Creating a water risk index to improve community resilience

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Flood risk reduction is an existent discourse and agenda in policy and insurance. Existing approaches such as linking hydrological models to economic loss models may be highly inequitable between areas of different socio-economic vulnerability. To our knowledge, no one has tried to adapt the more advanced known heat risk theory by first informing flood risk with the socio-economic vulnerability, and then investigating the sensitivity of risk reduction policies to that flood risk. In this article, we demonstrate two methods to combine water hazard data with a derived water vulnerability index to characterize water risk. We then compare the costs of two potential government policies: buyout of the home versus funding for foundation elevation. We use the case study area of Pittsburgh, PA, which faces severe precipitation and riverine flooding hazards. We find that while small differences in characterizing flood risk can result in large differences between flood risk maps, the cost of the flood risk reduction policy is not sensitive to the method of representing the socio-economic vulnerability. This suggests that while validation of flood risk incorporating socio-economic data is needed, for some policies, policymakers can prioritize environmental justice with little to no additional cost.

1 Introduction

Floods are expensive. In 2018, the National Oceanic and Atmospheric Administration (NOAA) recorded 10 of 14 billion-dollar disasters as related to hurricanes, severe storm events, or flooding, with another two such events already recorded as of April 2019 [1]. Exacerbating this, many of the nation's most devastating floods are expected to increase in magnitude and frequency in the future [2, 3]. This threat prompts the research community to consider flood risk and associated risk reduction options.

Classically, risk is combination of a number of hazard, exposure, susceptibility, resilience, adaptive capacity, and vulnerability [4], and sometimes strictly defined as hazard $\times$ exposure $\times$ vulnerability [5, 6]. Given there are multiple plausible ways these could be combined, existing flood risk literature has attempted multiple approaches to calculate flood risk. As a result, some studies seek to reflect risk by combining physical vulnerability and exposure, such as using flood data to represent vulnerability due to inundation [7] or using a hazard model to calculate economic losses due to inundation [8–10]. Other studies seek to create decision aids showing personalized flood hazard or exposure probabilities, such as the NOAA's Sea Level Rise Viewer, Climate Central's Surging Seas [11–13]. However, this type of approach fails to consider the socio-economic components of the flood risk vulnerability and adaptation efforts.

Political economy literature suggests adaptation is social in nature [14], and thus vulnerability is more than just proximity to a hazard. Indeed, since many different definitions of vulnerability exist, incorporating a vulnerability metric into flood risk is not straightforward [15]. Consider that vulnerabilities vary between communities; some communities may have aging infrastructure, or an older/poorer population less able to absorb a flood, putting them at increased risk from the hazards.

Using combinations of deductive, hierarchical, or inductive reasoning, researchers have attempted to identify the physical, social, economic, and environmental factors that contribute to flood vulnerability [16–19]. We conducted a literature review to determine characteristics that could be used as a proxy for water vulnerability. Of the

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sources identified, about half of these focused on general vulnerability to environmental hazards, such as social vulnerability or vulnerability to heat hazards (e.g., [20, 21]). We identified five papers that specifically focused on flood vulnerability indices [22–26] and three additional papers eliciting vulnerability characteristics from local experts [16–18]. These studies find that households at risk to flooding often share several characteristics, called vulnerability factors, which can be unified into a vulnerability index through statistical methods [20]. The literature identifies five main classes of vulnerability indicators (economic, infrastructure, social, emergency management, and land use). Note that, while some of the flood vulnerability indices mentioned physical characteristics and attempted to reflect risk by directly using the percent of land within the floodway within the vulnerability index (e.g., [24]), the majority of these characteristics are not physical. Rather, they are spread across socioeconomic variables related to people, infrastructure, social ties, and ground features.

Clearly, there are wide disagreements on the "correct" way to reflect socio-economic vulnerability in flood risk characterizations. However, to our knowledge, no one has attempted to ask the bigger question: Does this matter? More specifically, is the cost for different policy alternatives sensitive to the different approaches to characterizing flood risk, or does the choice of vulnerability/risk index not really matter? A study on heat vulnerability indices suggests that the choice of index does not really affect policy choices on where to cite cooling centers [21]. It may be that this is similar for a flood vulnerability or risk index.

