA 95616, USA

and relatively unprotected floodplain communities located along the state's large rivers. This suggests the economic impacts related to riverine flooding would be more severe in these rural jurisdictions, relative to their economic base, and likely exceed the economic resources these communities could assemble for flood recovery. The jurisdiction flood-vulnerability screening results indicated the primary driver of flood vulnerability was different between urban and rural communities. In urban jurisdictions, social vulnerability was the main driver in flood vulnerability where in the rural jurisdictions flood losses tended to be the primary driver. This suggests different mitigation strategies will likely need to be employed in urban versus rural jurisdictions in order to reduce flood vulnerability.

Keywords Flood-vulnerability assessment · Flood vulnerability index · Mitigation · Hazus-MH · Illinois

1 Introduction

Flooding is the most costly hazard in the USA and worldwide. Between 1993 and 2013, flood losses recorded in the National Oceanic and Atmospheric Administration's (NOAA's) National Climatic Data Center (NCDC) database exceed $200 billion, with $5.5 billion of these in Illinois alone (NOAA 2014). While flooding cannot be prevented, the impacts of flooding can be ameliorated.

In order to reduce flood losses and other hazard-related damages, the US Congress passed the Disaster Mitigation Act of 2000 (DMA 2000). One of the primary goals of the DMA 2000 was to encourage communities to undertake proactive hazard mitigation planning. Hazard mitigation planning (HMP) entails the development of pre-disaster plans, with the goals of reducing the damages and costs from future natural disasters. The overarching goal of such planning is to reduce vulnerability and increase resiliency of communities across the USA (Godschalk 2003; FEMA 2011; Frazier et al. 2013).

DMA 2000 requires states and counties to prepare HMPs in order to be eligible to receive Federal Emergency Management Agency (FEMA) hazard mitigation funds (Berke and Godschalk 2009; Frazier et al. 2010, 2013). DMA 2000 has established minimum requirements for HMPs which emphasize physical exposure and the identification of relevant mitigation actions for each natural hazard identified in a jurisdiction. While the requirements for assessing physical exposure are a first good step, probabilistic loss assessment coupled with socioeconomic vulnerability assessment could be more effective in targeted scarce mitigation funding (Frazier et al. 2010, 2013). To move toward more comprehensive flood hazard assessment, this paper describes construction of a flood vulnerability index (FVI) using FEMA's natural hazard loss estimation software (Hazus-MH), which can be used to systematically assess flood hazard and socioeconomic vulnerability across multiple spatial scales (e.g., census block, jurisdictional, and county scales). The modeling framework presented in this paper is intended to help planners screen flood vulnerability among locations and jurisdictions in order to target areas for more detailed flood hazard or mitigation assessment.

1.1 Social vulnerability

Social vulnerability refers to the characteristics of a person or a group and the circumstances that influence their capacity to anticipate, manage, or recover from the effects of a hazard (Wisner et al. 2004). Social vulnerability is often most pertinent after a hazardous event, when the different patterns of distress and recovery are observed among particular groups within the population such as the aged, poor, and minorities (Cutter et al. 2000; Heinz Center 2000; Cutter and Finch 2007). Economic status is also important consideration because a lack of access to economic resources can limit the ability of some socioeconomic groups to respond adequately to a disaster (Phillips et al. 2005; Masozera et al. 2007). These groups are often underprepared for an emergency, often reside in more hazardous locations, in substandard dwellings, have fewest resources, and lack knowledge and/or political efficacy to assert access to resources for recovery (National Resource Council [NRC] 2006). Social vulnerability analysis (SVA) describes social characteristics, vulnerability to hazards, and the distribution of tangible hazard effects.

SVA generally begins with a qualitative characterization of the study area, followed by identification of vulnerability drivers, development of a quantitative vulnerability model, and communication of findings to stakeholders (Polsky et al. 2007; Tate 2012). The model development stage usually involves the development of a social vulnerability index (SVI). The purpose of a SVI is to simplify the multi-dimensional complexity into a single metric. Development of a SVI involves successive stages, including the selection of demographics indicators, normalization of indicators to a common reference, and summation to a final value (Tate 2013).

There are three common designs of SVIs: deductive, hierarchical, and inductive models (Tate 2013). Deductive models generally contain less than ten vulnerability indicators, which are normalized and aggregated to an index (i.e., Cutter et al. 2000; Montz and Evans 2001; Wu et al. 2002; Collins et al. 2009; Lein and Abel 2010). Hierarchical models employ generally between 10 and 20 indicators, which are separated into sub-indices that share a common underlying dimension of vulnerability (e.g., Vincent 2004; Chakraborty et al. 2005; Flanagan et al. 2011; Mustafa et al. 2011). Within hierarchical models, individual indicators are aggregated into sub-indices, and sub-indices combined to formulate the SVI (Tate 2013). Inductive models start with a large set of indicators (>20), which are reduced to a smaller subset of uncorrelated latent factors using a principal component analysis (PCA). These factors are then combined to build an SVI. Inductive models were made popular by the "social vulnerability index" (commonly referred to as SoVI; Cutter et al. 2003) and are the basis for the majority of many recent SVIs (e.g., Rygel et al. 2006; Borden et al. 2007; Burton and Cutter 2008; Myers et al. 2008; Fekete 2009, 2011; Burton 2010; Finch et al. 2010; Schmidtlein et al. 2010; Tate et al. 2010; Wood et al. 2010; Cutter et al. 2013).

Despite the broad interest in the need to quantitatively model social vulnerability, there is a lack of consensus regarding the optimum method(s) for constructing SVIs (Tate 2012). The absence of consensus for formulating SVIs is largely attributable to the lack of an accepted external validation data set(s) (Tate 2012; Burton 2015). Recent work by Tate (2012, 2013) has focused on internal validation of SVIs using global sensitivity and uncertainty analyses. The results of the global sensitivity analysis revealed that hierarchical SVI design was found to be the most accurate, while inductive SVI design was the most precise. In addition, deductive SVI design was found to be the most sensitive to the choice of transformation method, hierarchical design was most sensitivity to selection of weighting scheme, and inductive model design was most sensitive to indicator set and scale of analysis. Tate's (2013) SVI uncertainty analyses revealed that SVI precision decreases with an increase in vulnerability rank.

1.2 Flood vulnerability and flood assessment vulnerability

In the literature, definitions and quantification of flood vulnerability have been proposed by several investigators (e.g., van der Veen and Logtmeijer 2005; Conner and Hiroki 2005; Balica et al. 2009, 2013; Karmakar et al. 2010). The goal of this investigation was to develop a framework from which to screen flood vulnerability over a large geographic region in order to help inform flood hazard assessment and mitigation efforts. The definition of flood vulnerability best suited to this investigation's goal is from Balica et al. (2013): "the extent to which a system is susceptible to floods due to exposure, a perturbation in conjunction with its ability to cope, recover, or basically adapt." This definition can be expressed mathematically as

$$\text{Flood Vulnerability} = \text{Exposure} + \text{Susceptibility} + \text{Social Vulnerability} \tag{1}$$

and serves as the tenet for development of our FVI. In this definition, exposure is defined as the estimated value of the buildings that are present in the areas potentially threatened by flooding. Susceptibility is defined as the probability of the human population affected and associated building stock damaged within the floodplain during a flood of a particular magnitude (Balica et al. 2009). Previous flood-vulnerability assessments can be grouped into two general approaches, deterministic and parametric. Deterministic approaches are those which use physically based modeling methods to estimate probability of a particular flood event and damage assessment models to quantify economic consequences which together provide an assessment of flood risk for a given area. Parametric approaches use readily available information, such as census and geospatial data (i.e., land cover, infrastructure, and precipitation) to develop a relative assessment of the flood vulnerability within a given area where the results rely on assumptions that cannot be validated from observed data (Balica et al. 2013). To parameterize Eq. 1, we developed a hybrid modeling framework in which we employ a deterministic modeling approach to estimate the physical flood hazard and a parametric model to estimate human vulnerability to the flood hazard using a SVI.

2 Methods

Our hybrid modeling framework evaluates relative flood vulnerability using a FVI at three spatial scales: census blocks, incorporated communities, and counties. Using the SFHA ($\leq$1 % annual chance flood) mapped on FIRMs, flood exposure and losses were estimated using FEMA's Hazus-MH flood loss modeling software. Census-based demographic data from Hazus-MH were employed to develop a parametric model (a SVI) from which to assess social vulnerability to flooding. Assessments of flood losses and social vulnerability were combined to produce a FVI to assess relative flood vulnerability across the state of Illinois.

2.1 Study region

Illinois is approximately 146,000 km^2 in size and is divided into 102 counties that contain $\sim$1370 incorporated jurisdictions. The state is bounded by three large rivers: the Mississippi River on the west, the Ohio River along the south, and the Wabash River along the state's eastern boundary. Within Illinois, there are river systems with extensive floodplains, including the Illinois, Kaskaskia, Sangamon, Rock, and Green Rivers.

Floodplain management in Illinois is largely driven by compliance with the US National Flood Insurance Program (NFIP). The NFIP was established by the US Congress in 1968 to slow flood disaster relief costs by offering federal flood insurance to property owners provided that their communities regulate future development in the special flood hazard areas (SFHA's; 100-year floodplain). The US Federal Emergency Management Agency (FEMA) has generated Flood Insurance Rate Maps (FIRMs) to delineate flood hazard areas, identify flood insurance rate zones, and in areas where detailed hydrologic and hydraulic modeling are performed, estimate flood water surface elevations (WSELs). On the FIRMs, three flood hazard types are depicted: (1) SFHAs ($\geq$1 % annual chance of inundation), (2) moderate flood hazard areas [$\geq$1.0 % (100 year) to $\leq$0.2 % annual chance (500 year) of inundation or area protected by accredited levees], and (3) areas in which flood hazards are minimal (>0.2 % annual chance of inundation or the flood probability is undetermined, but still possible; NRC 2009). The portion of the SFHA mapped across Illinois encompasses approximately 18,500 km^2 or 13 % of the state (Fig. 1).

In Illinois, 89 counties out of its 102 counties (78 %) participate in the NFIP. The counties which do not participate in the NFIP are rural counties generally concentrated in the south-central or southeastern portion of Illinois (Fig. 1). Of the 918 communities in Illinois evaluated by FEMA for flood hazard areas, 790 (86 %) participate in the NFIP. The 127 communities (14 %) which do not participate in the NFIP are generally small, rural communities located within the counties which do not participate in the NFIP (FEMA 2015).

In addition to the NFIP, FEMA also encourages communities to participate in its Community Rating System (CRS). This voluntary incentive program encourages communities to exceed the minimum NFIP requirements for floodplain management. Depending on the rating class of a participating jurisdiction and location of the insured property within or outside a SFHA, the insurance premium for policy holders located within these communities receives a 5–45 % reduction in their insurance premium. Only 3 counties (<3 %) and 13 communities (<1.5 %) participate in the CRS program in Illinois (FEMA 2012a).

Within Illinois's SFHA, 143 levee systems have been identified, which together protect 2400 km^2 of floodplain. Protection levels of Illinois's levees range from $\sim$10 to 2 % annual chance floods for agricultural areas up to 0.2–1 % annual chance floods for levees protecting more developed or urban areas (Fig. 1). Nearly all the levees with protection levels $\leq$1 %annual chance flood are FEMA accredited (Remo et al. 2013).

In the flood-vulnerability modeling approach described below (Sect. 2.2.3), effects of flood mitigation efforts through NFIP required land use restrictions are largely accounted for in general building stock (GBS). This is because the GBS model takes into account NFIP building regulations (FEMA 2012b). Areas protected by FEMA-accredited levees are explicitly accounted for in SFHA delineations and are presumed to be excluded from inundation for the $\leq$1 % annual chance flood. Given the low participation rate in FEMA's CRS program in Illinois and that flood damage reduction measures are only a small component of this program, the effect of this program on the flood losses is likely minimal.

2.2 Data sources

2.2.1 Floodplain maps

We compiled a SFHA data layer (>1.0 % annual chance floodplain) for the entire state of Illinois. This layer was compiled from two primary sources: (1) FEMA Digital Flood Rate Insurance Maps (DFIRMs) where available, or (2) digitized versions of the FIRMs where DFIRMs were not available. The DFIRMs were obtained from the FEMA Map Service