This article creates a method to combine water hazard data with a derived water vulnerability index to help a community understand their current and future water risk. We use the case study area of Pittsburgh, PA, USA, which faces severe precipitation and riverine flooding hazards. Building on present literature of factors influencing water vulnerability contextualized to the Pittsburgh region, we identify, quantify, and map the top factors impacting water vulnerability. We combine these with flood maps to identify the geospatial distribution of water risk. Then, we investigate whether costs for policy alternatives are sensitive to the calculated local variations in flood risk.

2 Method

We use the case study area of Pittsburgh, PA, which experiences precipitation, riverine flooding, and flash floods. Building on present literature of factors influencing water vulnerability contextualized to the Pittsburgh region, we identify, quantify, and map the top factors impacting water vulnerability. We combine these with flood maps to identify the geospatial distribution of water risk, and then calculate the cost of a government intervention to reduce risk. We then test the sensitivity of our results across two different approaches to mapping risk, two potential government policies to address risk (buyout versus foundation elevation), and two potential scenarios of prioritizing risk (prioritize riskiest versus no prioritization).

Table 1 Data used for the water vulnerability index calculation. While these metrics are included based on a literature review of other flood index methods, the majority of the data is census data. Data marked with an asterisk (*) are sourced from the Federal Emergency Management Agency, data marked with a double asterisk (**) are sourced from the City of Pittsburgh's Division of City Planning (2015), and all other data are sourced from the U.S. Census Bureau 2010.

Data	*Description*
Age, Elderly	% 65 years and older
Age, Youth	% younger than 14 years old
*Building Density***	Ratio area of buildings to area of land (square feet)
Educational Attainment	% without high school degree
*Flooding Risk**	% of land within floodway
Gender	% female
Housing, Rented	% of occupied houses rented
Housing, Vacancy	% of houses vacant
Race/ethnicity	% Non-white
Unemployment	% of labor force unemployed
Wealth	% with annual income below $25,000

2.1 Water vulnerability index calculation and data

It is clear that vulnerability is not simply the result of proximity to a body of water that exhibits creates flood hazards. Thus, researchers have identified physical, social, economic, and environmental factors that contribute to vulnerability.

Based on the literature review described in Section 1 [16–18, 22–26] and subsequent data limitations, we were able to collect data for 11 characteristics (mainly census data) that could be used as proxies for building vulnerability to flooding (see **Table 1**). Data collected include social and economic data from the U.S. Census Bureau (e.g., age, tenancy status, and education levels) [27] and infrastructure data from the City of Pittsburgh's Division of City Planning (e.g., structural properties of residences) [28]. All data were converted via Geographic Information System (GIS) to assignments at the 2010 census block group

level. Note that, while floodplain data were available, we consider this to be the hazard, not the vulnerability, and thus discuss its consideration in the next section.

Next, we created the water vulnerability index from the publicly available data via, first, a multicollinearity test, second, a factor analysis, and third, normalization. First, we note there are many datasets spatially distributed across the same region, some variables may be representing the same dynamics. To reduce "double counting," we conduct a multicollinearity test to identify and remove variables. To determine whether multicollinearity exists, we performed a multiple regression rotating through each variable as the new dependent variable, with the remaining variables as independent variables. This multiple regression tests for multicollinearity in groups of variables, which makes it more robust than a test comparing only two variables at a time.

After removing variables that fail the multicollinearity test, we performed a factor analysis using varimax rotation and standard statistical criteria (e.g., the fewest number of factors that explain 70% of the variance). This approach allows for dimension reduction by, first, identifying the ways in which certain indicator variables tend to clump together (providing the same information) and, second, collecting these indicator variables together into vulnerability factors that explain the majority of the variance in the data.

Finally, we converted units to even groups of standard deviations [29–32]. Here, for each factor, we calculated the value at each census block group, then divided the results into six equal increments of 1.0 standard deviation, and finally assigned each census block group an integer value ranging from 1 (more than two standard deviations less than the mean) to 6 (more than two standard deviations more than the mean). Finally, each block group's vulnerability index was mapped geospatially.

2.2 Combining the water vulnerability index with flood map hazard

Here, we investigated two potential models of combining hazard and vulnerability data in order to reflect risk. Both models considered only the subset of single-family homes listed in the publicly available Allegheny County tax record data [33] that was physically located in the Federal Emergency Management Agency floodplain [34, 35], or a total of 221 buildings. While this subset better enables the cost methodology in the next section, both models could be expanded to other types of housing.

In Model One, recall that risk is sometimes defined as hazard $\times$ exposure $\times$ vulnerability [5, 6]. Given binary floodplain maps (either in the 100-year floodplain or outside the 100-year floodplain), then risk would be a 1% chance per year (hazard) for the subset of homes within the floodplain (exposure) $\times$ the vulnerability map (vulnerability). We thus calculated the hazard $\times$ exposure by starting with the subset of single-family homes in City of Pittsburgh tax record data, geocoding the addresses, and using GIS to determine the overlap with the Federal Emergency Management Agency (FEMA) floodplain map. We then assigned each exposed house to a vulnerability score based on its census block group.

In Model Two, recall that some of the flood vulnerability indices mentioned physical characteristics had attempted to reflect risk by directly using the percent of land within the floodway within the vulnerability index (e.g., [24]). Here, we conducted a second vulnerability index calculation with the additional input dataset of the percent of land within the floodplain for each census block group. We then assigned the vulnerability to the subset of single-family homes listed in the Allegheny County tax record data that were physically located in the FEMA floodplain.

While these models are just two of the multiple approaches to risk that might be used, they provide a first look at investigating the sensitivity of policy recommendations to different water risk analysis approaches.

2.3 Cost analysis

Next, we investigated the sensitivity of costs for different water risk policies to the different water risk models. There are many different options a local, state, or federal government actor could undertake to reduce water risk, ranging from community-wide efforts to efforts focused on specific homes (e.g., [34, 36, 37]). To understand the sensitivity of results to different policies, we considered two existing policy alternatives that might be employed to support a single-family home: first, a government buyout of the house at the fair market value listed in the tax record data (buyout) and, second, funding to elevate the building out of the floodplain (foundation elevation).

To provide a comparable analysis, we assumed a few items were consistent for each policy alternative. First, we assumed that each policy alternative occurs over four years, with a government discount rate of 1.3% [38]. Next, the number of housing units processed per year was based on two scenarios. The first scenario (Scenario A) prioritized the riskiest units based on the risk score from either Model One or Model Two. More specifically, all units with scores less than or equal to 3 were processed in Year 1, between 3 and 3.5 in Year 2, between 3.5 and 4 in Year 3, and above 4 in Year 4. The second scenario (Scenario B) assumed no prioritization and, thus, an even distribution across all risks addressed each year.

For the buyout policy, we assumed the cost would be the market value of the building and the land as given in the Allegheny County tax record data.

For the elevation policy, we understand that elevation costs are a function of the height to be elevated and building characteristics (e.g., building size, condition of the building and foundation, and construction type) [37]. First, we

Table 2 Multiplicative factors for calculating the cost of the elevation as a function of building.

Elements	*Foundation Elevation*
Adj. Factor - Building Size	0.75 if < 2750 sqft.;
	1 if between and including 2750 and 4230 sqft.;
	1.25 if above 4230 sqft.
Adj. Factor - Building Status	0.9 if < 2;
	1 if between and including 2 and 4;
	1.1 if > 4
Adj. Factor - Construction Type	0.8 if Frame;
	1 if Frame with Masonry;
	1.2 if Masonry
Adj. Factor - Foundation Status	0.75 if A, 0.8 if B+,
	0.85 if B, 0.9 if B-,
	0.95 if C+, 1 if C,
	1.05 if C-, 1.1 if D+
	1.15 if D, 1.2 if D-
Adj. Factor - Elevation Method	1.2 for all units, i.e. assume the most expensive choice of elevating by one story due to lack of data on elevation height.

calculated a baseline cost by averaging over contractor estimates for the national average to elevate a house (assuming the foundation does not need rebuilt) [39, 40], yielding a national average baseline cost of $5,800. We then applied five multiplicative adjustment factors to adjust the cost for each specific building as described in the tax record data. Each factor was guided by FEMA documentation [37], and **Table 2** describes the resulting multiplicative factors applied. First, we considered building size (the square footage for each floor) and applied a multiplicative factor of –25% to +25% across quartiles visible in the data. Next, we considered the building status describing the overall condition of the data (with the smaller the number, the better the condition) and applied a –10% to +10% range. Third, we considered the construction type (frame, masonry frame, or masonry) and applied a range of –20% to +20% (assuming brick aligned with masonry). Next, we considered the foundation status ranging from "A" as best to "D–" as worst and applied ± 5% for each level above or below the midpoint "C." Finally, we assumed all buildings would be elevated one story, thus allowing for the new ground floor to be purposed into a garage or other storage space, which we assumed would add a +20% charge over baseline. Other factors that may affect the project cost including the number of floors, foundation type, time to