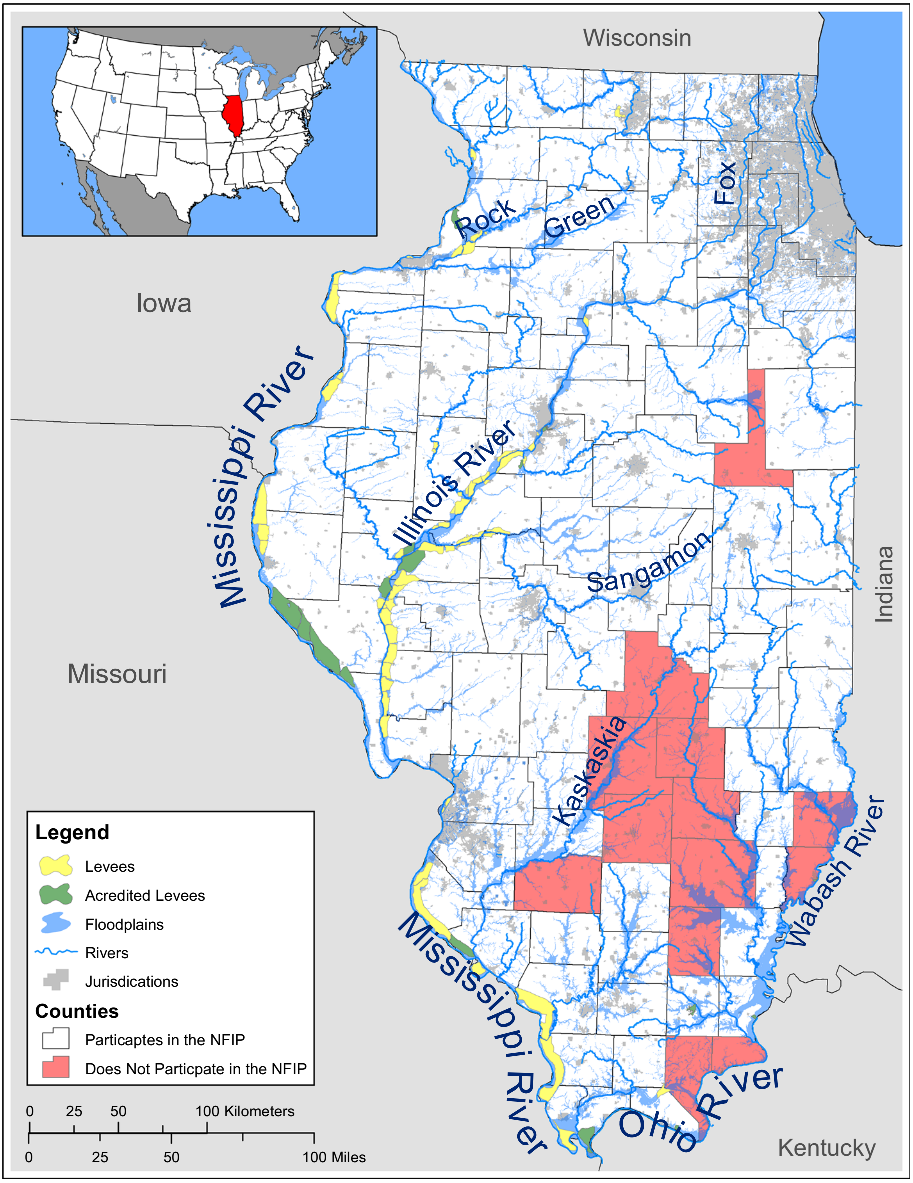

Fig. 1 Illinois special flood hazard area (SFHA; floodplains), levees, and major rivers. Levees systems shown in *green* are accredited by the Federal Emergency Management Agency and thus are not mapped within the SFHA on Flood Insurance Rate Maps

Center, and the digitized FIRMs were compiled and edited from the Illinois State Water Survey (ISWS 1996). At the time of this study, 77 out of 102 Illinois counties had effective DFIRMs, and three additional preliminary DFRIMs were available. DFIRMs are FIRMs which have been constructed in a GIS environment using orthoimagery, a digital elevation model (DEM), and flood data to map the SFHAs and other flood hazard delineations. The remaining 25 counties had either a FIRM or preliminary DFIRM depicting SFHA boundaries.

2.2.2 Digital elevation model

A DEM, which is used to characterize floodplain topography in the Hazus-MH flood loss model, was downloaded from the United States Geological Survey's National Map (USGS 2013). We used a 1/3-arc-second ($\sim$10-m resolution) DEM for the flood loss analyses performed in this study. The DEM is used in the construction of a flood depth grid (FDG) which defines the area of potential flood inundation and its related flood depths to determine flood losses (see Sect. 2.2.1 for additional details).

2.2.3 Demographic and building inventory data

Inventories within Hazus-MH include population, demographic, and infrastructure data. The demographic data contain information such as age, income, and race. These demographic data were compiled from the 2000 US Census. Hazus-MH provides a national-level database of essential and critical facilities, transportation networks, utility networks, and a data model of building inventory [general building stock (GBS)] for users that do not wish to create their own databases. The Hazus-MH GBS includes data models based on property insurance data, experts' knowledge, and tax records (FEMA 2012b). Enhancing Hazus-MH's default inventory is desirable for more realistic flood loss estimates, but compiling such a detailed data set for all of Illinois was beyond the scope of this study. In previous studies, Hazus-MH using the default inventory has been shown to be capable of producing reasonable flood exposure and flood loss estimates for coarse regional assessments (Scawthorn et al. 2006; Remo et al. 2012).

2.3 Flood-vulnerability assessment

To capture both the economic and social aspects of flood vulnerability, we used Hazus-MH to quantify potential flood losses within the FEMA-mapped SFHAs and developed social vulnerability scores for the census block, jurisdictional, and county spatial scales. Screening of the relative flood vulnerability in Illinois census blocks, incorporated jurisdictions, and counties was accomplished by developing a FVI. The FVI developed for this study is comprised of both a flood loss index (FLI) to quantify the relative economic losses (flood losses normalized to estimate exposure) and a social vulnerability index to assess the relative socioeconomic condition of floodplain communities in order to evaluate their potential ability to recover from a large damaging flood. The general procedure for developing the FVI is shown in Fig. 2 and described in detail below.

2.3.1 Flood loss modeling

The flood loss modeling in this study was performed using Hazus-MH version 2.1, service pack 3. Hazus-MH is a geographic information system (GIS)-based risk assessment tool designed by FEMA in collaboration with the National Institute of Building Sciences. The Hazus-MH flood module assesses the impact of flooding based on FEMA and US Army Corps of Engineers (USACE) damage relationships. These relationships are applied to Hazus-MH infrastructure inventories to estimate losses for different flood scenarios (Schneider and Schauer 2006).

Hazus-MH allows modelers either to choose default settings ("Level 1" analysis) or else to provide increasingly detailed user-supplied data to improve the resolution and