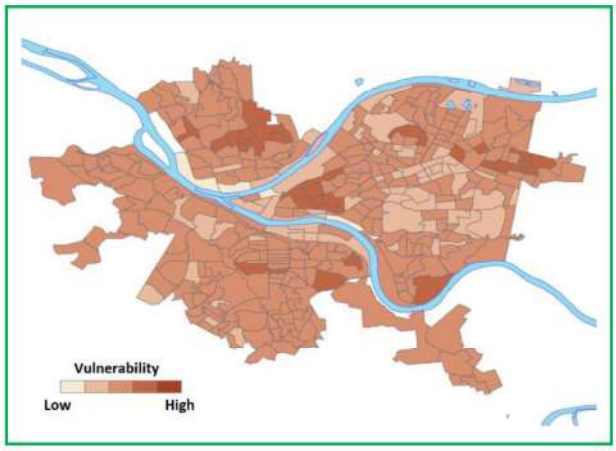

Figure 1

Water vulnerability index for Pittsburgh, PA. Light (dark) red means low (high) vulnerability on a scale of 1 to 6.

finish, labor costs, liability/insurance costs, landscaping costs, and other miscellaneous costs are also considered for this analysis. However, due to the lack of data on these factors, we assumed no adjustment to the baseline cost.

Given these assumptions, we then conducted a net present value (NPV) analysis for each policy alternative. We then conducted a sensitivity analysis across the input variables of discount rate (testing 1.3% to 4.5%) and the values in Table 2.

3 Results

3.1 Water vulnerability index

Figure 1 shows the resulting water vulnerability index, with the full factor analysis plots and resulting scree plots given in Appendix A. In the rotated matrix, we find two factors have an eigenvalue of more than one and explain more than 76% of the variance. The first factor appears to reflect wealth (percent of those below the poverty line), with the second reflecting education (percent of those without a high school education).

We find that the resulting flood vulnerability index shows that the areas near the rivers show low vulnerability, whereas the more vulnerable regions (e.g., Hill District, East Liberty/Larimer/ Homewood, Perry Hills, and Southside Slopes) are outside the floodway. This may be a reflection of Pittsburgh's efforts to move vulnerable communities outside of the floodway and away from flood hazards, such as efforts to repurpose the point where the three rivers meet into Point State Park.

3.2 Combining the water vulnerability index with flood map hazard

Figure 2 shows the resulting risk scores assigned as a function of census block groups for model one and model

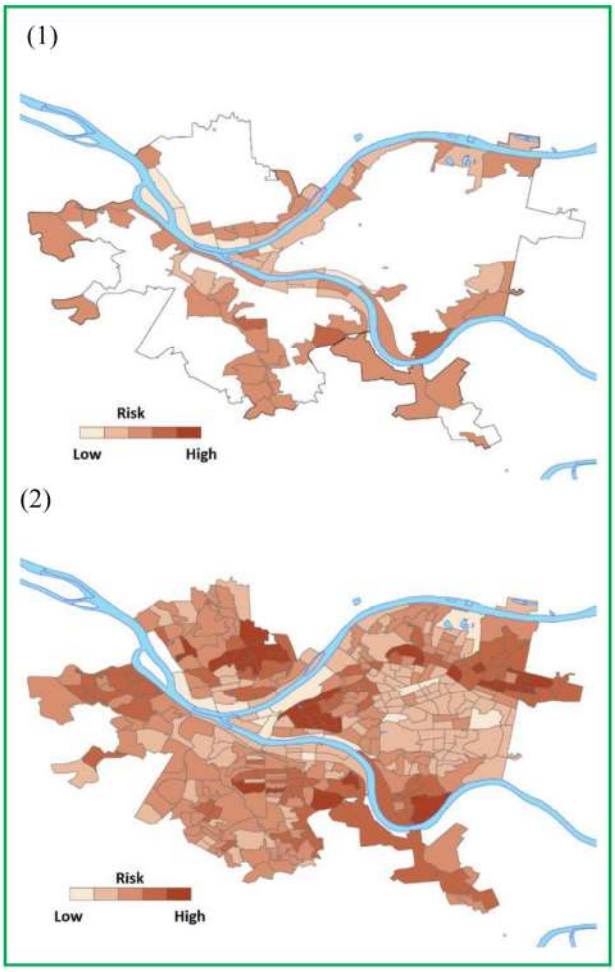

Figure 2

Water risk models for Pittsburgh, PA's floodway. Light (dark) red means low (high) risk on a scale of 1 to 6. 1) The top figure reflects Model One, and thus shows the subset of Figure 1 census block groups that are within the FEMA floodplain map (and thus which scores are assigned to the single family homes). 2) The bottom figure shows the full factor analysis results for Model Two.

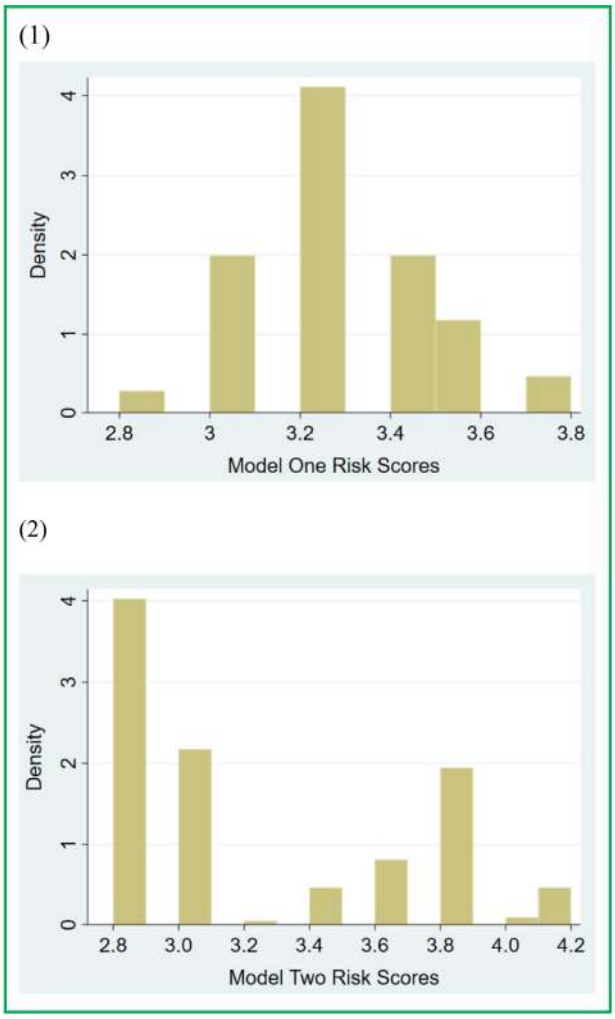

Figure 3

Histograms of risk scores assigned to single-family homes for 1) Model One (top) and 2) Model Two (bottom).

two (with the factor analysis and scree plot for Model Two given in Appendix A). At first glance, it appears that the risk scores assigned to the census block groups intersecting the floodplain (the subset of census block groups in Figure 2.1) seem similar. However, recall that we then assigned these risk scores to the single-family houses. **Figure 3** shows a histogram of the assigned scores, showing a marked difference between the models. Specifically, Model One (Figure 3.1) shows a histogram similar to a normal distribution, with most of the houses assigned a middle risk score. Conversely, Model Two (Figure 3.2) creates a histogram where the risk scores are clumped at low and high extremes. It is unclear which of these results are "more correct." This marked difference suggests that the decision maker's approach to floodplain management may result in very different outcomes if the policy choice is a strong function of risk.

3.3 Cost analysis

For Scenario One (prioritizing by risk), the NPV of the buyout was \$39.4 million for Model One and \$39.8 million for Model Two, and the NPV of foundation elevation was \$1.27 million using either Model One or Model Two. This suggests that when considering policies meant to address all houses at risk, the choice of policy intervention outweighs (by several orders of magnitudes) the differences between the two vulnerability models.

For Scenario Two (no particular prioritization for risk), the total NPV for both Model One and Model Two of buyout was \$39.2 million, whereas the NPV of cost of

foundation elevation is estimated to be $1.26 million. Taken in consideration with Scenario One, this further suggests that if all at risk properties are to be addressed over a 4-year period, choosing to prioritize more vulnerable properties does not greatly alter costs. That is, even though the quality and value of the housing stock may be inferior in cases of lower-income households, a decision maker could prioritize those properties with a minor effect on total costs.