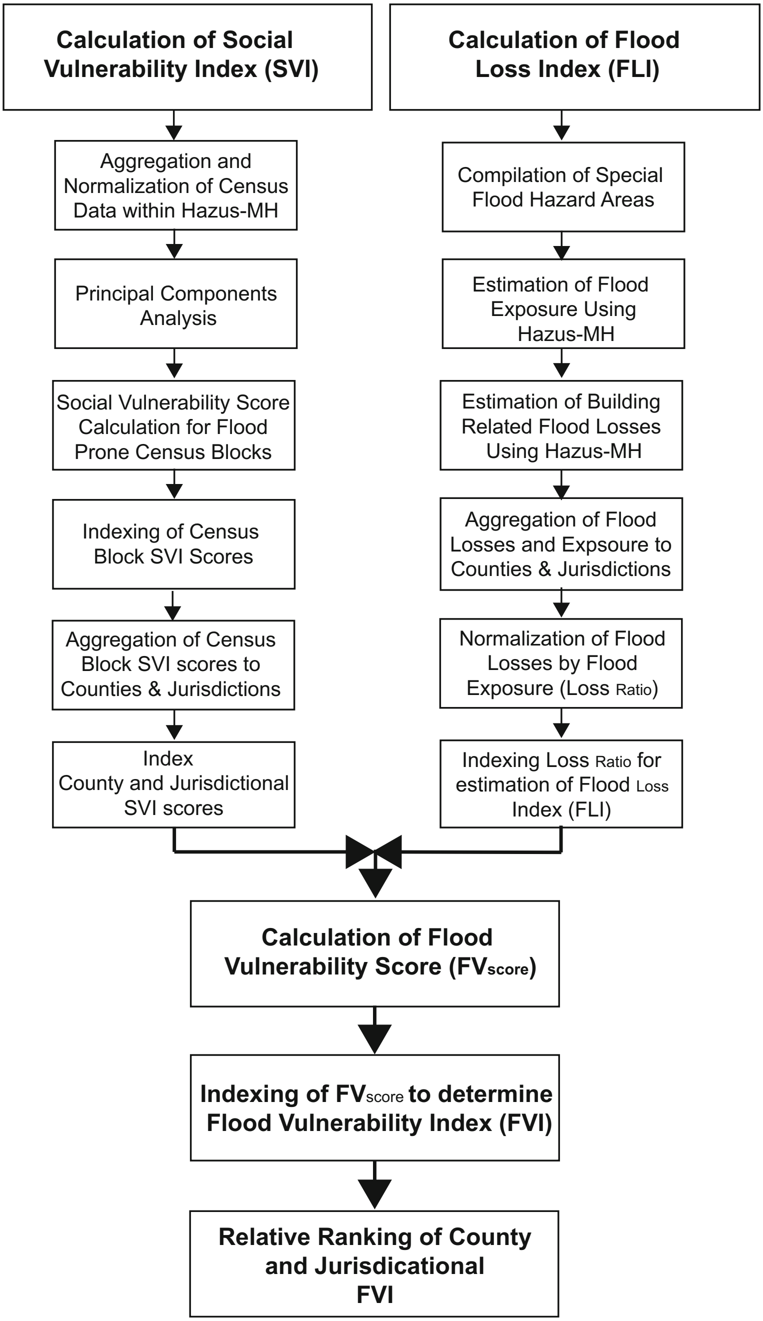

Fig. 2 Overview of the flood-vulnerability assessment framework

accuracy of loss estimates (“Level 2” or “Level 3” analyses). We performed Level 1 Hazus-MH flood loss analysis for the entire state of Illinois. Updating building and infrastructure data or performing hydrologic and hydraulic modeling to create a more detailed flood hazard assessment was beyond the scope of this project. For each county, we estimated the potential flood losses within the designated SFHA (>1 % annual chance flood). For floodplain areas protected by FEMA-accredited levees, we assumed the levees performed as designed [i.e., no levee failure(s)]. It is important to point out that the flood scenario modeled here does not represent a realistic flood. It is highly unlikely that all rivers and streams in a given jurisdiction, let alone the whole state of Illinois, would simultaneously experience the 1 % ("100-year") flood. Hence, the flood losses presented here should be viewed as a standardized estimate of building-related flood losses, which allows for comparison of relative riverine flood hazard between Illinois's jurisdictions.

Hazus-MH requires the construction of a flood depth grid (FDG) to define the area of potential flood inundation and flood depth to determine damages using depth–damage curves. To construct the FDGs here, we employed Hazus-MH's enhanced quick look (EQL) tool. The data required to generate a FDG using the EQL tool are a polygon layer representing the extent of the flood, in this case FEMA's SFHA, and a DEM representing floodplain topography. In each county, we used the DFIRM or digitized FIRM map to delineate the SFHA boundary. A 1/3-arc-second ($\sim$10 m) DEM was used to depict floodplain topography. Hazus-MH default aggregate GBS data were used for the loss estimation. The aggregated GBS uses building valuations from Dun and Bradstreet (2006) R.S. Means values. Consequently, all flood loss and flood exposure estimations presented in this paper are in 2006 dollars.

Hazus-MH flood losses reported in this study are for building-related losses only. Building-related losses include building damages, building inventory damages, and commercial inventory damages. These building-related flood loss estimates do not include damage to infrastructure (i.e., roads, bridges, and utilities), agricultural losses, or indirect economic losses (i.e., loss of business or industrial production). In addition, these flood loss and exposure estimates are based on full replacement cost (i.e., the estimated cost to replace the damaged portion of a building). Hence, the resulting flood loss estimates may be significantly higher than insured losses or loss estimates calculated using property assessment data. Insured losses and loss estimates using assessor data commonly use fair market values, which include depreciation of building values after initial construction.

2.3.2 *Social vulnerability assessment*

A community's wealth, race, class, and sociopolitical structures can influence the ability of a community to recover from a flood disaster, and geographic variations in these characteristics can be used to construct place-based metrics of disaster vulnerability (Ngo 2001; Tierney 2006; Burton and Cutter 2008; Cutter et al. 2013). The goal of this study was to develop a SVI informed by the social vulnerability literature (e.g., Cutter et al. 2003, 2013; Burton and Cutter 2008; Cutter 2010; Wood et al. 2010) and implemented using the socioeconomic data available within Hazus-MH.

To assess differences in socioeconomic factors among Illinois flood-prone jurisdictions, we developed a SVI using a mainly inductive modeling approach, employing socioeconomic data derived from the 2000 US Census and included within Hazus-MH (v 2.1). For the census blocks in Illinois which were at least partially located in the floodplain, we identified 27 vulnerability-relevant demographic parameters available within Hazus-MH from which to develop a SVI. We limited ourselves to these demographic parameters because they were readily available at a common spatial scale and covered the major vulnerability indicator categories (age, race, and wealth). To develop a relative SVI, we first consolidate the age, race, and wealth parameters. For this consolidation, we summed the number of persons under the age of 16 and over the age of 65 to create a single age parameter for each census block. We next consolidated six race classes into two race category parameters, white and nonwhite. The nonwhite race parameter was the sum of the number of Asian, Hispanic, Pacific Islander, Native American, and persons of other races (other than white) in each census block. The white race parameter was the sum of the number of white persons in each census bock. The household income levels (wealth parameter) were consolidated from nine to five categories. Next, we normalized the age, race, and general occupation parameters by total population within the census block (number of persons/total number of persons per census block). The income and housing parameters were normalized to the total number of households within a census block (number of households/total number of households per census block; see Table 1).

We next employed a principal components analysis (PCA) using the remaining 16 socioeconomic parameters to develop a smaller set of uncorrelated latent factors using SPSS (v19). Of the 16 parameters included in the PCA, eight explained 78.6 % of the variance within the assessed parameters. We selected these parameters (principle components) using a modified version of the "Kaiser's Rule" (Jolliffe 2002). The principle components with ratios exceeding 0.7 [a component's eigenvalue divided by the average eigenvalue (amount of joint variance)] were retained (Table 2; Wilks 2006).

The formulation of our SVI began with evaluating the eight socioeconomic parameters retained from the PCA (Table 2). Based on a review of the social vulnerability literature, directionality (positive for increasing and negative for decreasing social vulnerability) was assigned to each parameter. Elderly, youth, nonwhite race, and low income were associated positively with social vulnerability. High income and white race were associated negatively with social vulnerability (Cutter et al. 2003; Wood et al. 2010). For household income, we selected \$40,000 as the break between positive and negative directionality, because the household poverty income level for most family sizes in Illinois is ≤\$40,000 (US Census 2014).