A sensitivity analysis was conducted to test the effect on the foundation elevation project cost NPV from each of the five key adjustment factors listed above. We find that our results are most sensitive to the assumption of elevation height (±16%), followed by the assumption of construction type (±12%). Full results are given in Appendix B.

4 Conclusion

This study characterized two different types of approaches to incorporating socio-economic vulnerability into flood risk. We create several novel datasets (e.g., vulnerability and risk indices) and combine them in a novel way with tax record data to understand the performance of two flood risk reduction policies. We find that while the flood risk maps generally show higher risk near the three rivers of Pittsburgh, the resulting flood risk indices show different histograms of risk, suggesting that slight differences in approach to flood risk characterization can result in very different results. However, we then find that the cost of the two flood risk reduction policies considered (buyout and foundation elevation) is not sensitive to the method of representing the socio-economic vulnerability. This suggests that while validation of flood risk incorporating socio-economic data is needed, for some policies, policymakers can prioritize fair and equal treatment, or environmental justice (e.g., [41]), with little to no additional cost.

One limitation of this study is data availability. While not available for this study, data that could be collected include hazard data such as drainage and rain patterns to characterize flash flood and combined sewer overflow hazards, vulnerability data such as whether houses have floodproofing or not, and cost data such as the actual height required to elevate each house out of the base flood elevation level. Given a much larger dataset, the same factor analysis would be conducted again to determine which variables can explain greater variances in vulnerability, specifically as related to physical hazards such as location within a floodway. In addition, additional data and modeling could allow for investigation of other policy options. For example, one study has found that Pittsburgh residents may be willing to pay more on their utility bill for infrastructure that contains stormwater on site [42]. Another study found that the optimal strategy to elevate a house is a function of beliefs on how quickly uncertainty will be reduced [43]. Given improved local information on how green infrastructure could reduce the risk, this study could be extended to consider this type of policy alternative.

Then, a second limitation of this study is that we may not have picked "the right" set of flood vulnerability indices to consider. For example, an index that relies heavily on census data may be less applicable to a less populated rural area. Clearly, validation of the flood vulnerability/risk index would help ensure that the results are robust. Unfortunately, many existing indices hypothesize vulnerability based on the literature (e.g., [24; 26]) and/or subject matter expertise [16, 17], thus failing to validate the hypothesized vulnerabilities against actual damages [44]. Furthermore, some have noted that using a deductive, hierarchical, or inductive approach for choosing factors can greatly affect the resulting index [45]. For example, some approaches may lack proxies for risk characteristics [46], such as risk perception, coping strategies, and other local traits [47]. In other cases, it may be that resilience or social capital should be considered. As a result, some studies have tested vulnerability and risk indices against actual economic damages or deaths. Considering all types of hazard events, one study [48] finds that Peacock et al.'s Community Disaster Resilience Index [49] and Foster's Resilience Capacity Index [50] correlate significantly with economic damages and fatalities, whereas Cutter et al.'s Social Vulnerability Index [20] correlates significantly with presidential disaster declaration. Another study agrees, suggesting that after controlling for flood exposure, the Social Vulnerability Index may not predict damages and may instead predict housing assistance applicants [51]. However, both of these studies test general indices, as opposed to flood vulnerability or flood risk indices. This suggests that if a policy for flood risk reduction appears to be sensitive to the representation of socio-economic vulnerability, then more work is needed to understand and validate flood risk indices.

Appendix A: Factor analysis results

Tables A.1 and **A.2** and **Figures A.1** and **A.2** contain the full factor analysis results and resulting scree plot for this study.

Appendix B: Factor analysis results

Table B.1 contains the full results of the sensitivity analysis on the foundation elevation. Values are similar between choice of risk map (Model One and Model Two), with slight differences between whether more risky buildings are prioritized over others (Scenario A and Scenario B).

Table A.1 Factor analysis results (rotated component matrix) for water vulnerability index that does not include the floodplain (used in Model One). The rotation method was varimax with Kaiser normalization, and the rotation converged in eight iterations.