The first step in the SVI formulation was to calculate the social vulnerability score (SV_{score}) for each census block in which a portion of the block was located within the SFHA:

$$SV_{Score} = \frac{\mathrm{pp1} + \mathrm{pp2} + \cdots \mathrm{var}x}{\text{number of parameters}} - \frac{\mathrm{np1} + \mathrm{np2} + \cdots \mathrm{var}x}{\text{number of parameters}} \quad (2)$$

where pp are the positive social vulnerability parameters and np are the negative social vulnerability parameters. Next, the general indexing formula (Wu et al. 2002; Karmakar et al. 2010) was applied to the SV_{scores} to calculate the SVI. In this formulation, VI_i is the respective vulnerability index and the index I_i corresponding to the SV_{score} for ith census block is calculated using the following equation, which normalizes the SV_{score} from 0.0 to 1.0:

$$VI_i = \frac{I_i - I_{min}}{I_{max} - I_{min}} \quad (3)$$

where I_{min} and I_{max} are the minimum and maximum SV_{score} and I_i is the SV_{score} for the ith block.

To assess the relative importance of each of the eight socioeconomic parameters in the formulation of the SVI, a sensitivity assessment was performed by withholding one of the parameters and comparing the result to the complete SVI formulation. The average of the percent difference between the complete SVI formulation and the SVI with a parameter

Table 1 The 27 socioeconomic vulnerability-relevant parameters from Hazus-MH's demographic database which were evaluated for use in the formulation of the SVI

Normalized parameter description	Consolidated parameters
Percentage of male population <16 years of age	Percent of population under 16 and greater than 65 years of age
Percentage of female population <16 years of age	
Percentage of male population >65 years of age	
Percentage of female population >65 years of age older	
Percentage of the population white	Percent white
Percentage of the population black	
Percentage of the population Asian	Percent nonwhite
Percentage of the population Hispanic	
Percentage of the population Pacific Islander	
Percentage of the population Native American	
Percentage of the population other race	
Percentage of the households with income of \$0–\$10K	Percentage of households earning \$0–\$20K
Percentage of the households with income of \$10–\$20K	
Percentage of the households with income of \$20–\$30K	Percentage of households earning \$20–\$40K
Percentage of the households with income of \$30–\$40K	
Percentage of the households with income of \$40–\$50K	Percentage of households earning \$40–\$60K
Percentage of the households with income of \$50–\$60K	
Percentage of the households with income of \$60–\$75K	Percentage of households earning \$60–\$100K
Percentage of the households with income of \$75–\$100K	
Percentage of the households with income over \$100K	Percentage of households earning >\$100K
Percentage of owner-occupied units	
Percentage of renter-occupied units	
Percentage of vacant homes	
Percentage of the population working in commercial industry	
Percentage of the population working in industrial industry	
Percentage of homes owned	
Percentage of vacant houses	
Percentage of homes rented	

The age, race, and occupation parameter classes were normalized to total population within a census block (number of persons/total number of persons in a census block), and the income and housing status parameters were normalized to the total number of households within an census block (number of households/total number of households within a census block)

withheld was used to assess the parameters effect on the SVI score. This sensitivity assessment was performed at each geographic unit analyzed in this study (i.e., census block, jurisdiction, and county levels; Table 3).

2.3.3 Flood vulnerability index calculation

The FVI was calculated for each census block, jurisdiction, and county in Illinois using the following procedure. First, the flood exposure ($\mathrm{Flood}_{\mathrm{exposure}}$) and flood loss

Table 2 The results of the principal component analysis

Parameter	Component	Eigenvalue	Percent of variance explained
Percent under 16 years of age and percent over 65 years of age	**1**	**4.22**	**23.5**
Percent of nonwhite people	**2**	**2.08**	**11.6**
Percent of white people	**3**	**1.86**	**10.3**
Percent of households earning \$0–\$20K	**4**	**1.71**	**9.5**
Percent of households earning \$20–\$40K	**5**	**1.34**	**7.4**
Percent of households earning \$40–\$60K	**6**	**1.25**	**6.9**
Percent of households earning \$60–100K	**7**	**0.96**	**5.3**
Percent of households earning >\$100K	**8**	**0.74**	**4.1**
Explained variance			**78.6**
Percent households owned	9	0.66	3.9
Percent household rented	10	0.65	3.8
Percentage of vacant homes	11	0.55	3.1
Percentage of vacant houses	12	0.45	2.6
Percentage of the population working in industrial industry	13	0.41	2.4
Percentage of the population working in commercial industry	14	0.36	2.1
Percentage of owner-occupied units	15	0.33	1.9
Percentage of renter-occupied units	16	0.27	1.6
Total variance explained			100.0

Bold denotes parameters retained for formulation of the SVI

($\mathrm{Flood}_{\mathrm{loss}}$) estimates for the SFHA in each geographic unit were calculated using Hazus-MH (see flood loss modeling section above for details). Next, a flood loss ratio ($\mathrm{Loss}_{\mathrm{ratio}}$) was calculated to normalize flood loss estimation parameter for each geographic unit analyzed.

$$\mathrm{Loss}_{\mathrm{ratio}} = \frac{\mathrm{Flood}_{\mathrm{loss}}}{\mathrm{Flood}_{\mathrm{exposure}}} \tag{4}$$

Hazus-MH does not calculate flood exposure and losses at jurisdictional scales. In order to ascribe the flood exposure and flood loss estimates to a particular jurisdiction, we used the spatial join tool within Esri's ArcMap (v10.2) GIS software. The join tool summed flood exposure and flood loss estimates from the census blocks that were either fully or partly contained within each jurisdiction's boundaries. In order to account for the overlap of census blocks outside a jurisdictional boundary, a floodplain area weighting factor ($\mathrm{FP}_{\mathrm{wf}}$) was calculated by dividing the total area of the jurisdiction ($\mathrm{JD}_{\mathrm{area}}$) by the SFHA within the jurisdiction ($\mathrm{FP}_{\mathrm{area}}$; Eq. 5). $\mathrm{FP}_{\mathrm{wf}}$ was then multiplied by the jurisdiction's loss ratio to calculate the weighted flood loss ratio ($W\mathrm{Loss}_{\mathrm{Ratio}}$; Eq. 6).

$$\mathrm{FP}_{\mathrm{wf}} = \frac{\mathrm{JD}_{\mathrm{area}}}{\mathrm{FP}_{\mathrm{area}}} \tag{5}$$

$$W\mathrm{Loss}_{\mathrm{Ratio}} = \mathrm{Loss}_{\mathrm{Ratio}} \times \mathrm{FP}_{\mathrm{wf}} \tag{6}$$

Table 3 The sensitivity assessment results for the social vulnerability index (SVI) at the census block, jurisdiction, and county scales

Spatial unit	Block			Jurisdiction			County		
SVI parameter withheld	Ave. SVI value	SD of SVI values	Percent difference relative to complete SVI formulation (%)	Ave. SVI value	SD of SVI values	Percent difference relative to complete SVI formulation (%)	Ave. SVI value	SD of SVI values	Percent difference relative to complete SVI formulation (%)
Complete formulation	−0.14	0.11	–	0.27	0.13	–	0.41	0.19	–
Percent <16 years of age and percent >65 years of age	−0.20	0.12	12.8	0.25	0.13	7.7	0.19	0.41	4.6
Percent of nonwhite people	−0.13	0.09	6.7	0.35	0.13	39.0	0.48	0.20	26.6
Percent of white people	0.07	0.07	25.5	0.34	0.14	35.6	0.48	0.20	27.2
Percent households earnings									
$0–$20K	−0.12	0.13	2.6	0.28	0.14	9.4	0.39	0.18	9.9
$20–$40K	−0.12	0.13	11.8	0.2	0.11	27.1	0.33	0.18	22.9
$40–$60K	−0.21	0.13	11.4	0.32	0.13	26.2	0.45	0.18	15.5
$60–100K	−0.21	0.13	19.8	0.26	0.12	9.6	0.33	0.18	21.4
>$100K	−0.22	0.13	21.3	0.29	0.11	21.8	0.35	0.19	21.7