Characteristic	Component							
	1	2	3	4	5	6	7	8
Percent below poverty line	.805	.187	.238	.130	.137	.076	.180	-.102
Percent of buildings that are vacant	.125	-.007	.070	.941	-.012	.005	.165	-.034
Percent of buildings that are rented	.857	-.223	-.078	.035	-.146	.248	.027	.045
Percent with a high school degree or less	.102	.786	.009	.318	.146	.245	.211	.068
Percent unemployed	.167	.114	.163	.185	-.005	-.017	.942	-.053
Percent non-white	.511	.030	.653	.284	.122	-.068	.205	-.058
Percent older than 65 years	.000	.121	-.057	-.006	.971	.107	-.001	-.043
Percent younger than 14 years	-.003	.219	.841	-.028	-.143	.297	.106	-.095
Percent female	.239	.032	.202	.009	.133	.889	-.023	-.129
Building density (number per square feet)	.121	-.825	-.238	.248	-.052	.144	.018	.101

Table A.2 Factor analysis results (rotated component matrix) for water vulnerability index that includes the floodplain (used in Model Two). The rotation method was varimax with Kaiser normalization, and the rotation converged in eight iterations.

Characteristic	Component						
	1	2	3	4	5	6	7
Percent below poverty line	.809	.048	.191	-.006	.267	-.069	-.178
Percent of buildings that are vacant	.374	-.049	.149	.110	.879	-.024	.002
Percent of buildings that are rented	.591	-.339	.594	-.234	.154	-.123	.008
Percent with a high school degree or less	.203	.759	.319	.054	.280	.318	.094
Percent unemployed	.826	.186	.042	.292	.048	.171	.057
Percent non-white	.713	-.022	.049	.406	.324	.108	-.133
Percent older than 65 years	.057	.126	.044	.026	-.019	.968	-.112
Percent younger than 14 years	.289	.225	.225	.840	.098	.017	-.147
Percent female	.113	.031	.880	.308	.120	.103	-.170
Building density (number per square feet)	.017	-.841	.257	-.191	.237	.003	.172
Percent of land in the floodplain	-.109	-.069	-.121	-.118	-.003	-.110	.956

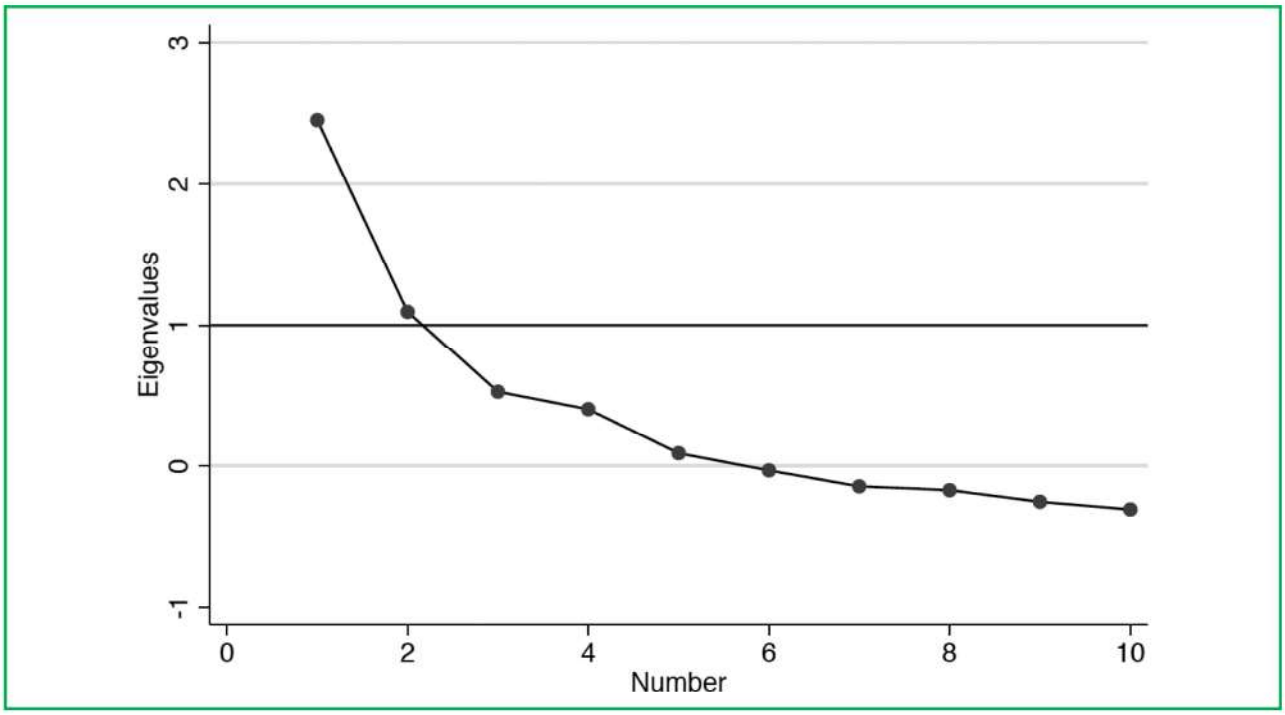

Figure A.1

Scree plot of factors for water vulnerability index that does not include the floodplain.