The results show the percent difference between the SVI and the SVI formulation with one of the parameters removed. This assessment revealed the race parameters were the most sensitive model parameters across each geographic unit analyzed. For the block and county units, percent white people was the most sensitive parameter and, at the jurisdiction unit, percent nonwhite people was the most sensitive parameter. Between the age and wealth parameters, the wealth parameters tended to be more sensitive, in general, than the age parameter

To assess a county's or jurisdiction's social vulnerability, we averaged the SV_{score} within each of the flood-prone census blocks in a given jurisdiction using an averaging spatial join.

For the county-scale analysis, we aggregated the census block flood exposure, losses, and SV_{score} values to the county scale using a spatial join tool within ArcMap. A sum spatial join was used to aggregate the Hazus-MH flood exposure and flood loss estimates to the county. The flood loss ratio for each county was then calculated using Eq. 4. An average spatial join was then used to aggregate the flood-prone census block SV_{score} to the county.

Next, Eq. 3 was applied to the $Loss_{ratio}$ or $WLoss_{ratio}$ to calculate the flood loss index (FLI) for the respective geographic unit under consideration. Then, the FLI and SVI were added together to calculate a flood vulnerability score (FV_{Score}) for each block, jurisdiction, and county.

$$FV_{score} = FLI + SVI \tag{7}$$

The FV_{score} was index using Eq. 3 to generate the FVI, so each census block's, jurisdiction's, or county's flood vulnerability could be ranked.

3 Results

Of Illinois's 1367 incorporated jurisdictions, 899 jurisdictions included mapped SFHAs within their boundaries, and Hazus-MH flood loss modeling suggested that 895 of them would experience at least some flood losses if the 1 % chance annual flood were to occur.

3.1 Social vulnerability results

The social vulnerability assessment results suggest that Hudson Village, in McLean County, was one of the least socially vulnerable communities in Illinois. Venice City, located on the border between St. Clair and Madison Counties, was one of the most flood vulnerable jurisdictions in Illinois. The least and most socially vulnerable counties in Illinois were Kendall and Pulaski Counties, respectively (Supplemental Materials Appendices 1 and 2).

As outlined in Sect. 2, we tested the sensitivity of our SVI scores to incremental removal of each of the input parameters, and we completed this test for each of the spatial scales in the study (census blocks, jurisdictions, counties). This assessment revealed that the resulting SVI scores did change, in some cases substantially (up to 39 %). The race parameters were the most sensitive model parameters across each geographic unit analyzed. For the block and county units, percent white people was the most sensitive parameter and, at the jurisdiction unit, percent nonwhite people was the most sensitive parameter. Between the age and wealth parameters, the wealth parameters tended to be more sensitive, in general, than the age parameter (Table 3).

We also compared our county-level SVI to the widely cited Hazards and Vulnerability Research Institute's (HVRI) county-level social vulnerability index (SoVI) for the USA 2006–2010 (HVRI 2012). Despite the difference in the data employed and the formulations of the two indices, the SoVI and SVI scores were generally in agreement ($\sim$80 %) in their relative vulnerability classification [i.e., high (top 25 %), medium (middle 50 %), low (bottom 25 %)] for Illinois counties.

3.2 Physical flood hazard assessment

The building-related flood exposure within the full SFHA in Illinois was estimated here to be ~\$300 billion. The greatest concentration of this flood exposure was located in Cook and adjacent five counties: Dupage, Kane, Lake, McHenry, and Will. These counties contain the urban centers of the Chicago metropolitan area, and together they contain ~\$191 billion or nearly 64 % of the flood exposure within Illinois's SFHA. The analyses of flood exposure at the census block and jurisdictional scales also showed the greatest exposure totals concentrated in Cook County and the surrounding areas (Supplemental Materials Appendices 1 and 2).

Total building-related flood losses within the full SFHA in Illinois were estimated here to be ~\$18 billion. Aggregated county-level losses ranged from a minimum of \$2.7 million in Ford County up to \$3.3 billion in Cook County (Fig. 3). At the jurisdictional level, flood losses ranged from less than a \$1000 in Bondville up to \$942 million in the city of Chicago. As with the flood exposure estimates, the largest flood losses were concentrated in and around the city of Chicago (Supplemental Materials Appendices 1 and 2).

Flood loss ratios were calculated in order to normalize losses to total building infrastructure exposure. As Fig. 3 shows, the flood loss ratio provides a different perspective on flood risk than flood exposure and flood loss estimates. When normalized to total exposure (total infrastructure within the SFHA), Cook and surrounding counties have average (0.05) to slightly below average ratios. Unlike the raw flood exposure and flood loss values, the highest flood loss ratios were outside of the Chicago area. The counties with the largest

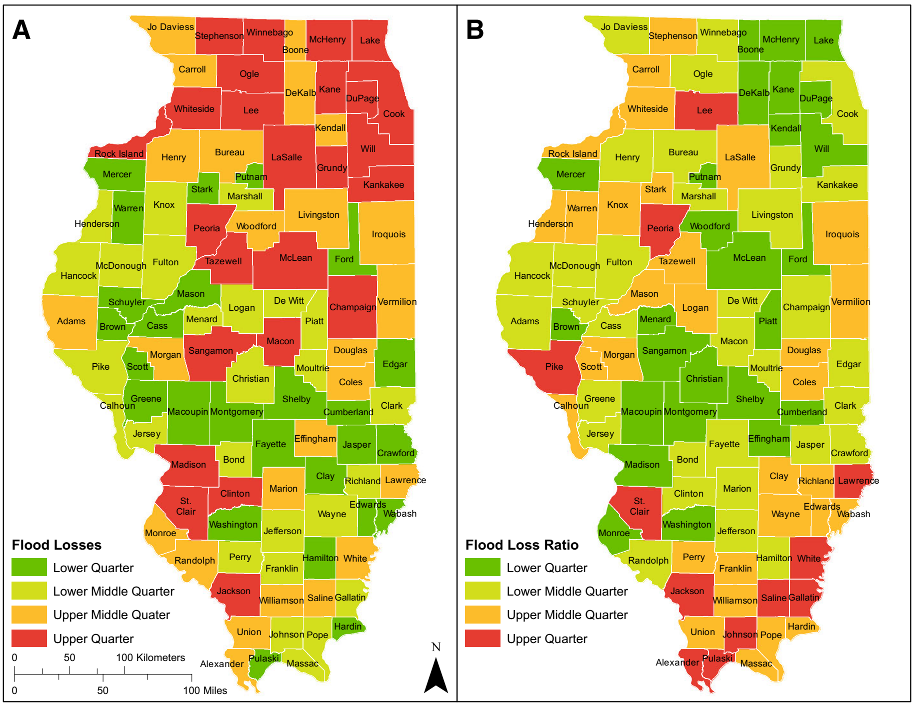

Fig. 3 Flood losses by Illinois county (**a**); flood loss ratio (flood losses/flood exposure) by county (**b**)