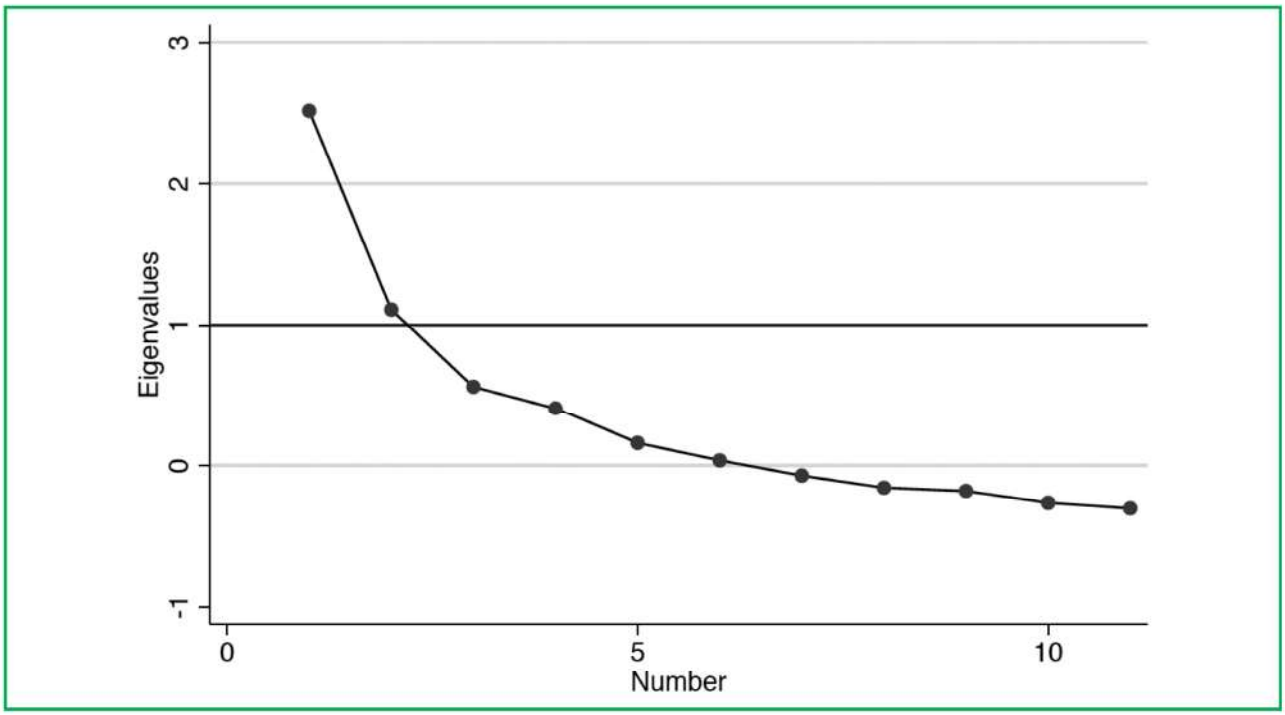

Figure A.2

Scree plot of factors for water vulnerability index that includes the floodplain. Note that while this is very similar to **Figure A.1**'s scree plot, there are differences.

Table B.1 Sensitivity analysis results

Sensitivity test	*Scenario A - Risk Prioritized (in $ millions)*	*% Change*	*Scenario B – No prioritization (in $ millions)*	*% Change*
All Adjustment Factors Unchanged	$1.27	-	$1.26	-
Controlling for 4.5% Discount Rate (Mortgage Interest)	$1.19	-6.00%	$1.17	-7.39%
Controlling for Building Size	$1.32	+4.18%	$1.31	+3.97%
Controlling for Building Status	$1.24	-1.80%	$1.24	-1.85%
Controlling for Construction Type	$1.42	+12.12%	$1.41	+12.11%
Controlling for Foundation Status	$1.27	-0.04%	$1.26	-0.11%
Controlling for Elevation Method	$1.06	-16.67%	$1.05	-16.67%

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