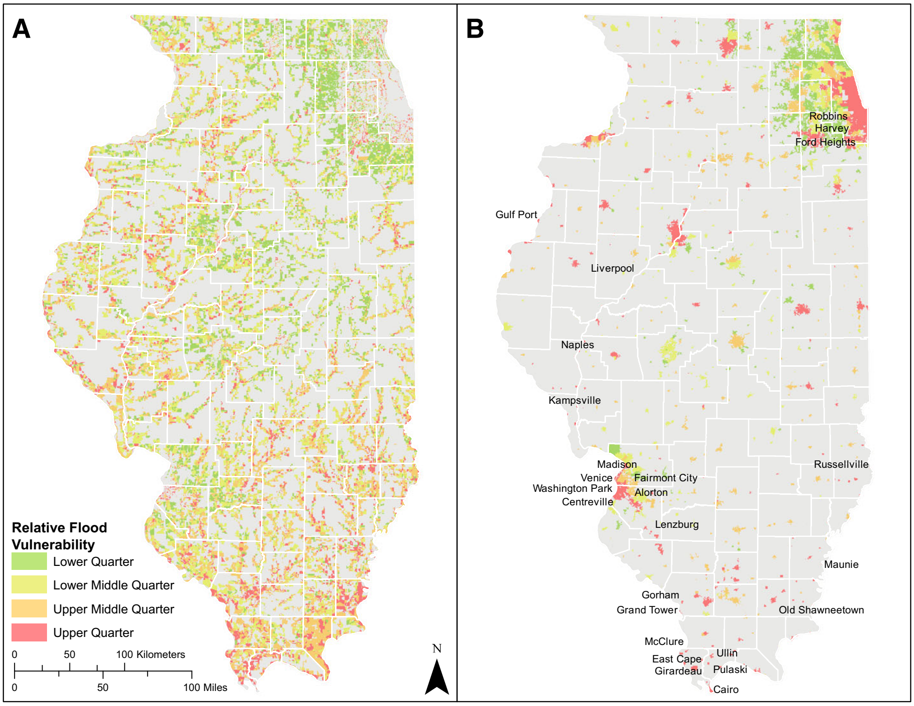

Fig. 4 Relative flood vulnerability by Illinois census block (**a**); relative flood vulnerability by Illinois incorporated jurisdiction (**b**). Jurisdictions with the highest flood vulnerability (top 1 %) are labeled

flood loss ratios are Lee, Peoria, Tazewell, White, and Pulaski Counties. These counties have large expanses of floodplain along larger rivers such as the Illinois, Rock, Green, Ohio, and Wabash. Jurisdictions with high flood loss ratios tend to be small river towns that lack large accredited levees or other structural protection (Fig. 4).

3.3 Flood vulnerability

The flood vulnerability analysis performed revealed nearly half (8530 km^2, or 46 %) of Illinois's SFHA (18,500 km^2) had low flood vulnerability (few people affected, with only minor flood losses). The flood vulnerability results here also suggest that Hudson Village, in Kane County, was one of the least flood vulnerable jurisdictions, and Madison City in St. Clair County was one of the most flood vulnerable jurisdiction in Illinois (Fig. 4). The least and most flood vulnerable counties in Illinois were Brown and Pulaski, respectively (Supplemental Materials Appendices 1 and 2).

4 Discussion

The FVI developed here is useful as an initial screening tool to identify areas of low, elevated, or high relative flood vulnerability. The flood-vulnerability assessment performed in this study provides a picture of relative flood vulnerability across the entire state of Illinois at three different scales of analysis (county, jurisdiction, and census block). Within

FEMA's SFHAs, the estimated building-related flood exposure is ~\$300 billion. Sixty-four percent (\$191 billion) of Illinois' building-related flood exposure is concentrated within the six counties which include and surround the city of Chicago. The building-related flood losses within the SFHA are estimated to be \$18.4 billion.

Unlike the flood losses, which are concentrated around Chicago, the communities in Illinois with the largest relative flood loss ratios (flood losses proportional to total floodplain exposure) were the rural jurisdictions located along Illinois's larger rivers. This suggests that the economic impacts related to riverine flooding would be more severe in these rural jurisdictions, relative to their total economic base, and it may be inferred, relative to the economic resources those communities could muster for flood recovery and reconstruction. This result is similar to the Cross (2001) finding that smaller communities often have a higher proportion of their populations vulnerable to natural hazards.

Three spatial scales of analysis were undertaken in this flood vulnerability analysis. The county and/or jurisdiction scales are the common spatial resolution for flood risk assessments performed in support of hazard mitigation plans (Frazier et al. 2013; Remo et al. 2013). In addition to these scales of flood risk assessment, we also evaluated flood vulnerability at the census block scale. While the results of the flood vulnerability analysis at these three scales mirrored one another (i.e., counties with high flood vulnerability had a substantial number of its jurisdictions and census blocks relatively ranked as highly vulnerability to flooding), the census block assessment revealed pockets (a small number of census blocks) of potential high flood vulnerability in all counties and a substantial number of jurisdictions with low-to-moderate flood vulnerability. This result suggests aggregation of flood risk or vulnerability assessments to the county or even the jurisdictional scale can potentially mask areas which have substantial flood vulnerability.

The jurisdictional flood vulnerability analyses revealed potential flood losses were a more substantial driver of flood vulnerability in rural floodplain communities than in urban jurisdictions. In urban jurisdictions such as Chicago and East St. Louis, social vulnerability was responsible for the relatively high FVI scores. This finding suggests that different mitigation strategies may have to be employed to reduce flood vulnerability in these communities. For example, in rural, relatively unprotected floodplain communities, partial or full community relocations may be required to substantially reduce flood vulnerability, while targeted buyouts may be sufficient to substantially reduce flood vulnerability in generally better protected urban floodplain communities.

4.1 Limitations of the flood-vulnerability assessment

In this and any similar studies, flood loss estimates and social vulnerability indicators are associated with broad uncertainty. Evaluation of modeling results is difficult, because external validation of regional flood loss models for hypothetical flood scenarios [i.e., specific return period(s)] is rarely possible, and social vulnerability has tangible symptoms, but no metric exists to directly measure it (Tate 2012). In the sections below, we discuss the specific sources of uncertainty in the flood-vulnerability assessment here.

4.1.1 Uncertainty in flood exposure and flood loss estimates

A variety of uncertainty and sensitivity analyses has been undertaken on the Hazus-MH flood loss model (e.g., URS Group 2007; Ding et al. 2008; Association of State Floodplain Managers [ASFPM] 2009; 2010a, b; Tate 2014). Tate (2014) showed that flood loss estimates can vary by up to a factor of three, and uncertainty generally increased with increased spatial resolution (FEMA 2012b). The primary sources of uncertainty in Hazus-MH flood exposure and flood loss estimates are related to: (1) the quantification of the flood hazard; (2) the use of the national-level infrastructure data for the building inventory; and (3) the assumption of an even distribution of inventory across each census block.

In this study, we chose to quantify the flood hazard using the SFHA because it was the only flood hazard definition readily available for the entire state of Illinois. National-level infrastructure data provided with Hazus-MH are coarse approximations of structure, contents, and inventory replacement values for a specific census block and maybe sustainably different than local values (FEMA 2012b). In addition, the Hazus-MH infrastructure data model assumes that buildings are evenly distributed throughout each census block which is attributed with being a substantial source of uncertainty. In Illinois, previous research has shown that building-related loss estimates can average up to 50 % greater than loss estimates using individual structure data with assessed values for regional-level assessments (Remo et al. 2012). Hence, the flood exposure and flood loss values presented in this study should be seen as coarse estimates useful for comparative purposes.

4.1.2 Uncertainty in the social vulnerability index

US Census of Population and Housing (2000) data contained within Hazus-MH were used to calculate the SVI in this study. Two main issues arise with using these data for such an analysis. The first is the age of the data. It has been approximately 15 years since these data were collected. Changes in populations and housing have changed over this period, increasing the uncertainty in the SVI values here. The second issue is that the US Census Bureau has long recognized chronic data collection error as a result of undercounts and overcounts (Clark and Moul 2003). The undercounts have historically been the greatest with racial and ethnic minorities, children, renters, and migrant farm workers, the homeless, and undocumented immigrants (Hannah 2001; Passel 2005).

Other sources of uncertainty in the social vulnerability analysis performed here include interaction between variables and compensability. The assumption of no interaction between variables in a social vulnerability analysis can be an issue because the magnitude of several vulnerability dimensions can vary relative to socioeconomic status (Phillips et al. 2005; Elliot and Pais 2006). Compensability occurs when high levels of one indicator mask a high value of another indicator. For example, the elderly in different circumstances can either be highly vulnerable or less vulnerable depending on income. In addition, some indicators will likely have greater significance than others depending on the hazard and its magnitude (Tate 2013).

4.2 Future flood-vulnerability assessment research

In this study, we developed a flood-vulnerability assessment framework to evaluate the spatial distribution of relative flood vulnerability across a large region and at multiple spatial scales. As indicated above, there are significant uncertainties and consequently room for improvement in the FVI developed here. The index was intended as a screening tool; it was not intended to be an absolute measure of flood vulnerability or mitigation potential. However, the modeling framework developed here allows for the use of improved data and the addition of assessment tools which could lead to improved modeling in the future that could better assess the mitigation potential of individual communities or areas.

Future improvements to the flood-vulnerability assessment performed here should begin with a global sensitivity and uncertainty analyses of the FVI construction and its associated models (indices). Such analyses would be useful in evaluating the effects of epistemic uncertainty in our flood-vulnerability assessment and limiting uncertainty in the FVI methodology (Hall et al. 2005; Tate 2014). Given the large spatial scale of this study and the consequent resource needs, no comprehensive global sensitivity and uncertainty analyses were attempted here. However, global sensitivity and uncertainty analyses of the individual components of our flood vulnerability model are currently a focus of ongoing research.

Other improvements to the flood-vulnerability assessment performed here could include a more comprehensive assessment of the flood hazard and improvements to the Hazus-MH general building stock. The addition of a realistic annualized flood loss assessment would increase the resolution of the flood hazard assessment. However, the hydrologic and hydraulic analyses required to realistically estimate annualized flood losses for the entire state of Illinois would be substantial undertakings. The Hazus-MH flood loss estimations could be improved by applying dasymetric mapping techniques (Sleeter 2008; Mennis 2009) or updating the GBS with local tax assessors' data. Applying dasymetric techniques to the census block-level data could potentially help reduce the uncertainty related to current assumption of uniform distribution of building stock. Updating the GBS with assessor data can improve measures of the number of buildings, building values, and other pertinent building parameters (i.e., square footage, number of stories, and foundation type; FEMA 2012b; Tate 2014).

Future studies should further investigate the spatial patterns of flood vulnerability. We only looked at broad spatial trends in flood vulnerability due to the limitations with the data and methods applied in this study. Future studies, with presumably higher fidelity of flood vulnerability, may have the potential to infer more information and insights about spatial relationships between the physical and socioeconomic divers of flood vulnerability.

Another consideration for future flood-vulnerability assessments is integrating future changes in flood risk. Executive Order (EO) 13690 issued by President Obama in January 2015 established a new Federal Flood Risk Management Standard (FFRMS). The new standard amends the previous EO 119988 issued in 1977 and aims to reduce the risk and cost of future flood disasters by ensuring that Federal investments in and affecting floodplains meet higher flood risk standards. The new standard requires agencies, when using federal funds, to use utilize best available, actionable hydrologic and hydraulic data and methods that integrate current and future changes in flooding based on climate science or substantially exceed the current (100-year flood level) standard (i.e., use the 500-year flood level or add more than 2 feet to the 100-year flood level).

5 Conclusions

The purpose of this flood-vulnerability assessment was to develop a reconnaissance tool to aid planners in screening for vulnerability over a large geographic region, so that resources can be focused on areas with the greatest need. We found that 46 % (8530 km^2) of Illinois's 18,500 km^2 SFHA had low flood vulnerability (i.e., few people affected, with little or no flood losses), reducing by ~half the area which Illinois planners may need to focus their mitigation efforts. The relative flood vulnerability across the three spatial scales evaluated in this study generally echoed each other (i.e., counties with high flood vulnerability had a substantial number of its jurisdictions and census blocks with high flood vulnerability). However, comparison of these analyses also revealed that counties and a substantial number of jurisdictions with moderate-to-low relative flood vulnerability often had pockets (one to a few census blocks) of high relative flood vulnerability. This suggests flood-vulnerability screening should be performed to at least the census block scale to ensure all areas with substantial flood vulnerability might be identified.

Jurisdictional flood loss ratios (flood losses proportional to total floodplain exposure) were generally largest in rural and relatively unprotected floodplain communities located along Illinois's large rivers. This suggests the economic impacts related to riverine flooding would be more severe in these rural jurisdictions, relative to their economic base. Given the relative severity of flooding impacts on these rural communities, the damages would likely exceed the economic resources these communities could amass for flood recovery and rebuilding.

The jurisdictional level analysis revealed that flood losses were a more substantial driver of flood vulnerability in the rural floodplain communities than in urban communities. In urban areas with high FVI scores, social vulnerability was responsible for the high flood vulnerability scores. This suggests different mitigation strategies or mitigation efforts may be required to reduce flood vulnerability in these respective community types.

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Compliance with ethical standards

Conflict of interest This research was carried out with support from the Illinois Emergency Management Agency and US National Science Foundation, award #1235317 (Infrastructure Management for Extreme Events). The contributing authors have no conflict of interest, including specific financial interests, relationships, or affiliations relevant to the subject matter or materials contained within this manuscript.

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